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Using convolutional neural networks to identify gravitational lenses in astronomical images

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ABSTRACT

The Euclid telescope, due for launch in 2021, will perform an imaging and slitless spectroscopy survey over half the sky, to map baryon wiggles and weak lensing. During the survey, Euclid is expected to resolve 100 000 strong gravitational lens systems. This is ideal to find rare lens configurations, provided they can be identified reliably and on a reasonable time-scale. For this reason, we have developed a convolutional neural network (CNN) that can be used to identify images containing lensing systems. CNNs have already been used for image and digit classification as well as being used in astronomy for star-galaxy classification. Here, our CNN is trained and tested on Euclid-like and KiDS (Kilo-Degree Survey)-like simulations from the Euclid Strong Lensing Group, successfully classifying 77 per cent of lenses, with an area under the ROC curve of up to 0.96. Our CNN also attempts to classify the lenses in COSMOS Hubble Space Telescope F814W-band images. After convolution to the Euclid resolution, we find we can recover most systems that are identifiable by eye. The PYTHON code is available on Github.

Key words: gravitational lensing: strong.

1 INTRODUCTION

Gravitational lensing is caused by the mass of a foreground object, such as a galaxy or galaxy cluster, deflecting light from another distant source object, such as a galaxy or quasar. Strong gravitational lensing is rare with only a few systems expected from surveying distant source objects, such as a galaxy or quasar. Strong gravitational lensing is caused by the mass of a foreground object, such as a galaxy or galaxy cluster, deflecting light from another object (Walsh, Carswell & Weymann1979). The Jodrell Bank-VLA (Very Large Array) Astrometric Survey (JVAS; Patnaik et al. 1992; Browne et al. 1997) and the Cosmic Lens All-Sky Survey (CLASS; Browne et al. 2003; Myers et al. 2003) have detected 22 radio loud lensed active galactic nuclei (Chae 2003). Currently, the Sloan Lens ACS Survey (SLACS) has provided the most strong lensed systems from a single survey with nearly 100 observed (Bolton et al. 2008). Other sources of strong lenses include the Kilo-Degree Survey (KiDS; de Jong et al. 2015) that uses the VLT Survey Telescope at the Paranal Observatory in Chile, the Dark Energy Survey (The Dark Energy Survey Collaboration 2005), and the Subaru Hyper Suprime-Cam Survey (Miyazaki et al. 2012), expected to observe thousands of lenses (Collett 2015). The BOSS Emission-Line Lens Survey (BELLS) have discovered at least 25 strong galaxy–galaxy gravitational lens systems with lens redshifts $0.4 < z < 0.7$, discovered spectroscopically by the presence of higher redshift emission lines within the Baryon Oscillation Spectroscopic Survey (BOSS) of luminous galaxies, and confirmed with high-resolution Hubble Space Telescope (HST) images (Brownstein et al. 2012).

Gravitational lensing is a unique tool for analysing mass distribution in the geometry of the source and the lens relative to the observer. This makes lensing a unique tool for analysing mass distribution in the foreground lens (Treu & Koopmans 2002). Using this dependence on mass alone, and combining mass models from mass–luminosity analysis, the baryonic and dark matter mass of the galaxy can be mapped to find dark matter substructure (Metcalf & Madau 2001; Vegetti et al. 2012). Gravitational lensing conserves surface brightness (a consequence of Liouville’s Theorem) but not the angular size of the source object (Marchetti, Serjeant & Vaccari 2017), causing a magnification of the source object’s flux, if the image of the source is enlarged. This enables the observation of fainter galaxies that would otherwise be missed, including galaxies...
Future telescopes are expected to observe many more strongly lensed systems. The Euclid telescope (Laureijs et al. 2011) and the Large Synoptic Survey Telescope (LSST Science Collaboration et al. 2009) will bring the total number of systems above $10^5$ (Oguri & Marshall 2010; Collett 2015). Euclid will map three-quarters of the extragalactic sky with 0.2 arcsec resolution to 24 AB magnitude (Amendola et al. 2018). Another project, the Square Kilometer Array (SKA; Rawlings & Schilizzi 2011), will take observations at a resolution of 2 mas at 10 GHz, and 20 mas at 1 GHz (Perley et al. 2009). The lensing surveys using SKA are expected to observe $\approx 10^5$ new radio-loud gravitational lenses (Serjeant 2014; McKean et al. 2015).

