

# Implementing a convolutional neural network in the DESGW pipeline

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## Background

Many gravitational wave (GW) sources are expected to emit an electromagnetic counterpart. The detection of both kinds of signals helps us understand more about these sources and gives us a measurement of the rate of expansion of the universe<sup>1</sup>. The Dark Energy Survey Gravitational Waves (DESGW) group at Fermilab uses observations from the Dark Energy Camera (DECam), mounted on a telescope at the Cerro Tololo Inter-American Observatory, to detect such electromagnetic follow-ups and to analyze them using a data processing pipeline<sup>2</sup>.

## The DESGW pipeline

To identify electromagnetic signals that are likely candidates to belong to the GW source, DECam takes observations from a region of the sky in which the source has been detected. These observations are calibrated and corrected for aberrations by the DESGW pipeline in the “Processing” stage<sup>3,4</sup>.

They then enter “Post-Processing”, in which all candidates are matched to potential host galaxies. The data from each candidate and host is written in data files and in web pages for further inspection.

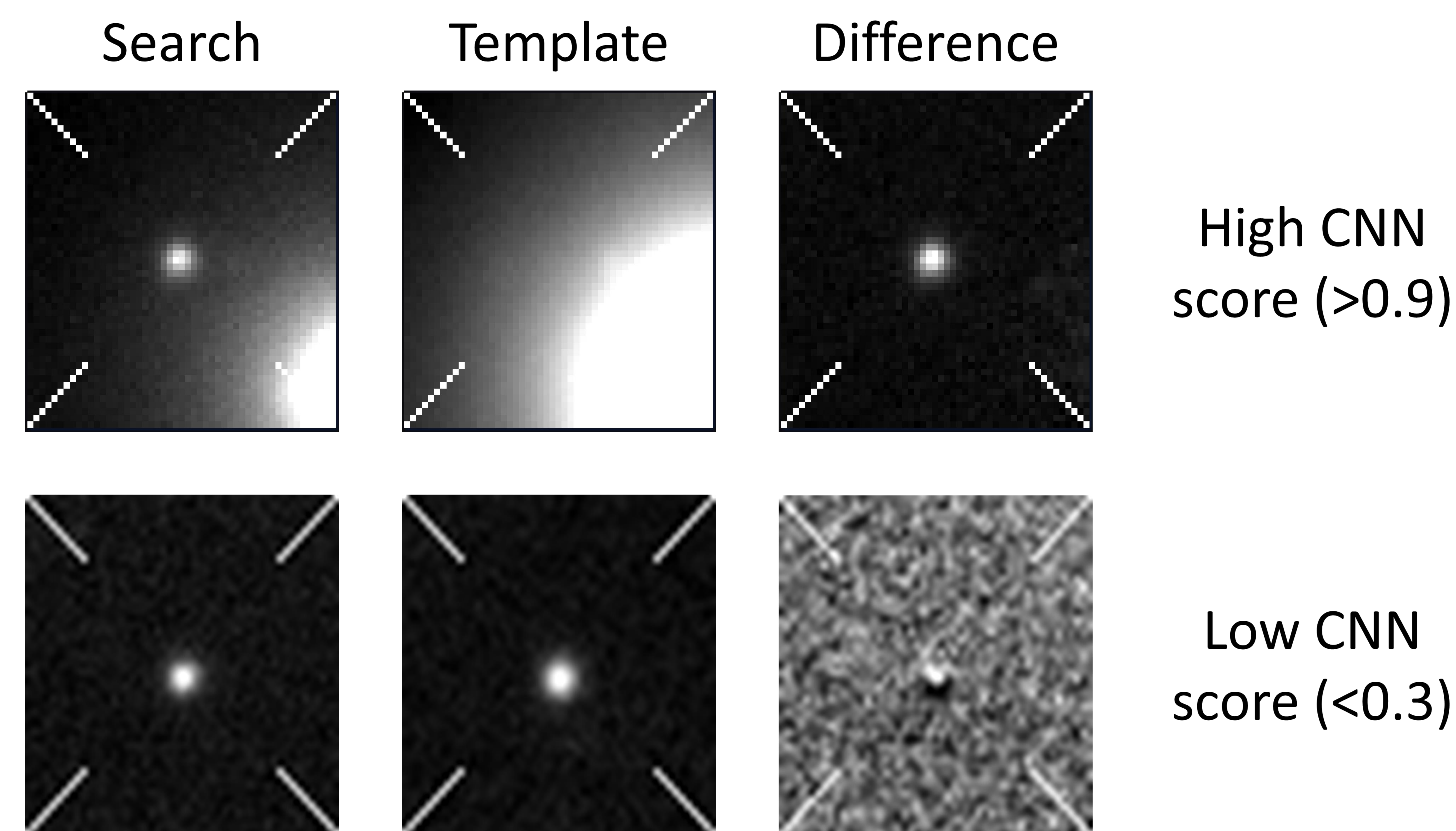
A significant limitation of this pipeline is that the final list of candidates still needs to be visually examined to reject artifacts and moving objects.<sup>4</sup> Common artifacts are “bad subtractions”, which are misalignments between the observations (search images) and images of the same region taken before the detection (template images).<sup>5</sup>

