A Machine Learning Approach to Detecting Kuiper Belt Objects for NASA's New Horizons Extended Mission

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Scan for Poster

Project Goals

- Use ground-based deep observations to discover new Kuiper Belt Objects bright enough for observation with the LORRI telescope (r_{Earth}~26, V_{LORRI}~21).
- To characterize the phase curves and high-phase light curves of discovered targets
- To search for any potential new flyby targets

The Kuiper Belt

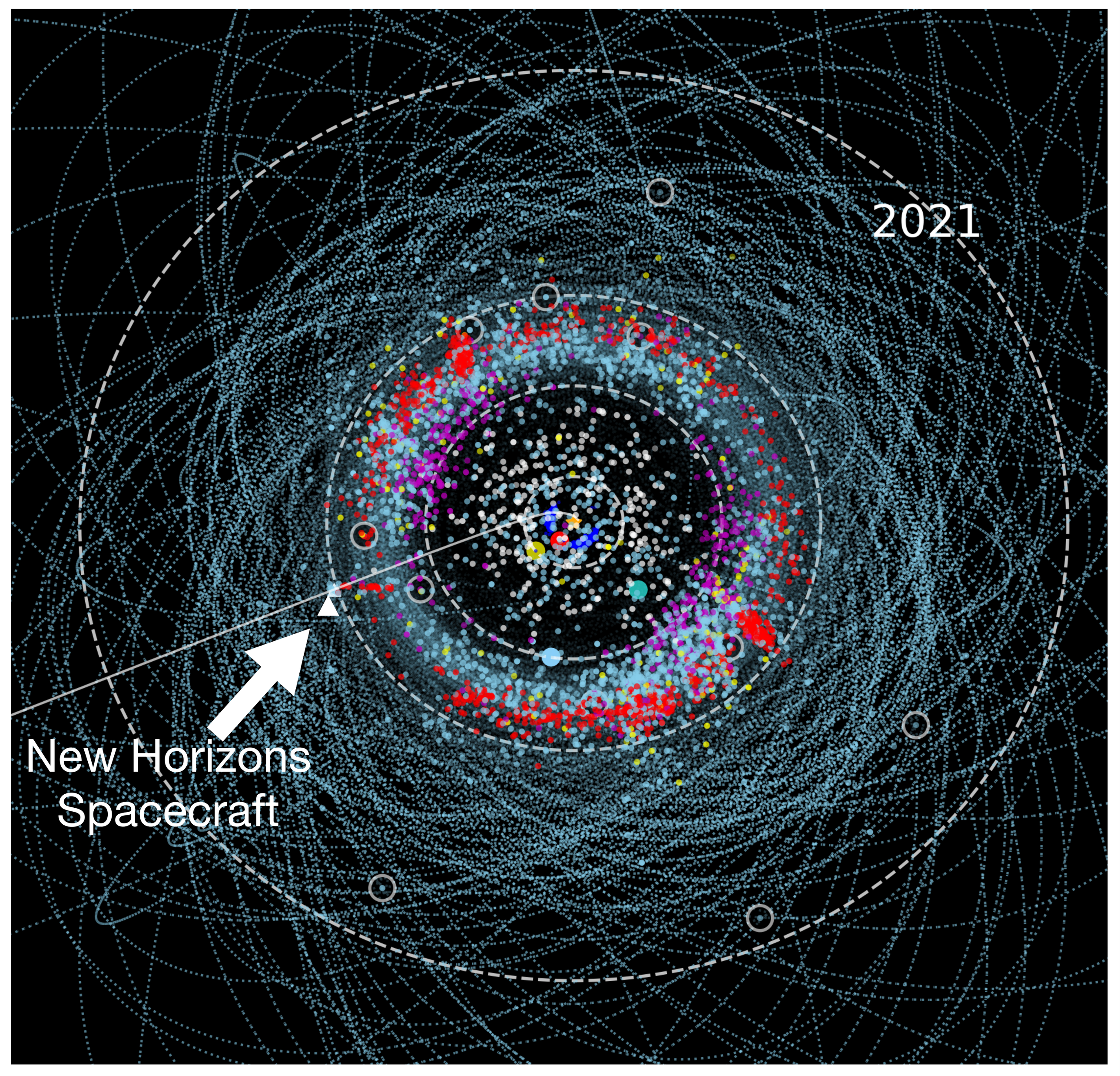

Figure 1: The Kuiper Belt. Points are known objects, colour coded by dynamical class. The white triangle marks the current position of the New Horizons Spacecraft. Program targets are scattered (blue) and cold classical (red) objects.

