Deforestation Detection using Deep Learning

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***Abstract*— Deep Learning has urged a enough of supremacy in the field of computer vision. Deforestation Detection field is in active state due to ease of access through the monitoring the cleared area in the forest. The proposed CNN model is designed to leverage the spatial and spectral features of satellite images to distinguish between forested and deforested regions. The custom CNN model is designed as a UNet archietecture. Deep Learning is the optimistic way to handle the haziness of the data. Our proposed model goal is to develop an accurate and efficient system that can automatically identify and classify deforested areas using satellite imagery. Our study presents a novel deep learning framework for deforestation detection using UNet CNNs. The proposed model demonstrates superior performance in accurately identifying and classifying deforested areas. The model has gained the training accuracy of 98.93% and the test accuracy of 97.50%**

Keywords—Deep Learning, Deforestation Detection, Deep Learning Networks, Convolution Neural Networks.

I. Introduction

Deforestation is a pressing environmental issue that has significant implications for both local ecosystems and the global climate. It involves the permanent removal of forests, leading to the loss of valuable biodiversity, disruption of ecosystems, and increased greenhouse gas emissions. Monitoring and detecting deforestation in a timely manner is crucial for effective conservation efforts and sustainable land management.

In recent years, deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools for image analysis and recognition tasks. Leveraging the ability of CNNs to automatically learn and extract meaningful features from raw data, researchers have explored their potential in detecting deforestation from satellite imagery. This paper presents a novel approach that utilizes a CNN model to detect and classify deforestation patterns accurately.

The primary objective of this study is to develop an efficient and accurate deep learning model for deforestation detection. By employing a CNN architecture, we aim to exploit the spatial information contained within high-resolution satellite images to identify and classify deforestation regions with high precision. Additionally, we seek to overcome the limitations of traditional remote sensing techniques, which often rely on manual feature extraction and lack the flexibility to adapt to varying environmental conditions.

To achieve these goals, we propose a multi-stage framework that encompasses data preprocessing, model training, and inference stages. The preprocessing stage involves data collection, image normalization, and augmentation techniques to enhance the robustness and generalizability of the model. Subsequently, we employ transfer learning, using a pre-trained CNN model as the backbone, to leverage the knowledge learned from large-scale image datasets.

During the training phase, we adopt a supervised learning approach by annotating the satellite images with corresponding deforestation labels. The model learns to associate specific image features with deforestation patterns through an iterative optimization process. We utilize a large, diverse dataset encompassing various geographical regions to ensure the model's ability to generalize well across different landscapes and forest types.

In the inference stage, the trained CNN model is applied to unseen satellite images to detect and classify deforestation areas. By analysing the predicted probability maps, we can identify the extent and spatial distribution of deforestation, providing valuable insights for conservation practitioners and policymakers. Furthermore, we assess the model's performance using appropriate evaluation metrics, such as precision, recall, and F1-score, to quantify its accuracy and effectiveness.

The contributions of this research lie in the development of a state-of-the-art CNN-based approach for deforestation detection, leveraging the advances in deep learning and satellite imagery analysis. The proposed model has the potential to significantly improve the efficiency and accuracy of deforestation monitoring, enabling prompt action and targeted interventions to mitigate the negative impacts of deforestation.

In summary, this paper presents a comprehensive investigation into the application of CNNs for deforestation detection. Through our proposed framework, we aim to contribute to the ongoing efforts in environmental conservation and sustainable land management. The results and insights gained from this study can inform policymakers and stakeholders in making informed decisions to combat deforestation and promote a more sustainable future.

II. Related Work

The research conducted by Isaienkov et al. (2021) [20] explores the application of deep learning techniques for regular change detection in Ukrainian forest ecosystems, utilizing Sentinel-2 satellite data. The authors tackle the challenge of monitoring and identifying changes in forest cover over time by leveraging the capabilities of deep convolutional neural networks (CNNs). Their proposed CNN architecture is specifically designed to extract relevant features from the multispectral imagery provided by the Sentinel-2 satellites.