There is currently a shift in the methodology for detecting strongly lensed systems in astronomical images as numbers of lens candidates becomes much larger. Traditionally most images were found by eye. 112 lens candidates, and at least 2 certain lenses, were found in a HST legacy programme, looking at the COSMOS field (Faure et al. 2008; Jackson 2008). But not all searching by eye has been carried out by people working in strong gravitational lensing. The public have been tasked with finding new lens candidates through the Space Warps citizen science project (Marshall et al. 2016). Space Warps made use of volunteers analysing 430 000 images by eye to look for lensing features, via an online webpage using the Zooniverse platform. Tens of new lens candidates have been identified with the help of these volunteers, using large ground-based surveys, e.g. the Canada–France–Hawaii Telescope Legacy Survey (More et al. 2016). But with the growth of survey size, there will be too many candidates to be examined by eye.

There have been several successful methods of computational searches for lenses. Arcfinder (Seidel & Bartelmann 2007) uses pixel-grouping methods to attempt to find cluster-scale lens systems. Ringfinder (Gavazzi et al. 2014) searches for blue residuals surrounding early-type galaxies using multiband data, also there are several programmes to find arc-like shapes (Lenzen et al. 2004; More et al. 2012).

In recent years, there has been a rise in machine-learning methods to detect lenses. 56 lens candidates were found in the KiDS data set using a convolutional neural network (CNN; Petrillo et al. 2017). Machine learning methods rely on large data sets in order to train and learn, something which has become available in recent years. Once a machine has been trained, thousands of images can be classified in seconds. Speed is an important factor due to the expected $10^5$ images from Euclid (Collett 2015). The use of citizen science could be used to create a data set of images for machine learning techniques to train on, once trained, citizen science can then be applied again to examine the output images from the machine learning technique.

In Section 2, we discuss neural networks (NNs) and why we use them for this problem. In Section 3, we discuss the simulated data we have used. In Section 4, we discuss our CNN and how we trained it, and the results are discussed in Section 5. The python code is available at github.¹

2 WHY USE NNS

Computers are very effective at tasks with a limited set of rules, such as chess. However, humans are still often better at real world tasks that cannot easily be described by a set of rules, e.g.

¹https://github.com/A-Davies/LensCNN
by how much the weights and biases are changed. Using Adam
(Kingma & Ba 2014) instead of only SGD allows the learning rate
to change as the network learns. Initially, the learning rate starts
off high and decreases as the network becomes more accurate and
the loss function value decreases. A small subset of images is used
for data validation. After every epoch, the validation images are
classified and validation loss is recorded, calculated the same way
as the training loss. The network is not trained on the validation
data, so no changes are made to the weights and bias. Validation is
done to prevent overtraining the network. Training is stopped once
the validation loss has reached a minimum. The validation loss
will increase after this point as the network becomes overtrained,
and this extra training is detrimental to classifying new data sets.
After training has been completed, new images can be classified
by passing the image through the network and obtaining a classi-
fication. Classifying an image makes no changes to the network
parameters. Batch training means that the weights and biases are
updated after seeing only a fraction of the training set. The batch
number is typically small compared to the training number. Batch
training is used to speed up training since the weights and biases
are changed after each batch instead of at the end of each epoch.

