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Research Paper

Detecting Density Changes of Mangrove Forest in India using Remotely Sensed Images

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Abstract: The use of deep learning technology in the domain of biodiversity has been expanding over the past few years, with applications in wildlife and vegetation monitoring. The Convolutional (CNN) is a powerful tool that has enabled new feature extraction methods in computer vision. Remote sensing techniques, such as satellite and drone-assisted images, have also contributed to the development of vegetation cover assessment. This study focuses on detecting changes in vegetation cover in the Sundarbans mangrove forest, which is the world's largest mangrove and a heritage site that supports over 4.37 million people and reduces 45 million tons of CO2. The study Neural Network used a deep learning model to analyze time-series data and achieved an accuracy score of 99.85% and a value of 1 for the other three metrics - precision, recall, and F1-Score. The study also includes a review of previous work in the field and proposes a novel model for vegetation cover assessment. This study emphasizes the importance of sustaining the ecology of the Sundarbans and provides valuable insights for future research in this field.

Keywords: Mangrove Forest; Deep Learning; Convolutional Neural Network; Remote Sensing Images.

1. Introduction

Sundarban is the largest and a heritage site of all the adjoining mangrove forests in the world. The mangrove shares geographical locations with two countries, India, and Bangladesh. Although Sundarban habitats multiple species, tigers are the primitive attractions and the object of preservation [1]. The mangrove also habitats an approximate count of 4.37 million people, and has till date aided in greenhouse gas consumption of 4.15 crore tons of carbon dioxide [2]. Climate changes have posed several challenges in Sundarban to a great extent such as rising sea levels resulting in subsidence of islands, increase of water salinity, soil salinity thereby affecting the mangrove, soil, and crop health [3]. Aiding to the effect, erratic rains and cyclones have contributed to the plight of fishing ecology. Recent cyclones such as Yaas, Amphan, Bulbul have destroyed the mangrove as the mangrove acts as a barrier to those natural events. Moreover, the mangroves also grow in saline soil, thereby behaving as the best natural risk reduction factor globally [4]. Studies have also stated that a concentration of 30 mangrove trees within a radius of 100 square meters can reduce the impact of tsunami waves by about 90% [5]. To arrest the events, and provide relief and restoration, certain institutes have been constituted by the government of India to tackle the effects of the climate change in the region [6].

To prevent the subsidence of the mangrove region, and collateral effects of the climate changes, attention has been shifted to renewable energy as a possible replacement of fossil fuels. Plantation of saline resistant trees and saplings also demand motivation along with flood relief centers, rapid action centers, and steps for poverty eradication need to be taken at the earliest. With growing computing capabilities, introduction of Artificial Intelligence (AI), and Remote Sensing (RS) technologies, a plethora of images and data are being generated. Deep Learning (DL) algorithms are being developed and deployed for analysis of such huge data recently which has presented certain directions for actions for arresting the deteriorating health of the mangroves. Computer Vision (CV) has been explored heavily for RS image analysis and has exhibited satisfactory results with deployment of Convolutional Neural Networks (CNN) [7]. CNNs form the most explicitly used DL framework for feature extraction and correlation.

The study in this paper concentrates on discussion on the existing latest proposals to analyze RS image employing CNNs, and further presents an enhanced model based on CNN for better classification of the RS images. Initially, the basics of the CNN framework are discussed within the context of data augmentation, batch normalization, and image classification. Satellite images provide insights into several factors such as climate change, deforestation, and land surface temperature to name a few. Recent analysis of these data has been resulted in classification of leaf areas, species mapping, and canopy height prediction with higher accuracies, which were near impossible to calculate using traditional methods.

The proposed model in this study identifies and calculates the density changes in the green coverage of the mangrove through CNN analysis of the RS images. The framework comprises of 9 layers; one input and one output layer, six inner layers, and one dense layer. The inner layers consist of 2 sets of 2 convolutional layers each coupled with single max pooling layer. The first set of convolutional layers consists of 32 filters of size 3*3 each. The second set of convolutional layers consists of 64 filters of size 3*3 each. The vanishing gradient issue has been arrested by use of ReLu as the activation function for all the layers. The max pool layer has a filter size of 2*2. Post flattening, the dense layer comprises of 256 neurons which are processed using the SoftMax activation function for classification. Dropouts of 40% and 50% have been used to eliminate the chances of over-fitting. This study presents a framework based on DL CNN for better classification of RS images in the Sundarban area.

