Photometric classification of faint & compact galaxies, stars and quasars using multiple neural nets

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Summary

We present `MargNet`: a deep learning-based photometric classifier for stars, quasars and compact galaxies in the faint limit. `MargNet` consists of multiple types of neural networks - Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) architectures. The input for this architecture consists of images, along with photometric parameters (in the 5 passbands - u, g, r, i, z) from the Sloan Digital Sky Survey (SDSS) Data Release 16.

`MargNet` is the first classifier focusing exclusively on faint and compact galaxies. We do this by imposing threshold conditions on the faintness and compactness of the objects. This approach performs better than other methods to classify compact galaxies from stars and quasars, even at fainter limits.

Introduction

Machine learning has become a ubiquitous tool in modern astronomy and has been used in numerous problems, including the classification of stars, galaxies and quasars. Typically, this classification is relatively straightforward as galaxies appear extended while stars and quasars appear pointlike, and thus machine learning performs exceptionally well [2, 3]. However, when galaxies appear faint and compact, their performance plummets, as they appear to be point sources.

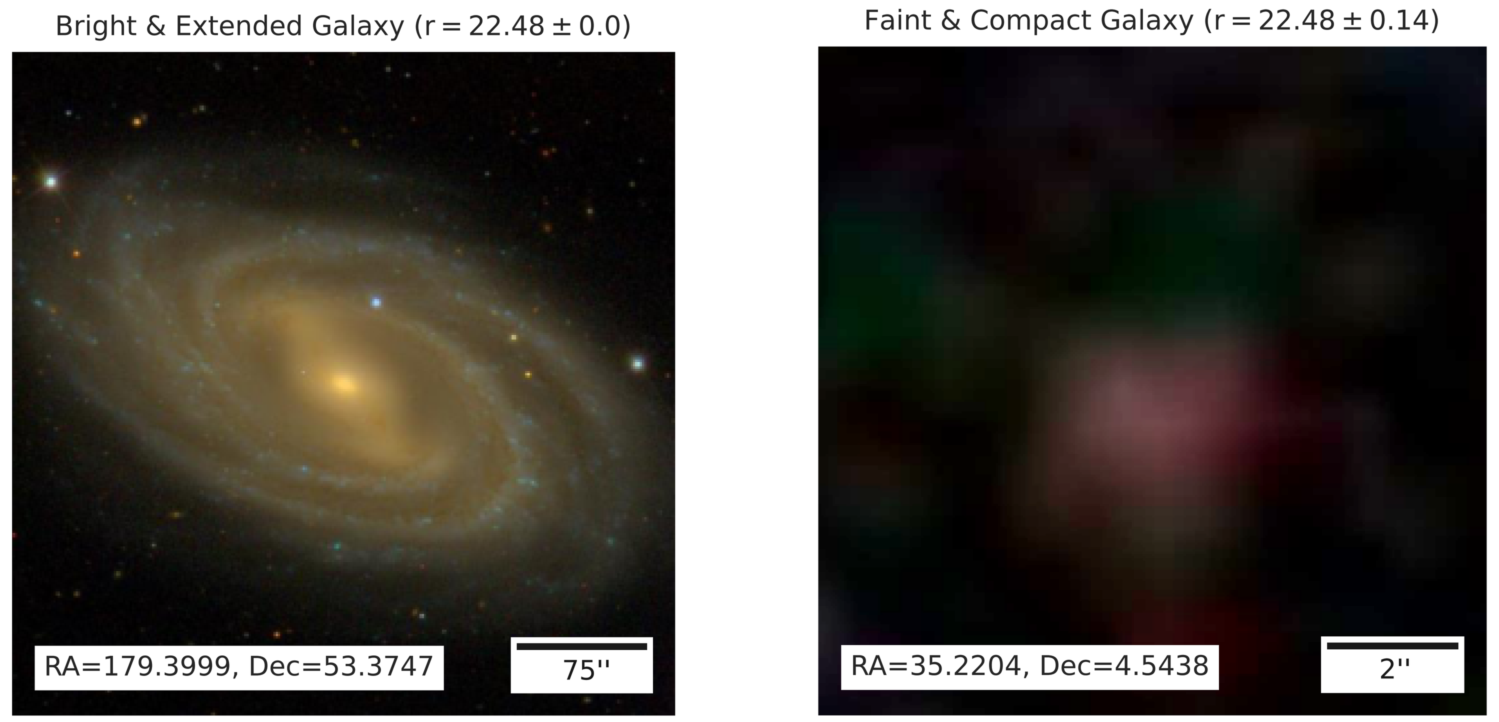

Figure 1. Classification of bright and extended sources is easier than faint and compact galaxies using traditional machine learning methods

Our Goal:

To accurately classify these faint and compact galaxies which are difficult to classify using traditional methods.

