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Deforestation Detection Using DeepLearning

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Abstract: This is a major environmental problem that affects many countries around the world" (World, 2020). In this paper, we have explored several methods of automatic method for deforestation detection such as Early Fusion Convolutional network (EFCN), Siamese Convolutional Network (S-CNN) and Support Vector Machine (SVM). As shown in all experimental results, EFCN can obviously outperform S-CNN and SVM. This work is aimed at presenting a novel curated dataset and also an approach based on deep learning, more specifically Convolutional Neural Networks (CNN) combined with cutting edge data processing techniques to solve the forestation problem. These tools, combined with more advanced deep learning models and higher resolution satellite imagery, have greatly expanded our ability to do this. Finally, this paper explains a tool for daily the detection of rainforests deforestation in satellite images from MODIS/TERRA sensor using Artificial Neural Networks and U-net architectures. "What Comes to Mind When Considering Deforestation. Image, satellite images, deep learning, and CNN (Convolutional Neural Network)."

I. Introduction

Forests are indispensable to the planet's ecological stability, influencing climatic conditions, soil quality, and biodiversity. They act as significant carbon sinks, absorbing a large fraction of atmospheric carbon dioxide. However, deforestation, the large-scale removal of forest cover, disrupts this balance and contributes to severe environmental issues, including increased greenhouse gas emissions, loss of biodiversity, and disruption of water cycles. Various anthropogenic activities, such as agricultural expansion, urbanization, logging, and natural factors like wildfires and droughts, drive deforestation. The alarming rate of forest loss necessitates robust monitoring and prevention strategies. Efficient and automated techniques are essential for timely and precise detection of deforestation, as traditional methods like field surveys and manual interpretation of satellite imagery are both time-consuming and susceptible to human error. This study suggests utilizing a machine learning model that utilizes satellite imagery to detect and monitor deforestation, with the goal of improving the accuracy and effectiveness of these endeavors.

II. Material & Methodology

1) Data Labelling:

This study utilized a dataset gathered from various open-access platforms, notably the Kaggle Satellite Imagery Dataset, which contains approximately 40,000 images manually labeled to identify deforestation areas. However, the manual labeling process encountered challenges such as overlooking instances of clearcutting, misidentifying objects, and positional inaccuracies. To maintain the quality of the labeled data, a rigorous verification process was implemented. This process included cross-checking by multiple annotators and selective validation of segments prone to errors [4].

2) Data Preprocessing:

Preprocessing the satellite images was crucial to prepare the data for effective model training [4]. The preprocessing steps included normalization, where the pixel values of the images were scaled between 0 and 1, and resizing, ensuring uniform dimensions across all images [4]. These steps help maintain consistency in the input data, preventing computational inefficiencies and improving the model's performance during training [4].

3) *Training*

The strength of training the model from scratch is the ability to learn features in a unique feature space for this dataset that may not be caught by other pre-trained models. Here the dataset is split into training and test sets to find out how well our model performs. These data pipelines were used to feed the training data in an organized manner so that model will get clean flow of, data at the time of training. This makes model much more capable to grasp subtle patterns in the data making model more accurate and precise [4].

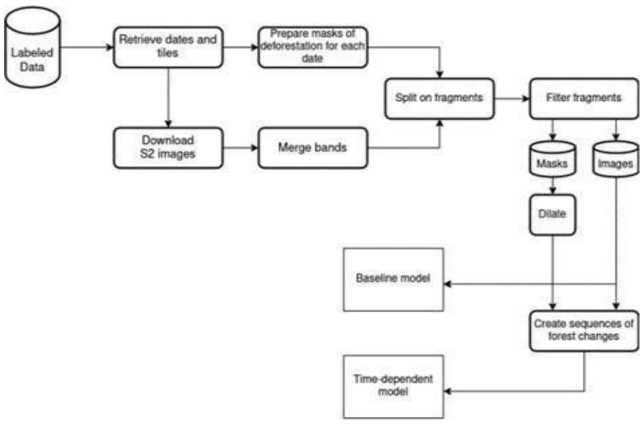

Fig. 1. Flowchart illustrating the application of deep learning for detecting deforestation.

