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Dataset Creation and Comparative Analysis of Machine Learning Models for Mangrove Classification in Coastal Maharashtra, India

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Abstract—This research paper presents a new dataset of Landsat 8 image tiles processed for mapping mangroves in the coastal region of Maharashtra, India using bandcombinations of Band 5, 6 and 4. The dataset includes labelled image tiles which can beused for binary classification of mangroves using Convolutional Neural Network (CNN) and Random Forest algorithms.The radiometric correction of images and creation of composite images were done usingArcGIS Pro, while the image tiles were extracted and labelled using the Geotile library in Google Colab. The performance of CNN and Random Forest algorithms were comparedfor the classification of mangroves. This dataset can be used for further research on mangrove mapping and monitoring using remote sensing techniques.

Keywords - Convolutional Neural Network; Deep Learning; Geospatial Data Analysis;Machine Learning; Mangrove Classification; Random Forest

I. Introduction

Mangroves are important coastal ecosystems that provide numerous ecosystem services, including carbon sequestration, fisheries production, and coastal protection [1], [2]. However, they are under threat from anthropogenic activities such as deforestation, pollution, and climate change. Monitoring and mapping of mangroves are essential for their sustainable management and conservation. Remote sensing techniques have proven to be effective in mapping and monitoring mangroves [3]. Landsat 8 satellite imagery is particularly useful for mapping mangroves due to its high spatial and temporal resolution.

In this research, we present a new dataset of Landsat 8 image tiles for mapping mangroves in the coastal region of Maharashtra, India, using band combinations of Band 5, 6 and 4. We also compare the performance of CNN and Random Forest algorithms for the binary classification of mangroves. The radiometric correction of images and creation of composite images were done using ArcGIS Pro, while the image tiles were extracted and labelled using the Geotile library in Google Colab.

The results show that CNN performed better with an accuracy of 84.926% compared to Random Forest with an accuracy of 76.47%. This research highlights the potential of remote sensing techniques for monitoring and mapping mangroves and can inform future conservation efforts by providing accurate and efficient methods for mapping and monitoring mangroves.

The following are the research outcomes of this paper:

- An image dataset for binary classification of Mangrove vegetation [4]
- A Machine Learning/ Deep Learning Technique for Mangrove Classification
- Comparison and evaluation of the performance of these techniques

The rest of the paper is as follows: section 2 summarizes the Background study, section 3 describes the Material Used followed by an explanation of the Methodology in section 4. Section 5 provides the Result analysis. Section 6 concludes the paper and section 7 includes the Future scope.

II. Background Study

A. *Significance of Mangrove Mapping as Geospatial Analysis task*

Mangrove mapping is a significant geospatial analysis task due to the crucial role that mangrove forests play in the ecological and economic well-being of coastal communities. Mangrove ecosystems are important breeding grounds for various fish and shellfish species and serve as natural barriers against coastal erosion and storm surges. Accurate mapping and monitoring of these ecosystems are essential for their conservation and sustainable management.

Geospatial analysis techniques, such as remote sensing and machine learning provide valuable tools for the accurate mapping and monitoring of mangrove forests [2]. Such research is critical for the management and conservation of these valuable resources, ensuring their continued provision of ecological and economic benefits to coastal communities.

B. *Machine Learning Techniques used for Mangrove Mapping*

The machine learning techniques that have been employed for mangrove mapping in this paper include:

TABLE I. LANDSAT-8 OPERATIONAL LAND IMAGERY & THERMAL INFRARED SENSOR BAND COMBINATIONS

Band Number	**Description**	**Wavelength**	**Resolution**
Band 1	Coastal/Aerosol	0.433 to 0.453 μm	30 meter
Band 2	Visible blue	0.450 to 0.515 μm	30 meter
Band 3	Visible green	0.525 to 0.600 μm	30 meter
Band 4	Visible red	0.630 to 0.680 μm	30 meter
Band 5	Near-infrared	0.845 to 0.885 μm	30 meter
Band 6	Short wavelength infrared	1.56 to 1.66 μm	30 meter
Band 7	Short wavelength infrared	2.10 to 2.30 μm	60 meter
Band 8	Panchromatic	0.50 to 0.68 μm	15 meter
Band 9	Cirrus	1.36 to 1.39 μm	30 meter
Band 10	Long wavelength infrared	10.3 to 11.3 μm	100 meter
Band 11	Long wavelength infrared	11.5 to 12.5 μm	100 meter

- **Random Forest:** Random forest is a Machine Learning algorithm that has shown great potential in mapping and monitoring mangrove ecosystems. The algorithm can process multispectral satellite imagery and other geospatial data to generate accurate and detailed maps of mangrove forests. Random forest uses a combination of decision trees and ensemble learning to classify different land cover types, including mangrove forests, and can also identify changes in land cover over time. This information is critical for monitoring the health and status of mangrove ecosystems, which provide a range of ecosystem services and are under threat from various anthropogenic and natural factors. The use of the random forest for mangrove mapping has the potential to improve our understanding of these valuable ecosystems and inform conservation and management efforts. Random forests have been used for both mangroves mapping by combining multiple decision trees to improve accuracy and reduce overfitting. [5].

