Optimizing Deep Learning Architecture for Remote Sensing Image Analysis

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Introduction

Deep Learning tools have become very efficient in high-resolution image analysis compared to traditional classification models. One such example is the implementation of semantic segmentation using a Convolutional Neural Network (CNN). Unlike image labeling, where images is are classified into one label, we can use semantic segmentation to identify the class labels of every pixel in an image. This makes CNN an ideal tool for Land Use Land Cover (LULC) modelling. This is especially true because current land cover classification techniques require a lot of time and resources to complete.

This project attempts to create a deep learning architecture for resource-constrained environments by reducing complex mathematical operations that plague the deployment of CNN. The proposed model will be trained using the Potsdam dataset and the Vaihingen dataset obtained from the International Society for Photogrammetry and Remote Sensing (ISPRS). Using the concept of transfer learning, the trained model will then be used to compare and assess the LULC change dynamics for the lower Chippewa Valley watershed region in Wisconsin.

Study Area

The Lower Chippewa Valley Watershed is a vital resource for the state of Wisconsin and the surrounding region. The watershed is also a vital piece of the much larger Mississippi watershed that encompasses most of the United States. The water inside the Lower Chippewa Valley helps power the region and provide fresh clean water to its occupants [3]. In 2008, the US Department of Agriculture estimated that 58.5% of land use was agricultural and 33.5% of land use was forest [3]. Since 2008, the estimated population of the region has nearly doubled [3]. This rapid growth has changed the landscape of the Chippewa Valley, and created a need for rapid land use classification.

Study area images are from the USGS Earth Explorer website and are a collection of three Landsat 8 images for Western Wisconsin on June 22 of 2020. The spatial resolution is 30 meters. And the following bands were stacked together:

- Landsat Band (2) Blue: 0.452 – 0.512
- Landsat Band (3) Green: 0.533 – 0.590
- Landsat Band (4) Red: 0.636 – 0.673
- Landsat Band (5) NIR: 0.851 – 0.879

The images were then resized to a pixel resolution of both 300-by-300 and 500-by-500. We will be testing both dimensions with varying degrees of overlap in our model

