SATELLITE IMAGERY SEGMENTATION OF THE CHESAPEAKE BAY WATERSHED
LIFE SCIENCES

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ABSTRACT

This project attempts to use deep learning to extract meaningful data from sets of satellite imagery regarding the potential sources of pollution around the Chesapeake Bay and other similar water-bodies, with the specific goal of identifying farmland located near water that leads to the Bay. Through deep learning, we hope to aid in identifying and eliminating pollution hot-spots in the Chesapeake Bay.

1 Introduction

Pollution is a problem that affects everyone on the planet, and its consequences can be seen in many different parts of life. Humans have severely disrupted the natural balance of nutrients entering the Chesapeake Bay. Since the industrial revolution, a population boom in the Bay's watershed has caused a sharp rise in nutrient pollution. The dramatic increase in nutrients flowing into the Bay has overburdened the Chesapeake's waters. Excessive amounts of nitrogen and phosphorus cause algae overgrowth, which in turn blocks sunlight that is necessary for the growth of organisms at the bottom of the aquatic food chain. Too much sediment in the water can also make it cloudy, causing the same problem of blocking sunlight for other organisms. These unnatural processes can disrupt the environment and its inhabitants. According to the Chesapeake Bay Foundation [1], agricultural runoff accounts for 45% of the nitrogen pollution in the bay, the largest contributor. As a whole, agriculture represents almost 70% of the remaining pollution reductions that Virginia must make in order to reach its 2025 goals of pollution reduction commitments. For this project, our aim is to determine whether or not it is feasible to use machine learning to identify agricultural areas in the Chesapeake Bay that may be contributing to this runoff problem. By doing so, we hope to help the Environmental Protection Agency, Chesapeake Bay Foundation, the Virginia Department of Environmental Quality, and others in their efforts to reduce and prevent water pollution in the Chesapeake Bay region. This study aims to help improve the annual water quality index around the Bay using Convolutional Neural Networks. Motivated by a similar project being tested in Denmark [2,6], we chose to implement ours focused around the declining Chesapeake Bay - the largest estuary in the United States.

2 Method

The goal of our project was to develop a neural network to identify agricultural fields near the Chesapeake Bay, with the purpose of classifying farms at high risk of polluting the bay based on proximity to the watershed. We started by gathering data from the Denmark Land Parcel Identification System [2,6], and utilized the preprocessing techniques included in the dissertation of Christoph Rieke [7] to extract and prepare the data. We then used the data to train a fully convolutional neural network (FCNN) to perform semantic segmentation on satellite imagery to identify these agricultural fields. We started by exploring various FCNN architectures, including U-Nets [8], Mask-RCNNs [3], and SegNets [4]. The SegNet model gave the highest initial performance on both the training set and validation set after training for one hour, so we decided to use this architecture in our final model. The standard architecture for a SegNet model is shown below in Figure 1.

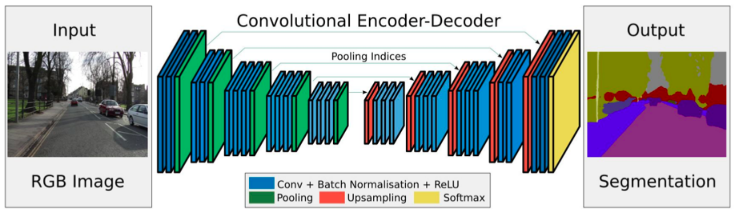

Figure 1. SegNet Model Architecture [4]

As seen in Figure 1, the model utilizes an encoder-decoder structure to output classifications for each pixel in the image. The model uses convolutional and pooling layers to encode the image, followed by more convolutional and up-sampling layers to decode the image back to its original size.

3 Experiments

After deciding on the SegNet model, we ran various experiments to determine the encoder and decoder structures that yield the highest performance. We started by using a simple encoder-decoder structure similar to what is shown in Figure 1. However, this simple structure severely underfit our data, giving pixelwise accuracies near 60% on the training set and 50% on the validation set. To enhance the performance of our model, we decided to utilize transfer learning to strengthen the ability of the model's encoder. We experimented with various CNN models trained on the ImageNet dataset, including DenseNet, MobileNet, Xception, VGG19, and ResNet. The Keras pre-trained ResNet152V2 model yielded the highest performance on both the training set and validation set, with pixelwise accuracies near 94% on the training set and 85% on the validation set. Given that the ResNet model was originally trained on images taken from a front-facing angle, rather than from above, we decided to not freeze any of the pre-trained weights, but simply use the weights as an initialization for training. This allowed the model to shift performance from classifying front-facing pictures to overhead pictures taken by satellites. The last experiment we conducted was to test whether the model trained on farmland images of Denmark generalized well to farmland located in northern Virginia. To do so, we downloaded satellite imagery from the Virginia Geographic Information Network (VGIN) [9] and hand-labeled a subset of the data using Labelbox [5] to serve as our testing dataset.

