Deep Learning Techniques for detecting vegetation with Satellite Imaginary

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We adopted satellite images and machine learning methods to show our model on various areas that are prone to destruction, thus prompting illegal logging detection for sustainable use of forest resources. This leads to precise indications about local communities' knowledge in order to conserve important natural assets which are relevant for flora and fauna diversity as well as capturing carbon hence providing solutions to climate change problems. The benefits associated with this research far surpass mere environmental protection. Such protection leads to sustainable economic growth, particularly for those who depend on the forest for their survival.Besides, the outcomes from this study will also be some of the key instructional guides to increase awareness about the effects of climate change, conservation methods and sustainable development issues. The research mainly emphasizes integration of science and technology, environmentalism and politics with respect to global deforestation and environmental degradation.

Additional Key Words and Phrases: Deep Learning, Satellite Imagery, vegetation, Predictive Modeling, Remote Sensing.

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1 Introduction

The project's main aim is to use machine learning especially in remote sensing using CNN algorithms. They are use satellite data semantic segmentation in order to classify land cover and detect it as well as vegetation. Datasets like Sentinel-2 and Landsat-8 which are part of Copernicus program help in acquiring high resolution multi-spectral images for the purpose of land monitoring including deforestation detection, vegetation cover analysis and environmental planning. Problem Statement:The problem is that traditional methods for studying land cover like hand-made cartography or morphology reconstruction are less effective and not scalable. However, new technologies have not necessarily overcome problems associated with using artificial intelligence because they have been limited in terms of data and refining capabilities for accurate prediction may still be difficult. A key challenge is automatically classifying various types of vegetation and land use from remote sensing images by means of machine learning algorithms.

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1.1 Objectives

The research objectives contain:

- To develop a satellite imagery based multi-modal dataset for various types of plants
- Architecture of convolutional neural networks (CNN) such as U-Net will be employed for semantic segmentation in remote sensing data;
- A number of models will be rated on accuracy, recall and F-score.

2 Related Work

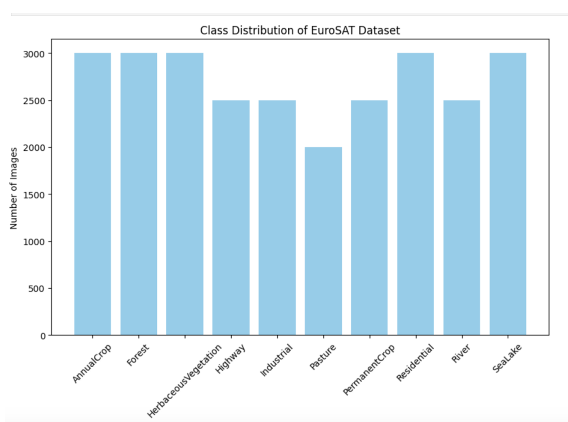
In image processing and analysis, machine learning and deep learning algorithms since recently have been used for detecting deforestation or classifying vegetation cover. Classical change detection approaches such as pixel-oriented algebraic operations, different image processing methods or multiple cp-species detectors (VZD) were used in earlier studies. For most cases where they were widely used at monitoring big areas of forests, low resolution satellite images from MODIS or Landsat are not too effective on the monitoring of smaller areas because of many computation-related problems. From our observation In this review, we will discuss the changes in remote sensing approaches from the conventional techniques to the recent deep learning techniques for achieving effectuality and precision during detection of deforestation and vegetation mapping.

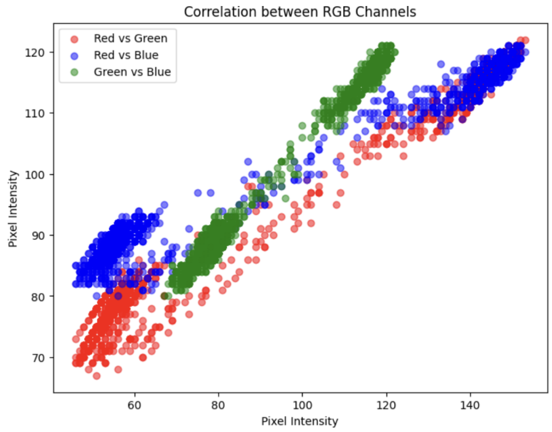
3 Methodology

We required High-resolution satellite imagery from sources such as the Sentinel-2 collection .The pertinent spectral bands are extracted, with particular emphasis on those responsive to vegetation health, including the Near-Infrared (NIR) band. We used the Eurosat Dataset. Eurosat is a dataset and an introduction for deep learning in land use and vegetation classification. The dataset includes Sentinel-2 satellite photos covering 13 spectral bands and includes 10 classifications, including 27,000 categorized and geo-referenced images.