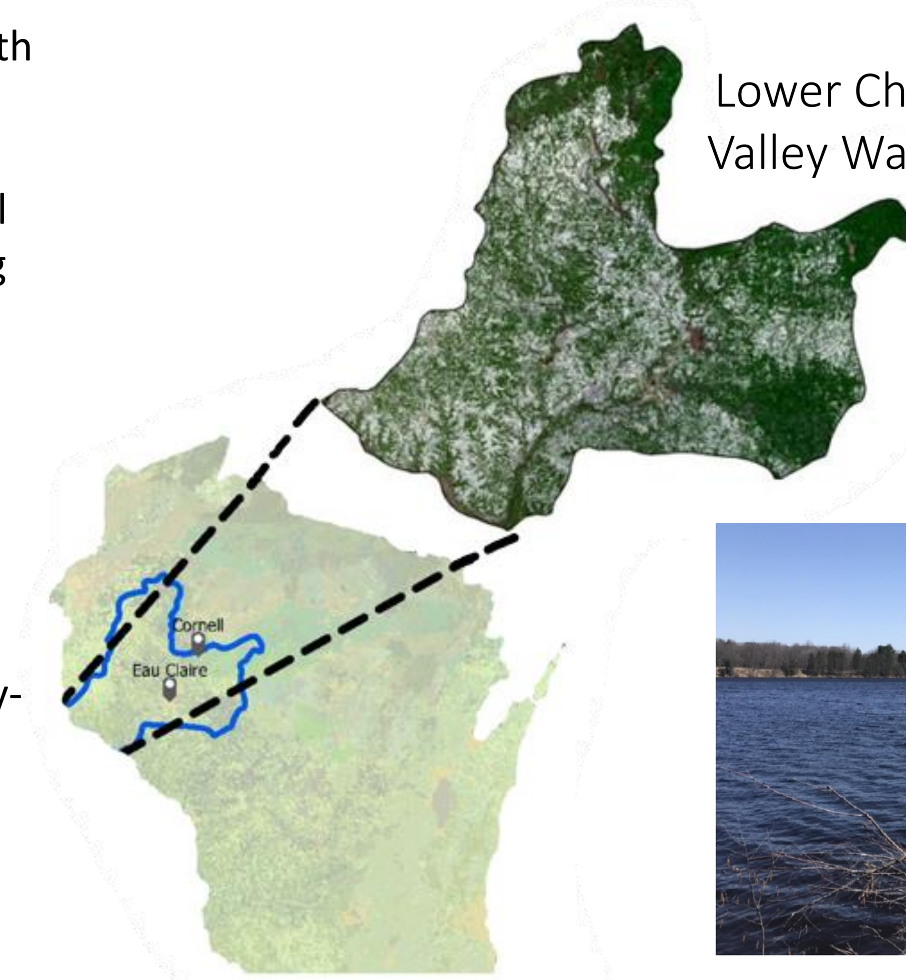

Figure 1: A picture of the Chippewa river at one of the most northern points in Cornell, Wisconsin

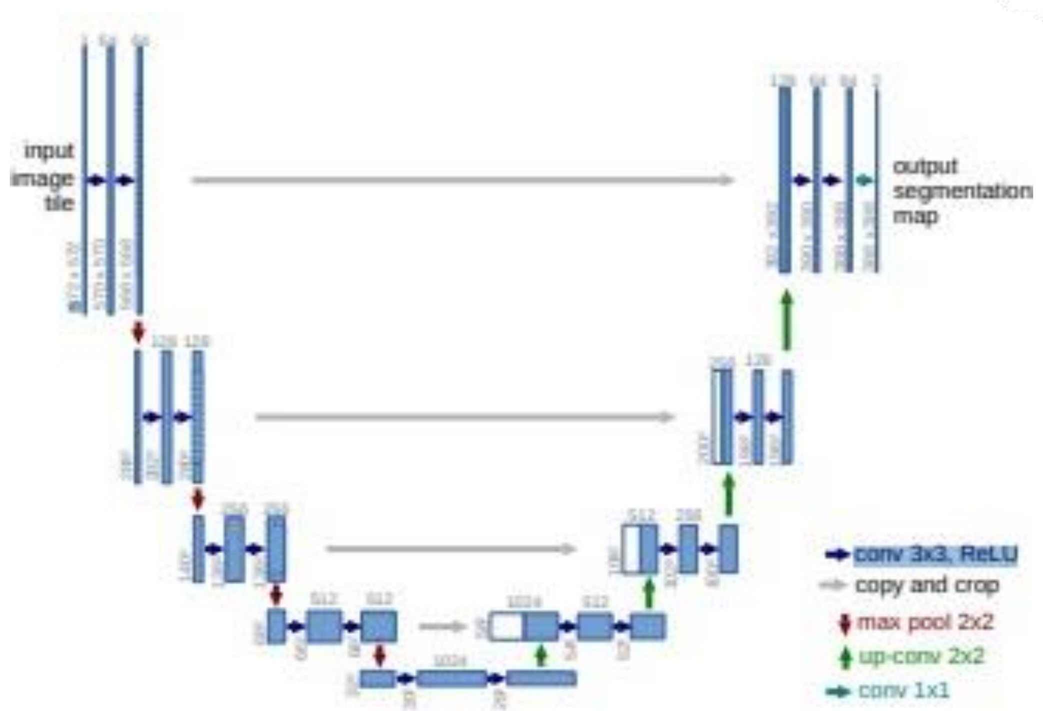

Figure 2: Diagram of U-Net Architecture [4]

Methodology

The research will utilize the ISPRS Potsdam [1] dataset for creating deep learning models. The multispectral images in this dataset are found in 4 bands namely Red, Green, Blue and Infra-Red. We intend to optimize the internal UNet structure in Figure 2 using dilated convolutions and ShuffleNet [2] modules. To verify accuracy of the model, 75% of the dataset will be used for training and 25% will be used for testing.

