

Virtual Observatory and machine learning for the study of low-mass objects in photometric and spectroscopic surveys



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TESIS DOCTORAL

*Observatorio Virtual y aprendizaje automático para el estudio de objetos
de baja masa en cartografiados espectroscópicos y fotométricos*

*Virtual Observatory and machine learning for the study of low-mass
objects in photometric and spectroscopic surveys*

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

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ABSTRACT

Low-mass objects are ubiquitous in our Galaxy. Their low temperature provides them with complex atmospheres characterised by the presence of strong molecular absorption bands which, together with their faintness, have made their accurate characterisation a great challenge for astronomers over the last decades. M dwarfs account for 75% of the census of stars within 10 pc of the Sun, and their suitability as targets in the search for Earth-like planets has led many research groups to focus on the study of these objects, which is crucial for the understanding of the structure and kinematics of our Galaxy. Very low-mass stars and substellar objects with spectral types M7 or later, including the extended L, T, and Y spectral types, constitute the domain of ultracool dwarfs. The study of these objects, discovered definitively in 1995, is key for understanding the boundary between stellar and substellar objects and promises to experience a quantum leap thanks to the characteristics of new-generation surveys such as *Euclid* or LSST.

Data analysis in the field of observational astronomy has undergone a paradigm shift during the last decades driven by an exponential growth in the volume and complexity of available data. In this revolution, the Virtual Observatory has become a cornerstone providing a system that fosters data access and interoperability between astronomical archives around the world. In response to this growth in data complexity, the astronomical community has increasingly adopted machine and deep learning techniques for the development of scalable, automated solutions capable of analysing huge amounts of data in an efficient way.

This thesis explores the discovery and characterisation of M dwarfs and ultracool dwarfs, always using a data-driven approach supported by Virtual Observatory technologies and protocols. We rely on a variety of machine and deep learning techniques to develop flexible methodologies aimed at advancing our understanding of M dwarfs and ultracool dwarfs in the coming years. In this context, we use J-PLUS multi-filter photometry to enrich the ultracool dwarf census by providing a characterised catalogue of candidates. In addition, we consolidate a novel deep transfer learning methodology to determine atmospheric stellar parameters of M dwarfs from high-resolution spectra, and provide new estimations for a sample of M dwarfs observed by the CARMENES survey. We demonstrate that this methodology can also be extended to the ultracool dwarf domain by adapting it to low-resolution spectroscopic data.

We expect that the work carried out in this thesis will lay the foundations for future advances in the low-mass domain. We make available to the astronomical community all the catalogues and methodologies developed throughout the thesis, in the hope that future researchers will find them valuable resources to advance the knowledge of these faint, cool, low-mass objects that populate our Universe.

RESUMEN

Los objetos de baja masa son omnipresentes en nuestra Galaxia. Su baja temperatura les confiere atmósferas complejas dominadas por fuertes bandas moleculares de absorción que, junto con su baja luminosidad, han hecho de su caracterización precisa un gran reto para los astrónomos en las últimas décadas. Las enanas M representan el 75% del censo de estrellas a menos de 10 pc del Sol, y su idoneidad como objetivos en la búsqueda de planetas similares a la Tierra ha llevado a muchos grupos de investigación a centrarse en el estudio de estos objetos, crucial para la comprensión de la estructura y cinemática de nuestra Galaxia. Las estrellas de muy baja masa y los objetos subestelares con tipos espectrales M7 o posteriores, incluidos los tipos espectrales extendidos L, T e Y, constituyen el dominio de las enanas ultrafrías. El estudio de estos objetos, descubiertos de manera definitiva en 1995, es de vital importancia para comprender la frontera entre los objetos estelares y subestelares y promete experimentar un gran impulso gracias a las características de varias misiones futuras.

El análisis de datos en el campo de la astronomía observacional ha experimentado un cambio de paradigma durante las últimas décadas, impulsado por un crecimiento exponencial en el volumen y la complejidad de los datos disponibles. En esta revolución, el Observatorio Virtual se ha convertido en una piedra angular proporcionando un sistema que permite el acceso a los datos y la interoperabilidad entre archivos astronómicos de todo el mundo. En respuesta a esta creciente complejidad de los datos, la comunidad astronómica ha adoptado cada vez más técnicas de aprendizaje automático y profundo para el desarrollo de soluciones escalables y automatizadas, capaces de analizar enormes cantidades de datos de manera eficiente.

Esta tesis explora el descubrimiento y la caracterización de enanas M y enanas ultrafrías, utilizando siempre un enfoque orientado a los datos y apoyado en tecnologías y protocolos del Observatorio Virtual. Utilizamos una variedad de técnicas de aprendizaje automático y profundo para desarrollar metodologías flexibles destinadas a avanzar en nuestra comprensión de las enanas M y las enanas ultrafrías en los próximos años. En este contexto, utilizamos fotometría multifiltro de J-PLUS para enriquecer el censo de enanas ultrafrías proporcionando un catálogo caracterizado de candidatas. Además, consolidamos una novedosa metodología de aprendizaje profundo por transferencia para determinar parámetros estelares atmosféricos de enanas M a partir de espectros de alta resolución, y proporcionamos nuevas estimaciones de estos parámetros para una muestra de enanas M observadas por CARMENES. Demostramos que esta metodología también puede extenderse al dominio de las enanas ultrafrías adaptándola a datos espectroscópicos de baja resolución.

Esperamos que el trabajo realizado en esta tesis sienta las bases para futuros avances en el dominio de los objetos de baja masa. Ponemos a disposición de la comunidad astronómica todos los catálogos y metodologías desarrollados a lo largo de la tesis, con la esperanza de que futuros investigadores encuentren en ellos valiosos recursos para avanzar en el conocimiento de estos objetos débiles, fríos y de baja masa que pueblan nuestro Universo.

1.1 M DWARFS AND THE SUBSTELLAR REALM

1.1.1 M dwarfs...

For centuries, humans have gazed at the night sky, wondering what the bright objects up there might look like. Thanks to the technological advances in the last decades, which allow an ever more detailed exploration of our universe, we now know that most of our nearest neighbours were so faint that we could not see them with our naked eyes. Faint, cool, low-mass stars known as M dwarfs are by far the most common type of star in the Solar Neighbourhood (Henry et al., 1994; Reid et al., 2004; Bochanski et al., 2010; Reyl   et al., 2021; Kirkpatrick et al., 2024). As presented by Reyl   et al. (2021), the ubiquity of M dwarfs is overwhelming in our vicinity (see Figure 1.1), with three out of every four stars within 10 pc being spectroscopically classified as M dwarfs (see Table 2 in Henry and Jao, 2024), often with planets orbiting around them. This abundance, together with their remarkable lifespan of tens of billions of years (Adams and Laughlin, 1997; Laughlin et al., 1997), makes them a fundamental piece in the study of Galactic structure and kinematics (Chabrier, 2003, 2005; Bochanski et al., 2007; Caballero et al., 2008b; Ferguson et al., 2017; Cort  s-Contreras et al., 2024). Thus, an accurate characterisation of the M dwarf population, with masses ranging from $\sim 0.6 M_{\odot}$ to $\sim 0.1 M_{\odot}$ (Cifuentes, 2023) and located at the lower tail of the main sequence (see Figure 1.2), is key to the understanding of our Galaxy.

One of the most active lines of research in stellar astrophysics at international level is the detection and characterisation of extrasolar planets. Along with projects dedicated to the search of terrestrial exoplanets in orbits up to the habitable zone of Sun-like stars, such as PLATO (Rauer et al., 2014), several programs have been established with the goal of identifying potentially habitable planets orbiting M dwarfs. Notable examples include the Transiting Exoplanet Survey Satellite (TESS, Ricker et al., 2015), the Echelle Spectrograph for Rocky Exoplanet and Stable Spectroscopic Observations (ESPRESSO, Pepe et al., 2021) and its predecessor, the High-Accuracy Radial velocity Planet Searcher (HARPS, Mayor et al., 2003; Bonfils et al., 2013), or the Calar Alto high-Resolution search for M dwarfs with Exoearths with Near-infrared and optical Echelle Spectrographs (CARMENES, Quirrenbach et al., 2016; Quirrenbach et al., 2020). The small size and low luminosity of M dwarfs, compared to Sun-like stars, make it easier to detect close-in terrestrial planets in their habitable zones (Zechmeister et al., 2019; Kossakowski et al., 2023; Su  rez Mascare  o et al., 2023; Dreizler et al., 2024). Moreover, M dwarfs have established themselves in recent years as very suitable targets in the search for Earth-like planets (Dressing and Charbonneau, 2015; Kopparapu et al., 2017; Gillon et al., 2017; Reiners et al., 2018; Sabotta et al., 2021; Nagel et al., 2023a), with several studies confirming an elevated occurrence rate of Earth-like planets around M dwarfs (Gaidos et al., 2016; Mulders et al., 2021; Sabotta et al., 2021).

The precise determination of the physical parameters of planet-hosting stars is crucial to improve our understanding of planetary formation and evolution, which depends

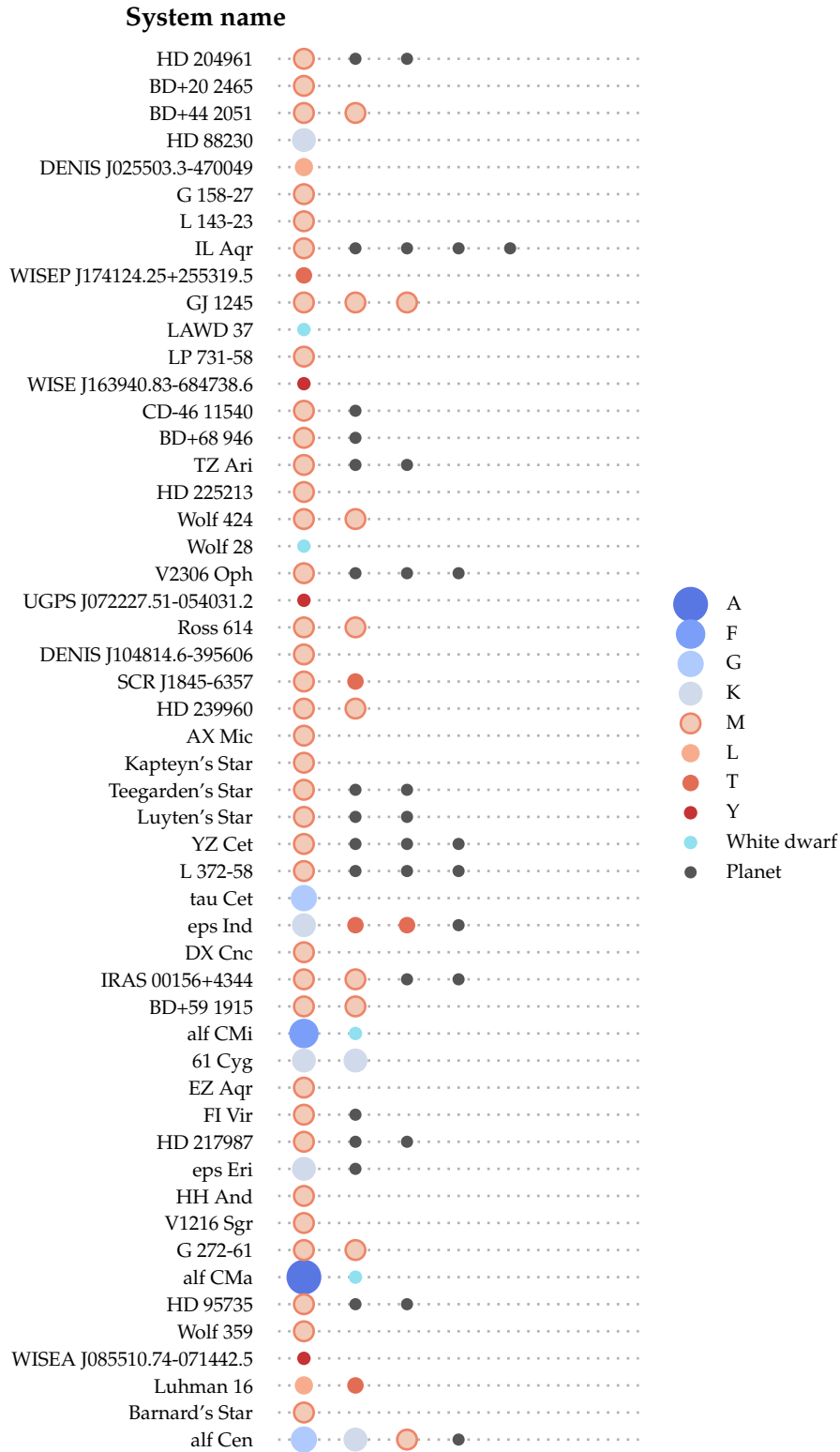


Figure 1.1: Sub-sample of the catalogue of stars, brown dwarfs, and exoplanets within 10 pc from the Sun provided by Reyl   et al. (2021). The Figure only shows a schematic representation of the systems within 5 pc for visualisation purposes, as it is sufficient to illustrate the ubiquity of M dwarfs in our vicinity.

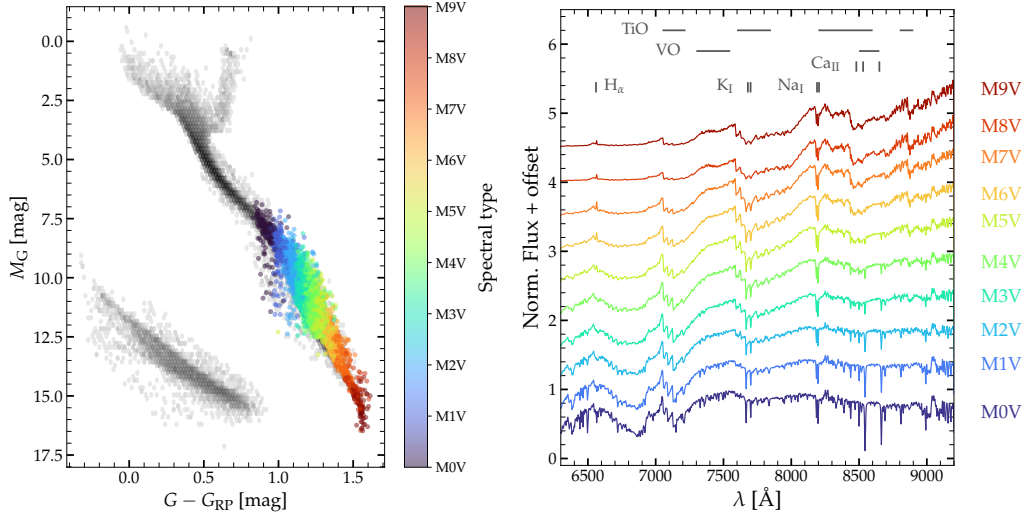


Figure 1.2: *Left panel:* Sample of M dwarfs spectroscopically classified by West et al. (2011), superimposed on a Hertzsprung-Russell diagram built with high-quality *Gaia* DR3 (Gaia Collaboration et al., 2023b) data. *Right panel:* M dwarf spectral sequence constructed with optical template spectra from Bochanski et al. (2007). Key spectral features are highlighted.

fundamentally on the thorough characterisation of their host stars (Souto et al., 2017; Cifuentes et al., 2020). However, well-established photometric and spectroscopic methods for determining the stellar atmospheric parameters of M dwarfs encounter several pitfalls, mainly due to the particular features of their cool atmospheres. The low temperatures, between ~ 2300 K and ~ 3900 K, of these atmospheres enable the formation of diatomic and triatomic molecules, with a spectral sequence characterised by the presence of strong molecular absorption bands, such as TiO and VO (Joy, 1947; Keenan and Schroeder, 1952; Boeshaar, 1976), as shown in Figure 1.2. Moreover, for late M-dwarfs (M5 or later), the outermost layers of the atmosphere are cool enough to form dust and clouds, which makes the modelling of these atmospheres and the consequent determination of their stellar parameters even more complex. This is further aggravated by the inherent faintness of M dwarfs, which makes it difficult to obtain high-S/N, high-resolution spectra, and their frequent manifestation of strong stellar activity. Despite these problems, numerous efforts have been devoted to estimating photospheric parameters in M dwarfs, including effective temperature, surface gravity, and metallicity. Several methods have proven successful in inferring these parameters, such as fitting synthetic spectra (Bayo et al., 2017; Passegger et al., 2018; Rajpurohit et al., 2018; Passegger et al., 2019; Schweitzer et al., 2019; Souto et al., 2020; Marfil et al., 2021; Sarmiento et al., 2021), pseudo-equivalent widths (Mann et al., 2013a, 2014; Neves et al., 2014; Khata et al., 2020; Almendros-Abad et al., 2022), spectral indices (Rojas-Ayala et al., 2010; Bayo et al., 2011; Rojas-Ayala et al., 2012; Khata et al., 2020), empirical calibrations (Casagrande et al., 2008; Neves et al., 2012; Rojas-Ayala et al., 2014; Rodríguez Martínez et al., 2019), interferometry (Boyajian et al., 2012; Rabus et al., 2019), and machine learning (Sarro et al., 2018; Antoniadis-Karnavas et al., 2020; Passegger et al., 2020; Li et al., 2021a; Bello-García et al., 2023; Mas-Buitrago et al., 2024; Rains et al., 2024).

The main difference between M dwarfs and other stellar objects is that their stellar properties change significantly from early to late types. Especially, for spectral types $\sim M3 - 4$ and later (masses below $0.35 M_\odot$; Chabrier and Baraffe, 1997), M dwarfs become fully convective and experience a critical transition in their structure and behaviour. In

this boundary, the radiative cores typical of earlier M dwarfs disappear and their interiors become fully convective, with energy transport dominated by convection throughout the stellar envelope (Delfosse et al., 1998; Reiners and Basri, 2009). As a result, a large fraction of low-mass stars, especially young, fast-rotating M dwarfs, are magnetically active, with a chromospheric activity often diagnosed by H α or Ca II H and K line emission (Cincunegui et al., 2007b; Ibañez Bustos et al., 2023). After reaching the main sequence, low-mass stars slowly spin-down due to the loss of angular momentum by stellar winds, thus undergoing a decrease in their magnetic activity over time (Yang et al., 2017; Davenport et al., 2019; Raetz et al., 2020) that may also be dependent on stellar metallicity (See et al., 2024). This abundant activity, combined with the proximity of the habitable zone of M dwarfs, makes exoplanets more exposed to energetic events related to stellar activity (Tilley et al., 2019; Günther et al., 2020; Chen et al., 2021), such as flares or coronal mass ejections, which are frequent in M dwarfs.

The faintness and low temperature of M dwarfs provide them with characteristics that push astronomers to the limit when it comes to accurately characterising them. But they are not the faintest. What do we find when we venture towards even lower masses? What separates our planet, the Earth, from the coolest stars?

1.1.2 ... and beyond

“WHAT distinguishes a star from a planet? Could we call Jupiter a failed star?” This is how Dr. Lorne Nelson began his article on page 102 of volume 377 of the journal *Nature* in September 1995. Twenty-seven pages below, Rebolo et al. (1995) reported the discovery of an object, in the young Pleiades star cluster, located on the boundary between the stars and the giant planets. Kumar (1963a,b) and Hayashi and Nakano (1963) had first postulated the existence of this substellar objects, termed as “brown dwarfs” in 1975 by Jill Tarter (Tarter, 2014), unable to maintain stable hydrogen (^1H) fusion in their interior due to their low mass. This substellar boundary is established for $\sim 0.072 M_{\odot}$ ($\sim 75 M_{\text{J}}$), depending on the models and the metallicity, beyond which the low mass makes objects unable to reach sufficient internal pressure and temperature to sustain thermonuclear processes of hydrogen-to-helium conversion. However, up to masses of $\sim 13 M_{\text{J}}$ (Chabrier and Baraffe, 2000) these substellar objects are massive enough to sustain deuterium fusion in their interiors at some point in their evolution, and this limit is often used to define the boundary between brown dwarfs and giant exoplanets.

Decades after they were first proposed theoretically, 1995 marked a turning point in the exploration of the substellar realm, with the first solid discoveries of brown dwarfs and exoplanets. First, Basri et al. (1995) presented evidence of lithium in PPl 15, identifying this object as a brown dwarf just below the substellar limit. This “lithium test”, or detection of lithium in the atmosphere, was of paramount importance for the detection of the first brown dwarfs and was first proposed by Rebolo et al. (1992) to distinguish between very low-mass stars and brown dwarfs close to the substellar boundary. Unlike very low-mass stars, objects with masses below $\sim 0.060 M_{\odot}$ (see Figure 2 in Chabrier and Baraffe, 2000) cannot reach the ^7Li burning temperature and preserve a significant amount of their original Li content, so the substellar nature of brown dwarfs can be confirmed by spectroscopic detection of the Li 670.8 nm resonance line. This is the test that Rebolo et al. (1996) used to finally confirm the brown dwarf nature of Teide 1 and Calar 3. In late 1995, at the same conference where the discovery of the first extrasolar planet was announced,

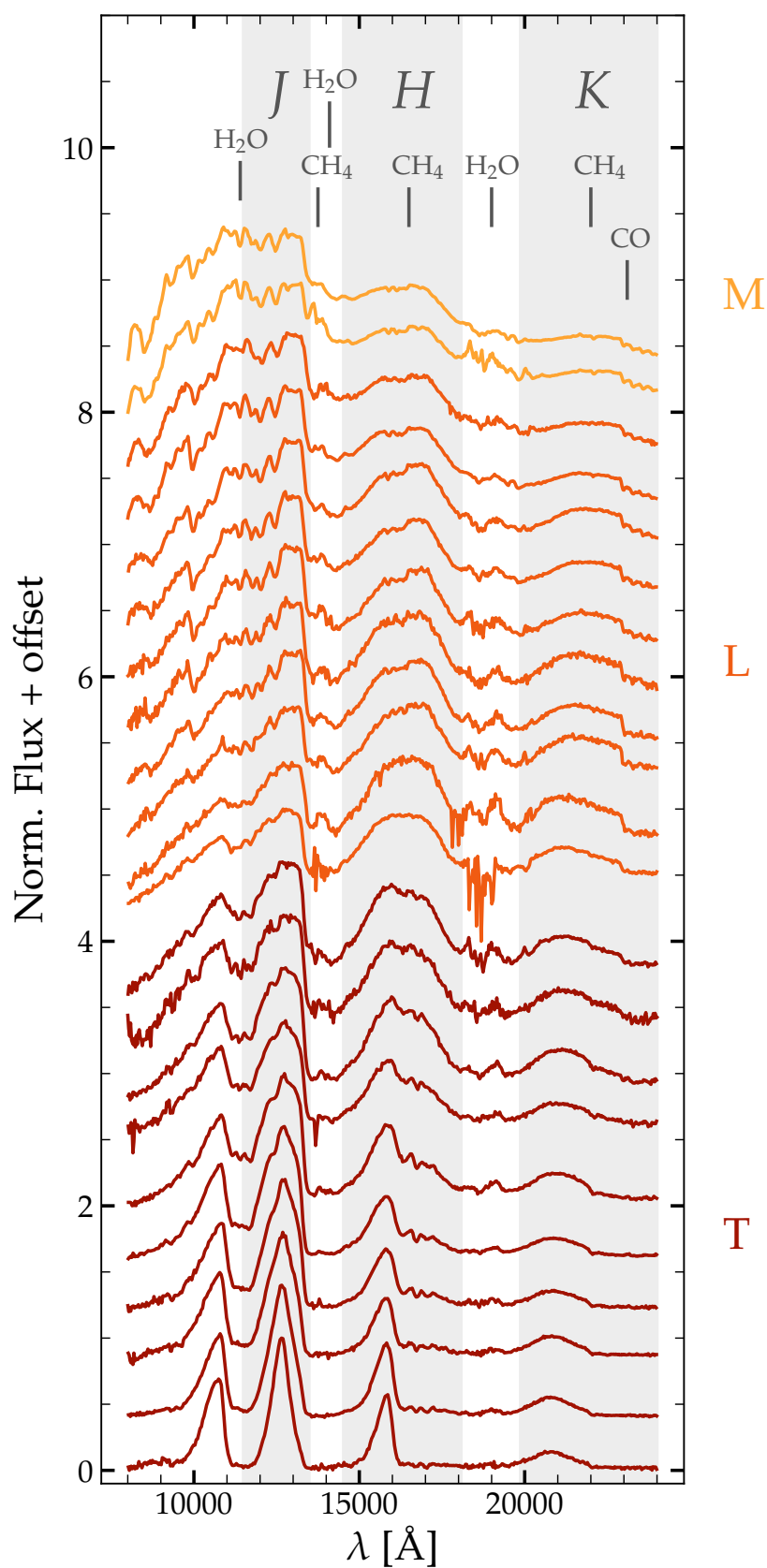


Figure 1.3: Near-infrared spectral sequence for ultracool dwarfs built using the standard spectra available in the SpeX Prism Library (Burgasser, 2014). The relevant molecular absorption bands discussed in the text are highlighted.

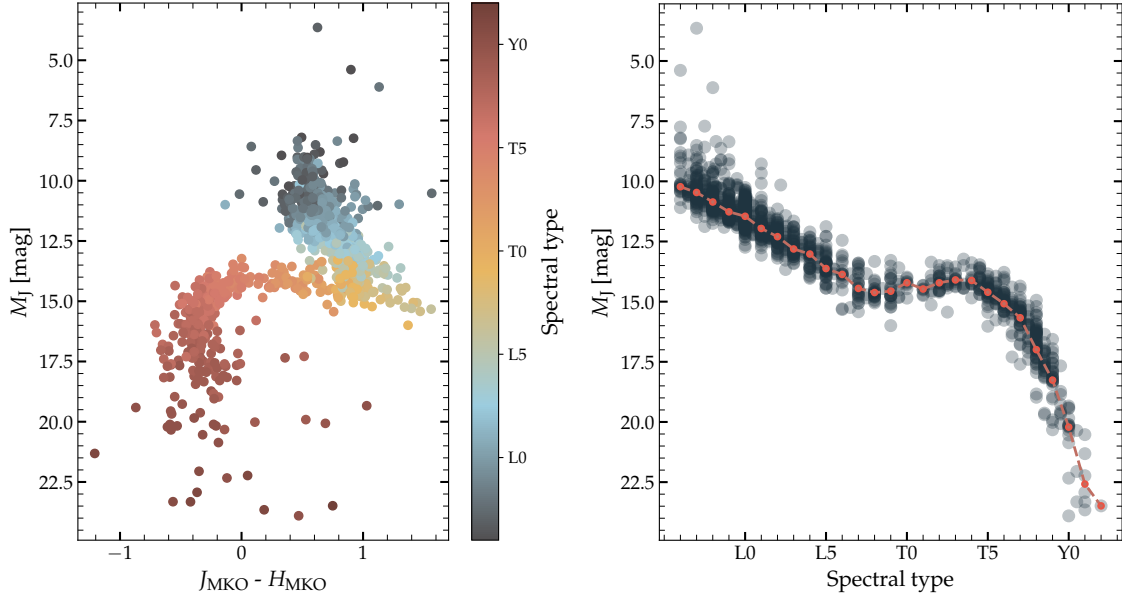


Figure 1.4: *Left panel:* M_J vs. $J - H$ colour-magnitude diagram, with the dots colour-coded by spectral type, of our sample of ultracool dwarfs. *Right panel:* Evolution of M_J with the spectral type for the same sample. The red dots indicate the median value for each of the spectral types. All values used in the figure have been taken from the UltracoolSheet catalogue.

the discovery of a cool brown dwarf (GJ 229B; Nakajima et al., 1995; Oppenheimer et al., 1995) was also reported.

The ultracool dwarf domain covers very low-mass stars and substellar objects with spectral types M7 or later (Kirkpatrick et al., 1997), including the extended L, T, and Y spectral types (Martín et al., 1997; Martín et al., 1999b; Kirkpatrick et al., 1999; Burgasser et al., 2006; Geballe et al., 2002; Burningham et al., 2008; Cushing et al., 2011). With effective temperatures of $T_{\text{eff}} \lesssim 2800$ K, the spectra of ultracool dwarfs are dominated by strong molecular absorption bands. The transition from late-M to L dwarfs (at about 2200 K) is characterised by the gradual disappearance of the TiO and VO oxide bands, the strengthening of H₂O and metal hydride (CrH, FeH, CaH) absorption bands, and an increasing steepness around the 6000 – 10000 Å interval (Kirkpatrick, 2000; Reid and Hawley, 2000; Geballe et al., 2002). Also, the neutral alkali metal absorption lines, especially Na I and K I, grow considerably by mid-L dwarfs in the optical. The beginning of the T dwarfs sequence, around 1300 K, is marked by the appearance of methane (CH₄) absorption in the near-infrared H and K bands, which strengthens along with H₂O absorption as the sequence evolves towards late-T spectral types. Due to the increasing depth of the CH₄ absorption bands, the flux in the H and K bands is reduced with respect to the J band (see Figure 1.3), and the near-infrared colours of T dwarfs become increasingly blue as compared to L dwarfs (Burgasser et al., 2002; Geballe et al., 2002). Finally, the transition to Y dwarfs, at about 500 K, is characterised by the presence of H₂O and ammonia (NH₃) photospheric clouds (Delorme et al., 2008; Cushing et al., 2011), in contrast to the CH₄ clouds typical of T dwarfs, and recent studies with the James Webb Space Telescope (JWST, Gardner et al., 2006) have also found the presence of phosphine (PH₃) (Burgasser et al., 2024).

The left panel in Figure 1.4 shows a near-infrared M_J vs. $J - H$ colour-magnitude diagram of a clean sample of ultracool dwarfs with spectroscopic spectral classification. To obtain our sample, we queried the UltracoolSheet catalogue (Best et al., 2024) and applied

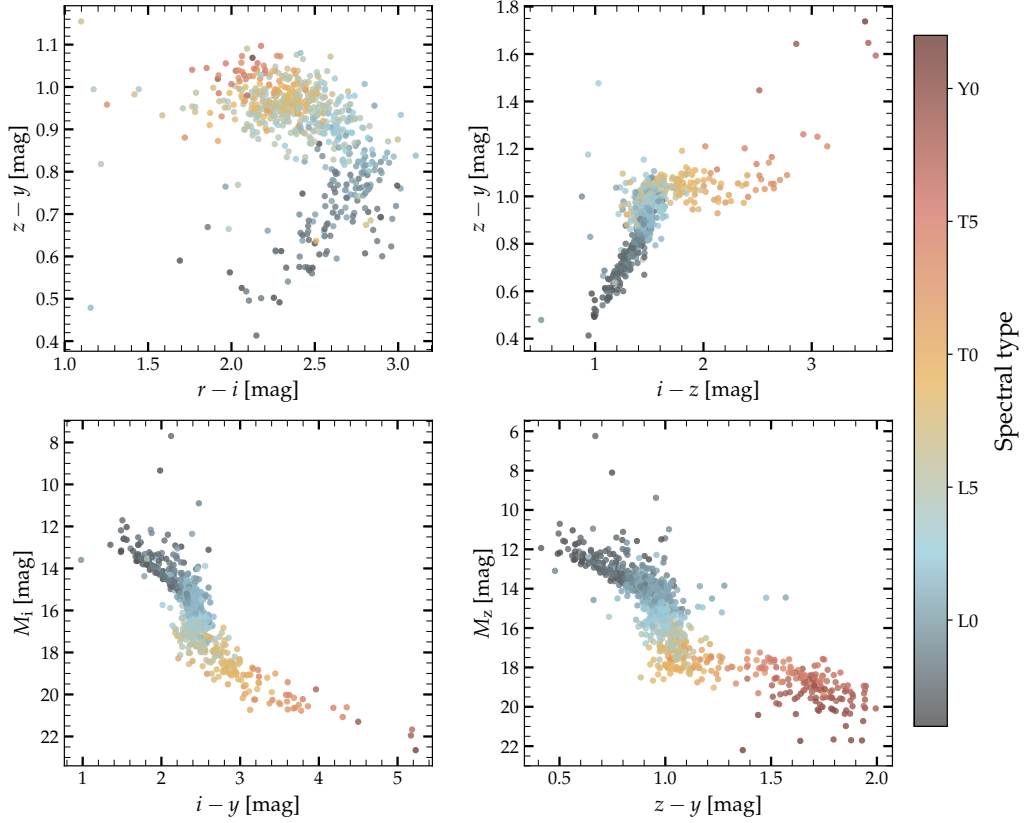


Figure 1.5: Optical colour-colour and colour-magnitude diagrams for our sample of ultracool dwarfs, using Pan-STARRS photometry. The dots are colour-coded by spectral type. All values used in the figure have been taken from the UltracoolSheet catalogue.

selection criteria to retain only resolved ultracool dwarfs with reliable photometry and parallax, discarding objects with a photometric spectral type. The final sample contains ~ 1500 ultracool dwarfs with a reliable spectroscopic classification of L0 or later. The colour-magnitude diagram shows how ultracool dwarfs, as they become fainter, evolve into redder $J - H$ colours until they reach the L/T transition. By spectral type L5, the photosphere is cool enough to allow the hydrogenation of CO to CH₄ (Noll et al., 2000; Canty et al., 2015), and CH₄ gradually becomes dominant over carbon monoxide (CO), typical of the photospheres of early- to mid-L objects. Throughout this transition to mid-T dwarfs, the absolute magnitude remains nearly constant while the $J - H$ colour grows bluer due to increased CH₄ absorption. Likewise, the right panel in Figure 1.4 shows how the relation between M_J (and also effective temperature) and spectral type is non-linear and exhibits a plateau in the L/T transition (Golimowski et al., 2004; Saumon and Marley, 2008; Kirkpatrick et al., 2021).

Discoveries of ultracool dwarfs have primarily been driven by wide-field optical and infrared imaging surveys such as the Deep Near Infrared Survey of the Southern Sky (DENIS; Epchtein et al., 1997), the Sloan Digital Sky Survey (SDSS; York et al., 2000), the Two-Micron All Sky Survey (2MASS; Skrutskie et al., 2006), the UKIRT Infrared Deep Sky Survey (UKIDSS; Lawrence et al., 2007), the Wide-Field Infrared Sky Explorer (WISE; Wright et al., 2010), the Panoramic Survey Telescope and Rapid Response System (Pan-STARRS; Chambers et al., 2016), and the Javalambre Photometric Local Universe Survey (J-PLUS; Cenarro et al., 2019). The *Gaia* mission (Gaia Collaboration et al., 2023b) has also contributed to the discovery of ultracool dwarfs in the whole sky. Despite all these

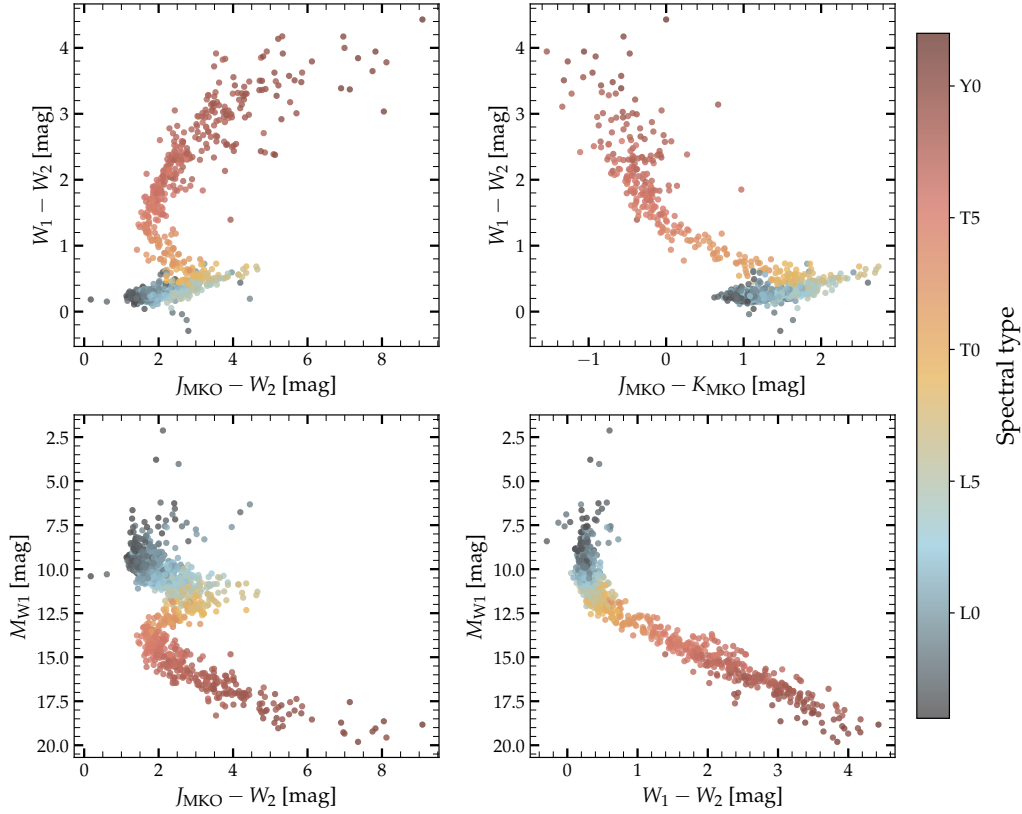


Figure 1.6: Near-infrared colour-colour and colour-magnitude diagrams for our sample of ultracool dwarfs, using MKO photometry available in the UltracoolSheet catalogue. The dots are colour-coded by the spectral type. All values used in the figure have been taken from the UltracoolSheet catalogue.

efforts, the 20 pc census of ultracool dwarfs is still incomplete (Kirkpatrick et al., 2024), with a completeness volume of 15 pc and 11 pc for spectral types later than $\sim T8.5$ and $\sim Y0$, respectively. A consolidated approach for the identification of ultracool dwarfs in these surveys is the definition of a locus in colour-colour or colour-magnitude diagrams in the optical (see Figure 1.5) or the infrared (see Figure 1.6) using previously known objects (Skrzypek et al., 2016; Smart et al., 2017; Best et al., 2018; Reyl  , 2018; Carnero Rosell et al., 2019; Mas-Buitrago et al., 2022; Sarro, L. M. et al., 2023; Mart  n et al., 2024).

Spectral classification, and its calibration to temperature or luminosity classes, is of utmost importance for characterising the ultracool dwarf (and any) astronomical population. There are several ways of doing this, such as direct comparison of the observed spectra with anchored optical (Kirkpatrick et al., 1999) and infrared (Burgasser et al., 2006; Kirkpatrick et al., 2010; Cushing et al., 2011) spectral standards. Late-M and L dwarfs classification is tied to the red optical region of the spectrum, while the T dwarfs are often characterised from the near-infrared region due to the presence of strong H_2O and CH_4 bands. Another approach is the classification through the measurement of different spectroscopic indices, defined as flux ratios that measure the strength of specific absorption or pseudocontinuum features (Kirkpatrick et al., 1995; Mart  n et al., 1997, 1999a; Burgasser, 2007). Over the last decade, analysis toolkits such as SPLAT (Burgasser and Splat Development Team, 2017)¹ have incredibly facilitated this classification task for the astronomical community. Once the spectral classification is done, it can be converted to

¹ <https://github.com/aburgasser/splat>

effective temperature or luminosity following predefined empirical relations (Pecaut and Mamajek, 2013; Filippazzo et al., 2015; Kirkpatrick et al., 2021).

These methodologies have proven to be broadly consistent throughout the literature, but how do we mine the large astronomical archives that make them possible? Most of the workflows followed in astronomical research require the combination of multi-wavelength data from different surveys. And here the Virtual Observatory is king. Moreover, the advent of huge volumes of data that will be provided in the coming years by missions such as *Euclid* (Euclid Collaboration et al., 2024) demand the development of fully automated solutions for ultracool dwarf identification and characterisation. Will machines fill this gap? Will deep learning be a cornerstone in the future study of the stunning ultracool dwarfs domain?

1.2 FROM STARS TO DATA: THE VIRTUAL OBSERVATORY

Just as a song means nothing if no one listens to it, data gains purpose only through the lens of analysis. And in the late 1990s and early 2000s, astronomy faced a crucial challenge in this aspect. The rapid advancement of astronomical instrumentation in recent decades has led to an exponential increase in the volume of astronomical data and the complexity of their processing. Until 1990, astronomical data were collected mainly with ground-based telescopes, but the launch of the Hubble Space Telescope (Bahcall, 1986) would bring a revolution in digital astronomy, with an unprecedented volume of data. However, it would not be alone up there, as other space observatories, such as the Infrared Astronomical Satellite (Neugebauer et al., 1984) and the International Ultraviolet Explorer (Boggess et al., 1978), a pioneer in the development of astronomical archives, were already in operation. During the 1990s, the digitisation of photographic plates enabled the generation of catalogues such as the Guide Star Catalog (Lasker et al., 1990; Lasker et al., 1996) and the USNO (Monet et al., 1998; Monet et al., 2003). Notable catalogues in the last years of the 1990s were the Tycho-2 (Høg et al., 2000) collected by the ESA Hipparcos satellite, with two-colour photometric data for 2.5 million stars, and other catalogues such as the ROSAT All-Sky Survey (Voges et al., 1999) or the NRAO VLA Sky Survey (Condon et al., 1998). The first data releases from large astronomical surveys, such as 2MASS in 1999 and SDSS in 2003, further fuelled this data revolution, ultimately breaking the Big Data barrier in the 2010s with the launch of the *Gaia* telescope (Gaia Collaboration et al., 2016). *Gaia* is the mission that pushed astronomy into the petabyte² domain, and has revolutionised observational astronomy by providing the largest, most precise map of the Milky Way. In short, all these efforts by the scientific community have meant that we are now living in the era of large astronomical catalogues such as Pan-STARRS1 (Chambers et al., 2016), *Gaia* DR3 (Gaia Collaboration et al., 2023b), SDSS DR12 (Alam et al., 2015) or UKIDSS DR9 (Lawrence et al., 2013), among many others³. But this is only the beginning, and this data tsunami will only get bigger and bigger with the next generation of observatories such as the Vera C. Rubin Observatory (Ivezić et al., 2019), the Square Kilometre Array (Dewdney et al., 2009), or the Nancy Grace Roman Space Telescope (Mosby et al., 2020).

The ability to fully utilize these vast datasets poses a major challenge to the astronomical community, and the Virtual Observatory (VO) is the response to this revolution. Just

² 1 petabyte = 1 048 576 gigabytes

³ A comprehensive list of large catalogues can be found at: <https://vizier.cds.unistra.fr/vizier/welcome/vizierbrowse.gml?bigcat>

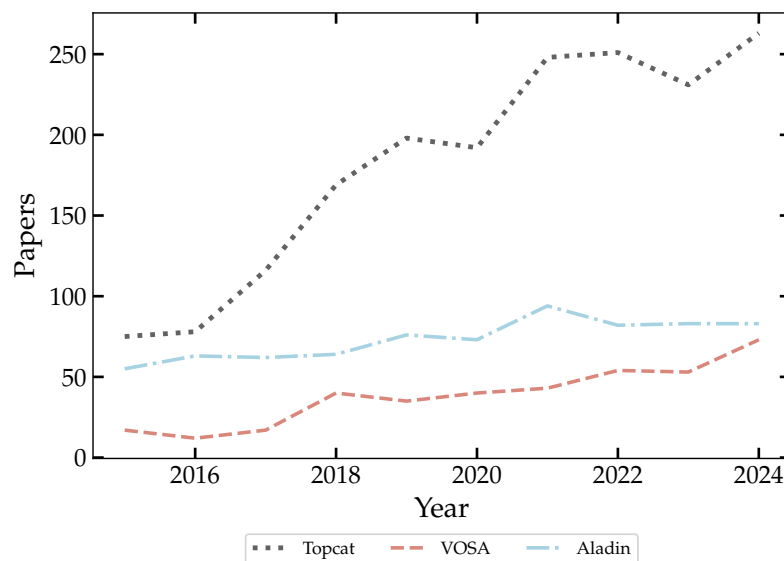


Figure 1.7: Evolution of the use of different VO tools over the last years, with the Y axis showing the number of referred papers in relevant astronomy journals. We note that the values should be taken as lower limits, as some of the works using the tools may not have been tracked. The data have been collected by the SVO team using the VOpubs tool: <https://sdc.cab.inta-csic.es/vopubs/>.

as 1995 was the year of the ultracool dwarfs, 2000 marked a turning point for data mining in astronomy. Two conferences held during the summer of this year, “Virtual Observatories of the Future” in Pasadena and “Mining the Sky” in Garching, laid the foundations for what two years later would become the International VO Alliance, or IVOA⁴. At its core, the VO is an international initiative aimed at removing the barriers imposed by the geographical and structural fragmentation of astronomical archives, by developing data standards and protocols⁵ to enable this interoperability. The main goal of the VO is to create a unified and interoperable system that allows astronomers to efficiently discover, retrieve, and analyse astronomical observations, models, and simulations, from multiple archives around the world.

A key aspect of the VO is the development of data discovery and mining tools that benefit from this data standardisation and enable the access and analysis of multi-wavelength data. TOPCAT (Taylor, 2005) is a tool that allows interactive manipulation and visualisation of tabular data, making it easier for the astronomer to access source catalogues, and to compare these catalogues with local data. Moreover, the Aladin interactive sky atlas (Bonnarel et al., 2000) is a service that provides simultaneous access to digitised sky images, astronomical catalogues and archives. Within IVOA, individual countries have developed national VO initiatives that further support and implement the VO framework. One particularly successful example is the Spanish VO (SVO)⁶, established in 2004 and coordinated by Dr. Enrique Solano Márquez at the Centro de Astrobiología. The SVO has played a pivotal role in developing and deploying VO services, such as the VO Sed Analyzer (VOSA)⁷ (Bayo et al., 2008), a tool that fits observed photometry to different collections of theoretical models to estimate physical properties, such as the effective

⁴ <https://ivoa.net/>

⁵ <https://www.ivoa.net/documents/>

⁶ <https://svo.cab.inta-csic.es/main/index.php>

⁷ <http://svo2.cab.inta-csic.es/theory/vosa/>

temperature or luminosity. In addition, VOSA offers a wide range of functionalities to the user, such as the possibility of querying several VO catalogues to enlarge the input data of the sources studied. Another of the flagship services of the SVO is the *Carlos Rodrigo* Filter Profile Service (FPS)⁸ (Rodrigo et al., 2024b), which is widely used by the astronomical community. The FPS contains detailed information on more than ten thousand photometric filters, the largest public collection of its kind. In addition, the SVO is responsible for the management of important astronomical archives⁹, notably the GTC and Calar Alto archives.

In modern astronomy, most of the research studies require the use of multi-wavelength data that is often stored in separate archives, and with different formats or query mechanisms. Without standardisation and interoperability between the archives, conducting multi-wavelength or multi-messenger (Abbott et al., 2017) astronomy would require an arduous and time-consuming technical process that, thanks to the VO, is fast and transparent to the user. This, aided by the data mining and analysis tools provided by the VO, is what we know as VO-science. Figure 1.7 illustrates the significant adoption of VO-science by the astronomical community at an international level, with an increasing trend over the last few years in the use of the developed tools.

Among the plethora of astronomical archives available to the astronomical community, during this thesis we have made extensive use of two of them in particular. J-PLUS is a multi-filter survey conducted from the Observatorio Astrofísico de Javalambre (OAJ; Cenarro et al., 2014) in Teruel, Spain, using the 0.83 m Javalambre Auxiliary Survey Telescope (JAST80). All data available in the J-PLUS archive¹⁰ is accessible through VO protocols, such as “Simple Image Access Protocol”, “Simple Cone Search”, or “Table Access Protocol”. Especially, we made use of the latter, which allows querying the archive using complex searches based on ADQL¹¹, which is an extension of the common SQL language to support astronomy-specific queries. The wide-field covered by J-PLUS (3 192 deg² in the last data release), combined with its unique system of 12 optical filters (López-Sanjuan et al., 2021) that allows an accurate estimation of stellar parameters such as the effective temperature, provide a suitable setting for the identification of ultracool dwarfs. The CARMENES instrument is installed at the 3.5 m telescope at the Calar Alto Observatory, located in Almería, Spain, and stands as one of the leading instruments in the quest for searching for Earth-like planets within the habitable zones around M dwarfs using the radial velocity technique. It comprises two separate spectrographs: one for the visible (VIS) wavelength range (from 520 to 960 nm) and the other for the near-infrared (NIR) range (from 960 to 1710 nm), each offering high-spectral resolutions of $R \approx 94\,600$ and $80\,500$, respectively (Quirrenbach et al., 2020; Reiners et al., 2018). The high-S/N, high-resolution spectra provided by the CARMENES data archive¹², which is part of the SVO, offer a unique opportunity to determine the photospheric stellar parameters of the observed M dwarfs.

