A Successful Machine Learning Approach to Detecting Kuiper Belt Objects for NASA's New Horizons Extended Mission. W. C. Fraser[1], S. B. Porter[2], H.-W. Lin[3], J. R. Spencer[2], JJ. Kavelaars[1], A. J. Verbiscer[4], F. Yoshida[5], T. Ito[6], K. Napier[3], D. Gerdes[3], S. D. Benecchi[7], S. A. Stern[2], S. Gwyn[1], H. A. Weaver[8], M. W. Buie[2], L. Peltier[9], K. N. Singer[2], the New Horizons LORRI and GGI Science Teams. [1]Herzberg Astronomy and Astrophysics Research Centre, wesley.fraser@nrc-cnrc.gc.ca, [2]Southwest Research Institute, [3]University of Michigan, [4]University of Virginia, [5]University of Occupational and Environmental Health, [6]National Astronomical Observatory of Japan, [7]Planetary Science Institute, [8]Johns Hopkins Applied Physics Laboratory, [9]Lowell Peltier.

The detection of moving sources in astronomical data is the backbone of many planetary astronomy projects. To date, this task has relied heavily on costly visual vetting to confirm moving sources amongst the much more numerous stationary sources. This is especially true of surveys which search stacks of sequential images that have been shifted at rates of motion relevant to the bodies of interest. When the shift rate matches that of a moving source, a point source is revealed (see Figure 1). Such a process provides a search depth that is comparable to the point-source depth that would be had from a single, sidereal stack. As sources are not visible in individual frames, the so-called shift'n'stack technique comes at the cost of not being able to link detections as a source moves through the frames. This has the effect of maximizing human search cost, even after applying modern processing techniques such as image subtraction to remove most of the stationary chaff. Here we present a new machine learning (ML) technique to identify high probability candidate moving sources, geared specifically for shift'n'stack data. We make use of a multi-layer 3D-convolutional neural network (see Figure 2) to perform the binary classification task: good or not good? Our network is trained on artificial sources that have been injected into the imagery before image subtraction, themselves trailed with rates of motion matching the objects of interest. We have applied this network to searching for Kuiper Belt Objects in data from the Hyper Suprime-cam on the Subaru telescope that were acquired as part of a search for targets for NASA's New Horizons Extended Mission. The classification performance of the network for real detections has been extremely good, resulting in a reduction of candidate sources by more than three orders of magnitude. An entire night's worth of search data requires only a few hours of human vetting. We report a detection efficiency of 70% or better for r<25.5, with a limiting magnitude of r~26.6 depending on the night, despite the fact that these data have been acquired at a galactic latitude of ~10 degrees. The ML-based search resulted in twice as many KBOs when compared to a human search of the same 2020 data. Our results show a promising new avenue for moving object detection that has the potential to greatly increase the depth of upcoming large surveys such as the Vera Rubin Observatory Legacy Survey of Space and Time, without massively increasing the human cost.

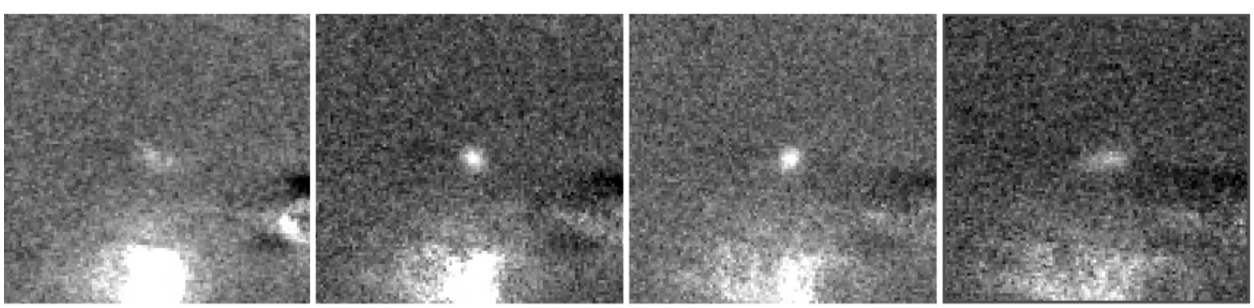

Figure 1: Example of shift'n'stack imagery for a real moving object detected through our pipeline. From left to right, the rates of motion are 1.5"/hr to 3.0"/hr in increments of 0.5"/hr. At this epoch, the target is moving at 2.4"/hr, corresponding to a distance of ~45 AU.

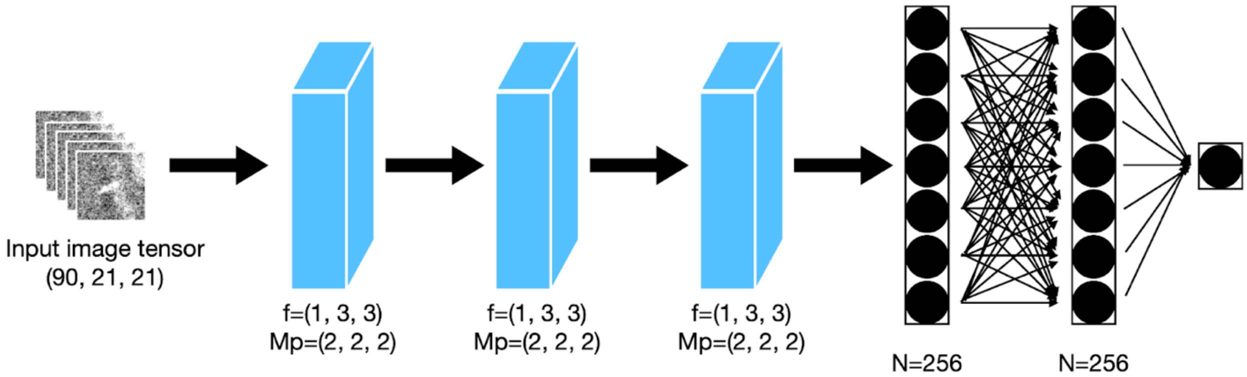

Figure 2: The convolutional neural network adopted for this project. Three convolutional layers utilizing 16, 16, and 8 filters, are represented in blue. Filter sizes are shown. Each layer also uses max. pooling, with filters shown. The outputs of the third convolutional layer are passed to two fully connected linear layers, that finally feed to a 2 unit softmax layer, which is responsible for outputting the binary classifications for each candidate source.