The rest of the paper is organized as follows. In Section 2 the literature review related to this context is given. Section 3 elaborates the detailed design and methodology and proposed approach of the model. Section 4 is for the result analysis of this system. Finally, the conclusion is in Section 5.

2. Related Work

The Earth weather is fluctuating, numerous lines of indication show significant warming in the sphere as well as in the oceans. The universal surface temperature is rising every day. Consequently, the "Remote sensing technique" has been proven its importance for improvements in understanding the climate system and its changes and impacts. Some renowned implementations using "Remote sensing and Image processing Method" are as follows:

The authors, Hoque, S. N. M. et al [6] Hoque, S. N. M. et al. in their composition examined geospatial information gathered by Sentinel-1A and Sentinel-1 Band SAR data in dual-polarization mode to identify rapid deforestation and the CO2 emission in Bangladesh.

De Bem P. P. et al. [7] detected deforestation in the Brazilian Amazon on Landsat data by comparing two CNN architectures, Random Forest (RF), and Multilayer Perceptron (MLP), in 2020.

Chamberlain, D. Et al. [8] Conducted experiments to investigate the dynamics of mangroves and estuarine areas in central Queensland, Australia, using different change analysis methods. The methods included post-classification change analysis utilizing a supervised classification technique, visual interpretation, examination of thematic change dynamics, and trend analysis. The results showed that the supervised pixel-based classification method provided the highest accuracy among these analysis methods.

A deforestation monitoring was proposed by Juarez V. d. O. et al. [9] in 2018 using Digital's remote sensing database obtained from the moderate-resolution imaging spectroradiometer sensor.

In the research, [10] Mortoja M. And Yigitcanlar T. used a remote sensing dataset from Brisbane to quantify the impact of global climate shift (global warming) on land use and land cover (LULC). The maximum likelihood supervised classification was found to provide the best solution for the analysis.

In 2018, H. He et al. [11] introduced an advanced approach to match diverse remote sensing images with varying backgrounds using the Siamese Convolutional Neural Network deep learning method. This methodology has demonstrated significant potential for accurate image matching.

J. Suresh Babu [12] employs innovative remote-sensing techniques, utilizing satellite data from the Moderate Resolution Imaging Spectroradiometer and accessible NASA satellites, to identify and study deforestation patterns. His analysis provides valuable insights into the extent of forest loss and contributes to conservation efforts.

In 2018, M.D. Behera et al. [13] utilized an on-screen digital interpretation method to predict land use and land cover (LULC) changes in the Mahanadi and Brahmaputra River basins by 2025. Their study aimed to offer early warnings about global warming and deforestation. By analysing LULC maps derived from Landsat images, the researchers shed light on the potential impacts of these changes on the environment, highlighting the urgency for sustainable land management practices.

[14] Salvaris, M., Dean, D., & Tok, W. H. delve into the capabilities of GANs in their 2018 publication, exploring their applications across diverse AI scenarios. They elucidate the inner workings of GANs and present code examples for Cycle GAN, a ground-breaking GAN model. Their study utilized an Azure DLVM for the computational environment.

In the work, [15] Jie Feng et al introduced a groundbreaking multiclass spatial-spectral GAN (MSGAN) method in 2019 to overcome limitations of traditional GANs. It employed two generators to produce samples with spatial and spectral information, while The discriminator captures integrated spatial-spectral features and delivers probabilities for multiple classes. Additionally, innovative adversarial objectives were formulated specifically for multiclass scenarios, enhancing the effectiveness of the proposed technique. This advancement offers promising prospects in the field of spatial-spectral image generation and analysis.

Researchers Yan, He, Yang, and Hu [16] have developed a semi-supervised learning approach for GANs, empowering the discriminator to acquire highly discriminative features from both labelled and unlabeled data. They also introduced a mix-up data augmentation method for their classification model, leading to more stable training. Promising results were obtained through experiments conducted on two datasets using a 5-fold cross-validation protocol, where a linear SVM was employed as the classifier.