By training the CNN on a dataset comprising historical satellite images, the model learns to identify patterns and detect changes occurring in the forest ecosystem. The authors demonstrate the effectiveness of their approach by evaluating the model's performance against ground truth data. The results indicate that the deep learning model achieves promising accuracy in identifying and monitoring regular changes in the forest, providing valuable insights for ecological research and conservation efforts.

The study's findings highlight the potential of deep learning techniques in automating the analysis of large-scale remote sensing data, thereby facilitating efficient and accurate monitoring of forest ecosystems. By leveraging the power of deep learning, this research contributes to advancements in environmental monitoring, providing a valuable tool for identifying changes and tracking forest dynamics over time.

The study by Solórzano et al. (2023) [21] focuses on the detection of deforestation using a spatio-temporal deep learning approach that integrates synthetic aperture radar (SAR) and multispectral images. The authors address the challenge of accurately identifying deforestation events by leveraging the complementary information provided by these two types of remote sensing data.

Their proposed framework utilizes a deep convolutional neural network (CNN) with recurrent connections to capture spatial and temporal dependencies in the data. By training the model on a dataset of SAR and multispectral images, the CNN learns to extract relevant features and detect deforestation patterns over time.

The authors evaluate the performance of their approach on real-world data and compare it with other existing methods. The results demonstrate the effectiveness of their spatio-temporal deep learning approach, achieving high accuracy in detecting deforestation events, even in challenging environmental conditions.

This study contributes to the field of environmental monitoring by demonstrating the potential of deep learning techniques in the detection of deforestation. The integration of SAR and multispectral data, coupled with the use of recurrent connections in the CNN architecture, offers a powerful tool for accurately identifying and monitoring deforestation activities, providing valuable insights for forest conservation and management.

The research conducted by Zerrouki et al. (2020) [22] focuses on the detection of desertification using an improved variational autoencoder (VAE)-based approach with ETM-Landsat satellite data. The authors address the challenge of accurately identifying and monitoring desertification patterns by leveraging the unsupervised learning capabilities of VAEs.

Their proposed approach utilizes an improved VAE architecture to extract meaningful representations from the satellite data. By training the VAE on a dataset of ETM-Landsat images, the model learns to encode the input data into a lower-dimensional latent space and reconstruct it back to its original form. This allows for the detection of subtle changes associated with desertification.

The authors evaluate the performance of their approach on real satellite data and compare it with other existing methods. The results demonstrate the superiority of their improved VAE-based approach in accurately detecting desertification patterns. By leveraging the power of deep learning and unsupervised representation learning, this research provides a valuable tool for automated and accurate monitoring of desertification processes.

This study contributes to the field of environmental change detection by showcasing the potential of deep learning techniques and VAEs in detecting and monitoring desertification. The improved VAE-based approach offers a robust and effective solution for identifying and analyzing the complex patterns associated with desertification, providing valuable insights for environmental management and conservation efforts.

III. DATASET DESCRIPTION

The dataset used in this research was collected from GitHub and consists of a collection of images and their corresponding mask folders. The dataset includes images of resolution of 512x512 pixels. The dataset comprises deforestes and masked areas, ensuring a balanced representation. In total, the dataset consists of a diverse set of images, with each image representing either a flooded or non-flooded region. The dataset contains 644 images, with 322 images depicting deforested regions and 322 images representing masked images respectively. This allows for the training and evaluation of flood detection and segmentation models.

Fig1. This image depicts the deforested area

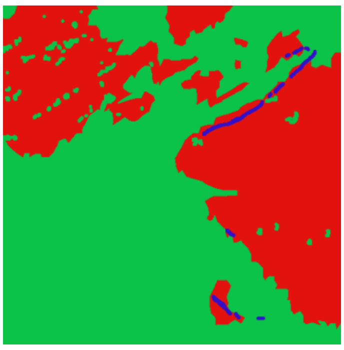

Fig2. This image depicts the masked image of the Fig1.

