Constraining stellar population parameters from narrow band photometric surveys using convolutional neural networks

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ABSTRACT

Upcoming large-area narrow band photometric surveys, such as Javalambre Physics of the Accelerating Universe Astrophysical Survey (J-PAS), will enable us to observe a large number of galaxies simultaneously and efficiently. However, it will be challenging to analyse the spatially resolved stellar populations of galaxies from such big data to investigate galaxy formation and evolutionary history. We have applied a convolutional neural network (CNN) technique, which is known to be computationally inexpensive once it is trained, to retrieve the metallicity and age from J-PAS-like narrow-band images. The CNN was trained using synthetic photometry from the integral field unit spectra of the Calar Alto Legacy Integral Field Area survey and the age and metallicity obtained in a full spectral fitting on the same spectra. We demonstrate that our CNN model can consistently recover age and metallicity from each J-PAS-like spectral energy distribution. The radial gradients of the age and metallicity for galaxies are also recovered accurately, irrespective of their morphology. However, it is demonstrated that the diversity of the data set used to train the neural networks has a dramatic effect on the recovery of galactic stellar population parameters. Hence, future applications of CNNs to constrain stellar populations will rely on the availability of quality spectroscopic data from samples covering a wide range of population parameters.

Key words: methods: data analysis – techniques: photometric – surveys – galaxies: evolution – galaxies: fundamental parameters.

1 INTRODUCTION

The determination of the stellar population properties in galaxies is one of the most powerful techniques to understand the formation and evolution of galaxies. Traditionally, this has been done by comparing the absorption line spectral features with stellar population synthesis models (e.g. Worthey 1994; Bruzual & Charlot 2003; Vazdekis et al. 2010; Conroy 2013), using spectral indices (e.g. Trager et al. 2000; Sánchez-Blázquez 2016) or, more recently, using full spectral fitting techniques (Panter, Heavens & Jimenez 2003). Over the past few years, galactic spectra have been obtained by integral field unit (IFU) surveys, including Calar Alto Legacy Integral Field Area (CALIFA; Sánchez et al. 2012), Mapping Nearby Galaxies at APO (MaNGA; Bundy et al. 2015), Sydney-Australian-Astronomical-Observatory-Multi-object Integral-Field spectrograph (SAMI; Croom et al. 2012), K-band Multi Object Spectrograph (KMOS; Wisnioski et al. 2015). These IFU surveys can be used to produce two-dimensional distributions of age and metallicity to be studied for different galaxy types. These spatially resolved spectra have put strong constraints on galaxy formation and stellar population synthesis models (e.g. Belfiore et al. 2019).

An alternative to spectroscopic surveys comes from narrow band filter imaging. Photometric surveys are more efficient at observing fainter objects than spectroscopic instruments, and can cover a greater area on the sky in a single observation. In photometric surveys, galaxies are not pre-selected, unlike in spectroscopic surveys. Instead, all galaxies that are brighter than the limiting magnitude in the field of view will be observed. Narrow and medium band filter surveys, such as Classifying Objects by Medium-Band Observations-17 (COMBO 17; Wolf, Meisenheimer & Röser 2001), Survey for High-z Absorption Red and Dead Sources (SHARDS; Pérez-González et al. 2013), Javalambre Physics of the Accelerating Universe Astrophysical Survey (J-PAS; Benitez et al. 2014), Javalambre Photometric Local Universe Survey (J-PLUS; Cenarro et al. 2019), and Southern Photometric Local Universe Survey (S-PLUS; Mendes de Oliveira et al. 2019), effectively act as low spectral resolution IFU surveys, producing spectral energy distributions (SEDs) at many positions within the galaxy. These SEDs contain enough information to derive an average stellar age and metallicity (e.g. San Roman et al. 2018). For example, Díaz-García et al. (2015) used Advanced Large Homogeneous Area Medium Band Redshift Astronomical Survey (ALHAMBRA) data to derive redshift, metallicity, and age and...
compare these values with spectroscopic observations of the same galaxies. The Multi-Filter Fitting for stellar population diagnostics (MUFFIT; Díaz-García et al. 2015) code they developed shows good recovery of the spectroscopic values, though results are highly dependent on the choice of stellar population model. San Roman et al. (2019) analyse two elliptical galaxies observed by J-PLUS. The radial gradients for age, metallicity, and extinction that are derived are in reasonable agreement with CALIFA survey observations of the same galaxies.