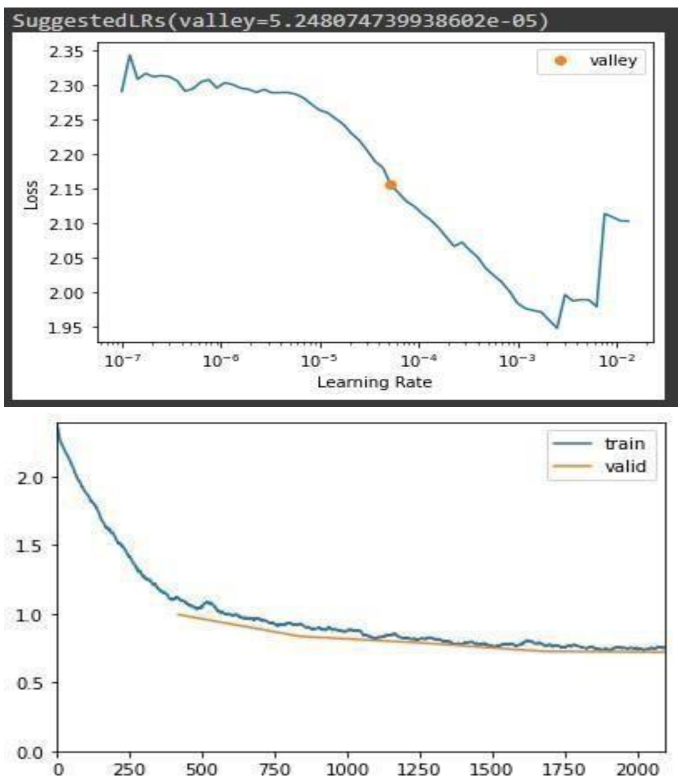

Fig.2.Graph of training and validation

4) Class spectral-temporal patterns:

An analysis of the training dataset revealed distinct patterns across three classes, particularly in near-infrared (NIR) reflectance and backscattering coefficients [4]. These patterns indicated significant changes in old-growth forests and secondary forests or plantations, which are key indicators of deforestation [4]. Understanding these spectral-temporal patterns is essential for developing accurate models for deforestation detection [4].

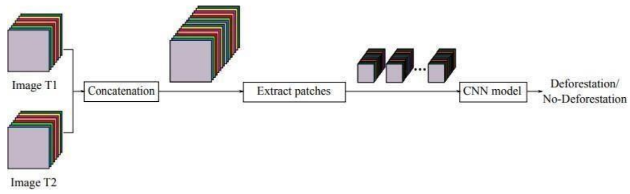

Fig. 3. EF approach. Images at different dates (T1 and T2) are concatenated to produce an image pair; then, patches are extracted and fed to the CNN model.

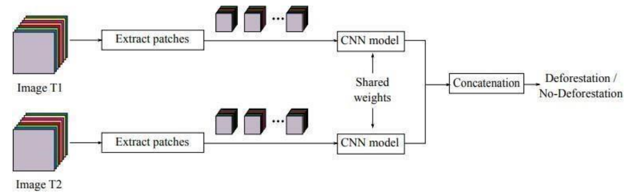

Fig. 3.1. Patches of each image (T1 and T2) are extracted and fed to the CNN model independently. The two branches in the network share exactly the same architecture and parameter values.

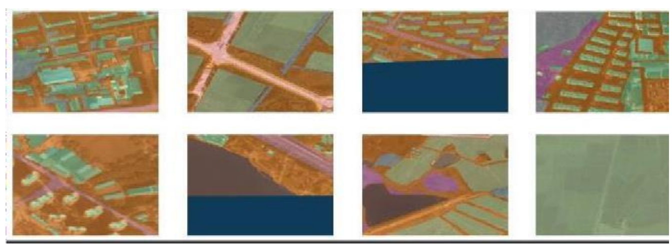

Fig. 4. Input image given the result of ground truth and model prediction

5) Deep Learning approach in Deforestation:

Deep learning, and especially Convolutional Neural Networks (CNN) have secured their place well in remote sensing tools; for image analysis and pattern recognition. CNNs achieve this through backpropagation — using multiple building blocks (such as convolution layers, pooling layers, and fully connected layers), CNN is able to automatically and adaptively learn spatial hierarchies of features. Such properties have made convolutional neural networks an attractive option for analyzing satellite imagery to locate different types of deforestation [5].

5.1.U-Net Architecture

The U-Net architecture is a type of CNN designed for image segmentation tasks [5]. It consists of an encoder-decoder structure, where the encoder captures the context in the image and the decoder enables precise localization [5]. U-Net has been successfully applied in various medical and remote sensing applications, including deforestation detection [5]. The architecture's ability to capture both the global context and the

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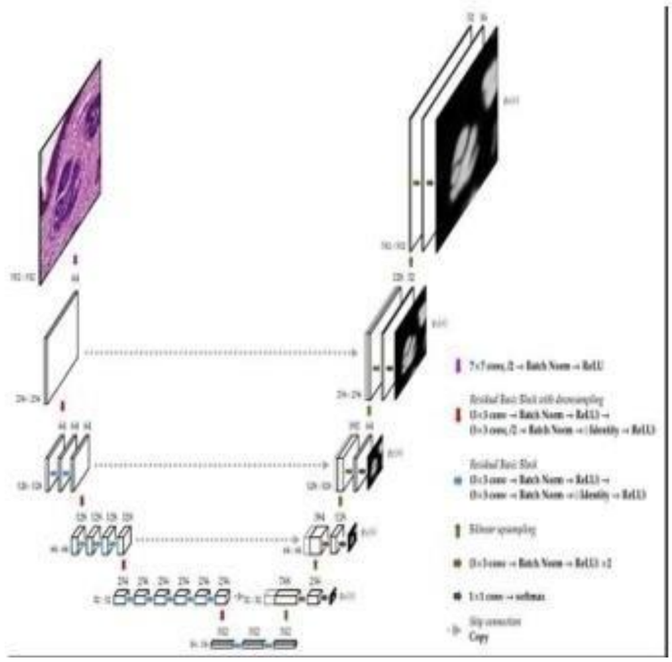
fine details in an image makes it particularly suitable for identifying the boundaries of deforested regions [5].