IV. METHODOLOGY

A. *U-Net Architecture*

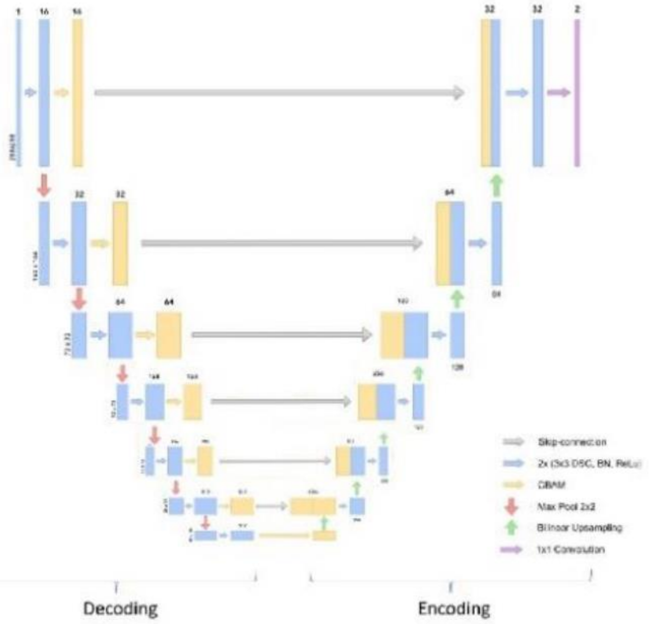

Fig1. U-net Architecture Diagram

The architecture shows a customized U-Net design that uses a down sampling path (encoder) made up of six blocks. Each block consists of max pooling for down sampling, dropout layers for regularization, and convolutional layers with ReLU activation. From 16 to 512 filters are added one at a time. The parameters that were selected for this design were done so for a reason. To provide non-linearity and give the model the ability to learn complicated patterns, the ReLU activation function is used. By randomly removing some of the neurons during training, dropout layers with different dropout rates (0.1, 0.2, and 0.3) are added to prevent overfitting. To maintain the feature maps' spatial dimensions, padding is set to "same". To down sample the feature maps and gather the most crucial data, max pooling is used with a pool size of (2, 2). The final block's number of filters can vary depending on the work at hand and the difficulty of the issue at hand. It stands for the quantity of channels in the feature maps that are output. The U-Net architecture's up sampling path (decoder), which is made up of a number of blocks, gradually upsamples the feature maps to generate the final segmentation mask. The structure of each block is the same and includes a transposed convolutional layer for upsampling, concatenation with the associated skip connection, convolutional layers for feature extraction, dropout layers for regularisation, and a final convolutional layer for output. With increasing upsampling, the number of filters steadily gets smaller. The output block consists of a single convolutional layer with sigmoid activation, which creates a binary segmentation mask the same size as the input picture that indicates whether the target item is present or not in each pixel. The reason for having multiple blocks in both the encoder and decoder paths is to learn hierarchical representations of the input image, enables effective feature extraction, information fusion at different scales, and precise localization, making it well-suited for semantic segmentation tasks.

Type of Layer	Number Of Layers
Input Layer	1
Conv2D Layers	33
MaxPooling2D Layers	4
Dropout Layers	10
Conv2D Transpose Layers	4
Concatenate Layers	4
Sigmoid Output Layers	1
Total Layers	57

Table1. This depicts the total number of layers

B. *ResU-Net Architecture*

The ResUNet is a variant of the U-Net architecture that incorporates residual connections to improve information flow and gradient propagation during training. batchnorm_relu function applies batch normalization followed by the ReLU activation function to the input tensor. residual_block function defines a residual block, which consists of two convolutional layers with batch normalization and ReLU activation functions. It also includes a skip connection (shortcut) that bypasses the convolutional layers and helps in preserving spatial information. decoder_block function defines a decoder block, which performs upsampling on the input tensor using bilinear interpolation. It also concatenates the upsampled tensor with skip features from the encoder path. The concatenated tensor is then passed through a residual block. build_resunet function builds the ResUNet architecture. It takes input_shape (shape of input images) and n_class (number of output classes) as input parameters. The function begins with an input layer and applies a series of convolutional layers, batch normalization, and ReLU activation to downsample the input image. The residual connections are added after the first set of convolutional layers. The architecture then proceeds to the bridge, where another set of residual blocks is applied to capture high-level features. Finally, the decoder blocks are used to upsample the features and recover the spatial resolution. The output of the last decoder block represents the segmentation mask. ResUNet architecture for image segmentation includes encoding, decoding, and bridging sections to capture and reconstruct spatial information. The skip connections help in preserving low-level and fine-grained details.