A challenge emerging from narrow-band surveys is the volume of data to be analysed. For example, J-PAS aims to observe a total of $9 \times 10^7$ galaxies with multiple pixels per galaxy. Additionally, J-PAS and J-PLUS together are expected to collect a maximum of 1.5 TB of data per night (Benítez et al. 2014). Therefore, a computationally efficient method for deriving stellar population parameters from the data is required, and will become invaluable in the future with larger surveys. In this paper, we present neural networks as a tool that shows promise in overcoming this challenge.

Neural networks are algorithms that allow non-linear mapping between input and target parameters, and are efficient methods of analysing large data sets. Supervised machine learning uses an input data set, such as photometric SEDs, and the set of ‘true’ values of the target parameter, e.g. age or metallicity, to learn how to make accurate predictions. Selecting an appropriate training set is a vital step in neural network methods. Galaxies have a diverse formation history and therefore the training set needs to cover this wide variety of galaxy evolution. Otherwise, the neural network will not be capable of accounting for the diversity present in galactic surveys.

Machine learning is applied widely in astrophysical research (e.g. Folkes, Lahav & Maddox 1996; Baron 2019) and has been used to derive the metallicity of galaxies from broad-band photometric surveys previously. Acquaviva (2016) and Wu & Boada (2019) applied random forest algorithms and neural networks, respectively, to calculate the metallicity of galaxies from multiwavelength Sloan Digital Sky Survey (SDSS) photometric observations, with SDSS spectral age and metallicities used as training data. Lovell et al. (2019) used the results of cosmological simulations of galaxies to synthesize SDSS-like spectra. The authors included simulated effects of extinction and noise when creating these SEDs. Convolutional neural networks (CNNs) were trained on these SDSS-like spectra to determine galactic star formation rate (SFR) over cosmic time. Wu & Boada (2019) noted that increasing the number of photometric filter bands used to train the neural network improved the accuracy of the predicted metallicity value of the galaxy. Therefore, the application of neural networks to narrow band photometric surveys, as in this paper, is an obvious step in deriving galactic evolution parameters. This paper is a proof of concept study, investigating whether neural networks can be used to derive the age and metallicity parameters from narrow-band-photometric data. We also examine how the accuracy of recovering age and metallicity gradients, compared to those derived directly from the spectra, depends on the training set use in the neural network.

In the next section, the synthesis of the data is discussed. This is followed by the methodology of the neural network and analysing gradient retrieval in Section 3. Section 4 presents the results of the neural network. Discussion and conclusions are provided in Section 5.

2 DATA

In this paper, we develop a neural network model to derive metallicity from the narrow-band filter photometric data, similar to the data that will potentially be gathered by the J-PAS survey. We targeted the J-PAS survey because it is the next-generation large-scale survey, and a computationally efficient analysis tool is required to derive stellar population properties for the many pixels of photometric data. To this end, we construct J-PAS-like narrow band filter data, i.e. ‘mock J-PAS data’, from CALIFA IFU spectra. We then assume that the spectroscopically derived ages and metallicities from the CALIFA data are the true values for each spectrum within each galaxy. The training and testing data sets for our neural network are composed of the mock J-PAS data and the spectroscopically derived age and metallicity. In Section 2.1, we explain the CALIFA data, and in Section 2.2 we describe how we make the synthesized J-PAS data from the CALIFA spectra.

2.1 CALIFA

The CALIFA survey (Sánchez et al. 2012) used the PMAS/PPAK integral field spectrograph, mounted on the Calar Alto 3.5 m telescope. Each galaxy in the data set was observed three times, with dithering to reach a spectral resolution of $\sim1$ arcsec. The integral field unit (IFU) allows 2D spectra in a grid over the surface of the galaxy to be collected, through exposure times of 1800 and 900 s for the blue and red gratings, respectively. The CALIFA parent sample consists of 937 galaxies selected from SDSS DR7 within $0.005 < z < 0.03$, with the majority being field galaxies. From the parent sample, $\sim600$ galaxies were observed with a diameter limit to fit within the IFU field of view and down to $M_B \sim -18.0$ mag (for more information about the CALIFA sample, see Sánchez et al. 2012; Walcher et al. 2014).

Galactic spectra are binned, and the code GANDALF (Sarzi et al. 2006) is applied to them. GANDALF simultaneously fits the absorption and emission lines, treating the latter as additional Gaussians. In the first step, emission lines are masked and the absorption line spectrum is fitted as the penalized pixel-fitting PPXF (Cappellari & Emsellem 2004), using the stellar population models of Vazdekis et al. (2010) as templates. In this step, radial velocities and absorption line broadening for the stellar components were derived. The best values of velocity and broadening and the best template mix are then used as initial values for the calculation of emission lines. The fit allows for low order Legendre polynomials in order to account for small differences in the continuum shape between the pixel spectra and the templates. Emission lines were subtracted from the observed spectra before extracting their star formation histories.