- **Convolutional Neural Networks (CNNs):** CNNs are type of deep learning model that is particularly well-suited for image analysis tasks, such as mangrove mapping. CNNs have been used for mangrove mapping by training on spectral features extracted from remote sensing data [6]. CNNs are designed to automatically learn spatial hierarchies of image features by applying a series of convolutional filters to the input data [7].

II. MATERIAL USED

One of the most common materials used for mangrove mapping is Landsat 8 satellite images. The images are processed using data analysis tools like ArcGIS to extract relevant information about the mangrove forests. Data analysis methods such as Random Forest and deep learning algorithms are also used to classify mangrove and non-mangrove areas. The Random Forest algorithm is a machine-learning technique that combines multiple decision trees to perform this classification. Deep learning algorithms, on the other hand, are neural network-based models that learn to classify mangrove species based on features extracted from satellite images. The combination of Landsat 8 satellite images, data analysis tools like ArcGIS, and advanced data analysis methods like Random Forest and deep learning algorithms have revolutionized mangrove classification and provided a better understanding of the distribution of mangrove forests.

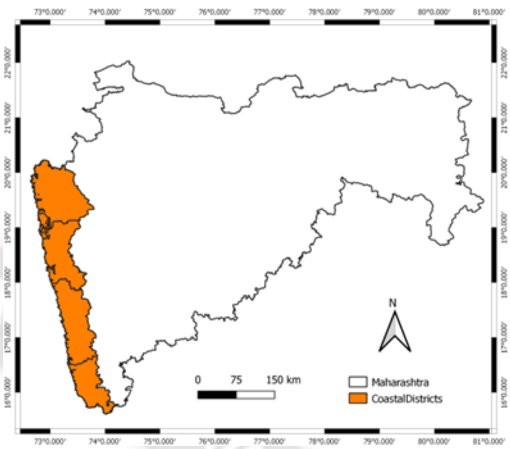

Figure 1. Coastal Districts of Maharashtra under study

A. *Satellite Imagery*

Both Landsat and Sentinel 2 are satellite-based Earth observation systems that can be used for mangrove mapping and change detection [8]. However, there are some differences between the two systems that may make one better suited for certain applications. Landsat sensors have a long history and a wider range of spectral bands compared to Sentinel 2. The Landsat 8 sensor, for example, has 11 spectral bands, including the near-infrared and shortwave infrared bands, which are important for vegetation mapping and monitoring [9]. These spectral bands can be used to distinguish between different types of vegetation and to detect changes in vegetation health over time. In addition, Landsat images have a spatial resolution of 30 meters, which is useful for mapping larger areas. Sentinel 2, on the other hand, has a higher spatial resolution of 10 meters and a larger swath width, which makes it better suited for mapping smaller areas with greater detail. It also has 13 spectral bands, including several narrow spectral bands in the red-edge and blue bands, which can be useful for vegetation classification and monitoring [10]. Overall, the choice between Landsat and Sentinel 2 for mangrove mapping and change detection depends on the specific application and the spatial and spectral requirements of the project [11]. For mapping larger areas, Landsat may be a better choice due to its wider spectral range and long history, while for mapping smaller areas with greater detail; Sentinel 2 may be more suitable due to its higher spatial resolution and additional spectral bands. To conduct mangrove mapping and change detection over a certain period use of Landsat sensors is preferred [8, 12]. Hence Landsat 8 has been used in this study.

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B. Data Analysis tool

- ArcGIS Pro is a powerful geographic information system (GIS) software developed by Esri. It is designed for professionals and organizations to create, manage, analyze, and visualize spatial data and maps.