CNNs are a subset of NNs that use convolutional layers in
the network for feature recognition or classification. An example
architecture of a CNN can be seen in Fig. 2. A convolutional layer
involves a kernel being convolved with an input image in order
to make a feature map. Often the convolution layer has several
different kernels for the same image, meaning several different
feature maps are given as output. The image kernel can either
be pre-determined, or can be another parameter that the network
trains and optimizes. Different layers may have different image
kernel sizes, as well as different sized image outputs. Between
convolution layers, pooling layers are often inserted. A pooling
layer is designed to greatly reduce the number of pixels in an input
image to speed up training and reduce the number of parameters.
Pooling is generally done one of two ways, max pooling or mean
pooling. Both methods look at a small section of the image, say a
2 × 2 section, and reduces this to one pixel value either by finding
the maximum value in the 2 × 2 square or by finding the mean.
The output is then a reduced image with fewer pixels than the
input. Pooling is done to reduce the number of variables, whilst
trying to keep as much spatial information as needed (Mallat 2016).

The convolution layers in a CNN are designed to process visual
information hierarchically, with earlier layers finding more basic
features, such as a face. After the convolutional layers, the network
will have a layer to flatten the output from the final
layer into a 1D vector to be used as input for a layer composed of
perceptrons. A layer in a network made from perceptrons that each
use every output from the previous layer as input is known as a fully
connected or dense layer. All layers in NN apart from the input and
output layers are known as hidden layers.

CNNs have been used to solve classification problems such as
digit recognition with the MNIST data base, a collection of 70 000
32 × 32 grey-scale images of handwritten digits. The problem is to
classify these as the digits 0 through 9. Using CNNs gives a solution
with an error rate of 0.23 per cent (Ciresan et al. 2013). CNNs have
also been successful in object recognition in images. The CIFAR-10
data base consists of 60 000 32 × 32 colour images in 10 classes,
such as truck, bird, and dog, with 6000 images per class. The error
rate in this classification problem when using CNNs is lower than
4 per cent.3 An astronomy classification problem where CNNs have
been used is classifying images as a star or galaxy. Here, the best
network had an error rate of only 0.29 per cent for galaxies (Kim
2007; Dieleman, Willett & Dambre 2015).

3 METHODS

The task of finding strong gravitational lenses in large data sets is
a problem within Euclid. Feature recognition by eye will not
be fast enough to cope with the amount of data received. The
Strong Lensing group within the Euclid consortium set up the
Euclid Strong Lensing challenge. This was a challenge aimed at
developing machine learning techniques to classify images as to
whether containing a lens or not. The simulated data was provided
by the Bologna Lens Factory.4 The images are producing using
GLAMER code (Metcalfe & Petkova 2014), which uses galaxies
from the Millennium Simulation5 and real galaxies from KiDS as
foreground lenses and background sources to produce the simulated
images. More details of the lensing process can be found in Metcalf
et al. (2018). The simulated images are provided as 101 × 101 pixel
sized images, centred on the foreground galaxy, either containing a
lensed source or not. In total 200 000 images were provided, 100 000
were Euclid VIS-like images, with ≈40 000 lenses and 100 000
were KiDS-like images, with ≈50 000 lenses. The Euclid-like space
images are single-band images, very broad-band (r + i + z), whereas
the KiDS-like images have four bands: u, g, r, i. The images have
an image resolution of 0.2 arcsecond, meaning each is a 10 × 10
arcsecond square image. Examples of the Euclid VIS-like images
can be seen in Fig. 3, and an example of the 4 KiDS-like bands can be
seen in Fig. 4. However, our close scrutiny of the simulated images
uncovered some unphysical examples. The COSMOS lenses6 were
used as a comparison to test the simulations against. Examples of the
COSMOS lenses can be seen in the Appendix. The band used for
the COSMOS images is the HST F814W wide band. F814W covers
the longer wavelength half of the VIS throughput. Visual inspection
of the VIS and smoothed COSMOS images shows qualitatively
similar features. Therefore, we argue that the COSMOS data set is
an appropriate and interesting test of our VIS-trained network.