Star formation histories were derived using the code STELLar Content and Kinematics via Maximum A Posteriori likelihood (STECKMAP; Ocvirk et al. 2006) on the emission line-cleaned spectra as described above, with the MILES stellar library (Sánchez-Blázquez et al. 2006), a Kroupa Universal initial mass function (Kroupa 2001) and Padova 2000 (Girardi et al. 2000) isochrones, which cover a range of ages and metallicities from 63 Myr to 17.8 Gyr and $-2.32 < [\text{Z/H}] < +0.2$, respectively (for a detailed description of the procedure see Sánchez-Blázquez et al. 2014). No cosmological priors were applied when the values for the ages of the stellar populations were determined. This means that the ages of the galaxies are allowed to be, in principle, higher than the age of the Universe. In a number of cases, we also run STECKMAP and mask the position of the emission lines instead of subtracting them, obtaining the same results (the differences in the mean values of ages and metallicities is lower than the random errors due to the noise of the spectra).

We have decided to use IFU data as it is the most suitable for radial gradient analysis of galaxies. IFU data allow better spatial averaging of galactic properties than long-slit instruments. The sample used in
was deemed to be poor (i.e. with reduced $\chi^2$ in the data set using spectral fitting. Any spectra whose fit was deemed to be poor (i.e. with reduced $\chi^2 > 2$) were ignored for this work, giving a data set composed of 19 727 spectra.

### 2.2 Synthesized J-PAS data

The J-PAS survey is a multiband photometric survey that runs at the Observatorio Astrofísico de Javalambre in Spain, with a 3.89m$^2$ collecting mirror. The J-PAS instrument covers a 4.7 deg$^2$ per observation, with a pixel size of 0.456 arcsec. The effective integration time is 4.96 h per field (Benítez et al. 2014).

The response curve of the 54 narrow-band filters are spaced 100 Å apart with a full width at half-maximum of 145 Å, covering the range of 3785–9100 Å. The magnitude limit is $21.0 < m_{AB} < 25.7$ mag, and varies by filters. These narrow-band filters act as a low-resolution spectrograph, with an effective resolution of 100 Å (compared to CALIFA’s resolution of 2Å) and are able to detect the broad galaxy emission features. A comparison of the CALIFA spectrum and synthesised J-PAS SED is shown in Fig. 1 for a spectrum taken from NGC 2530. It can be seen that there is a loss of all spectral line information due to the decreased resolution which increases the difficulty of determining stellar population properties.

The synthetic photometry was obtained by convolving each spectrum with the response function of the J-PAS filters. As the spectral range of CALIFA is 3700–7000 Å, we only measured 36 J-PAS magnitudes. We further exclude the two bands JPAS-6600 and JPAS-6700 to avoid being affected by the possible presence of the H$\alpha$ emission line.

The determination of ages and metallicities using broad-band colours is difficult due to the similar variations in the shape of the continuum caused by an increase of both parameters (the so-called age–metallicity degeneracy, Worthey 1994). Individual absorption lines are also affected by this problem, but each line has a different sensitivity to variations of age versus metallicity and therefore if we measure several lines we can alleviate the problem.

However, the usefulness of narrow-band photometry to derive stellar population properties has not been sufficiently explored. These magnitudes are much more sensitive to the strength of absorption lines than broader bands and can be measured with a much larger signal-to-noise ratio than the absorption lines. A derivation of age and metallicity using medium-band photometry from the ALHAMBRA survey was presented in Díaz-García et al. (2015). This study showed that age and metallicity can be measured with an rms uncertainty of 0.10 and 0.16 dex, respectively.

The increased number of J-PAS bands, compared to those of ALHAMBRA, mean that we have more information available to circumvent large errors caused by the age–metallicity degeneracy. Using SED fitting to the SDSS spectroscopy data and the J-PAS mock data created from the spectroscopy data, Mejía-Narváez et al. (2017) demonstrated that the age and metallicities of the galaxies can be obtained from the J-PAS data as accurately as from the spectroscopy data. Our work is motivated by their study showing promising results that J-PAS-like narrow-band data contain some information to break the age and metallicity degeneracies in a similar degree to the spectroscopy data. Hence, it would be interesting to explore if the neural network can learn such information and provide the accurate age and metallicity much faster than traditional methods.