Convolutional Neural Networks

The main component of a *neuron* in a convolutional network is the filter. Filters, or convolution kernels, have parameters that are learned through training so as to pickout features of the input images that help lead to accurate classification, eg., a cat or dog, a galaxy or Kuiper Belt Object.

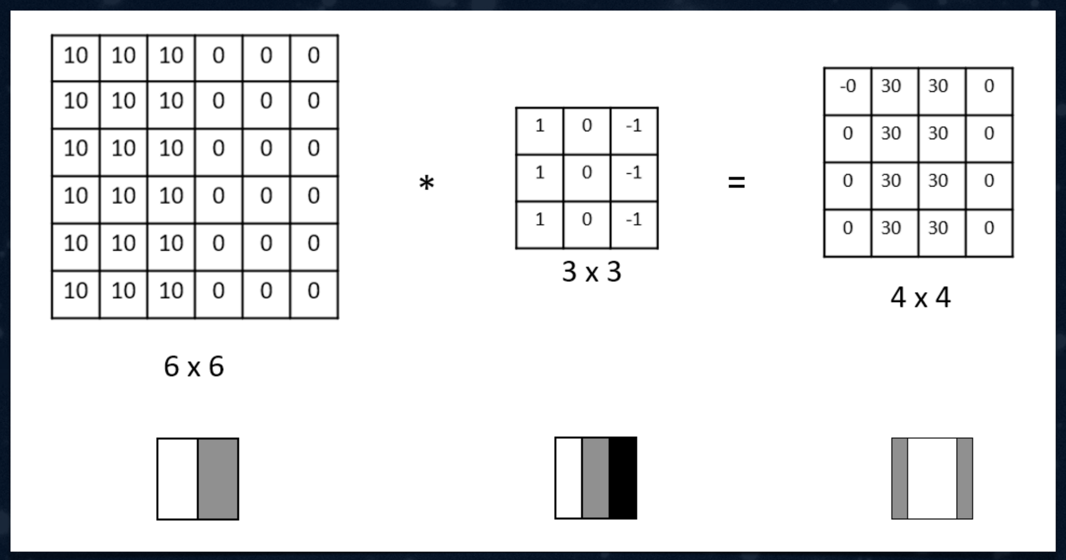

Figure 4: Convolutional filter example. The 3x3 filter (the kernel) is an example of a vertical edge detector, which when convolved with the left image, highlights the location of the sharp edge in that image (see Figure 5)[1].