By comparing histograms of the Einstein radius and lens magni-
ditudes of both the simulated Euclid VIS-like images and the real
COSMOS lens images, it was found that many of the simulations

3http://wwwstaff.ari.uni-heidelberg.de/mitarbeiter/cfaure/cosmos/
4https://wwwmpa.mpa-garching.mpg.de/galform/virgo/millennium/
5http://www.staff.ari.uni-heidelberg.de/mitarbeiter/cfaure/cosmos/
had unrealistically large Einstein rings and that the *Euclid* VIS-like and KiDS-like simulations were fainter than the COSMOS lenses. Because of this, images with Einstein radii greater than 4 arcsec, and lenses towards the faint end of the *Euclid* VIS-like and KiDS-like data sets have been removed in order to create a more representative subset. Histograms showing removal of some of the *Euclid* VIS-like images to make the data set more COSMOS-like can be seen in Fig. 5. A similar histogram also shows that by removing the larger Einstein radii, the *Euclid* VIS-like images have an Einstein radius distribution similar to that of COSMOS. The same has been done for the KiDS-like data set. In total, we now have four data sets for training and five for testing that can be seen in Table 1.

### 4 TRAINING TO FIND LENSES

Four networks have been built, two designed to work with KiDS-like images with four filter bands as input, and two to work with *Euclid* VIS-like data with a single filter input. They have the same architecture, but have been trained on different data using data sets 1–4 from Table 1. The networks have been built and trained in **PYTHON** 2.7 using the NN library Keras. Keras runs on top of **Theano**, **TensorFlow**, or **CNTK** back ends. We used Theano. The CNN architecture used here has been inspired by the work of Petrillo et al. (2017). The network architectures can be seen in Table 2. Robust initialization (HeNormal) is used to initialize the weights as this speeds up network convergence (He et al. 2015). The networks have four convolutional layers initially, with $2 \times 2$ max-pooling incorporated twice after the first two convolutional layers. After the convolutional layers, the 2D feature maps that have been made in the final convolutional layer are flattened into a 1D vector to be used as input into the dense layer of fully connected neurons. The final layer is a classification layer, where the network gives each image a classification between 0 and 1. This number can been seen as a probability that the image is a lens. The CNN is trained on a set of 75 per cent of the labelled images from the data set, using a process of batch training with a batch size of 500. Five per cent of the data set is used for data validation to avoid overtraining. Throughout our networks we used ReLU [Rectified Linear Units (Nair & Hinton 2010)] for the activation functions and binary cross-entropy was used as the loss function.

### 5 RESULTS AND DISCUSSION

An image is judged to contain a lens if the classification from the network is above or equal to 0.5, conversely if the classification is below 0.5 the image is judged to not contain a lens. This value can be increased to give a more accurate classification, causing the number of false positives to decrease. However, it also means that more lenses are misclassified. 20 per cent of each data set is passed through the appropriate network to be classified; this is the test set. The scores for each network can be seen in Table 3. By looking at the percentage of images classified correctly, and the percentage of lenses and non-lenses classified correctly, the KiDS-like networks are more successful than the *Euclid* VIS-like networks. This is not surprising since the KiDS-like images have four image bands compared to the single band of the *Euclid* VIS-like images. This would imply that colour information from the multiple bands of the KiDS-like images has been helpful in classifying the lenses correctly, as one would expect as it helps greatly when classifying by eye. A test of this (which we will conduct in future work) would

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**Figure 3.** Samples from the 100 000 *Euclid* VIS instrument simulated images. The top row of images do not contain lenses, while the bottom row contains lenses.

**Figure 4.** A sample from the 100 000 KiDS-like simulated images. The images are labelled above by their corresponding wavelength band. This example does contain lensing.

**Figure 5.** Histograms showing the AB magnitude across three data sets. Top: Original 100 000 *Euclid* VIS-like images. Middle: Subset of *Euclid* VIS-like images designed to have the same distribution as the COSMOS lenses. Bottom: The COSMOS lenses.