### 3 METHOD

#### 3.1 Neural network

We use supervised neural networks to predict the metallicity and age of a sample of galaxies from their J-PAS-like SEDs (see Section 2.2 for details on their synthesis) with the TENSORFLOW KERAS API (Abadi et al. 2015). The determination of age and metallicity are treated as a regression problem. The convolutional neural network (CNN) we develop uses the spectroscopic age and metallicity derived by CALIFA as the ‘true’ value for the purposes of training. Each of the neurons in the network begins with some randomized weight, the simulated magnitudes for each band pass through the CNN to calculate a predicted value for the age or metallicity. The mean-squared error (MSE) of predicted versus spectroscopic age or metallicity is back propagated through the network to adjust the weights of the neurons. This process is repeated to obtain an accurate output.

The CNN used in this work has an architecture as illustrated in Fig. 2. The starting point for the CNN was taken from Fabbro et al. (2018), who used a CNN to analyse stellar spectra. Our chosen architecture has two convolutional layers, a max pooling layer and two dense layers. The 1D convolutional layers capture patterns and multilayer features across the SED. The max pooling layer then reduces the dimensions of the convolutional layers’ output. This is applied to the classical dense neural network layers that calculate the age or metallicity via non-linear combinations of values given by the outputs of the max pooling layer. We experimented with

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1See https://github.com/ChoongLing/SimulatedJ-PAS for the code used for the methods discussed in this section.
Figure 2. A schematic view of the architecture used for the convolutional neural network (CNN). The CALIFA spectra are converted into mock J-PAS photo-SED, which are then passed through two convolutional layers. A max pooling layer reduces dimensionality, and its results are passed through a single dense layer. The predicted value of age or metallicity is then output by the CNN. The hyperparameters used for our CNNs are shown at the bottom of this figure.

architectures containing 1, 2, and 3 dense layers and found that models with two dense layers provide the most accurate predictions for both the age and metallicity of our data. The age and metallicity for each of Sets A and B (see Section 3.2) were determined by separate CNN models, which had identical architectures but different hyperparameters, which are shown at the bottom of Fig. 2. The layers’ hyperparameters were optimised by Hyperas.\(^2\) Comparisons showed that the set of hyperparameters chosen by Hyperas provide more accurate predictions than are made by CNNs with manually chosen hyperparameters.

We also adopted early stopping with a patience parameter of 25 for the CNN. This meant that if there was no improvement in the MSE of the parameter recovery after 25 epochs, training would stop. The CNN would train for a maximum of 5000 epochs or until the MSE stabilised. A total of 19,727 spectra from 190 galaxies was used in this analysis.

To train the neural network to predict metallicity and age for the full data set, 25 per cent of the data was kept aside for the testing of the trained CNN to produce our results. The other three quarters was used for training the CNN. This process was repeated three more times so that metallicity and age predictions were made for the full data set, with each iteration using a training set independent of the unseen testing set. Our final results are given by single realizations of the trained CNN models. The randomness in predictions is taken into account when gradients are calculated (see Sections 4.2 and 4.3) but not for individual predictions. This is because we do not have values for the errors of our spectroscopically determined ages and metallicities, and therefore we could not properly estimate the uncertainties of the model prediction, for example, through using Bayesian neural networks (e.g. Ciucă et al. 2020). Additionally, our CNNs are not designed or trained to handle noise. Although evaluating the uncertainties of individual predictions is important, it is beyond the scope of this study because the aim of this proof of concept study is to demonstrate the ability of CNNs to extract age and metallicity data from narrow-band spectra.

\(^2\)https://github.com/maxpumperla/hyperas

Figure 3. Illustrations showing how the spectral data are split into four subsets, as described in Section 3.2. The top four panels show the splitting for Set A and the lower four for Set B. In both sets of panels, the spatial distribution of the spectra in four different galaxies are shown. Each spectrum is represented by a coloured shape depending on which subset it belongs to (the black circles, the red triangles, the orange squares, or the yellow diamonds). In Set A, the spectra within each galaxy are split amongst the four subsets, whereas in Set B all of the spectra for a given galaxy are in the same subset.

3.2 Defining the training and testing sets

Two ways of splitting the data set into four subsets are explored in this work, which are illustrated in Fig. 3. The first is by splitting the spectra within each galaxy randomly into the four subsets, ensuring that one quarter of the data from each galaxy are put into each one of the four subsets. The CNN is then trained on three of the four subsets, with the final subset kept aside and unseen for testing. This will be referred to as Set A. The other method, Set B, is created by randomly splitting the 190 galaxies into four subsets, with all of the spectra from one galaxy in the same subset. This means that the testing set for Set B contains galaxies that have not been seen at all by the CNN during training. The key difference is that in Set A the training set contains spectral data from every galaxy therefore the training and testing data sets are not completely independent due to the covariance between adjacent spectra.
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Figure 4. Learning curves for the training of one CNN model for the ages of galaxies in Set A (upper) and Set B (lower). The black curve shows the mean-squared error (MSE) of the training set, and the red curve shows the MSE of the validation set. The initial MSE for the 0th epoch is set at 0.199, which is calculated from a set of random predictions. Early stopping with a patience parameter of 25 was used when training the CNNs.