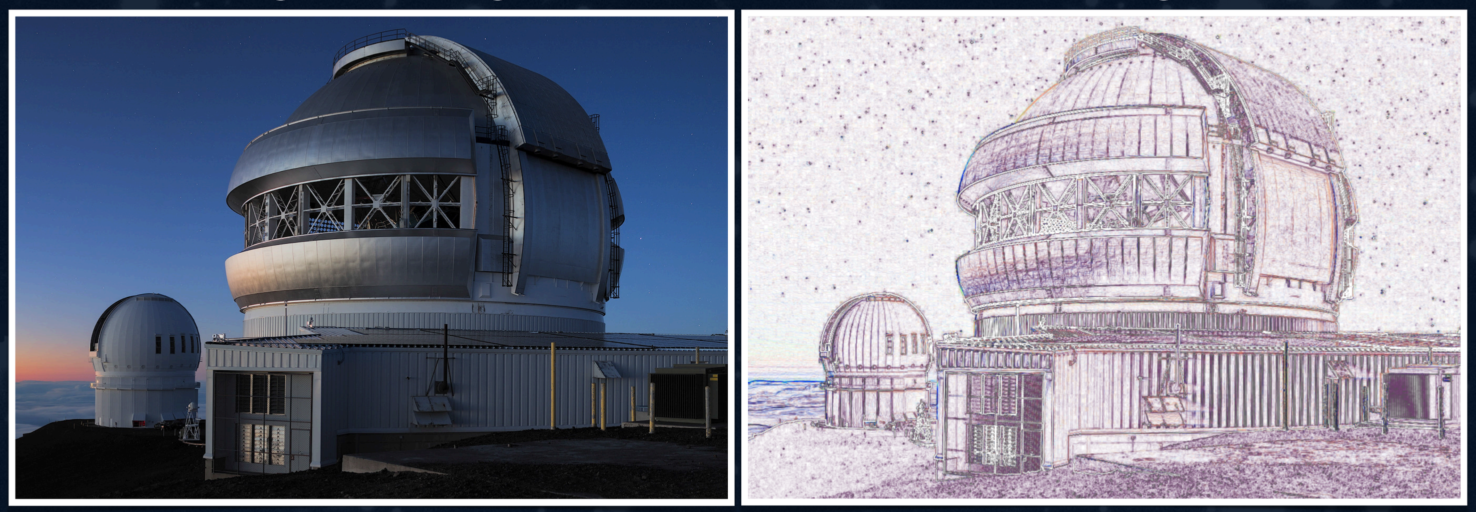

Figure 5: Example of an edge filter applied to the original image of the Canada-France-Hawaii and Gemini-North Telescopes.

In our adopted network architecture, each convolutional layer consists of a layer of neurons (each with its own learned filter), followed by a pooling layer which bins the convolved images by replacing each 2x2 region with that region's maximum value. After 3 convolutional layers, a flattened version of the image outputs is fed to a pair of fully connected layers where the probabilities of positive and negative source classification are determined.