A new data augmentation (DA) method [17] specifically designed to enhance the training of convolutional neural networks (CNNs) was proposed in 2019. The method involves randomly occluding pixels of rectangular spatial regions in the hyperspectral image (HIS) to generate training images with varying levels of occlusion, which effectively mitigates the risk of overfitting. This technique has been shown to improve classification accuracy and can be achieved at a low computational cost. The work was conducted by Juan Mario Haut, Mercedes E. Paoletti, Javier Plaza, Antonio Plaza, and Jun Li.

A scene-classification method based on vision transformers was proposed by Bazi. Y. et. al [18]. To enhance classification performance, the authors explored various data augmentation techniques to generate additional training data. Experiments conducted on different remote-sensing image datasets showed that the proposed model outperformed state-of-the-art methods, demonstrating its promising capabilities.

Song. J. et. al. presented [19] in his survey paper on the current state-of-the-art application of CNN-based deep learning in remote sensing image classification. They reviewed developments and improvements to CNN models and data augmentation techniques. The authors also discussed three typical CNN application cases in remote sensing image classification: scene classification, object detection, and object segmentation.

The researchers Wang C. and Zhang L. [20] proposed a new hyperspectral image (HIS) classification method that involves two steps. Firstly, a data mixture model is employed to perform quadratic augmentation of labelled data set, and a deep convolutional neural network (DCNN)-based classifier is trained on it. Secondly, by randomly sampling the coefficient in the data mixture model, several independent classifiers are obtained and fused using a voting strategy to produce the final classification results. The proposed method demonstrates superior performance in HIS classification, which is supported by experimental results on two benchmark HIS datasets.
In the research work, [21] a data augmentation technique that significantly expands small datasets was presented. Their findings revealed that employing data augmentation resulted in substantial performance enhancement, regardless of regularization (such as dropout) usage. Moreover, they noted that when data augmentation was excluded, dropout played a crucial role in improving the results.

Abbasi, A. N., and He, M [22] presented a novel deep learning method for hyperspectral image classification. Their method combines spectral reduction via Principal Component Analysis and batch normalization at each layer. By dividing the spatial dimension into 9x9 patches, the proposed network extracts discriminative features hierarchically. This spectral-spatial approach showcases the potential of deep learning in effectively analyzing hyperspectral data for classification tasks.

In the composition of Vaddi, R., and Manoharan, P., [23] a novel approach was introduced for hyper spectral image classification in remote sensing. By employing data normalization and convolutional neural networks (CNN), their method surpasses existing techniques, offering valuable applications in fields like forestry, agriculture, and food processing.

Li J., Liang B., and Wang Y. [24] present a solution to challenges in hyperspectral image classification. They introduce a novel hybrid neural network (HNN) that addresses issues with feature map extraction and information loss due to pooling operations. By employing a multi-branch architecture, the HNN effectively extracts features from multiple dimensional hyperspectral images, leading to improved prediction accuracy. This approach holds promise for enhancing the analysis and classification of hyperspectral data in various applications.

This article presents a novel CNN architecture inspired by previous researchers' proposals, addressing the motivation behind the innovation.

3. Approach and Methodology

3.1. Generative Adversarial Networks, Data augmentation and batch normalization

Hyperspectral remote sensing images (HSIs) hold immense research and application potential. Generative adversarial networks (GANs) have made significant advancements in this field. Effective techniques like data augmentation and batch normalization have proven beneficial for remote sensing image classification. This article provides a concise overview of previous research on generative models, emphasizing the methodology of GANs, data augmentation, and batch normalization.

Supervised learning with convolutional networks (CNNs) has gained significant traction in computer vision, but unsupervised learning with CNNs has been relatively overlooked. In 2015, Alec Radford, Luke Metz, and Soumith Chintala attempted to bridge this gap by introducing deep convolutional generative adversarial networks (DCGANs). Their groundbreaking paper showcased the success of DCGANs in learning a hierarchical representation of object parts to scenes. By training on diverse image datasets, they demonstrated that the deep convolutional adversarial pair could effectively learn and generate realistic visual content. This work marked a significant milestone in advancing unsupervised learning methods using CNNs.

