Can deep learning help us create better Point Spread Functions, faster?

NSERC-CREATE NTCO Training Program Research Project

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Introduction

What is a Point Spread Function (PSF)?

- PSFs mathematically describe how point source objects are distorted in an image.
- Images are a convolution between the true object and the PSF as shown in the figure above.
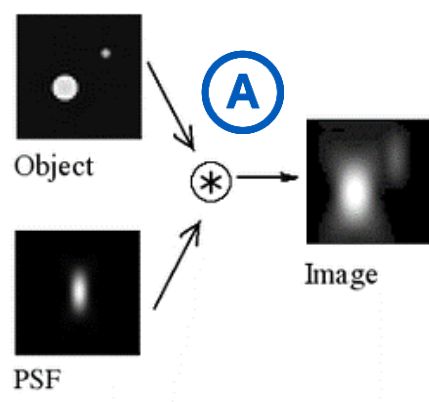
Why are PSFs important to astronomy?

- PSFs are necessary to study any object close to the resolution limit of a telescope with high precision.

What do we need in order to create PSFs?

- Examples of point-like sources in the image of interest are needed as inputs to PSF generation software.
- In astronomy, good point-like sources would be stars that are bright, round, and well isolated from other sources.
- The task of selecting these good sources for PSF generation is what this deep learning model has been trained to do.

Data & Methods

For this project, images from 2020 taken by the Hyper Suprime-Cam (HSC) on the Subaru telescope were used as follows:

- May 31: used to design and evaluate the model.
- May 26: used to gauge actual performance in good source selection and the resulting PSF generation.
- For each image, the top 25 sources were selected as those with the lowest flux outside the central source, as inferred by the flux of the most discrepant pixel in the source-PSF residual, and the standard deviation of all residual pixels.
- Of these top 25, the ones which fell in the accepted range of pixel brightness values were deemed good and labelled 1. All other sources were considered bad and labelled 0.
- Using this approach, there are far more bad sources than good ones and so a random selection of bad sources is made such that the 0 and 1 class sizes are equal.