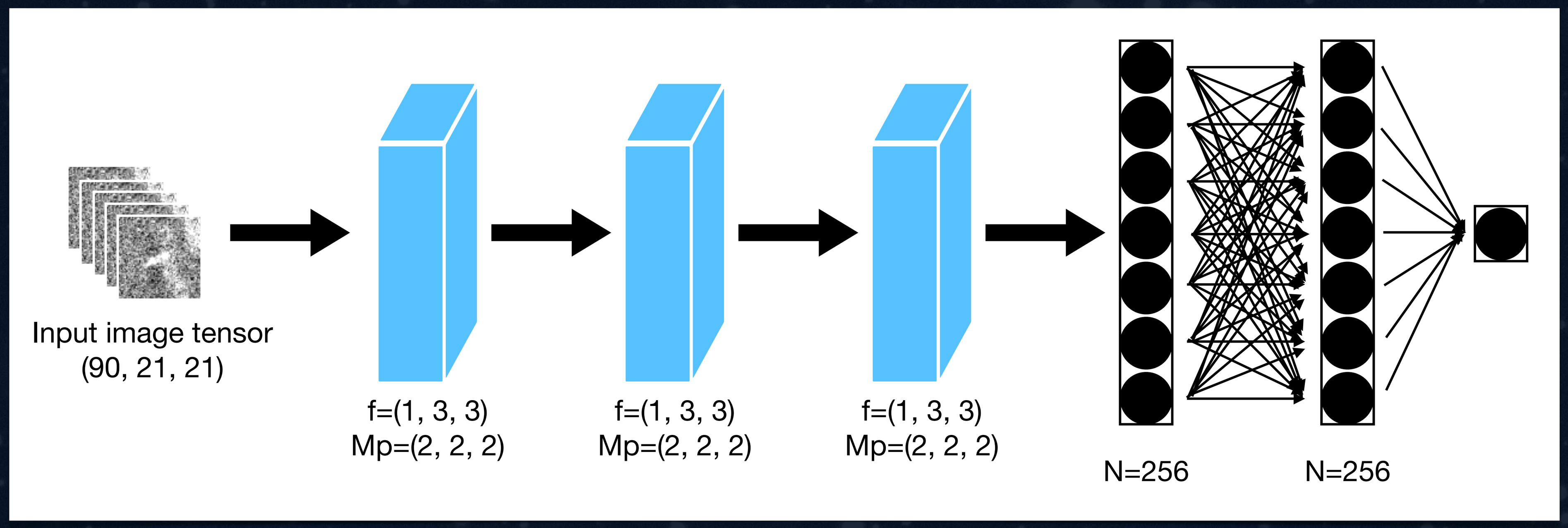

Figure 6: Diagram of our convolutional neural network structure. Structures like shown here are typically quite successful in simple binary classification[2].

Network Details:

- filters of size (1, 3, 3)
- 3 convolutional layers: 16, 16, and 8 neurons
- max pooling
- zero padding
- input data are the shift'n'stack images (see panel below)

Observations from New Horizons

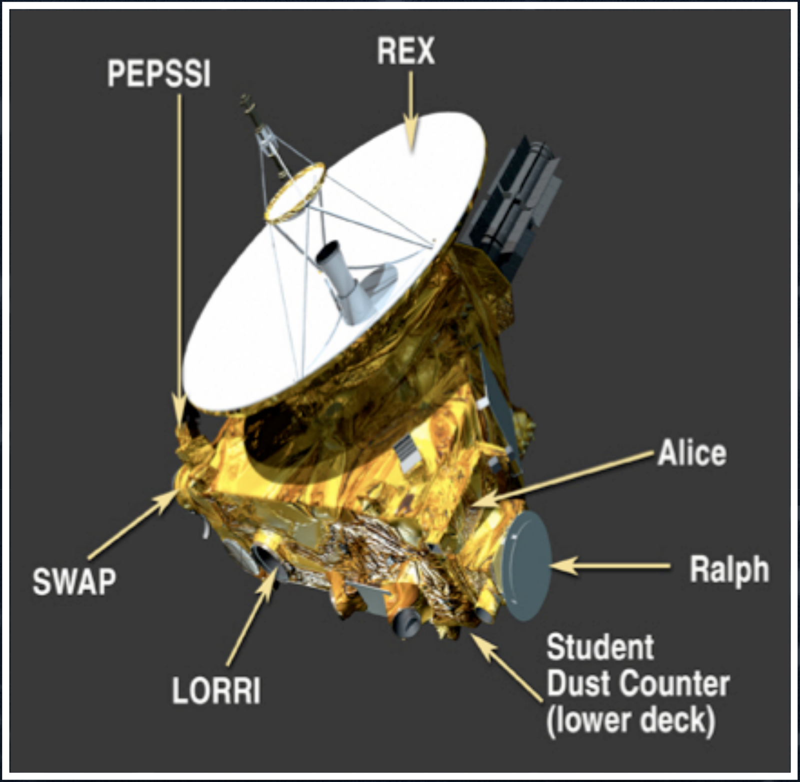

Figure 2: The New Horizons spacecraft, equipped with the Long Range Reconnaissance Imager (LORRI). The location of the spacecraft within the Kuiper Belt enables direct imaging of nearby objects at phase angles impossible from the Earth (see Figure 3). Depending on the proximity to the target, some LORRI observations have resolutions that surpass that of the Hubble Space Telescope.

