Detecting solar system objects with convolutional neural networks

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ABSTRACT
In the preparation for ESA’s Euclid mission and the large amount of data it will produce, we train deep convolutional neural networks on Euclid simulations classify solar system objects from other astronomical sources. Using transfer learning we are able to achieve a good performance despite our tiny dataset with as few as 7512 images. Our best model correctly identifies objects with a top accuracy of 94% and improves to 96% when Euclid’s dither information is included. The neural network misses ∼50% of the slowest moving asteroids (v < 10 arcsec h−1) but is otherwise able to correctly classify asteroids even down to 26 mag. We show that the same model also performs well at classifying stars, galaxies and cosmic rays, and could potentially be applied to distinguish all types of objects in the Euclid data and other large optical surveys.

Key words:

1 INTRODUCTION
The solar system small bodies (asteroids, comets, Kuiper-belt objects (KBO)) are the remnants of the rocky and icy bodies that accreted to form the planets in the early solar system. Their orbital, size, and compositional distribution are the results of the mass removal and radial mixing triggered by the planetary migration in the early history of the solar system, and of eons of collisions (Bottke et al. 2002; Michel et al. 2015). While their dynamics have provided the main constraints on the development of theoretical models over the last decade (e.g., Morbidelli et al. 2005; Raymond & Izidoro 2017) we are entering an era in which the compositional distribution of solar systems small bodies is maybe becoming even more important (DeMeo & Carry 2013, 2014).

In particular, the populations of small to medium-sized KBO (tracers of the conditions in the outer planetary nebula) and small main belt asteroids (belonging to collisional families and hence progenitors of the near-Earth asteroids and meteorites) are too faint for current facilities (e.g., LSST Science Collaboration et al. 2009; Spoto et al. 2015).

Whilst future large sky surveys such as LSST (LSST Science Collaboration et al. 2009) will likely uncover and characterise a large proportion of these undiscovered solar system bodies, ground based telescopes are limited to nighttime observations and good seeing conditions. With an estimated launch in 2022, ESA’s upcoming visible and near-infrared space telescope Euclid (Laureijs et al. 2011) is unlike many of the current surveys that typically focus on objects within the ecliptic plane. A survey like Euclid, can expect to detect 1.4 × 10^5 solar system objects (Carry 2018), high inclination (i > 15°) asteroids (for which there is currently a bias against in current census, see Mahlke et al. 2018) and possibly even some rare interstellar objects such as the recently discovered 1I/’Oumuamua (Meech et al. 2017; Katz 2018). It’s simultaneous measurements in both visible and near-infrared will enable us to detect and compositionally map SSOs at the same time. It will nicely complement from the visible photometry from LSST and spectroscopy from Gaia (Gaia Collaboration et al. 2016) in mapping the dynamics of SSOs. Identifying and removing asteroids in the data is also important for weak gravitational lensing to prevent contamination of the shear signal (Hildebrandt et al. 2017). Since Euclid will produce close to a terabyte of data per day, we need to prepare tools to deal with this big data quickly and accurately.

This paper applies machine learning techniques to the problem of solar system object (SSO) detection. The paper is structured as follows: in section 2 we describe the data and simulations, in section 3 we present the convolutional neural net (CNN) architectures, section 4 describes our results and we conclude in section 5.
2 DATA

Euclid\(^1\) is a 1.2m optical and near-infrared space telescope, that will observe \(\sim 15,000 \text{ deg}^2\) of the sky (or over a third of the extragalactic sky) down to a \(V_{AB}\) magnitude \(\sim 24.5\) over its planned mission time of 6.25 years. The Euclid survey will be carried out using the step and stare technique: the 0.5 \(\text{deg}^2\) field of view will observe the same portion of sky four times, using an optimised dither pattern (Racca et al. 2016) and as a result of this planned mission strategy, it should be trivial to identify any moving object within the solar system. However with the presence of cosmic rays, galaxies and instrumental effects there is a lot of room for the mis-identification of SSOs.