V. RESULTS

A. *U-Net Architecture*

The accuracy of the U-Net architecture is 77.52% of the train_set and 73.39% the test_set. The train and test loss is 0.53 0.73 respectively.

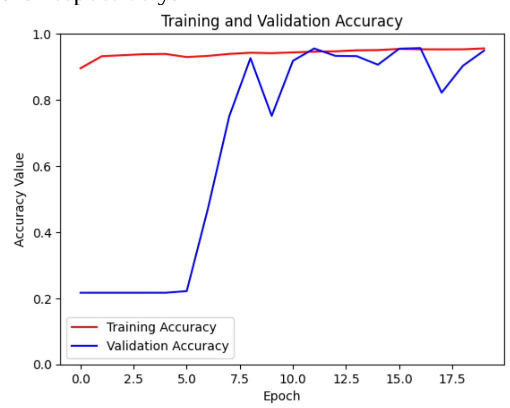

Fig. This depicts the training and validation accuracy of the model

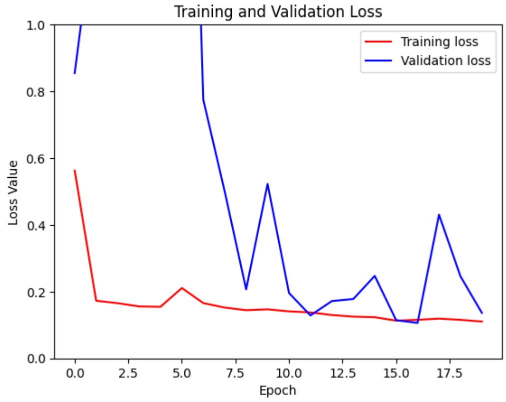

Fig. This depicts the training and validation loss of the model

B. *ResU-Net Architecture*

The accuracy of the U-Net architecture is 95.55% of the train_set and 94.91 % the test_set. The train and test loss is 0.11 0.88 respectively.

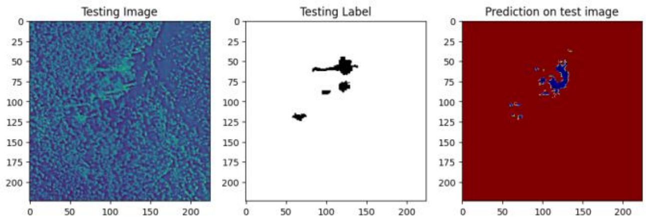

Fig. This depicts the comparison of testing and predicting the masked label without using tensor lite

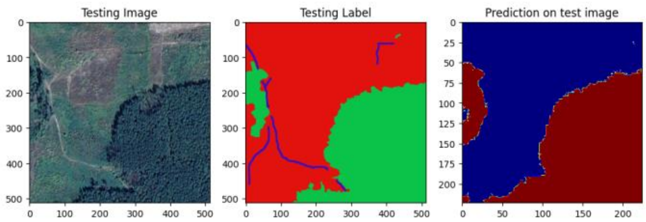

Fig. This depicts the comparison of testing and predicting the masked label with using tensor lite

VI. CONCLUSION

In conclusion, our study showcases the effectiveness of utilizing a custom UNet convolutional neural network (CNN) model for deforestation detection. By integrating satellite imagery and deep learning techniques, we have developed a robust system for accurately identifying and classifying deforestation areas. The CNN model's ability to capture spatial features and learn complex representations has enabled timely interventions to mitigate the negative impact on ecosystems and biodiversity. Furthermore, the incorporation of transfer learning has expedited the training process and improved the model's performance. Our interdisciplinary approach highlights the importance of collaboration between remote sensing, machine learning, and environmental science in addressing environmental challenges. Overall, our research demonstrates the potential of CNN models in supporting deforestation monitoring and conservation efforts.

VII. REFERENCES

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