Data Flow Diagram
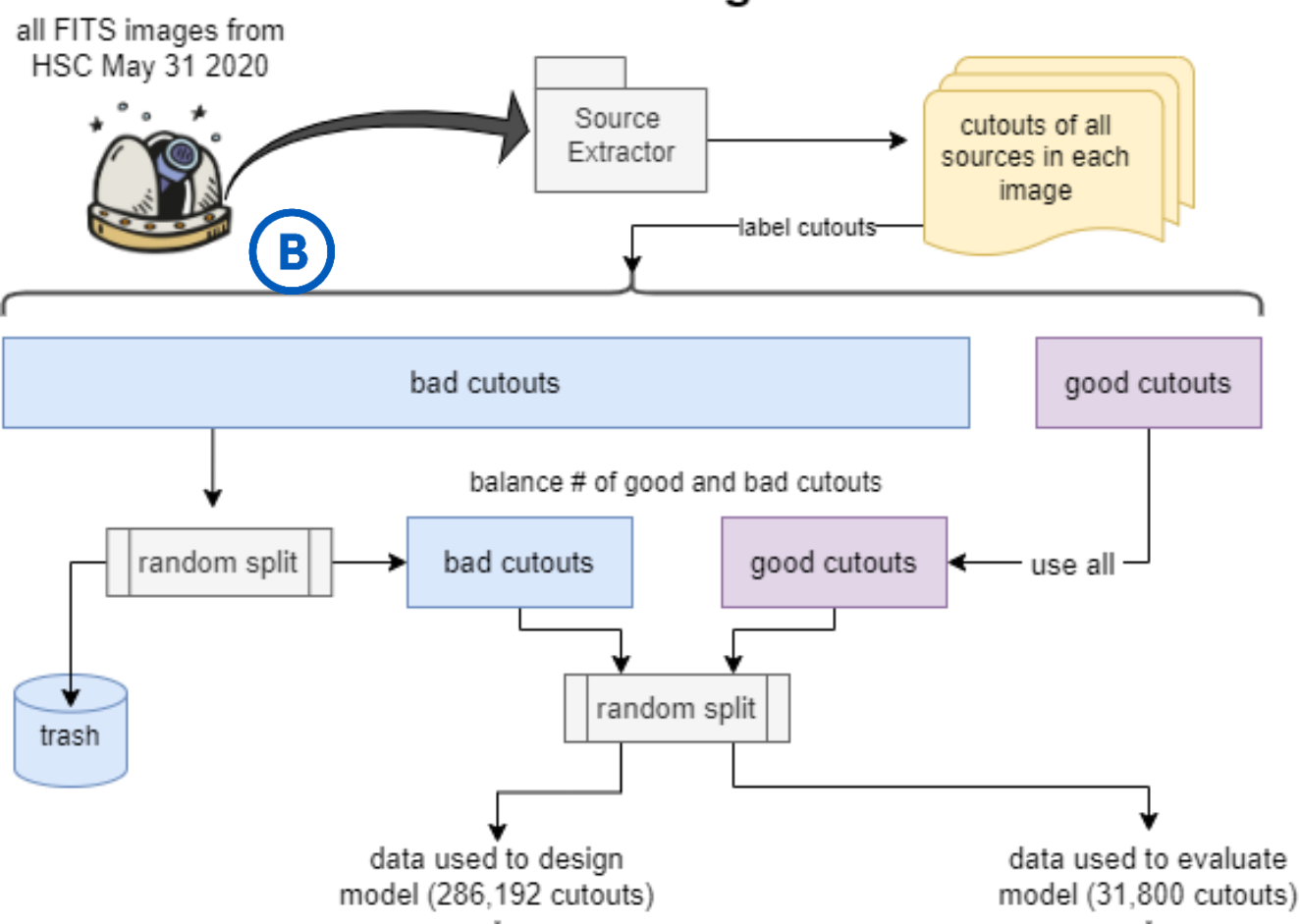
Convolutional Neural Network