3.1 Pre exploratory analysis

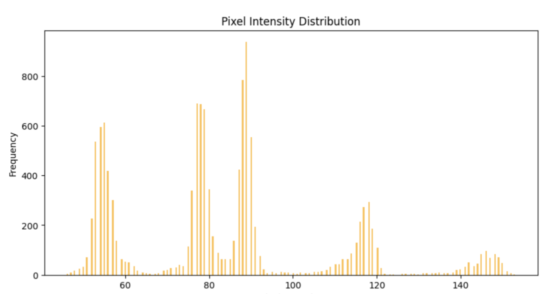
Data Distribution in classes The dataset has 27000 images which have a spectrum band of 13 and 10 classes. We first analyzed which class had more images. We found out that Herbaceous Vegetation,Residential and SeaLake had the highest number of images with 3000 images each. The Lowest was the Pasture class which had 2000 images only.





Visualize Sample Images After checking the class distribution of EUROSAT. We visualize images from each class to view if all classes and their data are loaded correctly. We generated the image randomly so that if there was any missing value the function would catch it.

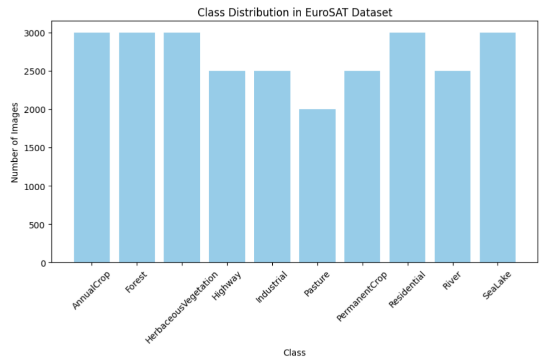
Pixel Intensity After viewing the images from classes. We took one sample image to check the pixel intensity. Pixel intensity means the sum , mean or median intensity pixels within a range. The pixel intensity can be 0 to 255 based on the sample image. In our sample image the intensity didn't get too high.



Correlation Between Channels: We checked after preprocessing the data if there were any missing values but there were none.. All the data in 10 classes were successfully loaded. The histogram shows us that the highest and lowest values of class distribution remain the same.

3.2 POST EXPLORATORY ANALYSIS

Data Distribution in classes We checked after preprocessing the data if there were any missing values but there were none.. All the data in 10 classes were successfully loaded. The histogram shows us that the highest and lowest values of class distribution remain the same.



Normalizing and Transforming images We checked after preprocessing the data if there were any missing values but there were none.. All the data in 10 classes were successfully loaded. The histogram shows us that the highest and lowest values of class distribution remain the same.

RGB Distribution In Pre EDA we check rgb distribution for a particular image. Here we have also visualized the rgb distribution for the same image. From the below histogram we can see that for every pixel value how many times red,green,blue appeared. Now it has changed. Here the pixel intensity is till 255 because we visualized on transformed image only

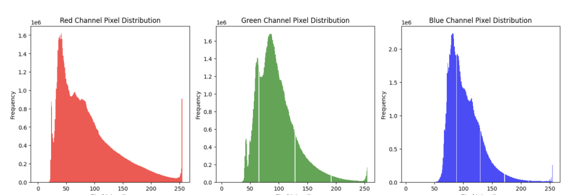
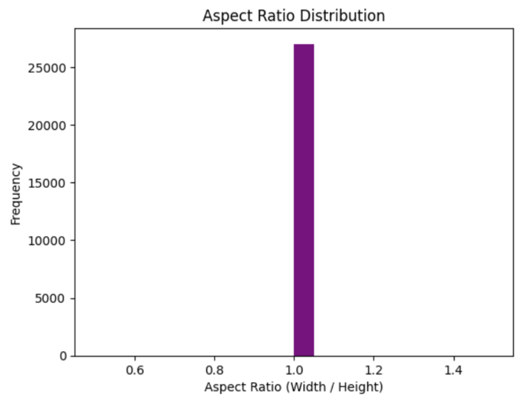
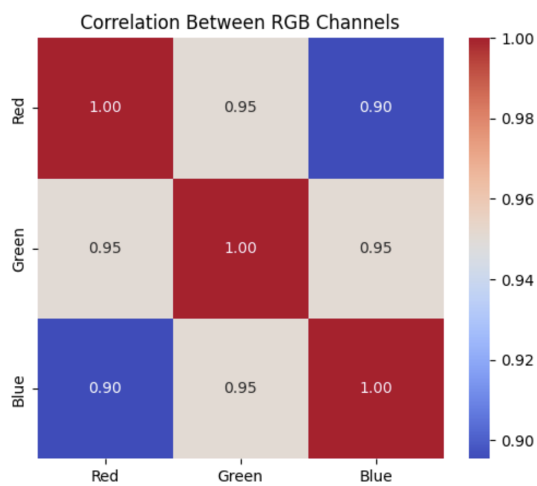


