

Do Neural Networks Dream of Gravitational Lenses?: Using CNN to Identify Gravitational Lenses & How They Do It

Convolutional Neural Network (CNN)

A CNN is used to classify images as lenses or non-lenses. The NISP band images are scaled up to 200 x 200 pixels. The images are normalised between 0 and 1. The images are classified as a lens if the output is 0.5 or higher. The CNN uses 45,000 images in the training dataset, 3,000 in the validation dataset, and 12,000 in the test dataset. The CNN used in our work is shown in Figure 1.

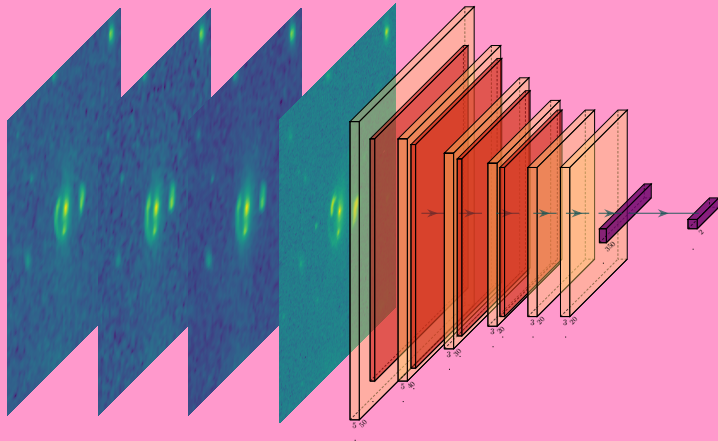


Figure 1. The architecture of our CNN used in this work.

Joshua Wilde
Supervisors: Stephen Serjeant, Jane Bromley
School of Physical Sciences, The Open University

Strong Gravitational Lenses

Gravitational lensing is where foreground matter, such as typically red elliptical galaxies, detectably distorts background galaxies along the same line of sight, due to the foreground spacetime curvature. The effects can be seen in Figure 2, as the blue galaxy bends around the central galaxy. Gravitational lensing can allow us to measure the dark matter halo around the central galaxy and if a variable source is lensed we can get an independent measurement of H_0 .

Data

The majority of this work uses simulated Euclid data containing 4 bands NISP(J,Y,H) and VIS. NISP bands are 66 x 66 pixels and VIS are 200 x 200 pixels. The images are 20 x 20 arcseconds. The lenses can be anywhere in the image. The training and test set contain 100,000 images each. Examples of images from this dataset are shown in figure 2.

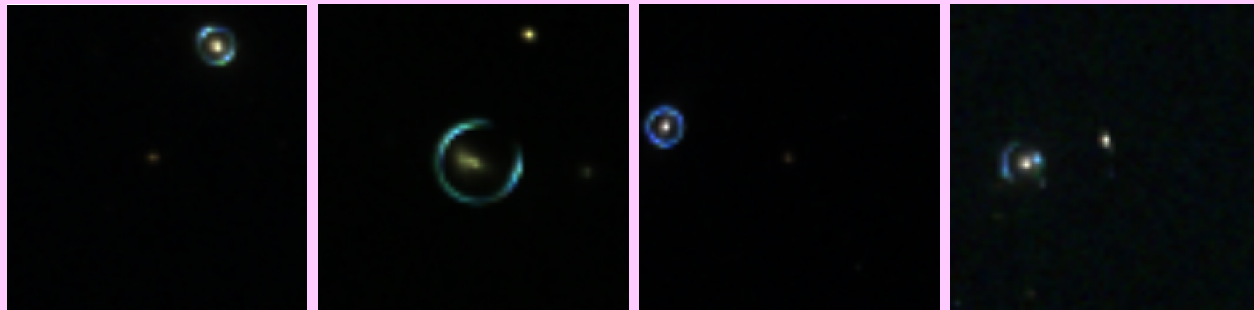


Figure 2. Examples of strong gravitational lenses in the NISP bands.

Occlusion Maps

A 4x4 pixel occlusion mask is moved across the image and the output from the CNN for each position is recorded (Zeiler & Fergus 2014). The change in output is shown on the right in Figure 3. The features the CNN associates with lensing can be seen in blue & the features associated with non-lensing can be seen in red. The CNN highlights the Einstein ring in blue indicating that the CNN associates Einstein rings with gravitational lensing.