Architecture Diagram
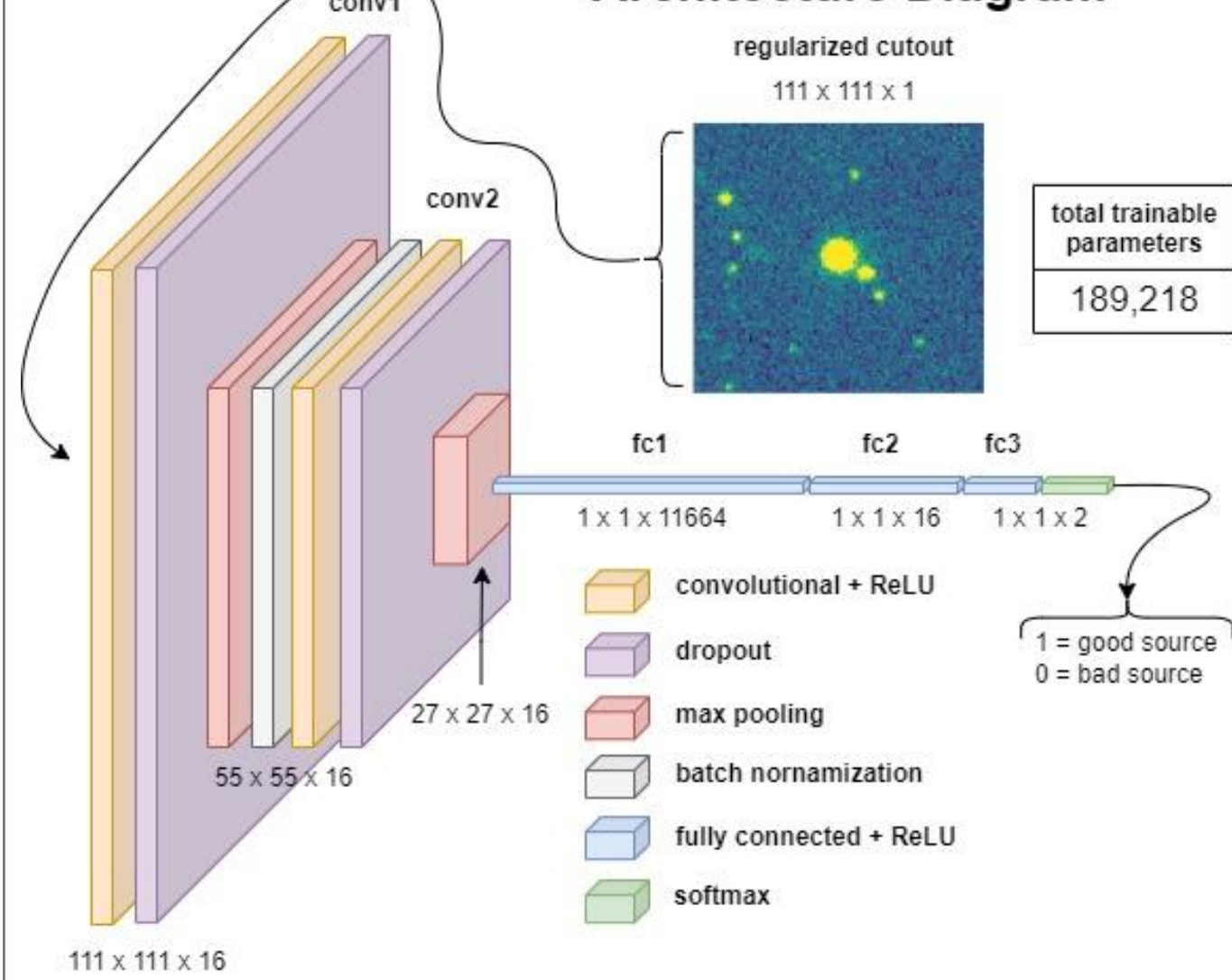
Evaluation Metrics