Restricting our dataset: Faintness and Compactness

Compactness

To put a constraint on the compactness of the galaxy, we use the following heuristic based on the de Vaucouleur's radius (deVRad) and the full width at half maximum (FWHM) of the PSF for the galaxy.

$$c = \left\langle \frac{\mathrm{deVRad}}{\mathrm{FWHM}} \right\rangle < 0.5 \tag{1}$$

where $\langle\rangle$ denotes an average over all the 5 passbands: u, g, r, i and z. The above equation qualitatively implies that when the deVRad-FWHM ratio is 0.5, the galaxy's diameter is roughly equal to the FWHM of its PSF. Because of this, we impose the criteria $c < 0.5$ for compactness.

Faintness

We further restrict the magnitude of our dataset to choose require that the average magnitude in the 5 passbands be greater than 20. That is:

$$\langle \mathrm{mag} \rangle > 20 \tag{2}$$

Data & Model

The input to our model, `MargNet`, consists of photometric images and tabular data. The photometric images are FITS images in the 5 passbands (u, g, r, i and z), while the tabular data consists of various photometric features given in Table 1.

Feature Name	Description	Total Parameters
dered_x	Simplified magnitude: corrected for extinction	5
deVRad_x	de Vaucouleurs fit scale radius	5
psffwhm_x	FWHM of the Point Spread Function	5
extinction_x	Extinction	5
u_g	Colour: u-g	1
g_r	Colour: g-r	1
r_i	Colour: r-i	1
i_z	Colour: i-z	1
		24

Table 1. List of photometric parameters used by the ANN part of `MargNet`. Note: Her x denotes either of u/g/r/i/z

Finally, to build our dataset, we impose the conditions from Eq. (1, 2), giving us a dataset consisting of faint and compact sources only. We choose 50,000 stars, galaxies and quasars each, and split them into train:validation:test in the ratio 8:1:1.

In our model, we use both CNNs and ANNs `MargNet`, we combine CNNs and ANNs in the form of a stacking ensemble, as shown below. The CNN, based on InceptionNet, takes the image data, while the ANN takes the parametric data, as shown below:

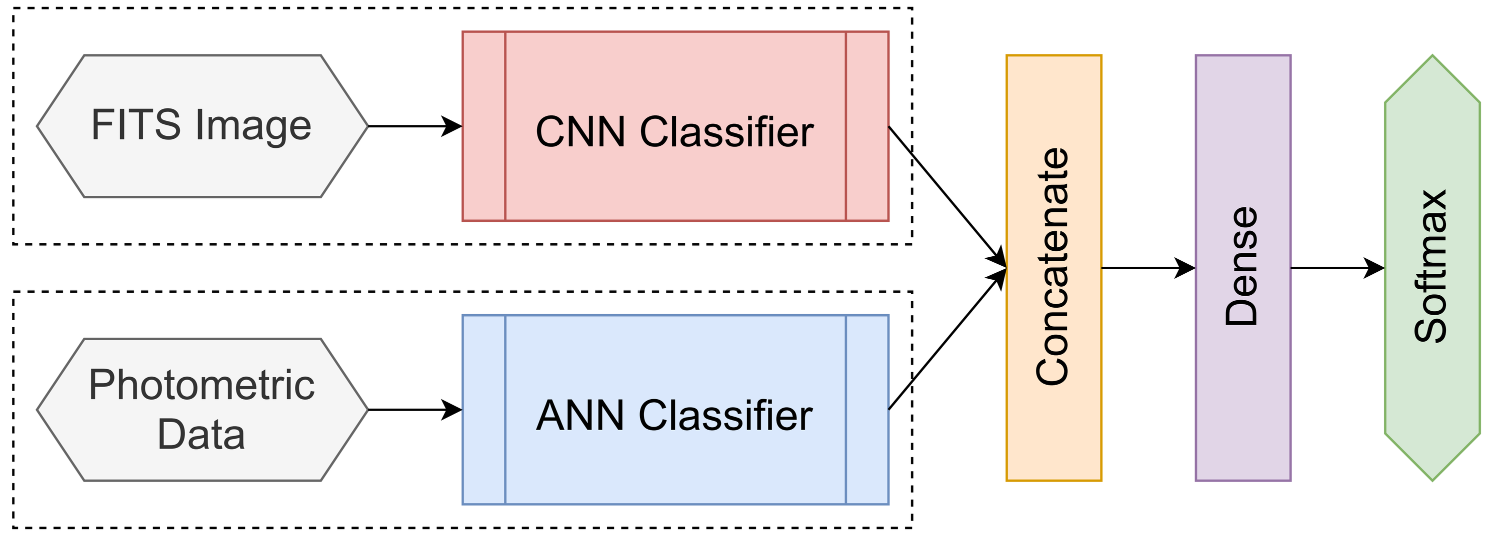

Figure 2. Schematic representation of `MargNet`. The two constituents are trained independently, before being merged into a stacking ensemble. Details of full implementation are available in our accompanying paper [1].