The VO represents a transformative milestone in astronomical research. By breaking down barriers to data access and fostering interoperability between astronomical archives around the world, it has become a cornerstone of modern observational astronomy. As the era of exabyte-scale¹³ archives approaches, the continued evolution of VO solutions and protocols will be essential to ensure that astronomy remains at the forefront of sci-

⁸ <http://svo2.cab.inta-csic.es/theory/fps/>

⁹ <https://svo.cab.inta-csic.es/docs/index.php?pagename=Archives>

¹⁰ <https://archive.cefca.es/catalogues/jplus-dr3>

¹¹ <https://www.ivoa.net/documents/REC/ADQL/ADQL-20081030.pdf>

¹² <http://carmenes.cab.inta-csic.es/gto/>

¹³ 1 exabyte = 1 073 741 824 gigabytes

entific discovery in the 21st century. In this sense, the development of science platforms that allow the user to bring the analysis to the data, and not the other way around, will be crucial for scientific analysis on massive amounts of data. As such platforms are gaining prominence in recent years (e.g. ESA Datalabs¹⁴), the VO is working on integrating its technologies and protocols into them.

The revolution in data management and accessibility of the last decades did not come alone. The unprecedented scale and complexity of these datasets raised new challenges, as traditional approaches struggle to efficiently process, classify, and extract knowledge from them. This has led to the increasing adoption of artificial intelligence and machine learning, which provide scalable and automated solutions for data analysis, capable of analysing huge amounts of data in an efficient way. From detecting rare astronomical phenomena to refining stellar classifications, artificial intelligence was here to stay.

1.3 THE AGE OF ARTIFICIAL INTELLIGENCE

“Can machines think?”. Six years passed from Turing’s famous enquiry (Turing, 1950) until artificial intelligence was consolidated as a research field in the Dartmouth Summer Research Project on Artificial Intelligence conference in 1956, whose organiser, John McCarthy, coined the term “artificial intelligence” for the field (McCarthy et al., 2006). Already in 1943, McCulloch and Pitts (1943) had proposed the first computational model of a biological neuron. In the nearly 80 years since then, artificial intelligence has undergone a remarkable transformation, moving from theoretical explorations to real-world applications that have redefined entire fields, and we have even come to normalise coming across driverless taxis (Chen et al., 2023) on the streets of San Francisco and having human conversations with large language models (Bubeck et al., 2023; DeepSeek-AI et al., 2024). Do machines think? Can machines be conscious? These questions have been at the centre of debates in recent years and depend heavily on how we define intelligence and consciousness. For a captivating discussion on this topic, we refer the reader to Qin et al. (2025). What is clear is that, nowadays, machines have the ability to accomplish very complex goals, and this can be of great help to us in building data-driven solutions that ensure that we do not miss out or delay scientific knowledge simply because we cannot cope with the vast amounts of data.

Artificial intelligence, broadly defined as the field focused on the development of machines that mimic human intelligence to solve problems, is a domain that encompasses the well-known subfields of machine and deep learning. While machine learning refers to all systems that automatically learn from the data and make predictions without being explicitly programmed to do so, deep learning focuses on multi-layered neural networks that automatically extract features and create a hierarchical representation of the data. In traditional machine learning, an essential step is feature engineering, where domain experts manually select or design the most relevant features from raw data to improve model performance. For example, in the classification of stellar spectra, an astronomer might compute spectral indices such as the TiO and VO band strengths to distinguish between different M dwarf spectral types. These indices serve as handcrafted features that are then used by machine learning models like support vector machines or decision trees. In contrast, deep learning models, particularly convolutional neural networks, automatically extract relevant features from raw data without requiring manual input.

¹⁴ <https://datalabs.esa.int/>

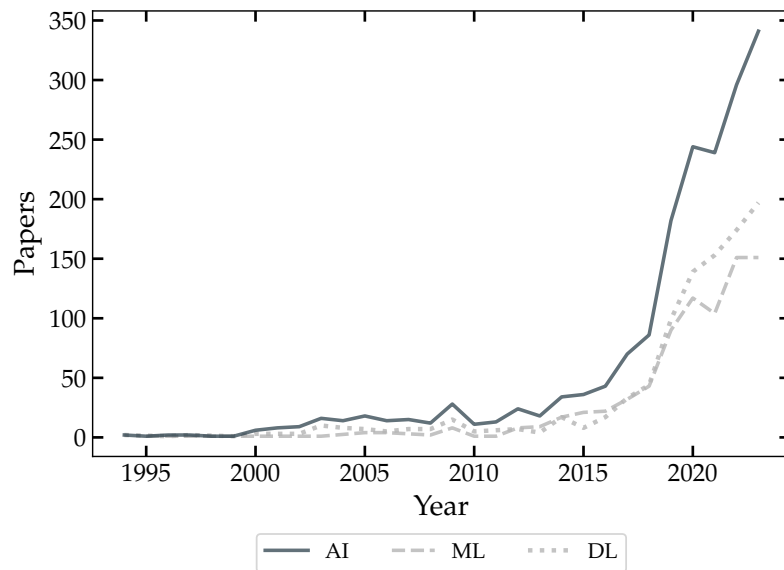


Figure 1.8: Diagram illustrating the increasing adoption of artificial intelligence by the astronomical community over the last years. The Y axis shows the number of referred papers inside arXiv:astro-ph. Papers were identified by searching for multiple keywords relevant to each of the categories in the abstracts. The raw data is publicly available at <https://www.kaggle.com/datasets/Cornell-University/arxiv>.

For instance, instead of relying on predefined spectral indices, a convolutional neural network trained on stellar spectra is capable of learning patterns directly from the full spectrum, identifying subtle absorption lines and continuum variations that may be difficult to define explicitly. This automatic feature extraction can enhance classification accuracy and reveal new insights that might be overlooked with traditional methods.

Depending on the nature of the problem to be addressed, machine learning algorithms fall into different categories. Supervised algorithms such as support vector machines (Qu et al., 2003; Huertas-Company et al., 2008; Kovács and Szapudi, 2015; Pashchenko et al., 2017) or supervised decision trees and random forests (Carliles et al., 2010; Möller et al., 2016; Ishida et al., 2019; Bluck et al., 2022), are used to map a set of features to a target variable based on input-output pairs that are often based on domain expertise. On the other hand, unsupervised machine learning algorithms such as K-means (Balazs et al., 1996; Sánchez Almeida et al., 2010; Garcia-Dias et al., 2018), hierarchical clustering (Hojnacki et al., 2007; Baron et al., 2015; Ma et al., 2018), principal component analysis (Boroson and Green, 1992; Vanden Berk et al., 2006; Bailey, 2012), or self-organising maps (Meusinger et al., 2012; Armstrong et al., 2016; Rahmani et al., 2018), are used to learn complex relationships within an unlabelled dataset for data exploration and visualisation, dimensionality reduction, or outlier detection tasks. It is important to note that several algorithms, such as random forests or artificial neural networks, can be used in both a supervised and unsupervised setting. When a small set of labelled data is available, semi-supervised learning techniques allow leveraging unlabelled data to learn a structured representation of the data or create pseudo-labels (Richards et al., 2011; Slijepcevic et al., 2022). Alternatively, self-supervised learning algorithms use large amounts of unlabelled data to supervise themselves, and have been widely used in representation learning (introduced in astronomy by Serra-Ricart et al., 1993), where algorithms extract meaningful compressed representations (embeddings) of complex high-dimensional data, during recent years (Yang and Li, 2015; Hayat et al., 2021; Sarmiento et al., 2021; Mas-Buitrago

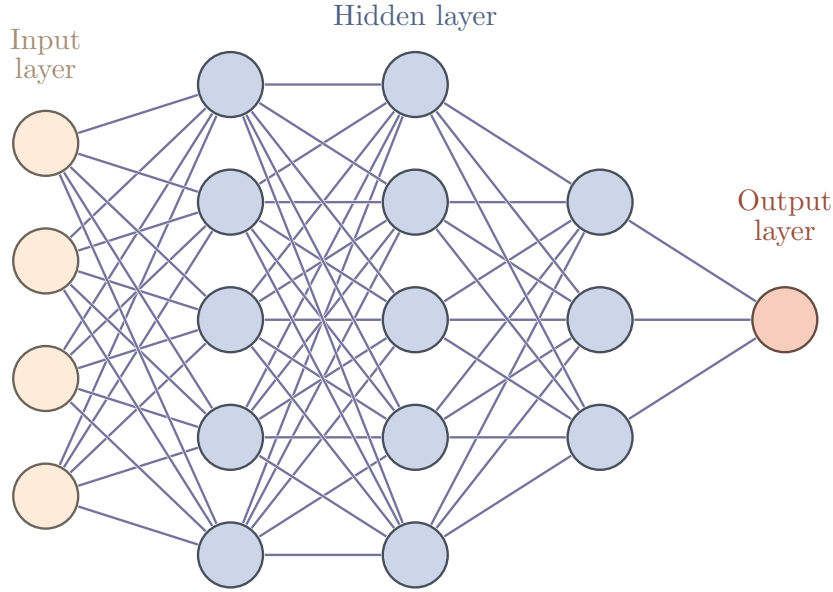


Figure 1.9: Schematic representation of a multilayer perceptron architecture. Source: https://tikz.net/neural_networks/.

et al., 2024). Reinforcement learning is an active branch of machine learning that optimises control tasks by interacting with a dynamic environment, evaluating outcomes and refining the actions of the system based on long-term rewards, and holds great promise as an approach for adaptive optics in astronomy (Nousiainen et al., 2021; Nousiainen et al., 2022; Gutierrez et al., 2024).

The last few years have witnessed an explosion in the number of deep learning methodologies (see Figure 1.8), driven by major advances in the field since the refinement of training techniques for deep neural networks (Bengio et al., 2006; Hinton et al., 2006; Hinton and Salakhutdinov, 2006) and the popularisation of convolutional neural networks (Krizhevsky et al., 2012; Simonyan and Zisserman, 2014), and also aided by the increase in computational power and the availability of massive datasets. However, machine learning made its debut in astronomy in the late 1980s (see Miller, 1993, and references therein), with artificial neural networks being the core of applications to star-galaxy classification (Odewahn et al., 1992, 1993; Bertin, E. and Arnouts, S., 1996; Bazell and Peng, 1998; Andreon et al., 2000; Qin et al., 2003), galaxy morphology classification (Storrie-Lombardi et al., 1992; Lahav et al., 1995, 1996; Odewahn et al., 1996; Cohen et al., 2003; Madgwick, 2003), photometric redshift estimation (Firth et al., 2003; Tagliaferri et al., 2003; Ball et al., 2004), characterisation of stellar spectra (Klusck and Napiwotzki, 1993; von Hippel et al., 1994; Bailer-Jones et al., 1997), quasar classification (Carballo et al., 2004; Claeskens et al., 2006), or cosmology (Auld et al., 2007, 2008). Moreover, in the early 2000s, decision trees and support vector machines began being used for galaxy morphology classification (Huertas-Company et al., 2008, 2011), photometric redshift estimation (Wadadekar, 2004), or AGN/galaxy separation (White et al., 2000; Gao et al., 2008). Within the SVO framework, the first studies using machine learning techniques emerged in the late 2000s, focusing on the automated supervised classification of eclipsing binary light curves (Sarro et al., 2006b), exoplanet light curves (Sarro et al., 2006a), and variable star light curves (Debosscher et al., 2007; Sarro et al., 2009). This was followed by an important contribution to the use of machine learning techniques for the determination of physical parameters of ultracool dwarfs in the scope of the *Gaia* mission

(Sarro et al., 2013a; Bailer-Jones et al., 2013). We refer the reader to Baron (2019), Ball and Brunner (2010), Huertas-Company and Lanusse (2023) and Smith and Geach (2023) for a complete and extensive review of machine and deep learning techniques applied to astronomy.

Deep learning represents a new approach to data analysis in astronomy and in science in general, as it enables the development of unsupervised and self-supervised fully data-driven solutions that do not rely on laborious manual feature engineering or labelling. The simplest artificial neural network is the perceptron, originally introduced by (Rosenblatt, 1958), which is equivalent to a single neuron node. This node consists of a set of numeric inputs x_i , which are multiplied by weights w_i that represent the strength of the connection between each of the inputs and the neuron. The perceptron then sums the list of products, adds a bias term b , which allows to the activation function to be shifted linearly, and passes the result to an activation function f , which gives the final output y :

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right). \quad (1)$$

Feed-forward artificial neural networks, or multilayer perceptrons, are fully-connected multilayer stacks of individual nodes (see Figure 1.9) that compute non-linear input-output mappings. At each layer, the input of each individual node is obtained as a weighted sum of the outputs of the nodes of the previous layer, and passed to a non-linear activation function in a process known as forward pass (see Figure 1.10). Typically, the rectified linear unit (ReLU; Nair and Hinton, 2010), $f(x) = \max(x, 0)$, is used as non-linear activation function due to its good scalability for networks with many layers and its ability to avoid vanishing gradients (Hochreiter, 1991). In the training of the network, this forward pass is performed across all layers to compute the prediction of the neural network, which is passed to a loss function that computes the difference between this prediction and the ground truth, or expected output. Then, the gradient of the loss function with respect to the weights of the network is computed using the backpropagation procedure (Werbos, 1974; Parker et al., 1985; Lecun, 1985; Rumelhart et al., 1986b), which propagates the gradients backwards from the last layer using the chain rule. Finally, the weights of the network are updated using gradient descent to minimise the loss function L :

$$w_{i+1} = w_i - \eta \frac{\partial L}{\partial w_i}, \quad (2)$$

where η is the learning rate, which controls how much the weights change. This process is repeated iteratively over multiple epochs, often using optimisation algorithms such as Adam (Kingma and Ba, 2014), until the network reaches a low enough loss.

Inspired by the hierarchical structure of the human visual nervous system (a precursor of convolutional neural networks; Fukushima, 1980), convolutional neural networks are a specific class of multilayered feedforward neural networks, initially developed for image classification and visual pattern recognition (Lecun et al., 1989, 1998). The distinctive factor of convolutional neural networks is the use of convolution operations, in the convolutional layers, to automatically extract features from data. After the convolutional structure, the set of features is flattened and passed to a multilayer perceptron to predict the output of the layer. In each forward pass process, the input of each unit of the convolutional layer is obtained with an element-wise dot product between a set of weights

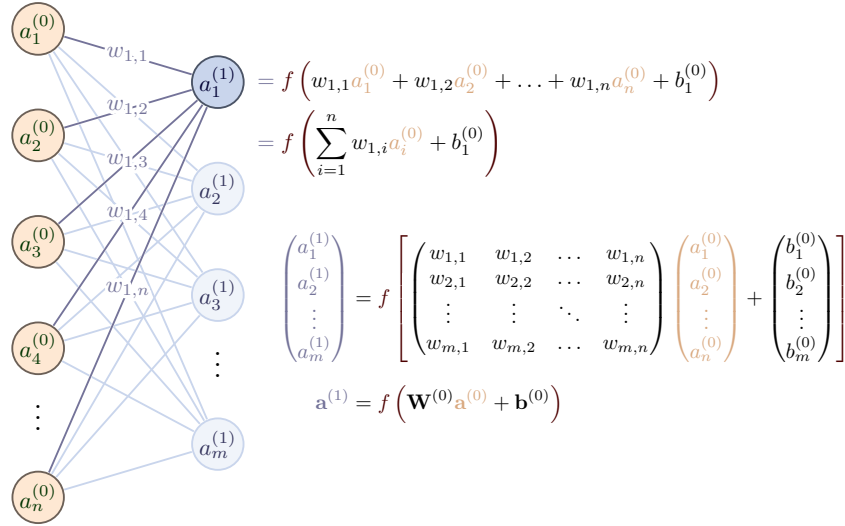


Figure 1.10: Schematic representation of the forward pass in a neural network node, as described in the text. Source: https://tikz.net/neural_networks/.

known as convolution kernel or filter, and the output feature maps of the previous layer (see Figure 1.11). In a same layer, different units use different filters. The resulting arrays and a tunable bias are added up and passed through an activation function to obtain the output feature map of each unit. The set of weights of each kernel and the weights of the multilayer perceptron are adjusted in the training process, so that the different feature maps of the convolutional layers represent specific features detected in the input data¹⁵. This feature representation learnt by the network is hierarchical, preserving the generic learning in the lower layers (closer to the input) and the more specific features in the higher layers.

The deep learning explosion started in 2012. In the ImageNet Large Scale Visual Recognition Challenge competition (Russakovsky et al., 2014) of this year, a deep convolutional neural network called AlexNet (Krizhevsky et al., 2012) achieved incredible results, far outperforming its competitors¹⁶ thanks to the use of graphics processing units, ReLU activation functions, data augmentation, and a technique known as dropout that prevents the network from overfitting (Srivastava et al., 2014). This success initiated a revolution in the field of computer vision, and the pace of improvement in the following years of the ImageNet competition was dramatic (Simonyan and Zisserman, 2014; Szegedy et al., 2014; He et al., 2016). It did not take astronomers long to notice. Due to their nature, it is not surprising that early work using convolutional neural networks in astronomy focused on image classification, for pulsar identification (Zhu et al., 2014) and for galaxy morphological classification (Dieleman et al., 2015; Huertas-Company et al., 2015; Aniyon and Thorat, 2017). Moreover, Hála (2014) pioneered the use of convolutional neural networks for spectral classification. These works signalled the beginning of the use of deep learning techniques in astrophysics, which has been growing at an overwhelming rate ever since.

As discussed in Section 1.2, astronomical datasets are becoming increasingly large and complex, making the exploration of these archives almost impossible without the use of

¹⁵ We refer the interested reader to <https://poloclub.github.io/cnn-explainer/> for an interactive visualisation of the internal workings of a convolutional neural network.

¹⁶ According to The Economist, “Suddenly people started to pay attention, not just within the artificial intelligence community but across the technology industry as a whole.”.

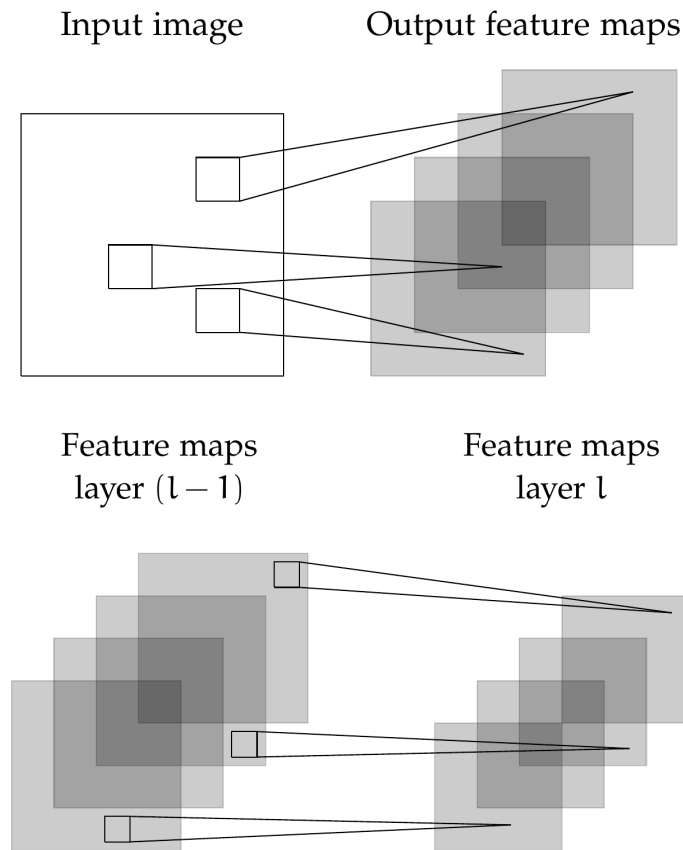


Figure 1.11: Schematic representation of the extraction of features in a convolutional layer. Source <https://davidstutz.de>.

data discovery techniques. In this sense, machine learning has emerged as a powerful tool for visualising or detecting anomalies in vast datasets. Data visualisation is essential for the exploration of high-dimensional astronomical datasets, bringing the data to a lower dimensionality that allows it to be analysed in a more interpretable way. Dimensionality reduction techniques, such as principal component analysis (Hotelling, 1933), t-SNE (Maaten and Hinton, 2008), UMAP (McInnes et al., 2018), or self-organising maps (Kohonen networks; Kohonen, 1982), are widely used in this regard. Moreover, unsupervised and self-supervised representation deep learning, especially using autoencoder architectures (Serra-Ricart et al., 1993) and more recently contrastive learning models (Chen et al., 2020), are used to extract meaningful embeddings from high-dimensional astronomical data, that can be used as input for a downstream classification or regression task. These methodologies constitute also a vital tool for the detection of anomalies or outliers in big data surveys (Chalapathy and Chawla, 2019), which enables the discovery of rare or unexpected phenomena within massive datasets, where the combination of deep learning methods with the VO technology is extremely useful (Skoda et al., 2020). Moreover, VO solutions are very helpful in further characterising these anomalous instances detected in surveys. This is particularly important for the field of transient astronomy, that will soon experience a revolution with the forthcoming LSST survey (Li et al., 2021b) of the Vera C. Rubin Observatory.

The dependence of deep learning algorithms on massive training data is a crucial hurdle to overcome when a research scenario requires labelled data, as building a large annotated dataset can be incredibly complex and expensive. This is the case, for example,

when a classification or regression task is to be performed on a small labelled sample. A straightforward, and widely used in astronomy, solution to this problem is the use of a data-rich labelled dataset similar to the target dataset or of synthetic data to train the deep learning models, but this may include a systematic error in the methodology if the training set is not identical to the observed data on which the inference is made (Passegger et al., 2020). Transfer learning, in which knowledge is transferred from a rich source domain to a related but not identical target domain, plays a key role in solving the above problems. Knowledge transfer is typically performed by training a deep learning model on a data-rich dataset and then fine-tuning the neural network weights using the target dataset (Domínguez Sánchez et al., 2018; Walmsley et al., 2022; Bello-García et al., 2023; Mas-Buitrago et al., 2024). Another approach to this problem is the use of active learning (Walmsley et al., 2019; Stevens et al., 2021), which reduces the number of required training samples by selecting the most informative data to label. For the simulation of data-rich labelled datasets, deep generative models (introduced in astronomy by Regier et al. 2015) such as variational autoencoders, generative adversarial networks, score-based generative models, or diffusion models, can be leveraged to generate massive amounts of data similar to astronomical observations. Deep generative models enable data-driven simulation as they capture the underlying probability distribution of a given dataset, and use that knowledge to generate new, realistic synthetic data from it.

With the captivating title “Attention is All You Need”, Vaswani et al. (2017) presented the revolutionary transformer neural network, based on a mechanism known as attention that computes the relevance of each input token with respect to all others in a sequence and captures contextual relationships, and which is still largely unexploited in astronomy (Donoso-Oliva et al., 2023; Cabrera-Vives et al., 2024). Transformer architectures are the pillars on which large language models, such as PaLM (Chowdhery et al., 2022), LLaMa (Touvron et al., 2023), or GPT-4 (OpenAI et al., 2023) are built, which have revolutionised the field of natural language processing in the last two years. Thanks to their versatility and their ability to handle multimodal data (Reed et al., 2022), transformers can be harnessed to build what we know as foundation models, which are models that are trained on vast amounts of data using self-supervised learning for subsequent fine-tuning tailored to diverse specific downstream tasks. Interest in foundation models in astronomy is growing rapidly (Dung Nguyen et al., 2023; Rózański et al., 2023; Leung and Bovy, 2024; Parker et al., 2024), since the natural evolution for the upcoming decades would be a transition from domain-specific deep learning models to fine-tuned versions of the same all-encompassing astronomical foundation model. The miscellaneous and rich nature of astronomical data generated from entirely different instruments, combined with the interoperability enabled by VO technology, represents a key opportunity in this regard. To this end, it is paramount that the astronomical community adopts a transparent, open-source, bazaar-style development, which has proven successful in large open-source projects such as Linux (Raymond, 2001), with a strong commitment to interpretability (see Ras et al. (2020) for a detailed discussion on explainable artificial intelligence). This open and democratised scenario would unlock the potential of state-of-the-art deep learning solutions for the entire astronomical community, solving the current inaccessibility of most astronomers to these models due to lack of resources.

The characterisation of M dwarfs and ultracool dwarfs is fundamental to advancing our understanding of stellar astrophysics, planetary formation and habitability, and the structure and kinematics of our Galaxy, yet their characterisation remains an ongoing challenge due to their intrinsic faintness and complex atmospheres. As astronomical datasets grow in size and complexity, the ability to efficiently mine and analyse these

vast archives has become a necessity, with the VO playing a key role in enabling multi-wavelength data discovery and interoperability. In parallel, the rise of machine and deep learning has transformed how we extract knowledge from astronomical data at an unprecedented scale, offering new approaches for classification, parameter estimation, anomaly detection, and data-driven discovery. The synergy between VO technologies and machine learning has set the stage for a new era in astronomical research, one in which automated, scalable, and interpretable solutions will be essential for maximising the scientific return of upcoming large-scale surveys. Recent applications of machine and deep learning in astronomy, as exemplified above, illustrate how artificial intelligence is not only optimising data analysis but also driving new discoveries that would otherwise be unfeasible with traditional methods. The fusion of artificial intelligence and astronomy is no longer just an option—it is a necessity.

1.4 AIMS AND OBJECTIVES OF THE THESIS

The aim of this thesis is to explore the application of machine learning and deep learning techniques to spectroscopic and photometric surveys, with a particular focus on M dwarfs and ultracool dwarfs, demonstrating how these methodologies can enhance our understanding of low-mass stars and substellar objects, and push the boundaries of data-driven astronomical research. The thesis can be divided into two main objectives. The first, covered in Chapter 2, is to consolidate a methodology for identifying ultracool dwarfs in wide-field multi-filter photometric surveys, using data from the J-PLUS survey, driven by VO data mining techniques and tools. In view of the vast surveys with these characteristics that will come to light in the very near future, this thesis aims to demonstrate that a machine learning approach is able to significantly accelerate this process. A sub-objective derived from this first one is to leverage these surveys for the automatic detection of flares in M dwarfs (Chapter 3), thanks to specific narrow-band filters located at specific spectral features. The second objective, which encompasses Chapters 4 and 5, is to develop an automatic and scalable deep learning-based methodology capable of determining the atmospheric parameters of M dwarfs and ultracool dwarfs from spectroscopic data. The strategy here starts with the use of M dwarf high-resolution spectra from CARMENES, and the subsequent adaptation to the ultracool domain is carried out with low-resolution spectra from the SpeX Prism Library.

Ultracool dwarfs (UCDs) comprise the lowest mass members of the stellar population and brown dwarfs, from M7 V to cooler objects with L, T, and Y spectral types. Most of them have been discovered using wide-field imaging surveys, for which the Virtual Observatory (VO) has proven to be of great utility. We aim to perform a search for UCDs in the entire Javalambre Photometric Local Universe Survey (J-PLUS) second data release (2176 deg^2) following a VO methodology. We also explore the ability to reproduce this search with a purely machine learning (ML)-based methodology that relies solely on J-PLUS photometry. We followed three different approaches based on parallaxes, proper motions, and colours, respectively, using the VOSA tool to estimate the effective temperatures and complement J-PLUS photometry with other catalogues in the optical and infrared. For the ML methodology, we built a two-step method based on principal component analysis and support vector machine algorithms. We identified a total of 7827 new candidate UCDs, which represents an increase of about 135 % in the number of UCDs reported in the sky coverage of the J-PLUS second data release. Among the candidate UCDs, we found 122 possible unresolved binary systems, 78 wide multiple systems, and 48 objects with a high Bayesian probability of belonging to a young association. We also identified four objects with strong excess in the filter corresponding to the Ca II H and K emission lines and four other objects with excess emission in the H α filter. Follow-up spectroscopic observations of two of them indicate they are normal late-M dwarfs. With the ML approach, we obtained a recall score of 92 % and 91 % in the $20 \times 20 \text{ deg}^2$ regions used for testing and blind testing, respectively. We consolidated the proposed search methodology for UCDs, which will be used in deeper and larger upcoming surveys such as J-PAS and Euclid. We concluded that the ML methodology is more efficient in the sense that it allows for a larger number of true negatives to be discarded prior to analysis with VOSA, although it is more photometrically restrictive.

2.1 J-PLUS

J-PLUS is a multi-filter survey conducted from the Observatorio Astrofísico de Javalambre (OAJ; Cenarro et al., 2014) in Teruel, Spain. Since it was primarily conceived to ensure the photometric calibration of J-PAS, it uses the second largest telescope at the OAJ, which is the 0.83 m Javalambre Auxiliary Survey Telescope (JAST80). J-PLUS is covering thousands of square degrees of the sky using the panoramic wide-field (2 deg^2 field of view) camera T80Cam (Marín-Franch et al., 2015), which is equipped with a CCD of $9.2\text{k} \times 9.2\text{k}$ pixels and a pixel scale of $0.55 \text{ arcsec pix}^{-1}$.

While J-PAS will use an unprecedented system of 56 narrow band filters in the optical, the J-PLUS filter system is composed of four broad ($g\text{SDSS}$, $r\text{SDSS}$, $i\text{SDSS}$, and $z\text{SDSS}$), two intermediate ($u\text{JAVA}$ and $J0861$) and six narrow ($J0378$, $J0395$, $J0410$, $J0430$, $J0515$, and $J0660$) band optical filters. The transmission curves, as well as additional information of

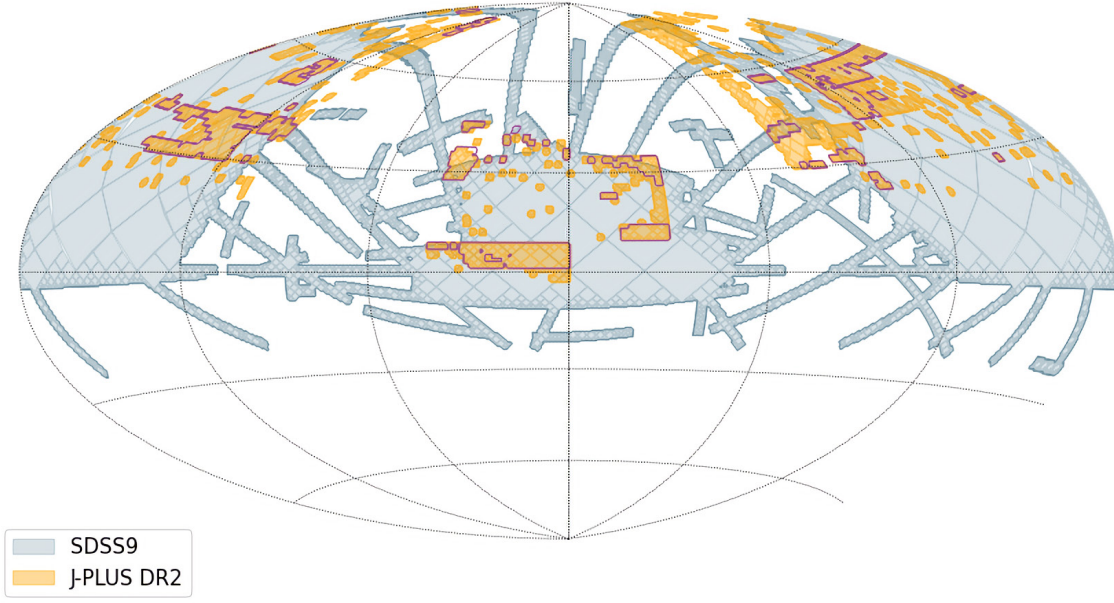


Figure 2.1: Sky coverage of J-PLUS DR2 (yellow) in α , δ coordinates (centred on $\alpha = 0$ deg, $\delta = 0$ deg, with α rising to the left). The SDSS DR9 footprint is superimposed in blue. The purple line represents the border of the J-PLUS DR1 coverage map.

these filters, can be found at the *Carlos Rodrigo* Filter Profile Service maintained by the Spanish Virtual Observatory¹ (Rodrigo et al., 2024b).

The J-PLUS DR2, available since November 2020, comprises 1088 fields, covering 2176 deg², observed in all the mentioned optical bands. Fig. 2.1 shows the sky coverage of this release. López-Sanjuan et al. (2021) presents the updated photometric calibration for the DR2, that was improved by including the metallicity information from LAMOST DR5 in the stellar locus estimation. The limiting magnitudes of the 12 bands can be consulted in the Table 1 of the same paper.

2.2 METHODOLOGY

We divided the sky coverage of J-PLUS DR2 in 37 regions of 20×20 deg². To cope with the fact that queries to the J-PLUS archive are limited to 1 million objects, we decided to tessellate each region into smaller circular subregions of 1 deg radius. We made use of TOPCAT² (Taylor, 2005) to cross-match each tessellated region with the J-PLUS DR2 sky coverage in order to avoid searching regions of the sky that are not covered by it.

We used the package STILTS³ (Taylor, 2006) to query the J-PLUS DR2 database through the Virtual Observatory TAP protocol. This allowed us to write ADQL⁴ code to search over all 20×20 deg² regions iteratively. A typical ADQL query example looks like this:

¹ <http://svo2.cab.inta-csic.es/theory/fps/index.php?&mode=browse&gname=0AJ&gname2=JPLUS>

² <http://www.star.bris.ac.uk/~mbt/topcat/>

³ <http://www.star.bris.ac.uk/~mbt/stilts/>

⁴ <https://www.ivoa.net/documents/REC/ADQL/ADQL-20081030.pdf>

```

SELECT objs.filter_id,objs.alpha_j2000,
       objs.delta_j2000,objs.class_star,
       objs.mag_aper_6_0,objs.mag_err_aper_6_0,
       objs.mask_flags,imgs.aper_cor_6_0,
       imgs.aper_cor_err_6_0
FROM jplus.MagABSingleObj as objs,
     jplus.TileImage as imgs
WHERE objs.tile_id = imgs.tile_id
AND objs.alpha_j2000 between 2 and 5
AND objs.delta_j2000 between 2 and 3
AND objs.flags=0
AND objs.filter_id between 1 and 4
AND objs.class_star>0.1

```

In our case, we used the 6 arcsec diameter aperture photometry, since the aperture correction to pass 6 arcsec aperture magnitudes to total magnitudes for point-like sources is available in the J-PLUS DR2 database. We constrained the search to records with good photometric conditions by imposing `flags=0` (no SExtractor flags⁵). Since object detection is performed independently on each filter, this means that for each source the `flags=0` condition is applied at the filter level. We also required `class_star > 0.1`. We were not very restrictive with `class_star` (SExtractor stellarity index) in order not to loose faint sources that may appear as extended objects.

For each $20 \times 20 \text{ deg}^2$ region, we concatenated the data for the corresponding circular subregions into a single table and removed duplicated instances (tessellated areas may overlap). As UCDs emit most of their flux at longer wavelengths, for the methodology described in Sects. 2.2.1, 2.2.2 and 2.2.3, we only considered the relevant filters for these objects, i.e., the reddest ones (filter IDs 1–4 and 10–12 in the J-PLUS DR2 database, see Table 2.1). Even so, we stored the data for all filters separately, as we required them for the flare detection workflow described in Sect. 2.6. Finally, we used the CDS X-Match service⁶ in TOPCAT with *Gaia* EDR3 J2016 (reference epoch 2016.0), using a 3 arcsec radius, to obtain the astrometric information. In those cases where more than one counterpart exists in the search region, only the nearest one was considered. In Sects. 2.2.1, 2.2.2 and 2.2.3 we describe the analysis carried out for each $20 \times 20 \text{ deg}^2$ region separately.

2.2.1 Parallax-based selection

From the cross-matched sample, we only kept sources with relative errors of less than 20% in parallax and less than 10% in both *G* and *G_{RP}* photometry. With these objects, we constructed a colour-magnitude diagram (see the left panel of Fig. 2.2), where the absolute *Gaia* magnitude in the *G* band was estimated using

$$M_G = G + 5 \log \varpi + 5, \quad (3)$$

where *G* is the *Gaia* apparent magnitude and ϖ is the parallax in arcseconds. To obtain a shortlist of candidate UCDs, we adopted a colour cut of $G - G_{RP} > 1.3 \text{ mag}$, which corresponds to spectral types M5 V or later according to the updated version of Table

⁵ <https://sextractor.readthedocs.io/en/latest/Flagging.html>

⁶ <http://cdsxmatch.u-strasbg.fr/>

Table 2.1: J-PLUS filter information, taken from the J-PLUS DR2 database, sorted from shortest to longest wavelength.

Filter ID	Filter	λ_{eff} [Å]
5.0	<i>u</i>	3542.20
6.0	<i>J0378</i>	3793.38
7.0	<i>J0395</i>	3938.55
8.0	<i>J0410</i>	4107.98
9.0	<i>J0430</i>	4298.36
2.0 ^a	<i>g</i>	4748.47
10.0 ^a	<i>J0515</i>	5139.67
1.0 ^a	<i>r</i>	6206.11
11.0 ^a	<i>J0660</i>	6606.67
3.0 ^a	<i>i</i>	7613.86
12.0 ^a	<i>J0861</i>	8610.16
4.0 ^a	<i>z</i>	8940.28

(^a) Relevant filters (reddest ones) for UCDs search.

5 in Pecaut and Mamajek (2013)⁷, and an absolute magnitude limit of $M_G > 5$ mag to leave aside the red giant branch.

2.2.2 Proper motion-based selection

Ultracool dwarfs may have photometric and morphological properties similar to those of objects such as giants, quasi-stellar objects (QSOs) or distant luminous red galaxies (e.g. Caballero et al., 2008a; Theissen et al., 2016, 2017). Assuming nearby objects will have high proper motions, reduced proper motion diagrams are a reliable tool for discriminating between nearby stellar populations and distant sources.

From the cross-matched sample introduced in Sect. 2.2, we only kept sources with a relative error of less than 20 % in both proper motion components and less than 10 % in both G and G_{RP} photometry. Furthermore, we only took into account sources with non-zero proper motion, i.e., sources with, at least, one of the proper motion components greater (in absolute value) than three times the associated error.

The right panel of Fig. 2.2 shows the reduced proper motion diagram defined as:

$$H_G = G + 5 \log \mu + 5, \quad (4)$$

where G is the *Gaia* apparent magnitude and μ is the total proper motion in mas yr^{-1} . Of these sources, we filtered out those already pre-selected in the parallax-guided analysis described in Sect. 2.2.1 and shortlisted as candidate UCDs those fulfilling the condition $G - G_{\text{RP}} > 1.3$ mag, and with a reduced proper motion $H_G > 22$ mag to leave aside the red giant branch.

As discussed in Sect. 2.2, the cross-match with *Gaia* EDR3 J2016 is done using a 3 arcsec radius. Since J-PLUS DR2 is based on images collected from November 2015 to February 2020, we might miss some objects with a proper motion larger than 750 mas yr^{-1} , as they could fall outside this 3 arcsec radius. However, we decided not to increase the radius to avoid finding erroneous counterparts.

⁷ http://www.pas.rochester.edu/~emamajek/EEM_dwarf_UBVIJHK_colors_Teff.txt

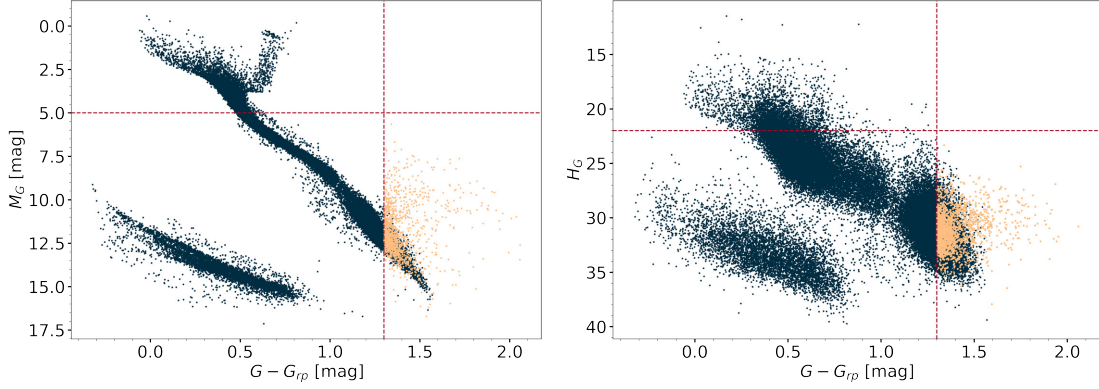


Figure 2.2: Location of the objects shortlisted as candidate UCDs via astrometric selection, for an example $20 \times 20 \text{ deg}^2$ region, in a colour-magnitude (left) and a reduced proper motion (right) diagram built using *Gaia* EDR3 sources with parallaxes larger than 10 mas (dark blue dots). The vertical and horizontal red lines mark the boundaries for a source to be shortlisted as candidate UCD. Sources fulfilling these conditions are overplotted in yellow.

2.2.3 Photometry-based selection

In the first two criteria (colour-magnitude and reduced proper motion diagrams) we are imposing parallax and proper motion constraints respectively, which makes these methods dependent on *Gaia* astrometric information. This means that objects with good photometry but poor astrometry will be excluded from the lists of candidate UCDs. To solve this limitation, in this section we describe a method solely dependent on photometric information. This procedure consisted of two separate steps. First, we built a colour-colour diagram with the purpose of defining a colour cut to identify the UCD locus. Then, we applied this criterion to each $20 \times 20 \text{ deg}^2$ region independently to obtain a shortlist of candidate UCDs.

To build the colour-colour diagram, we first searched in J-PLUS DR2 for true extended sources, defined as sources having `class_star` < 0.01. Likewise, true point sources were defined as sources with `class_star` > 0.99. Then, we performed a cross-match with 2MASS and built a $J - K_s$ (2MASS) vs. $r - z$ colour-colour diagram to separate the two types of sources. As discussed in Sect. 2.2.2, QSOs may have morphometric properties similar to those of UCDs, so it is crucial to also discriminate between these two types in the colour-colour diagram.

Fig. 2.3 shows the different types of objects in a colour-colour diagram. For the sample of QSOs, we cross-matched the SDSS-DR12 Quasar Catalog⁸ with the J-PLUS DR2. To define the UCD locus, we overplotted in this diagram the candidate UCDs obtained by the methods described in Sects. 2.2.1 and 2.2.2 for the region α : 0 – 20 deg; δ : 0 – 20 deg. As a compromise to balance the extended object contamination and the loss of candidate UCDs, we defined the UCD locus as the region fulfilling $r - z > 2.2 \text{ mag}$ and applied this criterion to all the sources of each $20 \times 20 \text{ deg}^2$ region. Of the sources fulfilling it, we filtered out those already pre-selected in the analysis described in Sects. 2.2.1 and 2.2.2 and shortlisted the remaining ones as candidate UCDs.

⁸ <http://cdsarc.u-strasbg.fr/viz-bin/cat/VII/279>

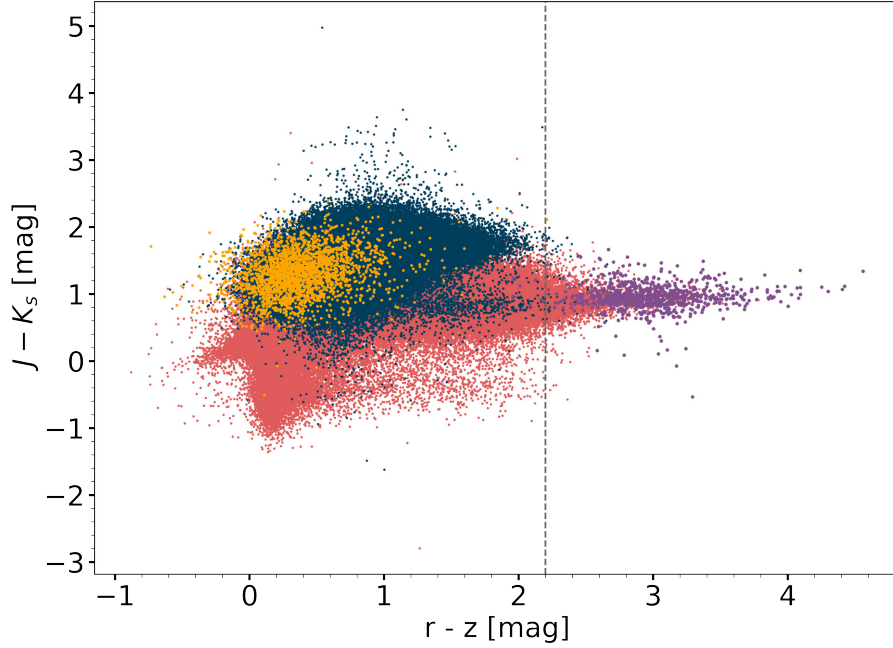


Figure 2.3: Colour-colour diagram built using true extended (dark blue) and true point (red) sources. Yellow dots represent the sample of 10481 QSOs. Purple dots represent the shortlisted candidate UCDs obtained by parallax-guided and proper motion-guided methods. The vertical grey line marks the $r - z > 2.2$ mag limit for a source to be shortlisted as candidate UCD.

2.2.4 VOSA filtering

To estimate physical properties, such as effective temperature, luminosity or radius of the shortlisted objects described in the previous sections, we made use of the tool *VOSA*⁹ (Bayo et al., 2008). This is a tool developed and maintained by the Spanish Virtual Observatory¹⁰ which fits observational data to different collections of theoretical models. An example of *VOSA* Spectral Energy Distribution (SED) fitting can be found in Fig. 2.4. Before doing the fit, we built the observational SEDs using the J-PLUS photometric information as well as additional photometry from the 2MASS, UKIDSS, WISE, and VISTA infrared surveys, and from the SDSS data release 12 optical catalogue, available in *VOSA*.

In our analysis, we used the BT-Settl (CIFIST) collection of theoretical models (Allard et al., 2012; Caffau et al., 2011). Thus, the effective temperature estimated by *VOSA* is discretised due to the step adopted in the CIFITS grid of models (100 K). We also assumed a surface gravity $\log g$ in the range 4.5 to 5.5 and solar metallicity. The limiting magnitude (5σ , 3 arcsec diameter aperture) of J-PLUS DR2 is 20.5 [AB] in the z band (López-Sanjuan et al., 2021). If we take, for example, the object TVLM 891-15871, which is one of the objects in the UCD catalogue presented in Reylé (2018) with the brightest absolute magnitude (11.36 [AB]) in the z band, we see that it could be detected at a maximum distance of ~ 680 pc. This leads us to expect a maximum distance of about 650-700 pc to find UCDs in the J-PLUS DR2.

Extinction plays a fundamental role in shaping the SED and, therefore, in the estimation of physical parameters (Laugalys and Straizys, 2002; Straizys et al., 2002). Considering the maximum distance at which UCDs can be detected with J-PLUS, we adopted a range of values between $A_V = 0$ mag and 0.5 mag. We relied on the calibration described

⁹ <http://svo2.cab.inta-csic.es/theory/vosa/>

¹⁰ <https://svo.cab.inta-csic.es>

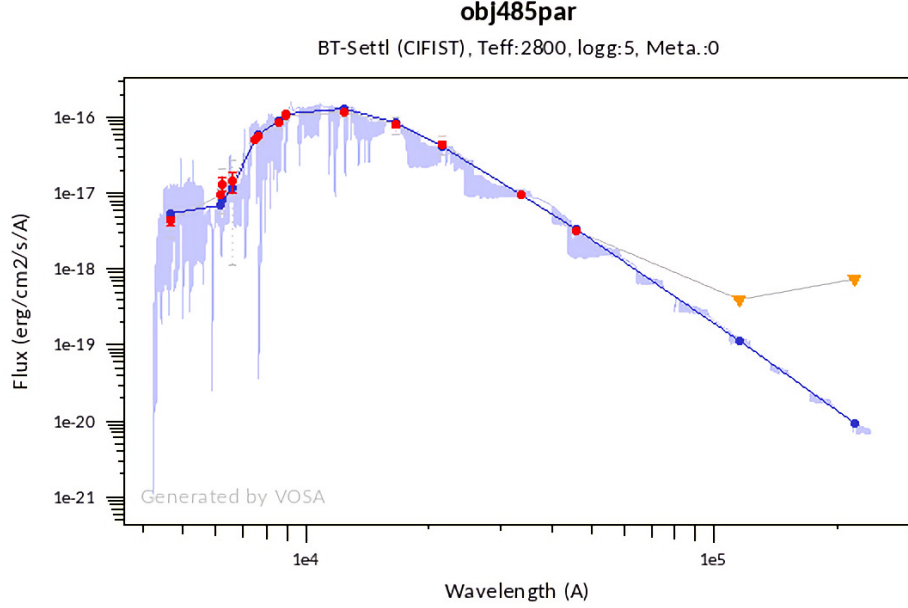


Figure 2.4: Example of an automatically generated SED fitting with VOSA. The blue spectrum represents the theoretical model that fits best, while red dots represent the observed photometry. The inverted yellow triangle indicates that the photometric value corresponds to an upper limit. These points are not considered in the fitting process.

in Table 1 of Solano et al. (2021) to adopt a temperature cutoff of 2900 K for UCDs if the BT-Settl (CIFIST) models are used in VOSA. The goodness of fit of the SED in VOSA can be assessed with the *vgfb* parameter, a pseudo-reduced χ^2 internally used by VOSA that is calculated by forcing $\sigma(F_{\text{obs}}) > 0.1 \times F_{\text{obs}}$, where $\sigma(F_{\text{obs}})$ is the error in the observed flux (F_{obs}). Only sources with good SED fitting (*vgfb* < 12) were kept.