The metrics used to evaluate the model are defined in this section. We are most interested in having a high TP rate, a low FP rate, and therefore a high good source classification accuracy. This is reflected in a precision value close to 1.

Confusion Matrix Explained

	Predicted 0	Predicted 1
Actual 0	True Negative (TN)	False Positive (FP)
Actual 1	False Negative (FN)	True Positive (TP)

$$Accuracy = \frac{TP+TN}{(TP+FN+TN+FP)}$$

$$Precision = \frac{TP}{(TP+FP)} \quad Recall = \frac{TP}{(TP+FN)} \quad Specificity = \frac{TN}{(TN+FP)}$$

Results

Using the test set we can determine how well the model predicts the labels of an unseen dataset:

**Confusion Matrix:** The accuracy was found to be 89.12% overall.

The cutout size 111x111 pixels is used so that images with a variety of Full Width at Half Maximum (FWHM) values can be used with the model. The differing FWHM values here are due to different seeing conditions but FWHM values are also related to the telescope itself.
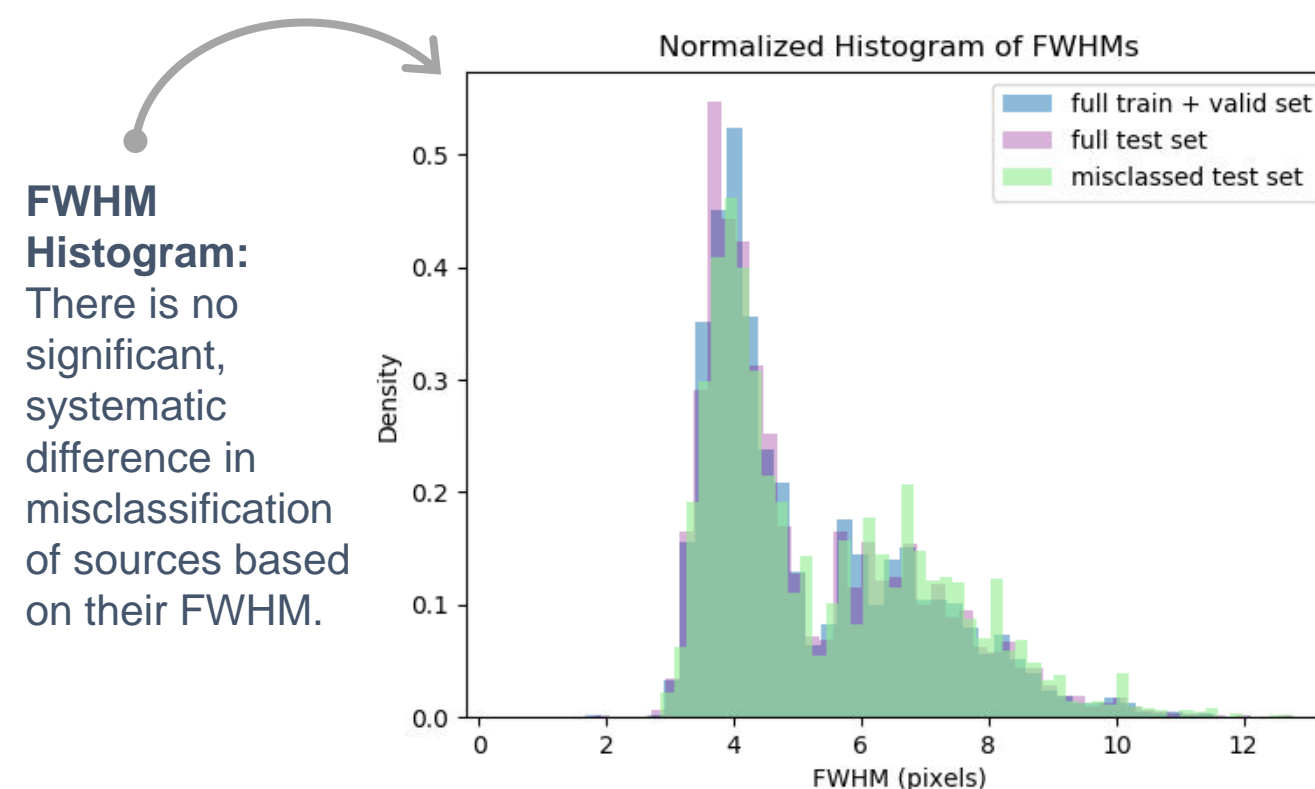
FWHM Histogram: There is no significant, systematic difference in misclassification of sources based on their FWHM.

