DATS 6203 Machine Learning II – Final Project

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Using Computer Vision Methods to Predict Building Density Measurements Using Geospatial Image Classification

1. Introduction

When considering options for a topic to study for the final project of this Deep Learning class, geospatial imaging systems was an area of both mutual experience and interests of all group members. Wanting to look at something a bit outside of the box, we decided to study the ability of deep learning algorithms to accurately measure building density in geospatial images and classify those images by that metric. We knew that we wanted to limit the geographic area that we used for our project so that we knew that most of the images we used would either contain some type of structure or forested area. We chose Maryland, Virginia, and the District of Columbia (Fig. 1) because of the abundance of buildings in those areas but also because we didn't want to imbalance the training/testing data with huge forested areas and no buildings (as if our split randomly selected Alaska for training and the New York City metro area for testing for example). After narrowing the scope of our project, we were able to proceed to select which Deep Learning methods would be used to accomplish our research.

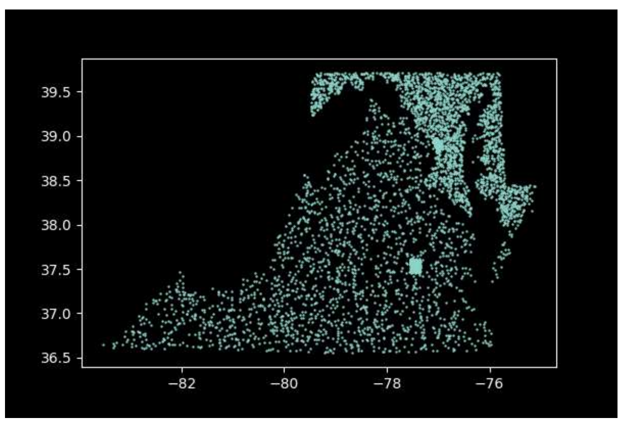

Figure 1

2. Experimental Setup

Satellite imagery was sourced, and pre-processing applied so that the images name included a percentage of building coverage contained within. When we limited the scope of the geographic images to be trained/tested we introduced the need to generate additional data as the scope of these three states was not enough to train a good image classifier. The images were then rotated and flipped multiple ways to provide enough data (50,000 + images) to train the algorithms (Fig. 2).

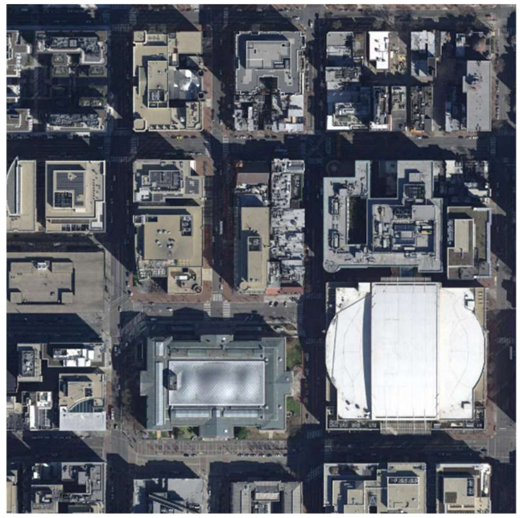

Figure 2 – Example Urban Image

In the selection of and training of the models, we knew that we wanted to try multiple different algorithms to classify our images. The first model chosen was the Multi-Layer Perceptron network since it has the ability to classify and was introduced in the class. This network contained multiple layers that could be looped through as much as necessary by tweaking the parameters in the code. We also chose to train a Convolutional Neural Network given how well it can analyze images and also was covered during the semester. Both models were built in Keras and use Mean Square Error to measure performance. The CNN contained five layers with Relu transfer functions and a sixth layer that contained a sigmoid function to allow for classification. Both algorithms utilized batch normalization to contain learning within given layers and introduced dropout to aviod overfitting.

3. Results

As expected, the Convolutional Neural Network performed better than the Multi-Layer Perceptron with Mean Squared Error used as a Performance Index. The Multi-Layer Perceptron and was able to successfully classify geospatial images in our test set with a Mean Square Error of 0.00272 (Fig. 3). The Convolutional Neural Network that was able to achieve a Mean Square Error of 0.00147 (Fig. 4). MSE was chosen as the validation metric because we are looking at predicting the building density of images can be viewed as a classification problem. I would also consider the CNN's improved performance to how much more effective CNN's tend to be as opposed to MLP when it comes to reading, recognizing, and analyzing image data.

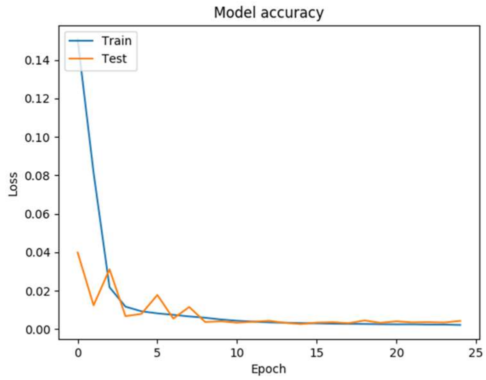

Figure 3 – MLP

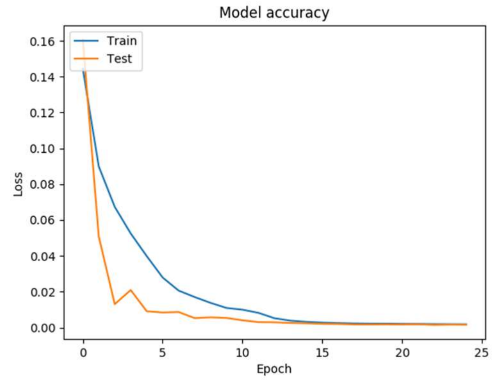

Figure 4 – CNN

Our results can be tested and explored in a web app found here: http://dats6203.azurewebsites.net/ . Given longitudinal and latitudinal coordinates, this application uses our CNN to classify what type of area those coordinates represent.

4. Summary & Conclusion

In the end, we were satisfied with what we were able to accomplish after starting from with no data to finding the data set and being able to manipulate it into a usable data source. The Convolutional Neural Network proved to be a reliable predictor of building density in a given geospatial image. Some improvements that could be added in further studies would be adding more layers to the CNN to try to minimize loss even more as well as adding in some different transfer functions. Another approach that could be considered would be to pre-process the images by classifying the pixels in the image themselves as either building, forest, etc… based off of their coloring.

References

1. (2019, September 16). Retrieved November 6, 2019, from https://github.com/microsoft/USBuildingFootprints.
2. SN5: Automated Road Network Extraction and Route Travel Time Estimation from Satellite Imagery. (n.d.). Retrieved November 11, 2019, from https://spacenet.ai/sn5-challenge/ .