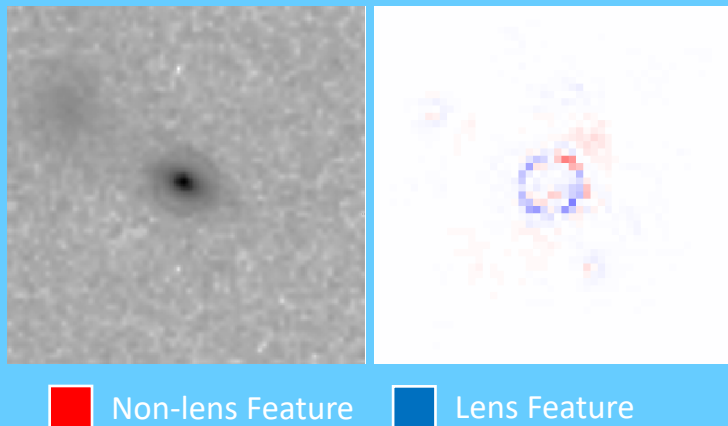


Figure 3. Left: VIS band image of a gravitational lens in log scale. Right: Occlusion map for the lens on the left.

Understanding Machine Learning

Deep Dream

Instead of using an image as input to the CNN to get a classification as an output, we reverse the data flow through the CNN and decide the classification we want from the CNN. Then we train the CNN to achieve this value, but instead of updating the weights we update the input image. This changes the input image to generate the desired value (Mordvintsev et al. 2015).

We can use this to infer what features in the image the CNN associates with lensing & non-lensing. The original image is in the centre, the image to the left activates non-lens, and the image to the right activates lens. In Figure 4, the non-lens image makes the Einstein ring redder, whilst the lens image makes the Einstein ring bluer.

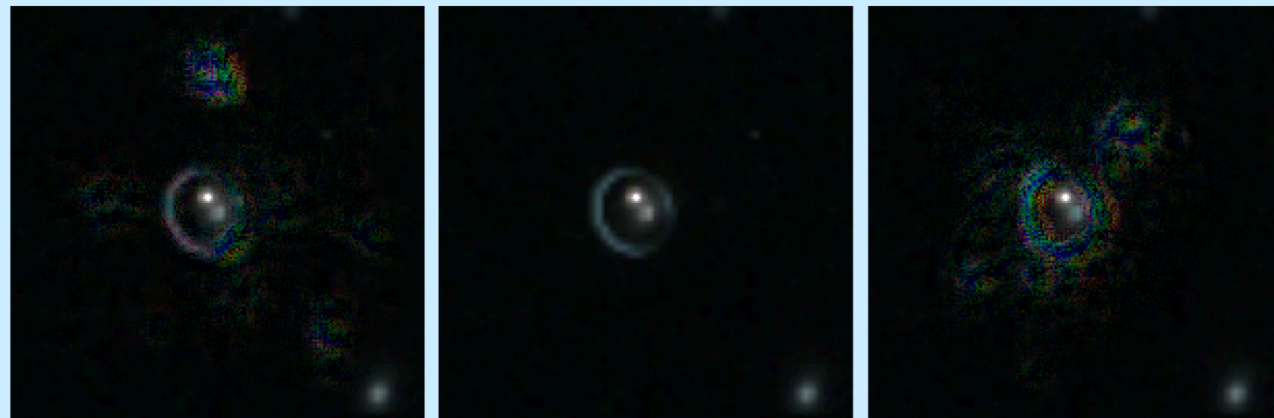


Figure 4. Left: Deep dream generation of a non-lens. Middle: Original lens image in NISP bands. Right: Deep dream generation of a lens.

Why is Compound Lensing Important?

LSST is expected to find ~90 compound lenses over 10 years (Mandelbaum et al. (2018)). Compound lensing allows for tighter constraints on lensing models. From ~50 compound lenses the values of Ω_m and ω can be measured to within a 10% accuracy (Gavazzi et al. 2008).

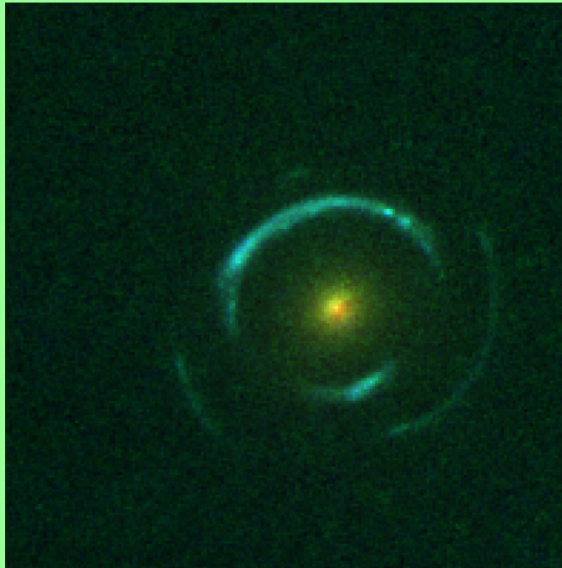


Figure 5. SDSS J0946+1006 an example of a compound lens

Compound Lenses

Simulated

Compound lensing occurs when two gravitational lenses align. These multiple lensing planes create multiple Einstein rings. We simulated 10,000 compound arcs and 10,000 compound rings, shown in Figure 6. Our CNN was never trained on compound lenses, we simulated these lenses to understand if our CNN can identify compound lenses as lenses. These are rare lens configurations and we want to ensure our CNN is not actively selecting against them.