After applying these effective temperature and *vgfb* conditions, we used TOPCAT to remove the objects with a non-zero confusion flag (*cc_flg*) in 2MASS, so as to ensure that objects are not contaminated or biased due to the proximity to a nearby source of equal or greater brightness. Moreover, we used the Aladin sky atlas (Bonnarel et al., 2000) to carry out a visual inspection of the coldest objects, in order to discard any problem related to blending or contamination by nearby objects. Finally, we ended up with 9810 final candidate UCDs. For the record, we checked that 204 of these objects have a renormalised unit weight error (RUWE; Lindegren et al., 2018) greater than 1.4 in *Gaia* EDR3, which could mean that the source is affected by close binary companions. These objects were not removed since a binarity analysis is performed in Sect. 2.3.3.

As we use multiple detection methods in our methodology, distinct candidate UCDs may have been detected by different methods, or by several of them. Fig. 2.5 shows the breakdown of the 9810 candidate UCDs according to the methods by which they have been detected. The fact that 2100 objects are only detected by the photometric methodology ('diag' bar in Fig. 2.5) and 4530 are only detected by the astrometric methodology ('par', 'pm', and 'par&pm' bars in Fig. 2.5) argues for the complementary nature of both approaches. Considering each method separately, we detected 6086 candidates with parallax-based selection, 6338 with proper motion-based selection, and 5280 with photometry-based selection.

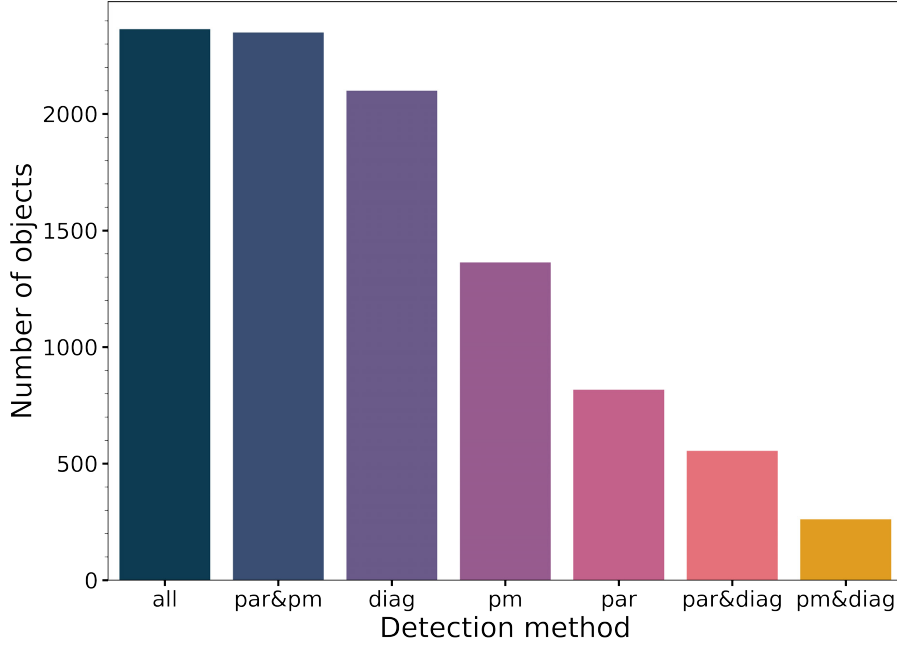


Figure 2.5: Breakdown of our candidate UCDs according to the methods by which they have been detected. ‘diag’ label represents photometry-based selection, while ‘par’ and ‘pm’ labels represent selections based on parallax and proper motion, respectively. The ‘all’ label comprises the candidate UCDs identified with the three approaches.

2.3 ANALYSIS

2.3.1 Temperatures and distances

Fig. 2.6 shows that the distribution of effective temperatures for our candidate UCDs is not the same depending on whether they have been detected by astrometric methodology (blue) or not. To prove this, we performed a two-sample Kolmogorov-Smirnov test on the two samples, which returned a p value = $3.66 \cdot 10^{-15}$, rejecting the possibility that both samples are coming from the exact same distribution. The number of cold objects ($T_{\text{eff}} \leq 2200$ K) is clearly higher in the only-photometry detected distribution (yellow). Most of our candidates ($\sim 86\%$) have $T_{\text{eff}} \geq 2700$ K, a clear consequence of the working wavelength, since UCDs peak in the near-infrared, and J-PLUS covers only up to the z filter ($\lambda_{\text{eff}} = 8940.28$ Å).

For the distance distribution of our candidate UCDs (Fig. 2.7), we only considered the candidates with a relative error of less than 20 % in parallax (6086 objects), so we can rely on the inverse of the parallax as a distance estimator (Luri et al., 2018). In our case, as mentioned in Sect. 2.2, the parallax are those of *Gaia* EDR3. About 70 % of the objects lie in the $96 < D(\text{pc}) < 222$ region (1σ limits), with a maximum and minimum distance of 471 pc and 11 pc, respectively. This upper limit is consistent with the value estimated in Sect. 2.2.4. We found 68 nearby objects, at distances smaller than 40 pc, that will be further discussed in Sect. 2.4.2. Fig. 2.8 gives a more in-depth view of the characteristics of our candidate UCDs. As expected, most of the cooler candidates are detected at closer distances and tend to have lower bolometric luminosity.

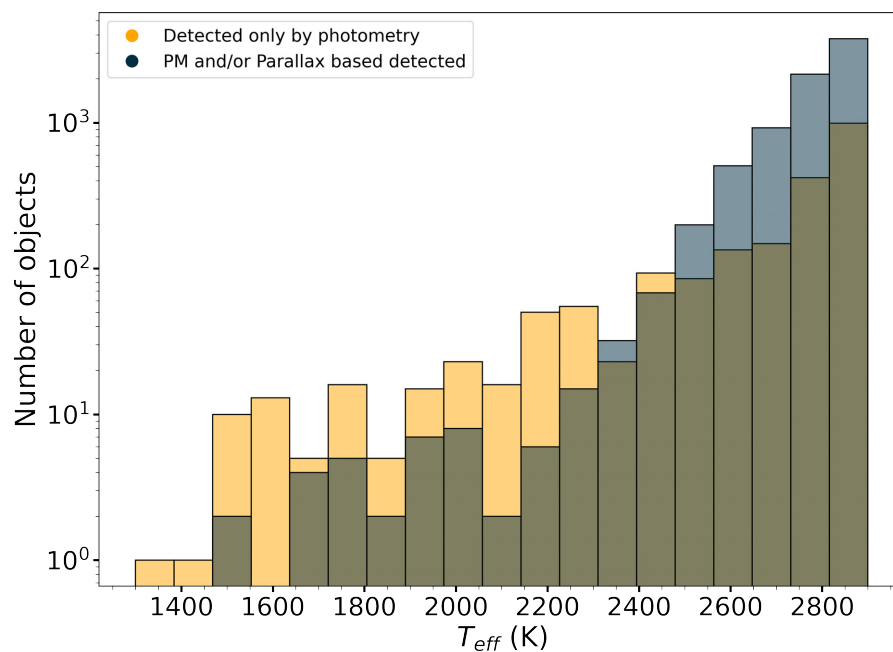


Figure 2.6: T_{eff} distribution for our candidate UCDs. In yellow we show the candidates that were only detected by photometry. In blue we show the candidates that were, at least, detected by astrometric methodology.

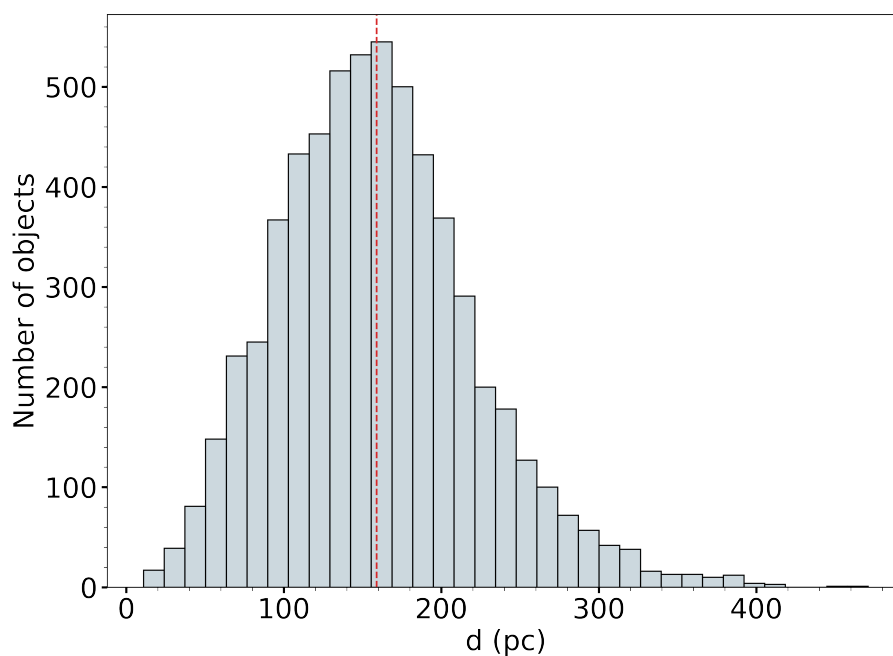


Figure 2.7: Distance distribution for our candidate UCDs with an error of less than 20% in *Gaia* EDR3 J2016 parallax. The mean value (red vertical line) of the distribution is 159 pc, with the closest and farthest objects at 11 pc and 471 pc.

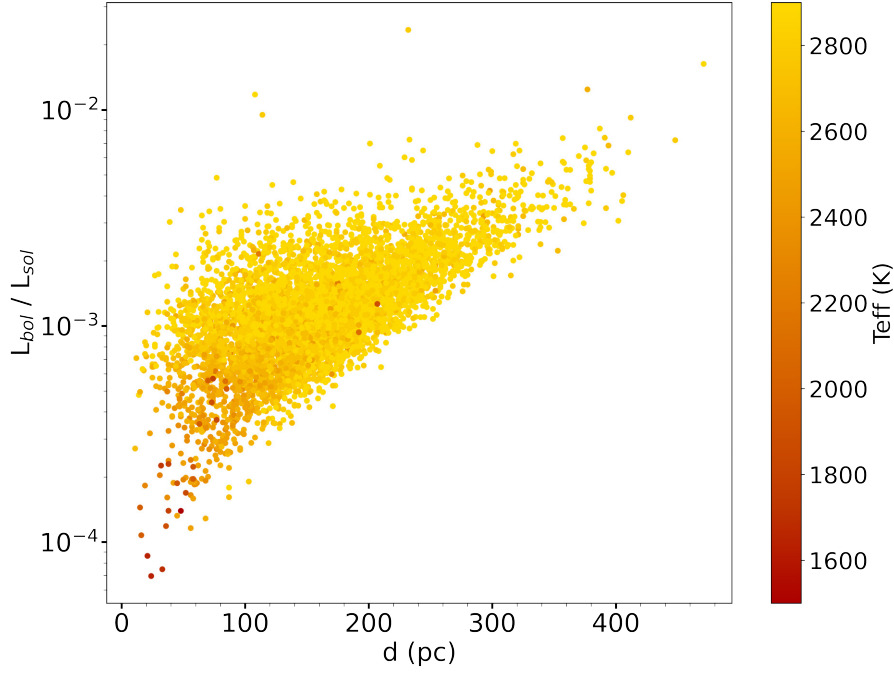


Figure 2.8: Bolometric luminosity (in solar units) vs. distance diagram of our candidate UCDs with good parallaxes. The points are colour-coded by temperature.

2.3.2 Kinematics

Stellar kinematics is a reliable proxy for segregating large-scale galactic populations (thin disk, thick disk, and halo) (Burgasser et al., 2015). Using *Gaia* EDR3 proper motions and parallaxes, we computed the tangential velocities of our candidate UCDs as $v_{\text{tan}} = 4.74\mu d$, where v_{tan} is given in km s^{-1} , μ is the total proper motion in arcsec yr^{-1} and d is the distance in pc. For a correct estimation of the tangential velocity, we only considered candidates that met both conditions described in Sects. 2.2.1 and 2.2.2 for good parallax and proper motion (4714). Fig. 2.9 shows the distribution of tangential velocities for these candidates, with a mean value of $v_{\text{tan}} = 39.78 \text{ km s}^{-1}$, a median value of $v_{\text{tan}} = 33.99 \text{ km s}^{-1}$, and a dispersion of $\sigma_{\text{tan}} = 24.85 \text{ km s}^{-1}$. Even taking into account objects located at the long tail of the distribution (134 objects, representing 2.8% of the total, with $v_{\text{tan}} > 100 \text{ km s}^{-1}$), these values agree with previous calculations for UCDs (Faherty et al., 2009).

Torres et al. (2019, Fig. 10) shows a breakdown of the tangential velocity based on the membership in the thin disk, the thick disk or the halo. Relying on these values, we can segregate our candidate UCDs into thin disk ($v_{\text{tan}} \leq 85 \text{ km s}^{-1}$), thick disk ($85 < v_{\text{tan}} < 155 \text{ km s}^{-1}$), and halo ($v_{\text{tan}} \geq 155 \text{ km s}^{-1}$) populations. We found 4441, 268 and five candidate UCDs in these intervals, respectively. According to Kilic et al. (2017), the corresponding ages are 6.8-7.0 Gyr (thin disk), 7.4-8.2 Gyr (thick disk), and $12.5^{+1.4}_{-3.4}$ Gyr (halo).

Three of the potential halo members show a very high tangential velocity. Two of them, with Simbad identifiers 2MASS J18030236+7557587 and 2MASS J13155851+2814524, are not far from the thick disk-halo threshold, with tangential velocities of $v_{\text{tan}} = 176.25 \text{ km s}^{-1}$ and $v_{\text{tan}} = 177.47 \text{ km s}^{-1}$, respectively. Furthermore, one of the objects has $v_{\text{tan}} = 206.16 \text{ km s}^{-1}$, which significantly exceeds the limit. This object, at a distance of 179 pc, is reported as an M7 in the catalogue provided by Ahmed and Warren (2019) with

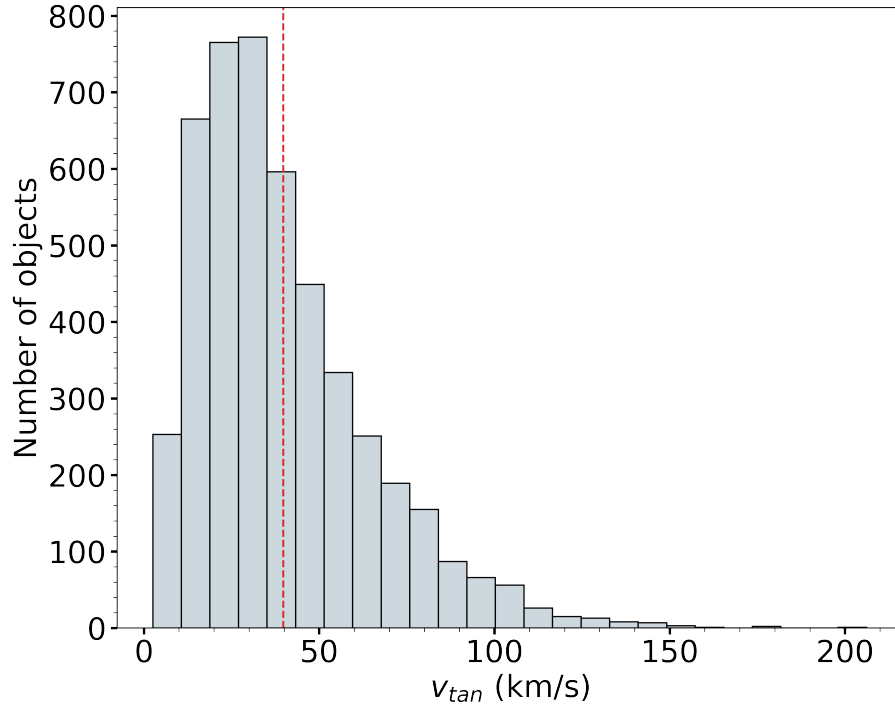


Figure 2.9: Tangential velocity distribution for our candidate UCDs with good parallax and pm conditions. The mean value (red vertical line) of the distribution is 39.78 km s^{-1} , with a maximum value of 206 km s^{-1} .

the id J132625.03+333506.7. Due to its high tangential velocity, we conclude this object could be a potential member of the Galactic halo. We used the $(J - K_s, i - J)$ colour-colour diagram presented in Lodieu et al. (2017) to study the metallicity of this object. With values of $J - K_s = 0.77$ and $i - J = 3.29$, the object exhibits subdwarf behaviour (low metallicity). Fig. 2.10 shows the mean and standard deviation of the tangential velocity for each value of the effective temperature. There is no evidence of correlation between effective temperature and tangential velocity among our candidates.

To study the possible membership of our candidate UCDs to nearby young associations, we relied on BANYAN Σ^{11} (Gagné et al., 2018), a Bayesian analysis tool to identify members of young associations. Modelled with multivariate Gaussians in six-dimensional XYZUVW space, BANYAN Σ can derive membership probabilities for all known and well-characterised young associations within 150 pc. As we found no radial velocity data available for any of the 4714 candidate UCDs with good parallax and proper motion, we introduced the sky coordinates, proper motion, and parallax of these objects as input parameters to the algorithm.

For 4666 of the candidate UCDs, the algorithm predicted that most of them are field stars. However, it gave a high Bayesian probability for 48 objects to belong to a young association, in 30 of the cases with a probability greater than 95%. In more detail, the algorithm mapped 34 candidate UCDs to the Pisces-Eridanus stellar stream (Meingast et al., 2019), five to the Argus Association (Zuckerman, 2018), four to the AB Doradus Moving Group (Zuckerman et al., 2004), two to the Columba association (Torres et al., 2008), and one each to the Tucana-Horologium (Torres et al., 2000), β Pictoris (Zuckerman et al., 2001), and Carina-Near (Zuckerman et al., 2006) associations. We verified all these 48 ob-

¹¹ <http://www.exoplanetes.umontreal.ca/banyan/>

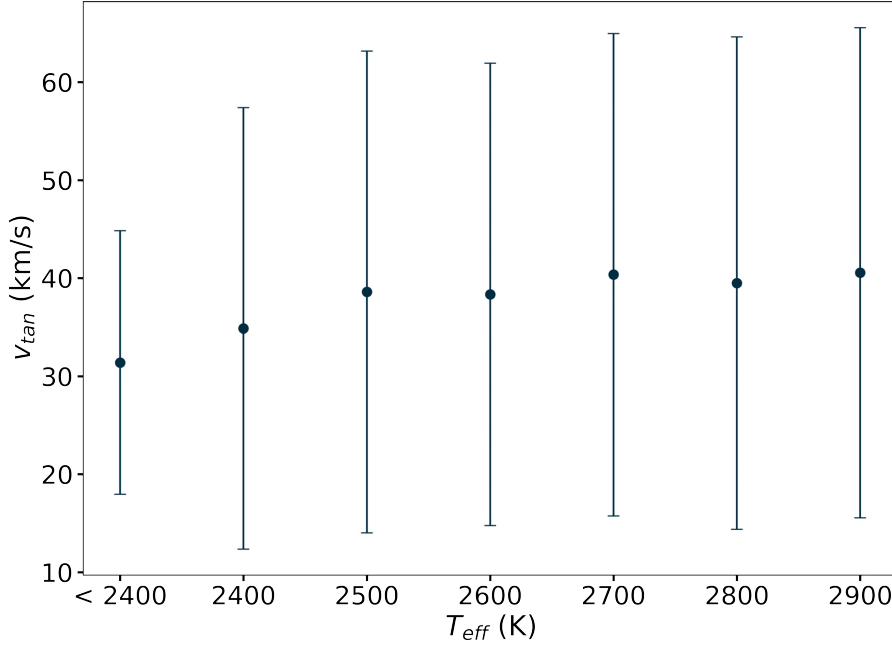


Figure 2.10: Mean tangential velocity for each value of effective temperature of our candidate UCDs with reliable parallax and proper motion. The error bars represent the standard deviation.

jects have tangential velocities typical of the thin disk, with mean $v_{\text{tan}} = 16.37 \text{ km s}^{-1}$ and standard deviation $\sigma = 6.17 \text{ km s}^{-1}$. As mentioned in BANYAN Σ , a high membership probability in a young association does not guarantee that the star is a true member, or young, so further follow-up would be needed to demonstrate the youth of the object. Moreover, we note that the absence of radial velocity may cause the membership probabilities given by BANYAN Σ to be inflated.

2.3.3 Binarity

We conducted a search for binary systems among our candidate UCDs in two ways. We searched for unresolved binaries using a methodology based purely on the photometry of our objects. Using the complementary photometry functionality of VOSA, we selected only the candidates fulfilling three conditions. First, with an excess detected by VOSA in any filter in the infrared. We discarded WISE W3 and W4 due to their poor angular resolution and sensitivity. Second, with good photometry in both 2MASS (Qf1 = A) and WISE (cc_flags = 0 and ph_qual = A or B). Third, with at least three good photometric points in the infrared, apart from the detected excess.

After applying these conditions, we ended up with 291 objects with an excess in the infrared that could be ascribed to circumstellar material or to the presence of a close ultracool companion. Then, we used the binary fit functionality of VOSA to fit the observed SED of these 291 objects using the linear combination of two theoretical models. After this, we ended up with 122 candidate UCDs for which the infrared excess detected is nicely reproduced by performing a two-body fit, suggesting the existence of an unresolved companion.

In parallel to this, we looked for *Gaia* companions of our candidate UCDs at large angular separations, using only those with reliable parallax and proper motion (4714). Firstly, we cross-matched these sources with *Gaia* EDR3 J2016 to get all the objects separated a

maximum of 180 arcsec in the sky (maximum separation allowed by the X-match service in TOPCAT) from each of our candidate UCDs. Then, we established a conservative upper limit of 100 000 au for the projected physical separation between a candidate and its companion. Finally, we relied on the conditions presented in Smart et al. (2019) to ensure that the companion shares a parallax and proper motion similar to that of our candidate UCD:

- $\Delta\varpi < \max[1.0, 3\sigma_\varpi]$
- $\Delta(\mu_\alpha \cos \delta) < 0.1\mu_\alpha \cos \delta$
- $\Delta\mu_\delta < 0.1\mu_\delta$

where ϖ and μ are the parallax and proper motion of our candidate UCDs, respectively. After applying these criteria, we ended up with 73 candidate UCDs with one *Gaia* companion and another five candidate UCDs with two *Gaia* companions identified. Of these 78 objects, six are already tabulated as known binary systems by the Washington Double Star catalogue (WDS; Mason et al., 2001). Table B.1 lists the coordinates (J2000), parallaxes, proper motions, angular separations ρ and projected physical separations s of the six known systems. A table with the same information for the identified multiple systems that are not tabulated by the WDS is accessible through the catalogue described in Section 6.2.

A deeper knowledge of the *Gaia* companion may allow us to infer properties, such as metallicity, of our candidate UCD. We only found spectral types in Simbad for two of the detected companions, with spectral types F2 and K3V. To obtain information about the rest of the companions, we first made use of VOSA to get an estimate of their effective temperature. Then, we relied on the updated version of Table 5 in Pecaut and Mamajek (2013) to map these effective temperatures to the spectral types of the companions. As result, we ended up with four F-type, one G-type, 16 K-type and 42 M-type stars among the companions with good SED fitting in VOSA. For the rest of the companions, we obtained a bad SED fitting in VOSA ($\text{vgfb} > 12$), so we could not get an estimation of the effective temperature.

2.4 KNOWN ULTRACOOL DWARFS

2.4.1 Recovered known UCDs

Here, we assess the number of known UCDs found in the J-PLUS DR2 field and the fraction of them that were recovered using our methodology. For this analysis, we used nine catalogues and services: SIMBAD¹² (Wenger et al., 2000), Zhang et al. (2009), Zhang et al. (2010), Schmidt et al. (2010), Skrzypek et al. (2016), Smart et al. (2017), Reyl   (2018), Best et al. (2018), and Ahmed and Warren (2019). Using the SIMBAD TAP service¹³ through TOPCAT, we selected objects with spectral types M7 V, M8 V, M9 V or labelled as brown dwarfs. A total of 18 282 objects were recovered. Also, from Best et al. (2018) we chose the 2 090 objects having spectral type M7 or later. As all the 33 665, 14 915, 1 886, 1 361, 806, 484 and 129 objects in the Ahmed and Warren (2019), Reyl   (2018), Smart et al. (2017), Skrzypek et al. (2016), Zhang et al. (2010), Schmidt et al. (2010), and Zhang

¹² <http://simbad.u-strasbg.fr/simbad/>

¹³ <http://simbad.u-strasbg.fr:80/simbad/sim-tap>

et al. (2009) catalogues, respectively, are within our scope (spectral type M7 or later), we included them in their entirety.

To select only the known UCDs that lie in the region of the sky covered by J-PLUS DR2 we made use of TOPCAT and its nearMOC functionality, which indicates whether a given sky position either falls within, or is within a certain distance of the edge of, a given MOC. The MOC¹⁴ (Multi-Order Coverage Map) is an encoding method dedicated to VO applications or data servers which allows to manage and manipulate any region of the sky, defining it by a subset of regular sky tessellation using the HEALPix method (Górski et al., 2005). Out of a total of 5 817 objects lying in the J-PLUS DR2 field of view, we ended up with 4 734 known UCDs with photometry in the relevant J-PLUS filters described in Sect. 2.2 (see Table 2.1), which are reduced to 4 649 objects after removing those with non-zero confusion and contamination flags in 2MASS. From this set, 1 983 were recovered using our methodology and 2 666 were not. We conducted an in-depth analysis of the 2 666 UCDs following the two methodologies (astrometric and photometric) separately, to see in which steps of the process these objects are discarded.

In short, of this 2 666 unrecovered objects, 1 520 are lost because they do not meet our parallax, proper motion, and photometry constraints, while another 119 are discarded in the $G - G_{RP}$ and $r - z$ cuts. The remaining 1 027 are lost in the temperature/vgfb cutoff after the analysis with VOSA, some due to a bad SED fitting ($vgfb > 12$) and most of them due to an estimated temperature higher than 2 900 K. We have checked the latter and the vast majority of them are M7 V from Simbad that lie at the temperature limit, with estimated temperatures of 3 000 - 3 100 K.

2.4.2 New candidate UCDs vs. previously known

In this section, we analyse the differences between previously known UCDs and the remaining candidate UCDs among our sample. For this, we cross-matched our candidate UCDs with the known UCDs sample described in Sect. 2.4. As indicated above, of the 9 810 candidates identified by the proposed VO methodology, only 1 983 were previously reported as UCD. This amounts to a total of 7 827 new candidate UCDs in the sky coverage of J-PLUS DR2, which represents an increase of about 135 % (7 827/5 817) in the number of UCDs for this area.

Fig. 2.11 shows the distance distribution for our candidate UCDs, with good parallax conditions, discriminated by colour according to whether or not they were previously reported as UCD. It is clear that the new candidates detected are, on average, more distant, driven by the improvement of the quality of parallaxes with *Gaia* EDR3. Of the 68 nearby objects found at distances smaller than 40 pc, eight have not been previously reported as UCD. To check whether these objects could have been missed by other photometric surveys due to anomalies in their colours, we constructed a colour-colour diagram using $J - K_s$ (2MASS) and $G - G_{RP}$ (*Gaia*) colours. Fig. 2.12 shows that this is not the case for any of these objects (black diamonds in the diagram).

A more in-depth view of this is the distance vs. effective temperature diagram shown in Fig. 2.13. Here we can see how previously reported candidate UCDs tend to be at shorter distances for any value of the effective temperature. This trend is more clearly observed for higher temperature values, where the diagram shows how the new candidate UCDs cover the range of distances of the previously reported candidates and extend

¹⁴ <https://www.ivoa.net/documents/MOC/>

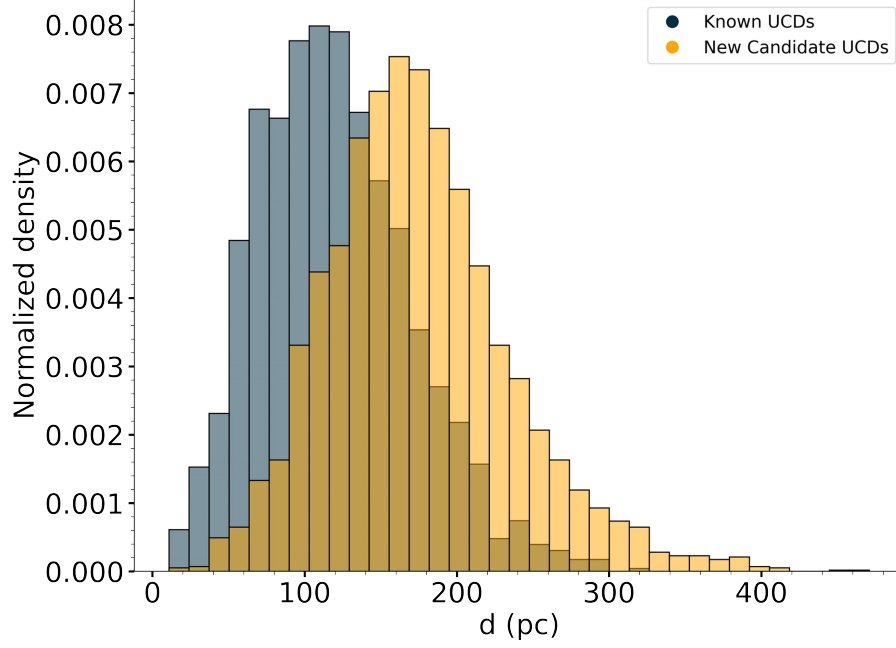


Figure 2.11: Distance distribution for previously reported (blue) and new (yellow) candidate UCDs with good parallax conditions.

it to larger values, suggesting that our methodology allows us to go further in the search for new UCDs.

Going further, in Fig. 2.14 we plot the absolute proper motions $|\mu_\delta|$ and $|\mu_\alpha \cos \delta|$ for our candidate UCDs with good proper motion conditions. It shows how the new candidate UCDs detected extend to smaller values of proper motion. Especially for values of proper motion of less than 15 mas yr^{-1} , the number of new candidates is significantly higher than the number of previously reported candidate UCDs, which reflects the improvement of the quality of proper motions with *Gaia* EDR3.

2.5 MACHINE LEARNING ANALYSIS

The filter system of J-PLUS offers a sufficiently high-dimensional space to reliably use ML techniques. We explored the ability to reproduce the presented search for candidate UCDs with a purely ML-based methodology that uses only J-PLUS photometry. Because the sample is strongly imbalanced, as a first step in the candidate UCDs identification, we proposed a filtering strategy to discard the objects that differ the most from the UCDs using the PCA algorithm. Then, with the reduced sample, SVM models were trained and fine-tuned to maximise the identification of candidate UCDs.

Principal component analysis (Hotelling, 1933), one of the most popular linear dimensionality reduction algorithms, is a non-parametric method that aims to reduce a complex data set to a lower dimension by identifying the axes that account for the largest amount of variance. The unit vectors defining each of these axes are called principal components. PCA works on the assumption that principal components with larger associated variance encompass the underlying structure of the data set in order to find the best basis for re-expressing it. The expectation behind this method, as with any method of dimensionality reduction, is that the entire data set can be well characterised along a small number

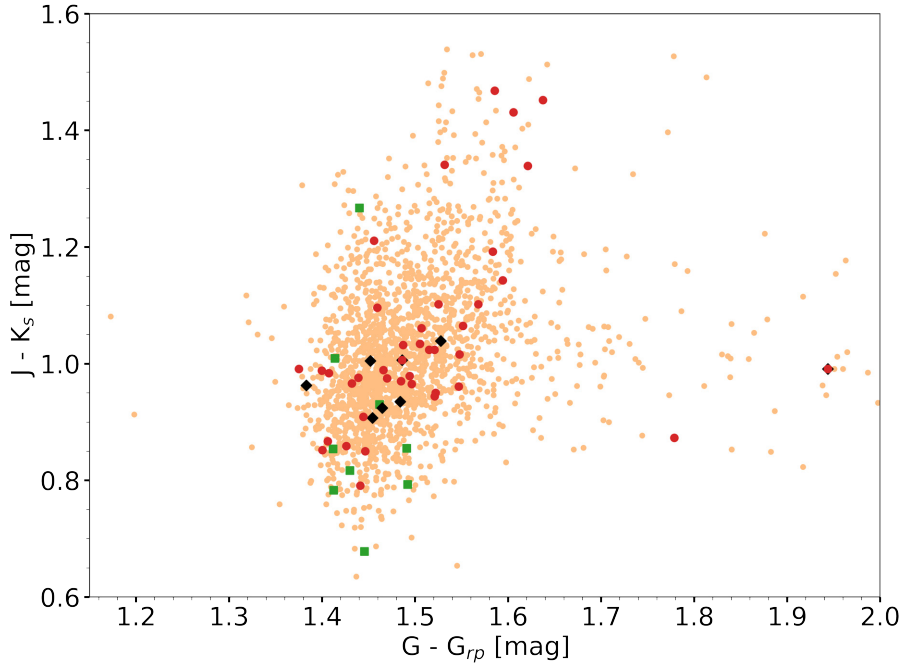


Figure 2.12: $J - K_s$ (2MASS) vs. $G - G_{RP}$ (*Gaia*) diagram of our candidate UCDs with good 2MASS photometric quality ($Q_{flg}=A$) in J and K_s bands. Black diamonds represent our eight new nearby candidate UCDs at distances $d < 40$ pc. Green squares stand for new candidate UCDs with tangential velocities $v_{tan} > 100 \text{ km s}^{-1}$. Red circles represent candidate UCDs with a possible membership in a nearby young association.

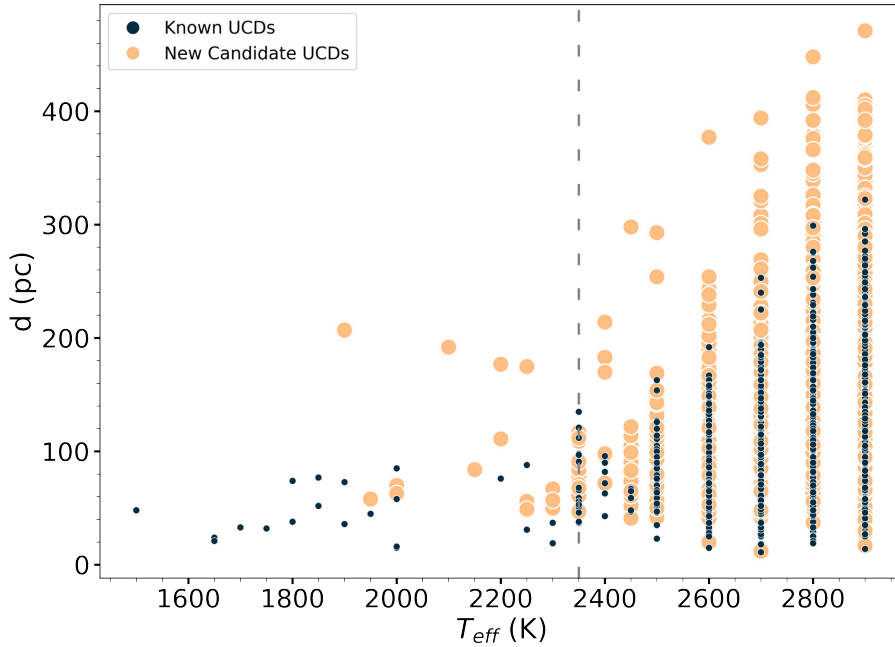


Figure 2.13: Distance vs. effective temperature diagram for previously reported (blue) and new (yellow) candidate UCDs with good parallax conditions. The vertical dashed line indicates the lower limit of effective temperature for M-type dwarfs (2359 K) according to Pecaut and Mamajek (2013).

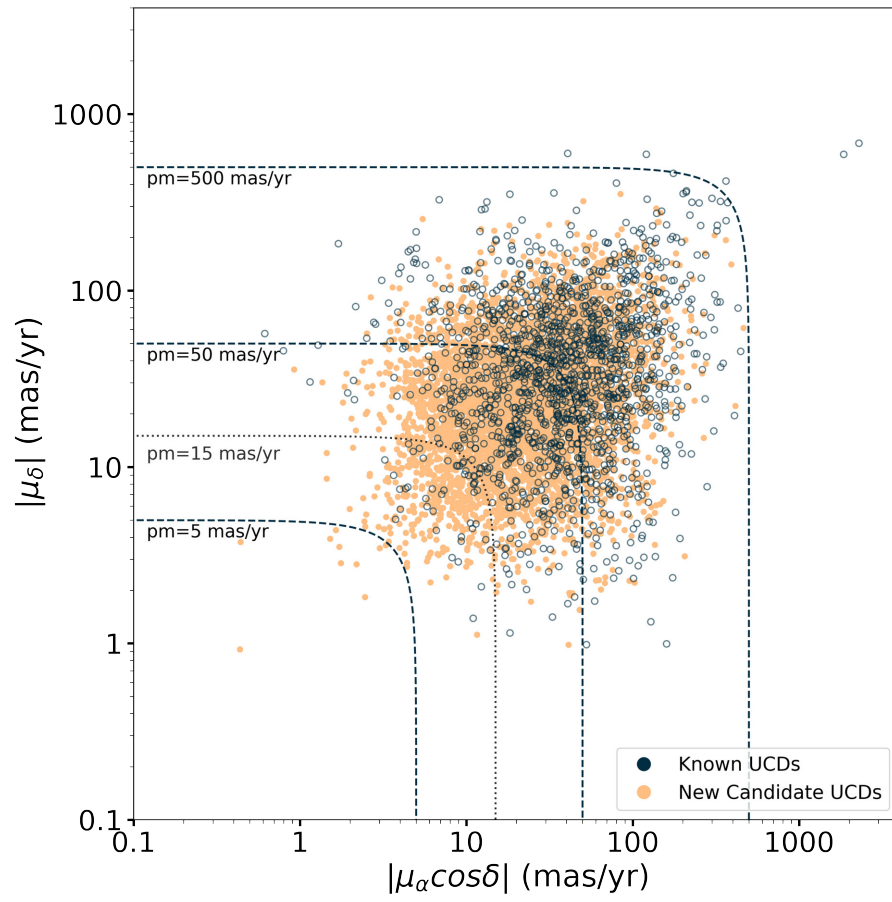


Figure 2.14: Absolute proper motion components for previously reported (blue) and new (yellow) candidate UCDs with good proper motion conditions.

of dimensions (principal components). By projecting the data set onto the hyperplane defined by these principal components, you ensure that the projection will preserve as much variance as possible.

The selection of PCA in our approach instead of other non-linear dimensionality reduction techniques, such as t-Distributed Stochastic Neighbor Embedding (t-SNE; Maaten and Hinton, 2008) or Uniform Manifold Approximation and Projection (UMAP; McInnes et al., 2018), is mainly based on (1) the computational efficiency, since PCA allows projecting new data along the new axes without having to reapply the algorithm, and (2) the deterministic nature of the PCA solution, i.e., different runs of PCA on a given dataset will always produce the same results. These properties of PCA are crucial in our proposal, since we use the 2D representation of PCA to perform the filtering as a first step in our ML task.

Support vector machine is a supervised (requires labelled training data) ML algorithm that has been widely used in classification and regression problems (Sarro et al., 2013b; González-Marcos et al., 2017). The origin of this algorithm dates back to the late 70s, when Vapnik (1979) delved into the statistical learning theory. The idea behind SVM is to find a hyperplane that separates data into two classes while maximising a margin, defined as the distance from the hyperplane to the closest point across both classes. Thus, the SVM chooses the best separating hyperplane as the one that maximises the distance to these points, so the decision surface is fully specified by a subset of points on the inner edge of each class, known as support vectors. The SVM is a linear classifier, so if the data is not linearly separable in the instance space, we can gain linear separation by mapping the data to a higher dimensional space. To do so, different kernels are used, such as the polynomial or the radial basis function (RBF), since the kernel trick allows us to define a high-dimensional feature space without actually storing these features.

2.5.1 PCA cut

In our methodology, we used J-PLUS DR2 data from one of the $20 \times 20 \text{ deg}^2$ mentioned in Sect. 2.2. We selected as features seven different J-PLUS colours built with the most relevant filters for UCDs, i.e., the reddest ones (see Table 2.1): $i - z$, $r - i$, $i - J0861$, $J0861 - z$, $(i - z)^2$, $(r - i)^2$, and $r - z$. We discarded the filter $J0660$ because the available photometry in this filter is less abundant than in the others. Thus, we first built these variables from the J-PLUS photometry, discarding objects with no information in any of the required filters, and labelled the instances as positive or negative class using the candidate UCDs obtained with the previous methodology. After this, we ended up with a sample composed of 317 UCDs and 495 274 non-UCD objects.

To perform the PCA, we first divided the sample into training (70 %) and test (30 %) sets using stratified sampling to ensure that these sets are representative of the overall population (have the same percentage of samples from each target class as the complete set). Thus, we trained the PCA model using the training set, obtaining that 93 % of the sample's variance lied along the two first principal components. Projecting the training data onto the hyperplane defined by these two principal components, the vast majority of non-UCD objects are clearly separated from the UCDs. Thus, it is possible to make a first cut in the identification of UCDs with this 2D projection, by defining a decision threshold (purple line in the Figure) and keeping only the objects that fall on the UCD side. Fig. 2.15 shows the same projection for the entire sample (training + test). After this cut, we reduced our sample to 317 and 29 732 UCD and non-UCD objects, respectively,

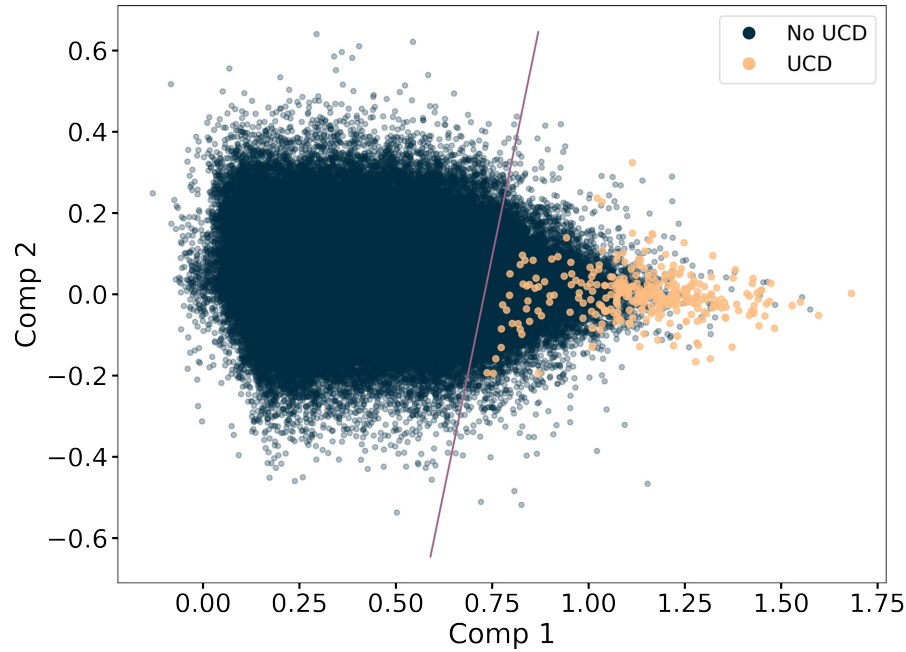


Figure 2.15: Projection of the sample used in the ML methodology onto the hyperplane defined by the first two principal components, with an explained variance ratio of 93 %. Points are colour-coded according to their class, UCD (yellow) or non-UCD (dark blue). The purple line represents the decision threshold used to make a first cut at identifying UCDs, keeping only the objects that fall on the UCD side.

achieving a 94 % reduction on the negative class. Despite still being strongly imbalanced, this reduced sample has a better balance between the negative and positive class, which facilitates better results when using the SVM.

2.5.2 SVM model

To develop the SVM model, we used the reduced sample obtained in the PCA filtering, keeping the same training and test set structure. We used the test set for the validation of the classification model. The seven J-PLUS colours described in Sect. 2.5.1 were used as features in the training step.

Then, we conducted a search for the SVM's optimal hyperparameters on the training test. To do this, we created a grid for the SVM kernel and hyperparameters and did an exhaustive search over this parameter space using the `GridSearchCV` class from the `scikit-learn` package, which optimises the hyperparameters of an estimator by k-fold cross-validation using any score to evaluate the performance of the model. In our case, we used the recall score, which measures the ability of the classifier to find all the positive instances, since our priority is to identify as many candidate UCDs as possible. For the `GridSearchCV` class, we used ten k-folds and set the hyperparameter `class_weight` to 'balanced' to address the imbalance by adjusting the weights inversely proportional to the class frequencies. In the grid of hyperparameters, we tested the regularisation parameter C for values of 1, 10, 100 and 1000, and the kernel scale γ of the RBF kernel for 0.001, 0.01, 0.1, 1, 10 and 100.

After this search for the optimal hyperparameters, we obtained the best recall score with an RBF kernel and hyperparameters $C = 10$ and $\gamma = 0.001$, with a total recall, pre-

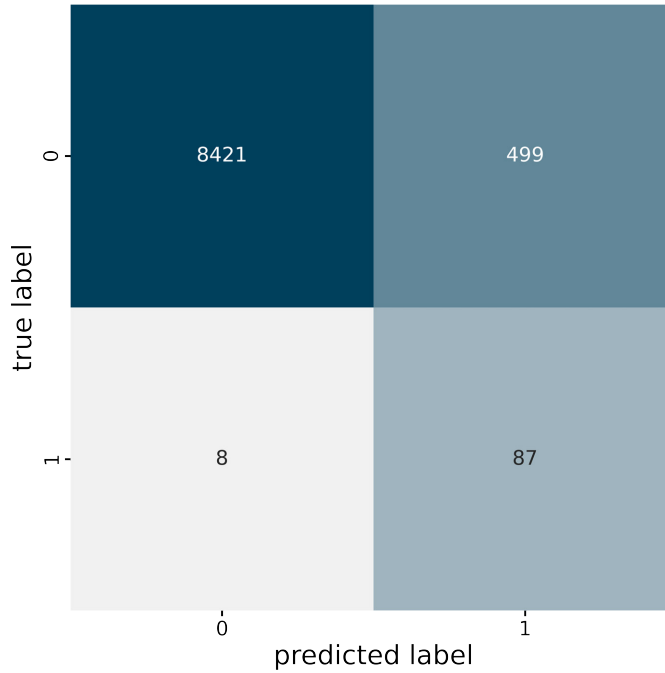


Figure 2.16: Confusion matrix for the test set, with a recall of 92 %.

cision, and F1 score of 92 %, 15 %, and 26 %, respectively, on the test set. Fig. 2.16 shows confusion matrix on the test set. The confusion matrix is a performance measurement in machine learning classification that compares the labels predicted by the model (x-axis) with the ground-truth labels in the data set (y-axis). The most important thing to note here is that the SVM model manages to recover nearly all positive instances, which is our main priority, as we do not want to lose any candidate UCD in the process. Also, the SVM performs very well at identifying True Negatives (TN, negative instances predicted as negative). In conclusion, the model allows us to filter out the vast majority of non-UCD objects, while keeping almost all the candidate UCDs. However, the class imbalance of the data causes the number of False Positives (FP, negative instances predicted as positive) to be larger than the number of True Positives (TP, positive instances predicted as positive). This makes the analysis with VOSA still necessary to differentiate the final candidate UCDs.

2.5.3 Blind test

To validate the classifier’s performance on unseen data, we applied our ML methodology on the J-PLUS DR2 data from another of the $20 \times 20 \text{ deg}^2$ regions containing 607 801 objects with good photometry in all relevant filters. Firstly, we used the same PCA model fitted with the previous region to perform the PCA filtering on this new region, reducing the total number of instances to 51 343. We used the previously fitted SVM model to predict over this reduced set, obtaining a recall, precision, and F1 score of 91 %, 9 %, and 16 %, respectively. Fig. 2.17 shows the confusion matrix for this blind test. Thus, we ended up with 2 606 (2 379 + 227) objects to be analysed with VOSA for the final UCD

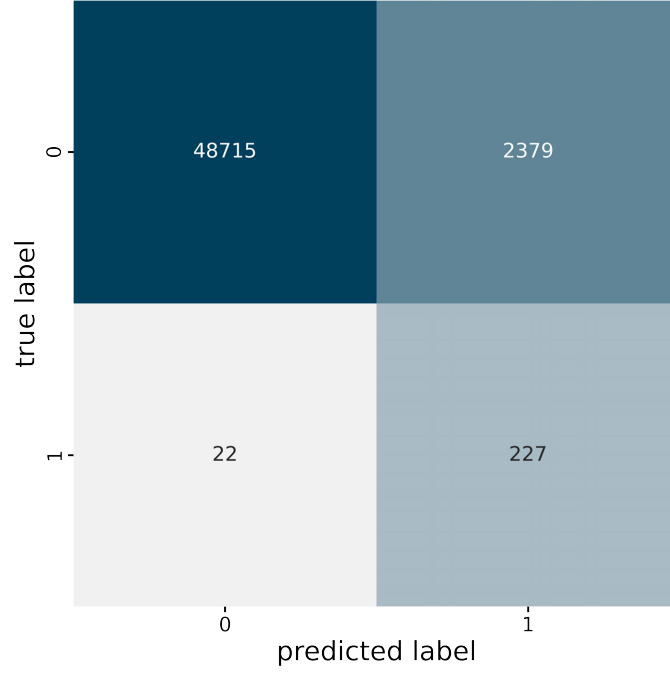


Figure 2.17: Confusion matrix for the blind test, with a recall of 91 %.

identification, which means the SVM model achieved to discard $\sim 95\%$ ($1 - 2379/51\,094$) of the non-UCD objects that pass the PCA filtering.