Euclid payload consists of 2 instruments, VIS (Crapper et al. 2016) will obtain high-resolution optical imaging and NISP (Maciaszek et al. 2016) will provide photometry in three near-infrared bands as well as slit-less spectroscopy measurements. The data from NISP could be used to study asteroid collisions and the identification of important compounds in the Solar System such as organic matter and water (Emery et al. 2011).

2.1 Simulations

In order to develop the science ground segment tools (pipeline, data analysis software, system infrastructure, etc.) in preparation for the Euclid launch and to assess its capabilities in meeting its scientific goals, detailed and extensive simulations of Euclid dataset are carried out within the Euclid consortium. Our simulations are created using instrument simulators developed for such purposes. The simulator we use is based on the Euclid Visible InStrument Python Package (VIS-PP)\(^2\).

We ingest simulations of SSOs to create state of the art, Euclid-like images for training our model. The simulated images are generated as follows:

(i) The simulator reads in a catalogue of objects (stars, galaxies, SSOs) with coordinates, magnitude, orientation and, for the SSOs, apparent speed.

(ii) For the objects that fall onto the CCD, the number of electrons are computed from the object’s magnitude.

(iii) If the object is a galaxy it is simulated as an input snapshot taken from Hubble and then convolved with the Euclid PSF.

(iv) If the object is an SSO, this is simulated as many stars correctly aligned (using an oversampling of 10).

(v) Once the noiseless image is generated, electrons bleeding, ghosts, cosmic rays, CTI, read-out and dark noise, conversion from electrons to ADU, additive bias are applied. We note that pointing inaccuracies and focal plane distortions are not simulated. As long as they can be fixed using the Gaia reference catalogue (Gaia Collaboration et al. 2016), these effects should have no influence on the detection of SSOs.

For the objects that are stars, we use the optimised dither pattern (Racca et al. 2016) and as a result of this planned mission strategy, it should be trivial to identify any moving object within the solar system. However with the presence of cosmic rays, galaxies and instrumental effects there is a lot of room for the mis-identification of SSOs.

\(^1\) http://sci.esa.int/euclid/
\(^2\) http://www.mssl.ucl.ac.uk/~smn2/

2.2 Preparing the data

We extract postage stamp cutouts of objects of 4 categories; SSOs, cosmic rays, galaxies and stars. The size of the postage stamp is chosen such that the image is filled by the object plus a padding of \(N(65,5)\) pixels. We investigate how our method performs both with (multi-channel) and without (single channel) temporal information from the dithers. In the multi-channel model, we combine dithers 1, 2, 3 and dithers 2, 3, 4 into 2 images of RGB channels and extract postage stamp cutouts centred on each object. We only use 3 of the 4 Euclid dithers at a time due to constraints from our model (see subsection 3.4 for more details). For these images the pixels of galaxies and stars should appear in all 3 channels, whereas the pixels of cosmic rays and asteroids (aside from the very slow moving) should only appear in one channel. The differentiating characteristic feature of cosmic rays compared to SSOs are that the latter are convolved with the PSF. Examples of the data are shown in Figure 1 and Figure 2.

Figure 1. Examples of SSO images used in the single channel data set (top row) and those used in the three channel data set (bottom row). The SSOs are the objects closest to the centre of the image. The first three images are SSOs with magnitudes in the 20-21 mag bin and the last object is a 25-26 mag SSO. From left to right, the SSOs have speeds of 10, 40, 80 and 10 arcsec h\(^{-1}\) respectively. The contrast levels of the images have been adjusted to enhance the appearance of object of interest.

Figure 2. Examples of the other classes used in the three channel data set. The left most images are galaxies, the centre two images are stars, and the right most images are cosmic rays. The lower left image has had adjustments made to the contrast levels to enhance the appearance of the galaxy.
3 METHOD

3.1 Neural networks

Artificial neural networks (ANNs) are a class of machine learning algorithm that maps some arbitrary inputs to outputs (McCulloch & Pitts 1943). They were inspired by the visualisation process of the human brain and the hierarchical perception of images. The visual cortex has a layered architecture of neurons, each layer represents a different feature (such as hair, color, eyes etc) which may get activated depending on if a feature is detected in what is being visualised. In artificial neural networks, each neuron takes a vector of inputs \( \mathbf{x} = \{x_1, x_2, ..., x_n\} \) and applies a set of weights \( \mathbf{w} = \{w_1, w_2, ..., w_n\} \) and a bias \( b \) to it,

\[
y = \phi \left( \sum_x w_i x_i + b \right).
\]