3.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) have redefined the field of computer vision and have become a fundamental tool for various image-related tasks. CNNs are a type of deep learning model designed to process and analyze visual data, making them particularly effective for image classification, object detection, and other visual recognition tasks.

CNNs draw inspiration from the intricate organization of the visual cortex in the human brain. They are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers cooperate to learn and extract layered representations of the input data.

Convolutional layers are the basic elements of CNNs. They include learnable filters that slide over the image which is given as input, computing convolutions at each position to extract local patterns and features. By learning these filters, CNNs can automatically detect edges, textures, and other meaningful visual patterns.

Pooling layers are used to down sample the feature maps generated by the convolutional layers. They reduce the spatial dimensions of the data while retaining the most relevant information. This helps to extract invariant features and improve the computational efficiency of the model.

Fully connected layers are the links between every neuron in one layer to every neuron in the next layer. They integrate the extracted features and perform the final classification or regression task.

CNNs are typically trained using large labeled datasets through a process called backpropagation, where the model learns to adjust its internal parameters to lower the gap between predicted and actual outputs.

To summarize, CNNs have exerted a noteworthy influence on diverse computer vision tasks, encompassing image recognition, object detection, and semantic segmentation. By autonomously acquiring hierarchical representations from visual data, they emerge as a potent instrument for analyzing and comprehending intricate images.

3.3 Data Augmentation (DA)

Data augmentation is a technique, to expand the size of the dataset to enhance the efficiency of deep learning models. Traditional transformations like rotations, zoom, sheer, shift, coloration, and filling can be applied to create new images. This technique is especially useful when working with limited data, improving the model's accuracy and preventing overfitting. Involving affine transformations, the primary image transforms using the equation:

$$y = Wx + b \tag{1}$$

Larger datasets hinder noisy images and overfitting in models. Unsupervised data augmentation is employed, utilizing Keras' Image Data Generator class to pass relevant augmentation arguments and perform operations for enhanced performance. Some of the major operations are:

3.3.1 Rotation

Images are randomly rotated by defining the rotation range argument, introducing variation and diversity to the dataset.

3.3.2 Zoom.

To enhance dataset diversity, images are modified by applying zooming techniques within a specified range value; <1 for zooming in and >1 for zooming out.

3.3.3 Shift.

In image processing, pixels can be shifted horizontally or vertically. The width_shift_range and height_shift_range parameters control these shifts.

3.3.4 Fill mode

To fill points outside an image's boundaries, the fill_mode argument is used, allowing the specification of a filling mode. The default mode is 'nearest', which is applied to ensure accurate image processing.

Data augmentation not only increases data quantity but also improves the generalization of CNN models, enhancing their performance with real-world examples. GANs, such as style transfer, apply six different image styles to the input image for artistic transformations.

3.4 Batch Normalization (BN)

Training deep neural networks with numerous layers poses challenges such as overfitting and the distribution conversion of inputs at each layer during training, known as "internal covariate shift." To address this, batch normalization normalizes inputs for every training mini-batch, stabilizing the training process. By reducing the number of required epochs and improving model accuracy, batch normalization proves to be an effective technique in training deep neural networks.

In a CNN, a layer receives output x from the preceding layer and applies an affine transformation to obtain y = Wx + b. The resulting y, consisting of components y1, y2, ..., yn, is then passed through the activation function h(y) to produce an output h(y) = [h(y1), h(y2), ..., h(yn)]. Batch normalization, as described in [68], is a technique based on this transformation.

$$\hat{y}\mathrm{i} \leftarrow \frac{y_i - F[y_i\,]}{\sqrt{F[(y_i - F[y_i\,])^2]}} \tag{2}$$

Here, $F[y_i\,]$ represents the mean and $\sqrt{F[(y_i - F[y_i\,])^2]}$ represents the standard deviation of the random variable y_i. These values are estimated using a batch of training images during training.