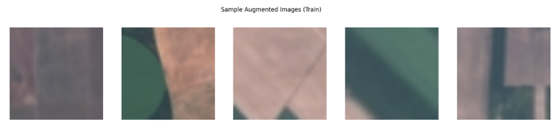
Image Ratio Distribution We have to check if the image size is still constant because the pixel size will change because of normalization but the height and width should remain the same. From the below distribution we can see that it has remained constant.

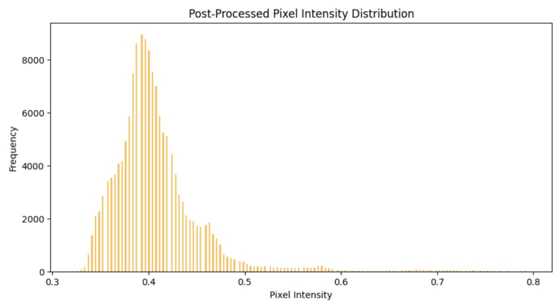


Correlation between Channels After Normalizing the images the correlation has improved significantly . The matrix shows us that the three variables are now more dependent on each other.



Post process pixel intensity distribution After processing the image the images pixel values are now in 0 to 1 so the pixel intensity has changed. In 0.4 we see that the pixels are more. In the pre process we saw that pixels were scattered but here they are more correlated to each other

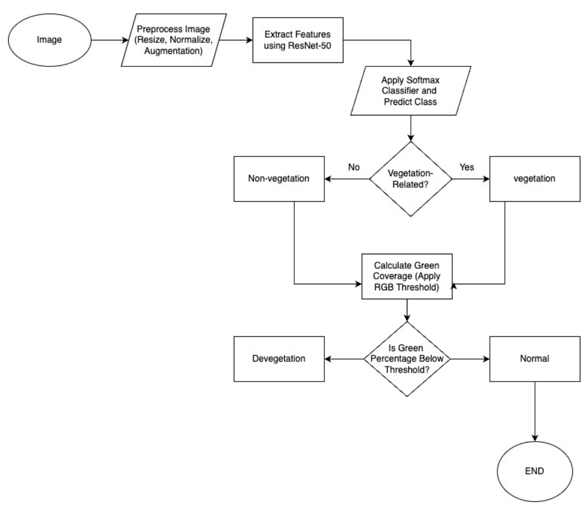




Data Augmentation We have applied the transform function which we had built previously. But here we have also used permute from pytorch.It permutes images randomly to do augmentation.