We can raise the confidence threshold beyond which the model labels a source as good. A threshold of 90% was adopted such that we can achieve a precision of 93.87% while still having a significant number of sources considered good.
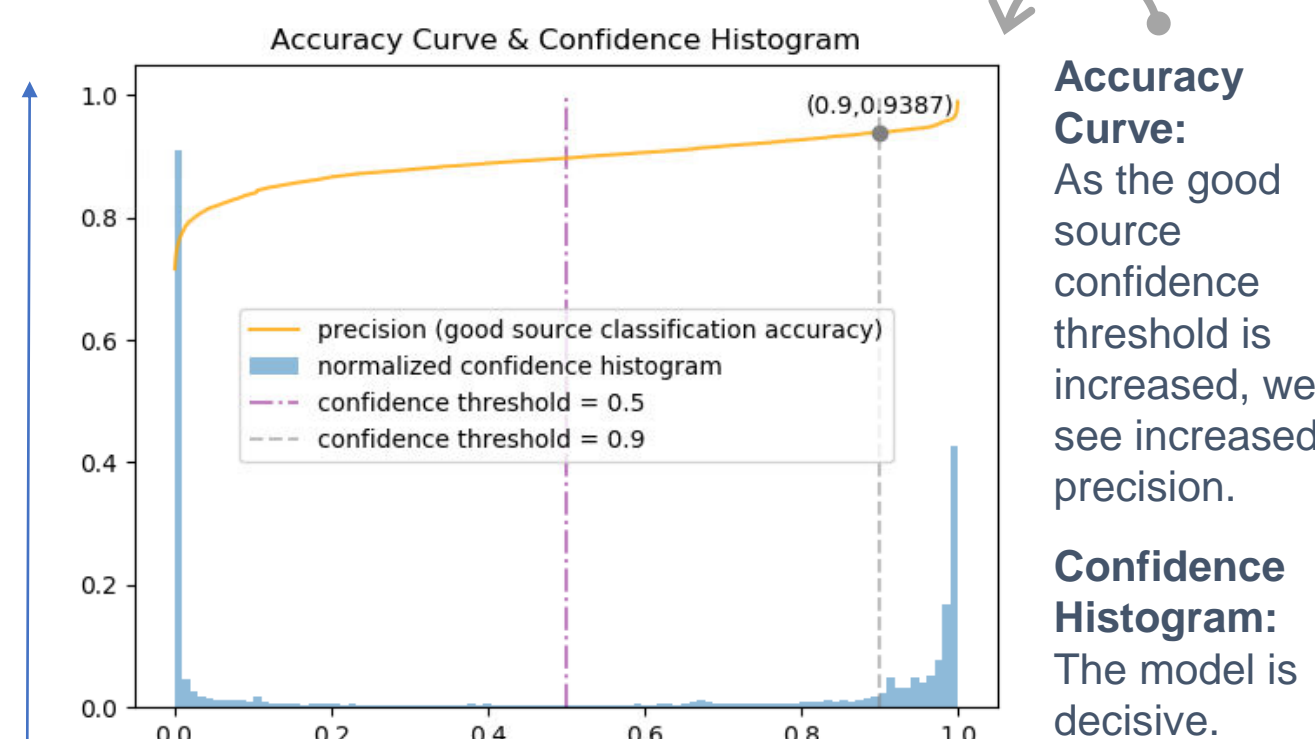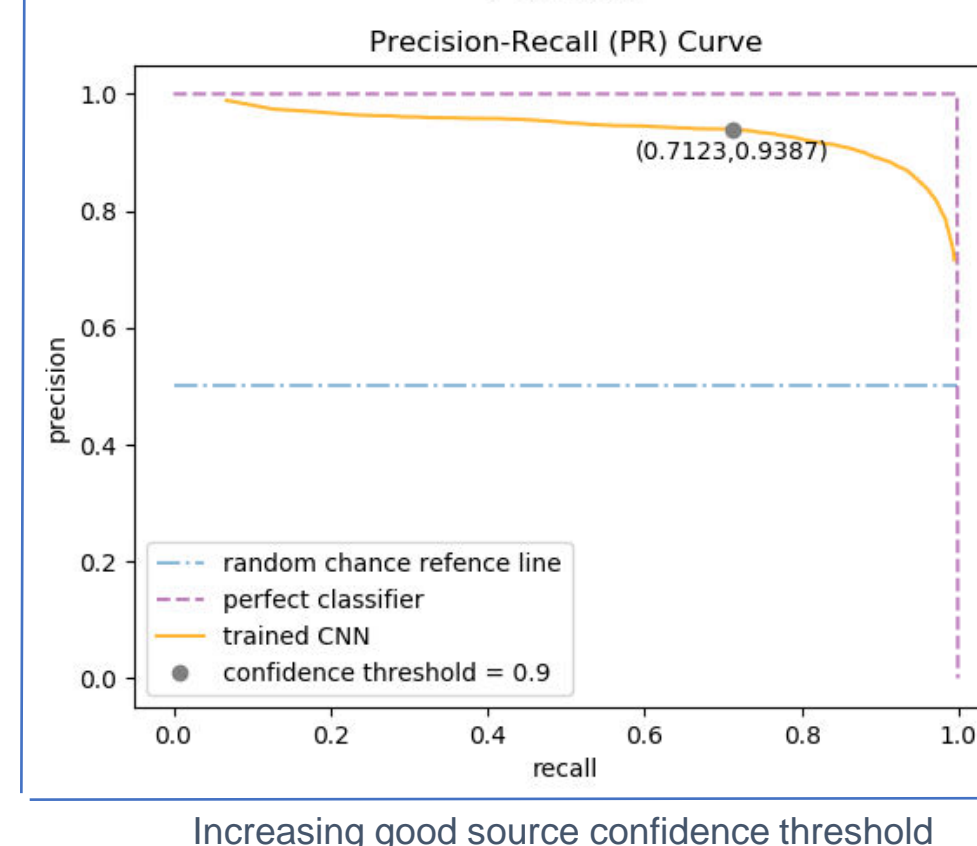
Accuracy Curve: As the good source confidence threshold is increased, we see increased precision.