It is possible that spectra from the same galaxy will have similar stellar and chemical evolution histories, even at different positions within the galaxy. In this way, Set A mimics a situation where a large number of galaxies are included in the training set, which will cover the diversity in galactic evolutionary history, so that the training set contains data from similar galaxies to those in the application set. Set B demonstrates the realistic case, where we do not have any previous knowledge about a galaxy in the testing set. In this proof of concept study, we compare the ideal case of Set A with the realistic case in Set B. Although it is more realistic, Set B suffers due to the relatively small size of our data set. Conversely, Set A is a suitable way of exploring the potential benefits of a large, comprehensive training data set. Therefore, this comparison will show the potential of the CNN method when a large data set becomes available in the future.

The learning curves obtained when training the CNNs to predict ages are presented in Fig. 4, using MSE as the metric. The MSE for the 0th epoch is set at 0.199, which is the MSE of random predictions made from the set of age labels. It can be seen that the MSE of the training sets converges quickly, but the validation set (which is not used for training, and is also the set that the final trained CNN model will be applied to) does not reach the same level of accuracy as the training set. In the idealized case of Set A, there is a small difference between the MSE of the training and validation data. This implies that there is a subtle difference between the properties of galactic spectra at different regions within the galaxy as the training and validation data came from different spaxels, but the same galaxy.

3.3 Radial gradient analysis

Radial gradients for the age and metallicity within the effective (half-light) radius, \( R_e \) of the galaxy are also calculated and analysed for both the CNN predictions (Section 3.1) and CALIFA spectroscopic age and metallicity. We analysed the gradients only for the galaxies that have at least 25 spectral data points within \( R < R_e \) and there is at least one data point at \( R > R_e \), to ensure that enough spectra to cover up to \( R < R_e \). This allows us to produce reliable radial gradients.

To obtain the gradient, the inclination of each galaxy was corrected to determine the face-on projected radius for the position of each spectrum. A linear fit to age or metallicity against radius was computed using Monte Carlo (MC) bootstrapping to randomly select a sample of 75 percent of the data. A least-squares fit was obtained for 100 MC samples. Then, the mean gradient and its standard deviation were calculated from these samples. This was performed on both the spectroscopic and CNN predicted values, which were then compared. As no uncertainties were computed from the CNN predictions or spectroscopic values, the uncertainty in the gradient fitting was determined by the standard deviation of the MC derived gradients. Therefore, the uncertainties in the linear gradient fitting do not consider any intrinsic uncertainties in the CALIFA spectroscopic analysis or CNN predictions. Fig. 5 shows an example where metallicity and age are plotted against radius for the galaxy NGC 7671 using Set A (see Section 3.2). The top row shows metallicity and the bottom panels display age. The left-hand column shows the parameter values derived directly from CALIFA spectra, and the right contains predictions from the CNN. The value of each spectrum is shown as the grey crosses. The linear fits to these data computed by 100 iterations of MC bootstrapping are shown as the red lines, with the mean values for these fits plotted as the solid black line.
solid black line shows a 1:1 correlation, i.e. a CNN prediction that is identical to the spectroscopic value. The recovery here is excellent, which can be seen as most points lie close to the 1:1 recovery line. The robust standard deviation (calculated from the median absolute deviation) of the difference between CNN and spectroscopic values for Set A are 0.03 for both age and metallicity. These uncertainties are epistemic, i.e. the difference between the spectroscopic and predicted values, showing how well our CNN model is able to reproduce the spectroscopically determined values from the given set of synthetic fluxes (see Hüllermeier & Waegeman 2019, for more information). Therefore, the fact that our uncertainties here are lower than the statistical uncertainties reported elsewhere (e.g. Sánchez-Blázquez et al. 2014) is not concerning as these errors measure different effects.