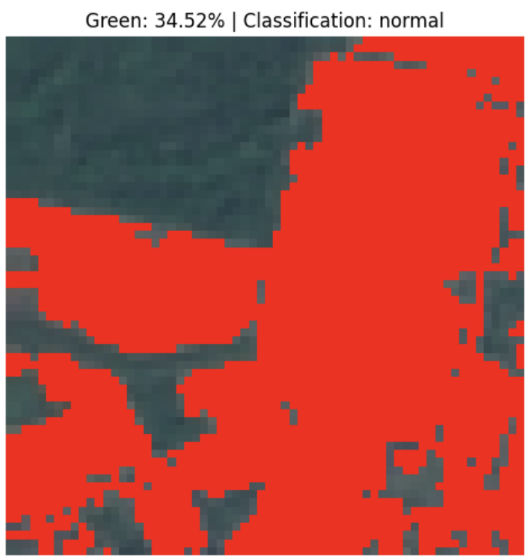
3.3 Model training

This approach uses a pre-trained ResNet-50 model for the extraction of features, which is fine-tuned on the given dataset to derive essential characteristics from satellite images. The model's final fully linked layer is substituted with one that produces the appropriate number of classes, for instance, 10 for EuroSAT. The model produces a feature map that encapsulates the image's high-level attributes. A softmax classifier is utilized on the feature map to give probabilities to each class, with the class exhibiting the highest probability designated as the anticipated label (e.g., Forest, Industrial, Residential). The anticipated category is further verified to ascertain its affiliation with vegetation-related classifications, such Forest, Pasture, or River.



4 Results

In this assessment, the actual data and the predicted vegetation degradation are compared. Additionally, the model's shown ability to detect areas that have degraded over time will be evaluated through comparison with past satellite data and field observations.An analysis of the spatial distribution of the expected output would demonstrate how well the model identified degraded areas within different vegetation zones.



The results would highlight significant areas experiencing significant degradation, represented by heatmaps or vegetation health visualizations using color coding. When vegetation deterioration is detected using satellite data and deep learning techniques, the outcomes are typically presented in terms of spatial analysis and model effectiveness. By examining accuracy, precision, recall, and F1-score.

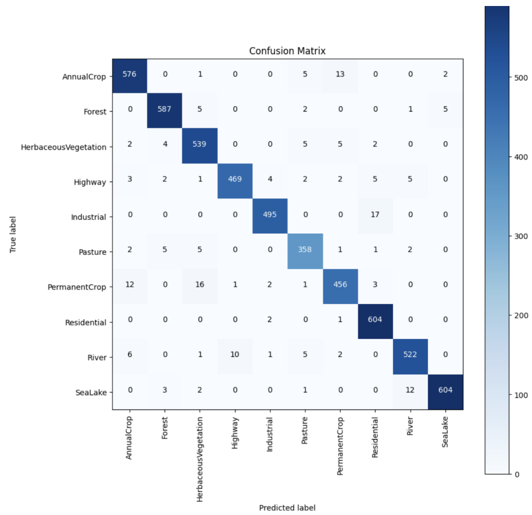


Fig. 1. Confusion Matrix

5 Discussion

The improvement of recall and precision reflect the potential of deep learning to monitor ecosystems on long and large-term scales.

ResU-Net performed better than U-Net and FC-DenseNet consistently when considering several networks. It accomplished significantly better segmentation accuracy with a reduced false positive and false negative rate. The overall recall scores for both the Sentinel-2 and Landsat-8 datasets were high using the ResU-Net and FC-DenseNet models, indicating that these two models performed better in detecting deforestation events. But, the architectures like SegNet and MobileNetV2 failed to reach the accuracies of ResU-Net and FC-DenseNet in discovered smaller patches with deforested regions.

However, as advanced as these models are becoming, they continue to struggle with generalization and detection of space-limited deforestation areas. ResU-Net was able to attain a good performance thanks to the higher accuracy of predictions overall, but not without issues in detecting changes at polygon boundaries and small deforested regions (particularly on high-resolution images such as Sentinel-2). Seasonal variation and incongruence between the images due to mixed sources also affected the performance of the models. Despite accounting for the time of year — and thereby excluding winter images, forest types that would otherwise appear on semi-transparent trees in other biomes are prevalent, little detail is missing from these models.

6 Conclusion

This area from our papers using satellite images to detect deforestation and measure vegetation), but here we demonstrate that deep learning models actually work quite well on these kinds of data, in particular convolutional neural networks (CNNs). In that work the architectures of U-Net, ResNet and FCNs were used for processing and classification of multispectral data coming from Sentinel-2 and Landsat-8 image arrays. The models were very successful at detecting changes in the environment, such as deforestation and forest degradation. Nonetheless, recognition of challenges such as lack of data accessibility, seasonality and overfitting through the process could be seen as a call for further improvement.

Follow up work, will focus on expanding the dataset with additional tiles and regions, enhancing model accuracy for complex segmentation, and investigating other architectures. They also recommend improving the current models to include seasonal data over more years and adding further sources of data, such as radar from Sentinel-1. These methods aim to improve the generalization ability and reduce the current limitations on segmentation accuracy.

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