Results

We evaluate the performance of `MargNet` for both star-galaxy and star-galaxy-quasar classification, the former being important to compare `MargNet` with other networks. We look at the performance of our network in two ways:

Overall Performance of `MargNet`

On our full test set consisting of 5,000 objects of each class, we calculate the accuracy and F1 Score for the whole set, as given below:

Classification	Accuracy (%)	F1 Score (%)
Star-Galaxy	96.9 ± 0.1	96.9 ± 0.1
Star-Galaxy-Quasar	86.7 ± 0.1	86.8 ± 0.1

`MargNet` performs better on star-galaxy classification, because of it being a binary class problem as compared to the ternary problem of star-galaxy-quasar classification.

Performance as a function of magnitude

Apart from overall performance, we also want to see how `MargNet`'s performance changes with magnitude. So, we divide the test set into bins of 0.1 in r-magnitude. In order to maintain a large enough sample size for better analysis, we choose an equal number of objects from each class while maintaining a minimum of 50 objects each.

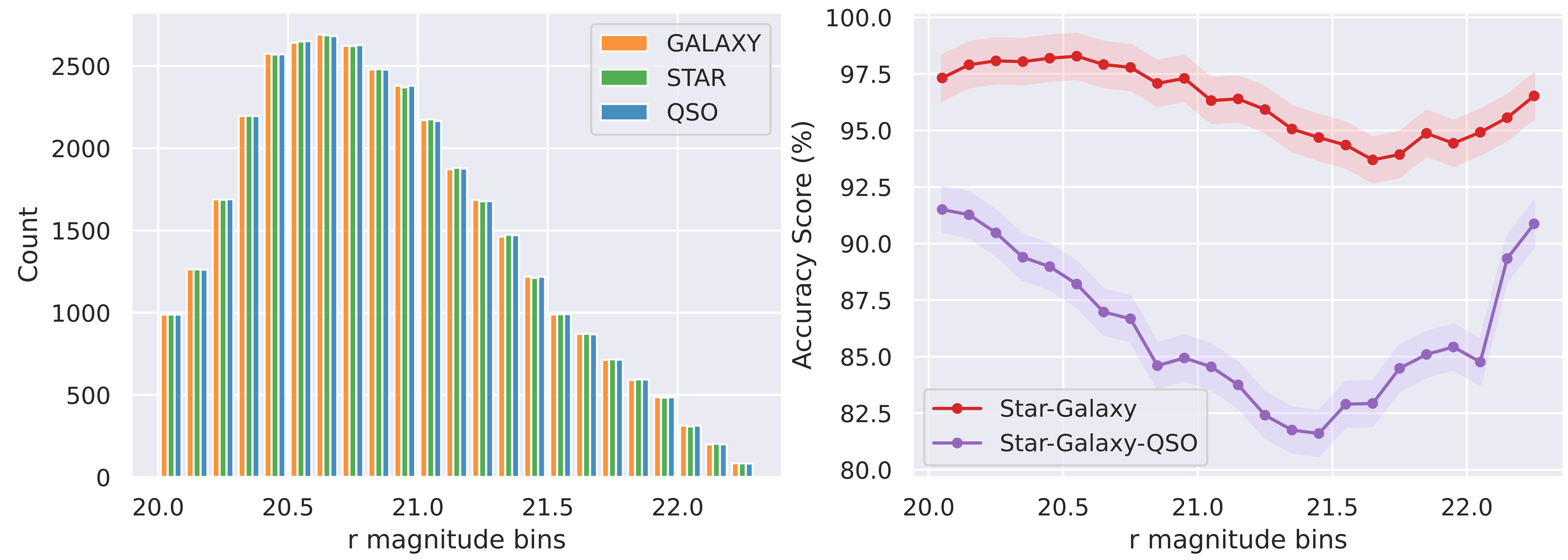

Figure 3. (Left) Number of objects in each bin of r-magnitude. (Right) Performance of `MargNet` as a function of r-band magnitude for star-galaxy and star-galaxy-quasar classification

We find that initially, the accuracy decreases with an increase in magnitude, as expected. This drop is steeper in the case of star-galaxy-quasar classification. However, we note that there is an unexpected rise in accuracy for both cases at $r > 22$.

Thus, we observe that `MargNet` can provide better performance than previous works involving neural networks for compact and faint sources of galaxies. This difference is significant in the range where older methods start to fail. Future surveys like the LSST will explore deeper in space and are likely to capture many more faint and compact sources. Here, models like `MargNet` will be useful in providing high-accuracy insight. A point that needs further investigation is why the performance changes for $r > 22$. We see an improvement in accuracy above this threshold. These findings are interesting and open for discussion.

References

[1] Chaini S., Bagul A., Deshpande A., Gondkar R., Sharma K., Vivek M., Kembhavi A., (*In Preparation*), Photometric Classification of Compact Galaxies, Stars and Quasars Using Multiple Neural Networks, `https://siddharthchaini.github.io/redirects/chaini_et_al_2021.html`

[2] Clarke A. O., Scaife A. M. M., Greenhalgh R., Griguta V., 2020, Astronomy & Astrophysics, 639, A84

[3] Kim E. J., Brunner R. J., 2017, Monthly Notices of the Royal Astronomical Society, 464, 4463