On Predicting Forest types and vegetation from NDVI data using Deep Learning

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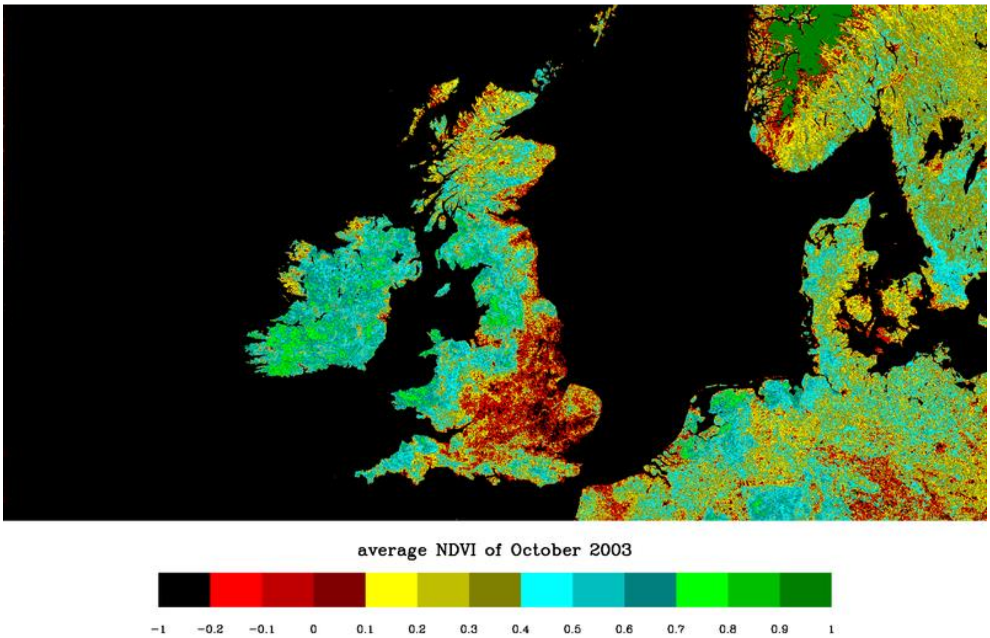
Abstract

Understanding vegetation is one of the most important aspects of land management and utilization. The following paper discusses how Mapped multi-temporal remote sensing data from Japan can be used. The goal is to map different forest types using spectral data. A Deep learning classifier is used to classify land into 4 categories (water, forest, farm, impervious).

1 Introduction

The Normalized Difference Vegetation Index (NDVI) is a graphical indicator that is used to analyze remote sensing data which is collected via satellites or planes. This data is used to assess whether a land area has vegetation or not. And if vegetation exists to what extent is it found and its condition. The Index is calculated using the Near Infrared Waves via remote sensing satellites. The NDVI values range from -1 to 1. With negative values corresponding to water and high values (close to 1) corresponding to tropical forests and grasslands.



Above – NDVI for the British Isles

Source - Gennaro Cappelluti

The Index is used in a number areas.

For example in agriculture farmers use NDVI to measure biomass. foresters use NDVI to quantify forest supply and leaf area index.

Furthermore, NASA states that NDVI is a good indicator of droughts[1]. When water limits vegetation growth, it has a lower relative NDVI and density of vegetation.

Since this data is collected using satellites, much of the data collection is already automated. Over the years scientists have looked at these indicators to decide the type of vegetation or land in an area.

In the following report we attempt to build a classifier that takes in NDVI for various times of the year and predicts the type of vegetation present; without any human intervention.

2 About the Dataset

The dataset was acquired from the online machine learning repository at the University of California Irvine[2].

It contains 27 features which consist of the NDVI reading taken at different times during the year of 2015. There are a total of 10545 training examples.

This data set contains training data from a remote sensing study which mapped different forest types based on their spectral characteristics at visible-to-near infrared wavelengths, using ASTER satellite imagery. The output (forest type map) can be used to identify and/or quantify the ecosystem services (e.g. carbon storage, erosion protection) provided by the forest.