4 Results

Table 1. Final Model Results

	Training Set	Validation Set	Test Set
Pixelwise Accuracy	*0.9402*	*0.8619*	*0.6884*
Mean Intersection Over Union	*0.8937*	*0.8716*	*0.8614*

As seen in Table 1, the model obtained 94% pixelwise accuracy on the training set, and 86% pixelwise accuracy on the validation set. Our model also obtained a mean intersection over union of approximately 89% on the training set and 87% on the validation set. An example of how the model's predictions compared to the ground-truth labels can be seen below in Figure 2.

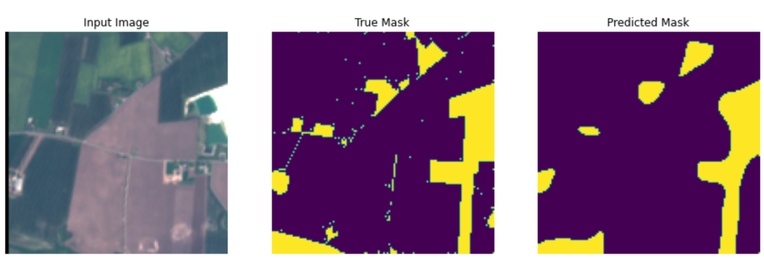

Figure 2. Validation Set Prediction

The model performed somewhat worse on the test set, with a pixelwise accuracy of roughly 69% and a mean intersection over union of 86%. An example of the model's prediction on an image in the test set is shown below in Figure 3.

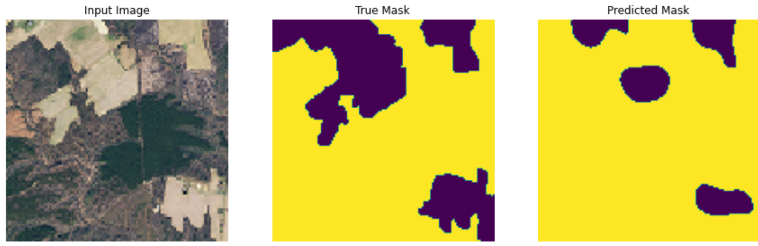

Figure 3. Test Set Prediction

5 Conclusion

Based off of our model's pixelwise accuracy and mean intersection over union scores, we believe that it could be successfully used in order to help environmental agencies identify farmland areas in the Chesapeake Bay region. Our results suggest that our model is able to successfully distinguish between farmland and non farmland areas. If used, the Virginia Department of Environmental Quality and the Chesapeake Bay Foundation would be able to more easily identify and target areas that may be contributing to the nutrient run off problem. This would allow them to enforce or suggest conservation measures that limit pollution runoff such as stream buffers and rotational grazing. This would lead to a reduction in nitrogen and phosphorus pollution in the bay, which would improve water quality. An improvement in water quality would be beneficial to both Virginia residents and the Chesapeake Bays' inhabitants/wildlife. The Chesapeake bay is an important source of drinking water and seafood for its residents. According to the Chesapeake Bay Foundation, the Chesapeake Bay Watershed provides drinking water for roughly 13 million Virginia residents, the seafood industry in Maryland and Virginia accounts for 34,000 local jobs a year, and harmful bacteria and population from the bay can appear after heavy rains in the area. Clearly the water quality of the Chesapeake Bay has a large impact on millions of Virginia residents, and is an important issue.

To ameliorate the performance of our model, the simplest next step would be to collect more, better quality training data to build the model off of. This would help to improve the models pixelwise accuracy and mean intersection over union scores. It would also be important to provide the model with more training data that does not have any farmland so it is more easily able to recognize non-farmland areas from satellite imagery. Most, if not all, of the images that we fed to our model to train on had some areas of farm in them. This hurt our model as it was not able to generalize as well as we hoped for. There were a few instances when the model thought that bodies of water were farmland when running on our Chesapeake Bay test set. There were also instances where the model did not recognize large areas of farmland in the test set. If we had trained the model using Virginia satellite imagery as well, it most likely would have been able to generalize better. Going forward, we would spend time labeling more Virginia satellite imagery in order to improve our model's ability to generalize. Future work for this project could also include identifying waterways as another class, which would make it even easier to identify which farmlands areas are contributing the most to pollution runoff. By determining which waterways each farm is most likely to runoff into and how close each farm is to a waterway, officials would have an easier time preventing runoff. This would all help to improve the water quality of the bay.

References

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Contributions

Will Lampert: Data preperation, K-means clustering testing, U-Net Architecture testing, video editing, video voice over, Chesapeake Bay and pollution research.

John Chrosniak: Data preparation, data labeling, model research, development of SegNet model architecture, model training, error analysis.

Yusuf Farooqui: Model research