The input is passed to every neuron in a layer and the output of each neuron will be passed as an input to each neuron in the subsequent layer (Figure 3). The weights and bias values are parameters of the network, and \( \phi(x) \) is a non-linear activation function which determines whether or not the neuron is fired, in other words it maps the input to the response. The most commonly used non-linear activation function is the rectified linear unit (ReLU), which takes the form, \( \phi(x) = \max(0, x) \). This activation function is popular since both the function itself and its derivative is quick to calculate,

\[
\frac{\partial \phi(x)}{\partial x} = \begin{cases} 0 & x \leq 0 \\ 1 & x > 0 \end{cases}
\]

The input \( (\mathbf{x}) \) and parameters \( (\mathbf{w}, b) \) give a predicted output \( \hat{\mathbf{y}} = \{\hat{y}_1, \hat{y}_2, ..., \hat{y}_n\} \). In supervised learning the true output \( \mathbf{y} = \{y_1, y_2, ..., y_n\} \) is known and backpropagation (Rumelhart et al. 1986) is typically used to efficiently adjust the parameters to minimise a loss function \( L(\mathbf{y}, \hat{\mathbf{y}}) \) (a measure of the distance between the true and predicted output). Using the gradient descent method to find the minima, the weights are iteratively updated,

\[
\mathbf{w} \rightarrow \mathbf{w} - \eta \frac{\partial L}{\partial \mathbf{w}} \quad b \rightarrow b - \eta \frac{\partial L}{\partial b}
\]

Here \( \eta \) is a tunable learning rate that determines the size of steps that the parameters can take on each update. A large learning rate will explore more of the parameter space but will make convergence to the minimum more difficult. A low learning rate is more precise but will take a long time to reach the minimum.

The calculation of the gradients can be computationally expensive when a cycle of the entire data set is required to update the parameters (batch gradient descent) and the number of training samples is large \( (O \sim 10^6) \). Alternatively the gradients can also be averaged over several randomly selected single samples or small samples (mini-batches) of the training data. This is known as stochastic gradient descent (SGD). It is much faster since it uses less RAM, and is better for finding multiple local-minima, however it requires the specification of the batch size. If the batch size is too small the convergence to the global minima will be slow and tends to be noisy (LeCun et al. 2012).

3.2 Convolutional neural nets

Convolutional neural nets (CNNs, Lecun et al. 1998) are deep artificial neural networks designed for image recognition. Similarly, the CNN architecture contains multiple hidden layers, local connections between nodes and spatial invariance. The convolutional layer of a CNN takes an input image and convolves it with a small filter (kernel) whose values are weight parameters to be learnt. The filter is applied across the entire image with a bias and activation function creating a feature map layer. Figure 4 - left, shows an example of a simplified CNN. For images where there are multiple channels (e.g RGB colour images), standard convolutional filters will combine all the channels using a weighted sum. Computationally this is not very efficient. Pooling layers are used to reduce the dimensionality of the feature maps, usually by reducing small areas to their maximum pixel value.
Figure 4. Left: Visualisation of a simple convolution filter layer with a 3x3 convolutional filter, no padding and a stride of 1. The input represents the pixel values of an image and the kernel is applied by sliding the kernel’s centre pixel value over pixels of the input. The output pixel is a weighted sum of overlapping input and kernel pixels. Right: Visualisation of a pooling layer, with a 3x3 maxpool and a stride of 2. Again this is applied sliding across the input pixels. The pooling layer reduces the dimensionality of the input by mapping only the highest pixel values.

| Model              | Number of parameters | Top-1 Accuracy* | Top-5 Accuracy* |
|--------------------|----------------------|----------------|-----------------|
| Inception v4       | 35M                  | 80.2           | 95.2            |
| MobileNet_v1_1.0_224 | 4.2M                | 70.7           | 89.5            |
| NASNet-A_Large_331 | 88.9M                | 82.7           | 96.2            |

Table 1. CNN architecture versions used in this paper. *Accuracies taken from Google’s internal training on the ILSVRC-2012-CLS dataset using single image crop and may differ from values listed elsewhere.

