Truck Detection Using Deep Learning

Ben Ruelas, Hy Dang, Minh Nguyen, Trang Dao, Dorian Dhamo

Client: Greg Adams from Fort Capital, Advisor: Bingyang Wei

Department of Computer Science, Texas Christian University, Fort Worth, TX

Abstract

Identifying new and cutting-edge investment strategies is a crucial step in establishing any large business within its relative industry. Fort Capital, whose primary investment focus is on industrial-grade buildings, is taking an innovative and insightful approach to geographic understanding. Fort Capital aims to identify trade routes used by major market players, such as Amazon and Walmart, to find the areas where industrial warehouses and large-scale distribution centers are in highest demand. To locate such trade routes, identifying the main travelers on these routes is essential, and Truck Detective aims to do exactly that. Using machine learning and artificial intelligence models such as a deep neural network, Truck Detective enables Fort Capital to detect, with high accuracy, the location of big rig trucks, and can additionally help identify where they came from or where they are heading. This, in turn, illuminates geographically important areas with promising investment opportunities for Fort Capital.

Dataset

In this project, we have developed an python program to gather satellite images using Mapbox API, which allows us to use URL requests to get images back. Using this python program, we can achieve a raw dataset of satellite images from any location. Since our client only asked us for the truck detection of the DFW area, we have been using this program to generate dataset for this particular area. The dataset contains around ten thousand and 5 hundred raw (unlabeled) images. We have been using Pixel Annotation Tool to hand labeled those images. The labeling is a very time consuming process, but we have developed a tool to help us atomized the labeling process. The labeled images then be stored with its masks in the predicted directory.

Deep Learning Model: Mask R-CNN from Detectron2

Detectron2: is Facebook AI Research's next generation software system that implements state-of-the-art object detection algorithms

Mask R-CNN: Mask R-CNN is a state of the art model for instance segmentation, developed on top of Faster R-CNN. Faster R-CNN is a region-based convolutional neural networks, that returns bounding boxes for each object and its class label with a confidence score.

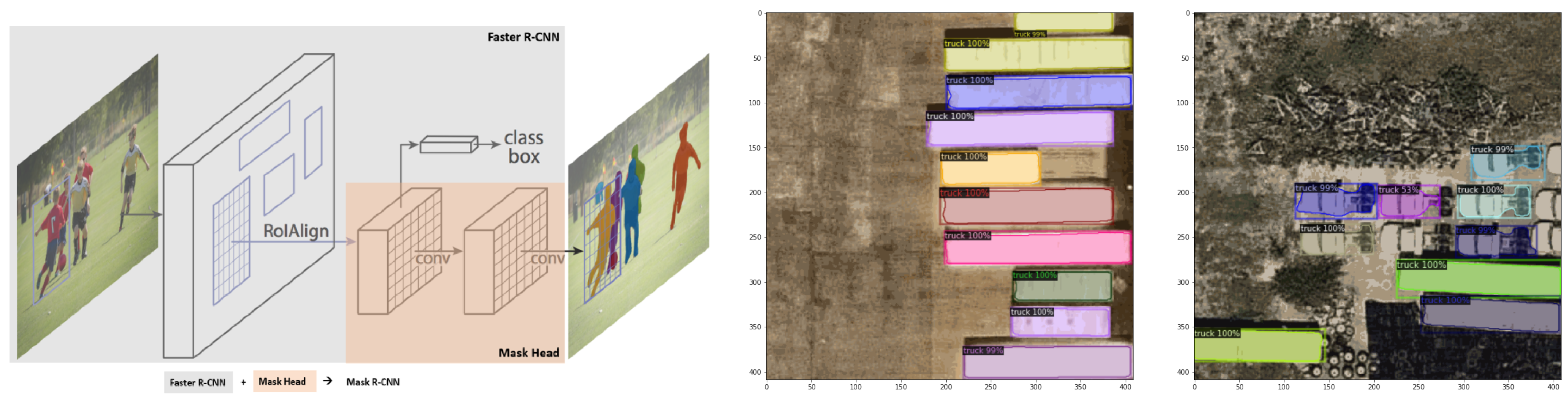

Figure 1: On the left, a visual explanation of Mask R-CNN, The two images to the right is the model applied to satellite images with trucks in them.