The images will be resized and cropped to 300-by-300 pixels with 50% overlap. The training process would also incorporate image augmentation techniques such as rotation, zoom, horizontal and vertical flip to provide more training features. Finally, the weight of the model with the highest training and testing accuracy would be deployed on the Chippewa Valley dataset for landcover classification. We will investigate the performance of this transfer learning given that both datasets share similar spectral signatures. The entire process in shown in Figure 3

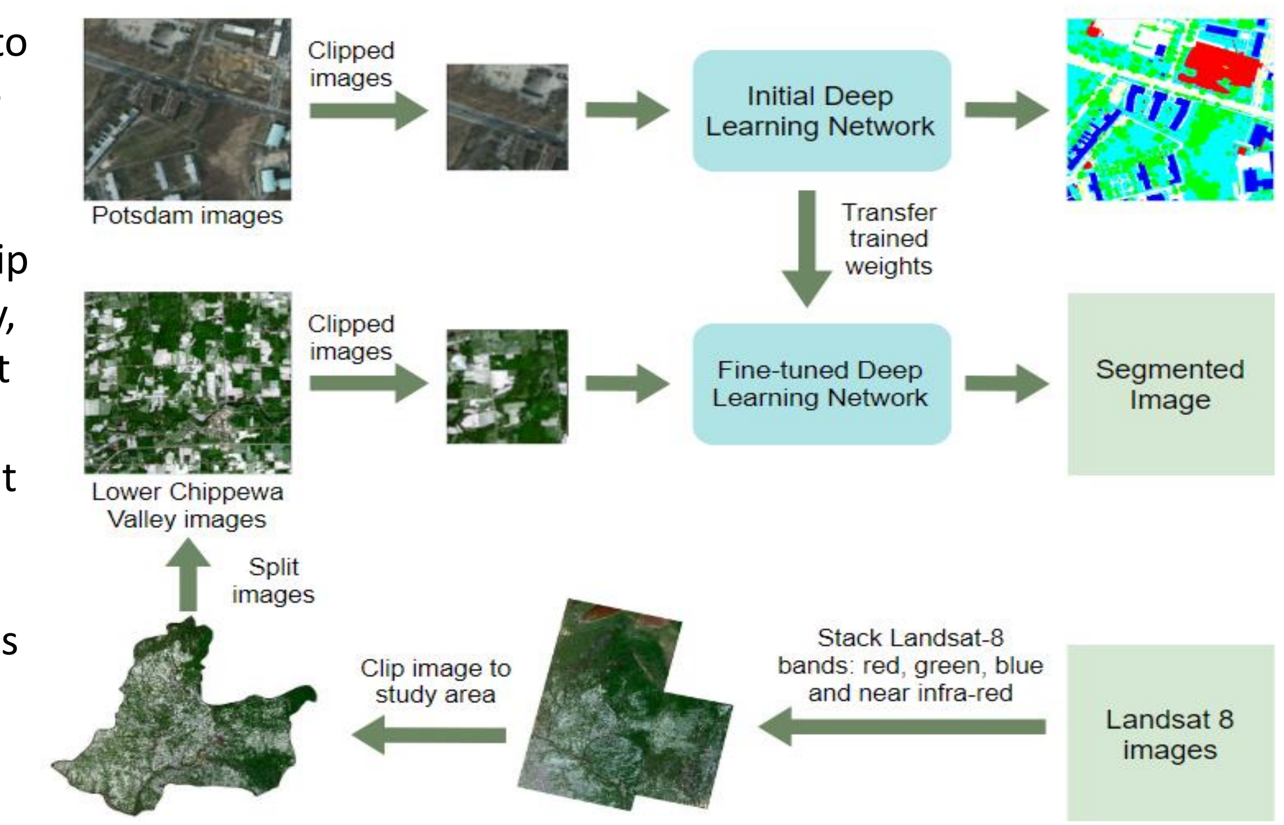

Figure 3: Proposed diagram of deep learning classification with transfer learning

Results

Preliminary results for classification of the Chippewa Valley dataset have been presented in Figure 4. For this classification we utilized Random Trees from ArcGIS. The algorithm was set to use 50 trees with a cut-off dept of 30. The accuracy metrics are shown in Figure 5. We intend to use this classification result as a benchmark to evaluate our transfer learning approach.