Confidence Histogram: The model is decisive.
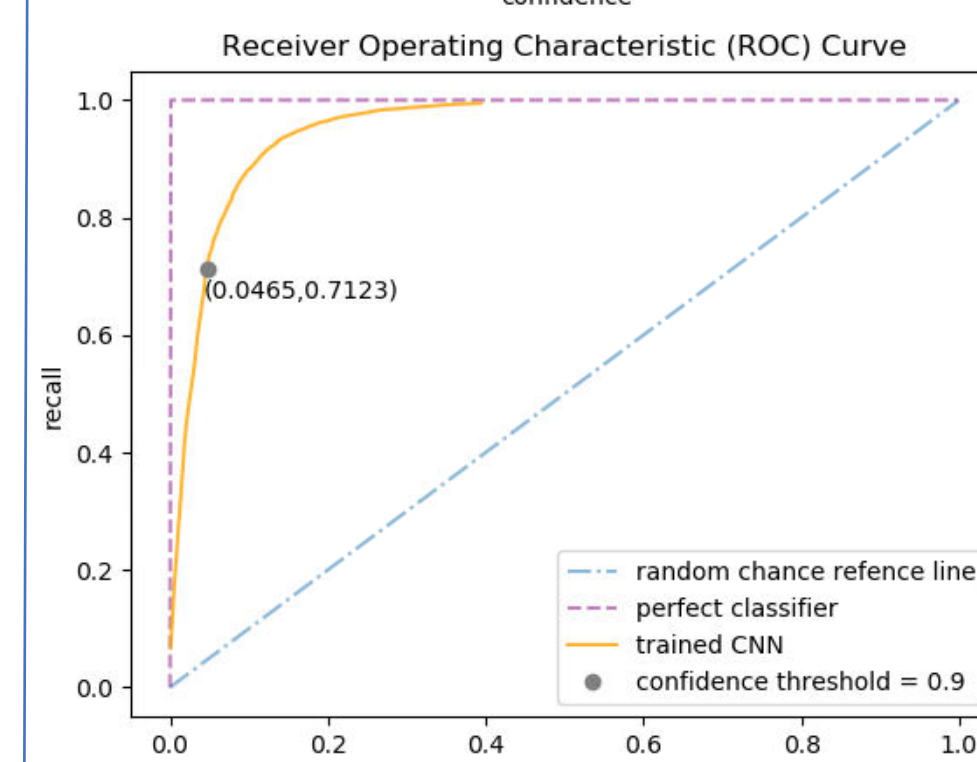
ROC Curve + PR Curve: The behavior is as we would hope for, not perfect but far better than random guessing.