This level of accuracy in reproducing age and metallicity is encouraging, and shows that the CNN is working well. Once the model has been trained, its application to the test data set is very rapid, meaning it is suitable for use in the large data sets, such as those that will be produced by J-PAS. The standard deviation in the CNN predictions is comparable to those obtained by CALIFA spectral fitting (e.g. Sánchez-Blázquez et al. 2014). The value of the Pearson’s correlation coefficient (PCC) between the age and metallicity residuals of the CNN prediction and the spectroscopic values is $r = -0.24$, showing a weak negative correlation between the two predictions. This shows that our CNN models make predictions that are no more affected by the age–metallicity degeneracy than the values obtained with a full spectral fitting.

4.2 Set A: gradient analysis

The values of age and metallicity from each point – both spectral and CNN predicted – are used to calculate a radial gradient, as described in Section 3.3. The differences between the CNN predicted and spectroscopic gradients are plotted in Fig. 7. The black crosses show the difference between the calculated gradients, with the red lines showing 1σ error bars computed using the MC bootstrap sampling. The top and right-hand panels show histograms of the difference between the gradients of metallicity and age, respectively, with bins of 0.05 dex/R_e. There is strong clustering of the differences in gradient in the central 0.1 dex/R_e. The gradient recovery is found to be accurate to within a robust standard deviation of 0.02 dex/R_e for both age and metallicity. It can also be seen that there is no clear correlation between the age and metallicity gradient deviations of the CNN values from the spectroscopic gradients, which shows that the quality of CNN predictions are not affected by the age–metallicity degeneracy.

4.3 Set B: age and metallicity prediction and gradient analysis

The recovery of age and metallicity for Set B is shown in Fig. 8. The contour levels are the same as in Fig. 6. The epistemic robust standard deviations in this case are 0.16 dex for both age and metallicity with a PCC of the residuals of $r = -0.24$. This is the same value as the PCC in Set A, and therefore the more independent data used to train our Set B models does not affect the ability of the CNNs to overcome the age–metallicity degeneracy. It can be seen that the contours are much more spread out, and not concentrated around the black 1:1 recovery line. The age recovery, in particular, shows an offset with CNN predictions systematically lower than the spectroscopic values. At lower metallicities, the predictions of the CNN become less accurate, which can be seen as the contours spread further from the black 1:1 line. This effect is likely due to the rarity of spectra with $\log{(Z/Z_{\odot})} < -0.75$ in the training set. The use of synthetic spectra or data
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Figure 7. The difference between the gradients from CNN predicted age, \( \text{grad}(\log(\text{Age}_\text{CNN})) \), and the spectroscopically derived age, \( \text{grad}(\log(\text{Age}_\text{spec})) \), against the difference in the CNN predicted metallicity gradient, \( \text{grad}(\log(Z_{\text{CNN}}/Z_\odot)) \), and spectroscopically derived metallicity, \( \text{grad}(\log(Z_{\text{spec}}/Z_\odot)) \). The red error bars show 1σ confidence limits for the gradient fitting. The top and right-hand panels show histograms of the gradient differences in bins of 0.05 dex/R_e. The robust standard deviation for the difference in gradients is 0.02 dex/R_e for both age and metallicity. There is no visible correlation between differences in CNN predictions for age and metallicity gradient and the respective spectroscopic gradients.

4.4 Dependence of predictions on galactic parameters

To study the importance of the similarity of stellar populations between the training and testing sets, we explore the dependence of the accuracy of CNN predictions of age and metallicity on specific SFR \( (\text{SFR}/M_\odot) \), galactic inclination, extinction \( (A_V) \), and galaxy morphology. We also examined the effect of the fractional size of the galactic bulge on the accuracy of our predictions but found that there was no visible correlation.

The median and robust standard deviation of the difference between the CNN predictions and spectroscopically derived values are computed from each SED within the galaxy. In Figs 10, 11, and 12, the median values for each galaxy are shown in the left-hand column of the figures. The robust standard deviations for each galaxy are given in the right-hand columns. Each of these values are plotted against specific SFR, inclination and \( A_V \) in Figs 10, 11, and 12, respectively. The upper four panels in each figure show the results of Set A, while the lower four panels show the results of Set B. The first and third row of panels for each set corresponds to the metallicity and the second and fourth rows correspond to age.

In Fig. 10, it can be seen that the robust standard deviation for accuracy of predictions of age and metallicity slightly increases with specific SFR. However, this is not reflected in the median values. Additionally, there is no visible trend in either median or robust standard deviation of predictions with inclination (Fig. 11) or extinction (Fig. 12), which shows that our CNN models are not affected severely by these galactic properties.

The 190 galaxies in our sample were split by morphology (taken from the SIMBAD data base, Wenger et al. 2000) giving 44 early-type galaxies and 146 late-type galaxies. CNNs were trained on 33 of the elliptical galaxies and 114 spiral galaxies, respectively, using the
method for Set B, as in Section 4.3. These CNNs were then applied separately to the remaining galaxies in each morphology set.