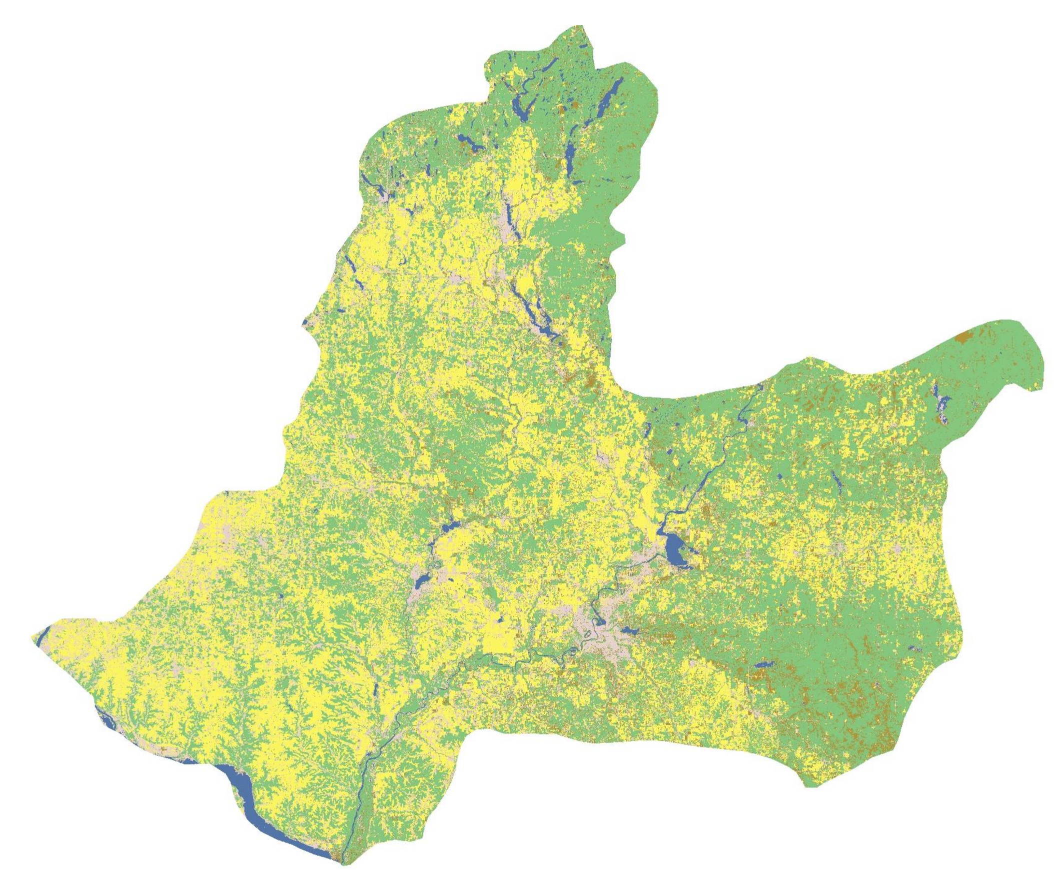

Figure 4: Classified image of the Chippewa Valley

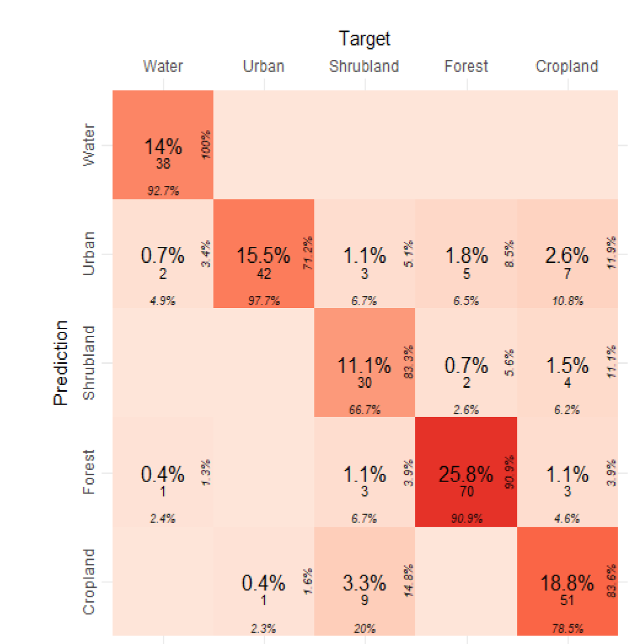

Figure 5: Confusion matrix showing the accuracy of the classification

References

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[4] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) Medical Image Computing and Computer – Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science, vol 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28

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