We used the objects analysed with *VOSA* in the VO methodology for this same region to make a thorough analysis of our ML method. Thus, we found that, of these objects, the PCA filter removes those with $T_{\text{eff}} \gtrsim 4\,100\text{ K}$, so this first cut is able to purge the initial set of the hottest objects. The ML methodology is more restrictive in terms of photometric quality, as it is only applicable to the objects with photometry in all the filters used to build the input features. This means that all the final candidate UCDs with no photometry in any of these filters (around 50 % for this region), obtained with the VO methodology, are not captured by the ML procedure. In summary, we concluded that the ML methodology is more efficient in the sense that it allows for a greater number of true negatives (non-UCD objects) to be discarded prior to analysis with *VOSA*, although it is a more restrictive method as it relies only on the photometry of the J-PLUS filters used. Another advantage of the proposed ML approach is that it consists of a single process instead of the three separate ones required in the VO methodology.

2.6 DETECTION OF STRONG EMISSION LINE EMITTERS

Strong emission lines have been detected serendipitously in UCD optical spectra, both as transient flaring phenomena (Liebert et al., 1999, 2003; Martín and Ardila, 2001; Schmidt et al., 2007) as well as steady features (Schneider et al., 1991; Mould et al., 1994; Martín et al., 1999a; Burgasser et al., 2011). Stellar flares, events powered by the sudden release of magnetic energy, that is converted to kinetic energy of electrons and ions due to magnetic reconnection in the stellar atmosphere, are a common phenomenon around M dwarfs.

Works such as those presented in Hambaryan et al. (2004), Berger et al. (2010) and Route and Wolszczan (2016) have confirmed that optical, radio and X-ray flares do occur in UCDs.

We decided to focus our search for strong emission on the $H\alpha$ and Ca II H and K lines, important chromospheric activity indicators (Cincunegui et al., 2007a), which correspond to filters 11.0 (J0660) and 7.0 (J0395) in the J-PLUS filter system, respectively. Since this is a rare phenomenon, we decided to conduct this search on a larger sample of objects, including all the objects that met the $G - G_{\text{RP}}$ and $r - z$ colour criteria presented in Sects. 2.2.1, 2.2.2 and 2.2.3. Therefore, since we did not apply the effective temperature cutoff, the search also covered spectral types hotter than those of the UCDs.

With this purpose, we developed a Python algorithm that detects any drop in magnitude in filters J0395 and J0660. Firstly, the algorithm joins the J-PLUS DR2 photometry obtained in the search described in Sect. 2.2 to the shortlisted objects obtained with the methodology described in Sect. 2.2.1, 2.2.2 and 2.2.3. Then, object by object, it computes the magnitude ratio between the filter of interest and all its neighbours. We chose as neighbours the filters 6.0, 8.0 and 9.0 for the filter 7.0 (Ca II H and K) and the filters 1.0 and 3.0 for the 11.0 ($H\alpha$). If this ratio is lower than a fixed threshold value (entered by the user) for any neighbouring filter, the algorithm recognises a possible strong line emitter and plots the photometry of the object. For the object to be recognisable, we need at least photometry in one of the neighbouring filters, so we can detect this emission peak. The algorithm receives as input a file with the candidate UCDs photometry and returns both the plotted photometry of the objects with possible strong emission and a table with the computed magnitude drop for each of them. We were permissive with the fixed threshold, so as not to discard any interesting object, and imposed a value of 0.96. Then, we visually inspected all the possible strong emitters detected by the algorithm given this threshold.

Finally, we ended up with eight objects that exhibit significant emission peaks in the filters of interest, that are presented in Table 3.5. We used VOSA to estimate the effective temperature of these objects and found only one UCD, with $T_{\text{eff}} = 2500 \text{ K}$, among the eight objects (fifth object in Table 3.5). The remaining seven objects have estimated effective temperatures (see Table 3.5) typical of mid-M dwarfs (Zhang et al., 2018). Fig. 2.18 shows the photometry of the object with the highest line emission excess (first object in Table 3.5). Also, in Fig. 2.19 we include images from the J-PLUS DR2 archive with the emission in different filters for the object with highest excess activity in the Ca II H and K (first object in Table 3.5) and $H\alpha$ (seventh object in Table 3.5) emission lines. With this analysis, we underline the possibility of systematically detecting strong emission lines in UCDs and earlier M-type stars with photometric surveys such as J-PLUS.

For the fifth object listed in Table 3.5, namely LP 310-34, we carried out a follow-up optical spectroscopy monitoring study. Five exposures of half an hour integration time each were obtained on January 12th, 2020 in service time (proposal 60-299, PI Martín) with ALFOSC attached to the Nordic Optical Telescope in La Palma. The grism number 4 and the slit width of 1.0 arcsec were selected providing a dispersion of $3.75 \text{ \AA pixel}^{-1}$ and a resolving power of $R=700$. Our spectra confirm that it is a very late M dwarf (dM8) with $H\alpha$ in emission (Schmidt et al., 2007). We measured an $H\alpha$ equivalent width of $-14.6 \text{ \AA}$, using the gaussian profile integration option available in the IRAF task *splot* applied to the co-added spectrum of the five exposures. Individual measurements of the equivalent width in each spectrum ranged from -7.0 to $-20.7 \text{ \AA}$, suggesting variability in the strength of the $H\alpha$ emission. This level of $H\alpha$ emission is not uncommon among late-M dwarfs

Table 2.2: Objects with strong flux excess in H α (filter *J0660*) or Ca II H and K (filter *J0395*) emission lines, identified with our Python algorithm.

α [deg]	δ [deg]	Filter of interest	Magnitude ^(a)	Ratio ^(b)	Simbad ID	Estimated T_{eff} [K]
18.53140	7.94229	<i>J0395</i>	16.811	0.799	...	3 200
36.68415	34.75973	<i>J0660</i>	18.100	0.884	...	3 300
107.18550	71.90704	<i>J0660</i>	18.199	0.915	...	3 200
116.14374	40.14576	<i>J0395</i>	19.333	0.946	...	3 100
121.85651	32.21826	<i>J0395</i>	17.002	0.806	LP 310-34	2 500
135.92497	34.80495	<i>J0395</i>	18.319	0.895	LP 259-39	3 200
138.52385	23.87355	<i>J0660</i>	17.443	0.850	...	3 200
199.02058	56.12370	<i>J0660</i>	20.233	0.911	...	3 300

^(a) In the filter of interest. ^(b) Ratio of magnitudes between filter of interest and neighbour filter.

(Martín et al., 2010; Pineda et al., 2016). No other emission lines were detected in our spectra.

One of the new strong line-emission candidates (sixth object in Table 3.5) was observed on April 21st, 2022 with the long-slit low-resolution mode of the SpeX instrument (Rayner et al., 2003) at the NASA Infrared Telescope Facility (IRTF, program 2022A011, PI A. Burgasser). Preliminary analysis of the data indicates that the near-infrared spectrum is well matched by a M5 dwarf template (A. Burgasser, private communication). Further details of these observations and additional spectroscopic follow-up of the J-PLUS candidates presented in this work is planned for a future paper.

This study suggests that our J-PLUS search for strong emission lines may be revealing previously unknown sporadic very strong activity in otherwise normal late-M dwarfs. It is worth noting that our search for strong line emitters has detected as many objects with Ca II H and K excess than with H α excess, and no object showing both excesses simultaneously. Events of strong Ca II H and K line emission in normal late-M dwarfs may have important implications for studies of exoplanetary space weather and habitability (Yamashiki et al., 2019).

2.7 CONCLUSIONS

Using a Virtual Observatory methodology, we provide a catalogue of 9 810 candidate UCDs over the entire sky coverage of J-PLUS DR2. With 7 827 previously not reported as UCD, we show there is still room for the discovery of these objects even with a small telescope such as the JAST80. Our main goal is to consolidate and further develop a search methodology, introduced in Solano et al. (2019), to be used for deeper and larger surveys such as J-PAS and Euclid, both being an ideal scenario for the study and discovery of UCDs thanks to their unprecedented photometric system of 54 narrow-band filters and excellent sensitivity, respectively. Further confirmation by spectroscopy of the UCD nature of these candidates goes beyond the scope of this study. However, the candidate UCDs that are reported in Simbad, but are not in our sample of known UCDs (see Sect. 2.4), mostly present spectral type M6 V or are left out because they lack the luminosity class, so we expect the degree of contamination to be small.

The use of different approaches based on astrometry and photometry tends to minimise the drawbacks and biases associated to the search of ultracool objects: photometric-

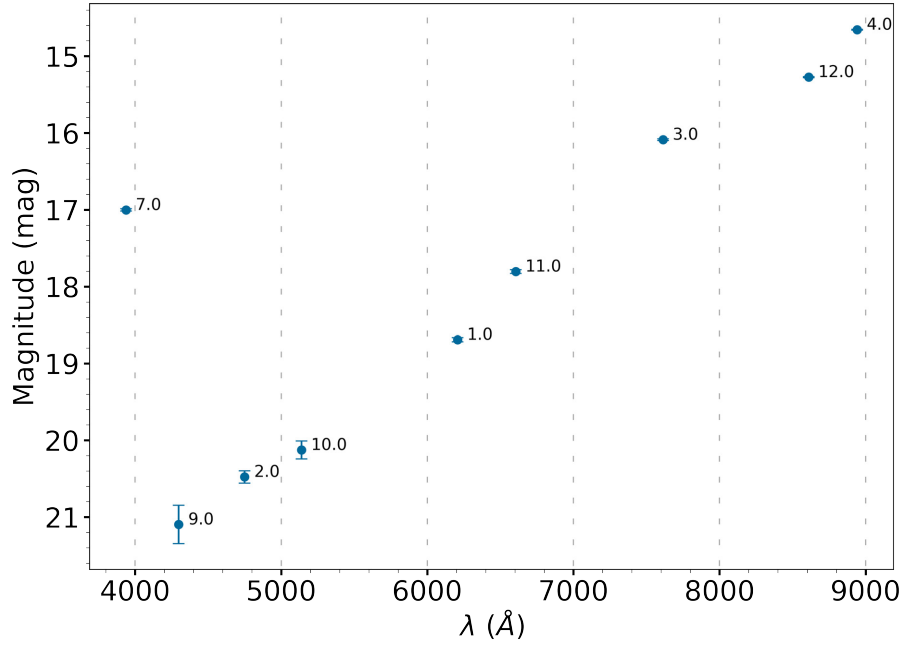


Figure 2.18: Example of a detected strong excess in the filter 7.0 (*J0395*), which corresponds to Ca II H and K emission lines. The Figure shows the J-PLUS photometry of the first object in Table 3.5, with error bars representing the error in the magnitude. The algorithm detects that the magnitude in the filter *J0395* is 0.8 times the magnitude in the filter 9.0 (*J0430*), and recognises this as a possible emission line. In this case, the threshold value for the excess detection was 0.96.

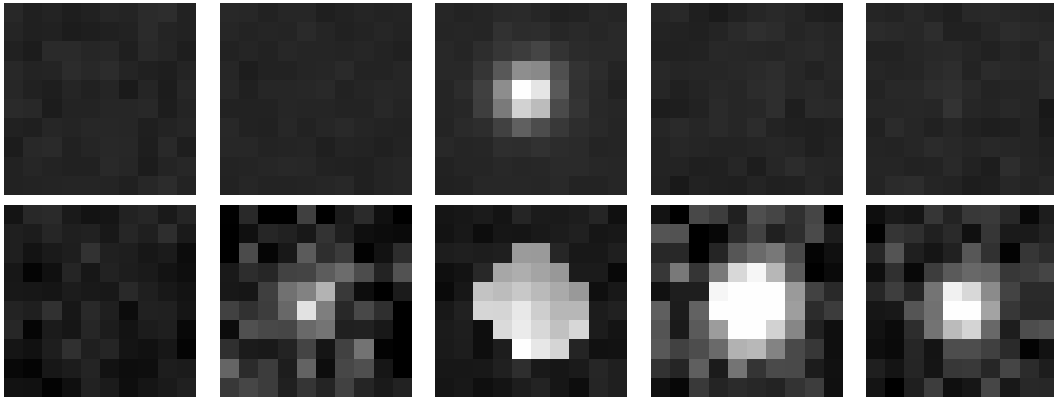


Figure 2.19: Images from the J-PLUS DR2 archive with the photometry in different filters for two of the strong line emitters detected. The first row corresponds to an excess in the Ca II H and K (filter *J0395*) emission lines (first object in Table 3.5), with images in the filters *u*, *J0378*, *J0395*, *J0410*, and *J0430* (from left to right). The second row shows an excess in the H α (filter *J0660*) emission line (seventh object in Table 3.5), with images in the filters *J0515*, *r*, *J0660*, *i*, and *J0861* (from left to right). For both objects, all images shown were taken within a time interval of about 40 minutes.

only selected samples may leave out peculiar UCDs not following the canonical trend in colour-colour diagrams and they can also be affected by extragalactic contamination. Proper motion searches may ignore objects with small values of projected velocity in the plane of the sky. Regarding parallax-based searches, they will be limited to the brightest objects with parallax values from *Gaia*.

Based on our kinematics study, almost all our candidate UCDs can be considered thin disk members, with 268 of them being potential members of the thick disk. Also, five of the candidates are likely to belong to the Galactic halo. Using the BANYAN Σ tool, we find 48 candidate UCDs with a high Bayesian probability of belonging to seven different young moving associations, in 30 of the cases with a probability greater than 95 %. A further spectroscopic follow-up will be required to search for spectral signatures of youth. In the binarity analysis, we find 122 possible unresolved companions among our candidate UCDs. Searching for wide *Gaia* companions of our candidate UCDs, we find 78 possible multiple systems (73 binary + 5 triple), six of them already tabulated by the WDS. We use VOSA to get an estimation of the effective temperature of the wide *Gaia* companions identified in all the systems, finding that most of them are M-type stars.

Among the non-recovered known UCDs that lie in the sky coverage of J-PLUS DR2, we find that more than half are lost due to lack of photometric or astrometric information with enough quality. The remaining objects are discarded due to our conservative temperature cutoff at 2900 K or a bad SED fitting ($vgfb > 12$). Compared to previously reported candidates, the new ones are on average more distant and extend to smaller values of proper motion.

We achieve promising results when reproducing the search for UCDs with a purely ML-based methodology. In this approach, we find crucial the preliminar PCA filtering to deal with the strong imbalance of the data and discard the hottest objects. This allows us to significantly reduce the negative class and improve the classification capability of the posterior SVM model. Using the developed ML methodology to predict on unseen data, we are able to recover 91 % of the candidate UCDs found with the VO methodology, discarding a larger number of true negatives (non-UCD objects) before the analysis with VOSA in a faster way. This is a significant achievement, since the main bottleneck of the VO methodology is the high number of objects to be analysed with VOSA.

In this line, the real turning point would be to develop a ML methodology that more significantly filters the number of objects we need to analyse with VOSA for the final UCD identification. This is not a straightforward task due to the imbalance of the data and because the analysis with VOSA is based on complex theoretical models. To this end, we are exploring the use of independent component analysis in the initial filtering and ensemble learning in the classification step.

Finally, we develop an algorithm capable of detecting strong emission line emitters in the optical range. We identify four objects with strong excess in the filter corresponding to the Ca II H and K emission lines and four other objects with excess emission in the H α filter.

3

DETECTION OF FLARING M DWARFS WITH MULTI-FILTER PHOTOMETRY

Understanding and characterising the magnetic activity of M dwarfs is of paramount importance in the search for Earth-like exoplanets orbiting around them. Energetic stellar activity phenomena, such as flares or coronal mass ejections, which are common in these stars, are deeply connected with the habitability and atmospheric evolution of the surrounding exoplanets. We present a follow-up of a sample of M dwarfs with strong H α and Ca II H and K emission lines identified with J-PLUS photometry in a previous work. We collected low-resolution NOT/ALFOSC and GTC/OSIRIS spectra, measuring the PC3 index for the spectral type determination. We used two-minutes cadence TESS calibrated light curves to identify and characterise multiple flares, and to calculate the rotation period of the two active M dwarfs found in our sample. We confirmed that the strong emission lines detected in the J-PLUS photometry are caused by transient flaring activity. We found clear evidence of flaring activity and periodic variability for LP 310-34 and LP 259-39, and estimated flare energies in the TESS bandpass between 7.4×10^{30} and 2.2×10^{33} erg for them. We characterised LP 310-34 and LP 259-39 as very rapidly rotating M dwarfs with Ca II H and K and H α in emission, and computed a rotation period of 1.69 d for LP 259-39 for the first time. This work advocates the approach of exploiting multi-filter photometric surveys to systematically identify flaring M dwarfs, especially to detect episodes of strong Ca II H and K line emission that may have important implications for exoplanetary space weather and habitability studies. Our results reveal that, apart from the already known H α flares, flare events in Ca II H and K can also be detected using optical narrow-band filters in common M dwarfs.

3.1 OBSERVATIONS

3.1.1 Sample selection

The sample studied in this work is the result of the search for strong emission lines performed in our previous work (Mas-Buitrago et al., 2022), using multi-filter optical photometry from the Javalambre Photometric Local Universe Survey (J-PLUS; Cenarro et al., 2019). For this, we developed a Python algorithm capable of detecting excess in the J-PLUS filters corresponding to the H α (J0660) and Ca II H and K (J0395) emission lines. Following this approach, we identified eight M dwarfs with emission excess in these filters (four of them in each of the filters and none showing both excesses simultaneously). In the end, one of these objects was discarded for spectroscopic follow-up because it was not bright enough, resulting in a final sample of seven M dwarfs. Table 3.1 lists the selected targets.

The J-PLUS spectral energy distribution (SED) of each target star is provided in Appendix C. The excess emission in the J0395 filter is evident for J-PLUS0114, J-PLUS0744, J-PLUS0807, and J-PLUS0903. On the other hand, the SEDs of J-PLUS0226, J-PLUS0708, and J-PLUS0914 show strong emission in the J0660 filter. We attribute this behaviour

Table 3.1: Targets selected for spectroscopic observation.

Object ^(a)	SIMBAD	α ^(b) [J2016.0]	δ ^(b) [J2016.0]	T ^(c) [mag]	VOSA T_{eff} [K]	Excess
J-PLUS DR2 J0114+07	...	01:14:07.54	07:56:32.2	15.78 ± 0.01	3 200	Ca II HK
J-PLUS DR2 J0226+34	...	02:26:44.20	34:45:35.0	18.91 ± 0.05	3 300	H α
J-PLUS DR2 J0708+71	...	07:08:44.51	71:54:25.3	18.19 ± 0.01	3 200	H α
J-PLUS DR2 J0744+40	...	07:44:34.50	40:08:44.7	14.79 ± 0.01	3 100	Ca II HK
J-PLUS DR2 J0807+32	LP 310-34	08:07:25.60	32:13:06.0	14.72 ± 0.01	2 500	Ca II HK
J-PLUS DR2 J0903+34	LP 259-39	09:03:41.95	34:48:18.6	13.83 ± 0.01	3 200	Ca II HK
J-PLUS DR2 J0914+23	...	09:14:05.74	23:52:24.9	18.39 ± 0.08	3 200	H α

^(a) Hereafter we use J-PLUSHHMM as an abbreviation. ^(b) From *Gaia* Data Release 3 (DR3; *Gaia* Collaboration et al., 2023b). ^(c) TESS magnitude from Paegert et al. (2022).

to the fact that the star experiences flaring activity during the corresponding J-PLUS observing block, in which all filters are observed sequentially. The strategy for each J-PLUS observing block is to obtain, for the same pointing, three consecutive exposures per filter, with a total exposure time of approximately one hour (Cenarro et al., 2019). Flaring phenomena during the exposures for the filters of interest would explain the SED behaviour found. Given the low probability of observing a flare during the exposures for the filters of interest, it is easier to detect the less energetic and shorter-lived flares, which are more frequent and last a few minutes as we confirm in Section 3.2.2.

The estimated effective temperatures for these objects, obtained with the tool VOSA¹ (Bayo et al., 2008), locate them as mid-M dwarfs except for one, namely LP 310-34, with a $T_{\text{eff}} = 2\,500$ K. As mentioned in Mas-Buitrago et al. (2022), we already carried out an spectroscopic follow-up for the latter that confirmed it as a late M dwarf (dM8) with H α in emission (Schmidt et al., 2007).

3.1.2 Observational details

We collected low-resolution optical spectra of our seven targets with The Alhambra Faint Object Spectrograph and Camera (ALFOSC) mounting on the 2.56-m Nordic Optical Telescope (NOT) with proposal number 66-208 (P.I. ELM). Also, we observed two bright targets (J-PLUS DR2 J0807+32 and J-PLUS DR2 J0903+34 in Table 3.1) with the Optical System for Imaging and low-Intermediate-Resolution Integrated Spectroscopy (OSIRIS) mounting on the 10.4-m Gran Telescopio Canarias (GTC), at the Roque de los Muchachos Observatory on the island of La Palma, Spain, with programme GTCMULTIPLE2I-22B (P. I. ELM).

ALFOSC is equipped with a Teledyne e2v CCD231-42-g-F61 back illuminated, deep depletion, astro multi-2 detector. The detector dimension is 2048×2064 pixels with a scale of 0.2138 arcsec/pix. The NOT/ALFOSC observation was executed under visitor mode during the nights of January 26-27, 2023 (observers PMB & JYZ). We used a 1.0-arcsec slit, and #4 grism, which provide a wavelength range from 3 200 Å to 9 600 Å with a resolution power $R \approx 360$.

OSIRIS is a commonly used instrument of GTC. It covers the wavelength range 3 650 – 10 050 Å and has an effective field of view of 7.5×6.0 arcmin. OSIRIS has two Marconi CCD44-82 (2048×4096 pixels) detectors with gap in between. The 2×2 binned pixel size is 0.254 arcsec/pix. In the mode of long-slit spectroscopy, the object is centred on the slit at the coordinate $X = 250$ of the CCD2. The GTC/OSIRIS observation was executed

¹ <http://svo2.cab.inta-csic.es/theory/vosa/>

Table 3.2: Record of observations.

Object	Date	Configuration	Slit width	Grism	Exposures
J-PLUS0114	26 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1800s×2
J-PLUS0114	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1800s×1
J-PLUS0226	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	2000s×5
J-PLUS0708	26 Jan. 2023	ALFOSC Long Slit	1.0"	#4	2000s×5
J-PLUS0744	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1500s×3
J-PLUS0807	29 Oct. 2022	OSIRIS Long Slit	1.2"	R1000B	180s×6
J-PLUS0807	26 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1800s×2
J-PLUS0807	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1800s×1
J-PLUS0903	29 Oct. 2022	OSIRIS Long Slit	1.2"	R1000B	90s×6
J-PLUS0903	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	1000s×3
J-PLUS0914	26 Jan. 2023	ALFOSC Long Slit	1.0"	#4	2000s×4
J-PLUS0914	27 Jan. 2023	ALFOSC Long Slit	1.0"	#4	2000s×1

Targets are ordered first by right ascension and then observation date.

under service mode. We requested as conditions a maximum seeing of 1.2 arcsec, cloud free sky, and grey moon phase, using the R1000B grism and a 1.2-arcsec slit under the parallactic angle. This configuration yields a wavelength coverage from 3 600 Å to 7 900 Å with a resolution power $R \approx 500$. Table 3.2 shows the record of observations.

3.1.3 Data reduction

We reduced both the GTC/OSIRIS and NOT/ALFOSC data using v1.12 of PyPeIt (Prochaska et al., 2020a,b), a community-developed open-source Python package for semi-automated reduction of spectroscopical data in astronomy. PyPeIt supports a long list of spectrographs and provides the code infrastructure to automatically process the image, identify the slit in a given detector, extract the object spectra, and perform wavelength calibration. We observed the standard stars HD 19445 and Feige 110 for flux calibration of NOT/ALFOSC and GTC/OSIRIS data, respectively.

3.2 RESULTS AND DISCUSSION

3.2.1 Reduced spectra

Figure 3.1 shows the co-added spectra for the observed targets. We note that no intense steady line emission is observed in the spectra (for examples of strong line emission in low-resolution spectra, see Fig. 1 in Burgasser et al., 2011 or Figs. 10 and 11 in Schmidt et al., 2007), confirming that the excess emission detected in the J-PLUS photometry is not steady and is indeed caused by transient flaring activity. Moreover, objects with excess emission in the J-PLUS Ca II H and K filter show no apparent differences in their spectral features compared to objects with excess emission in the J-PLUS H α filter (see Table 3.1), suggesting that the flaring activity detected in Ca II H and K is not particular to a specific type of star. Hence, it follows that common M dwarfs experience two types of flares, those already well-known in H α and those in Ca II H and K revealed in this work.

Several spectroscopic indices have been explored for the spectral classification of M dwarfs (Lépine et al., 2003) and, in particular, for late-M dwarfs using low-resolution

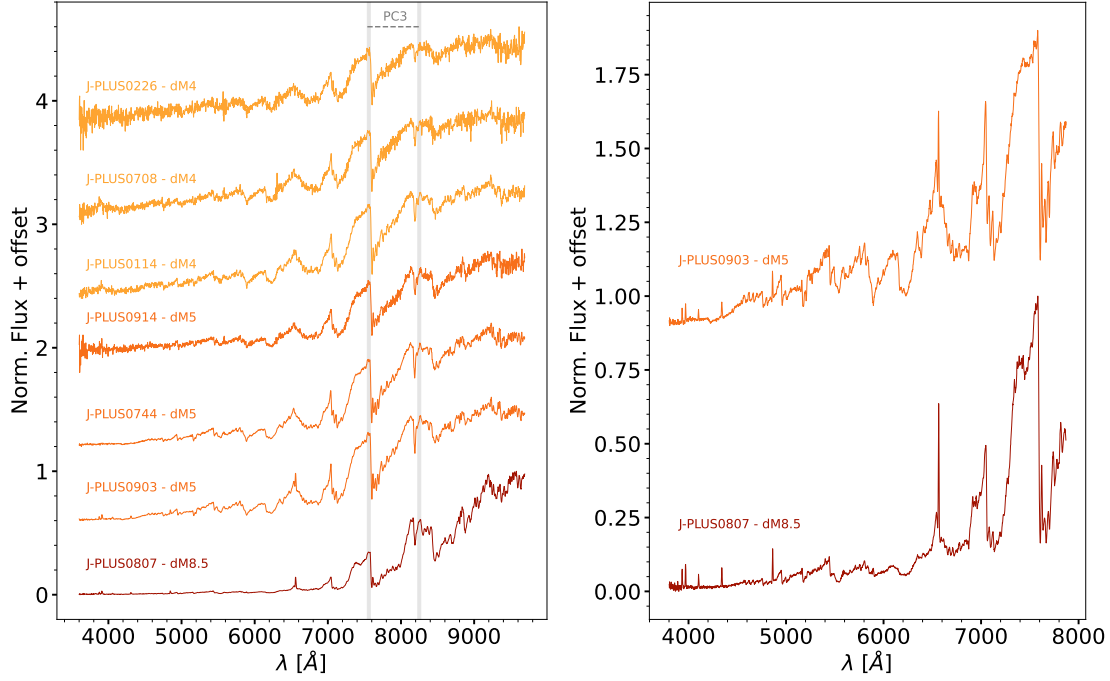


Figure 3.1: Co-added spectra observed with NOT/ALFOSC (*left panel*) and GTC/OSIRIS (*right panel*), sorted from top to bottom by the derived PC3 index (see Table 3.3). The grey shaded bands in the *left panel* show the spectral regions used to derive the PC3 index.

optical spectra (Kirkpatrick et al., 1995; Martin et al., 1996; Martín et al., 1999b). To derive spectral types for our sample, we measured the PC3 index (Martín et al., 1999b), which is a reliable indicator of spectral type in the [M2.5, L1] range and has been used consistently in the literature (Crifo, F. et al., 2005; Martin et al., 2006; Martín et al., 2010; Phan-Bao, N. and Bessell, M. S., 2006; Reylé et al., 2006; Phan-Bao et al., 2008). The PC3 index is a pseudo-continuum spectral ratio between the 8230 – 8270 $\text{\AA}$ (numerator) and 7540 – 7580 $\text{\AA}$ (denominator) intervals, which can be used to derive spectral types between M2.5 and L1 following the calibration presented by Martín et al. (1999b):

$$\text{SpT} = -6.685 + 11.715 \times (\text{PC3}) - 2.024 \times (\text{PC3})^2. \quad (5)$$

Table 3.3 lists the PC3 index and the adopted spectral type, with an uncertainty of ± 0.5 subclasses, for our targets. The classification obtained for J-PLUS0807 is consistent with that provided in Schmidt et al. (2007), who derived a spectral type of dM8, with an uncertainty of ± 0.5 subclasses, by visual comparison of the spectra to spectral standards. These results confirm the rest of our sample, still spectroscopically unclassified in the literature, as mid-M dwarfs.

The obtained spectra confirm both J-PLUS0807 and J-PLUS0903 as active M dwarfs with Ca II H and K and H α in emission, while the rest of the targets show no signs of activity. Figure 3.2 shows a close-up view of the spectral region of interest for these stars, with prominent Ca II H and K, H δ , H γ , H β and H α emission lines. We quantified the H α emission using the `specutils`² (Earl et al., 2022) Python package, obtaining an H α equivalent width of $-16.80 \text{ \AA}$ and $-5.90 \text{ \AA}$ for the co-added NOT/ALFOSC spectra, and of $-18.36 \text{ \AA}$ and $-6.08 \text{ \AA}$ for the co-added GTC/OSIRIS spectra of J-PLUS0807 and

² <https://specutils.readthedocs.io/en/stable/index.html>

Table 3.3: PC3 index and adopted spectral type for our targets.

Object	PC3	SpT
J-PLUS0114	1.12	dM4
J-PLUS0226	1.09	dM4
J-PLUS0708	1.12	dM4
J-PLUS0744	1.29	dM5
J-PLUS0807	1.94	dM8.5
J-PLUS0903	1.29	dM5
J-PLUS0914	1.29	dM5

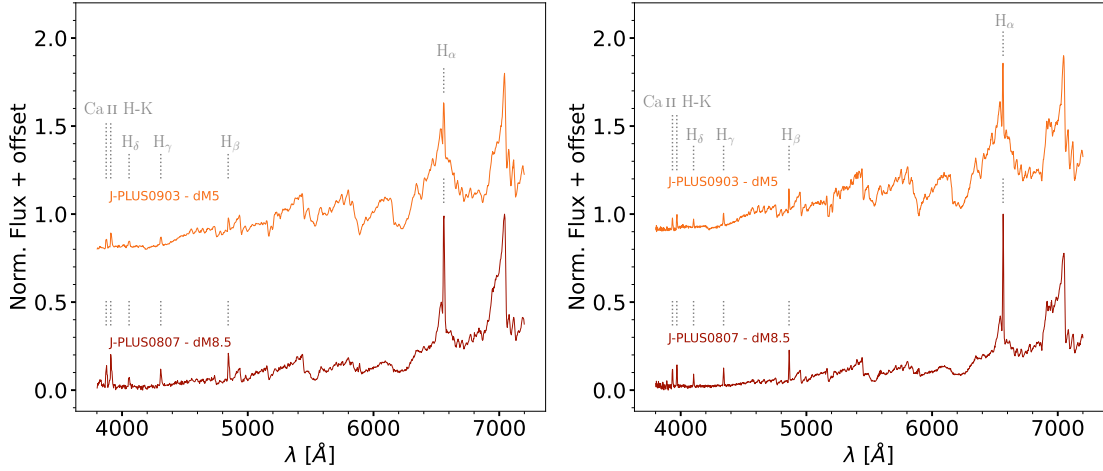


Figure 3.2: Zoom-in for the NOT/ALFOSC (*left panel*) and GTC/OSIRIS (*right panel*) co-added spectra of J-PLUS0807 and J-PLUS0903. The grey dashed lines mark Ca II H and K, H δ , H γ , H β , and H α emission lines.

J-PLUS0903, respectively. These results correspond to levels of H α emission that are not uncommon among this type of stars (Schmidt et al., 2007; Martín et al., 2010). We found no significant differences between the equivalent width measurements for the individual spectra of each exposure.

3.2.2 Light curve analysis

We queried the Mikulski Archive for Space Telescopes (MAST³) to fetch high-cadence photometric data for our sample. We found two-minutes cadence TESS calibrated LCs for the two closest stars, J-PLUS0807 and J-PLUS0903, with TIC IDs 461654150 and 166597074, respectively. Table 3.4 shows the details of the retrieved LCs, which are processed using the pipeline developed by the Science Processing Operations Centre SPOC; Jenkins et al., 2016. The contamination ratio, R_{cont} , listed in the TESS Input Catalog (Paegert et al., 2022) is 10% and 0.22% for J-PLUS0807 and J-PLUS0903, respectively. To further study a possible contamination of the TESS photometry for these two stars, we used the `tpfplotter`⁴ (Aller et al., 2020) tool to explore the target pixel files (TPFs) of the fields of our targets. Thus, we only found a $\sim 1\%$ contamination, obtained from the difference in *Gaia* magnitudes, from *Gaia* sources within the photometric apertures selected by the SPOC pipeline to process the LCs of the two stars.

³ <https://mast.stsci.edu/portal/Mashup/Clients/Mast/Portal.html>

⁴ <https://github.com/jlillo/tpfplotter>

Table 3.4: Details of two-minutes cadence TESS LCs used in this work.

TIC ID	TESS Sectors	Observation length [d]
461654150	20, 44, 45, 46, and 47	112.41
166597074	21	23.96

We identified clear evidence of flaring activity and periodic variability in the retrieved two-minutes cadence LCs for J-PLUS0807 and J-PLUS0903, which are analysed in detail in Sections 3.2.2 and 3.2.2. For the remaining five stars in our sample, that do not have processed, short-cadence TESS data, we used the Python package `lightkurve` (Lightkurve Collaboration et al., 2018) to manually extract LCs from the TESS Full Frame Images cutouts, but did not find any flare events or periodic variability signals. We also searched for time-resolved UV data from the NASA Galaxy Evolution Explorer (GALEX; Martin et al., 2005) mission for our targets, using the `gPhoton` (Million et al., 2016) database and software, but we did not find any.

Flares

For our analysis, we used the Pre-search Data Conditioning Simple Aperture Photometry (PDCSAP; Smith et al., 2012; Stumpe et al., 2012, 2014) flux, available in the TESS LCs retrieved for J-PLUS0807 and J-PLUS0903, which is already corrected from long-term trends, instrumental effects, and excess flux due to starfield crowding. We removed all data points with non-zero quality flags, after visually verifying that points with 512 ('Impulsive outlier removed before cotrending') or 1024 ('Cosmic ray detected on collateral pixel row or column') quality flags were not actually part of a real flare. We identified several flare events in all the J-PLUS0807 and J-PLUS0903 TESS LCs. For example, Figure 3.3 shows the LC of J-PLUS0903 (top left panel) and one of the LCs of J-PLUS807 (sector 44, bottom left panel), with multiple flaring episodes observed in both of them. Moreover, the right panel provides a zoomed-in view of the flare event occurring around day 1890 (BJD - 2457000 days) in the J-PLUS0903 LC.

We used the open-source Python software `AltaiPony`⁵ (Davenport, 2016; Ilin et al., 2021) to automatically identify and characterise flares in the LCs. Prior to flare detection, we detrended the LCs using a Savitzky-Golay filter (Savitzky and Golay, 1964) to remove rotational modulation trends. For flare detection, we followed the same procedure as Davenport et al. (2014), Doyle et al. (2019), Doyle et al. (2022) and Kumbhakar et al. (2023), identifying flares as two or more consecutive points that are 2.5σ above the local scatter of the data (Chang et al., 2015). As reported by Vida et al. (2017) and Doyle et al. (2018), we found no obvious relationship between flaring activity and rotational phase. `AltaiPony` automatically determines several flare properties, such as start and end times, flare amplitude, and equivalent duration (ED), which is the area under the flare light curve in units of seconds. Using the observed NOT/ALFOSC spectra and the tool `Specphot`⁶ (Rodrigo et al., 2024a), developed and maintained by the Spanish Virtual Observatory⁷, we obtained the star quiescent flux in the TESS bandpass. We relied on the calculated flux and *Gaia* distances of our targets to derive the quiescent stellar luminosity and multiplied it by the ED to obtain the flare energy in the TESS bandpass. We obtained

⁵ <https://altaipony.readthedocs.io/en/latest/>

⁶ <http://svo2.cab.inta-csic.es/theory/specphot/>

⁷ <http://svo2.cab.inta-csic.es>

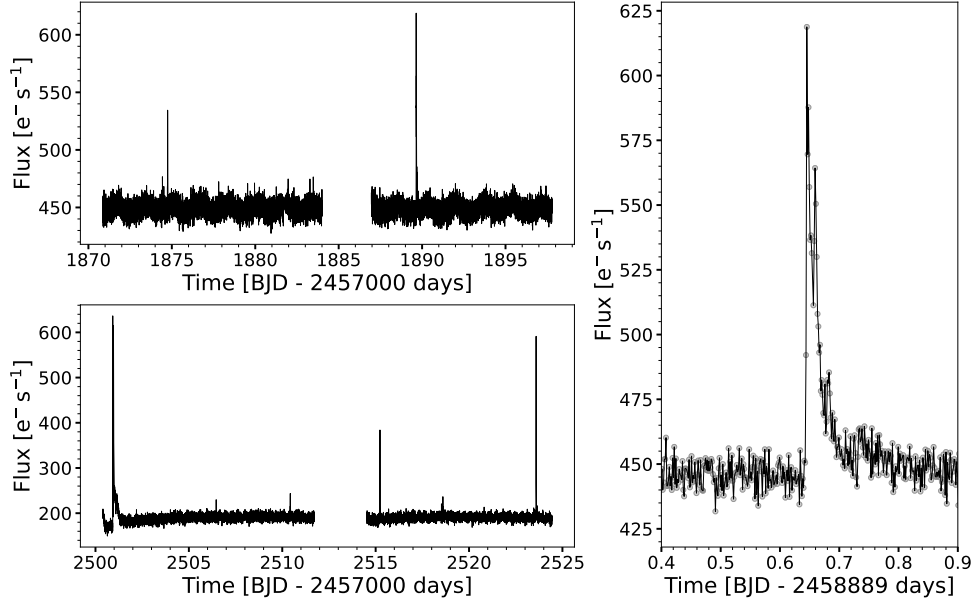


Figure 3.3: LCs of J-PLUS0903 (sector 21, *top left panel*) and J-PLUS0807 (sector 44, *bottom left panel*). The *right panel* shows the largest flare event of the J-PLUS0903 LC.

Table 3.5: Detailed flare properties of our targets with TESS processed LCs.

Object	Sector	Number of flares	$\log(E)$ range [erg]	Duration range [min]	Flare rate [d ⁻¹]
J-PLUS0807	20	5	30.9–32.1	4.0–32.0	0.22
J-PLUS0807	44	6	31.2–33.4	6.0–416.0	0.28
J-PLUS0807	45	5	30.9–32.9	6.0–54.0	0.23
J-PLUS0807	46	7	31.1–32.6	4.0–36.0	0.30
J-PLUS0807	47	4	31.0–33.3	6.0–368.0	0.17
J-PLUS0903	21	4	31.6–33.0	4.0–60.0	0.17

$L_{\text{TESS}} = 2.3 \times 10^{29} \text{ erg s}^{-1}$ and $L_{\text{TESS}} = 2.2 \times 10^{30} \text{ erg s}^{-1}$ for the quiescent luminosity in the TESS bandpass of J-PLUS0807 and J-PLUS0903, respectively. Table 3.5 details the flare properties for each target.

The flare energy and rate obtained for our targets are typical of active, fast rotating mid- and late-M dwarfs (Doyle et al., 2019; Ramsay et al., 2020; Stelzer et al., 2022). With the observed flares for J-PLUS0807, we built the cumulative flare frequency distribution (FFD) to study the flare rate as a function of flare energy. This was not possible for J-PLUS0903 due to the low number of events available. FFDs can be expressed as a power-law relation (Stelzer, B. et al., 2007; Lin et al., 2019):

$$\frac{d\nu}{dE_F} \sim E_F^{-\alpha}, \quad (6)$$

where ν is the cumulative flare rate for a given flare energy E_F , and $1 - \alpha$ is the slope of a linear fit to a log-log representation. To fit the FFD, we relied on AltaiPony's `FFD.fit_powerlaw()` method, which fits the power-law parameters simultaneously using the Markov Chain Monte Carlo method described in Wheatland (2004). Since the detection probability decreases in the low-energy regime, where flares may go undetected due to the noise present in the LC, we discarded the low-energy tail of the FFD in the fit of the power-law (Hawley et al., 2014; Chang et al., 2015; Ilin et al., 2021). Figure

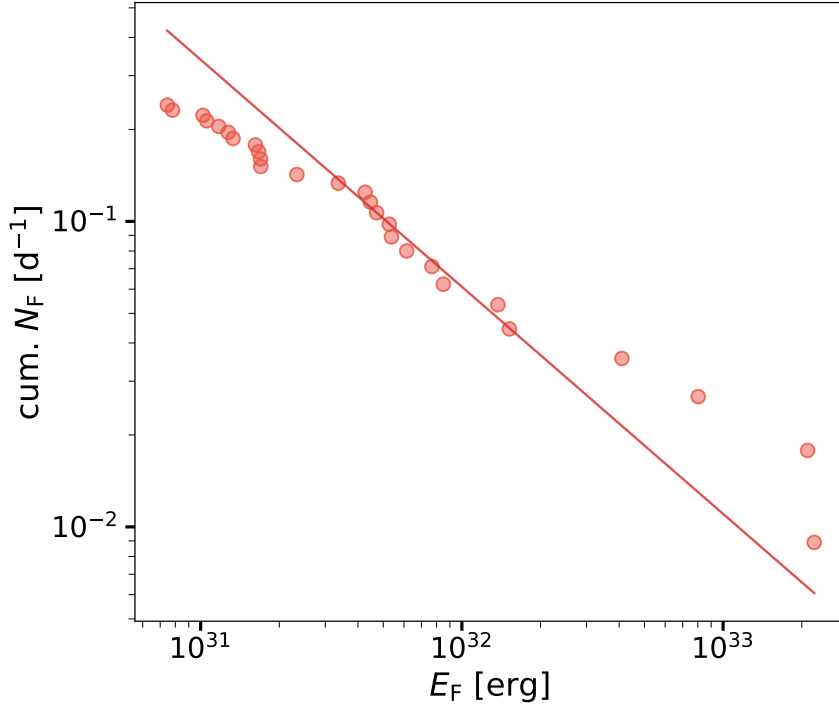


Figure 3.4: Cumulative FFD for J-PLUS0807. The red solid line represents the power-law fit obtained with AltaiPony.

3.4 shows how the power-law relation breaks down around $E_F = 10^{31.5}$ erg, which is the threshold we applied to consider flares in the FFD fitting. Following this methodology, we obtained $\alpha = 1.74^{+0.20}_{-0.17}$ for J-PLUS0807, which is in agreement with what Lin et al. (2019), Raetz et al. (2020), and Murray et al. (2022) found for their samples of 548, 56 and 85 flaring M dwarfs, respectively. We found that the less energetic flares, which are more frequent as illustrated in the FFD, are also shorter in duration and the easiest to detect with the J-PLUS observation strategy (see Section 3.1.1).

Rotation periods

All TESS LCs retrieved for J-PLUS0807 and J-PLUS0903 show a clear periodic variability, which usually arises due to co-rotating star-spots that appear and disappear from the line of sight. Therefore, we relied on a Lomb-Scargle periodogram (Lomb, 1976; Scargle, 1982), using the astropy Python package (Astropy Collaboration et al., 2013), to search for the rotation period of each of our targets. Figure 3.5 shows the periodogram for each of the targets and the phase-folded LCs with the chosen periods, which are very prominent in the periodograms.

For J-PLUS0807, we computed the period using the data from all available sectors and obtained $P_{\text{rot}} = 0.3450$ d, which is consistent with the values reported by Li et al. (2024) using TESS data from sectors 20, 45, 46 and 47, Seli et al. (2021) using only TESS data from sector 20, and Newton et al. (2016), who relied on photometry from the MEarth Project (Berta et al., 2012). For J-PLUS0903, we obtained $P_{\text{rot}} = 1.69$ d, which is the first estimation for the rotation period of this object. As a measure of the uncertainty of the peak position in the periodogram, we used the standard deviation of all the values with a power greater than the half height of the periodogram peak, obtaining 0.0002 d and 0.02 d for J-PLUS0807 and J-PLUS0903, respectively.

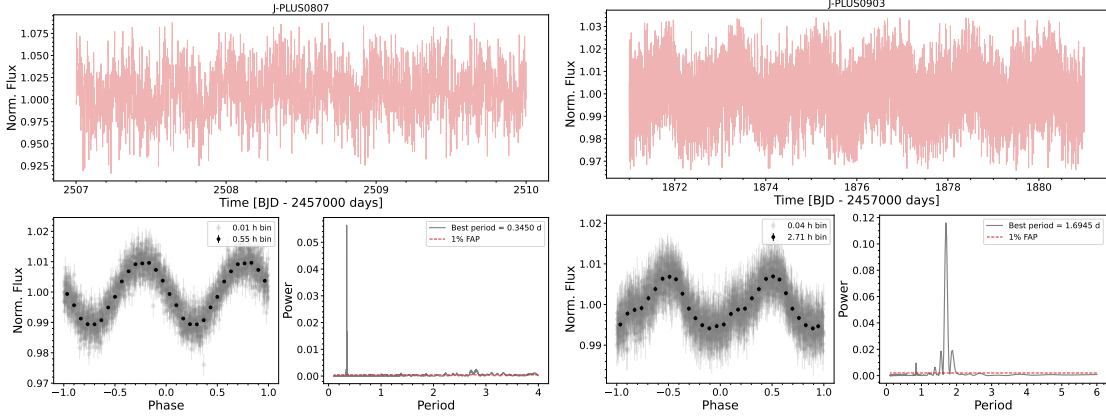


Figure 3.5: TESS LCs (*top panels*), phase-folded LCs (*bottom left panels*), and periodograms (*bottom right panels*) for our two targets. The *top panel* shows only a small section of the LCs for better visibility. Two different bin sizes are shown for the binned phase-folded LCs, with grey and black dots. In the periodograms, the red dashed line represents the 1% FAP level.

We confirmed that our targets were the sources of the detected variability using the `TESS_localize`⁸ (Higgins and Bell, 2023) Python package.

The computed rotation periods place our two targets as very fast rotators (Irwin et al., 2011), which is deeply interlinked with the activity level observed. After reaching the main sequence, low-mass stars slowly spin-down due to the loss of angular momentum by stellar winds, thus undergoing a decrease in their magnetic activity over time (Yang et al., 2017; Davenport et al., 2019; Raetz et al., 2020) that may also be dependent on stellar metallicity (See et al., 2024), which makes obtaining robust age estimations for low-mass stars notoriously difficult. To explore this, we relied on `stardate`⁹ (Angus et al., 2019), a Python tool that combines isochrone fitting with gyrochronology for measuring stellar ages. In our case, we included magnitudes from the Two-Micron All Sky Survey (2MASS; Skrutskie et al., 2006), parallax and magnitudes from *Gaia* DR3, magnitudes from the Sloan Digital Sky Survey (SDSS; York et al., 2000), and the rotation periods obtained in this work as input parameters. Following this procedure, we obtained an age of $0.79^{+0.62}_{-0.09}$ Gyr and $1.94^{+1.74}_{-1.26}$ Gyr for J-PLUS0807 and J-PLUS0903, respectively, which is in agreement with the values found in the literature for fast rotators (Newton et al., 2016; Doyle et al., 2019). Here, the chosen value and uncertainties correspond to the median and $\pm 1\sigma$ thresholds of the Markov Chain Monte Carlo samples computed by `stardate`.

