Systematic Investigation

This project continued from the previous period with its principal objective of detecting and geolocating transformers (with 75% accuracy) from street level images, but with the added objective of also detecting pedestals. As the input data set images are large, efficient processing is a second project objective. Within the input images there is a wide variety of similarly sized features (e.g., streetlights), diverse lighting conditions and partial occlusions which could affect identification accuracy.

In the first efforts, we moved our technology base forward with TensorFlow v2, a new deep learning model (EfficientDet-4 with Efficient-Net backbone) using pretrained COCO (Common Objects in Context) dataset training. In the first tests we observed the COCO model failed to concurrently detect both pedestals and fire transformers – necessitating a reduction in the inter-class difference between different transformers and pedestals. We then hypothesized that employing transfer learning (TL) for model training could reduce the learning time and sample space size and enable faster convergence. Additionally, we established the need to employ a detection rate evaluation metric to track the number of objects the model missed. We next applied predefined functions to measure the precision of the base processing pipeline, but it failed to provide the predicted multidimensional outputs. We next hypothesized that a custom testing pipeline where precision and detection rate are calculated (through a set of optimized equations performing towards the expected output) under a defined probability could provide the metric we required. In the first trial, we observed that due to the diversity of objects’ size, the model struggled to converge. To tackle this problem, we sorted objects based on their sizes and object smaller than a threshold are discarded – knowing the same feature will be subsequently identified when it better fills the field-of-view (FOV). This trial resulted in 50% precision and detection rate.

In this trial of prototype testing, we also observed issues associated to the fairness of comparison. Differences in processing architectures (configuration and backbone) renders inter-architecture comparisons inherently challenging. To resolve this challenge, we hypothesized that defining the metrics on which the comparison relies, should remain unrelated to the outputs’ comparison.