TABLE II. RADIOMETRIC CORRECTION PARAMETERS OF LANDSAT 8 OLI IMAGE

Band Number	Reflectance	
	Multiplicative	*Additive*
Band 2	2.0000E-05	0.100000
Band 3	2.0000E-05	0.100000
Band 4	2.0000E-05	0.100000
Band 5	2.0000E-05	0.100000
Band 6	2.0000E-05	0.100000
Band 7	2.0000E-05	0.100000

ArcGIS Pro offers a modern and intuitive interface, making it user-friendly and accessible.

- Google Colab, short for Google Colaboratory, is a cloud-based platform provided by Google that enables users to write, run, and share Python code collaboratively. It offers free access to a virtual machine with GPU support, making it particularly attractive for machine learning and data analysis tasks. By integrating *geotile* library with Google Colab, you can efficiently divide georeferenced images or maps into smaller tiles while preserving their spatial context.

III. METHODOLOGY

In this section, we present the comprehensive methodology employed in our research. Our approach encompasses the utilization of ArcGIS Pro for preprocessing of Landsat images and Google Colab as a versatile platform for machine learning and deep learning implementation, focusing on the classification of mangroves and non-mangroves using image datasets. We also detail the processes of Landsat image segmentation into tiles using the geotile library, storing these tiles on Google Drive, and subsequently labeling them. The following subsections will provide a thorough explanation of each step in our research methodology.

A. Geographical Area under research

The study site for this research was the coastal region of the state of Maharashtra, India as shown in Fig. 1. There are seven coastal districts in Maharashtra: Palghar, Thane, Mumbai City, Mumbai Suburbs, Raigad, Ratnagiri and Sindhudurg. Maharashtra accounts for 6.5% of the total mangrove cover in India. Maharashtra is home to 20 of the 47 kinds of mangroves that exist in India. The mangrove distribution in various districts of Maharashtra is as mentioned in table III according to the ISFR 2021 report.

B. Data Collection

The remote sensing images utilized in this study were Landsat 8 OLI covering part of the Coastal Districts of Maharashtra (path 147 row 48 and path 147 row 49 acquired on 27 January 2022 and path 148 row 46 and path 148 row 47 acquired on 4 February 2022). These images have a pixel size of 30 meters and eleven bands and are freely available on Earth Explorer(https://earthexplorer.usgs.gov/). In this study, we only focus on the bands used for Mangrove Detection [13] such as Visible red (640-670 nm), Near Infrared (NIR, 850-880 nm), and Short Wave Infrared1 (SWIR1, 1570- 1650 nm). These bands were incorporated into the land cover image classification process. The Band combinations of Landsat 8 OLI are given in table I.

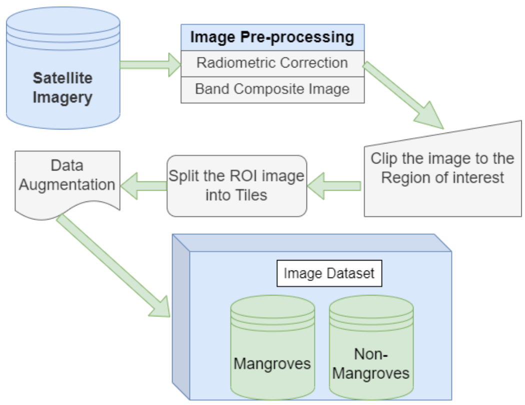

Figure 2. Steps in Mangrove Dataset Creation

C. Image Processing

The dataset generated through the image processing steps described below is a novel contribution to the field of mangrove ecology in the study area. No such dataset currently exists, which makes this research unique and valuable. Applying radiometric correction and spectral indices to the Landsat 8 image it is possible to generate a dataset of tiles that accurately represents the distribution of mangrove vegetation in the study area. This dataset can then be used to train a deep learning algorithm to automatically recognize and distinguish mangrove vegetation from non-mangrove vegetation. This methodology has the potential to improve the understanding of the spatiotemporal dynamics of mangrove ecosystems, which is crucial for their effective management and conservation. Therefore, this dataset can be a valuable resource for researchers and stakeholders interested in mangrove ecology and management in the study area.