3.3 PLANETARY HABITABILITY

Understanding the impact of the magnetic activity of M dwarfs on a planet’s evolution and habitability is of crucial interest in the search for Earth-like planets. The common flaring activity and CMEs, together with the nearby habitable zone of these stars, can lead to substantial alteration of planetary atmospheres or even their erosion. It is unclear whether stellar flares are beneficial or detrimental to the habitability of exoplanets. It is possible that UV radiation emitted during flare events can trigger the development of prebiotic chemistry (Rimmer et al., 2018; Airapetian et al., 2020). Although abiogenesis would potentially be slower compared to prebiotic Earth due to the lower emission of

⁸ <https://github.com/Higgins00/TESS-Localize>

⁹ <https://stardate.readthedocs.io/en/latest/>

M dwarfs at these wavelengths (Rugheimer et al., 2015; Ranjan et al., 2017), flares could provide the lacking UV energy (Buccino et al., 2007; Jackman et al., 2023). In this line, the flare events in Ca II H and K emission lines revealed in this work may play an important role.

Continued exposure to $E_{\text{bol}} > 10^{34}$ erg flares would make the presence of ozone layers impossible on any habitable zone terrestrial exoplanet orbiting an M dwarf (Tilley et al., 2019; Chen et al., 2021). Moreover, Berger et al. (2024) recently demonstrated that the 9000 K blackbody commonly assumed for flares underestimated the FUV emission for 98% of their sample, which would significantly increase the number of stars with sufficient flaring activity to fall into the ozone depletion zone from previous studies. Following the relation provided by Seli et al. (2021), we converted the TESS energies of the detected flares to bolometric flare energies. Thus, we obtained a rate of 0.02 day^{-1} for $E_{\text{bol}} > 10^{34}$ erg flares for J-PLUS0807, which is an order of magnitude lower than the rate found by Tilley et al. (2019) for the ozone layer to be eroded in habitable zone terrestrial exoplanets around M dwarfs. For J-PLUS0903, none of the flares exceeded this energy threshold.

3.4 CONCLUSIONS

This work serves as a follow-up study of the sample of M dwarfs with strong excess emission in the J-PLUS filters corresponding to Ca II H and K and H α emission lines, identified in our previous work (Mas-Buitrago et al., 2022). Using low-resolution spectra collected with NOT/ALFOSC and GTC/OSIRIS, we measured the PC3 spectral index of our targets and spectroscopically confirmed the mid-M dwarf nature of six of them for the first time. We confirmed that the strong excess emission detected in the J-PLUS photometry is caused by transient flare events, suggesting that two types of flares are detected using narrow-band optical photometry in common M dwarfs, those already well-known in H α and those in Ca II H and K presented in this work. Work dedicated to the study of flares in large M dwarf samples usually focuses only on H α flare events, which could lead to an underestimation of the number of flaring M dwarfs. In the future, multi-wavelength simultaneous observations will be essential to further study the flaring activity of M dwarfs.

We analysed two-minutes cadence TESS LCs for J-PLUS0807 and J-PLUS0903 and performed a thorough characterisation of the multiple flare events observed in them. We estimated the flare energies in the TESS bandpass and found them to be in the range of $7.4 \times 10^{30} - 2.2 \times 10^{33}$ erg. We found clear signs of a periodic variability in the TESS LCs, confirming the previously reported ultra-fast rotating nature of J-PLUS0807 with data from sectors 20, 44, 45, 46, and 47. Also, we computed for the first time a rotation period of 1.69 d for J-PLUS0903.

This work demonstrates the potential of multi-filter photometric surveys such as J-PLUS or the upcoming J-PAS to systematically detect flare events in M dwarfs, especially episodes of strong Ca II H and K line emission that may have important implications for exoplanetary space weather and habitability studies. Using a detection algorithm such as the one developed in Mas-Buitrago et al. (2022), it is possible to identify a sample of candidates that can be confirmed and analysed with spectroscopic follow-up and high-cadence photometric LCs from TESS or similar missions such as K2. It also highlights the fundamental role of stellar flares in shaping the habitability of exoplanets. A high frequency of energetic flares implies that planets around these stars may experience sig-

nificant atmospheric erosion and elevated levels of surface radiation, although it could also trigger the development of prebiotic chemistry.

4

AUTOENCODERS AND DEEP TRANSFER LEARNING IN CARMENES

Deep learning (DL) techniques are a promising approach among the set of methods used in the ever-challenging determination of stellar parameters in M dwarfs. In this context, transfer learning could play an important role in mitigating uncertainties in the results due to the synthetic gap (i.e. difference in feature distributions between observed and synthetic data). We propose a feature-based deep transfer learning (DTL) approach based on autoencoders to determine stellar parameters from high-resolution spectra. Using this methodology, we provide new estimations for the effective temperature, surface gravity, metallicity, and projected rotational velocity for 286 M dwarfs observed by the CARMENES survey. Using autoencoder architectures, we projected synthetic PHOENIX-ACES spectra and observed CARMENES spectra onto a new feature space of lower dimensionality in which the differences between the two domains are reduced. We used this low-dimensional new feature space as input for a convolutional neural network to obtain the stellar parameter determinations. We performed an extensive analysis of our estimated stellar parameters, ranging from 3050 to 4300 K, 4.7 to 5.1 dex, and -0.53 to 0.25 dex for T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$, respectively. Our results are broadly consistent with those of recent studies using CARMENES data, with a systematic deviation in our T_{eff} scale towards hotter values for estimations above 3750 K. Furthermore, our methodology mitigates the deviations in metallicity found in previous DL techniques due to the synthetic gap. We consolidated a DTL-based methodology to determine stellar parameters in M dwarfs from synthetic spectra, with no need for high-quality measurements involved in the knowledge transfer. These results suggest the great potential of DTL to mitigate the differences in feature distributions between the observations and the PHOENIX-ACES spectra.

4.1 CONTEXT

The precise determination of the stellar parameters of M dwarfs is crucial to improve our understanding of planetary formation and evolution, which depends fundamentally on the thorough characterisation of their host stars (Cifuentes et al., 2020). However, well-established photometric and spectroscopic methods for determining these parameters encounter particular challenges, mainly due to the inherent faintness of M dwarfs and their frequent manifestation of strong stellar activity. Specifically for spectroscopic analyses, establishing the spectral continuum can be a difficult task. Despite these problems, numerous efforts have been devoted to estimating photospheric parameters in M dwarfs, including effective temperature (T_{eff}), surface gravity ($\log g$), and metallicity ($[\text{M}/\text{H}]$). Several methods have proven successful in inferring these parameters, such as fitting synthetic spectra, as in Passegger et al. (2019, hereafter Pass19) and Marfil et al. (2021, hereafter Mar21), pseudo-equivalent widths (pEWs) (e.g. Mann et al., 2013a, 2014; Neves et al., 2014), spectral indices (e.g. Rojas-Ayala et al., 2010, 2012), empirical calibrations (e.g. Casagrande et al., 2008; Neves et al., 2012), interferometry (e.g. Boyajian et al., 2012;

Rabus et al., 2019), and machine learning (e.g. Antoniadis-Karnavas et al., 2020; Passegger et al., 2020, hereafter Pass20).

The approaches based on pEWs, measurements of the strength of absorption lines in a spectrum, and spectral indices, calculated from carefully chosen spectral regions –and often derived from absorption lines or bands–, leverage their sensitivity and correlation with stellar parameters (mainly, T_{eff} and $[\text{Fe}/\text{H}]$). As a recent example of these approaches, Khata et al. (2020) determined T_{eff} and metallicities, among other parameters, for 53 M dwarfs using H - and K -band pEWs and H_2O indices. Another approach relies on empirical calibrations based on observations of M dwarfs that have an F, G, or K binary companion with known metallicity. This is grounded in the idea that the metallicity of an M dwarf is comparable to that of the hotter primary star, assuming the system originated from the same proto-stellar cloud (Neves et al., 2012; Montes et al., 2018; Duque-Arribas et al., 2024). For example, Rodríguez Martínez et al. (2019) employed the relationships of Newton et al. (2015) and Mann et al. (2013b) to derive T_{eff} and metallicity, respectively, from moderate-resolution spectra of 35 M dwarfs from the $K2$ mission. Numerous spectral indices have also been empirically calibrated. For instance, Veyette et al. (2017) determined T_{eff} , $[\text{Fe}/\text{H}]$, and $[\text{Ti}/\text{H}]$ from high-resolution Y -band spectra of 29 M dwarfs by combining spectral synthesis with empirically calibrated indices and pEWs using FGK+M systems (Bonfils et al., 2005; Mann et al., 2013a).

Interferometric measurements have also proven useful for deriving index-based calibrations for T_{eff} (Mann et al., 2013b), performing empirical calibrations for T_{eff} (Maldonado et al., 2015; Newton et al., 2015), or determining T_{eff} from interferometric observations in combination with parallaxes and bolometric fluxes (Boyajian et al., 2012; von Braun et al., 2014; Rabus et al., 2019). However, their application is limited to a relatively small number of stars due to the requirement that they must be bright and nearby.

The fitting of synthetic spectra relies on a minimisation algorithm to find the synthetic spectrum that best matches the observed spectrum. Variations exist in terms of the synthetic grid employed (e.g. BT-Settl, PHOENIX-ACES, MARCS), using high or low spectral resolution, and the number and wavelength of features selected for comparison. For example, the BT-Settl models (Allard et al., 2012, 2013) were used by Gaidos and Mann (2014a) and Mann et al. (2015) to derive T_{eff} values for M dwarfs with low-resolution visible SNIFS (Supernova Integral Field Spectrograph) spectra, and by Rajpurohit et al. (2018) to compute T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ for 292 M dwarfs using high-resolution CARMENES spectra (Reiners et al., 2018). Kuznetsov et al. (2019) applied BT-Settl models to intermediate-resolution spectra from the visible arm of VLT/X-shooter (intermediate resolution, high-efficiency spectrograph, Vernet et al., 2011) to determine T_{eff} , $\log g$, $[\text{Fe}/\text{H}]$, and $v \sin i$ for 153 M dwarfs. More recently, Hejazi et al. (2020) derived T_{eff} , $\log g$, metallicity $[\text{M}/\text{H}]$, and alpha-enhancement $[\alpha/\text{Fe}]$ of 1544 M dwarfs and subdwarfs from low- to medium-resolution spectra collected at the Michigan-Dartmouth-MIT observatory, Lick Observatory, Kitt Peak National Observatory, and Cerro Tololo Interamerican Observatory. Additionally, Mar21 determined T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ for a sample of 343 M dwarfs observed with CARMENES using a Bayesian implementation of the spectral synthesis technique, the SteParSyn¹ code (Tabernero et al., 2022).

Based on the PHOENIX-ACES library (Husser et al., 2013), Birky et al. (2017) derived T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ for late-M and early-L dwarfs from high-resolution near-infrared APOGEE spectra (Wilson et al., 2010). Similarly, Passegger et al. (2018) and Schweitzer et al. (2019, hereafter Schw19) determined these parameters for M dwarfs observed with

¹ <https://github.com/hmtabernero/SteParSyn>

CARMENES in the visible wavelength region. Building upon these works, [Pass19](#) extended the analysis by determining T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ not only from the visible range covered with CARMENES but also from the near-infrared and the combination of visible and near-infrared data. The comparison conducted in [Pass19](#) led to the conclusion that utilising both spectral ranges for parameter determination maximises the amount of available spectral information while minimising possible effects caused by imperfect modelling. The MARCS model atmospheres ([Gustafsson et al., 2008](#)) have also been employed to compute photospheric parameters. For instance, in a recent study by [Souto et al. \(2020\)](#), T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ were determined for 21 M dwarf mid-resolution APOGEE *H*-band spectra using MARCS models and the `turbospectrum` code ([Plez, 2012](#)) through the `bacchus` wrapper ([Masseron et al., 2016](#)). Similarly, [Sarmiento et al. \(2021\)](#) derived T_{eff} , $\log g$, $[\text{M}/\text{H}]$, and microturbulent velocity v_{mic} for 313 M dwarfs from APOGEE *H*-band spectra using MARCS models, `turbospectrum`, and `iSpec` python code ([Blanco-Cuaresma, S. et al., 2014](#)).

As large surveys release extensive databases containing thousands of stars, there is a need for flexible and automated methods capable of handling vast amounts of data to infer stellar atmospheric parameters. In this sense, machine learning (ML) techniques have also been used for determining photospheric parameters for M dwarfs from stellar spectra. For example, [Sarro et al. \(2018\)](#) proposed an automated procedure based on genetic algorithms to identify pEWs and integrated flux ratios from BT-Settl models that yield good estimations of T_{eff} , $\log g$, and $[\text{M}/\text{H}]$ for spectra from the NASA Infrared Telescope Facility (IRTF). Also based on pEWs, [Antoniadis-Karnavas et al. \(2020\)](#) present an ML tool, named ODUSSEAS, to derive T_{eff} and $[\text{Fe}/\text{H}]$ of M dwarf stars from 1D spectra for different resolutions. In [Birky et al. \(2020\)](#), The Cannon ([Ness et al., 2015](#); [Casey et al., 2016](#)), a data-driven spectral-modelling and parameter-inference framework, is used to estimate T_{eff} and $[\text{Fe}/\text{H}]$ for 5875 M dwarfs in the APOGEE ([Abolfathi et al., 2018](#)) and *Gaia* DR2 ([Gaia Collaboration et al., 2018](#)) surveys. Using the Stellar Label Machine (SLAM, [Zhang et al., 2020](#)), [Li et al. \(2021a\)](#) trained a model with APOGEE stellar labels and synthetic spectra from the BT-Settl model, resulting in the determination of T_{eff} and $[\text{M}/\text{H}]$ for M dwarfs from the LAMOST DR6² catalogue.

This study extends previous works on applying deep learning (DL) to predict stellar parameters from high-resolution spectra observed with CARMENES. [Pass20](#) presented a DL approach where convolutional neural networks (CNNs) were trained on synthetic PHOENIX-ACES models to estimate T_{eff} , $\log g$, $[\text{M}/\text{H}]$, and $v \sin i$ for 50 M dwarfs observed with CARMENES. After a thorough analysis of their methodology, in which different architectures and spectral windows were tested, they found that all DL models were able to estimate stellar parameters from synthetic spectra in a precise and accurate way. However, when testing these models on the CARMENES spectra, they found significant deviations for the metallicity because of the synthetic gap ([Fabbro et al., 2018](#); [Tabernero et al., 2022](#)), which is the difference in feature distributions between synthetic and observed data. In a more recent study, [Bello-García et al. \(2023, hereafter Bello23\)](#) employed a deep transfer learning (DTL) approach to mitigate the uncertainties associated with the synthetic gap (see their Figs. 1 and 2). Following the training of DL models on a large set of synthetic spectra from the PHOENIX-ACES model, the models underwent fine-tuning based on external knowledge about stellar parameters. This external knowledge included 14 stars from the CARMENES survey with interferometric angular diameters measured by [Boyajian et al. \(2012\)](#), [von Braun et al. \(2014\)](#), and references therein. Additionally,

² <http://dr6.lamost.org/>

it was supplemented with five mid-to-late M dwarf stars from Passegger et al. (2022). They achieved the determination of new T_{eff} and $[M/H]$ values for 286 M dwarfs from the CARMENES survey, and although this approach improved the estimation of T_{eff} and $[M/H]$ for M dwarfs from high-resolution spectra obtained with CARMENES, the lack of sufficiently large number of reference stars to transfer knowledge is a limitation for the technique. If the reference dataset is limited in size, diversity, or representation across the parameter space, the models may not generalise well to a broader range of M dwarfs.

In this work, we present a novel transfer learning approach for estimating photospheric parameters in M dwarfs based on their stellar spectra. The primary goal of the proposed method is to address the aforementioned limitation identified by Bello23 by eliminating the requirement for interferometric values in the knowledge transfer process. To achieve this, instead of employing a model-based transfer learning approach, as in Bello23, where the transferred knowledge is encoded into model parameters, priors or model architectures, we propose a feature-based transfer learning. In this approach, the knowledge to be transferred can be considered as the learned feature representation. The idea is to learn a ‘good’ feature representation so that, by projecting data onto the new representation, the differences between domains (source and target, i.e. synthetic and observed spectra in our case) can be reduced. This allows the source domain labelled data (synthetic spectra with known parameters) to be used to train a precise model for the target domain constituted by the observed spectra (Yang et al., 2020).

4.2 DATA

The proposed approach was tested using the same sample spectra as Pass19. This sample, listed in their Table B.1, comprise 282 M dwarfs observed with CARMENES. Additionally, four more stars from an independent interferometric sample, as described by Bello23, were included.

CARMENES is installed at the Calar Alto Observatory, located in Spain, and stands as one of the leading instruments in the quest for searching for Earth-like planets within the habitable zones around M dwarfs. It comprises two separate spectrographs: one for the visible (VIS) wavelength range (from 520 to 960 nm) and the other for the near-infrared (NIR) range (from 960 to 1710 nm), each offering high-spectral resolutions of $R \approx 94\,600$ and 80 500, respectively (Quirrenbach et al., 2020; Reiners et al., 2018).

A detailed description of the data reduction procedure is available in Zechmeister et al. (2014), Caballero et al. (2016b), and Pass19. Similar to the latter, we used a high signal-to-noise (S/N) template spectra for each star. These templates are generated as byproducts of the CARMENES radial-velocity pipeline, known as *serval* (SpEctrum Radial Velocity AnaLyser; Zechmeister et al., 2018). In the standard data flow, the code constructs a template for each target star from a minimum of five individual spectra to derive the radial velocities through least-square fitting to the template. The S/N of the observed CARMENES sample used in this work was above 150. Concerning the wavelength window, we adopted the range 8 800–8 835 Å, consistent with Bello23, as this window displayed the smallest mean squared error among all the investigated windows in Pass20.

To train the neural network models, we utilised the PHOENIX-ACES spectra library³ (Husser et al., 2013). This library is chosen for its consideration of spectral features present in cool dwarfs. Furthermore, the use of synthetic models enables the gener-

³ <https://phoenix.astro.physik.uni-goettingen.de/>

ation of a large number of spectra with known parameters, eliminating the need for limited samples of observations with well-known stellar parameters. We used the same PHOENIX-ACES grid as in previous works (Pass20; Bello23), which was generated by linearly interpolating between the existing grid points using pyterpol (Nemravová et al., 2016). The complete dataset contains a grid of 449 806 synthetic high-resolution spectra between 8800 Å and 8835 Å with T_{eff} between 2300 and 4500 K (step 25 K), $\log g$ between 4.2 and 5.5 dex (step 0.1 dex), $[M/H]$ between -1.0 and 0.8 dex (step 0.1 dex), and $v \sin i$ between 1.5 and 60.0 km s⁻¹ (with a variable step of 0.5, 1.0, 2.0 or 5.0; see Table 1 in Pass20). A degeneracy between T_{eff} , $\log g$, and $[Fe/H]$ was described by Passegger et al. (2018), who found exceptionally high values of $\log g$ and $[Fe/H]$ for well-fitting PHOENIX-ACES models. This degeneracy was further underscored by Pass19 and Pass20 during the application of DL models to the observed CARMENES spectra, and the latter imposed additional constraints to the grid leveraging the PARSEC v1.2S evolutionary models (Bressan et al., 2012; Chen et al., 2014, 2015; Tang et al., 2014). Degeneracies between stellar parameters are often found when fitting synthetic spectra, and some authors have explored several ways to help break them (Buzzoni et al., 2001; Brewer et al., 2015). The refinement performed by Pass20 aimed to exclude parameter combinations for M dwarfs that do not fit the main sequence, as discussed in Section 4.2 of their work. Notably, Pass20 demonstrated that the imposition of these constraints on the synthetic model grid used in the training of the DL models is capable of breaking the observed parameter degeneracy. After applying these restrictions, the grid includes 22 933 PHOENIX-ACES spectra.

Due to the negligible presence of telluric features in the investigated range, telluric correction was not applied to the VIS spectra. For normalisation, we employed the Gaussian Inflection Spline Interpolation Continuum (GISIC⁴), the same method and routine used by Pass20 and developed by D.D. Whitten, designed for spectra with strong molecular features. Following the same approach as Bello23, we applied this procedure to both observed and synthetic spectra within the spectral window 8800–8835 Å with an additional 5 Å on each side to mitigate potential edge effects. Moreover, the observed spectra underwent radial velocity correction to align with the rest frame of the synthetic spectra, achieved through cross-correlation (crosscorrRV from PyAstronomy, Czesla et al., 2019) between a PHOENIX model spectrum and the observed spectrum. To ensure a universal wavelength grid, essential for applying the proposed method, the wavelength grid of the observed spectra was linearly interpolated with the grid of the synthetic spectra.

In spite of the performed spectra preparation, differences in the feature distributions of the synthetic and observed sets of spectra (i.e. synthetic gap) were identified. We used the Uniform Manifold Approximation and Projection (UMAP; McInnes et al., 2018), with a metric that considers the correlation between the spectra, to project the high-dimensional input space (3500 flux values for each spectrum) into a two-dimensional space while preserving inter-distances. As shown in Fig. 4.1, akin to Pass20 and Bello23, most of the CARMENES spectra (grey triangles) do not align precisely within the synthetic spectra (colour-coded dots). Thus, a transfer learning approach appears appropriate to extend the applicability of the regression models trained with the synthetic spectra to the observed spectra.

⁴ <https://pypi.org/project/GISIC/>

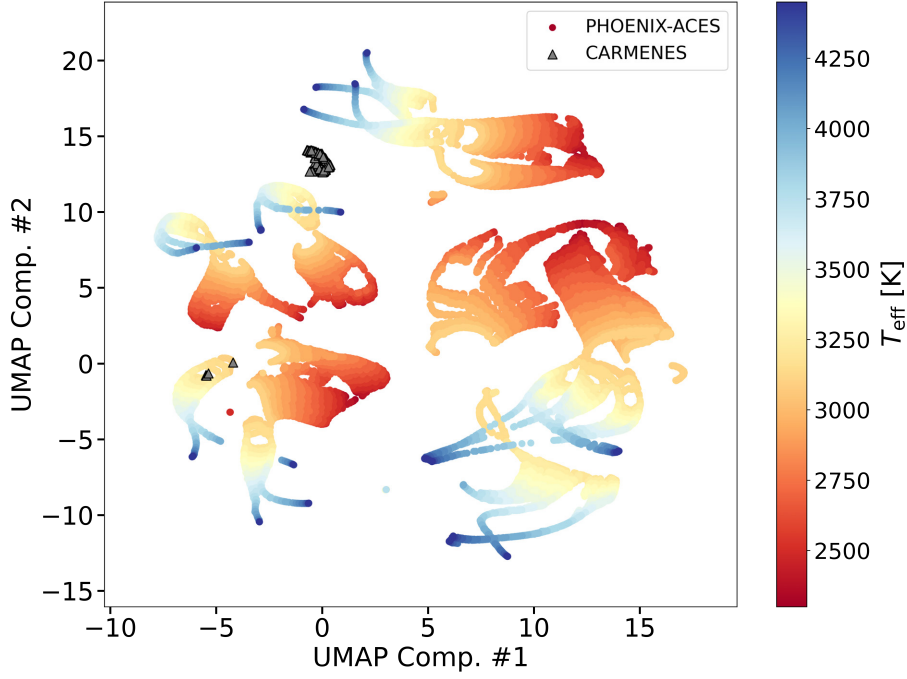


Figure 4.1: Two-dimensional UMAP projection of PHOENIX-ACES (dots colour-coded by T_{eff}) and CARMENES (grey triangles) spectra from the 8 800–8 835 Å window. Almost all CARMENES spectra are isolated from the PHOENIX-ACES family feature space.

4.3 METHODOLOGY

The DTL approach proposed in this paper can be summarised as follows. Initially, we extract a low-dimensional representation of synthetic spectra based on the PHOENIX-ACES library using autoencoders (AEs), a special kind of neural network initially proposed for dimensionality reduction (Hinton and Salakhutdinov, 2006). Then, the knowledge transfer process is performed by fine-tuning these AEs with high-resolution spectra observed with the CARMENES instrument. It must be noted that no stellar parameters were used during this re-training. With the low-dimensional representations of the synthetic spectra resulting from the initial step, we trained CNNs. Finally, using these CNNs, we estimated the stellar parameters (T_{eff} , $\log g$, $[M/H]$, and $v \sin i$) for 286 CARMENES M dwarfs by using their low-dimensional representations obtained after the fine-tuning step.

4.3.1 Feature extraction using an autoencoder

In this study, we explore unsupervised feature extraction from stellar spectra using AEs to facilitate feature-based transfer learning and leverage the new representations for estimating photospheric parameters. Belonging to representation learning –a subfield of machine learning–, AEs have the capability to capture the underlying factors hidden in the observed data (Bengio et al., 2013; Goodfellow et al., 2016). They have been successfully used in various astrophysical applications, including unsupervised feature learning from galaxy spectral energy distribution (Frontera-Pons et al., 2017), learning of non-linear representations from rest-frame spectroscopic data for redshift estimation (Frontera-Pons et al., 2019), galaxy classification (Cheng et al., 2021), astrophysical component separation (Milosevic et al., 2021), reconstruction of missing magnitudes from

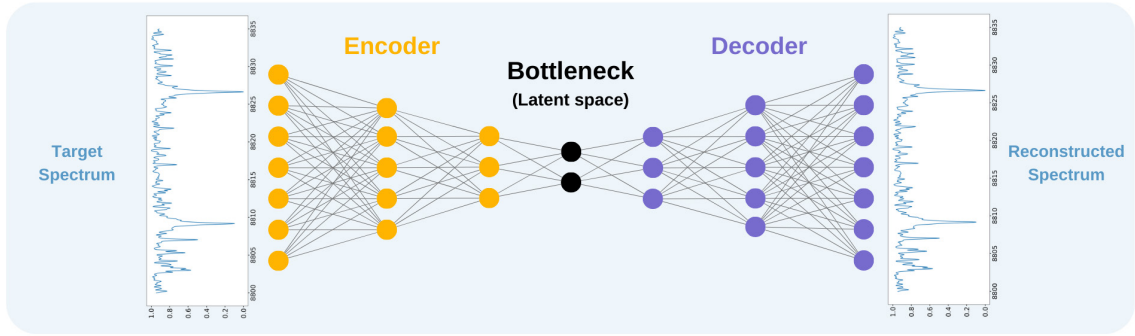


Figure 4.2: Schematic representation of the AE architecture used in this work.

observed objects before classifying them into stars, galaxies, and quasars (Khramtsov et al., 2021), and telluric correction (Kjærsgaard et al., 2023). In addition, some authors have used AEs to estimate stellar atmospheric parameters from spectra (Yang and Li, 2015; Li et al., 2017). However, their approach is different from our proposal since the training of the models was performed in a supervised manner: spectra from SDSS/SEGUE DR7 (Abazajian et al., 2009) were used, and T_{eff} , $\log g$, and $[\text{Fe}/\text{H}]$ were obtained from the SDSS/SEGUE Spectroscopic Parameter Pipeline (SSPP; Lee et al., 2008a,b; Prieto et al., 2008; Smolinski et al., 2011) for stars in the temperature range 4 088-9 747 K (earlier than our CARMENES targets). In our case, we are interested in the use of AEs to enable transfer learning, as representation learning enables the transfer of knowledge when there are features useful for different settings or tasks that correspond to underlying factors appearing in more than one setting (Goodfellow et al., 2016).

The rationale behind the first step of our methodology is to find a meaningful low-dimensional representation, referred to as the latent space, of the synthetic spectra. To accomplish this, we employed an AE, which consists of an ‘encoder’ trained to transform the high-dimensional spectrum into a low-dimensional code, and a ‘decoder’ trained to reconstruct the original spectrum as accurate as possible from its lower-dimensional latent space (see Fig. 4.2).

First, we divided the grid of synthetic spectra into a training set (70 %) and a test set (30 %). We considered multiple AE architectures, developing a python code to create a flexible AE structure. The number of neurons on each layer, the L1 regularisation term for the dense layers (used to prevent overfitting), and the learning rate for the Adam optimisation (a computationally efficient stochastic gradient descent method, Kingma and Ba, 2014) were passed as parameters. For this code, we relied on the Keras⁵ (Chollet, 2015) deep learning API, which runs on top of the Tensorflow⁶ (Abadi et al., 2015) machine learning platform. Next, we created a grid for these hyperparameters and performed an exhaustive search using the GridSearchCV class from the scikit-learn⁷ package, which optimises the hyperparameters of an estimator through k-fold cross-validation, using any scoring metric to evaluate the model. In our case, we used 4-fold cross-validation and the mean squared error between the reconstructed and the original validation data as the scoring metric. To integrate our python code into a scikit-learn workflow, we used the KerasRegressor wrapper from the scikeras⁸ python package.

⁵ <https://keras.io/about/>

⁶ <https://www.tensorflow.org/>

⁷ <https://scikit-learn.org/stable/>

⁸ <https://adriangb.com/scikeras/stable/>

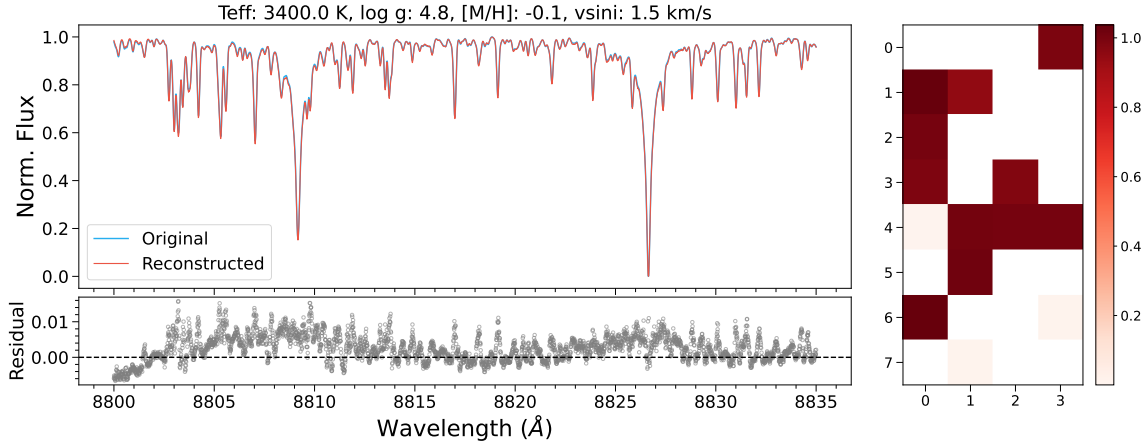


Figure 4.3: Reconstructed spectrum (*left*) and latent representation (*right*) of a PHOENIX-ACES synthetic spectrum for one of the trained AEs. *Left panel*: comparison of the original (blue) and reconstructed (red) spectrum. Both spectra overlap as they are almost similar. The title shows the stellar parameters of the synthetic spectrum. Reconstruction residuals (original–reconstructed) are shown in the *bottom panel*. *Right panel*: 32-dimensional latent space of the input spectrum obtained by the encoder, reshaped to a 8×4 matrix only for a better visibility. The colour scale indicates the strength of the features. The decoder uses this compressed representation to obtain the reconstructed spectrum.

After this search for the best hyperparameter combinations, we only kept those with a mean cross-validation score below the median, evaluated using the entire grid. We trained an AE for each of these architectures, adding a contractive regularisation term in the loss function, consisting of the squared Frobenius norm of the Jacobian matrix of the encoder activations with respect to the input:

$$\|J_f(x)\|_F^2 = \sum_{ij} \left(\frac{\partial h_j(x)}{\partial x_i} \right)^2, \quad (7)$$

where f represents the encoding function that maps the input x to the hidden representation h . The main idea of contractive AEs is to make the feature extraction more robust to small perturbations in the training data. In the overall loss function optimisation, the trade-off between the reconstruction and the L1 regularisation terms will retain the important variations in the latent space for the reconstruction of the input (Rifai et al., 2011).

We only kept the AEs with a learning rate equal to 0.0001, as we found that some of them with a higher learning rate were not able to converge properly, leading to a poor latent representation of the spectra. With this, we ended up with 26 final AE architectures and evaluated them on the test set, obtaining mean squared reconstruction errors $\sim 5 \cdot 10^{-5}$. Fig. 4.3 shows the reconstruction and the latent space of a PHOENIX-ACES synthetic spectrum for one of the AEs. Using the encoder networks of the AEs, we obtained 26 sets (one for each AE) of 32-dimensional compressed representations for the grid of synthetic spectra.

4.3.2 Deep transfer learning

The dependence of DL algorithms on massive training data is a crucial hurdle to overcome when a research scenario requires labelled data. In some fields, such as astrophys-

ics, building a large, annotated data set can be incredibly complex and expensive. A straightforward and widely used solution to this problem is the use of synthetic data to train the DL models, but this may include a systematic error in the methodology if the synthetic gap (see Section 4.2) is significant, as is the case in this work.

Transfer learning (TL) plays a key role in solving the above problems, as it allows knowledge to be transferred from a rich source domain to a related but not identical target domain. The transition from TL to DTL, with incomplete DTL as an intermediate stage (deep neural networks are only used as feature extractors in TL models; Yu et al., 2022), came with the integration of DL techniques into the TL paradigm.

In the context of TL, a domain can be represented as $D = \{\mathcal{X}, P(X)\}$, where $\mathcal{X}$ denotes a feature space and $P(X)$ represents the marginal probability distribution for $X = \{x_1, \dots, x_n\} \in \mathcal{X}$. Also, a task can be represented as $T = \{Y, f(\cdot)\}$, where Y denotes a label space and $f(\cdot)$ is a predictive function. According to the definition provided by Pan and Yang (2010), given a source domain D_S and task T_S , and a target domain D_T and task T_T , TL aims to enhance the performance of a predictive function $f_T(\cdot)$ in D_T , using the knowledge available in D_S and T_S , where $D_S \neq D_T$ and/or $T_S \neq T_T$. In our work, the source domain is represented by the grid of synthetic PHOENIX-ACES spectra, while the target domain is built from the 286 CARMENES observed spectra. Moreover, the predictive function is defined as the encoder network of the AE architecture, responsible for compressing the input spectra into the low-dimensional latent representation.

The purpose of this step in the methodology is to adopt a DTL-based strategy, in particular the fine-tuning approach (Chu et al., 2016; Yosinski et al., 2014), using the AE architectures we already trained in the source domain to obtain a meaningful low-dimensional latent representation of our data-poor target domain. In this process, we kept the weights frozen in all encoder layers until the last one, leaving only the deepest encoder layer, the bottleneck (i.e. the latent space or compressed representation of the spectrum, as illustrated in Fig. 4.2), and the decoder network to be re-trained. The motivation for keeping the lower layers frozen is to prevent generic learning from being overwritten, thus preserving the knowledge acquired by the network to recognise relevant spectral features, while the more specific features are tailored to the target domain (Vafaei Sadr et al., 2020).

Pan et al. (2008) already explored the possibility of finding a low-dimensional latent space in which source and domain data are close to each other, and using it as a bridge to transfer the knowledge from the labelled source domain to the unlabelled target domain. In our case, the ultimate goal of this process is to find a low-dimensional representation of the observed spectra that is closer to the synthetic latent representation than in the initial high-dimensional space of the spectra (see Fig. 4.1). Furthermore, we want for these target representations to be as meaningful as possible, since we intend to use them later as a starting point for estimating the stellar parameters.

First, we divided the target set of 286 CARMENES spectra into a training set (80%) and a test set (20%), with the latter being used to assess the reconstruction error across the target domain. Then, we fine-tuned the 26 AE architectures, following the process explained above, obtaining mean squared reconstruction errors $\sim 4 \cdot 10^{-4}$ on the test set, in contrast to the reconstruction errors ($\sim 3 \cdot 10^{-3}$) obtained on the CARMENES set using the AEs pre-trained on the PHOENIX-ACES spectra. It must be noted that no stellar parameters were used during this re-training.

Fig. 4.4 illustrates the importance of this step for the AE to effectively adapt to our specific target domain, ensuring that the compressed representations provided by the fine-tuned encoders will be more meaningful than those we would have obtained with

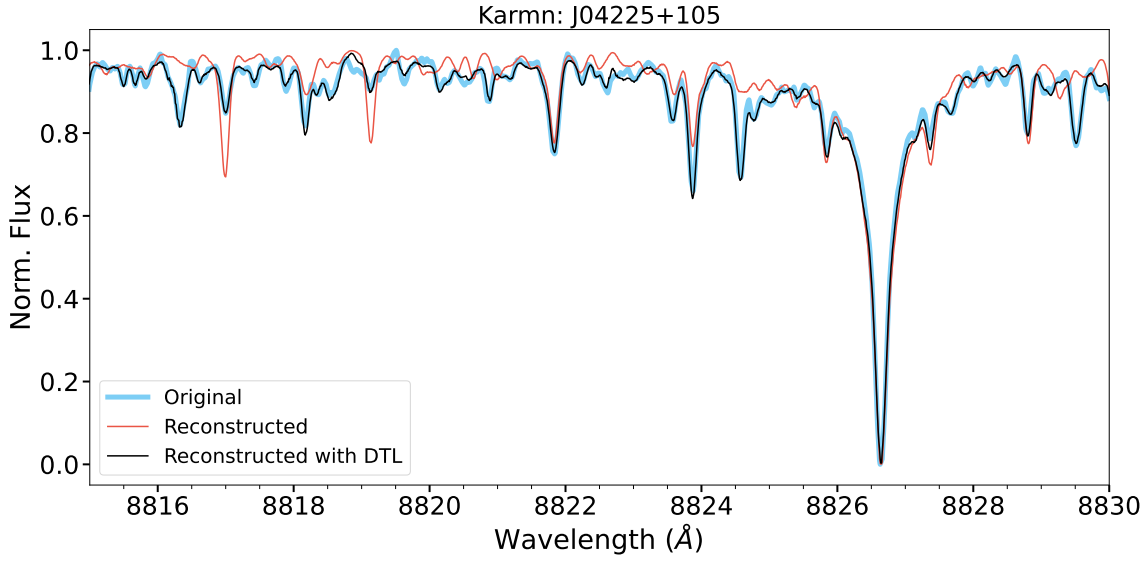


Figure 4.4: Original (blue) vs. reconstructed CARMENES spectrum for LSPM J0422+1031 (Karmn J04225+105, M3.5 V). The Figure only shows a section of the spectrum for better visibility, with the unique purpose of emphasising how the reconstruction after fine-tuning (black) captures much more detailed spectral features than the reconstruction with the initial training (red).

the initial training. Using these fine-tuned encoder networks, we obtained the final 26 sets of 32-dimensional representations for the observed CARMENES spectra.

While our goal was to preserve the meaningfulness of the low-dimensional representations of the synthetic and observed spectra, we aimed, above all, to minimise the disparity between the observed and synthetic compressed representations. For instance, Fig. 4.5 illustrates a UMAP two-dimensional projection, using the same metric as in Fig. 4.1, for one of the 26 sets of PHOENIX-ACES and CARMENES representations. In contrast to Fig. 4.1, in this case, the CARMENES objects are integrated over the space occupied by the PHOENIX-ACES family of projections, leading to a significant reduction of the differences in feature distributions between the two domains. Consequently, we calculated the minimum Euclidean distance from each CARMENES instance to the synthetic grid in both the initial high-dimensional space and the new low-dimensional feature space. While the mean distance is 2.72 when evaluated in the initial feature space (Fig. 4.1), it is reduced to a mean value of 0.086 for the encoded representations (Fig. 4.5), averaged over the 26 sets. In this manner, a latent space that encodes the shared knowledge from both domains was learned, effectively bridging the gap between them.

4.3.3 Stellar parameter estimation

In the final step of our methodology, we employed CNNs, one of the oldest deep learning approaches (Lecun et al., 1998), to estimate the stellar parameters of the 286 CARMENES stars. As a starting point for this process, we used the 26 sets of encoded representations for the PHOENIX-ACES and CARMENES spectra obtained in the previous steps of our work.

Inspired by the hierarchical structure of the human visual nervous system (a precursor of CNNs; Fukushima, 1980), CNNs are therefore generally used to deal with image data. They are a specific class of multilayered feedforward neural networks, initially developed for image classification and visual pattern recognition (Lecun et al., 1998; Krizhevsky

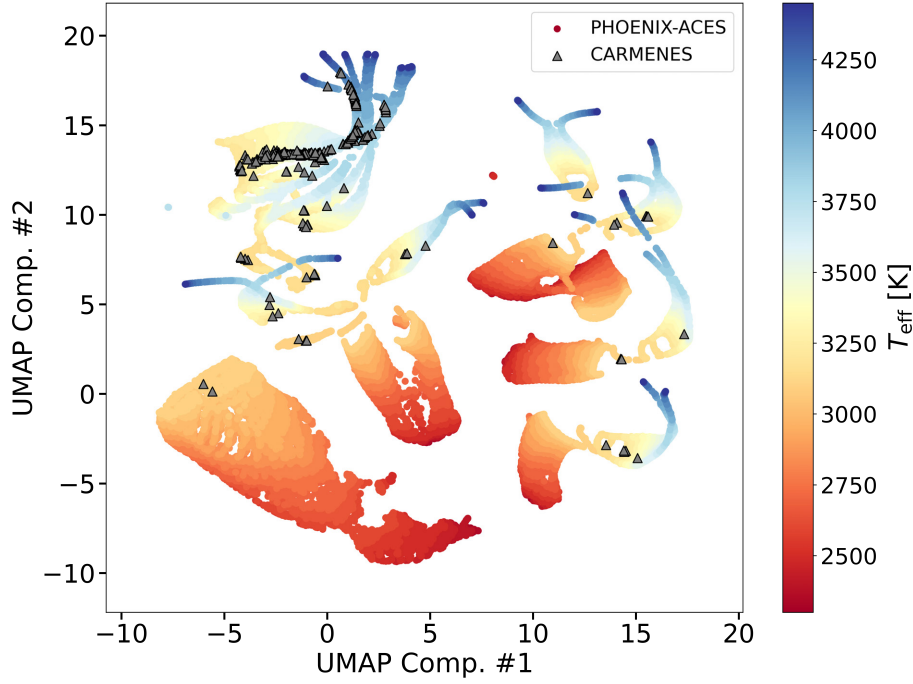


Figure 4.5: Two-dimensional UMAP projection of one of the 26 sets of PHOENIX-ACES (dots colour-coded by T_{eff}) and CARMENES (grey triangles) compressed representations. PHOENIX-ACES encodings are obtained with the initially trained AE and CARMENES encodings with the fine-tuned network.

et al., 2012; Simonyan and Zisserman, 2014). The distinctive factor of CNNs is the use of convolution operations, in the convolutional layers, to automatically extract features from data. After the convolutional structure, the set of features is flattened and passed to an artificial neural network (ANN) to perform the classification or regression task.

In each forward-propagation process, the input of each neuron of the convolutional layer is obtained with an element-wise dot product between a convolution kernel (or filter), with trainable coefficients, and the outputs of the previous layer. The resulting arrays and a tunable bias are added up and passed through an activation function to obtain the output feature map of the neuron. The set of kernels is tuned during the training process, as the weights of the deep ANN layers are adjusted, so that the different feature maps of the layer represent specific features detected in the input data. Li et al. (2021c) provided a detailed review of CNNs.

In one-dimensional (1D) CNNs (see Fig. 4.6), the convolution kernel slides along a sequence of non-independent values to extract relevant features, and they have proven to be highly performant in several applications during the recent years (Kiranyaz et al., 2021). Sharma et al. (2020) presented a semisupervised learning approach to handle the scarcity of labelled samples, using AE and 1D CNN architectures for stellar spectral classification. Zheng and Qiu (2020) explored how the generation of stellar spectra to balance the training data set can significantly improve the performance of a 1D CNN classifier.

Since we used 32-component vectors as input data for the stellar parameter estimation, we built a 1D CNN architecture. This architecture consists of two convolutional layers (Conv1D) with a variable number of filters (see Table D.2), followed by four fully-connected (Dense) layers. A flattening step is incorporated between the convolutional and the ANN components to reshape the output of the final convolutional layer (number

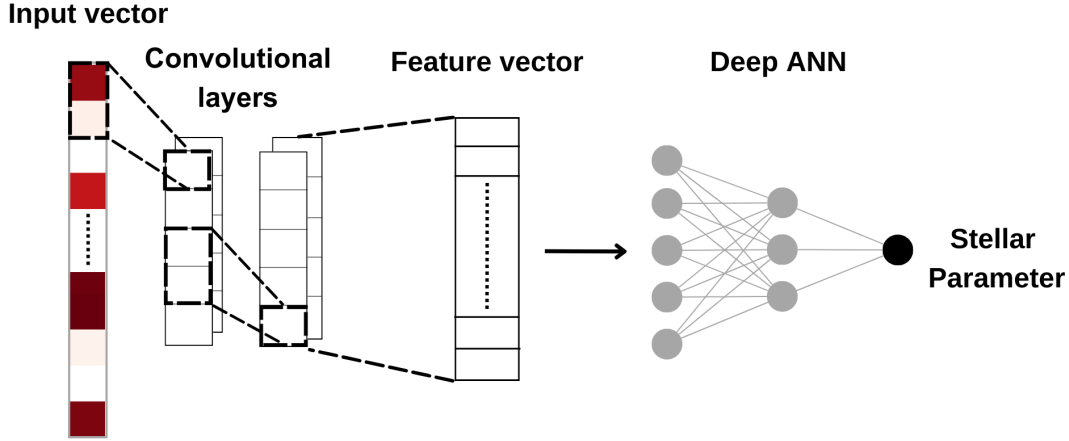


Figure 4.6: Schematic representation of a one-dimensional CNN architecture.

of outputs $\times$ number of filters) into a one-dimensional vector. This vector is then fed into the dense layers. We used a rectified linear unit (ReLU) activation function in all layers except the output layer, with a linear activation. We estimated T_{eff} , $\log g$, $[M/H]$, and $v \sin i$ independently, searching for the optimal hyperparameters of the 1D CNN architecture (same procedure as in Section 4.3.1) in the estimation of each parameter. Table D.2 describes in detail the CNN architectures used. We followed the same procedure in the independent estimation of the different stellar parameters. To have a significant number of final estimates and to assess the robustness of our methodology, we built five CNN models for each of the 26 sets of encoded representations, thus obtaining a total of 130 regressors for each of the parameters.

To train the CNN models, we use stratified sampling to create the indices of the training (70%) and test (30%) sets from the PHOENIX-ACES low-dimensional representations, ensuring that the distribution of the target parameter is representative of the overall distribution in both sets. For this, we relied on the `StratifiedShuffleSplit` class of the `scikit-learn` python package, which automatically performs stratification based on a target variable and generates indices to split data into training and test set. We trained the CNN models using the synthetic compressed representations, with a mean squared error loss function, and evaluated them on the test set. As final regressors, we kept the 80 models with the lowest mean squared error in the test set, obtaining an upper value of 353 K, 0.0042 dex, 0.0016 dex, and 0.054 km s^{-1} for T_{eff} , $\log g$, $[M/H]$, and $v \sin i$, respectively. Using these models, we obtained 80 final parameter estimates for each of the CARMENES stars.

We followed the same strategy used by Pass20 and Bello23 for the uncertainty estimation of the stellar parameters. For each star, we gathered the 80 estimations and approximated the probability density function using the Kernel Density Estimate (KDE; Chen et al., 1997; Poggio et al., 2021) technique. We took the maximum of this probability density function as the confident estimation for the stellar parameter, together with the 1σ thresholds as the corresponding uncertainties. Here, the final stellar parameter is derived from a distribution of parameter estimates which come from 26 different sets of input features, together with the five CNN models built for each set. Therefore, the

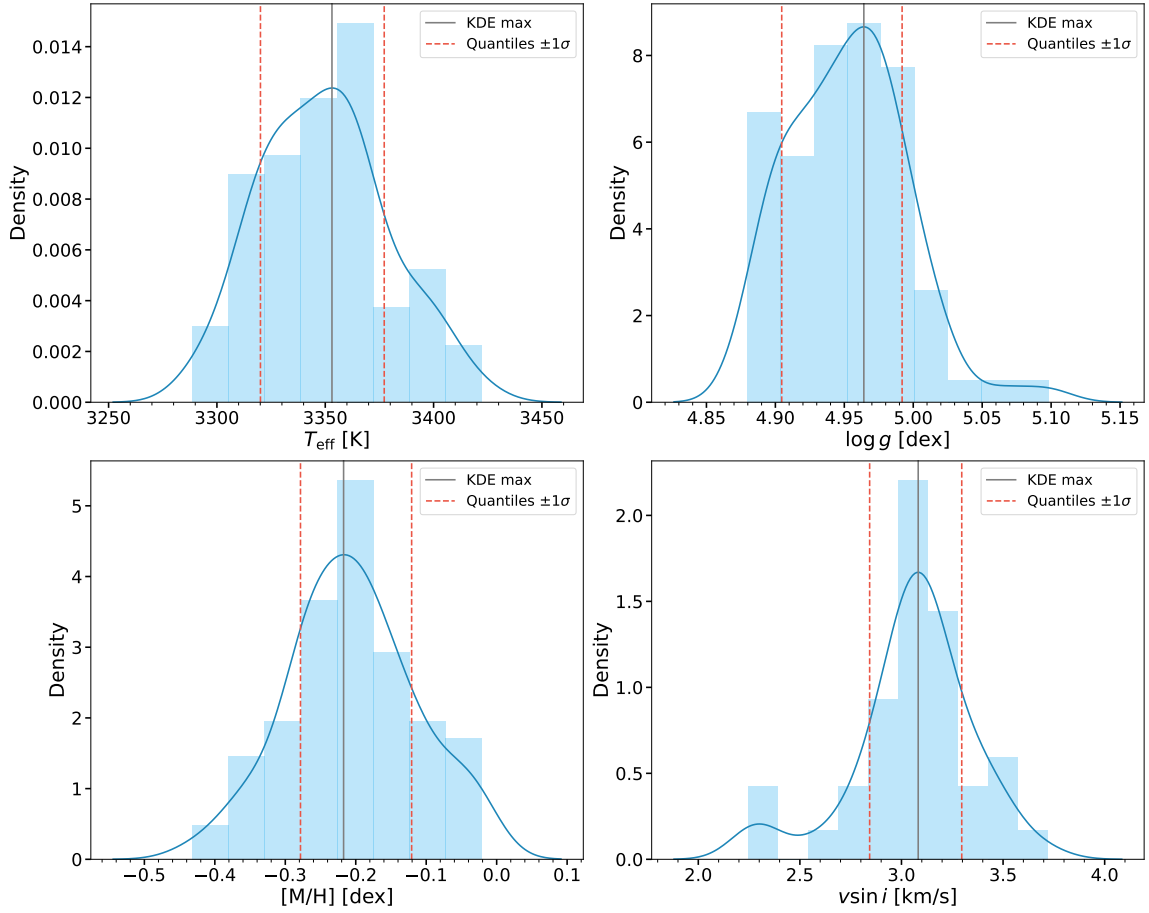


Figure 4.7: Distribution of stellar parameter estimations of J17578+046 (Barnard’s star, M3.5 V; Alonso-Floriano et al., 2015). The blue solid line represents the KDE, with the maximum marked with a grey solid line. The red dashed lines represent the $\pm 1\sigma$ uncertainties.

uncertainties provided should be understood as an intrinsic error of our methodology. Fig. 4.7 shows an example of the results for a single star.