(Figure 4 - right). An alternative to the standard convolutional filter is to use depthwise separable convolution (Chollet (2016), Figure 5) which requires less parameters since the convolutional filters are first applied on each colour channel separately and then on each pixel across all channels. This also reduces the sensitivity to small positional shifts and distortions of a feature. Batch normalisation layers are used to improve speed and generalisation of the trained network by re-normalising mini-batches to their mean and variances during training, and fully connected layers connect all neurons in the previous layer and enables the mapping to a classification label.

3.3 Architectures

The layers of a neural network make up its architecture. Designing a good architecture is difficult, time consuming and requires expert knowledge. The hyper-parameters, those that need to be defined before training, include the number of convolutional filters, filter size (typically 3x3 pixels), padding (which defines the margin used when the convolutions are applied), stride (which determines if any pixels are skipped during the convolution), pooling layer size and dropout (a random probability of a neuron being ignored) to name a few. Whilst much research has been done to choose the best hyper-parameters (e.g. Simonyan & Zisserman 2014; Szegedy et al. 2015; Murugan 2017), in practice it is trial and error, and complexity is added slowly. We use Google’s Tensorflow library\(^5\) and three different architecture models (Table 1).

Inception (Szegedy et al. 2015) is a state of the art convolutional neural network. In comparison, humans will typically obtain a top-5 error rate of \(\sim 5\%\).\(^6\) The original Inception-v1 deep convolutional architecture was named GoogLeNet. It was inspired by Lin et al. (2013)’s Network In Network, and was one of the first CNN architectures to implement modules of parallel operations (inception modules) instead of the traditional sequential stacking. We implement the latest version Inception_v4 (Szegedy et al. 2016) which has since been refined to include batch-normalisation, additional factorisation ideas, more inception modules and a more simplified uniform architecture.

Another CNN we use is NASNet-A-large (Zoph et al. 2017). Nasnet is an architecture that was created by a controller neural network Neural Architecture Search (NAS). With a small dataset, NAS uses a recurrent neural network (RNN, Zoph & Le 2016) and reinforcement learning to continuously propose improvements to the architecture. Since the use of NAS on larger datasets would be computationally expensive, it was applied to CIFAR-10, a dataset of \(8\times10^7\) small images in 10 classes to search for an optimal but scalable convolutional cell. Using a larger dataset ImageNet 2012\(^7\) which consists of \(\sim 1.4\times10^7\) images and 1000 classes, NASNet-A-large retrained the weights of its on repetitions of these cells and filters in the penultimate layer. The final architecture consists of 18 repeated cells with 168 convolutional filters per cell. NASNet-a-large exceeds the performance of any human-designed model to date.

The last architecture we use is mobilenets_1.0_224 (mbnet, Howard et al. 2017) which is the most accurate of the MobileNets architectures. MobileNets are not conventional CNN’s. Traditional mobile neural networks relied on

\(^4\) http://www.image-net.org/challenges/LSVRC/2012/
\(^5\) https://www.tensorflow.org
\(^6\) https://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/
\(^7\) http://image-net.org/
Figure 5. Depthwise separable convolution consists of first a depthwise convolution that is applied separately on each channel and then a pointwise convolution that is the same as a normal convolution (combines all channels) with a 1x1 kernel.

Figure 6. Activation images showing an input image (here a star) changing after convolution with the mbnet filters. Here we show only the outputs of the first 4 filters of each layer. Layer 1 contains 32 3x3 standard convolutional filters, layer 2 contains 32 3x3 depthwise filters, layer 4 contains 64 1x1x32 pointwise filters, layer 11 contains 256 3x3 depthwise filters and layer 14 contains 512 3x3 depthwise filters. Also note that the image size decreases with the layers due to the pooling layers.

cloud computing, but the increasing computational power of mobile devices means that we no longer require dependency on an internet connection to perform deep learning tasks. Whilst other new CNN’s focus on maximising accuracy, MobileNets were designed to be very small and very fast. The standard convolutional filters in CNN’s are factorised into depthwise and pointwise (1x1) convolutional filters which allow MobileNets to achieve competitive classification accuracies whilst optimising for latency, size, and power restrictions. Figure 6 is an example of how the layers of the MobileNets architecture affect an input image.