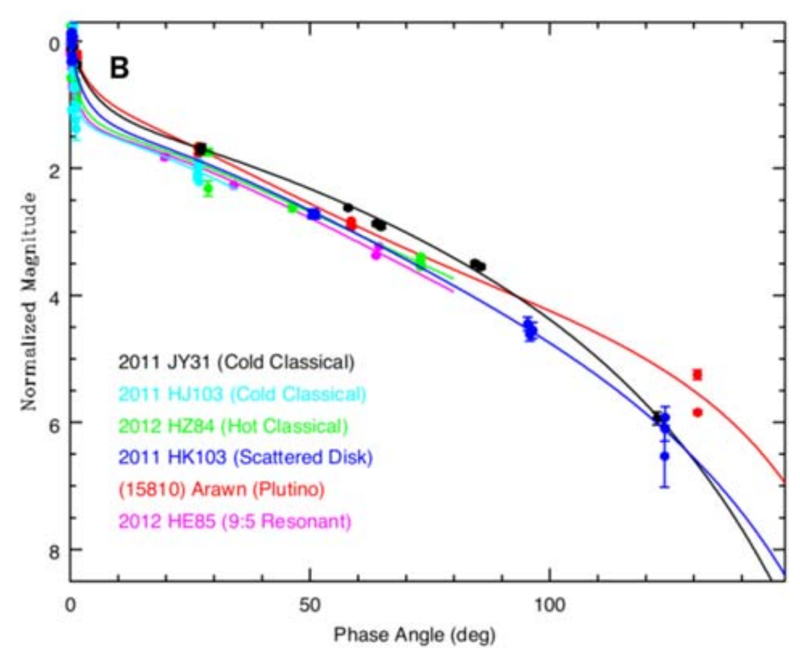

Figure 3: Phase curves of Kuiper Belt Objects observed by LORRI (Verbiscer et al. 2019). Phase curves provide detail on microscopic (pores, dust) and macroscopic (craters, mountains) surface properties. New Horizons-LORRI provides coverage for phase angles >2° which is unachievable from Earth-based observatories.

Image and Training Data

Observations were acquired at 16 epochs from May to Aug. 2020 with Hyper Suprime-Cam on the Subaru telescope. A sequence of ~100 90s images was acquired at each epoch.

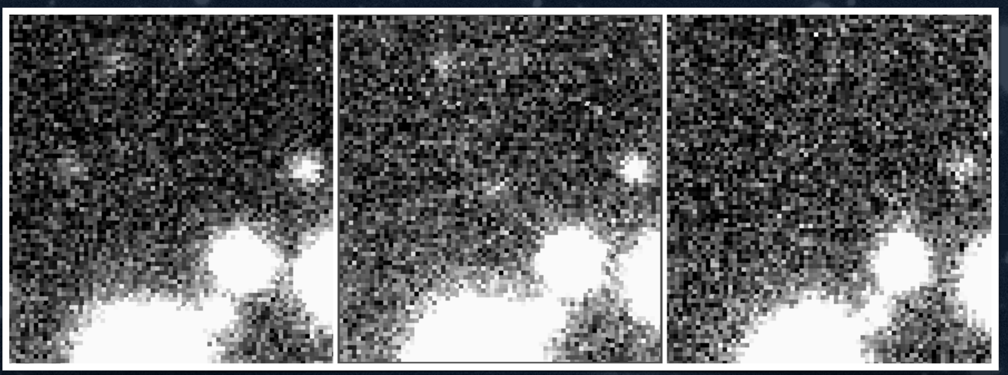

Figure 7: Example discovery image cutouts. Can you spot the moving object?

Image calibration, preprocessing, and image subtraction was performed with the LSST pipeline. Artificial source injection was performed with TRIPPy (Fraser et al. 2016). Images were shifted and stacked at rates of motion consistent with Kuiper Belt Object motions and provide input for the search network.