The robust standard deviations for the differences between spectroscopic and CNN predicted values are given in Table 1. It can be seen that predictions for the ages of each of the morphology groups are more accurate when the CNN has been trained on the same morphology group. Additionally, when the CNN has been trained on only early-type galaxies, the age prediction performs best for early-type galaxies and has a robust standard deviation of 0.10 dex. Predictions of the age and metallicity of late-type galaxies are of similar quality regardless of whether the CNN is trained on early- or late-type galaxies. This is unexpected, but is likely due to the presence of similar stellar populations between early-type galaxies and the bulges of late-type galaxies. Overall, the recovery of early type galactic properties is significantly better than the full data set for Set B, whereas values are shown in the third row and column of each table, but is still worse than for Set A. We believe that the increased accuracy in recovery of early-type galaxies is due to the greater degree of similarity between the stellar populations found in early types than between late types. This supports our conclusion that the CNN is more capable of predicting age and metallicity values for stellar populations similar to those present in the training set. Therefore, a larger, high-quality data set would be crucial for future deep learning analysis of stellar populations.

4.5 Training set size

The size of the training set is very important in neural networks. Typically, very large data sets are used in analysis using CNNs. This is because a large volume of data increases the accuracy of neural network predictions. In this section, we discuss the impact of how the size of the training set affects the predictions of our CNN model, though we are still limited by our relatively small data set.

Fig. 13 shows the robust standard deviation of the difference between spectroscopic and CNN predicted age values for Set A (the solid lines) and Set B (the dashed lines) as a function of the training set size, given as a fraction of the total size of the data set. Note that we only used the results for data points whose spectroscopic values are reliable (i.e. with reduced $\chi^2 < 2$), to evaluate the performance when the CNN model is applied to the similar quality data to the training set. Training and application of the CNN model was performed 100 times with randomly selected training and application sets for each iteration. The standard deviation for the recovery of age was recorded for each model, and the mean and uncertainty of these standard deviations is shown in Fig. 13. The horizontal red-dotted
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Figure 11. As in Fig. 10 but plotted against inclination. The inclination has been adjusted to be between 0 and 90°.

Figure 12. As in Fig. 10 but plotted against extinction, $A_V$. There does not appear to be any correlation between the accuracy of predictions and the extinction.

Table 1. The robust standard deviations of the difference between spectroscopic and CNN predicted age (upper) and metallicity (lower table) defining the training and application sets as for Set B (see Section 4.3). The columns indicate whether the CNN was trained on early or late-type galaxies, and the rows indicate whether the application set (appl set) set was composed of early-type or late-type galaxies. The uncertainty for the full set, as derived in Section 4.3, is given in the third row and column of each table for comparison. See the text for more information.

| Age | Training set | Early types | Late-types | Full set |
|-----|--------------|-------------|------------|----------|
|     | Appl         | 0.10        | 0.14       |          |
| Z   | Early types  | 0.12        | 0.13       | 0.16     |
|     | Late-types   | 0.16        | 0.15       |          |
|     | Full set     | 0.19        | 0.17       | 0.16     |

These findings imply that the stellar populations in different regions within the same galaxy are significantly more similar than stellar populations in different galaxies with the same age and metallicity. Therefore, in order to use CNNs to predict the age and metallicity in a galaxy, we require a very large training data set, covering the full parameter space of stellar population properties.
therefore showing similar trends to Sánchez-Blázquez et al. (2014). 

The gradients derived from spectral values (left-hand panel) and by our analysis from Set A (central panel) is similar to that of the previous work. It can be seen that the gradients produced by simply choosing a random value from the set of spectroscopic ages.

The late-type galaxies show similar trends in the same mass range, than those in González Delgado et al. (2015). This could be due to the differing methods of gradient derivation or differences in stellar population modelling (see González Delgado et al. 2015, for details).

4.6 Mass dependence of radial gradients

The dependence of age gradients on galactic stellar mass is of interest when evaluating how galaxies evolve. The relationships we have found between these quantities are shown in Fig. 14. The left-hand panel in this figure shows the gradients derived from the spectroscopically measured age. The relationship of the late-type (the black squares) galaxies’ age gradients on mass resembles that of Fig. 6 from Sánchez-Blázquez et al. (2014), which uses the same spectroscopically derived age values as this paper. This demonstrates that our method of gradient derivation provides consistent results to that of the previous work. It can be seen that the gradients produced by our analysis from Set A (central panel) is similar to that of the gradients derived from spectral values (left-hand panel) and therefore showing similar trends to Sánchez-Blázquez et al. (2014). Conversely, Set B (right-hand panel) shows significant differences from the gradients calculated from the spectroscopically derived age (left-hand panel), which can be seen in both the medians for stellar mass bins (the filled symbols) and the derived gradient for individual galaxies (the open symbols).