4. Proposed Model

In our study, we propose an architecture consisting of 9 layers to detect density changes in mangrove forests using remotely sensed images in India. The architecture includes 6 inner layers, 1 input layer and 1 dense layer serving as the output layer. It leverages convolutional layers with filters of varying sizes and max-pooling layers to extract relevant features from the images. The rectified linear unit (ReLU) function is used as the activation function for all layers to address the vanishing gradient problem. To prevent overfitting, dropout layers are incorporated, with a dropout rate of 40% after each convolutional-pooling set and 50% after the first dense layer. Additionally, data augmentation methods, like rotation, zooming, and shifting, are applied to diversify the dataset, while batch normalization is implemented to enhance model independence and training accuracy. By utilizing this architecture, we aim to improve the detection of density changes in mangrove forests, aiding in monitoring and conservation efforts in India. The proposed approach holds the potential to contribute to the preservation of these valuable ecosystems.

We aim to improve test accuracy by incorporating Bata Augmentation (DA) & Batch Normalization (BN) techniques. DA is applied to the training and validation sets, diversifying the dataset and enabling the model to explore new low-level and high-level features. Operations such as rotation (10 degrees), zoom (5% increase), and random shifting (-5% to +5%) are applied to the images. BN enhances the model's independence and is added after each set of convolutional layers before max-pooling. We trained the model using four different combinations of DA and BN to achieve a more accurate and robust model.

We employ the Adam optimizer, a powerful gradient descent algorithm, along with cross-entropy as the loss function, to detect density changes in Indian mangrove forests. This approach combines memory-efficiency, high performance, and accurate monitoring of mangrove ecosystems using remotely sensed images. The flow-diagram of the process is described in the Fig. 1 whereas the proposed CNN architecture can be found in Fig. 2.

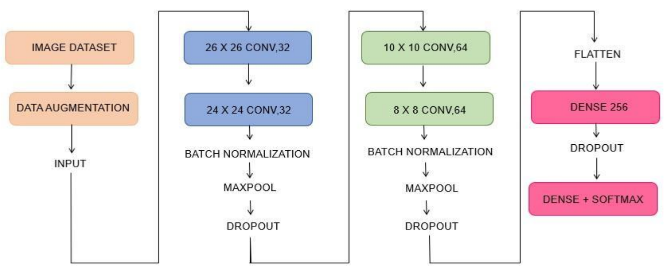

Figure 1- Flow-diagram of the DABNCNN model

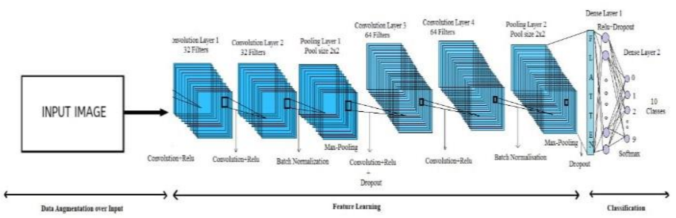

Figure 2-Diagram of the proposed DABNCNN architecture

4.1 Brief about Dataset

In this work, popular Landsat 8 dataset has been used for collecting remote sensing images including its ground truth (https://www.usgs.gov/landsat-missions/landsat-8). The data contains 12 bands with the shape of (12,954,298). The ground truth data contains 6 different classes namely water, trees, plants, bare lands etc.

5. Result and Discussion

The experimental results have been carried out in Google colab (colab.research.google.com) with selection of TPU as running tool. To visualize the data properly, RGB images have been considered here which have band nos. as 4, 3, and 2 of red, green and blue colors. As the experiment has been implemented using python and as python indexing starts from 0 so, 1 is subtracted from each index and final values of bands set as 3, 2, and 1 of corresponding colors. Next to avoid the darkness of some pixels of the images, "stretch=True" command in python has been used so that all pixel values can be extended to the range of 0-255. Next pre-processing of the data has been done by a scaling technique called standardization in which mean values of the attribute become zero whereas standard deviation becomes unique. In the experiment 30% data are chosen for training whereas remaining are left as testing purpose. The proposed DABNCNN model has been compared with the DL models with CNN [25], Deep CNN [35], and Adaptive Residual CNN [36] on the mentioned dataset.