4.4 RESULTS AND DISCUSSION

4.4.1 Stellar parameters analysis

Table D.1 presents the stellar atmospheric parameters determined with our methodology. The top left panel in Fig. 4.8 shows a Kiel diagram that relates all our estimated parameters, along with isochrones based on the PADova and TRIeste Stellar Evolution Code (PARSEC release v1.2S; Bressan et al., 2012) for 5 Gyr and $[M/H] = -0.4, 0.0$, and 0.1 dex. The results obtained with our methodology follow the trend set by the isochrones and the structure observed in the estimated metallicities is also consistent with them. The remaining three panels in Fig. 4.8 show a Hertzsprung-Russell diagram (HRD) of our results, with different features highlighted in each of them. We computed the bolometric luminosities, L_{bol} , as Cifuentes et al. (2020) using the latest astrometry and photometry from *Gaia* DR3 (Gaia Collaboration et al., 2023b). Theoretical isochrones, for solar metallicity, from PARSEC v1.2S and from evolutionary models presented by Baraffe et al. (2015) are overplotted in the top right panel for 0.1 and 5 Gyr. Both the Kiel diagram and the

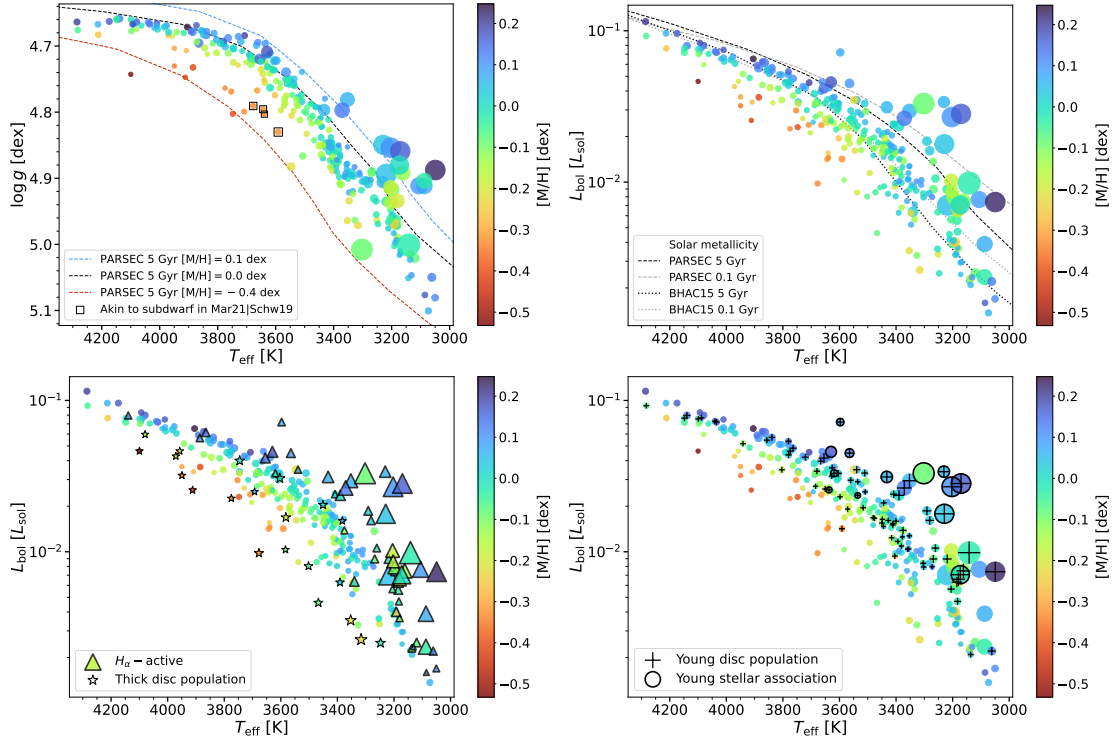


Figure 4.8: Analysis of the stellar parameters derived with our methodology. The dots are colour-coded according to the estimated metallicity. The size of the dots is proportional to the estimated projected rotational velocity. The *top left panel* shows a Kiel diagram, with the red, black, and blue dashed lines corresponding to 5 Gyr PARSEC isochrones with $[M/H] = -0.4, 0.0$ and 0.1 dex, respectively. Empty squares represent the stars reported to have a behaviour akin to subdwarfs both in Mar21 and Schw19 (same for *bottom left panel*). *Top right*: black and grey dashed lines correspond to solar metallicity PARSEC isochrones for 5 and 0.1 Gyr, respectively. Black and grey dotted lines correspond to solar metallicity Baraffe et al. (2015) isochrones for 5 and 0.1 Gyr, respectively. *Bottom left*: triangles represent stars identified as $H\alpha$ active in Schöfer et al. (2019). Empty stars depict members of the thick disc Galactic population (Cortés-Contreras et al., in prep.). *Bottom right*: plus symbols correspond to stars identified as members of the young disc Galactic population by Cortés-Contreras et al. (in prep.). Empty circles represent stars with a possible membership in a young stellar association, as explained in Section 4.4.1.

HRD reveal a clear outlier region at the lowest temperatures (mid M-dwarf regime; Cifuentes et al., 2020; Pecaute and Mamajek, 2013), populated mostly by the stars with a high estimated projected rotational velocity ($v \sin i$). These fast rotators in our sample are located at the expected M-dwarf regime, following the relation between the spectral types from the CARMENES input catalogue (Carmencia; Alonso-Floriano et al., 2015; Caballero et al., 2016a) and the $v \sin i$ values calculated by Reiners et al. (2018) (see Fig. 2 in Mar21).

The bottom panels in Fig. 4.8 help to understand the outliers that deviate from the main sequence. The bottom left panel shows that almost all the overluminous outliers in the HRD are identified as H α active stars by Schöfer et al. (2019), considered as such if the pseudo-EW of the H α line satisfies $pEW'(H\alpha) < -0.3 \text{ \AA}$ (H α flag from Table B.1 in Mar21). As found in previous works (e.g. Jeffers et al., 2018; Reiners et al., 2018), the fraction of H α active stars is higher at later spectral types. There are clear patterns in the HRD which arise from the kinematic membership of the targets. For instance, and in agreement with Jeffers et al. (2018), most H α active and rapidly rotating stars are kinematically young (dots marked with a + in the bottom right panel).

To study the possible membership of our sample to nearby young stellar associations, we relied on BANYAN Σ^9 (Gagné et al., 2018), a Bayesian analysis tool to identify members of young associations. Modelled with multivariate Gaussians in six-dimensional XYZUVW space, BANYAN Σ can derive membership probabilities for all known and well-characterised young associations within 150 pc. In our case, we used the python version of BANYAN Σ^{10} , and included the *Gaia* DR3 sky coordinates, proper motion, radial velocity, and parallax of our target stars as input parameters to the algorithm. The classifier gave a high probability (>80 %) for 9 objects to belong to a young stellar association, in 7 of the cases with a probability greater than 95 %. Table 4.1 lists the details of these objects. All these stars with a possible membership in a young stellar association are represented with a thick open circle in the bottom right panel of Fig. 4.8. Here, we also considered four extra stars, namely J09133+688 (G 234-057), J12156+526 (StKM 2-809), J15218+209 (GJ 9520), and J18174+483 (TYC 3529-1437-1), which Schw19 mentioned as young age-based outliers.

The bottom left panel in Fig. 4.8 shows that outliers below the main sequence are typically members of the thick disc Galactic population (Cortés-Contreras et al., in prep.; Cortés-Contreras, 2017).

Furthermore, four of these outliers are reported to have a behaviour akin to subdwarfs (empty squares in top and bottom left panels) both by Mar21 and Schw19. Table D.3 details all the outliers we identified with low-metallicity behaviour, along with the metallicity estimations found in the literature. As discussed by Jao et al. (2008), with the decrease in the metallicity of these objects the TiO opacity also strongly decreases, and this less blanketing from the TiO bands causes more continuum flux to radiate from the deeper and hotter layer of the stellar atmosphere, so that these stars appear bluer than their solar metallicity counterparts (see Fig. 1 in Jao et al. 2008). Our [M/H] determinations for these stars are, in general, in good agreement with the literature.

Fig. 4.9 shows the distribution of our predicted metallicities broken down by kinematic membership in the thick disc (TD), thick disc-thin disc transition (TD-D), thin disc (D), and young disc (YD) Galactic populations (Cortés-Contreras et al., in prep.; Cortés-Contreras, 2017). This breakdown reveals the distinction between metal-rich thin disc stars and metal-poor stars in the older thick disc (Bensby et al., 2005; Gaia Collabor-

⁹ <http://www.exoplanetes.umontreal.ca/banyan/>

¹⁰ <https://github.com/jgagneastro/banyan-sigma>

Table 4.1: Stars in our sample classified by BANYAN Σ with a high probability of belonging to a young stellar association.

Karmn	BANYAN Σ Prob. ^(a)	Young association ^(b)	Association reference
J02088+494	99.94 %	AB Doradus	Zuckerman et al. (2004)
J02519+224	99.79 %	β Pictoris	Zuckerman et al. (2001)
J03473-019	99.94 %	AB Doradus	Zuckerman et al. (2004)
J05019+011 ^(c)	99.91 %	β Pictoris	Zuckerman et al. (2001)
J05062+046 ^(c)	99.79 %	β Pictoris	Zuckerman et al. (2001)
J09163-186	95.01 %	Argus	Zuckerman (2018)
J10289+008	99.97 %	AB Doradus	Zuckerman et al. (2004)
J19511+464	94.17 %	Argus	Zuckerman (2018)
J21164+025	85.20 %	Argus	Zuckerman (2018)

^(a) The probability that this object belongs to the young stellar association. ^(b) Most probable Bayesian hypothesis (including the field). ^(c) Already mentioned in Schw19 as candidate members of the corresponding young stellar association.

ation et al., 2023a), with the TD-D transition as an intermediate step. To prove this, we performed a two-sample Kolmogorov-Smirnov test (Kolmogorov, 1933; Smirnov, 1948) on the thin and thick disc samples, which returned a p value = 0.0071, rejecting the hypothesis that both samples come from the same distribution.

Also, the 2MASS-*Gaia* $G_{BP} - G_{RP}$ versus $G - J$ colour-colour diagram in Fig. 4.10 shows how the evolution in our estimated effective temperatures is coherent with the colour-colour relationship (see Fig. 14 in Cifuentes et al. 2020). For this diagram, we only considered stars with reliable 2MASS J-band and *Gaia* DR3 G_{BP} and G_{RP} photometry.

4.4.2 Comparison with the literature

We compared our results with different collections found in the literature. Whereas this section focuses on the latest studies using CARMENES data, namely Bello23, Mar21, Pass19, Pass20, and Schw19, a more extensive compilation of literature, together with the uncertainties of the estimations, is provided in Appendix D.2. For Pass19, we considered the parameters derived from VIS spectra. Table 4.2 lists the mean difference ($\bar{\Delta}$; literature—this work), root mean squared error (rmse), and Pearson correlation coefficient (r_p) for the comparison with each of the literature collections. An interactive version of the results presented in this section is available to the astronomical community¹¹.

Figure 4.11 depicts the comparison with literature values for T_{eff} . The left panels show a similar linear trend among Mar21, Pass19, and Schw19 with our values, all of them with a slope of less than one, for the region T_{eff} (this work) $\lesssim 3750$ K. From this value onwards, where the number of stars in our training set is smaller, the dispersion increases significantly and our T_{eff} estimations deviate towards hotter values, resulting in a mean difference of $\bar{\Delta} = -19$ K, $\bar{\Delta} = -80$ K, $\bar{\Delta} = -40$ K for Mar21, Pass19, and Schw19, respectively. The figures provided in Appendix D.2 show that the uncertainties intrinsic to our methodology are also larger for estimations above 3750 K. The right panels show how the agreement with the values obtained following the approach described by Pass20 is excellent, which is expected since their methodology is the closest to the one presented in this

¹¹ <https://cab.inta-csic.es/users/pmas/>

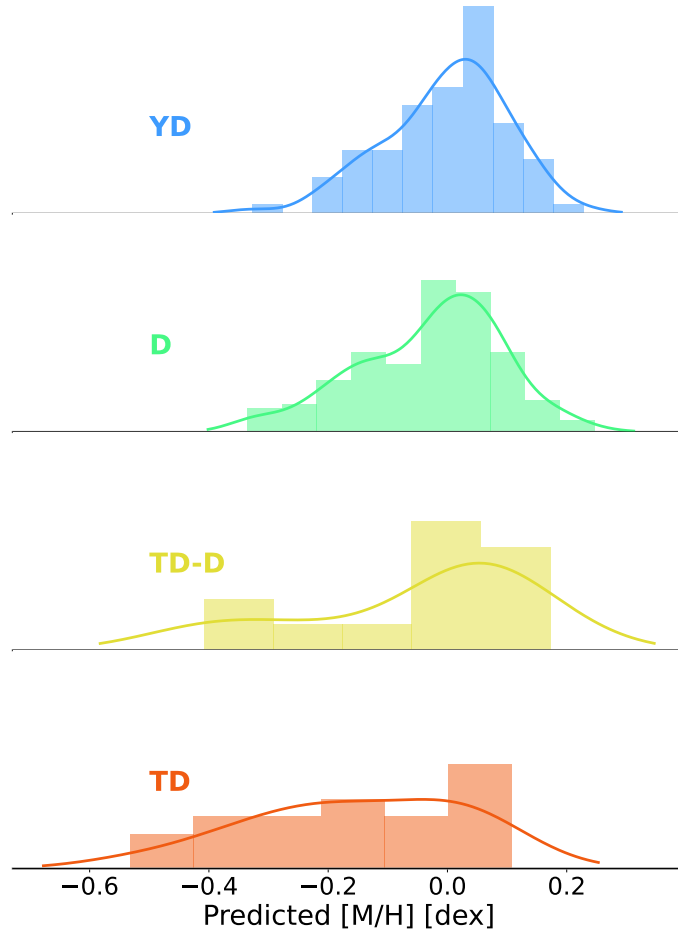


Figure 4.9: Distribution of our predicted metallicities broken down by kinematic membership in the thick disc (TD), the thick disc-thin disc transition (TD-D), the thin disc (D), and the young disc (YD) Galactic populations (Cortés-Contreras et al., in prep.; Cortés-Contreras, 2017). The bins are normalised so that the total area of the histogram equals one, and the solid lines represent the KDE.

Table 4.2: Mean difference ($\bar{\Delta}$; literature—this work), root mean square error (rmse), and Pearson correlation coefficient (r_p) for the comparison between our results and the literature.

Reference	T_{eff} [K]			$\log g$ [dex]			[Fe/H] [dex]			$v \sin i$ [km s ⁻¹]		
	$\bar{\Delta}$	rmse	r_p	$\bar{\Delta}$	rmse	r_p	$\bar{\Delta}$	rmse	r_p	$\bar{\Delta}$	rmse	r_p
Bello23	-117	180	0.87	...	...	...	0.01	0.14	0.60	...	...	...
Mar21	-19	102	0.94	0.12	0.18	0.39	-0.11	0.16	0.65	...	...	...
Pass19	-80	117	0.96	0.00	0.05	0.86	0.06	0.15	0.52	...	...	...
Pass20	-35	51	0.99	-0.04	0.06	0.93	0.23	0.25	0.76	1.64	1.94	0.99
Rein18 ^(a)	...	...	...	...	...	...	...	...	...	-0.86	1.51	0.98
Schw19	-40	93	0.96	0.13	0.14	0.89	0.00	0.10	0.63	...	...	...

^(a) From Reiners et al. (2018).

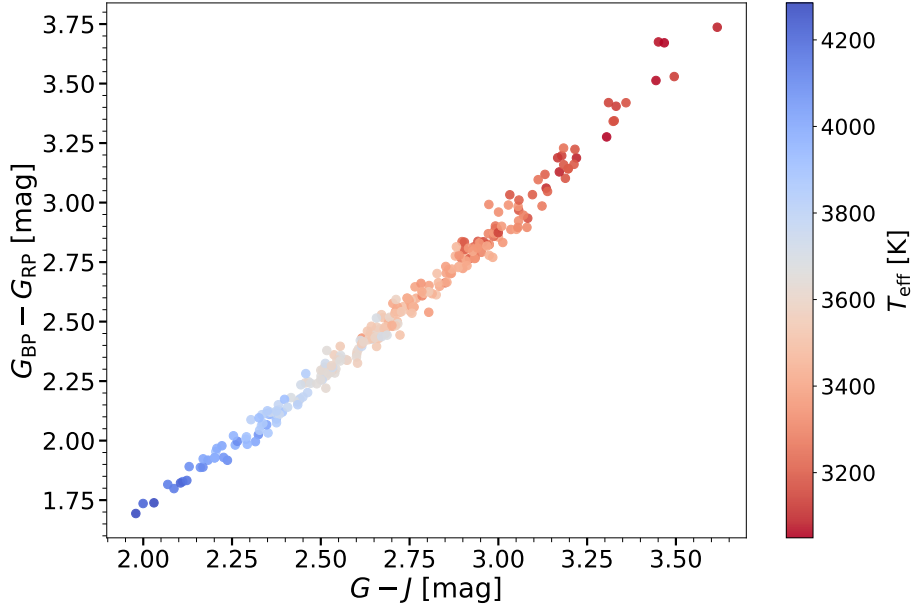


Figure 4.10: 2MASS-*Gaia* $G_{BP} - G_{RP}$ versus $G - J$ diagram of our target stars with good photometric quality (2MASS Qf1g=A and a relative error of less than 10% in *Gaia* DR3 photometry). The points are colour-coded according to the effective temperatures derived in this work.

work. Moreover, the comparison with the results from Bello23 reveals the same structure, but inverted, as shown in Fig. 9 of their work, with a larger dispersion than that observed for the other literature collections. The black stars in the top right panel represent the 14 interferometrically derived T_{eff} values (see Table 1 in Bello23), which are on average cooler than the temperatures obtained with our methodology ($\bar{\Delta}_{\text{interf}} = -119$ K). The r_p values listed in Table 4.2 show a strong correlation with all the collections.

Figure 4.12 shows a similar literature comparison for $\log g$. For Schw19, we considered the values derived using their mass-radius relation and the Stefan-Boltzmann’s law. The $\log g$ values from Mar21 show a large dispersion ($r_p = 0.39$), as already mentioned in their work, and are generally spread towards higher values ($\bar{\Delta} = 0.12$ dex). While the results from Pass19 cover the same range and are similar on average to our obtained $\log g$ ($\bar{\Delta} = 0.00$ dex), those from Schw19 extend to higher values and are on average higher than ours ($\bar{\Delta} = 0.13$ dex). It should be noted that, while Pass19 and Schw19 fix $\log g$ using theoretical isochrones, Mar21 has $\log g$ as a free parameter. Moreover, our results show a good correlation ($r_p = 0.93$) with those obtained following the methodology described by Pass20, although the latter are deviated to lower values ($\bar{\Delta} = -0.04$ dex).

As discussed in Passegger et al. (2022), several discrepancies can be found when comparing metallicities of M dwarfs obtained with different methodologies. Figure 4.13 shows the comparison with literature values for our $[M/H]$ estimations, which directly translate into $[Fe/H]$ values (Passegger et al., 2020, 2022). For Mar21, we considered the values corrected for alpha enhancement. Our results are similar on average to those from Schw19 ($\bar{\Delta} = 0.00$ dex), while Pass19 and Mar21 results tend to be higher and lower, with $\bar{\Delta} = 0.06$ and $\bar{\Delta} = -0.11$ dex, respectively. As already mentioned in Passegger et al. (2022), the results from the DL methodology described by Pass20 are deviated towards more metal-rich values, with $\bar{\Delta} = 0.23$ dex. We note that this deviation, which is attributed to the synthetic gap by Pass20, does not appear in the DTL methodologies presented by Bello23 and here. Bello23 metallicities cover more or less the same range as our results,

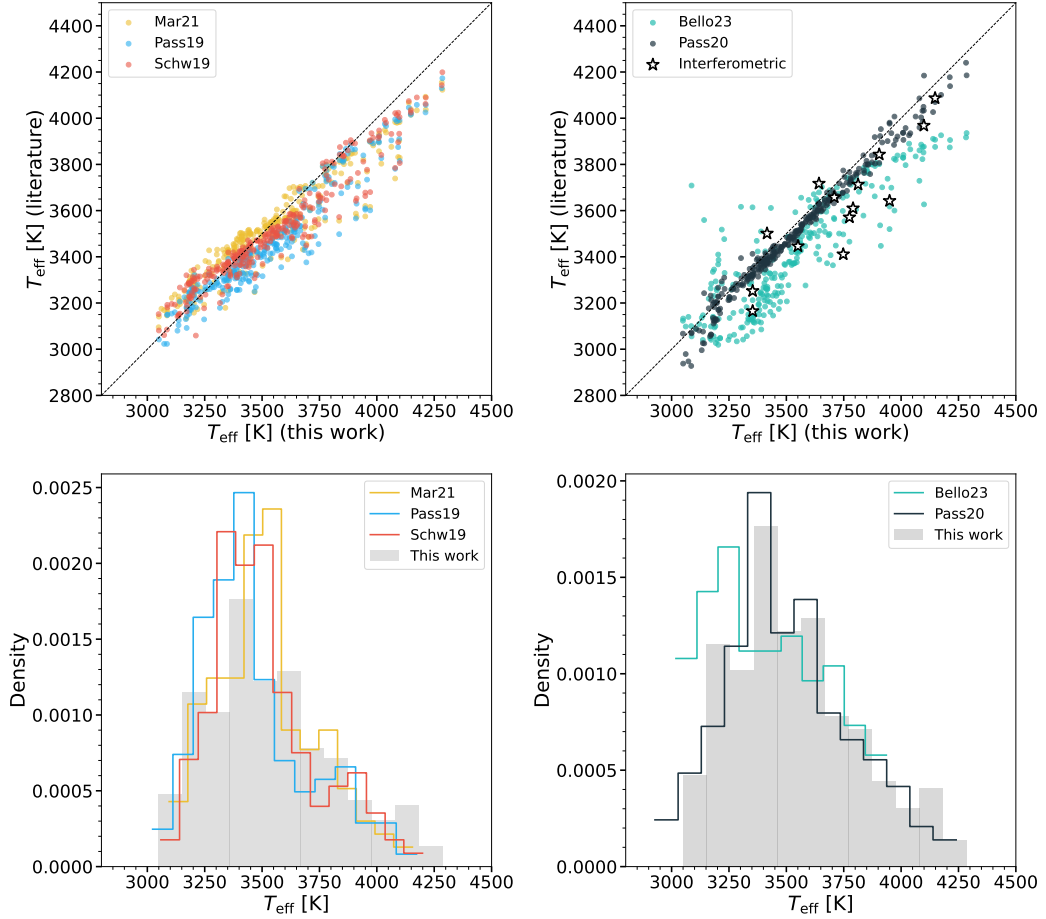


Figure 4.11: Comparison between our derived T_{eff} values and the literature. The *left panels* include the results from [Mar21](#) (yellow), [Pass19](#) (blue), and [Schw19](#) (red). The *right panels* include the work from [Bello23](#) (cyan) and the results obtained following the DL methodology described by [Pass20](#) (dark blue). The black stars in the *top right panel* correspond to the interferometrically derived T_{eff} values from [Bello23](#). The dashed black lines in the *top panels* correspond to the 1:1 relation. For the bin width in the histograms shown in the *bottom panels*, we used the default parameters of the `seaborn histplot` function.

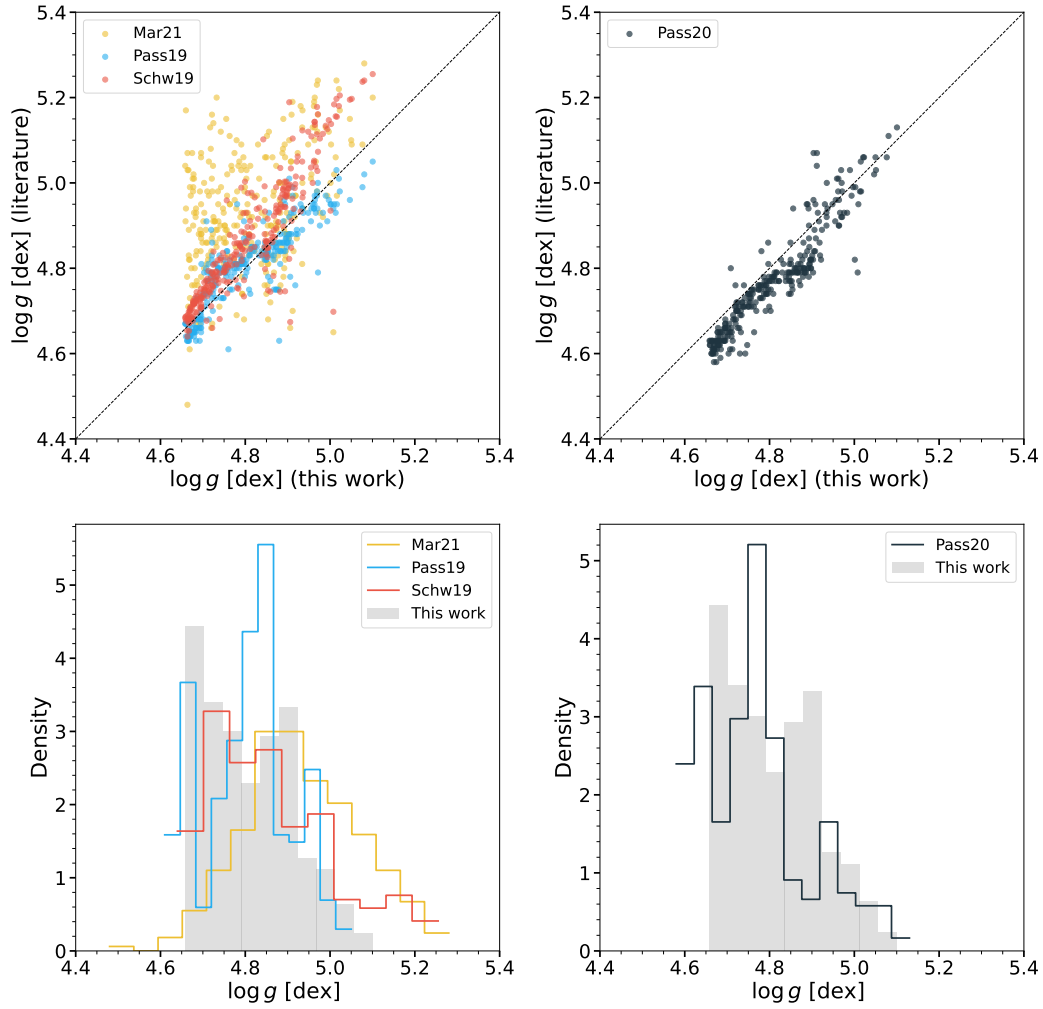


Figure 4.12: Comparison between our derived $\log g$ values and the literature. Colours and symbols are the same as in Fig. 4.11.

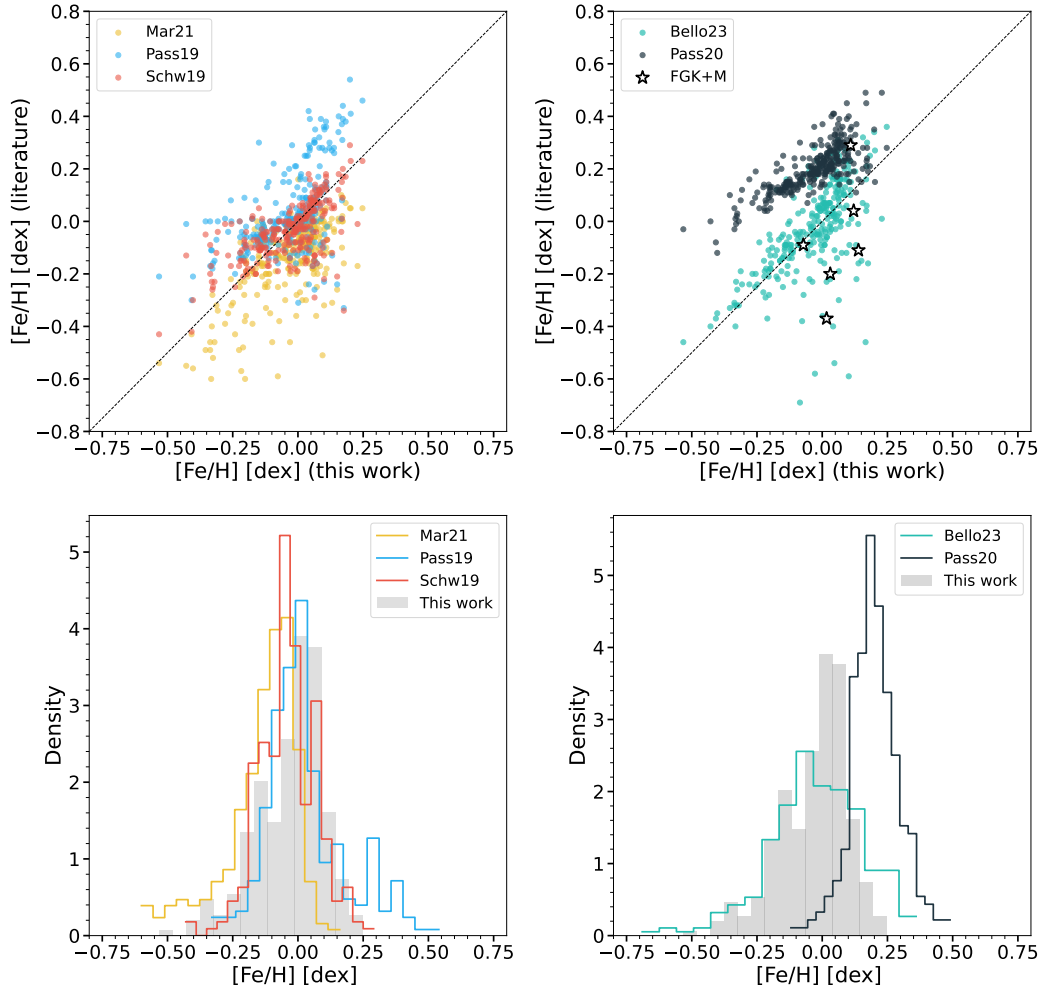


Figure 4.13: Comparison between our derived $[\text{Fe}/\text{H}]$ values and the literature. Colours and symbols are the same as in Fig. 4.11. The black stars in the *top right panel* correspond to the spectroscopically determined $[\text{Fe}/\text{H}]$ values from FGK+M systems presented in Bello23.

and the spectroscopically determined $[\text{M}/\text{H}]$ values from FGK+M systems (see Table 3 in Bello23) (black stars in the top right panel) are systematically lower ($\bar{\Delta} = -0.13$ dex).

We also compared our $v \sin i$ determinations with the ones derived by Reiners et al. (2018) using the cross-correlation method and with those obtained following the DL methodology described by Pass20. Fig. 4.14 shows how our derived $v \sin i$ are mostly consistent with the literature within their errors. Both Pass20 and Reiners et al. (2018) results show a good correlation with our values ($r_p = 0.99$ and 0.98 , respectively). Since most of the objects are located at lower $v \sin i$ values, it is convenient to split the analysis provided in Table 4.2 at a cut-off value of $v \sin i$ (this work) = 12 km s^{-1} . Below this value, Pass20 presents $\bar{\Delta} = 1.83 \text{ km s}^{-1}$ and $\text{rmse} = 1.97 \text{ km s}^{-1}$, with $\bar{\Delta} = -1.22 \text{ km s}^{-1}$ and $\text{rmse} = 1.45 \text{ km s}^{-1}$ for faster rotators. Similarly, for Reiners et al. (2018), we obtained $\bar{\Delta} = -0.68 \text{ km s}^{-1}$ and $\text{rmse} = 1.24 \text{ km s}^{-1}$ for values below the threshold, and $\bar{\Delta} = -3.47 \text{ km s}^{-1}$ and $\text{rmse} = 3.71 \text{ km s}^{-1}$ for values above.

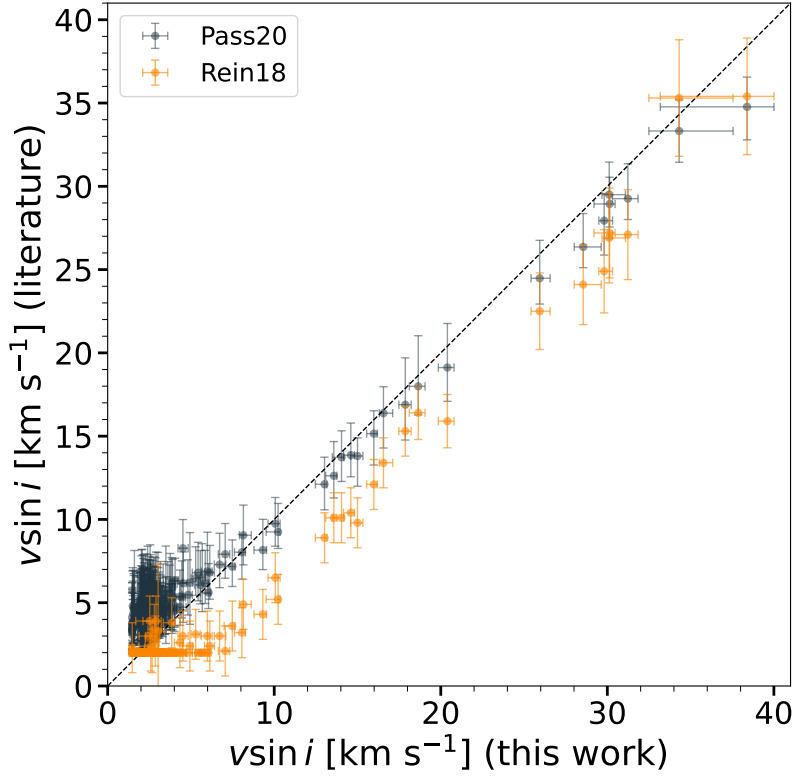


Figure 4.14: Comparison between our derived $v \sin i$ values and the literature. The ‘Rein18’ label stands for the results presented in Reiners et al. (2018).

4.5 CONCLUSIONS

This work serves as an extension of a series of papers (Pass20; Bello23) dedicated to exploring the use of DL for stellar parameter estimation of CARMENES M dwarfs, based on synthetic spectra. Bello23 developed a model-based DTL technique to bridge the significant differences in flux features between the two spectral families, reported by Pass20. Here, we propose a parallel feature-based DTL strategy that addresses the limitations mentioned in their work regarding the need for high-quality stellar parameter estimations in the knowledge transfer process.

Using a methodology that combines the use of AEs and CNNs, we derived new estimations for the stellar parameters T_{eff} , $\log g$, $[M/H]$, and $v \sin i$ of 286 M dwarfs observed with CARMENES. The AE models were trained on PHOENIX-ACES synthetic spectra and then fine-tuned using the CARMENES high-S/N, high-resolution spectra. In the fine-tuning process, no data other than the observed spectra are required, which gives our methodology great flexibility, as no measured stellar parameters are involved in the knowledge transfer. We used the low-dimensional representations of the synthetic and observed spectra, resulting from the initial training and the fine-tuning steps, respectively, as input to the CNNs for the estimation of the stellar parameters. In this way, parameter estimation is conducted using a dataset in which no significant differences in the feature distributions between the synthetic and observed data are evident.

We performed an in-depth analysis of our estimated stellar parameters, using the diagram shown in Fig. 4.8 to study the objects that deviate from the main sequence. We found that almost all the overluminous outliers are identified as H α active stars by Schöfer et al. (2019), while outliers located below the main sequence are typically metal-

poor stars from the thick disc Galactic population. In particular, using the BANYAN Σ tool, we found 9 objects with a high Bayesian probability of belonging to five different young stellar associations, in 7 of these cases with a probability of more than 95%. Together with the low-metallicity objects already reported in [Mar21](#) and [Schw19](#), we identified eight more stars that exhibit the same behaviour.

We also conducted a comparative study between our results and the latest studies using CARMENES data, finding good consistency with the literature in most cases. Both our T_{eff} and $\log g$ determinations are, in general, strongly correlated with the results from the literature, with a systematic deviation in our T_{eff} scale towards hotter values for estimations above 3 750 K. As expected, our parameter determinations are in very good agreement with [Pass20](#), since their methodology is the most similar to the one presented in this paper. More importantly, the deviation in metallicity attributed to the synthetic gap in their work is not observed in ours thanks to the DTL approach. This, together with the work presented by [Bello23](#), demonstrates the great potential of DTL-based strategies to bridge the synthetic gap in stellar parameter estimation from synthetic spectra.

5

CHARACTERISATION OF ULTRACOOLO DWARFS WITH DEEP TRANSFER LEARNING

The future is bright for the field of ultracool dwarfs. The Visible Instrument (VIS) and the Near-Infrared Spectrometer and Photometer (NISIP) aboard the ESA *Euclid* mission will provide a unique combination of wide-area ($\sim 15\,000\text{ deg}^2$) coverage, high-spatial resolution, and unprecedented sensitivity, with a low-resolution near-infrared spectroscopic survey that will enable the spectral characterisation of a huge number of previously undiscovered ultracool dwarfs. This was recently demonstrated by Zhang et al. (2024), who highlighted the reliability that the data provided by the slitless spectroscopic mode of the NISIP instrument will deliver for the spectral characterisation of ultracool dwarfs in both the deep and wide surveys. In the summer of 2027, the NASA Nancy Grace Roman Space Telescope will join *Euclid* to explore the infrared sky as never before possible, with a much deeper and more precise core survey, but over a smaller area ($\sim 2\,000\text{ deg}^2$). These surveys will be complemented in the optical by the LSST, carried out in the Vera C. Rubin Observatory, expected to start operations in mid-2025. The LSST will provide a high-spatial resolution, high-cadence, and high-sensitivity multi-band photometric survey over the entire Southern Hemisphere sky, that will supersede the previous SDSS and Pan-STARRS optical datasets. The combination of all these upcoming surveys will lead to a quantum leap of over an order of magnitude in the number of ultracool dwarfs detected (Solano et al., 2021; Martín et al., 2023), enabling the study of more distant ultracool dwarf populations than ever before.

The low-resolution near-infrared spectroscopic survey conducted by *Euclid* represents a key opportunity for developing a flexible, automated, and reliable methodology capable of harnessing these vast amounts of data to spectroscopically classify ultracool dwarfs and determine their effective temperature. In this line, we leveraged of the deep transfer learning framework introduced by Mas-Buitrago et al. (2024) and explored its adaptation to the low-resolution, ultracool dwarf domain, with a view to its further application to the *Euclid* dataset.

5.1 TESTBED ENVIRONMENT WITH SPEX

To adjust our methodology and prepare it to the arrival of the first spectroscopic data from *Euclid*, we created a testbed environment using low-resolution spectra from the SpeX Prism Library, an online repository of over 3 000 low-resolution, near-infrared spectra, primarily of ultracool dwarfs. The spectra available in the SpeX Prism Library were observed with the prism mode of the SpeX spectrograph (Rayner et al., 2003) of the NASA Infrared Telescope Facility, with a resolving power ~ 200 across $0.8 - 2.5\text{ }\mu\text{m}$ when using the 0.8 arcsec slit. This repository is easily accessible using SPLAT (Burgasser and Splat Development Team, 2017), a python-based access and analysis package designed to search for spectral data in the SpeX Prism Library and perform comprehensive spectral analysis. To obtain our sample of spectra, or target domain, we cross-matched the sample

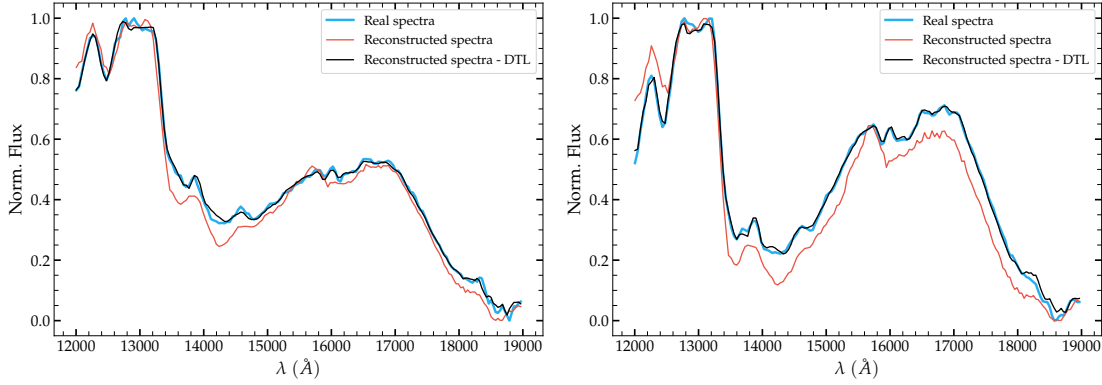


Figure 5.1: Original (blue) vs. reconstructed SpeX spectra of 2MASS J02540582-1934523 (M8) and 2MASSW J0015447+351603 (L2). The figure shows how the reconstruction after fine-tuning (black) captures much more detailed spectral features than the reconstruction with the initial training (red).

of high-quality ultracool dwarfs from the UltracoolSheet catalogue, presented in Section 1.1.2, with the SpeX Prism Library and obtained a final sample of 692 spectra with a spectroscopic classification in SpeX covering spectral types from M6 to T9.

As source domain for our deep transfer learning methodology, we built a grid of synthetic spectra based on the recent Sonora Elf Owl (Mukherjee et al., 2024) substellar atmosphere models, which present developments in atmospheric chemistry compared to earlier model collections such as Sonora Bobcat (Marley et al., 2021) or Sonora Cholla (Karlidi et al., 2021). For this, we adjusted the Sonora Elf Owl models to the resolution and wavelength solution of SpeX¹, and added three different random Gaussian noise values to each spectrum to enrich the dataset, ending up with a final synthetic grid of 31 050 spectra (see Table 2 in Mukherjee et al. 2024 for the grid of parameters). For both the synthetic and the observed spectra, we only considered the wavelength interval 12 000 – 19 000 Å, since this will be the range covered by the *Euclid* wide survey (Euclid Collaboration et al., 2023). Moreover, given the temperature constraints of the Sonora Elf Owl models, we retained only the SpeX spectra corresponding to spectral types M8 or later, and only kept the highest SNR spectrum when several were available for the same source. Doing this, we ended up with a sample of 585 SpeX spectra.

5.2 ULTRACOOL DWARF CHARACTERISATION

To determine the effective temperature of our sample of low-resolution, near-infrared ultracool dwarf spectra, we replicated the deep transfer learning methodology presented by Mas-Buitrago et al. (2024). First, we trained the autoencoder neural networks using the grid of synthetic spectra, obtaining reconstruction errors $\sim 10^{-4}$ on the test set. Since the number of input features is significantly smaller than in Mas-Buitrago et al. (2024) due to the lower resolution of the data, we adjusted the number of neurons in the input layer and reduced the number of hidden layers to two in the autoencoder architectures (see Fig. 4.2). For the knowledge transfer process, we fine-tuned the autoencoder neural networks with the SpeX spectra, tailoring the high-level features of the encoder network to our target domain. Figure 5.1 shows the importance of this step to adapt the autoencoder

¹ The adapted models are available in the ucdmcmc package of Dr. Adam Burgasser: <https://github.com/aburgasser/ucdmcmc/tree/main>

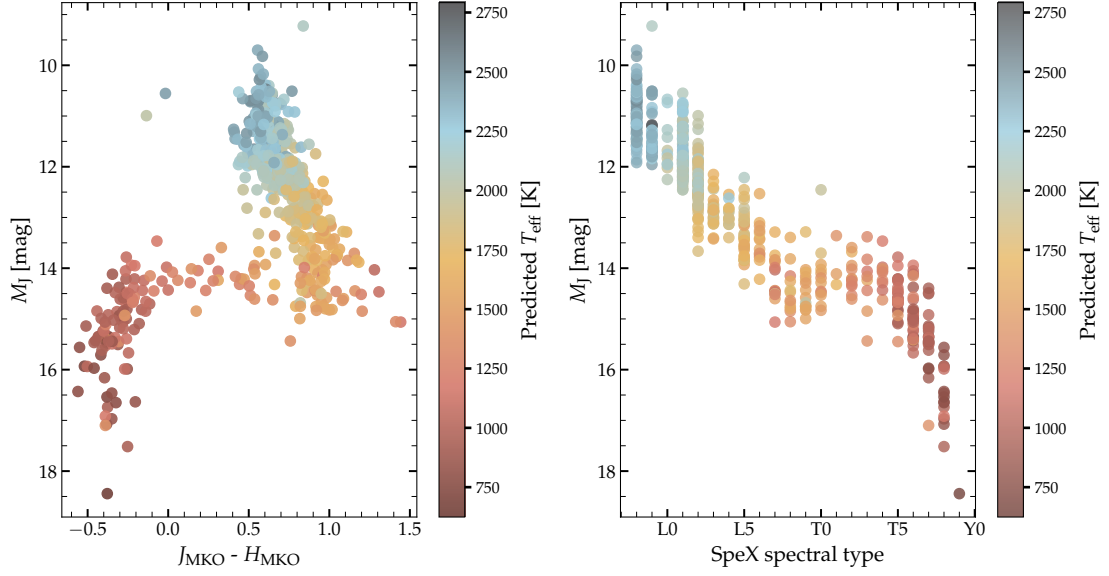


Figure 5.2: *Left panel:* M_J vs. $J - H$ colour-magnitude diagram, with the dots colour-coded by spectral type, of our sample of ultracool dwarfs. *Right panel:* Evolution of M_J with the spectral type for the same sample. The dots are colour-coded by the T_{eff} determined in this work. The magnitudes and the spectral types have been taken from the UltracoolSheet and SpeX, respectively.

to our target domain, ensuring that the compressed representations obtained with the fine-tuned autoencoders are more meaningful than those obtained without the transfer learning process.

We used the low-dimensional representations of the Sonora Elf Owl and SpeX spectra, resulting from the initial training and the fine-tuning of the autoencoders, respectively, as input to the convolutional neural networks (see Fig. 4.6) for the estimation of the effective temperature of our target sample. We calculated the minimum Euclidean and correlation distances from each SpeX instance to the synthetic grid in both the initial high-dimensional space and the new low-dimensional feature space, obtaining a reduction of over an order of magnitude for the compressed low-dimensional representations, averaged over all the sets obtained from the different autoencoder architectures. In this way, we effectively bridge the gap between the two domains, and parameter estimation is conducted using a dataset in which discrepancies in feature distributions between the synthetic and observed data are reduced.

Figure 5.2 reproduces the diagrams presented in Fig. 1.4, colouring the dots with the effective temperatures determined for our target sample to illustrate the temperature evolution of ultracool dwarfs. The near-infrared colour-magnitude diagram in the left panel shows how, when the trend changes abruptly to bluer $J - H$ values, the effective temperature of the ultracool dwarfs remains roughly constant at ~ 1450 K. During this L/T transition, visible in both panels as a plateau in M_J , the effective temperature evolves very slowly (Golimowski et al., 2004; Kirkpatrick et al., 2021), decreasing only ~ 200 K throughout the entire transition. Table E.1 lists all the effective temperatures determined for our sample of ultracool dwarfs.