3.4 Transfer learning

Deep neural networks can have millions of parameters that can take weeks, if not months to train, transfer learning (Donahue et al. 2013) significantly reduces the time required for training without requiring GPU. In transfer learning there is no need to fully train a deep architecture. An existing architecture can be retrained and fine tuned to new classification labels (see e.g. Khosravi et al. 2018). This method has already been successfully applied in astronomy to detect galaxy mergers (Ackermann et al. 2018) and to classify galaxy morphologies (Domínguez Sánchez et al. 2018). Since our dataset is small ($O \sim 10^3$), we implement transfer learning to avoid overfitting and to prevent getting stuck at local minima. The layers of weights are already defined through
pre-training on the ImageNet 2012 dataset. We only need to retrain a new top layer to include the new classes of images. CNN layers consist of a 3 dimensional volume of neurons with a width, height and depth. The depth means that we can incorporate the dithers of Euclid, with each dither corresponding to a different depth layer. However, since the architectures we use were pre-trained on RGB (3 channel) images, in order to use transfer learning it is not possible to combine all 4 dithers. To do so would require complete retraining of all the layers in the architectures.

For retraining we append a new top layer that consists of a softmax activation function,
\[ \phi(x_i) = \frac{\exp(x_i)}{\sum_{n=1}^{N} \exp(x_n)} \] (4)
that gives us a probability of each class \(i\) over all \(N\) classes, and a fully-connected (dense) layer. Since we use the softmax function, the output of our models are probabilities assigned to each class label. We take the class label with the highest probability as the predicted class. For optimisation we use the standard gradient descent (GradientDescentOptimizer) and minimise on the mean cross entropy loss
\[ L(y, \hat{y}) = -\sum_{i} p_i \log q_i \] (5)
where \(p \in \{y, 1-y\}\) and \(q \in \{\hat{y}, 1-\hat{y}\}\). We initiate the learning rate at 0.0001 and reduce it by 5\% every 1000 iterations. This provides good accuracy within an acceptable training time.

3.5 Regularisation and augmentation
Apart from transfer learning and increasing the amount of data, there are several other tricks that can be used to prevent overfitting. Regularisation by batch-norm was discussed in subsection 3.2, another regularisation technique is dropout, where connected nodes are randomly disconnected. We implement a 20\% drop-out probability. Note however that the dropout does not significantly improve fits since there are few parameters in the final layer and convolutional neural networks are applied across several locations of an image. Augmentation prevents overfitting by adjusting the properties of the training data. Resizing, cropping, rotating, transposing, and other image adjustments can also improve the results however this also significantly increases the time required for training so we do not implement this.

We split our data into training, validation and test sets with 70\%, 20\% and 10\% respectively. The training is run using Monte Carlo cross-validation (Xu & Liang 2001) and stochastic gradient descent with validation batches and training mini-batches of 100 images. The validation is performed every 10th iteration and the test data is only seen after the training is complete and is not used to update the parameters of the architecture.

3.6 Performance metrics
Our testing set is based on simulations so the number of images in each class can easily be defined, however we do not train our model on an astronomically representative training dataset. Classification models generally do not perform well when trained on imbalanced datasets. They tend to overfit the more abundant class. This leads us to The Accuracy Paradox - a predictive model with a given accuracy, may have greater predictive power than a model with higher accuracy. Accuracy is defined as,
\[ \text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}. \] (6)
where TP, FP, TN, FN are true positives, false positives, true negatives and false negatives respectively. It is clear that for an imbalanced data set with 1 SSO and 99,999 non-SSOs a high accuracy can be achieved by predicting all images to be non-SSOs, however this model would be useless for our purpose (detection of SSOS). Receiver Operating Characteristic (ROC) curve’s are a common way to visualise the performance of a binary classification model. It shows the true positive rate (TPR = TP / (TP + FN)) against the false positive rate (FPR = FP/ (FP + TN)) respectively.