The comparative classification outcomes of various CNN techniques along with the ground with image have been shown from Fig. 1 to Fig. 5. Fig. 1 shows ground truth image of Sundarbans data whereas Fig. 4 shows the classified outcome of the proposed approach along with 6 classes. Colors are specified of each class which help to find out the accuracy of the outcomes.

In Fig. 6 ROC curve of all the models have been shown. From the result Area Under Curve (AUC) values for all classes of the proposed model are higher than other models. It touches exact values of 0 and 1 which state prominent classification of data. The values of other models have also been noted in the Fig. 6 for better understanding of the proposed model. Further confusion matrix score is also evaluated for various models. It contains Precision, Recall, F1 Score and Accuracy parameters. Measurements of all the mentioned parameters are described as following:

Precision= $\frac{TP}{TP+FP}$, Recall= $\frac{TP}{TP+FN}$, F1 Score=2 $\times \frac{Precion*Recall}{Precion+Recall}$, Accuracy=$\frac{TN+TP}{TN+FP+TP+FN}$

Where TP, TN, FP, FN denote true positive rate, True negative rate, false positive rate and false negative rate of identifying objects. In Table 1, these corresponding values are noted and results show that proposed approach outperform other approaches in respect to all parameters.

Table 1- Comparison of Precision, Recall, F1 score

Model	Precision	Recall	F1 score	Accuracy
Model 1	0.98	0.85	0.90	96.48
Model 2	0.98	0.99	0.98	98.21
Proposed model	1.0	1.0	1.0	99.85
Model 4	0.99	0.99	0.99	98.93

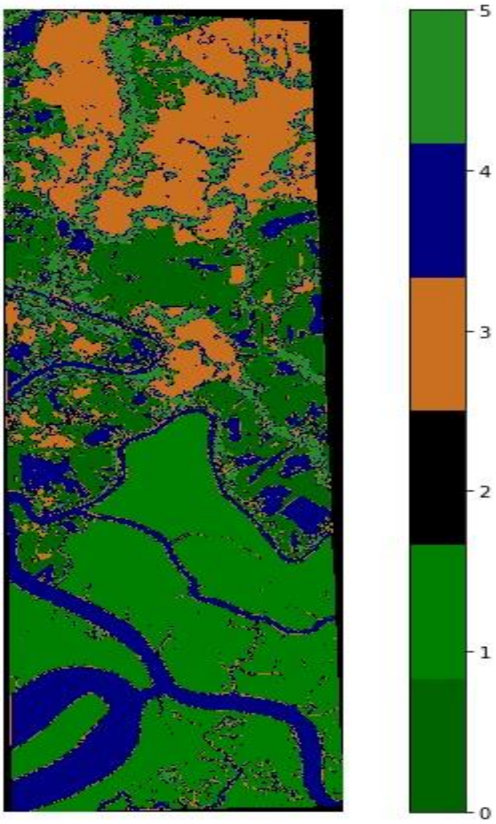

Figure 3- Ground Truth Image

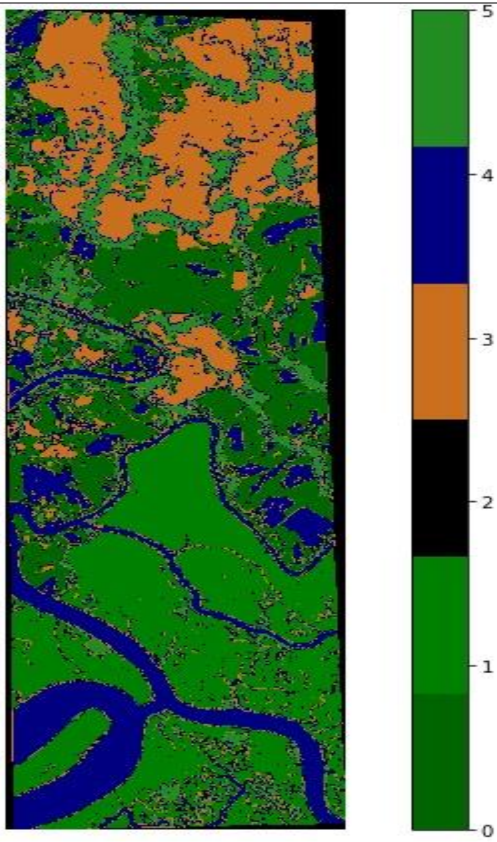

Figure 4- DL with CNN classification (Model-1)