Figure 5.3 shows the determined effective temperatures as a function of spectral type, together with the mean weighted with the uncertainties derived in this work and standard deviation for each of the spectral types (right panel), which are listed in Table 5.1. Both panels demonstrate how the temperature decreases steeply for spectral types M8-

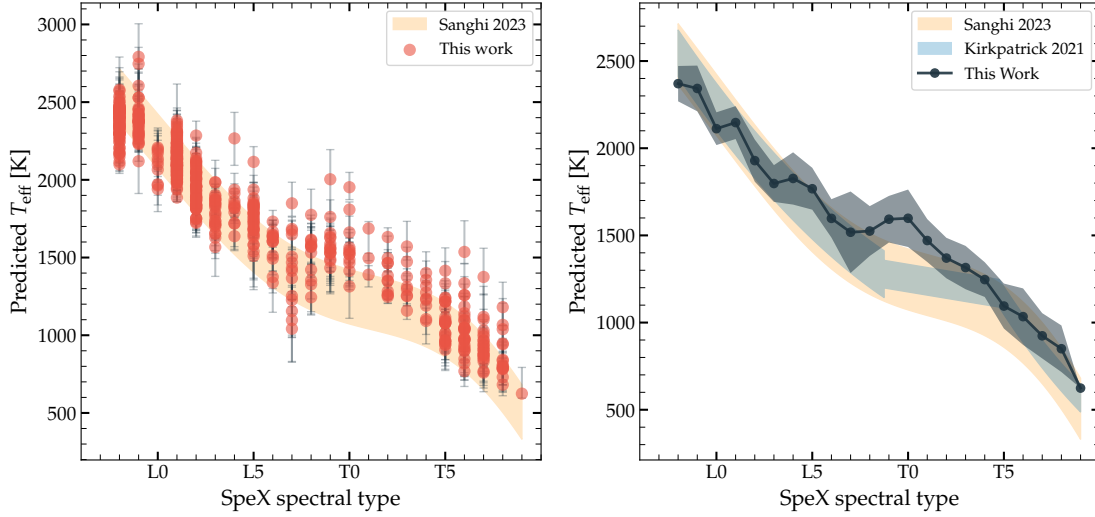


Figure 5.3: *Left panel:* Effective temperatures derived in this work, for our sample of ultracool dwarfs (red dots with grey error bars), as a function of the spectral type listed in SpeX. The shaded orange area indicates the semi-empirical relation by Sanghi et al. (2023). *Right panel:* Mean effective temperatures (black dots), weighted using the uncertainties derived in this work, for each of the spectral types. The shaded black area marks the standard deviation for each of the spectral types. The shaded orange and blue areas indicate the semi-empirical relations by Sanghi et al. (2023) and Kirkpatrick et al. (2021), respectively.

L7 and $\sim$ T2-T9, with the well-known narrow range of effective temperature throughout the L/T transition. The right panel shows how the calculated effective temperatures are in general in very good agreement with the semi-empirical relations from Kirkpatrick et al. (2021) and Sanghi et al. (2023). Our values are in average higher than the aforementioned relations during the L/T transition. Since Sanghi et al. (2023) uses also a sample of ultracool dwarfs extracted from the UltracoolSheet catalogue, we can directly compare our effective temperature determinations with their semi-empirical values. Figure 5.4 illustrates this comparison, confirming a good consistency between the two sets and a deviation towards higher values in our temperatures for the L/T transition. This transition is still a less understood phase of ultracool dwarf evolution. The increase of cloud opacity from early-L to late-L dwarfs, and the evolution to cloudless T dwarfs, hugely complicates the modelling of these atmospheres. In the future, a better treatment of clouds for this transition in atmospheric models will be the key to mitigating this effect.

The results obtained in this study indicate that the methodology presented by Mas-Buitrago et al. (2024), developed for the determination of stellar parameters of M dwarfs from high-resolution spectra, can be successfully adapted to the low-resolution domain to estimate the effective temperature of ultracool dwarfs. In this line, the methodology consolidated in this chapter will serve as a basis for the characterisation of ultracool dwarfs in the promising surveys to come in the next years, which envisage a scientific leap in this field, starting with its direct application to the wide-field *Euclid* low-resolution spectroscopic survey. We are already making progress in this regard, working with the first spectroscopic data from *Euclid*, and have successfully tailored the procedure to its wavelength solution. Doing this, we have applied the methodology to near-infrared, low-resolution *Euclid* spectra of a sample of confirmed ultracool dwarfs (see Figure 5.5), and determined the effective temperatures of these objects, which are in excellent agreement

Table 5.1: Relation between spectral type and effective temperature for ultracool dwarfs derived in this work.

Spectral type	Weighted mean T_{eff} ^(a) [K]	Standard deviation [K]	Number of objects ^(b)
M8	2370	101	86
M9	2343	131	36
L0	2112	94	11
L1	2147	94	132
L2	1929	121	62
L3	1798	105	25
L4	1827	150	12
L5	1768	120	32
L6	1598	110	13
L7	1518	234	14
L8	1525	143	12
L9	1593	134	15
T0	1598	165	12
T1	1471	123	3
T2	1370	116	11
T3	1316	124	8
T4	1247	100	9
T5	1095	129	26
T6	1034	162	28
T7	924	130	22
T8	850	134	15
T9	624	...	1

^(a) The uncertainties derived in this work are used as weights. ^(b) Number of objects within each spectral type.

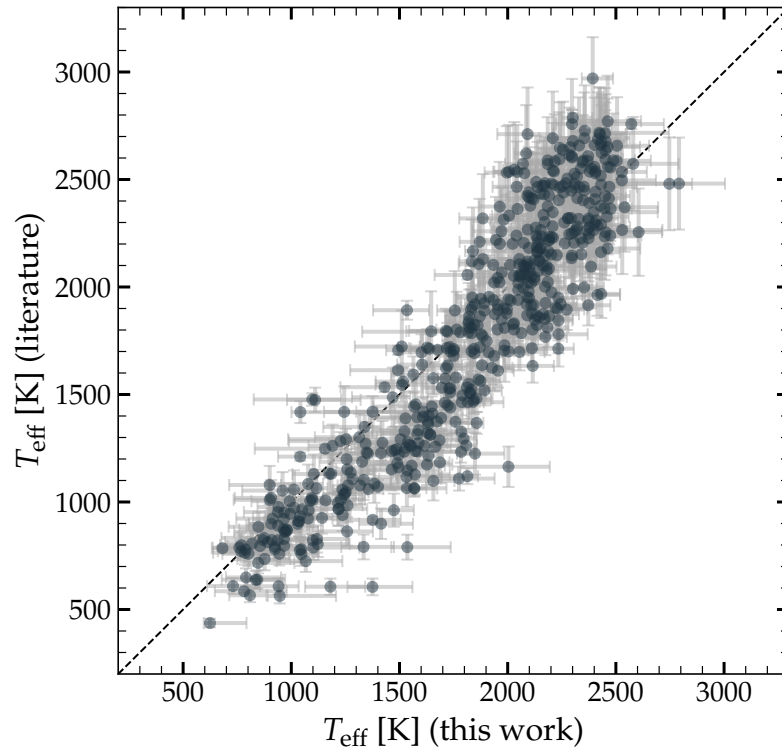


Figure 5.4: Comparison between our derived effective temperatures (X axis) and those in Sanghi et al. (2023).

with the spectral types derived by comparing them to the standard templates published by SPLAT (see Dominguez-Tagle et al. in press.).

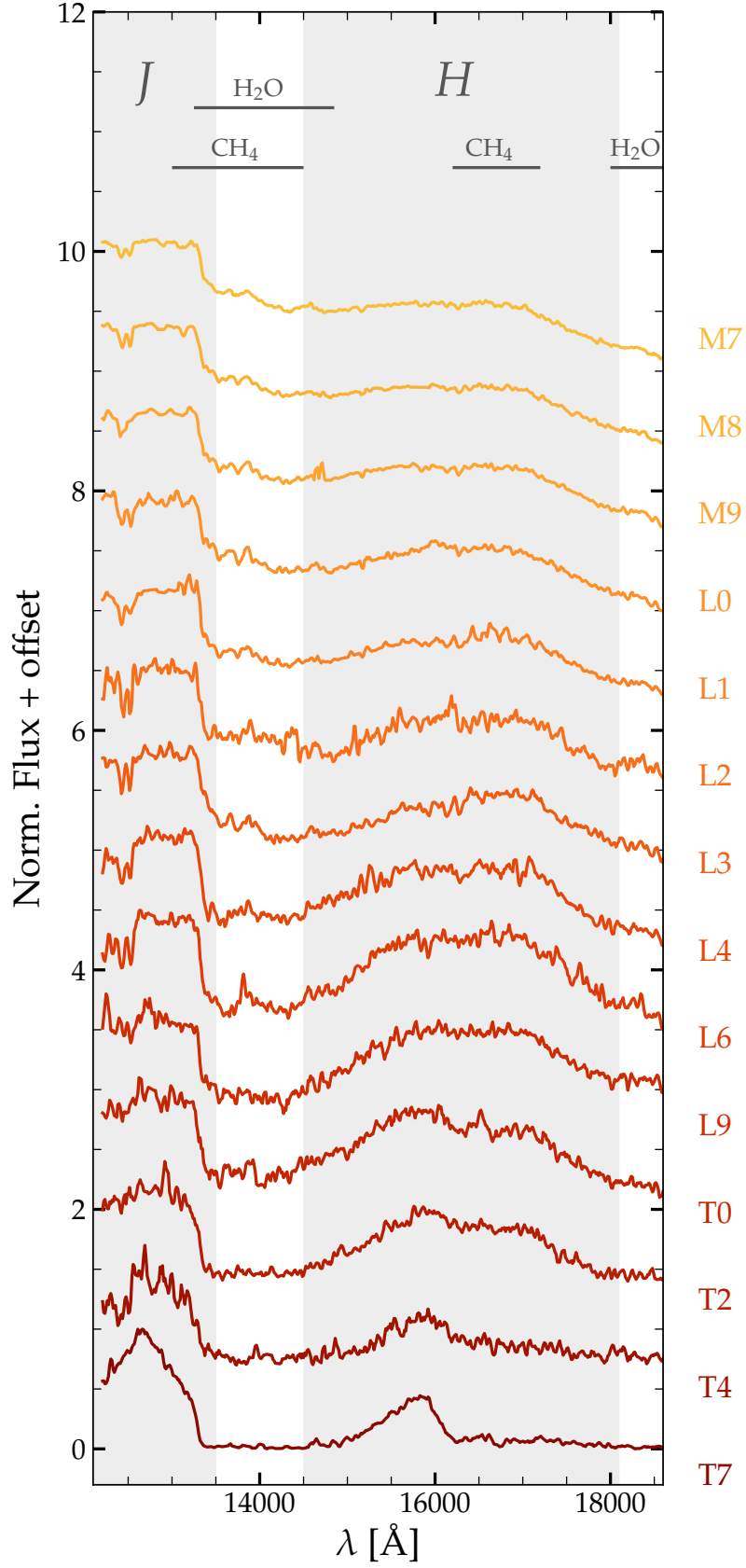


Figure 5.5: Spectral sequence for a sample of confirmed ultracool dwarfs using *Euclid* spectra. The spectra were classified by comparing them to the standard templates published by SPLAT (see Dominguez-Tagle et al. in press.). The relevant bands, as discussed in Section 1.1.2, are highlighted.

6

GENERAL CONCLUSIONS AND FUTURE WORK

This thesis delves into the discovery and characterisation of low-mass objects from a data-driven perspective, providing a rich catalogue of ultracool dwarf candidates and a deep transfer learning methodology for the estimation of stellar parameters of M dwarfs that we hope will be of great value for the astronomical community to exploit. In recent years, astronomy is undergoing a paradigm shift driven by an exponential growth in observational data, with new-generation surveys that have produced vast amounts of information that have pushed traditional methods of data analysis to their limits. We address this challenge by exploring the application of machine and deep learning techniques, in combination with Virtual Observatory technologies, for the development of methodologies to advance our understanding of M dwarfs and ultracool dwarfs in the years to come. The results obtained reinforce the growing role of machine learning in astronomy, highlighting its transformative potential for handling large astronomical datasets, and advocate data-driven approaches that combine Virtual Observatory technologies with machine and deep learning techniques as the way forward for the future of observational astronomy. These results have led to the publication of three scientific papers in the course of this thesis: Mas-Buitrago et al. (2022), Mas-Buitrago et al. (2024), and Mas-Buitrago et al. (2025).

6.1 SUMMARY OF THE THESIS

The primary contributions of this work are as follows:

- This thesis has demonstrated how Virtual Observatory data mining technologies can be harnessed to streamline the discovery and characterisation of ultracool dwarfs. Combining multi-filter photometry from several surveys and astrometric data, we consolidated a Virtual Observatory methodology to efficiently identify ultracool dwarf candidates in wide-field surveys and subsequently characterise them. Using this approach, we provided a catalogue of ultracool dwarfs over the entire sky coverage of the J-PLUS second data release, increasing the number of ultracool dwarfs reported in this region by $\sim 135\%$. We demonstrated how a machine learning approach could accelerate this process, which is an important achievement considering the application of this methodology to larger and deeper surveys such as J-PAS and *Euclid*. In this sense, future work could be focused in mitigating the main limitations of the developed methodology, which is based on a combination of principal component analysis and support vector machines, namely the significant number of false positives obtained prior to the determination of the effective temperature. An approach involving cost-sensitive learning techniques (Ling and Sheng, 2008) could be the way forward.
- We consolidated a deep transfer learning approach, based on autoencoder neural networks, to determine atmospheric stellar parameters of M dwarfs from high-

resolution spectra. Using this methodology, we provided new estimations for the effective temperature, surface gravity, metallicity, and projected rotational velocity for 286 M dwarfs observed by the CARMENES survey, mitigating the deviations in previous works attributed to the differences between synthetic and observed data. Since no other data than the observed spectra are required in the transfer learning process, our methodology proves to be very flexible and represents a significant step forward in bridging the synthetic gap in stellar parameter estimation from synthetic spectra. We further demonstrated this by successfully adapting the procedure to the low-resolution domain to estimate the effective temperature of ultracool dwarfs using near-infrared spectra from SpeX Prism Library.

- We demonstrated the potential of multi-filter photometric surveys to systematically detect flare events in M dwarfs. Combining Virtual Observatory capabilities to query huge amount of data and a flexible detection algorithm developed for this end, we managed to analyse millions of spectral energy distributions and obtain a sample of flaring M dwarfs. We confirmed and studied the flaring nature of these objects using low-resolution spectra collected with NOT/ALFOSC and GTC/OSIRIS, and high-cadence photometric data from TESS. This procedure, which can easily be used in other multi-filter photometric surveys, allowed the detection of episodes of strong Ca II H and K line emission, which are not usually taken into account in the study of flares in large M dwarf samples and may have important implications for exoplanetary space weather and habitability studies.

The results of this thesis have broad implications for both stellar and substellar astrophysics. This work has contributed to expanding the census of ultracool dwarfs, which are among the least understood populations due to their intrinsic faintness and complex atmospheres, by employing a flexible and scalable Virtual Observatory approach that integrates multi-filter photometry and astrometric data. The newly identified 7827 candidates constitute valuable targets for follow-up observations and further refinement of ultracool dwarf population statistics. By identifying Ca II H and K flaring M dwarfs, and a methodology to detect them in multi-filter photometric surveys, this thesis contributes to the ongoing discussion of how stellar activity affects the long-term viability of planetary systems around these stars, which are ubiquitous in the solar neighbourhood and are prime targets for exoplanet searches.

A persistent challenge in stellar astrophysics is the discrepancy between synthetic models and observed spectra. By using a deep transfer learning approach to project synthetic and observed data into a common feature space, this thesis consolidates a novel approach to overcoming the gap between them, improving the reliability of parameter estimation from synthetic spectra in low-mass objects with a flexible and scalable methodology that can be easily applied to the large surveys expected in the years to come. As machine learning becomes more widespread, it will continue to contribute to the development of astronomical data analysis methodologies, superseding or complementing traditional methods, enabling discoveries that would otherwise be difficult or impossible to achieve.

6.2 FUTURE DIRECTIONS

The methodologies developed in this thesis open up several promising avenues for future research. In this sense, future efforts should focus on scaling up these approaches and integrate them into the workflow of next-generation astronomical surveys such as J-PAS,

Euclid or LSST, which will dramatically increase the amount of data available. Since machine learning pipelines will play a crucial role in managing the vast datasets produced by these missions, the techniques developed in this thesis can be adapted to upcoming surveys to automate the discovery and characterisation of low-mass stellar and substellar objects.

The most direct application of the work developed in this thesis is the use of the deep transfer learning methodology presented in Chapters 4 and 5 for the discovery and characterisation of ultracool dwarfs in the first data release of *Euclid*, which will be publicly available in mid-2026. In this sense, we will go a step further in the methodology, taking advantage of the power of autoencoder architectures for outlier detection, to identify ultracool dwarfs using the whole dataset of low-resolution spectra from the *Euclid* wide-field spectroscopic survey. This can be achieved by using autoencoder neural networks trained with a grid of synthetic spectra, and fine-tuned with real *Euclid* spectra corresponding to well-known ultracool dwarfs. By analysing the reconstruction error of this system, we will study the use of a limiting value to discard all objects for which a significantly higher reconstruction error is obtained, which will make it possible to analyse huge amounts of spectroscopic data in a very efficient way, retaining only the ultracool objects of interest. A cornerstone of this process will be ESA Datalabs¹, a new infrastructure built around the ESA science archives that provides unique archival data access capabilities, bringing the solution to the data rather than the other way around, playing a pivotal role in the development of the aforementioned system due to the huge volume of data that will be processed. After the discovery phase, we will follow a procedure similar to that discussed in Chapter 5 to characterise the low-resolution spectra of the identified ultracool dwarfs, creating a rich catalogue of spectroscopically characterised ultracool dwarfs that could be of great value to the astronomical community. The main strength of this methodology lies in its ability to eliminate biases that are present in other classical methodologies, in which objects are first selected on the basis of colours and then its ultracool nature is confirmed using spectra. Furthermore, we plan to test this methodology using different sets of atmosphere and evolutionary models, such as the ATMO 2020 (Phillips et al., 2020), to study in detail the differences with our current setup.

As the data tsunami in observational astronomy continues to grow, artificial intelligence will become increasingly essential in processing, analysing, and interpreting the information about our cosmos. This thesis has demonstrated how machine and deep learning-driven methods, combined with the infrastructure of the Virtual Observatory, can empower the discovery and characterisation of M dwarfs and ultracool dwarfs. The data-driven techniques developed in this work pave the way for the automation of astrophysical analysis in the low-mass regime, enabling researchers to fully exploit the potential of the vast and growing datasets expected by upcoming astronomical surveys.

¹ <https://datalabs.esa.int/>

DATA AND SOFTWARE AVAILABILITY

During the development of this thesis, we have endeavoured to build several publicly accessible catalogues, codes and tools that can be exploited by the astronomical community. To help the researchers use our catalogues of ultracool dwarfs presented in Chapter 2, we provide an archive system that can be accessed from a webpage² or through a Virtual Observatory ConeSearch³. The archive system implements a very simple search interface that allows queries by coordinates and radius as well as by other parameters of interest. The user can also select the maximum number of sources (with values from ten to unlimited). The result can be obtained as an HTML table or downloaded as a VOTable or a CSV file. Detailed information on the output fields can be obtained placing the mouse over the question mark located close to the name of the column. The archive also implements the SAMP⁴ (Simple Application Messaging) Virtual Observatory protocol, which allows Virtual Observatory applications to communicate with each other in a seamless and transparent manner for the user. In this way, the results of a query can be easily transferred to other Virtual Observatory applications, such as, for instance, TOPCAT.

All the resources presented in Chapter 4, including the code developed to build the methodology described in Section 4.3 and the code to reproduce the figures displayed in Section 4.4 are publicly available at GitHub⁵. The catalogue of stellar atmospheric parameters for 286 CARMENES M dwarfs determined using our deep transfer learning methodology is available at Vizier⁶, and we also provide a data discovery interface that allows its interactive exploration⁷. Moreover, the files with the reduced spectra and processed TESS light curves used in Chapter 3, and the code to reproduce the figures displayed in Section 3.2 are publicly available at GitHub⁸.

On the other hand, we have also carried out several parallel projects dedicated to bringing new data analysis technology closer to the user. The author has created several tutorials, available at GitHub⁹, that cover useful Python features, and developed a tool help the user create and share interactive visualizations without the need to write any code¹⁰. Moreover, the author has contributed to the organisation and development of sessions at the Centro de Astrobiología, aimed at sharing knowledge about Python tips and modules that are generally useful in Astrophysics data analysis¹¹.

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- 2 http://svocats.cab.inta-csic.es/jplus_ucds1;http://svocats.cab.inta-csic.es/jplus_ucds2
 - 3 e.g. http://svocats.cab.inta-csic.es/jplus_ucds1/cs.php?RA=0.023&DEC=35.457&SR=0.1&VERB=2;http://svocats.cab.inta-csic.es/jplus_ucds2/cs.php?RA=238.569&DEC=52.742&SR=0.1&VERB=2
 - 4 <http://www.ivoa.net/documents/SAMP>
 - 5 <https://github.com/pedromasb/autoencoders-CARMENES>
 - 6 <https://cdsarc.cds.unistra.fr/viz-bin/cat/J/A+A/687/A205>
 - 7 <https://cab.inta-csic.es/users/pmas/>
 - 8 <https://github.com/pedromasb/flaring-MDwarfs>
 - 9 <https://github.com/pedromasb/tutorials>
 - 10 <https://magicplotter.streamlit.app/>
 - 11 <https://github.com/PyCoffees/notebooks>

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Part of this work is based on observations made with the Gran Telescopio Canarias (GTC), installed at the Spanish Observatorio del Roque de los Muchachos of the Instituto de Astrofísica de Canarias, on the island of La Palma. We obtained data with the instrument OSIRIS, built by a Consortium led by the Instituto de Astrofísica de Canarias in collaboration with the Instituto de Astronomía of the Universidad Autónoma de México. OSIRIS was funded by GRANTECAN and the National Plan of Astronomy and Astrophysics of the Spanish Government. We collected spectra with the Nordic Optical Telescope, owned in collaboration by the University of Turku and Aarhus University, and operated jointly by Aarhus University, the University of Turku and the University of Oslo, representing Denmark, Finland and Norway, the University of Iceland and Stockholm University at the Observatorio del Roque de los Muchachos, La Palma, Spain, of the Instituto de Astrofísica de Canarias. The data presented here were obtained (in part) with ALFOSC, which is provided by the Instituto de Astrofísica de Andalucía (IAA) under a joint agreement with the University of Copenhagen and NOT. We thank NOT support astronomers David Jones and Tapio Pursimo for their help on site.

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¹² <https://github.com/pandas-dev/pandas>

¹³ <https://github.com/plotly/plotly.py>

¹⁴ <http://www.exoplanetes.umontreal.ca/banyan/>

¹⁵ www.github.com/jlillo/tpfplotter

¹⁶ <http://www.coolstarlab.org>

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¹⁷ <https://mast.stsci.edu/portal/Mashup/Clients/Mast/Portal.html>

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LIST OF PUBLICATIONS

A.1 FIRST AUTHOR

1. **P. Mas-Buitrago**, J.-Y. Zhang, E. Solano, E. L. Martín.
“Ca II and H α flaring M dwarfs detected with multi-filter photometry.”
Astronomy & Astrophysics, 695, A182. March 2025.
2. **P. Mas-Buitrago**, A. González-Marcos, E. Solano, V. M. Passegger, et al.
“Using autoencoders and deep transfer learning to determine the stellar parameters of 286 CARMENES M dwarfs.”
Astronomy & Astrophysics, 687, A205. July 2024.
3. **P. Mas-Buitrago**, E. Solano, A. González-Marcos, C. Rodrigo, et al.
“J-PLUS: Discovery and characterisation of ultracool dwarfs using Virtual Observatory tools. II. Second data release and machine learning methodology.”
Astronomy & Astrophysics, 666, A147. October 2022.

A.2 CONTRIBUTING AUTHOR

1. C. Dominguez-Tagle, M. Žerjal, N. Sedighi, E. L. Martín, et al. (including **P. Mas-Buitrago**).
“Euclid Quick Data Release (Q1) - Euclid ultracool dwarfs. II: Spectroscopic search, classification and analysis”
Submitted to *Astrophysical Journal*.
2. M. Žerjal, C. Dominguez-Tagle, N. Sedighi, E. L. Martín, et al. (including **P. Mas-Buitrago**).
“Euclid Quick Data Release (Q1) – Euclid ultracool dwarfs. I: A photometric search”
Submitted to *Astronomy & Astrophysics*.
3. E. L. Martín, M. Žerjal, H. Bouy, D. Martin-Gonzalez, et al. (including **P. Mas-Buitrago**).
“Euclid: Early Release Observations – A glance at free-floating new-born planets in the sigma Orionis cluster.”
Accepted for publication in *Astronomy & Astrophysics*, as part of the special issue on “Euclid on the sky”.
2. C. Rodrigo, P. Cruz, J. F. Aguilar, A. Aller, et al. (including **P. Mas-Buitrago**).
“Photometric segregation of dwarf and giant FGK stars using the SVO Filter Profile Service and photometric tools.”
Astronomy & Astrophysics, 689, A93 (September 2024).

A.3 CONFERENCE PROCEEDINGS

1. M. Galvez Ortiz, C. Rodrigo, P. Cruz, J. F. Aguilar, et al. (including **P. Mas-Buitrago**).
"Photometric segregation between dwarfs and giants using AI and Spanish Virtual Observatory photometric tools"
 European Astronomical Society Annual Meeting. July 2024.
2. E. L. Martín, H. Bouy, D. Martin, M. Žerjal, et al. (including **P. Mas-Buitrago**).
"Substellar science in the wake of the ESA Euclid space mission"
 Windows on the Universe 2023 - Rencontres du Vietnam. December 2023.
3. **P. Mas-Buitrago**, E. Solano, A. Aller, M. Cortés-Contreras, et al.
"Remote Virtual Observatory schools."
 Highlights of Spanish Astrophysics XI, Proceedings of the XV Scientific Meeting of the Spanish Astronomical Society. May 2023.
4. **P. Mas-Buitrago**, E. Solano, A. González-Marcos.
"Identification of ultracool dwarfs in J-PLUS DR2 using Virtual Observatory tools and machine learning techniques"
 Highlights of Spanish Astrophysics XI, Proceedings of the XV Scientific Meeting of the Spanish Astronomical Society. May 2023.

B | ADDITIONAL TABLES FOR CHAPTER 2

Table B.1 lists the coordinates (J2000), parallaxes, proper motions, angular separations ρ , and projected physical separations s of the six systems already tabulated as known binary systems by the Washington Double Star catalogue (WDS; Mason et al., 2001)

Table B.1: Identified binary systems that are already tabulated by the WDS.

Name ^(a)	Spectral type ^(b)	α (deg)	δ (deg)	ω (mas)	μ_{tot} (mas yr ⁻¹)	ρ (arcsec)	s (au)
2MASS J01560053+0528562	M6	29.00219	5.48230	11.66 ± 0.09	153.33 ± 0.14	7.3	621.4
2MASS J01560037+0528494	M7.5	29.00194	5.47979	11.74 ± 0.21	154.39 ± 0.32		
LSPM J0209+0732	...	32.39985	7.54052	8.27 ± 0.08	166.00 ± 0.11	27.1	3881.2
2MASS J02093416+0732196	...	32.39316	7.53862	6.99 ± 1.00	166.29 ± 1.82		
SLW J0851+4134A	M4.5	132.94640	41.57082	21.84 ± 0.04	114.65 ± 0.05	32.7	1503.1
2MASS J08514823+4134453	M7 V	132.95016	41.57936	21.69 ± 0.18	114.10 ± 0.24		
Gaia EDR3 803883569892552320 ^(c)	...	151.67670	41.58267	5.94 ± 0.13	52.53 ± 0.15	18.3	3110.5
SDSS J100640.86+413503.9	M6 V	151.67006	41.58431	5.88 ± 0.21	52.66 ± 0.23		
SDSS J164331.99+634340.6	...	250.88343	63.72784	13.55 ± 0.12	74.66 ± 0.20	5.8	415.1
Gaia EDR3 1631815065395291392 ^(c)	...	250.88663	63.72773	13.71 ± 0.12	75.58 ± 0.20		
SLW J1840+4204A	M7.9	280.23178	42.06685	14.11 ± 0.11	59.67 ± 0.19	17.4	1217.5
SLW J1840+4204B	M8.1	280.23762	42.06474	14.59 ± 0.39	59.75 ± 0.68		

^(a) Primaries and secondaries are sorted as in the WDS. ^(b) When it is not available in Simbad, we show the spectral type given in the WDS. ^(c) The *Gaia* source id is displayed, since the object is not reported in Simbad.

C

ADDITIONAL FIGURES OF CHAPTER
3

In this appendix we provide the J-PLUS SEDs of each target star, as discussed in Section 3.2.1. Figures C.1, C.2, C.3, and C.4 show the SED of J-PLUS0114, J-PLUS0226, J-PLUS0708, J-PLUS0744, J-PLUS0807, J-PLUS0903, and J-PLUS0914, respectively.

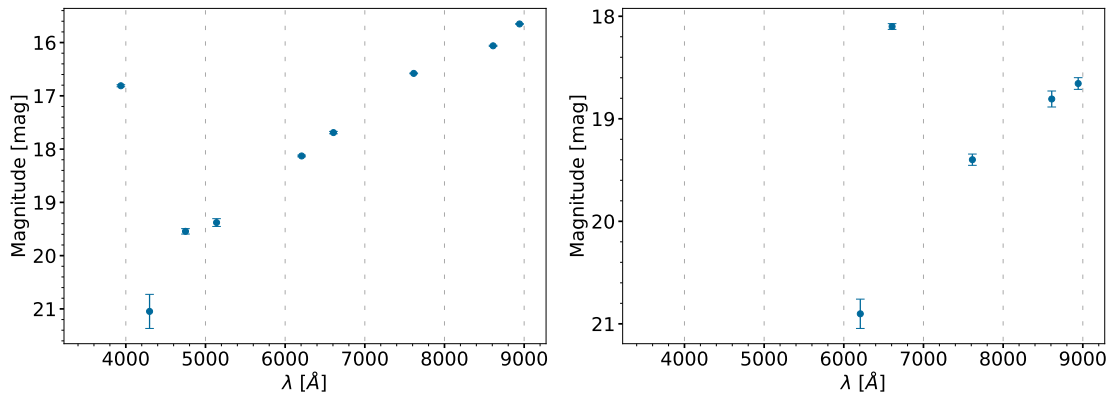


Figure C.1: J-PLUS photometry for J-PLUS0114 and J-PLUS0226.

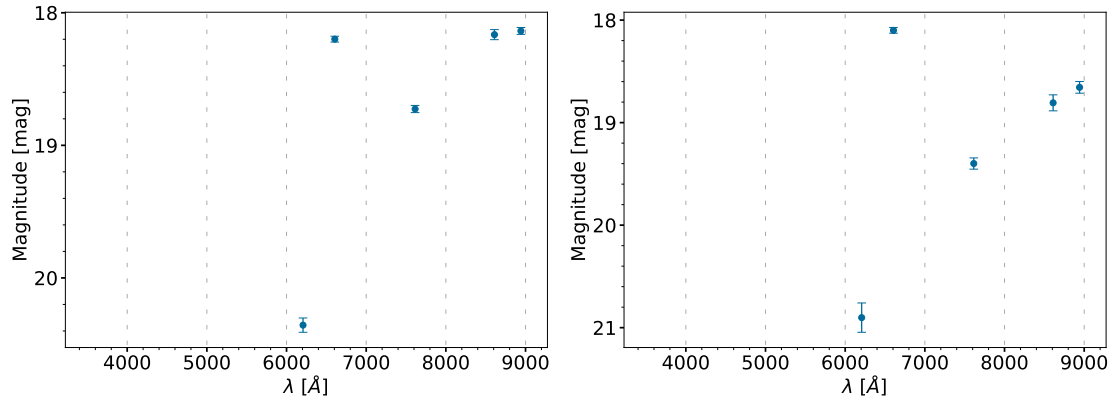


Figure C.2: J-PLUS photometry for J-PLUS0708 and J-PLUS0744.

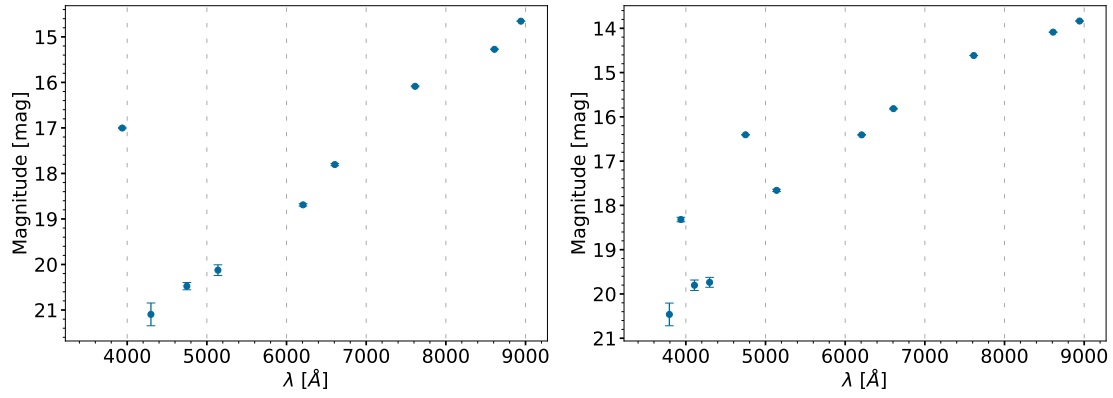


Figure C.3: J-PLUS photometry for J-PLUS0807 and J-PLUS0903.

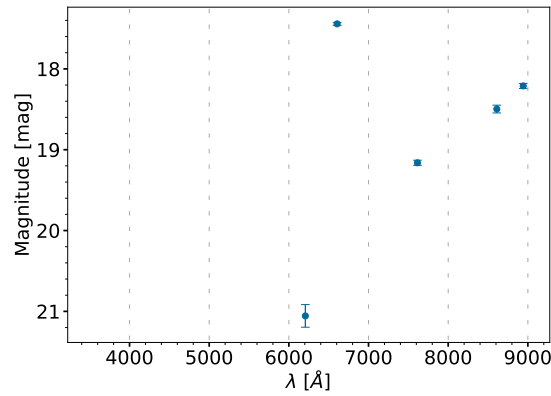


Figure C.4: J-PLUS photometry for J-PLUS0914.

D

ADDITIONAL TABLES AND FIGURES OF CHAPTER 4

D.1 ADDITIONAL TABLES

Table D.1 is available in its entirety in electronic form at the CDS. This appendix only shows an extract of the table to facilitate its understanding. Table D.2 describes in detail the CNN architectures used for the estimation of each stellar parameter. Table D.3 details all the outliers identified with low-metallicity behaviour, along with the metallicity estimations found in the literature.

D.2 ADDITIONAL COMPARISON WITH THE LITERATURE

In this appendix, we provide an extensive comparison of this work with different results from the literature, as discussed in Section 4.4.2. Also, we repeat the comparison shown in Figs. 4.11, 4.12 and 4.13, but including the error bars. Table D.4 replicates Table 4.2 for the additional literature collections. Figures D.1, D.2, D.3, D.4, D.5, D.6, D.7, D.8, and D.9 show the comparison with Bello23, Mar21, Pass20, Pass19, Schw19, Passegger et al. (2018), Mann et al. (2015), Gaidos et al. (2014), and Gaidos and Mann (2014b), respectively.

Table D.1: Stellar atmospheric parameters, together with their uncertainties, determined with our methodology. Only the first five rows of the table are shown.

Karmn	$\alpha^{(a)}$ [J2016.0]	$\delta^{(a)}$ [J2016.0]	T_{eff} [K]	$\log g$ [dex]	[Fe/H] [dex]	$v \sin i$ [km s ⁻¹]
J00051+457	00:05:12.22	03:03:08.6	3780 ⁺⁴¹ ₋₃₄	4.70 ^{+0.01} _{-0.04}	0.03 ^{+0.06} _{-0.04}	3.19 ^{+0.48} _{-0.16}
J00067-075	00:06:42.32	23:29:48.8	3073 ⁺¹⁸ ₋₂₇	5.10 ^{+0.04} _{-0.09}	0.06 ^{+0.08} _{-0.15}	3.02 ^{+0.33} _{-0.66}
J00162+198E	00:16:16.96	01:19:26.6	3362 ⁺³⁴ ₋₂₅	4.90 ^{+0.02} _{-0.06}	0.07 ^{+0.02} _{-0.17}	2.13 ^{+0.30} _{-0.22}
J00183+440	00:18:27.17	02:56:05.9	3709 ⁺¹⁵ ₋₄₃	4.80 ^{+0.03} _{-0.07}	-0.33 ^{+0.06} _{-0.17}	2.02 ^{+0.20} _{-0.30}
J00184+440	00:18:30.07	02:56:06.9	3251 ⁺³⁶ ₋₁₃	4.96 ^{+0.05} _{-0.03}	-0.20 ^{+0.09} _{-0.10}	2.82 ^{+0.22} _{-0.24}

^(a) From *Gaia* DR3.

Table D.2: CNN architectures used for the estimation of T_{eff} , $\log g$, $[M/H]$, and $v \sin i$.

Layer	T_{eff}	$\log g$	Output size $[M/H]$	$v \sin i$	T_{eff}	Number of filters $\log g$	$[M/H]$	$v \sin i$	T_{eff}	Number of parameters $\log g$	$[M/H]$	$v \sin i$
Conv1D	32	32	32	32	64	16	32	64	192	48	96	192
Conv1D	32	32	32	32	32	64	8	8	4128	2112	520	1032
Flatten	1024	2048	256	256	...	...	...	...	0	0	0	0
Dense	256	256	256	256	...	...	...	...	262400	524544	65792	65792
Dense	128	128	128	128	...	...	...	...	32896	32896	32896	32896
Dense	64	64	64	64	...	...	...	...	8256	8256	8256	8256
Dense	1	1	1	1	...	...	...	...	65	65	65	65

Table D.3: Low-metallicity stars identified in Fig. 4.8.

Karmn	Name	$[Fe/H]_{\text{AE}}^{(a)}$ [dex]	$[Fe/H]_{\text{DTL}}^{(b)}$ [dex]	$[Fe/H]_{\text{Mann15}}^{(c)}$ [dex]	$[Fe/H]_{\text{corr,Mar21}}^{(d)}$ [dex]	$[Fe/H]_{\text{Schw19}}^{(e)}$ [dex]	Pop. $^{(f)}$
J00183+440	GX And	$-0.33^{+0.06}_{-0.17}$	$-0.26^{+...}_{-...}$	-0.30 ± 0.08	-0.52 ± 0.11	-0.25 ± 0.16	D
J02123+035	BD+02 348	$-0.35^{+0.12}_{-0.10}$	$-0.33^{+0.01}_{-0.01}$	-0.36 ± 0.08	-0.49 ± 0.06	-0.05 ± 0.16	TD
J06371+175	HD 260655	$-0.41^{+0.11}_{-0.13}$	$-0.37^{+0.02}_{-0.02}$	-0.34 ± 0.08	-0.43 ± 0.04	-0.42 ± 0.16	TD-D
J11033+359	Lalande 21185	$-0.34^{+0.08}_{-0.13}$	$-0.31^{+...}_{-...}$	-0.38 ± 0.08	-0.49 ± 0.10	-0.09 ± 0.16	TD
J11054+435	BD+44 2051A	$-0.40^{+0.07}_{-0.18}$	$-0.35^{+...}_{-...}$	-0.37 ± 0.08	-0.56 ± 0.09	-0.3 ± 0.16	TD-D
J12248-182 $^{(g)}$	Ross 695	$-0.33^{+0.06}_{-0.18}$	$-0.40^{+0.02}_{-0.04}$	...	-0.60 ± 0.09	-0.17 ± 0.16	TD
J13450+176	BD+18 2776	$-0.53^{+0.09}_{-0.27}$	$-0.46^{+0.06}_{-0.05}$	-0.54 ± 0.08	-0.54 ± 0.03	-0.43 ± 0.16	TD
J16254+543 $^{(g)}$	GJ 625	$-0.33^{+0.05}_{-0.15}$	$-0.32^{+0.02}_{-0.03}$	-0.35 ± 0.08	-0.28 ± 0.07	-0.26 ± 0.16	YD
J17378+185	BD+18 3421	$-0.33^{+0.11}_{-0.08}$	$-0.23^{+0.01}_{-0.03}$	-0.25 ± 0.08	-0.40 ± 0.07	-0.23 ± 0.16	D
J19070+208 $^{(g)}$	Ross 730	$-0.34^{+0.05}_{-0.18}$	$-0.32^{+0.01}_{-0.02}$	-0.33 ± 0.08	-0.46 ± 0.07	-0.20 ± 0.16	D
J19072+208 $^{(g)}$	HD 349726	$-0.32^{+0.05}_{-0.17}$	$-0.32^{+0.02}_{-0.02}$	-0.35 ± 0.08	-0.46 ± 0.06	-0.23 ± 0.16	D
J23492+024	BR Psc	$-0.43^{+0.11}_{-0.12}$	$-0.40^{+0.02}_{-0.03}$	-0.45 ± 0.08	-0.55 ± 0.08	-0.13 ± 0.16	TD

As explained in [Passegger et al. \(2020, 2022\)](#), our $[M/H]$ results directly translate into $[Fe/H]$ values. $^{(a)}$ From this work. $^{(b)}$ From [Bello23](#). $^{(c)}$ From [Mann et al. \(2015\)](#). $^{(d)}$ From [Mar21](#), corrected from the α enhancement. $^{(e)}$ From [Schw19](#). $^{(f)}$ Galactic populations, including the thick disc (TD), the thick disc-thin disc transition (TD-D), the thin disc (D), and the young disc (YD), following [Cortés-Contreras et al. in prep.](#) $^{(g)}$ Reported to have a behaviour akin to subdwarfs in [Mar21](#) or [Schw19](#). In particular, J19070+208 and J19072+208 are both components of the wide binary system LDS 1017, and Houdebine (2008) already identified them as subdwarfs.

Table D.4: Comparison between our results and the additional literature collections. The structure is the same as in Table 4.2.

Reference	T_{eff} [K]			$\log g$ [dex]			$[\text{Fe}/\text{H}]$ [dex]		
	$\bar{\Delta}$	rmse	r_p	$\bar{\Delta}$	rmse	r_p	$\bar{\Delta}$	rmse	r_p
Pass18 ^(a)	-59	98	0.96	0.12	0.14	0.89	0.01	0.09	0.73
Mann15 ^(b)	-109	136	0.96	...	...	...	0.04	0.11	0.89
Gaid14 ^(c)	-69	151	0.87	...	...	...	0.05	0.14	0.75
GM14 ^(d)	-42	102	0.93	...	...	...	0.04	0.10	0.88

(a) From Passegger et al. (2018). (b) From Mann et al. (2015). (c) From Gaidos et al. (2014). (d) From Gaidos and Mann (2014b).

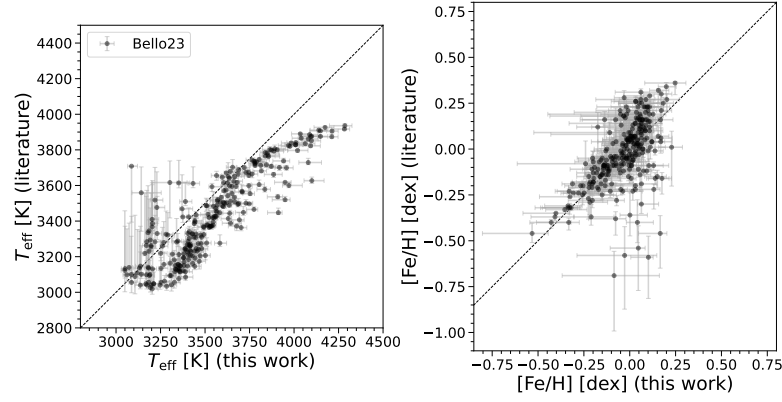


Figure D.1: Comparison with Bello23.

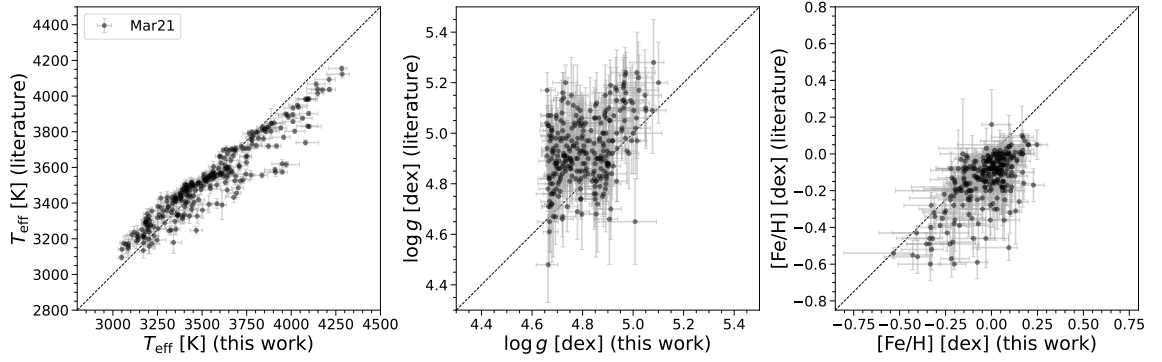


Figure D.2: Comparison with Mar21.

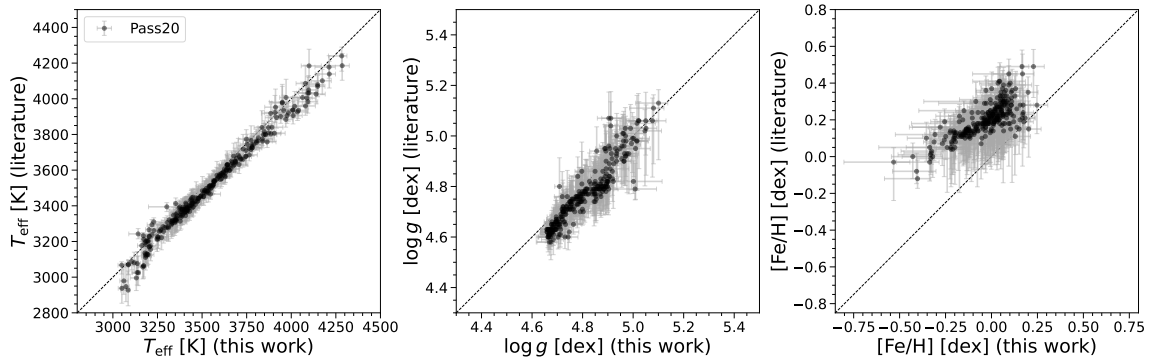


Figure D.3: Comparison with Pass20.

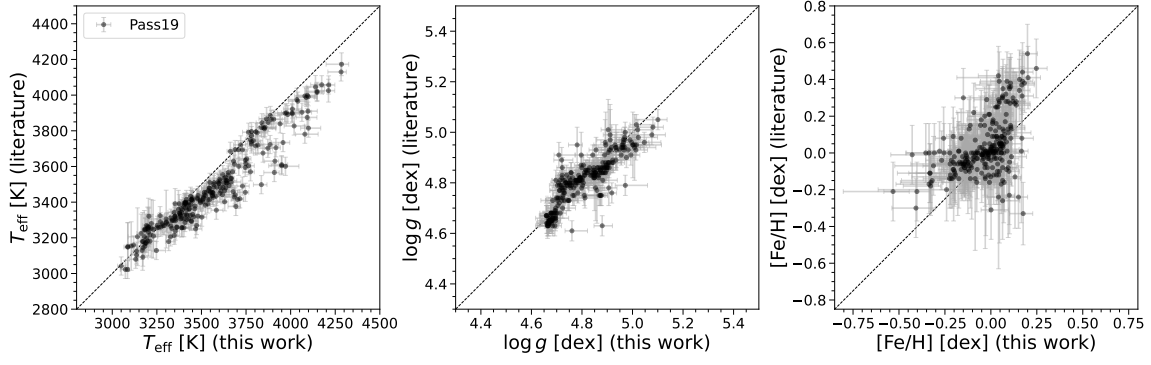


Figure D.4: Comparison with Pass19.