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6https://keras.io/
be to compare single-band KiDS-like images with multiband KiDS-like images. In both the COSMOS-like data sets, the percentage of lenses correctly identified is less than the original data sets. This is probably because the images with the largest rings (>4 arcsec Einstein radius) have been removed to make the data set. These images are easy to identify as lenses and so removing them decreases the success rate for lenses. However, non-lens classification success has increased with the same number of non-lens images involved. Although both the data sets have a similar overall success rate, the network trained on the Euclid VIS-like data set performed significantly worse at recognizing the images containing lenses. The difference in overall performance is most clear by looking at the receiver operating characteristic (ROC) curves for the data sets together in Fig. 6. A true positive is when a true image, one with a lens, is classified as such, while a false positive is when a false image, one without a lens, is classified as having a lens. The area under the ROC curve determines the results, 1 being the score for all classifications correct, 0 the score for all classifications incorrect, and 0.5 being the result of random selection. True negatives and classifications correct, 0 the score for all classifications incorrect, and 0.5 being the result of random selection. True negatives and false negatives are defined similarly. Fig. 6 confirms that the KiDS-like data set performed best, although the network only improved slightly using a subset of the images, unlike the Euclid data set that improved significantly by removing images from the data set.

As well as using simulated data, we tested on 65 real images from COSMOS. These are single-band images made from larger image cut-outs and modified to have the same PSF as the Euclid images by convolving with a suitable kernel. The full width at half maximum (FWHM) of Euclid squared is equal to the FWHM of COSMOS squared plus the FWHM of the kernel squared:

$$\text{FWHM(Euclid)}^2 = \text{FWHM(COSMOS)}^2 + \text{FWHM(kernel)}^2.$$

After convolution to match the Euclid PSF, the COSMOS images also had their pixels resampled to match the Euclid pixel scale. Images of the COSMOS lenses before and after applying the convolution can be seen in the Appendix. The resulting images were also 101 × 101 pixels. Having only 65 available images meant that training on these images was not a possibility, but testing them with the trained Euclid-like networks was. The results can be seen in Table 4. The scores for both networks were very low, and can be expected after training on a different type of image. Every COSMOS lens that has been classified incorrectly is a false negative. All of the images from the COSMOS survey can be seen in the Appendix. Nevertheless, our network recovers 16/31 of the lenses identifiable by eye at the Euclid resolution (see the Appendix), and 8/34 of the lenses that cannot be identified by eye. Although our network at Euclid resolution only recovers 20 per cent of the lenses known to exist at HST resolution, this is in itself quite interesting: it implies

### Table 1. Table describing the contents of each data set.

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Number of lenses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclid VIS-like simulations</td>
<td>100 000 single-band 1 × 101 × 101 simulated images</td>
<td>39 975</td>
</tr>
<tr>
<td>KiDS-like simulations</td>
<td>100 000 multi-band 4 × 101 × 101 simulated images</td>
<td>49 862</td>
</tr>
<tr>
<td>Euclid VIS-like simulations with COSMOS distribution</td>
<td>68 923 single-band 1 × 101 × 101 simulated images</td>
<td>24 029</td>
</tr>
<tr>
<td>KiDS-like simulations with COSMOS distribution</td>
<td>60 144 multi-band 4 × 101 × 101 simulated images</td>
<td>29 960</td>
</tr>
<tr>
<td>COSMOS lenses</td>
<td>65 single-band real lenses cropped to 101 × 101 images</td>
<td>65</td>
</tr>
</tbody>
</table>

### Table 2. Table shows the architecture of the four networks: Euclid VIS-like and KiDS-like. What each layers contains, as well as each layers initial weights and biases. The final sigmoid layer gives an output between 0 and 1. For the convolutional and max-pooling layers, a stride length of 2 was used, meaning each pixel was only used once in pooling, padded with the same edge pixels where required.