## Objectives

In this project, I incorporate a convolutional neural network (CNN) to the DESGW pipeline to decrease the amount of human inspection needed in the analysis of the candidates. I also update a section of the pipeline to a state in which it is prepared to take data from DECam upon detection.

## Convolutional Neural Network

The convolutional neural network, developed through machine learning by Shandonay et al.<sup>5</sup>, takes cutouts, or “stamps”, from the search and template images from a given candidate, as well as the difference between the two. It then evaluates their quality in terms of the presence of a bad subtraction and assigns a score from 0 to 1, where a higher score indicates a higher-quality observation. Observations with scores lower than 0.7 are rejected.<sup>5</sup> Given that the CNN evaluates a set of stamps in under one second, it provides for a faster examination of candidates compared to visual inspection.

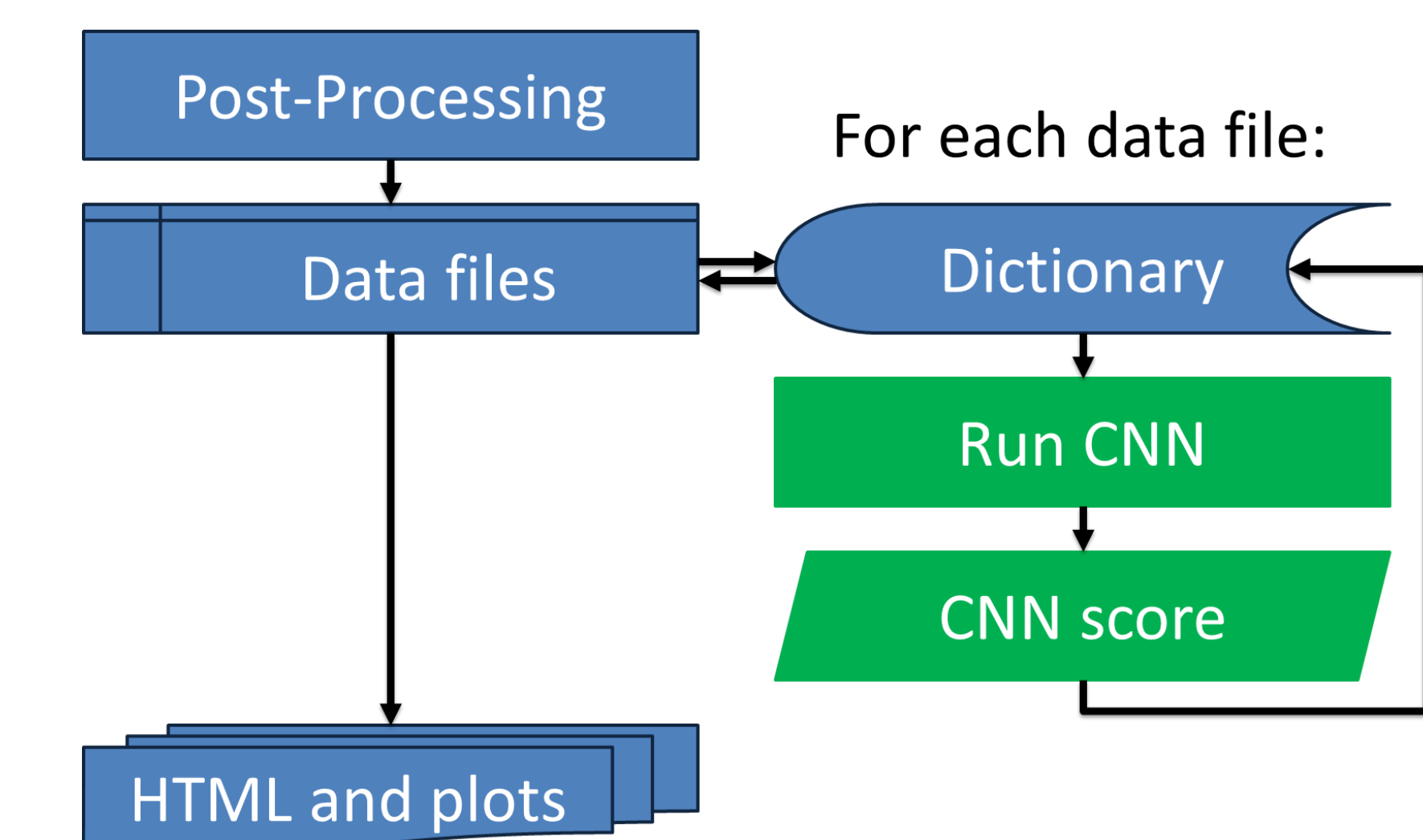


Two sets of stamps from GW170817. The top panel shows a transient object and its host, with a clear difference image. The lower panel shows a bad subtraction, in which the difference image has a dipole like-structure (white and black dots).

## Implementing the CNN

In order to incorporate the CNN into Post-Processing, I updated it from Python 2 to Python 3. Most of the modifications consisted in altering syntax and in checking for incompatible or deprecated commands. I tested the pipeline on different sets of observation exposures to ensure its functioning.

I then added the CNN code into one of the functions called by Post-Processing. Here, data about the observation is read from a data file and written into a Python dictionary. The CNN function takes this data to yield the score, which is added to the dictionary and appended to the data file.



Flowchart of relevant processes in Post-Processing. The blue symbols represent the original functioning of the pipeline, while the green symbols are the additions incorporated to the CNN.