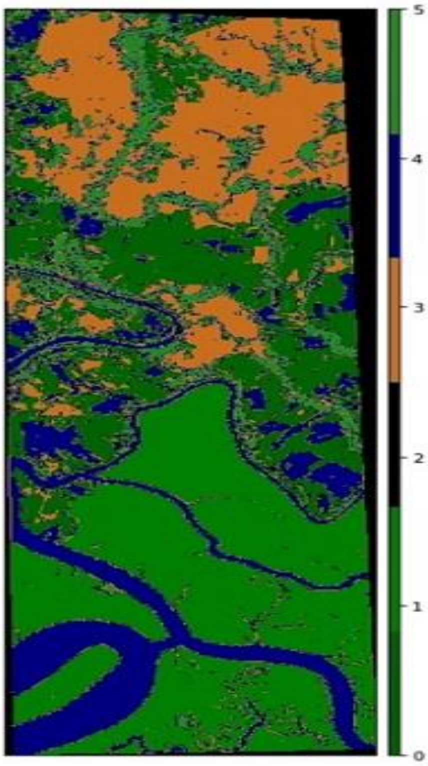

Figure 5- Deep CNN classification (Model-2)

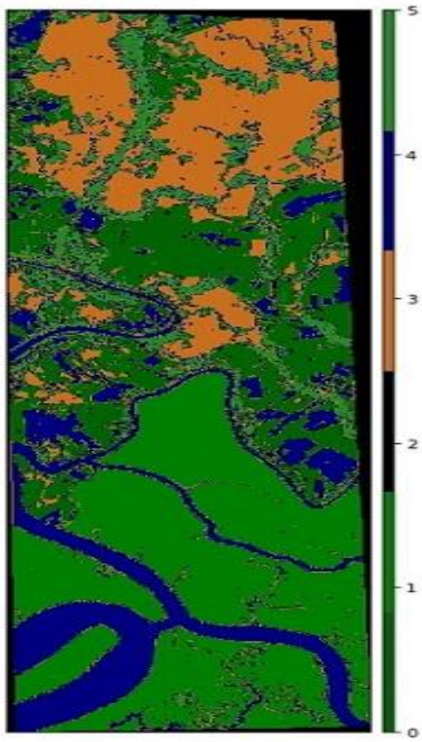

Figure 6- Proposed DABNCNN classification (Model-3)

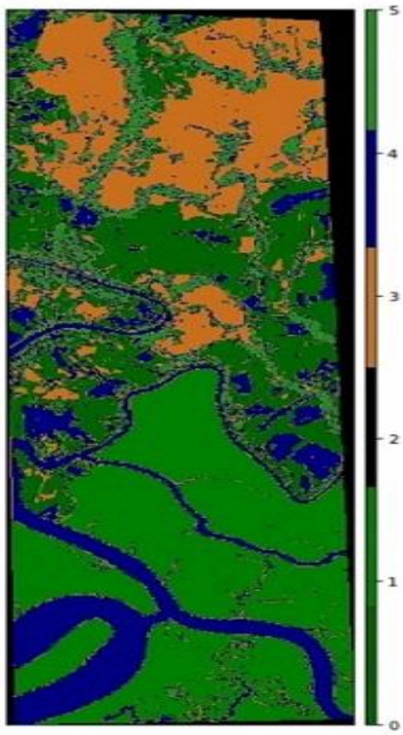

Figure 7 - Adaptive Residual CNN classification (Model-4)