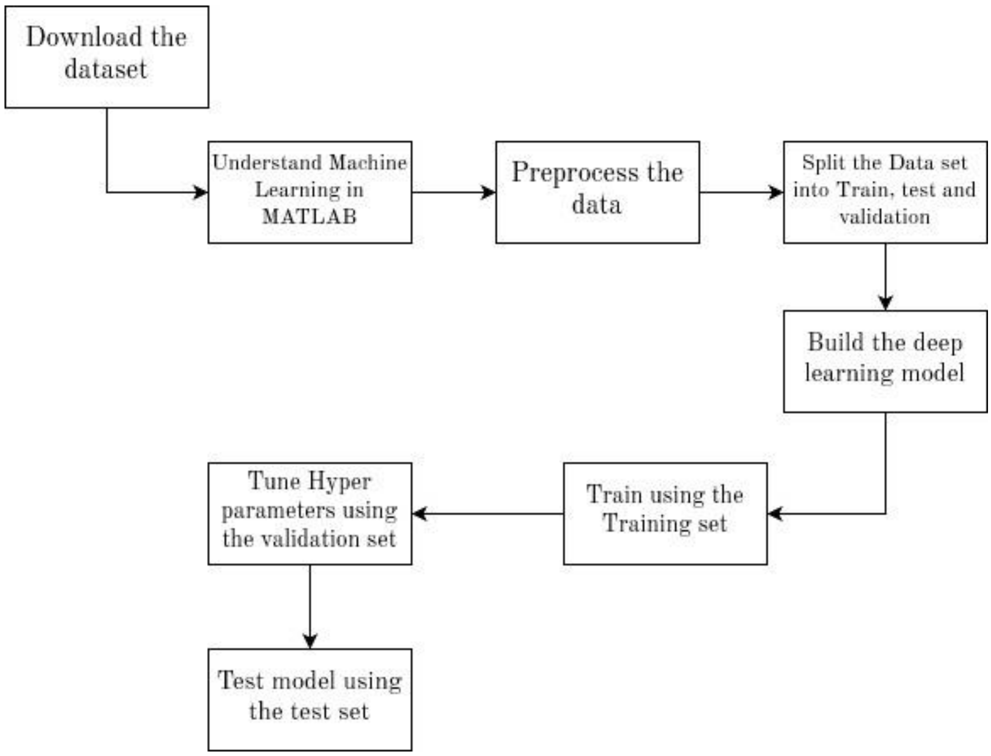
There are a total of 4 output classes in the dataset, namely

- Water
- Forest
- Farm
- Impervious

3 Workflow Diagram

To accomplish this task we first needed to train a Deep learning based model on the large dataset.

The following workflow was followed in building and training the model.

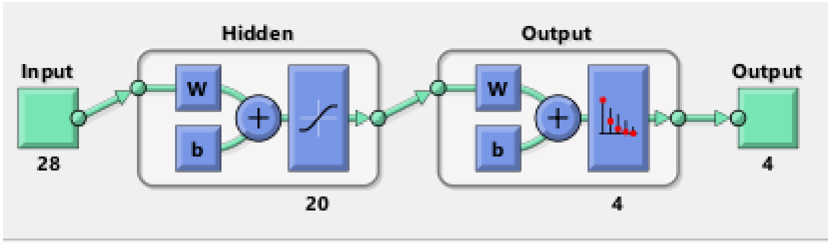


4 Neural Network Models

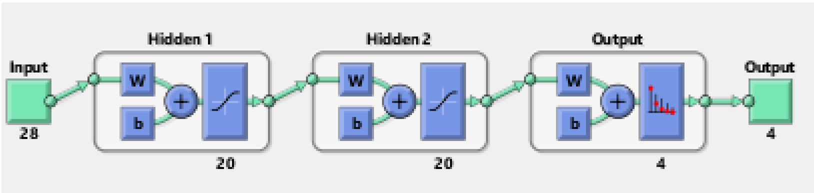
To further understand how changing certain aspects of the model, affects the overall performance in prediction. We built two models:

I) Model A with a single hidden layer of 20 neurons

II) Model B with two hidden layers of 20 neurons each



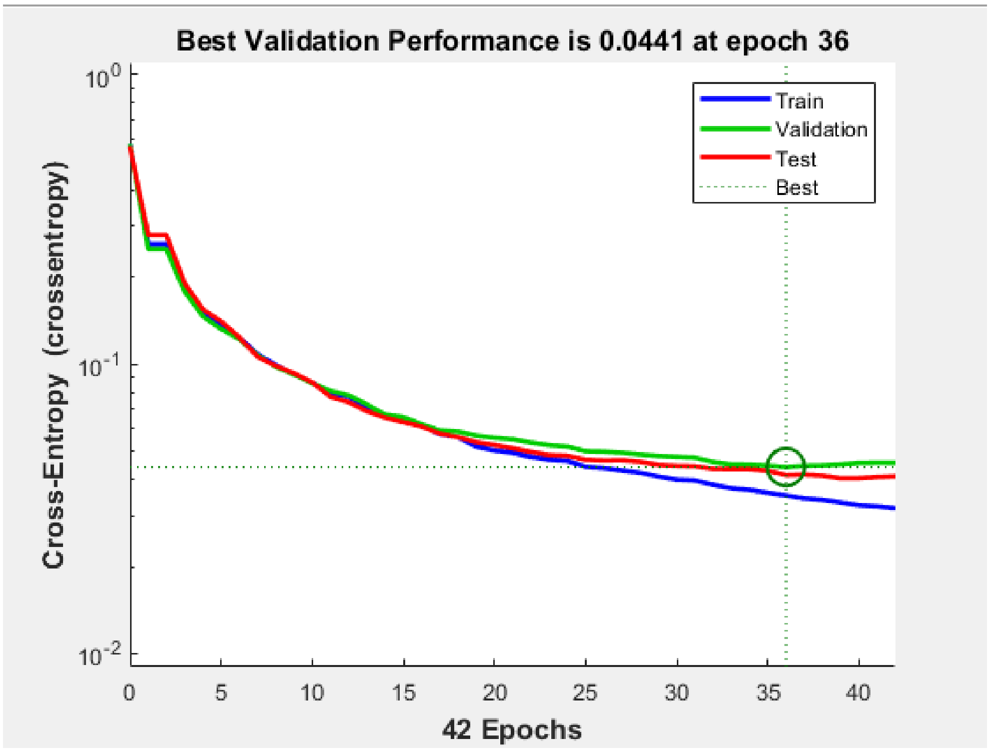
Model A



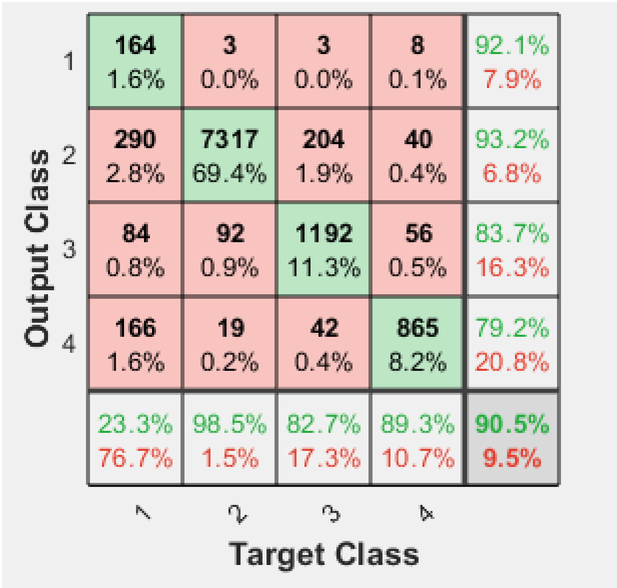
Model B

5 Results

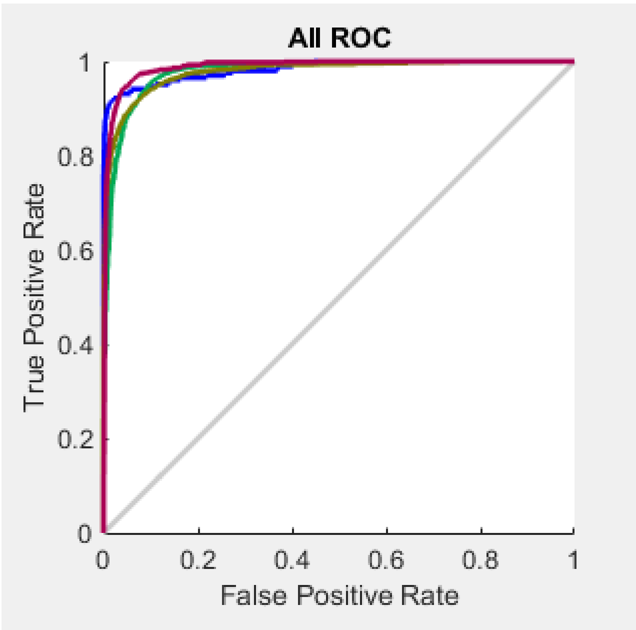
The following results were obtained:



