

# Pushing the Limits of Exoplanet Discovery via Direct Imaging with Deep Learning

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## Abstract

Further advances in exoplanet detection and characterisation require sampling a diverse population of extrasolar planets. One technique to detect these distant worlds is through the direct detection of their thermal emission. The so-called direct imaging technique, is suitable for observing young planets far from their star. These are very low signal-to-noise-ratio (SNR) measurements and limited ground truth hinders the use of supervised learning approaches. In this paper, we combine deep generative and discriminative models to bypass the issues arising when directly training on real data. We use a Generative Adversarial Network to obtain a suitable dataset for training Convolutional Neural Network classifiers to detect and locate planets across a wide range of SNRs. Tested on artificial data, our detectors exhibit good predictive performance and robustness across SNRs. To demonstrate the limits of the detectors, we provide maps of the precision and recall of the model per pixel of the input image. On real data, the models can re-confirm bright source detections.

## 1. Introduction

Detecting a planet via direct imaging poses a significant challenge. Despite significant efforts and technological advances made with this technique, the number of confirmed detections – only 16 exoplanets so far [1] – remains far behind those of other methods. This is usually limited by instrument-specific systematics. This systematic noise pattern is known as the ‘*speckle*

*noise*’ and is an instrument specific, quasi-static pattern of light on the detector [3]. Speckle suppression techniques are available such as using image subtraction to remove speckle noise. However, these techniques are not available for space based instrument, hence other methods must be sought.

There have been attempts to resolve the issue via machine learning approach, but most of them suffer from problems like limited ground truth and lack of positive examples (systems with confirmed planet detection).

### 1.1. Overview of the paper

In this work, we introduced an intermediate step of generative modelling between the real data and the final discriminative model. By training a *Generative Adversarial Network (GAN)* [2] on real data from the *Near Infrared Camera and Multi-Object Spectrometer (NICMOS)* on the HST, we obtain a generative model of the distribution of the most prominent component of the data: the *speckle noise pattern*, which is the main component of systematic noise in direct imaging. At this stage, any planet signals in the training data are regarded as statistical noise since their occurrence is random and usually buried within the speckle pattern. Our generative model can produce negative class examples (images without planets). We can then create an equal amount of synthetic positive examples (images with planets) by ‘injecting’ planets on images generated by the GAN.

We use this dataset to train a *Convolutional Neural Network (CNN)* to classify images as positive/negative. By doing so, we avoid the problem of using the real data directly and all the issues that come with it (class imbalance, unknown ground truth,

model’s performance being upper-bounded by current detection techniques). With the use of *Gradient-weighted Class Activation Mapping (Grad-CAM)* [4], we are able to locate injected planets within the images, as a byproduct. Finally, we turn to real data for evaluation and demonstrate that our model can identify *confirmed bright sources*<sup>1</sup> in the dataset.

## 2. Results on real data

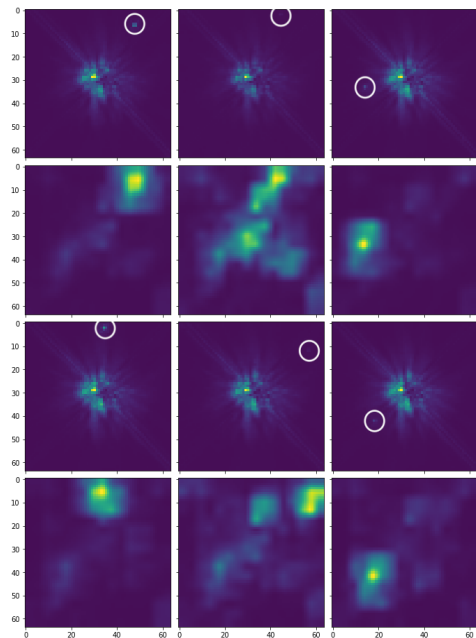


Figure 1: Original images of CQ-Tau [Left], DQ-Tau [Middle] & HD10578 [Right], each in 2 orientations [1st Row & 3rd Row]. The images contain confirmed bright sources (marked with a circle). [2nd Row & 4th Row]: CNN activation heatmaps of model trained at SNR = 0.75; We see that the model’s activation peaks on the bright sources.

<sup>1</sup>There are no confirmed planet detections on NICMOS filter F110W yet. These *bright sources* are almost certainly background stars. However, detecting these showcases the potential for any bright source –including planets– to be detected.

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