Whilst accuracy and area under the (ROC) curve (AUC) are the typically preferred performance summary statistics, it only reflects the underlying class distribution and is not very informative when the training classes are imbalanced. It is therefore also important to consider: precision, a measure of how pure our sample is (i.e. what fraction are SSOS), recall, a measure of how complete our sample is (i.e. what fraction of all SSOS are in the sample), and the F1-score which is a weighted mixture of the two. A more relevant statistic for an unbalanced dataset is the Cohen kappa score, a measure of the accuracy normalised by the imbalance of classes. Another common solution is to use a weighted loss function or fed weighted samples to the mini-batch. With transfer learning, we have sufficient data to train on a balanced training set.

In astronomy, to determine how well a classifier method performs we can look at the purity and completeness of the samples. In machine learning, purity and completeness are equivalent to precision and recall. It is clear that purity and completeness is a trade-off, the sample can be very pure if the threshold value of SSOs is very high however this will lead to a low number of classified SSOs, likewise, the sample can be very complete by classifying all images (SSOs and non SSOS) as SSOS.

However to see how well the CNN performs on real astronomical data we need to rescale our test results to the astronomical abundance of the classes.

\[ \text{Purity} = \text{Precision} = \frac{TP}{TP + FP}. \] (7)
\[ \text{Completeness} = \text{Recall} = \text{TPR} = \frac{TP}{TP + FN}. \] (8)
\[ \text{Astronomical Purity} = \frac{\text{TPR \times AB}}{\text{TPR \times AB} + \text{FPR \times (1 - AB)}}. \] (9)

where AB is the astronomical abundance (the number of SSOS / the number of all objects).
Figure 7. ROC curve for the test data set with the same log scale plot inset. Left: 2 category model. Right: 4 category model. The dashed line represents a false positive rate equal to true positive rate. This would be equivalent to the model prediction occurring purely by chance. The colours indicate different architectures and data used.

Loss and accuracy curves for 2-label model.

Loss and accuracy curves for 4-label model.

Figure 8. Top left: Training loss as a function of iteration for 2-label runs. The dotted line shows the smallest loss and is solely for visual purposes. Top right: Training and validation accuracy as a function of iteration for the 2-label runs. Bottom: the same as the top row but for the 4-label models.
4 RESULTS AND DISCUSSION

4.1 Considering two categories

Initially we treat each dither independently and combine cosmic rays, galaxies and stars collectively into the category non-asteroids. The complete dataset contains 3756 images of SSOs and non-SSOs. Of the 3 models tested; mbnet, nasnet and inception (see subsection 3.3), we surprisingly found that the mbnet architecture outperformed the other 2 on the test data set. Next we apply the same architectures to the 3 channel images (col_mbnet, col_nasnet, col_inception) and similarly the top performing architecture is mbnet despite being the quickest architecture to train. We believe this is due our dataset consists of low resolution images and mbnet having been pre-trained on low resolution (224x224 pixel images) is able to better characterise low resolution features, whereas Inception and NASNet are both higher resolution (299x299 and 331x331 respectively) and deeper models but the added complexity is not adding any extra information and conversely suppressing the ability to generalise classification performance on new images. Figure 7 shows the ROC curve for these models as applied to the test data set. The dashed line shows the expected ROC curve if the predictions from the model are down to chance. ROC curves above the dashed line perform better than a random guess and a ROC curve below the line would be performing worse than randomly guessing and is usually an indication of a bug. As expected, adding the dither information improves the performance of the neural networks.

4.2 Considering four categories

It is not uncommon within the astronomical community to write algorithms specifically to classify a single object, however convolutional neural nets, unlike other machine learning methods, do not require feature engineering which means the same network can be easily adapted to multiple class problems. It is therefore a more efficient use of personnel and resources to develop a single network that can identify multiple classes in the Euclid data than to have several networks each classifying a different astronomical object. We retrain the network with 4 labels; cosmic rays, galaxies, stars and SSOs, using single and multi-channel images (Figure 7). Each class contains 3756 images. The 4-label models perform slightly worse than 2-label model, this is not unexpected since the 2 label case requires at least a threshold probability of 0.51 to be classified as an asteroid, whereas in the 4-label case it could be as low as 0.26. Also there are more degeneracies between classes. Once again the MobileNet architecture is the superior model. Table 2 lists the performances of all the variations of architectures and schemes we run.