5.2. ResUnet Architecture

ResUnet [7] combines the principles of these two models so that we can make use of best part from both of them. Where skip connections from ResNet [7] are incorporated into the U-Net architecture making it easier for a model to learn and generalize from complex patterns within the data. For deforestation mapping, the two are best combined for the model to be able to learn fine-grained spatial features and at the same time it is capable of accurately segmenting pseudo-deforested areas (see Section 7) [7]. The architecture of ResUnet is quite compatible with the analysis of high-resolution satellite imagery [7].



5)Neural Network Model:
This study developed two sets of models: one focusing on spectral-spatial dimensions and the other on time-dependent models to identify changes in deforestation regions [5]. The spectral-spatial models scrutinize the spectral traits and spatial arrangements within satellite images, while the time-dependent models monitor alterations over time, offering a dynamic perspective on deforestation activities [5]. The CNN architecture utilized in this study comprises multiple convolutional layers, followed by pooling layers and fully connected layers [5]. Convolutional layers extract features from the input images, pooling layers decrease the dimensionality of feature maps, and fully connected layers execute the final classification [5]. This design enables the model to capture intricate patterns in the data, thereby contributing to its remarkable accuracy in deforested area detection [5].

III. Result

While many projects demonstrate the functionality of detection of deforestation using deep learning, detailed working of project indicates some interesting findings. This shows the power of our deep learning model! The ResUnet model is used in this project for detection as well as prediction. the first step of the project implementation is data implementation which include define the dataset as below: If the caption contains “satellite” then that is the main purpose we want to detect, use it as lable and classify all classes of images. The model reveals an average accuracy of about 75%. Plotting a complete pixel count on forest class after that the model has represented the percentage of forested and deforested as 31.18% and 68.82%, respectively

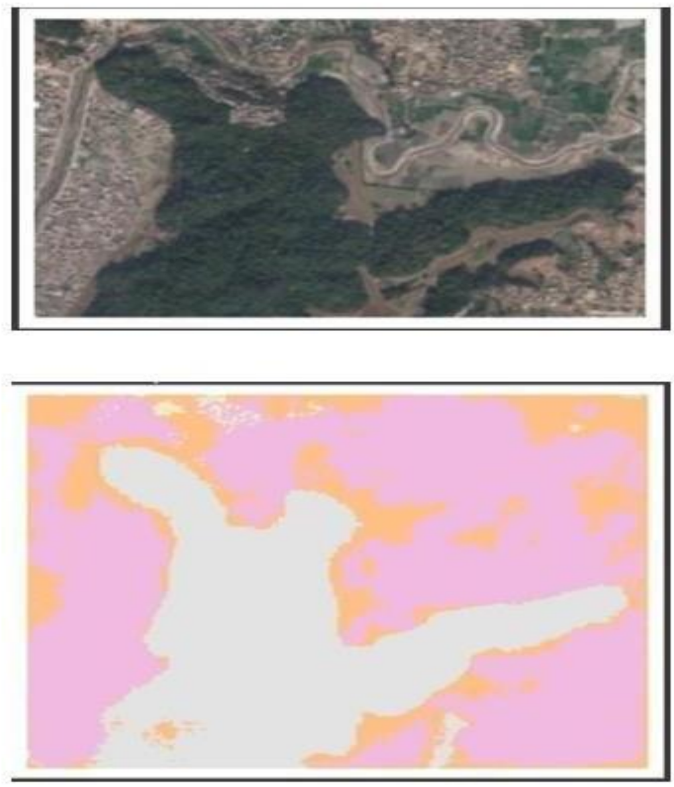


Fig no .6. Prediction of satellite image

epoch	train_loss	valid_loss	dice_multi	time
0	0.742990	0.715650	0.733504	12:43
1	0.732202	0.706600	0.738192	12:43
2	0.732817	0.701676	0.738013	12:41
3	0.710316	0.698270	0.740622	12:42
4	0.717951	0.700329	0.739740	12:44
5	0.722597	0.698299	0.737118	12:41
6	0.702310	0.684811	0.743913	12:44
7	0.702311	0.682651	0.746301	12:43
8	0.704103	0.684681	0.744876	12:41
9	0.689756	0.691085	0.742374	12:42

IV. Conclusion

In this investigation, we assessed the efficacy of employing the ResUnet model in detecting deforestation patterns utilizing remote sensing data. Our results illustrate that the ResUnet architecture, amalgamating features from U-Net and ResNet, attains precise segmentation of deforested regions. Through the utilization of deep learning methodologies, we make a meaningful contribution to sustainable environmental stewardship and conservation initiatives. Subsequent research endeavors may concentrate on refining hyperparameters and incorporating supplementary contextual data to augment the model's effectiveness.

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