Prediction Result

We compare the accuracy and the loss between U-Net, Mask R-CNN and Detectron 2 in our early days, leading to the result that even though U-Net was a good starting point, we needed to move to something more reliable. Mask R-CNN, allowed us to have the results that we wanted. At the end were able to populate the Mapbox API with our data (Picture on the bottom right) and achieve the results shown below.

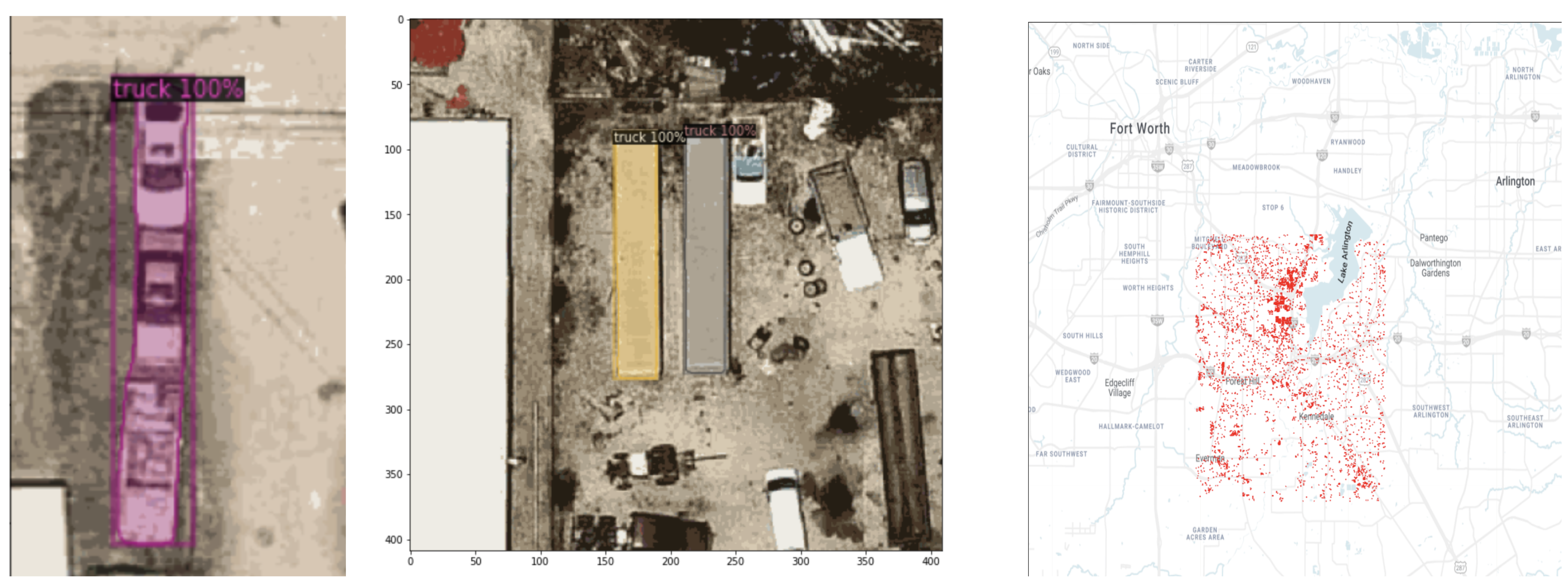

Figure 2: On the left we have our initial results. In the middle is the trained model and the Picture on the right is our end result.

Project Evolution

This project began with a simpler model, called U-NET. The u-net is convolutional network architecture for fast and precise segmentation of images. U-NET is a segmentation model that uses image masks to identify shapes and specific objects. U-NET is used for many types of segmentation predictions, for example, like wound identification in biomedical fields.The only downside to U-NET was that while we could identify when a truck was in a certain image, we were unable to count how many trucks were found, and could not guarantee with any level of certainty whether the object detected was or was not a truck. After building our U-NET model with great accuracy we began to explore other options to better refine this project and its prediction accuracy. This led us to find Mask R-CNN, a much faster and more accurate model which gives us the ability to use confidence levels and various other metrics of certainty in our predictions.

Conclusions

- We have successfully implemented Deep Learning models for the truck segmentation problem.
- We believe that **Mask-RCNN** is a promising model for this problem.
- By analyzing the heatmap results generated from Deep Learning model and kepler.gl, we could tackle the problem of Fort Capital for this problem.

However, due to the limitation of the storage, we couldn't work with all the DFW area. Our approach for this problem is dividing the map into small batches and delete the processed results when the storage is full.