- **Radiometric correction**

  Landsat 8 images downloaded from https://earthexplorer.usgs.gov covering the study area of the coastal region of Maharashtra were in digital number (DN) format. Radiometric correction is a process that aims to correct or compensate for any errors or distortions in the digital numbers (DN) recorded by a remote sensing sensor, in order to obtain more accurate and consistent measurements of the reflectance values of the Earth's surface. One of the factors that affect radiometric correction is the sun elevation angle, which determines the amount of solar radiation that reaches the earth's surface. The specific formula for radiometric correction may vary depending on the type of correction being performed, the sensor used, and the atmospheric conditions at the time of data acquisition. This step is essential to convert DN values to surface reflectance values and to

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reduce the effects of atmospheric interference on the image. The rescaling coefficients in the Wavefront Material Template Library (MTL) file which is a library that can contain one or more named material definitions, each of which can specify colour, texture, and reflection characteristics of the Landsat 8 Image can be used to transform DNs into Top Of Atmosphere (TOA) reflectance. The radiometric correction was done according to the formula

TABLE III. MANGROVE COVERAGE IN VARIOUS DISTRICTS OF MAHARASHTRA

Sr. No.	District	Total Mangrove coverage in Sq. Km.
1.	Mumbai City	2
2.	Mumbai Suburb	63.22
3.	Raigad	126.99
4.	Ratnagiri	30.33
5.	Sindhudurg	12.07
6.	Thane	89.68

mentioned in [14] as follows:

$$\rho\lambda' = M\rho Qcal + A\rho$$

where

$\rho\lambda'$ = TOA planetary reflectance, without correction or solar angle. Note that $\rho\lambda'$ does not contain a correction for the sun angle.

$M\rho$=Band-specific multiplicative rescaling factor from the metadata (REFLECTANCE MULT BAND x, where x is the band number)

Qcal = Quantized and calibrated standard product pixel values (DN)

$A\rho$ =Band-specific additive rescaling factor from the metadata (REFLECTANCE ADD BAND x, where x is the band number) as specified in the table II

- **Composite Band Image and Spectral Indices**
  A composite band image is generated using the ArcGIS Pro software for each of the Radiometrically corrected Landsat 8 images. Each image is then clipped to the region of interest covering only the coastal region of the Thane, Mumbai, Mumbai Suburban, Raigad, Ratnagiri and Sindhudurg as shown in Fig. 3. Radiometric correction is an mportant step in remote sensing analysis, and it can help to improve the accuracy and reliability of spectral indices used to identify particular vegetation [15]. Hence it is recommended to perform radiometric correction before applying spectral indices to identify Mangroves. According to the [13] Landsat 8 Band combination of 5, 6 and 4 can be used to distinguish Mangroves from other vegetation. Hence it has been used in this study.
- **Tile generation for deep learning algorithm**
  To facilitate the application of deep learning algorithms, the image classified using the spectral indices is divided into tiles using the Geotile library in Python in Google Colab. Each tile is of size [256x256] pixels. The tiles were manually separated into two folders, one containing tiles with mangrove vegetation and the other without mangrove vegetation. The separation was done based on the visual interpretation of the tiles in ArcGIS Pro.
- **Data Augmentation**
  To increase the size of our dataset, we performed data augmentation techniques on the image tiles. Precisely, we rotated the 116 mangrove image tiles by 90, 180, and 270 degrees, resulting in an additional 348 images. This brought the total number of mangrove image tiles to 464. We also added 440 non-mangrove image tiles to the dataset, resulting in a total of 904 image tiles. The image class distribution is as shown in Fig. 4. This augmentation process was performed to increase the dataset's variability and enhance the model's

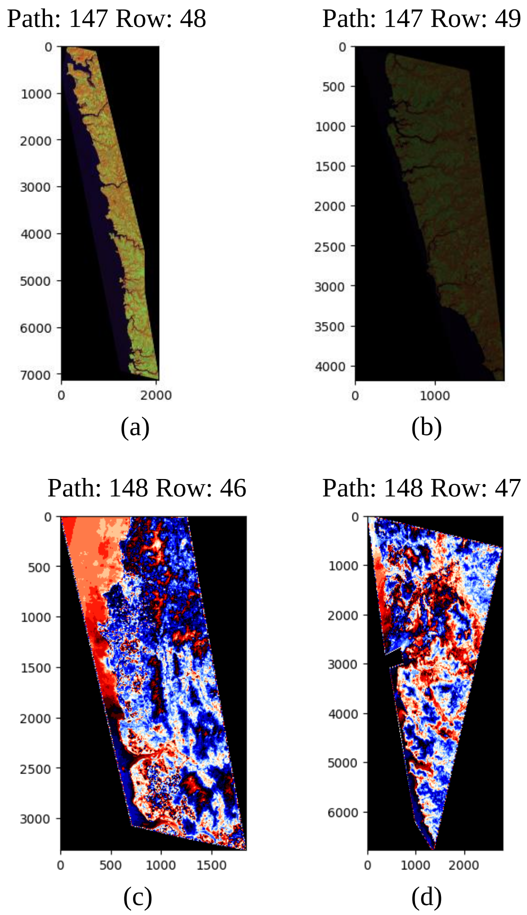

Figure 3. Radiometrically corrected Landsat 8 images cropped to the Region Of Interest

robustness. The above-mentioned procedure was used to classify and extract mangrove vegetation from the Landsat 8 image, which will be used in the subsequent analysis of mangrove ecosystem dynamics in the study area.