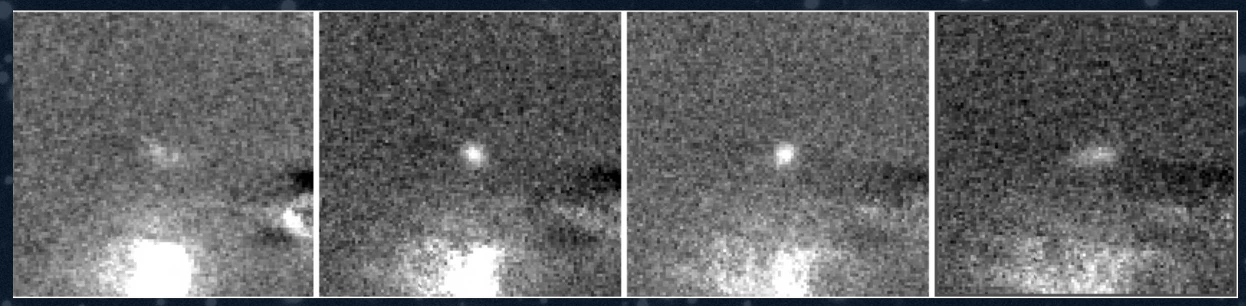

Figure 8: Four separate shift stacks of the source shown in Figure 7.

The Search Results

The network provides a >3 order of magnitude reduction in false positives and the discovery of more than 100 new objects. Visual vetting of ~3,000 sources per epoch was still required. The detection efficiency is excellent considering that the discovery imagery is near the galactic plane (see background image).

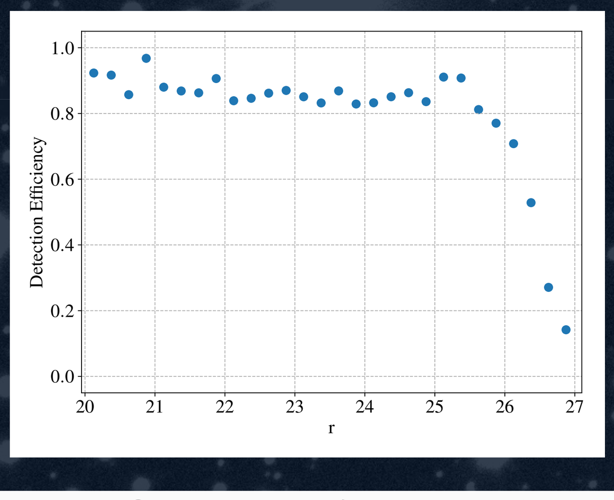

Figure 9: The detection efficiency of one example June 2020 observation run. For reference, the approximate detection limit in blank sky is r~27.

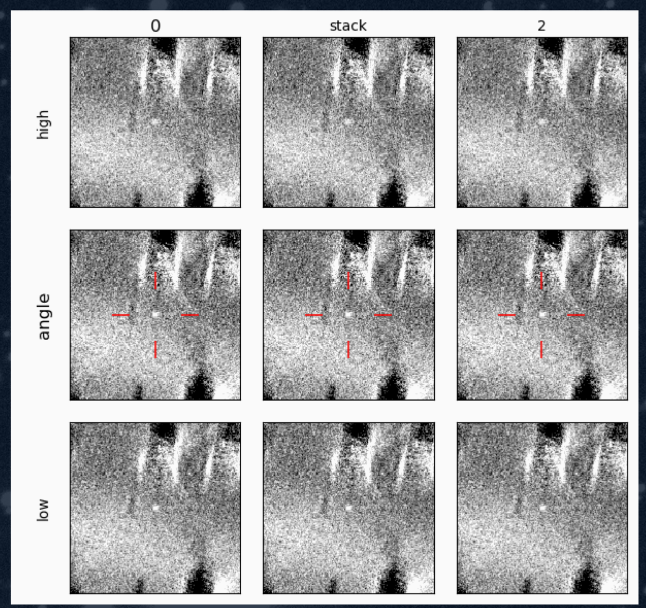

Figure 10: An example of a newly discovered real object. The grid shows interleaved stacks (left to right) for three angles of motion (top to bottom).

References: TRIPPy - Fraser et al. 2016, AJ, 151, 158 • Verbiscer et al. 2019, AJ,158,123 • LSST Science Pipeline https://pipelines.lsst.io • NH-LORRI - Cheng et al. 2008, SSR, 140, 189.

1 - https://steemit.com/javascript/@petarjs/ 2 - https://towardsdatascience.com