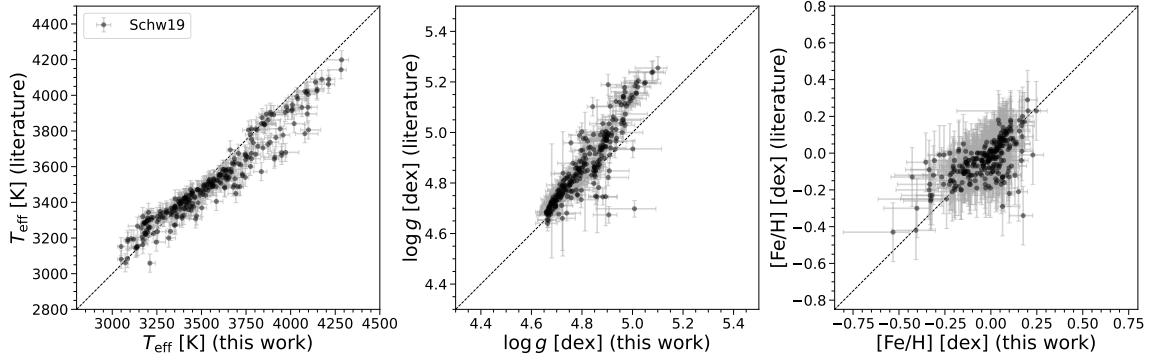


Figure D.5: Comparison with Schw19.

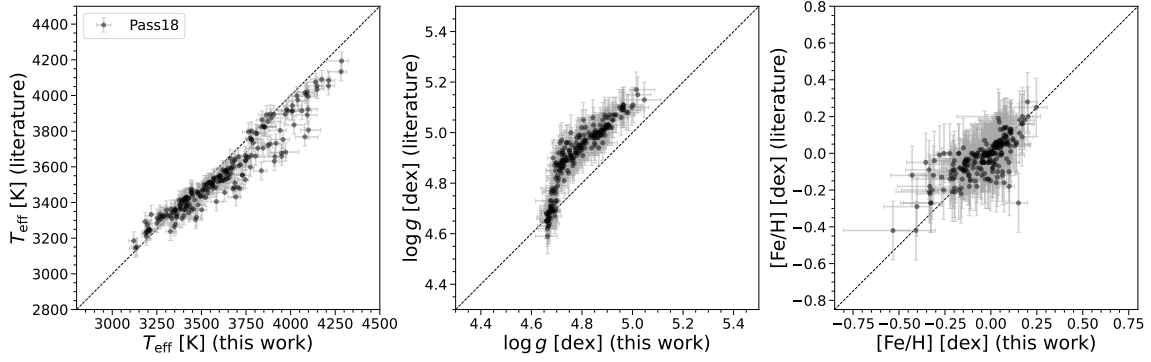


Figure D.6: Comparison with Passegger et al. (2018).

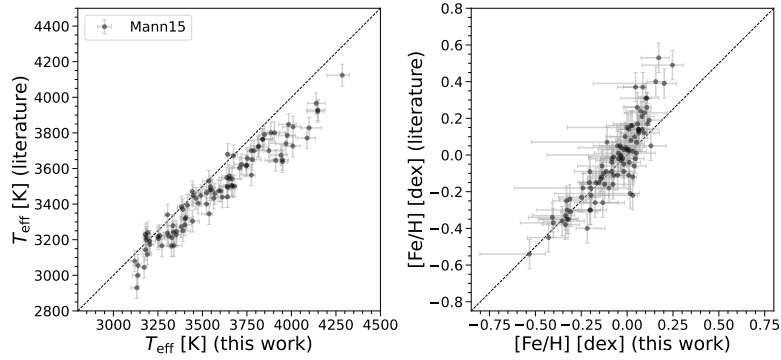


Figure D.7: Comparison with Mann et al. (2015).

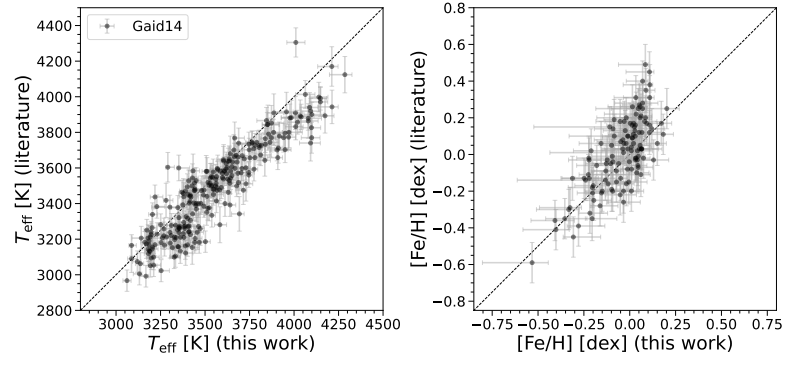


Figure D.8: Comparison with Gaidos et al. (2014).

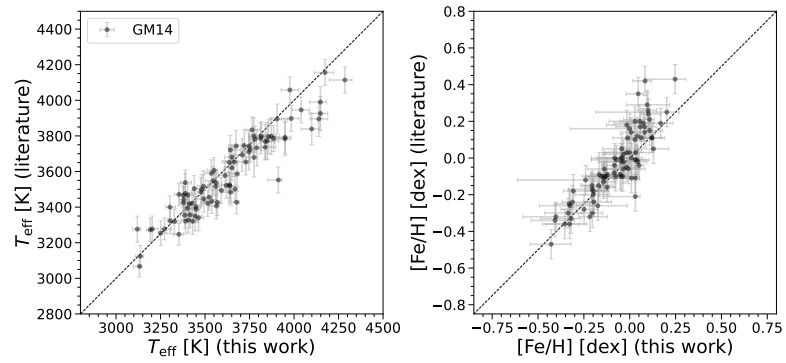


Figure D.9: Comparison with Gaidos and Mann (2014b).

In this appendix we provide the effective temperatures determined for our sample of ultracool dwarfs with the developed deep transfer learning methodology discussed in Chapter 5.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5.

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
SDSS J000013.54+255418.6	0.0565	25.905	1104	99	71
LP 584-4	0.5259	1.2600	2340	61	76
2MASS J00054844-2157196	1.4519	-21.9555	2352	42	129
2MASS J0006205-172051	1.5854	-17.3475	1837	73	78
2MASS J00070787-2458042	1.7829	-24.9679	2355	147	209
2MASS J00100009-2031122	2.5004	-20.5201	2297	62	111
2MASS J00132229-1143006	3.3430	-11.7168	1158	56	139
2MASS J0013578-223520	3.4908	-22.5890	1711	87	110
2MASS J00145575-4844171	3.7324	-48.7380	1982	124	92
2MASSW J0015447+351603	3.9366	35.2674	1876	63	110
SDSS J001637.62-103911.2	4.1568	-10.6530	2293	60	125
2MASS J00165953-4056541	4.2481	-40.9483	1637	85	122
SDSS J001911.65+003017.8	4.7986	0.5049	2210	120	127
Koenigstuhl 1B	5.2747	-42.7454	2129	208	101
SDSS J002209.31-011040.2	5.5388	-1.1778	2458	58	101
BRI 0021-0214	6.1026	-1.9722	2160	94	94
2MASS J00285545-1927165	7.2310	-19.4546	2044	111	95
2MASSW J0030438+313932	7.6827	31.6589	1866	93	103
WISE J003110.04+574936.3	7.7892	57.8268	1662	195	105
2MASS J00320509+0219017	8.0212	2.3172	2123	140	113
2MASS J0032431-223727	8.1796	-22.6242	2180	43	154
EROS-MP J0032-4405	8.2327	-44.0849	1814	152	148
SDSSp J003259.36+141036.6	8.2473	14.1769	1528	171	72
2MASS J00332386-1521309	8.3495	-15.3586	1634	96	79
SDSS J003843.99+134339.5	9.6833	13.7276	2150	84	95
HD 3651B	9.8288	21.2547	682	49	169
WISE J004024.88+090054.8	10.1039	9.0152	891	197	96
SDSS J004154.54+134135.5	10.4773	13.6932	2173	71	112
WISE J004542.56+361139.1	11.4276	36.1947	1013	99	55
WISEP J004701.06+680352.1	11.7517	68.0651	1155	324	75
WISEPC J004928.48+044100.1	12.3678	4.6826	1627	215	117
WISE J004945.61+215120.0	12.4415	21.8556	809	96	76

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J00501994-3322402	12.5836	-33.3775	1046	172	71
SIPS J0050-1538	12.6017	-15.6387	2264	82	88
2MASSW J0051107-154417	12.7950	-15.7380	1602	102	140
SDSSp J005406.55-003101.8	13.5274	-0.5173	2092	91	74
SDSS J005705.55-084624.2	14.2731	-8.7734	2309	86	63
2MASSW J0058425-065123	14.6773	-6.8567	2097	76	96
LHS 132	15.7127	-37.6288	2476	67	97
2MASSI J0103320+193536	15.8837	19.5935	1684	207	50
ULAS2MASS J0106+1518	16.6555	15.3153	2447	61	106
2MASS J01165457-1357342	19.2274	-13.9595	2427	100	118
2MASSI J0117474-340325	19.4479	-34.0572	1819	88	120
2MASS J01194279+1122427	19.9283	11.3786	2148	55	106
SSSPM J0124-4240	20.9961	-42.6687	2320	39	93
2MASSI J0125369-343505	21.4038	-34.5847	1954	74	67
CTI 012657.5+280202	21.9131	28.0982	2348	65	109
WISE J013525.64+171503.4	23.8580	17.2514	923	26	126
2MASSW J0135358+120522	23.8994	12.0894	1953	68	174
SIMP J013656.5+093347.3	24.2357	9.5631	1262	34	115
2MASSW J0141032+180450	25.2635	18.0806	1871	93	73
2MASS J01443536-0716142	26.1475	-7.2706	1609	112	114
2MASS J01460119-4545263	26.5049	-45.7573	2462	138	154
2MASS J01472702+4731142	26.8625	47.5207	2054	108	117
2MASSW J0147334+345311	26.8894	34.8864	2092	124	98
2MASSW J0149090+295613	27.2875	29.9368	2035	70	109
WISEPA J015010.86+382724.3	27.5423	38.4572	1433	152	94
SDSS J015141.69+124429.6	27.9240	12.7412	1656	169	97
SDSS J015354.23+140452.9	28.4759	14.0814	2452	109	160
2MASS J02042212-3632308	31.0922	-36.5419	2241	60	89
2MASSW J0205034+125142	31.2645	12.8617	1631	217	76
WISEPA J020625.26+264023.6	31.6048	26.6730	1327	197	134
SDSS J020735.60+135556.3	31.8983	13.9323	1962	72	127
2MASSW J0208183+254253	32.0766	25.7148	2029	90	100
2MASSW J0208236+273740	32.0986	27.6277	1715	170	73
2MASSI J0213288+444445	33.3700	44.7459	2382	102	235
2MASSI J0218291-313322	34.6213	-31.5564	1822	94	74
2MASS J02192196+0506306	34.8415	5.1085	1946	88	75
SSSPM J0219-1939	34.8669	-19.6448	2141	112	65
WISEPC J022322.39-293258.1	35.8406	-29.5477	836	43	125
HIP 11161B	35.9029	52.6685	1885	26	229
2MASS J02271036-1624479	36.7930	-16.4132	1941	145	135
2MASSW J0228110+253738	37.0460	25.6273	2071	83	126
2MASS J02284243+1639329	37.1768	16.6592	2258	76	84
WISE J023038.90-022554.0	37.6612	-2.4319	1529	252	58

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
DENIS J0230450-095305	37.6875	-9.8848	2049	91	105
WISE J023318.05+303030.5	38.3257	30.5086	1081	55	137
SDSS J023547.56-084919.8	38.9482	-8.8222	2073	98	91
GJ 1048B	38.9997	-23.5223	2006	79	105
2MASS J0239424-173547	39.9269	-17.5965	2367	102	95
2MASS J0241536-124106	40.4738	-12.6853	1927	74	95
2MASSW J0242435+160739	40.6815	16.1275	2049	110	105
2MASS J0243137-245329	40.8071	-24.8917	939	146	75
WISE J024512.62-345047.8	41.3029	-34.8466	1039	208	22
BR B0246-1703	42.1708	-16.8561	2462	105	150
TVLM 831-161058	42.8052	0.7934	2475	67	99
2MASS J0251148-035245	42.8125	-3.8800	2267	173	167
TVLM 832-10443	43.1096	0.9396	2792	416	213
2MASS J02540582-1934523	43.5243	-19.5812	2334	55	59
PSO J043.5395+02.3995	43.5319	2.3989	941	143	93
DENIS-P J025503.3-470049	43.7654	-47.0143	2004	222	191
2MASS J03001631+2130205	45.0680	21.5057	1816	65	165
SSSPM J0306-3648	46.5483	-36.7980	2430	45	98
2MASSW J0309088-194938	47.2871	-19.8275	1715	105	96
2MASS J03101401-2756452	47.5583	-27.9460	1646	115	68
2MASS J03140344+1603056	48.5143	16.0515	2175	79	91
2MASS J0316451-284852	49.1881	-28.8145	2080	142	79
2MASS J03201720-1026124	50.0717	-10.4368	2330	72	110
LP 412-31	50.2488	18.9063	2345	76	131
2MASS J03250136+2253039	51.2559	22.8843	1872	92	71
WISE J032547.72+083118.2	51.4485	8.5218	869	102	53
SDSS J032553.17+042540.1	51.4718	4.4279	960	186	47
2MASSW J0326137+295015	51.5570	29.8376	1698	80	121
2MASS J03264225-2102057	51.6761	-21.0350	1432	204	89
SDSSp J032817.38+003257.2	52.0725	0.5492	1723	93	66
2MASS J0328426+230205	52.1776	23.0348	1523	147	102
SDSSp J033035.13-002534.5	52.6464	-0.4264	1736	69	94
2MASS J03320043-2317496	53.0019	-23.2971	2401	48	83
LEHPM 3396	53.5509	-49.8922	2397	66	124
2MASS J03354535+0658058	53.9390	6.9683	2452	62	79
WISE J033651.90+282628.8	54.2160	28.4421	1116	75	52
2MASSW J0337036-175807	54.2649	-17.9688	1512	122	146
LP 944-20	54.8969	-35.4288	2234	54	123
2MASP J0339527+245728	54.9700	24.9576	2424	89	96
2MASS J03521086+0210479	58.0453	2.1800	2414	104	124
SDSS J035308.54+103056.0	58.2853	10.5157	2143	139	102
2MASS J03540135+2316339	58.5058	23.2761	2302	60	84
2MASS J04012977-4050448	60.3741	-40.8458	2309	145	63

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
WISE J040137.21+284951.7	60.4066	28.8313	1834	88	55
WISE J040418.01+412735.6	61.0753	41.461	1878	107	40
2MASS J04070752+1546457	61.7814	15.7793	1628	135	119
2MASS J04070885+1514565	61.7866	15.2491	1098	213	45
2MASS J04081032+0742494	62.043	7.7137	2451	58	60
2MASSI J0408290-145033	62.1211	-14.8427	2014	96	93
2MASSI J0409095+210439	62.2897	21.0775	1872	74	85
2MASSI J0415195-093506	63.8324	-9.5851	731	120	124
2MASS J04174743-2129191	64.4477	-21.4886	2528	101	158
2MASS J04270723+0859027	66.7802	8.9841	2171	66	126
2MASSI J0428510-225323	67.2124	-22.8896	2061	85	150
2MASS J04305157-0849007	67.7149	-8.8169	2301	50	91
2MASS J04362054-4218523	69.0856	-42.3145	2173	85	97
2MASS J04362788-4114465	69.1162	-41.2462	2349	25	166
2MASSI J0439010-235308	69.7542	-23.8857	1685	164	97
2MASSI J0443058-320209	70.7743	-32.0358	1840	210	30
2MASS J04441479+0543573	71.0616	5.7326	2571	151	151
2MASSI J0445538-304820	71.4746	-30.8057	2234	182	71
WISEPA J044853.29-193548.5	72.2194	-19.5987	1334	103	140
2MASSI J0451009-340214	72.7539	-34.0375	2192	129	94
2MASSI J0453264-175154	73.3603	-17.8651	1874	58	93
WISE J045746.08-020719.2	74.4418	-2.1217	1352	69	80
WISEPA J050003.05-122343.2	75.0146	-12.397	947	56	260
2MASS J05002100+0330501	75.0875	3.5139	1710	85	122
2MASS J05012406-0010452	75.3504	-0.1793	1649	94	92
2MASSI J0502134+144236	75.556	14.7102	2290	41	77
LSR J0510+2713	77.5837	27.2339	2450	55	102
2MASSI J0512063-294954	78.0265	-29.8316	1339	191	73
2MASS J05160945-0445499	79.0392	-4.7640	1185	95	64
2MASS J05170548-4154413	79.2728	-41.9115	2423	120	322
2MASS J05173766-3349027	79.4071	-33.8175	2297	65	74
WISE J052126.29+102528.4	80.3571	10.4267	786	147	46
2MASSI J0523382-140302	80.9093	-14.0506	2009	110	80
2MASS J05264348-4455455	81.6812	-44.9293	2111	117	154
2MASS J05301261+6253254	82.5525	62.8904	2092	126	87
2MASS J05345844-1511439	83.7435	-15.1955	2309	51	110
HIP 26653B	84.9564	52.8999	1937	74	102
SDSSp J053951.99-005902.0	84.9667	-0.9837	1786	130	61
2MASS J05441150-2433018	86.0480	-24.5507	2580	157	210
WISE J054601.19-095947.5	86.5050	-9.9965	1215	118	72
WISEA J055007.94+161051.9	87.5323	16.1819	1845	90	72
2MASS J05591914-1404488	89.8299	-14.0803	1191	111	70
2MASS J06020638+4043588	90.5265	40.7330	995	107	103

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J06022216+6336391	90.5924	63.6108	1904	86	93
LSR J0602+3910	90.6269	39.1829	2202	102	112
2MASS J06050196-2342270	91.2582	-23.7075	2338	71	110
WISEP J060738.65+242953.4	91.9126	24.4991	1490	111	157
WISEA J060742.13+455037.0	91.9251	45.8453	1885	43	163
SIPS J0614-2019	93.5499	-20.3218	2051	109	66
DENIS-P J0615493-010041	93.9557	-1.0116	2227	138	85
2MASS J06195260-2903592	94.9692	-29.0664	2120	208	155
WISE J062442.37+662625.6	96.174	66.442	2098	107	58
2MASS J06244595-4521548	96.1914	-45.3652	1539	228	137
SDSS J062621.22+002934.2	96.5884	0.4928	2153	96	73
WISEPA J062720.07-111428.8	96.8337	-11.2401	1051	156	47
WISE J062905.13+241804.9	97.2715	24.3022	1564	127	95
2MASS J06411840-4322329	100.3268	-43.3757	2028	76	99
DENIS-P J0652197-253450	103.0823	-25.5807	2353	55	92
PSO J103.0927+41.4601	103.0927	41.4601	1414	103	104
2MASSI J0652307+471034	103.128	47.1764	1631	155	83
WISEPA J065609.60+420531.0	104.039	42.0916	1571	87	162
ESO 207-61	106.972	-49.014	2099	58	167
WISEA J071552.38-114532.9	108.9661	-11.758	1833	81	196
DENIS-P J0716478-063037	109.1996	-6.5103	2074	79	99
2MASSW J0717163+570543	109.3178	57.0953	1653	124	59
UGPS J072227.51-054031.2	110.6164	-5.6761	624	29	169
2MASS J07231462+5727081	110.8109	57.4522	2158	106	151
2MASSI J0727182+171001	111.8265	17.1665	925	135	38
2MASS J07290002-3954043	112.2501	-39.9008	877	126	118
SDSS J073519.59+410850.4	113.8318	41.1474	2409	110	84
SDSS J074149.15+235127.5	115.4549	23.8578	966	128	112
2MASS J07415784+0531568	115.4910	5.5325	2112	93	71
SDSS J074201.41+205520.5	115.5050	20.9221	965	142	53
SDSS J074756.31+394732.9	116.9847	39.7924	2322	67	201
SDSS J075054.74+445418.7	117.7282	44.9056	2262	94	86
DENIS-P J0751164-253043	117.8183	-25.5120	2148	105	93
2MASSI J0753321+291711	118.3840	29.2866	1835	57	80
2MASSI J0755480+221218	118.9496	22.2048	967	70	123
HIP 38939B	119.5057	-25.6499	1242	95	56
SDSS J075840.33+324723.4	119.6681	32.7900	1283	51	123
2MASS J08041429+0330474	121.0595	3.5132	2297	81	66
WISE J080700.23+413026.8	121.7511	41.5084	1615	209	157
SDSS J080959.01+443422.2	122.4948	44.5719	1415	231	79
SDSS J081110.35+185527.9	122.7932	18.9245	2247	114	115
DENIS-P J0812316-244442	123.1322	-24.7451	2285	117	136
SDSS J081757.49+182405.0	124.4895	18.4014	2307	132	116

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
SDSS J081812.28+331048.2	124.5513	33.1800	2054	134	133
2MASS J08194602+1658539	124.9417	16.9816	2468	72	78
WISEPA J081958.05-033529.0	124.9924	-3.5908	1229	26	111
2MASSW J0820299+450031	125.1249	45.0087	1375	75	220
WISEPA J082131.63+144319.3	125.3821	14.7228	1218	122	133
2MASS J08230838+6125208	125.7847	61.4224	1892	64	103
2MASS J08234818+2428577	125.9507	24.4827	1811	73	103
2MASSI J0825196+211552	126.3317	21.2643	1354	217	116
SDSS J082642.65+193922.0	126.6776	19.6562	2279	102	172
SSSPM J0829-1309	127.1424	-13.1555	1984	75	112
2MASSW J0829066+145622	127.2776	14.9395	1891	53	115
SDSSp J083008.12+482847.4	127.534	48.4799	1537	184	144
LHS 2021	127.6357	9.7876	2402	90	108
SDSS J083048.80+012831.1	127.7034	1.4754	1012	44	108
2MASSW J0832045-012835	128.0188	-1.4767	2011	52	119
WISE J083450.79+642526.8	128.7124	64.4248	2428	57	92
2MASS J08352366+1029318	128.8486	10.4922	2463	82	89
2MASSI J0835425-081923	128.9272	-8.3232	1673	106	88
SDSS J083545.33+222430.9	128.939	22.4086	2269	63	95
2MASS J08355829+0548308	128.9929	5.8086	1963	95	107
SDSS J083621.98+494931.5	129.0917	49.8255	2165	105	89
SDSS J083646.35+052642.6	129.1932	5.4452	2086	55	111
SDSSp J083717.22-000018.3	129.3215	-0.0051	1687	207	45
2MASS J08391608+1253543	129.817	12.8984	2417	57	102
SDSS J084106.85+603506.3	130.2785	60.5852	2108	111	99
SDSS J084307.95+314129.2	130.7831	31.6915	1839	37	159
SDSS J084333.28+102443.5	130.8885	10.4131	2003	129	68
SDSS J084457.38+120825.4	131.2391	12.1405	2198	109	86
2MASSI J0847287-153237	131.8698	-15.5437	2174	179	99
SDSS J085234.90+472035.0	133.1454	47.3431	1547	157	80
SDSSp J085758.45+570851.4	134.4936	57.1476	1244	93	214
SDSS J085834.42+325627.7	134.643	32.9407	1486	193	109
SDSS J085836.98+271050.8	134.6539	27.1811	2077	72	121
2MASSI J0859254-194926	134.856	-19.824	1532	149	166
2MASS J08593854+6341355	134.9106	63.6932	2448	85	155
2MASS J08594029+1145325	134.9179	11.759	2374	100	138
2MASS J09054654+5623117	136.4439	56.3866	1652	172	119
2MASSI J0908380+503208	137.1584	50.5356	1814	257	49
SDSS J090948.13+194043.9	137.4509	19.6786	2605	320	108
DENIS-P J090957.1-065806	137.4895	-6.9718	2091	54	126
2MASS J09161504+2139512	139.0625	21.6642	2245	61	76
WISEA J091657.18-112104.7	139.2379	-11.3501	2529	257	186
2MASSW J0918382+213406	139.6592	21.5682	1827	81	73

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J09211410-2104446	140.3088	-21.079	2116	131	98
SDSS J092308.70+234013.7	140.7859	23.671	2202	138	84
2MASSW J0928397-160312	142.1654	-16.0535	1861	113	46
SDSS J093237.47+672514.5	143.1562	67.4209	2164	101	182
2MASS J09352803-2934596	143.8668	-29.5832	2206	105	73
2MASSI J0937347+293142	144.3952	29.5282	819	77	129
2MASS J09384022-2748184	144.6676	-27.8051	2431	55	85
SDSS J093858.88+044343.9	144.7453	4.7288	2747	408	106
2MASS J09393548-2448279	144.8979	-24.8077	843	165	129
SDSS J094047.88+294653.0	145.1996	29.7815	2105	95	162
SDSS J094134.92+100942.0	145.3955	10.1619	2388	108	116
2MASSW J0944027+313132	146.0116	31.5258	1954	121	95
2MASS J09474477+0224327	146.9366	2.4091	2370	49	90
2MASS J09490860-1545485	147.2859	-15.7635	1464	50	68
LHS 2195	147.3426	8.1125	2470	72	128
WISEPC J095259.29+195507.3	148.2473	19.919	1008	42	159
2MASS J09532126-1014205	148.3386	-10.2391	2171	106	149
2MASS J10031918-0105079	150.8298	-1.0856	2434	47	91
2MASSW J1004392-333518	151.1638	-33.5886	1818	79	62
SDSS J100711.74+193056.2	151.7994	19.5155	1534	267	90
WISE J100926.40+354137.5	152.3598	35.6947	2306	74	87
2MASSI J1010148-040649	152.5615	-4.1139	1666	168	71
2MASS J10163470+2751497	154.1445	27.8636	2297	73	118
SDSS J101742.51+431057.9	154.4271	43.1828	2125	45	97
2MASSW J1018588-290953	154.7449	-29.1649	2023	90	112
WISEPA J101905.63+652954.2	154.7737	65.4979	831	77	108
DENIS J1019245-270717	154.8518	-27.1214	2374	54	110
2MASS J10213232-2044069	155.3846	-20.7353	2541	110	155
SDSS J102204.88+020047.5	155.5204	2.0133	2415	71	104
HD 89744B	155.562	41.2407	2171	99	64
2MASS J10224821+5825453	155.7009	58.4293	2030	66	123
WISEA J102304.04+155616.4	155.7672	15.9397	2329	66	113
SDSS J102552.43+321234.0	156.4681	32.2097	1568	222	149
2MASSI J1029216+162652	157.3404	16.4478	1820	106	42
ULAS J102940.52+093514.6	157.4201	9.5877	802	120	138
2MASS J10315064+3349595	157.9609	33.8332	1750	66	172
2MASS J10321706+0501032	158.0711	5.0175	2444	67	110
SDSS J103309.11+121626.0	158.2878	12.274	2378	98	188
SDSS J103405.67+035016.3	158.5235	3.8379	2120	119	82
2MASSW J1035245+250745	158.8522	25.1291	2148	135	74
WISE J103907.73-160002.9	159.783	-16.0003	965	149	122
2MASS J10430758+2225236	160.7815	22.4234	1314	205	83
SDSS J104335.08+121314.1	160.8962	12.2208	1556	190	153

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
SDSS J104409.43+042937.6	161.0393	4.4938	1610	218	88
2MASS J1045240-014957	161.3499	-1.8327	2115	71	118
2MASS J10461875+4441149	161.5783	44.6874	1833	101	87
DENIS-P J104731.1-181558	161.8794	-18.266	2235	148	64
2MASS J1047538+212423	161.9735	21.4063	769	98	100
SDSS J104842.84+011158.5	162.1784	1.1995	2125	124	81
SDSS J105151.25+131116.3	162.9636	13.1879	2092	140	119
WISE J105257.95-194250.2	163.2405	-19.7132	847	45	167
2MASS J10554733+0808427	163.9473	8.1453	2432	63	88
DENIS-P J1058.7-1548	164.6993	-15.8048	1865	73	79
2MASS J11000965+4957470	165.0402	49.963	1787	69	102
2MASS J1104012+195921	166.0053	19.9894	1723	59	114
2MASS J11145133-2618235	168.7131	-26.3066	1181	117	160
2MASS J1117369+360936	169.4039	36.16	2113	116	89
2MASS J11220826-3512363	170.5344	-35.2102	1496	49	142
2MASSW J1122362-391605	170.651	-39.2682	1985	153	140
WISEPC J112254.73+255021.5	170.7323	25.8403	1536	74	201
2MASS J11240487+3808054	171.0204	38.1348	2403	57	102
WISE J112438.12-042149.7	171.1602	-4.3638	874	197	70
2MASS J11263991-5003550	171.6658	-50.0652	1937	168	46
SDSS J112647.03+581632.2	171.6959	58.2757	2100	145	80
2MASS J11414406-2232156	175.4335	-22.5375	2354	52	110
SDSS J114912.31-015300.6	177.3013	-1.8835	2474	83	144
2MASS J11533966+5032092	178.4153	50.5359	2006	68	121
2MASS J11544223-3400390	178.6759	-34.0109	2045	50	96
2MASSW J1155395-372735	178.9147	-37.4599	2099	56	69
LP 851-346	178.9285	-22.4163	2506	110	147
SDSS J115553.86+055957.5	178.9747	5.9994	1634	198	67
DENIS-P J1157480-484442	179.4504	-48.7452	1971	133	109
DENIS-P J1159+0057	179.9104	0.9574	2219	93	83
SDSS J115940.72+540938.6	179.9198	54.1607	1996	103	130
SDSSp J120358.19+001550.3	180.9922	0.2639	1846	93	81
2MASS J1204303+321259	181.1265	32.2165	2192	119	120
SDSS J120602.51+281328.7	181.5103	28.2247	1255	67	71
SDSS J120610.49+624257.2	181.5438	62.716	1933	128	106
DENIS J1206501-393725	181.7088	-39.6239	2076	109	93
2MASS J12070374-3151298	181.7655	-31.8583	1820	143	72
2MASS J12073804-3909050	181.9085	-39.1514	2093	160	90
2MASS J12123389+0206280	183.1412	2.1078	2039	68	152
2MASS J1213033-043243	183.2639	-4.5455	1791	71	87
2MASS J1217110-031113	184.2958	-3.1869	937	139	124
SDSS J121951.45+312849.4	184.9647	31.4804	1521	187	76
2MASS J12212770+0257198	185.3655	2.9555	2109	44	194

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
WISE J122152.28-313600.8	185.4657	-31.6014	1100	198	41
BRI B1222-1222	186.2174	-12.6433	2191	73	153
WISE J122558.86-101345.0	186.4959	-10.2283	900	187	52
2MASS J12312141+4959234	187.8392	49.9898	1982	63	108
2MASS J12314753+0847331	187.9482	8.7924	900	167	37
2MASS J12321827-0951502	188.0762	-9.864	2302	92	109
2MASS J12373919+6526148	189.4129	65.4373	760	123	92
2MASSW J1246467+402715	191.6949	40.4542	1718	174	39
SDSS J124908.66+415728.6	192.2864	41.958	2273	59	81
WISE J125448.52-072828.4	193.7018	-7.4742	1118	95	147
SDSSp J125453.90-012247.4	193.7246	-1.3798	1348	44	96
2MASS J12565688+0146163	194.237	1.7712	1844	96	68
WISE J125715.90+400854.2	194.315	40.148	1046	202	78
2MASSW J1300425+191235	195.1771	19.2096	2179	82	81
2MASS J13015465-1510223	195.4778	-15.1729	2171	93	131
2MASSI J1305410+204639	196.4211	20.7776	1677	181	103
2MASS J13061727+3820296	196.572	38.3416	2133	59	99
WISEPC J132004.16+603426.2	200.0212	60.5743	910	95	86
2MASS J13204427+0409045	200.1845	4.1513	1935	116	93
DENIS-P J1323-1806	200.8999	-18.1105	2185	106	105
2MASS J13243553+6358281	201.1479	63.9744	1376	118	130
2MASSW J1326201-272937	201.5836	-27.4936	1367	229	97
SDSSp J132629.82-003831.5	201.6242	-0.6421	1505	240	120
SDSS J132715.21+075937.5	201.8136	7.9938	2285	163	93
2MASSW J1328550+211449	202.2293	21.2467	1604	115	105
2MASS J13313310+3407583	202.888	34.1328	2230	111	138
SDSS J133148.92-011651.4	202.9538	-1.2809	1809	207	49
SDSS J133312.79+150956.6	203.3034	15.1658	2293	60	124
SDSS J133345.36-021600.2	203.4391	-2.2667	2124	90	122
2MASS J13364062+3743230	204.1691	37.723	2202	107	102
2MASSW J1343167+394508	205.8194	39.7525	1731	135	72
SDSSp J134646.45-003150.4	206.6934	-0.5307	1037	163	54
LHS 2803B	207.0113	-13.7356	941	97	59
SDSS J135852.68+374711.9	209.7197	37.7869	1077	148	114
2MASS J13595510-4034582	209.9796	-40.5829	2025	73	142
SDSS J140023.12+433822.3	210.0966	43.6394	1587	215	133
WISE J140035.40-385013.5	210.1475	-38.8363	1474	79	93
2MASS J14022235+0648479	210.5932	6.8133	2255	48	90
2MASS J14044495+4634297	211.1873	46.575	2214	65	70
SDSS J140601.47+524931.0	211.5063	52.8252	2397	116	296
2MASS J14075361+1241099	211.9734	12.6861	1735	105	71
2MASS J14090310-3357565	212.263	-33.9657	2060	136	98
2MASSW J1411175+393636	212.8224	39.6101	2102	68	78

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J14122268+2354108	213.0945	23.903	2488	83	100
2MASSW J1412244+163312	213.1021	16.5533	2203	86	64
2MASS J14182962-3538060	214.6235	-35.635	2004	116	67
SDSS J142058.30+213156.6	215.2434	21.5321	2190	107	94
2MASSW J1421314+182740	215.3809	18.4613	2207	73	126
SDSS J142257.15+082752.1	215.7383	8.465	2048	84	120
GD 165B	216.1629	9.2863	1822	86	90
DENIS-P J142527.97-365023.4	216.3666	-36.8398	1493	221	73
2MASS J14283132+5923354	217.1304	59.3932	1856	84	74
LHS 2924	217.1801	33.1776	2373	87	102
SDSS J143242.10+345142.7	218.1757	34.8619	2135	109	101
2MASSI J1438082+640836	219.5345	64.1434	2402	106	80
2MASSW J1438549-130910	219.7292	-13.1529	1764	94	69
2MASSW J1439284+192915	219.8673	19.4878	2184	96	98
2MASS J14403186-1303263	220.1329	-13.0573	2135	156	51
SDSSp J144600.60+002452.0	221.5025	0.4144	1735	94	88
2MASSW J1448256+103159	222.1068	10.5331	1582	226	82
ULAS2MASS J1452+1114	223.0076	11.2498	2120	139	144
SDSS J145255.58+272324.4	223.2318	27.3904	2340	137	108
WISEA J145408.03+005325.7	223.5343	0.8903	2116	62	171
2MASSI J1456014-274735	224.0058	-27.7935	2173	61	128
LHS 3003	224.1594	-28.1635	2528	71	115
Gliese 570D	224.3129	-21.364	769	108	129
WISEPC J145715.03+581510.2	224.3153	58.2531	1101	58	213
2MASS J14582453+2839580	224.6022	28.6661	2404	65	75
TVLM 513-46546	225.2841	22.8339	2319	58	76
2MASS J15031961+2525196	225.8317	25.4222	938	157	58
2MASSW J1506544+132106	226.7264	13.3517	1893	78	80
TVLM 868-110639	227.5701	-2.6856	2242	50	93
SDSS J151240.67+340350.1	228.1693	34.0639	1913	99	140
SDSS J151506.11+443648.3	228.7753	44.6134	1469	188	81
SDSS J152039.82+354619.8	230.1655	35.7725	1588	181	133
SDSS J152103.24+013142.7	230.2635	1.5285	1248	43	81
2MASS J15230657-2347526	230.7773	-23.798	2237	83	95
Gl 584C	230.8443	30.2489	1573	253	103
2MASP J1524248+292535	231.1032	29.4254	2443	45	91
2MASSI J1526140+204341	231.5584	20.7279	1796	208	62
SDSS J153453.33+121949.2	233.722	12.3304	1643	105	123
DENIS-P J153941.96-052042.4	234.9247	-5.3452	1834	109	68
SDSS J154009.36+374230.3	235.0392	37.7088	1554	220	145
2MASS J15461461+4932114	236.5611	49.5362	1259	52	63
2MASSI J1546271-332511	236.6134	-33.4198	953	110	122
SDSS J154849.02+172235.4	237.2046	17.3766	1775	85	165

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J15485834-1636018	237.243	-16.6006	2376	86	78
SDSS J155120.86+432930.3	237.837	43.4918	1885	109	67
2MASSW J1552591+294849	238.2461	29.8135	2072	41	123
2MASSW J1555157-095605	238.8157	-9.935	2137	132	117
SDSS J155644.35+172308.9	239.1848	17.3858	2031	52	133
WISE J155755.29+591425.3	239.4821	59.2398	2372	75	78
2MASS J16150413+1340079	243.7681	13.6688	1032	113	73
2MASS J16154255+4953211	243.9275	49.8893	1042	41	357
2MASSW J1615441+355900	243.934	35.9832	1781	47	98
2MASS J16184503-1321297	244.6876	-13.3583	2285	110	73
SDSS J161928.31+005011.9	244.868	0.8366	2108	193	75
GJ 618.1B	245.109	-4.2755	1836	53	76
WISEPA J162208.94-095934.6	245.5371	-9.993	1095	169	54
SDSSp J162414.37+002915.6	246.0597	0.4877	979	220	62
SDSS J162603.03+211313.0	246.5126	21.2204	1912	127	62
WISEPA J162725.64+325525.5	246.8572	32.9245	848	138	64
PSO J247.3273+03.5932	247.3267	3.5936	1384	61	78
SDSS J163030.53+434404.0	247.6273	43.7343	1568	222	106
2MASS J16304139+0938446	247.6725	9.6457	2040	72	97
WISE J163236.47+032927.3	248.1518	3.4908	1078	179	69
SDSS J163256.13+350507.2	248.2338	35.0854	2137	77	74
SDSS J163359.23-064056.5	248.4972	-6.6821	1785	125	63
2MASS J16351919+4223053	248.83	42.3848	2393	50	94
WISE J163645.56-074325.1	249.1902	-7.7234	1401	63	137
2MASS J16452207+3004071	251.3419	30.0686	1844	98	107
2MASSW J1645221-131951	251.3421	-13.3312	2235	115	135
WISEPA J164715.59+563208.2	251.8158	56.535	1421	188	115
2MASS J16490419+0444571	252.2675	4.7492	2338	59	83
WISEPA J165311.05+444423.9	253.2963	44.7408	791	92	162
SDSS J165329.69+623136.5	253.3737	62.5268	2115	131	93
SDSS J165450.79+374714.6	253.7116	37.7874	2138	109	88
2MASS J16573454+1054233	254.394	10.9065	1986	97	103
WISE J165842.56+510335.0	254.6786	51.0605	1779	150	124
SDSS J165850.26+182000.6	254.7096	18.3334	2191	93	105
SDSS J165950.91+351508.0	254.9621	35.2523	2239	94	104
SDSS J170316.71+190636.0	255.8197	19.11	2138	83	176
DENIS-P J170548.38-051645.7	256.4514	-5.2795	2134	114	93
2MASS J17065487-1314396	256.7286	-13.2444	1936	118	106
2MASSI J1707333+430130	256.8889	43.0251	2222	54	95
SDSS J171049.35+332325.2	257.7056	33.3903	2296	51	110
2MASS J17111353+2326333	257.8063	23.4426	2091	63	125
2MASS J17114559+4028578	257.9401	40.4827	1882	152	72
SDSS J171714.10+652622.2	259.3086	65.4395	1511	217	82

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASSI J1721039+334415	260.2651	33.738	1953	80	95
WISE J172134.46+111739.4	260.3939	11.2939	1142	162	108
SDSS J172244.32+632946.8	260.6847	63.4963	2097	99	65
SDSS J172543.84+532534.9	261.4327	53.4264	2433	62	108
VVV BD001	261.6693	-27.6333	2101	128	76
WISEPA J172844.93+571643.6	262.1869	57.2782	1123	69	147
2MASS J17312974+2721233	262.8739	27.3565	2296	83	93
2MASS J17320014+2656228	263.0006	26.9397	1973	69	138
WISE J173332.50+314458.3	263.3865	31.7493	1752	114	78
DENIS-P J1733423-165449	263.4261	-16.9139	2095	161	100
2MASS J17343053-1151388	263.6272	-11.8608	2302	66	109
WISE J174102.78-464225.5	265.2615	-46.7059	1097	271	133
WISE J174113.12+132711.9	265.3049	13.4539	1176	24	155
2MASSW J1743415+212707	265.9229	21.452	1750	75	101
DENIS-P J1745346-164053	266.3944	-16.6817	2185	95	77
2MASS J17461199+5034036	266.5499	50.5676	1759	105	60
SDSS J175024.01+422237.8	267.5993	42.3771	1632	100	60
2MASS J17502484-0016151	267.6034	-0.2708	1857	214	31
SDSSp J175032.96+175903.9	267.6372	17.9844	1252	61	105
2MASS J17545447+1649196	268.726	16.8221	1041	162	35
SDSS J175805.46+463311.9	269.5227	46.5531	1030	225	70
2MASS J18000116-1559235	270.0049	-15.99	1903	204	69
2MASSI J1807159+501531	271.8164	50.2588	1986	75	131
WISE J180901.07+383805.4	272.2566	38.6363	1067	135	169
2MASS J18212815+1414010	275.3673	14.2336	1692	186	99
2MASS J18283572-4849046	277.1488	-48.8179	1259	105	70
2MASSW J1841086+311727	280.2859	31.2912	1721	151	64
WISE J185101.83+593508.6	282.7574	59.5845	1761	84	110
WISEPA J185215.78+353716.3	283.0649	35.6221	944	153	45
2MASS J19010601+4718136	285.2752	47.304	1080	103	86
WISEPA J190624.75+450808.2	286.6031	45.1362	981	157	67
WISEP J190648.47+401106.8	286.7003	40.1857	1964	63	153
DENIS-P J1909081-193748	287.2842	-19.63	1961	84	86
vB 10	289.2401	5.1504	2431	64	87
WISE J191915.54+304558.4	289.8134	30.7651	1849	83	136
WISE J192841.35+235604.9	292.1729	23.9339	914	168	33
2MASS J19285196-4356256	292.2166	-43.9404	1657	80	114
WISE J195113.62-331116.7	297.8064	-33.1869	2090	117	100
2MASS J19561542-1754252	299.0643	-17.907	2209	55	101
2MASS J20025073-0521524	300.7113	-5.3646	1227	238	82
WISE J200804.71-083428.5	302.0188	-8.5742	907	104	91
DENIS J2013108-124244	303.2951	-12.7126	2042	111	201
WISE J203042.79+074934.7	307.6764	7.8266	1496	138	31

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASS J20343769+0827009	308.657	8.4503	2064	86	75
2MASS J20360316+1051295	309.0132	10.8582	1889	72	92
2MASS J20414283-3506442	310.4285	-35.1123	1830	74	113
WISE J204356.42+622048.9	310.9834	62.3455	1390	79	58
SDSS J204749.61-071818.3	311.9567	-7.305	1478	157	118
2MASS J20491972-1944324	312.3323	-19.7424	2453	78	99
SSSPM J2052-4759	313.1171	-47.979	2400	119	169
2MASSI J2057540-025230	314.4754	-2.8751	1995	61	100
SDSS J205755.92-005006.7	314.483	-0.8352	2310	52	103
2MASSI J2107316-030733	316.882	-3.126	2180	72	66
2MASS J21075409-4544064	316.9754	-45.7351	2139	124	72
HB88 M18	319.6324	-45.0979	2406	49	116
SDSS J212413.89+010000.3	321.0579	0.9999	1219	84	45
2MASS J21263403-3143224	321.6418	-31.7229	2389	69	125
HB88 M19	321.8589	-42.2551	2376	86	125
HB88 M20	322.536	-44.7745	2406	52	116
2MASSW J2130446-084520	322.686	-8.7557	2146	118	72
SDSS J213240.36+102949.4	323.1681	10.497	1823	90	70
2MASS J21324898-1452544	323.2041	-14.8818	1295	92	88
2MASS J21371044+1450475	324.2935	14.8466	2060	97	74
2MASS J21373742+0808463	324.4058	8.1462	1677	129	131
DENIS J2139136-352950	324.8069	-35.4974	2132	69	100
2MASS J21392676+0220226	324.8615	2.3396	1357	109	69
2MASS J21403907+3655563	325.1629	36.9323	2208	96	156
2MASS J21420580-3101162	325.5243	-31.0212	1736	113	82
2MASS J21481628+4003593	327.0679	40.0665	1253	268	68
2MASS J21495655+0603349	327.4857	6.0597	2357	58	73
2MASS J21512543-2441000	327.8562	-24.6833	1567	189	73
2MASS J21513839-4853542	327.9101	-48.8984	1318	104	160
2MASS J21542494-1023022	328.6038	-10.3841	1275	38	109
2MASS J21543318+5942187	328.6382	59.7051	1087	43	137
2MASS J21580457-1550098	329.519	-15.8361	1844	77	79
DENIS J220002.0-303832B	330.0085	-30.6423	2381	125	198
2MASS J22092183-2711329	332.341	-27.1925	1465	55	86
2MASS J22114470+6856262	332.9361	68.9406	1955	96	73
WISEPC J221354.69+091139.4	333.4779	9.1943	856	151	37
WISE J222219.93+302601.4	335.5829	30.433	1575	121	177
WISEPC J222623.05+044003.9	336.597	4.6688	789	106	109
2MASS J22282889-4310262	337.1205	-43.174	1258	134	119
WISEPC J223729.53-061434.2	339.373	-6.2432	1415	102	147
WISEPC J223937.55+161716.2	339.9052	16.287	1310	29	117
2MASS J22425317+2542573	340.7217	25.7159	1730	72	83
2MASSI J2254188+312349	343.5788	31.3972	1236	42	115

^(a) From the UltracoolSheet catalogue.

Table E.1: Catalogue of determined effective temperatures for the sample of ultracool dwarfs discussed in Chapter 5 (continued).

Name ^(a)	α ^(a) [deg]	δ ^(a) [deg]	T_{eff} [K]	Lower error [K]	Upper error [K]
2MASSI J2254519-284025	343.7164	-28.6737	2189	87	97
SDSSp J225529.09-003433.4	343.8712	-0.576	2280	89	135
WISEPC J225540.74-311841.8	343.9189	-31.3112	782	135	197
WISE J230133.32+021635.0	345.3891	2.2768	970	162	46
DENIS J2308113-272200	347.0475	-27.3668	2089	100	68
SSSPM J2310-1759	347.577	-17.986	2168	106	75
2MASS J23174712-4838501	349.4463	-48.6473	1582	215	39
2MASS J23185497-1301106	349.729	-13.0197	1092	147	165
WISEPC J231939.13-184404.3	349.9128	-18.7349	1375	115	185
2MASS J2320292+412341	350.122	41.3949	2209	63	105
2MASS J23211254-1326282	350.3024	-13.4412	2054	97	87
2MASS J23224684-3133231	350.6951	-31.5565	2112	121	107
2MASS J23231347-0244360	350.8062	-2.7433	2504	73	158
WISEPC J232728.75-273056.5	351.8689	-27.5159	1464	143	115
2MASS J23302258-0347189	352.5942	-3.7886	2153	100	103
2MASS J23312378-4718274	352.8491	-47.3076	1335	88	125
SDSS J233129.35+155222.5	352.8723	15.873	2187	55	111
SDSS J233358.42+005012.1	353.4934	0.8366	2363	94	171
SDSS J233526.42+081721.3	353.86	8.2893	2239	56	126
2MASSI J2339101+135230	354.7926	13.8749	1095	102	54
WISEPC J234026.62-074507.2	355.1105	-7.7516	992	177	41
ULAS J234228.97+085620.1	355.62	8.939	907	168	85
2MASS J23440624-0733282	356.026	-7.5579	1756	82	102
SIMP J23444256+0909020	356.1773	9.1506	2065	81	189
2MASS J23453903+0055137	356.4126	0.9205	2372	67	87
APMPM J2347-3154	356.7281	-31.8983	2331	82	163
WISEPC J234841.10-102844.4	357.1694	-10.4794	967	148	81
2MASS J23512200+3010540	357.8417	30.1816	1642	124	100
2MASS J23520507-1100435	358.0211	-11.0122	2463	55	102
2MASS J23535946-0833311	358.4977	-8.5588	2450	82	116
LHS 4039C	358.5387	-33.2741	2276	49	72
DENIS J2354599-185221	358.7497	-18.8727	2085	108	107
SSSPM J2356-3426	359.0451	-34.4346	2431	65	100
2MASSI J2356547-155310	359.2282	-15.8868	1237	129	37
WISE J235716.49+122741.8	359.3187	12.4629	973	237	73
SSSPM J2400-2008	359.9902	-20.1279	2385	74	118

^(a) From the UltracoolSheet catalogue.

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