Increasing good source confidence threshold

Conclusion

- Considering the results from evaluating the model and examples of star selection with the resulting PSFs we see that the model can reproduce the source labels most of the time.
- One of the key advantages to using this CNN model over the non-CNN method by which we created the labels is that once the model is trained it is significantly faster.
- The figure below compares CPU time for 7 images, and it is found that on average the CNN method takes only 6% the time of the non-CNN method.
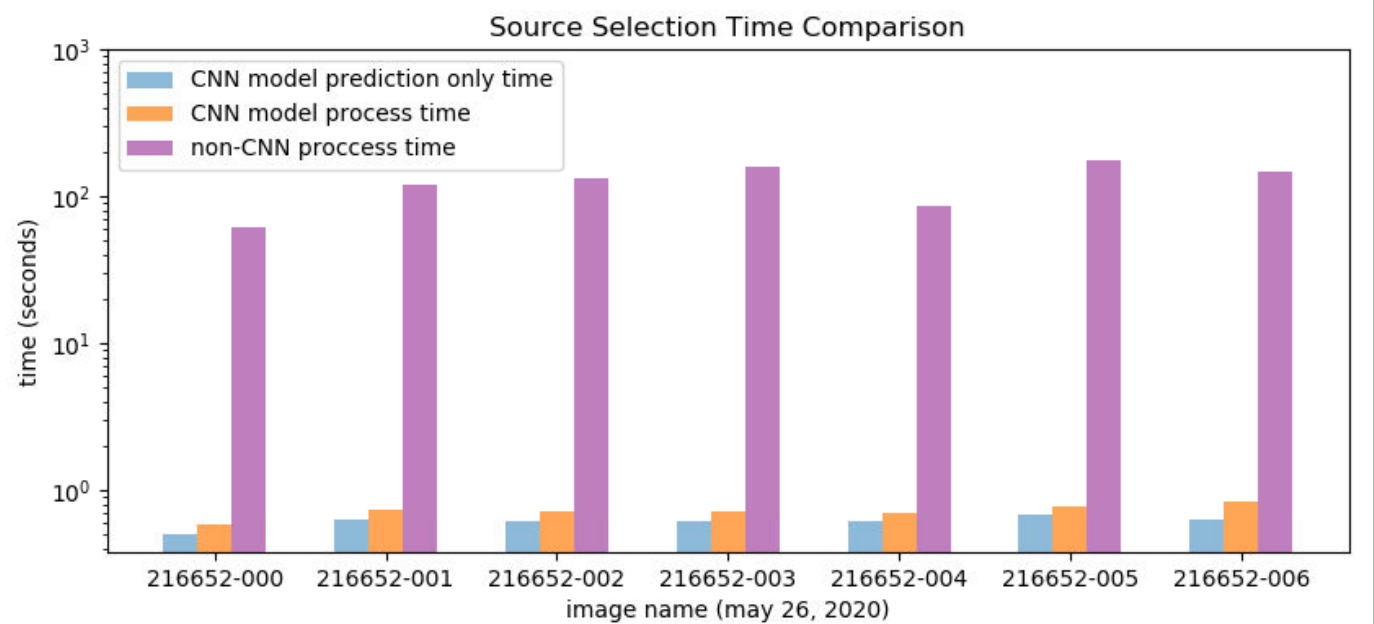
Next Steps

- **Make model public:** model to be incorporated into PSF generation software TRIPPy as option to help users with source selection. Using a platform such as OpenML to share data, model, and results with others interested in similar work.

Possible Improvements

- **Model + hyperparameters:** model architecture and hyperparameters were tweaked until acceptable performance was reached, however, a more thorough approach where all experiments are tracked with a tool such as Weights and Biases in order to find an optimal model could be worthwhile.
- **Improving labelled data:** data labels used are not perfect and so any efforts involving manual relabeling, clustering, or further investigating the accepted range of pixel values could improve results.

Future Directions

- **Apply to other telescopes:** this model should be able to work with data from other telescopes, however methods such as down/up sampling might need to be used to use 111x111 inputs.
- **Increasing scope of model:** using similar data it may be possible someday to have a model find the sources from the image directly and/or generate a PSF as the output instead of using pre-made cutouts of sources and just outputting a prediction on if they should be used for PSF generation or not.

GitHub Repository: CNN model as well as code used to develop and test it

Google Slides Examples: Z-scaled examples of good source selection and resulting PSF lookup tables

MDA Internship

While I can't show my MDA work in as much detail, I had a great time interning in the robotics and space operations division helping to improve anomaly detection and fault diagnosis AI/ML algorithms to be used on Canadarm2 and potentially Canadarm3.

References & Acknowledgements

(A) Source: Convolution Illustrated eng on Wikimedia Commons
(B) Source: Space Observatory Icon from Good Stuff No Nonesense

SExtractor to extract sources from FITS images
TRIPPy to generate PSFs
CANFAR used as compute environment