Exoplanet Detection from Starshade Images using Convolutional Neural Networks

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PROBLEM

To fully harness the potential of **direct imaging for exoplanet detection,** there is a need for **image processing algorithms** that address 3 main challenges:

1. **Efficiency & Scalability** – Data management for petabytes[1] of direct imaging data
2. **Versatility** — Design validation for diverse mission architectures, including starshades
3. **Accuracy** — Detection from low signal-to-noise images

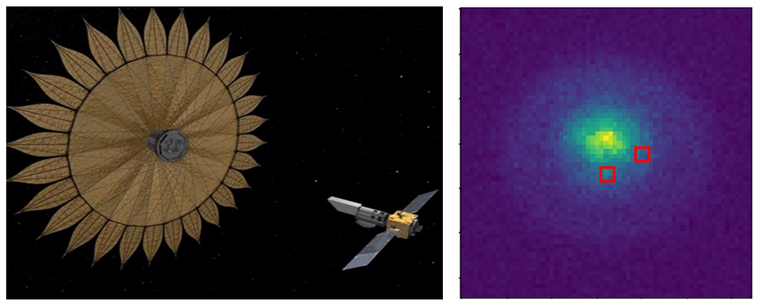

Fig. 1: (Left) Rendering of starshade-telescope system. Credit: NASA/JPL **(Right)** Synthetic starshade image with two exoplanet signals (red boxes).

CONVENTIONAL APPROACHES

Conventional image processing algorithms have primarily been **tailored to coronagraph images** and often **rely on visual inspection** to make accurate detections. Specific techniques include:

- **Spectral Differential Imaging (SDI):** An observing technique that captures sequences of images across multiple wavelengths and can be paired with post-processing algorithms
- **Independent Component Analysis (ICA):** A statistical technique for decomposing multivariate signals, which can be used to estimate and remove background noise

REFERENCES

1. Astro2020 Decadal Survey
2. Ronneberger et al. 2015
3. Lin et al. 2018
4. Hildebrandt et al. 2021
5. Wang et al. 2015
6. Hu et. al 2021
7. Dunne 2022

NEW APPROACH

Convolutional Neural Networks (CNN)

CNNs are an efficient and versatile alternative to state-of-the-art image processing algorithms but have had limited application to direct imaging due to lack of training data.

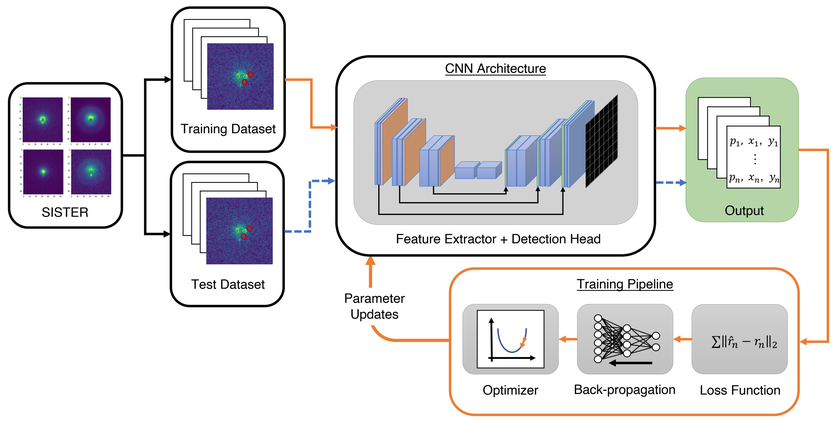

Fig. 2: CNN training (solid orange line) and inference (dashed blue line) pipelines.

Modified U-Net[2] Architecture and Training Pipeline

3 main modifications:

1. Network Depth
2. 3-channel Detection Head
3. Mean-squared error and focal loss[3]

Synthetic Starshade Dataset

The dataset was generated using the Starshade Exoplanet Simulation Toolkit for Exoplanet Reconnaissance (SISTER)[4] and consists of 1,440 broadband images.