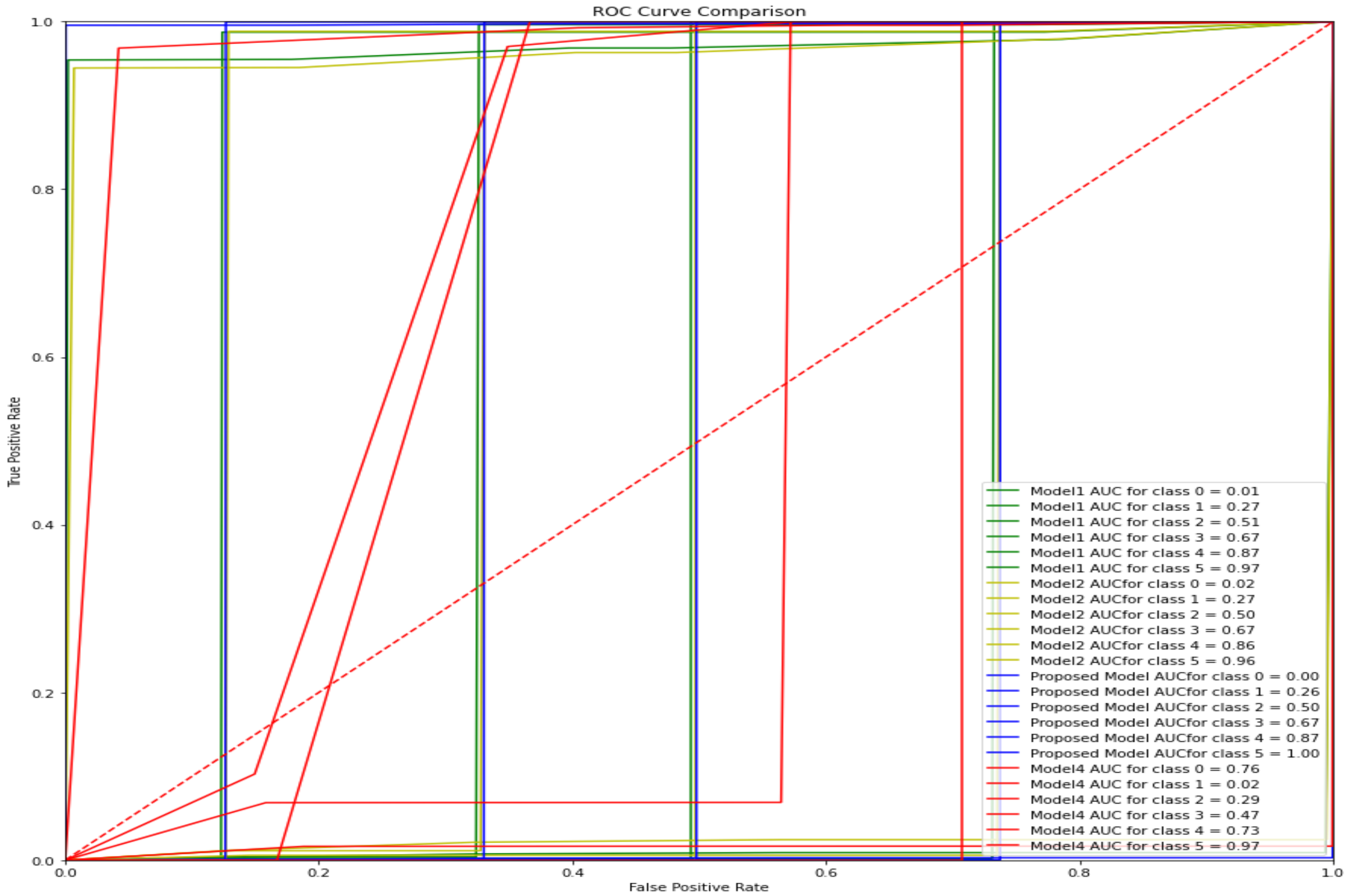

Figure 8 - TPR vs FPR (ROC curve) of all the methods

6. Conclusion and Future Scope

The proposed improved CNN approach with data augmentation (DA) and batch normalization (BN) showed superior
model loss and exploring other CNN architectures and optimization techniques.
classification outcomes compared to existing techniques, overcoming the challenges of limited data and overfitting. This will aid in identifying less dense areas of mangroves for targeted plantation. Future work will focus on reducing overall.

Data Availability
None.

Conflict of Interest
We all are hereby declare that we do not have any conflict of interest of any financial, personal, or other relationships with other people or organizations that could inappropriately influence, or be perceived to influence, their work.

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Authors' Contributions
All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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