4.3 Convergence

The chosen number of iterations used in training needs to be carefully defined to avoid under or overfitting. This is when the model has not had enough time to learn the feature or has had too much time that it is completely fine tuned to perform well on the training set but performs badly on the test set. We monitor the training error as a function of the iteration to determine an ideal stopping point (Figure 8).
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Table 2. Summary statistics for the different runs. The right most columns are the confusion matrix. This shows the number of predictions for each class against the true label when the model was applied to the test dataset.

| Model     | time | iterations | test acc (%) | test AUC | precision | recall | F1 score | cohen κ | predicted SSO | truth SSO | non-SSO SSO | SSO CR galaxy star | MobileNet 4cat |
|-----------|------|------------|--------------|----------|-----------|--------|----------|---------|--------------|-----------|---------------|---------------------|-----------------|
| Inception | 1192 | 100k       | 0.726        | 0.911    | 0.730     | 0.726  | 0.727    | 0.634   | SSO          | 348       | 22            | 5 17                | 359             |
| MobileNet | 615  | 100k       | 0.790        | 0.949    | 0.793     | 0.790  | 0.791    | 0.719   | SSO          | 359       | 15            | 3 3                 | 286             |
| NASNet    | 2576 | 100k       | 0.725        | 0.914    | 0.727     | 0.725  | 0.726    | 0.633   | SSO          | 352       | 26            | 6 17                | 255             |

4.4 Purity and Completeness

The expected abundance of asteroids observed with Euclid is \( \sim 0.0001 \) but varies with ecliptic latitude. For this abundance we can hope to achieve 100% purity for at most a 60% complete sample of asteroids (Figure 9). None the less, it is clear that this significantly improves if the abundance of asteroids fed to the model is 0.5. The neural network approach would make a good follow up method for the confirmation of potential asteroids detected from existing methods to improve the abundance ratio. Otherwise, another way purity can be further improved is to check the 4 dithers for counter part images (see e.g. Bouy et al. 2013; Mahlke et al. 2018). We note however that an abundance of 0.0001 is a pessimistic
estimate and an advanced Euclid pipeline would be able to remove the majority of cosmic rays.

4.5 Biases

To infer whether our method is biased in any particular way we look at the distribution of the false negatives as a function of asteroid AB magnitude and speed (Figure 10). We find that there is no particular trend with magnitude, which means the CNN can pick up even the faintest asteroids rather well however it does not perform very well in picking out the slowest moving asteroids. From the confusion matrices of the 4-label models (Table 2), we see that SSOs are most likely to be misidentified as galaxies which is not surprising since they are small, extended and convolved with the PSF just like the asteroids.

5 CONCLUSIONS

We use 3 of the best deep convolutional neural nets currently available and apply transfer learning to retrain them for the classification asteroids. The neural nets are retrained on Euclid-like images, to identify asteroids and non-asteroids. The MobileNet model is found to be the best performing architecture on this dataset and is also the quickest CNN to train. Our model reaches top-accuracies of 94% and marginally increases to 96% when we include an additional 2 of Euclid’s 4 dither images. We expect to further improvement when all 4 dithers are used however currently this is not possible given that we are training data limited. Our model is robust to the expansion of more labels. When the non-SSO class is replaced with classes; galaxies, stars and cosmic rays, the AUC (area under the receiver operating characteristic curve) score on asteroids decreases slightly by 2%. This means that method has the potential to perform well on the classification of all objects in Euclid, provided that a more complex training data set of simulations were to be produced. This includes both astronomical objects and instrumental artefacts such as supernova, satellite trails and ghosts. Our CNNs perform well on even the faintest asteroids but are more susceptible to missing the slowest moving asteroids. The true abundance of asteroids will be low, therefore to achieve a high purity and completeness sample we could preprocess the data with a method such as SExtractor (Bertin & Arnouts 1996) for an initial removal of stars, galaxies and cosmic rays. Nonetheless, the Euclid pipeline will likely remove the majority of cosmic rays anyway.

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