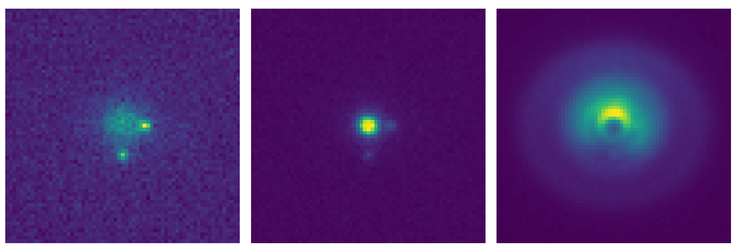

Fig. 3: Sample SISTER images with varying levels of noise.

SISTER convolves the optical response of the starshade and telescope, including perturbations, with an astrophysical scene. The optical response is modeled using the boundary diffraction wave algorithm.

RESULTS

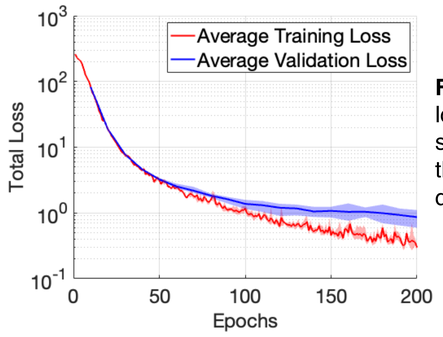

Fig. 4: Training and validation loss converged consistently and show good agreement, indicating that the model did not overfit despite limited training data.

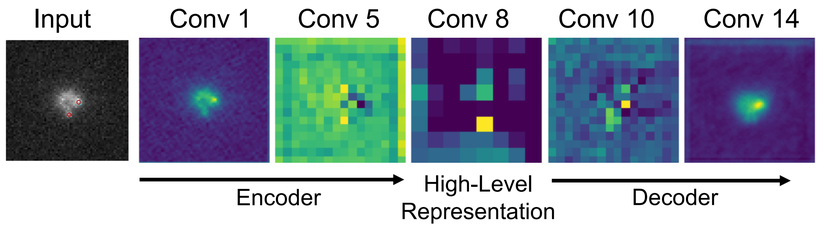

Fig. 5: Feature maps show how input is transformed through CNN.

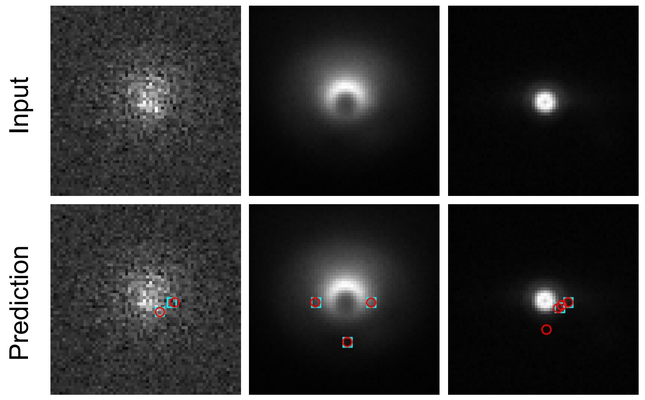

Fig 6: Sample CNN predictions (red circle) versus ground truth (blue square).

Table 1: CNN performance versus SDI[5] and ICA[6,7] pipelines.

Method	Precision	Recall	L_2 Error [px]
SDI	0.197	0.223	1.88
ICA	0.600	0.490	1.057
CNN	0.925 ± 0.012	0.923 ± 0.018	0.584 ± 0.017

CNN achieves precision and recall > 0.9 and can perform inference on single images without the need for background subtraction.

FUTURE WORK

1. Expand starshade dataset to increase robustness of CNN and improve ability to generalize.
2. Tailor CNN architecture to incorporate physics models of exoplanet signals

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