<table>
<thead>
<tr>
<th>Type of layer</th>
<th>Layer contains</th>
<th>Initial weights</th>
<th>Initial bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Convolutional</td>
<td>8 (15 × 15) image kernels</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
<tr>
<td>Max-pooling</td>
<td>Pooled over each (2 × 2) square</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Convolutional</td>
<td>8 (15 × 15) image kernels</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
<tr>
<td>Max-pooling</td>
<td>Pooled over each (2 × 2) square</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Convolutional</td>
<td>16 (5 × 5) image kernels</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
<tr>
<td>Convolutional</td>
<td>16 (5 × 5) image kernels</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
<tr>
<td>Flatten</td>
<td>Convert image maps into 1D vector</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Dense</td>
<td>512 fully connected neurons</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
<tr>
<td>Dense</td>
<td>1 sigmoid output neuron</td>
<td>HeNormal</td>
<td>Zeros</td>
</tr>
</tbody>
</table>

### Table 3. This table shows the percentage of images classified correctly, for lenses, non-lenses, and total correct.

<table>
<thead>
<tr>
<th>Images</th>
<th>Lenses correct (per cent)</th>
<th>Non-lenses correct (per cent)</th>
<th>Total correct (per cent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclid VIS-like simulations</td>
<td>60.32</td>
<td>93.26</td>
<td>80.13</td>
</tr>
<tr>
<td>KiDS-like simulations</td>
<td>88.17</td>
<td>86.82</td>
<td>87.49</td>
</tr>
<tr>
<td>Euclid VIS-like simulations with COSMOS distribution</td>
<td>56.14</td>
<td>98.86</td>
<td>93.33</td>
</tr>
<tr>
<td>KiDS-like simulations with COSMOS distribution</td>
<td>76.83</td>
<td>97.46</td>
<td>93.62</td>
</tr>
</tbody>
</table>
that the detectability of lensing is a very strong function of angular resolution. Roughly doubling the angular resolution (from Euclid to HST resolution) results in roughly a fivefold increase in the numbers of detectable lensing systems.

Even though the KiDS-like subset showed a great deal of success, there are still things to be wary of: all the images used in this work in training and testing are simulated images, but real images may not be classified as accurately, which can be seen by looking at the results from the COSMOS images. The percentage of images containing a lens is much higher in these simulated cases than for real data.

Once implemented with real data, the number of lenses observed will increase. This, in turn, will increase the number of rare lens systems found, such as double-source plane lens systems (Collett & Auger 2014). These rare systems can be used to constrain the dark-energy equation of state parameter $\omega$ (Gavazzi et al. 2008). Lens models can be made from the systems observed, and when coupled with visible images can infer dark matter substructure within the lensing galaxy.

Future work will include training and testing the networks on updated simulations incorporating cluster lenses and Euclid’s grism data. The problems from these first simulations have been noted so that the next training set will not include large Einstein rings (>4 arcsec) and will add more complex images to classify, such as face on spiral galaxies. A further complication to be modelled is the diversity of non-lensed interloper populations, such as polar ring galaxies, or galaxies with tidal tails. The most effective approach here may be to degrade HST images to an appropriate Euclid-like resolution. However, the network presented here will be an excellent starting point for training quickly on such a more comprehensive training set, because CNNs can be efficiently adapted to new but similar application domains (Domínguez Sánchez et al. 2019). The networks will also be trained and tested on different simulations from Collett (2015).

6 CONCLUSIONS

A well-designed CNN can be used with future observations from Euclid and other similar surveys, as they are demonstrably successful on simulated data. Making more realistic simulations, more accurate distributions of Einstein radii and faint lens galaxies, will give a more accurate account of how CNNs will perform with real data. Machine learning techniques will provide a subset of ostensibly reliable lens systems, where verification by visual inspection can be achieved in a realistic time-scale that can then be used to refine the CNN.

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APPENDIX: COSMOS LENSES

The following figures show the 65 lenses from COSMOS that our CNNs were tested with. Each lens has the ID number below. Images with an asterisk after the ID number were the ones that were correctly identified as a lens. Each image has the usual North up, East left configuration, and are 10 × 10 arcsec. Images in the left column are from the COSMOS survey, in the right are the same images after being convolved with a kernel to give the image the same PSF as Euclid. The images have been grey-scale altered to best show the lens.

Figure A1. Images of the COSMOS lenses before (left) and after (right) applying a convolution to match the Euclid PSF.
Figure A1 continued
Using CNNs to identify gravitational lenses

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