Real

The CNN is applied to real data from the Hubble Space Telescope and Hyper Suprime Cam, shown in Figure 7. This allows us to see if our CNN can adapt to other telescopes and how it performs on non-simulated data.

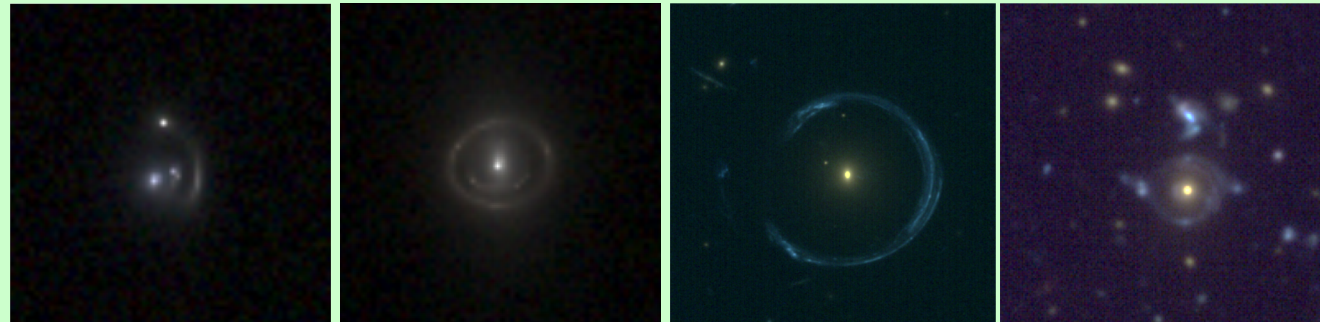


Figure 6. Left: Example of a simulated compound arc. Right: Example of a simulated compound ring

Figure 7. Images of SDSS J1148+1930 (left) and HSC J142449-005322 (right). Compound lenses given to our CNN for classification

Results

$$precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F_1\ Score = 2 \times \frac{precision \times recall}{precision + recall}$$

The CNN performance on the datasets used in this work are shown in Table 1. Both single lens datasets perform similarly and are the only datasets to include non-lens images. A histogram of the CNN output of each dataset is shown in Figure 8. This shows that our CNN predicts a large amount of images as being close to 1, indicating that the CNN identifies them strongly as being a lens. In the single lens datasets there is peak near the threshold value, possibly caused by difficult to classify images in the training data.

Our CNN can identify all of the HSC & HST compound lenses as gravitational lenses. As can be seen in Table 2, all of the compound lenses have outputs greater than 0.5. As can be seen in Table 2, all of the compound lenses have outputs greater than 0.5.

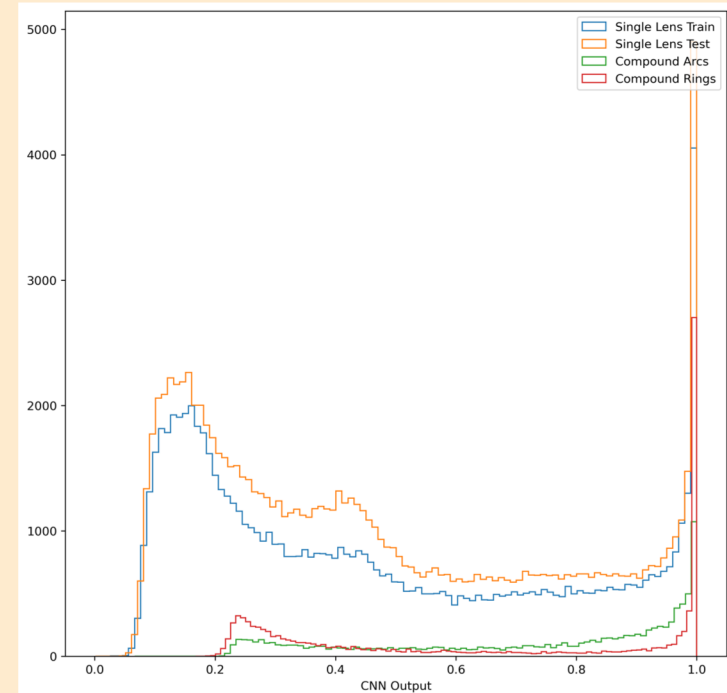


Figure 8. Histogram of the outputs of the CNN for each dataset.

Table 1. The F1 score and recall of the datasets used in this work.

Data	F1 score	Recall
Single Lens Training	0.547	0.436
Single Lens Test	0.580	0.473
Compound Arcs	0.857	0.751
Compound Rings	0.715	0.557
Real Lenses	1.0	1.0

Table 2. The CNN output for all real compound lenses given to the CNN.

Real Lens Name	Output
SL2S J02176-0513	0.9580
HSC J142449-005322	0.7104
SDSS J1148+1930	0.9953
SDSS J0946+1006	0.8228