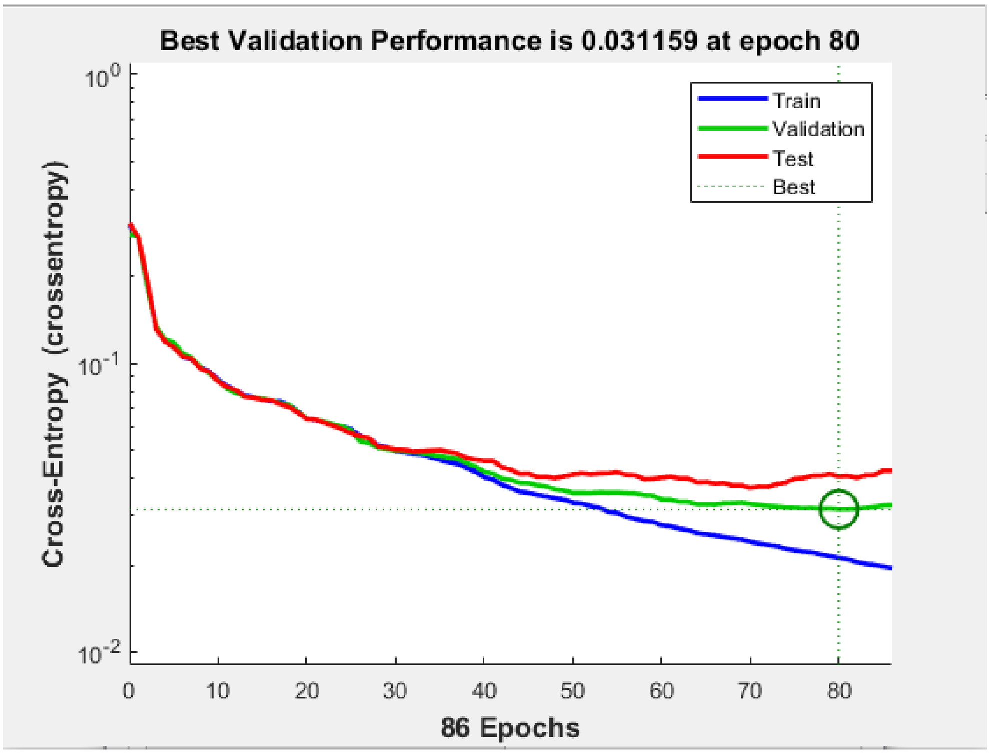
Performance Measure for Model A



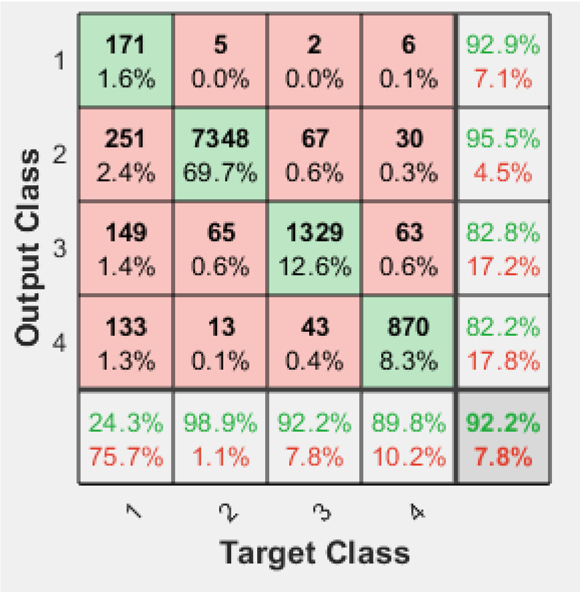
Confusion Matrix for Model A



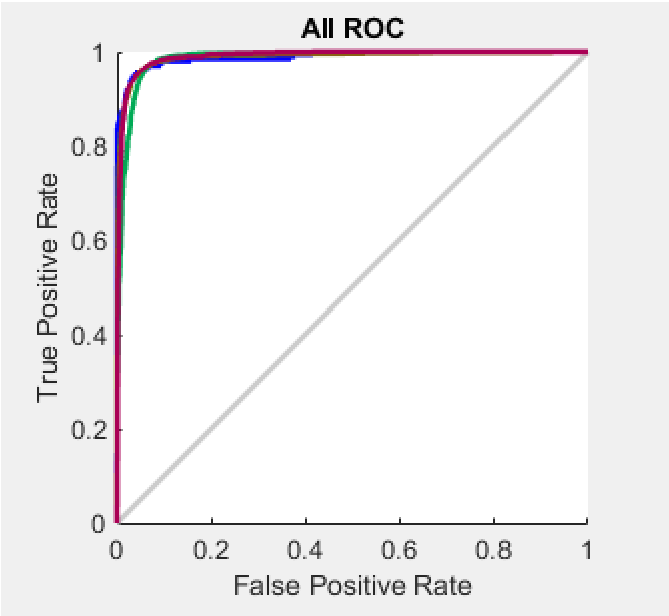
Reciever Operating Characterstic for Model A



Performance Measure for Model B



Confusion Matrix for Model B



Receiver Operating Characterstic for Model B

6 Comparison

Model	Model A	Model B
Accuracy	90.5 percent	92.2 percent

It is clear from the above that predictions made by Model B are slightly more accurate than Model A, meaning that in this dataset a deeper model seems to perform better.

Also it seems that the ROC curve for Model A isn't as ideal as that of Model B.

Finally the model error is lower for Model B than Model A by a slight margin.

References

[1] W. John, D. Herring. Measuring Vegetation (NDVI and EVI), 2000 https://earthobservatory.nasa.gov/features/MeasuringVegetation

[2] B. Johnson Forest type mapping dataset, 2015 https://archive.ics.uci.edu/ml/datasets/Forest+type+mapping

Releated Works

Johnson, B., Tateishi, R., Xie, Z., 2012. Using geographically-weighted variables for image classification. Remote Sensing Letters, 3 (6), 491-499.