The mass dependence of age gradients for a variety of galactic morphologies was studied in González Delgado et al. (2015). In Fig. 10 of their paper, the early-type galaxies show higher values of the age gradient in the higher mass galaxies at log(M/M_☉) ≥ 10.5. The late-type galaxies show similar trends in the same mass range, but show systematically lower gradient than the early-type galaxies. Then, at log(M/M_☉) ≤ 10.5 the gradient values become larger for the smaller mass galaxies in the late-type galaxies. These trends are qualitatively reproduced in the left-hand panel of Fig. 14. However, the values of the gradients we derived here are systematically higher than those in González Delgado et al. (2015). This could be due to the differing methods of gradient derivation or differences in stellar population modelling (see González Delgado et al. 2015, for details).

5 SUMMARY AND DISCUSSION

We present a proof of concept study of an application of a CNN model to recover age and metallicity of nearby galaxies. The data used in this work are taken from the CALIFA data set and is synthesized to produce data resembling 36 J-PAS-like photometric bands that were used to train a CNN model. A total of 21 230 spectra from 190 galaxies are used in this analysis. The CNN was able to predict age and metallicity accurately in the ideal case of Set A (Sections 4.1 and 4.2), where the data used in both the training and application sets came from spectra in the same galaxies. The recovery for age and metallicity is excellent and has a robust standard deviation of 0.03 dex. The radial gradients of age and metallicity are calculated from the CALIFA spectroscopically derived age and metallicity, and the CNN predictions of these values for each galaxy. The robust standard deviation of the difference between the gradients with spectroscopically derived values and the CNN predicted values is 0.0 dex/R_e for both age and metallicity. Radial gradients are also recovered well with the CNN.

On the other hand, for the more realistic case of Set B (Section 4.3), where the training and application data sets are composed of spectra located in different galaxies, the CNN’s recovery of age and metallicity is markedly worse. The robust standard deviation for the recovery in Set B is a factor of ~7 worse for age and ~8 worse for metallicity than Set A. There is also a significant degree of difference between the radial gradients derived from the spectroscopically measured values and those calculated using predictions from the CNN trained using Set B, due to the greater dispersion of CNN predictions for each spectra. We attribute this decrease in prediction accuracy with respect to Set A to the lesser degree of similarity in stellar populations between different galaxies compared to different regions within the same galaxy. This is supported by the smaller error in recovery for early-type galaxies compared to late-type galaxies in Set B, as the latter have a greater range of stellar populations. Our data set contains a relatively small number of galaxies, which was not enough to account for the vast diversity of stellar populations. If we had a larger number of galaxies with a great enough overlap of stellar properties, we expect that the CNN predictions would improve greatly and approach the level of accuracy obtained by Set A.

In this work, only the errors from gradient fitting are considered. An improvement to the method would be to consider the error in the CNN predictions of age and metallicity. This would be an important step in properly evaluating the uncertainties of the CNN predictions for the analysis of real observational data.

We have demonstrated that the CNN model is able to predict age and metallicity values on a relatively small proportion of the training set provided it has enough high-quality data to cover the range of stellar populations present in the application set. We show our models are not strongly affected by degeneracies with SFR, relative bulge size, inclination angle, or extinction. This, along with the low computing power required to apply the trained model to new data, makes CNNs a suitable method of analysis for large data sets such as those that will be produced by the J-PAS survey. However, constructing a large enough high-quality training data set to improve machine-learning models is crucial. Therefore, we will continue to need additional large spectroscopic surveys and high-performance spectral fitting codes. More high quality spectral (preferably IFU) data and sophisticated stellar population models to fit these spectra would be invaluable for creating a high quality training set for further neural network studies. The efforts in increasing the coverage of IFU surveys, such as SAMI (Croom et al. 2012) and MaNGA (Bundy et al. 2015), and their improving fitting pipelines will be essential in future applications of CNNs to situations similar to that of Set B in this work. Additionally, the use of synthetic spectra from simulated galaxies with a large range of evolutionary histories could also be
used, in combination with transfer learning (Zhuang et al. 2019), to improve the accuracy of predictions in the future.

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DATA AVAILABILITY

The data underlying this article will be shared on reasonable request to the corresponding author.

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