## Results

- Updating Post-Processing to Python 3 ensures its compatibility with applications developed in this newer version.
- I tested the pipeline with data from GW170817 to compare the results of host galaxy matching with a known source. Despite issues with the output, the pipeline replicated the matching of the signal with elliptical galaxy NGC 4993.<sup>2</sup>
- Ongoing testing on data from GW signal S190814 shows that taking the stamps of a final list of candidates and running the CNN takes about ten seconds per candidate, resulting in a run time of only over one hour.

## References

- <sup>1</sup>Soares-Santos, M., Holz, D. E., Annis, J., et al. (2017). “The Electromagnetic Counterpart of the Binary Neutron Star Merger LIGO/Virgo GW170817. I. Discovery of the Optical Counterpart Using the Dark Energy Camera.” The Astrophysical Journal Letters, 848, L16, doi:10.3847/2041-8213/aa9059
- <sup>2</sup>Herner, K., Annis, J., Brout, D., et al. (2020). “Optical follow-up of gravitational wave triggers with DECam during the first two LIGO/VIRGO observing run.” Astronomy and Computing, 33, 1000425, doi:10.1016/j.ascom.2020.100425
- <sup>3</sup>Herner, K., Annis, J., Garcia, A., et al. (2020). “The updated DESGW processing pipeline for the third LIGO/VIRGO observing run.” EPJ Web of Conferences 245, 01008, doi:10.1051/epjconf/202024501008
- <sup>4</sup>Morgan, R., Soares-Santos, M., Annis, J., et al. (2020). “Constraints on the Physical Properties of GW190814 through Simulations Based on DECam Follow-up Observations by the Dark Energy Survey.” The Astrophysical Journal, 901:83, doi:10.3847/1538-4357/abafaa
- <sup>5</sup>Shandonay, A. Morgan, R., Bechtol, K., et al. (2021). “Expediting DECam Multimessenger Counterpart Searches with Convolutional Neural Networks.” Dark Energy Survey. Fermi National Accelerator Laboratory. arXiv:2106.11315