D. Model Development

The goal of this study is to classify images into Mangroves and Non-Mangroves. Image classification can be used to distinguish between images of mangroves and non-mangroves, which can be important for conservation efforts and ecological studies. Two common data analysis methods used for image classification are the Random Forest algorithm and Convolutional Neural Networks (CNN). The steps involved in the implementation of these methods can be summarized in figure

- **Random Forest Classifier**

  Random forest is a supervised learning algorithm that is used for classification, regression, and other tasks. It works by constructing a multitude of decision trees and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees as shown in Fig. 6. Random forest is a popular choice for image classification due to its ability to handle large datasets with many features, and its ability to handle noisy data. In the context of mangrove image classification, a random forest algorithm can be tuned to optimize the performance of the model. Some of the important hyperparameters include the number of trees in the forest, the maximum depth of each tree, and the minimum number of samples required to split a node. To use the Random Forest classifier from scikit-learn for image classification, the pixel values of the images can be used as features. The classifier can then be trained using a labelled dataset of images, with each image labelled as either mangrove or non-mangrove. Once the classifier is trained, it can be used to predict the class of new, unlabeled images. The Random Forest classifier from scikit-learn is a powerful and versatile machine learning tool that can be used for a wide range of classification and regression tasks, including image classification of mangroves and non-mangroves. Its implementation in Python and the availability of several tuning hyperparameters make it a popular choice for data scientists and researchers.

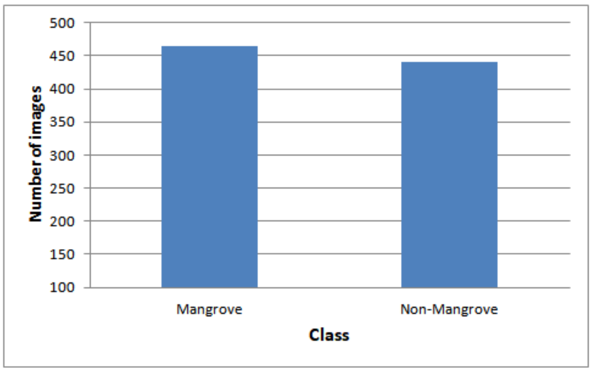

Figure 4. Number of images in each class

- **Convolutional Neural Network**

  A Convolutional Neural Network (CNN) for image classification has been implemented in this study to classify the images into Mangroves and Non-Mangroves. The architecture of the network consists of several layers of convolutional and pooling layers, followed by fully connected layers as shown in Fig. 7. The input to the network is a grayscale image with dimensions 256 x 256 pixels. The first layer of the network is a Conv2D layer with 32 filters of size (3, 3) and ’relu’ activation. This layer takes the input image and applies a set of convolutional filters to it, producing a set of feature maps. The ’relu’ activation function is used to introduce nonlinearity into the network and improve its ability to learn complex patterns in the data. The next layer is a MaxPooling2D layer with a pool size of (2, 2), which reduces the dimensionality of the feature maps and helps to prevent overfitting. This pattern of convolutional and pooling layers is repeated several times, with increasing numbers of filters in each convolutional layer. Specifically, the network has 64 filters in the second Conv2D layer, 128 filters in the third Conv2D layer, and 256 filters in the fourth Conv2D layer. Each Conv2D layer is followed by a MaxPooling2D layer with a pool size of (2, 2). After the final pooling layer, the output is flattened into a vector and fed into a fully connected Dense layer with 256 neurons and ’relu’ activation. This layer combines the features learned by the convolutional layers into a dense representation that can be used for classification. The final layer of the network is a Dense layer with a single neuron and ’sigmoid’ activation. This layer produces a binary classification output indicating whether the input image belongs to the ’mangrove’ or ’non-mangrove’ class. The ’sigmoid’ activation function is used to produce a probability score between 0 and 1, with values closer to 1 indicating a higher probability of belonging to the ’mangrove’ class. The implementation of the CNN thus uses several layers of convolution and pooling to extract features from input images, followed by fully connected layers to perform classification. The ’relu’ activation function is used to introduce nonlinearity into the network, and the ’sigmoid’ activation function is used to produce a binary classification output.

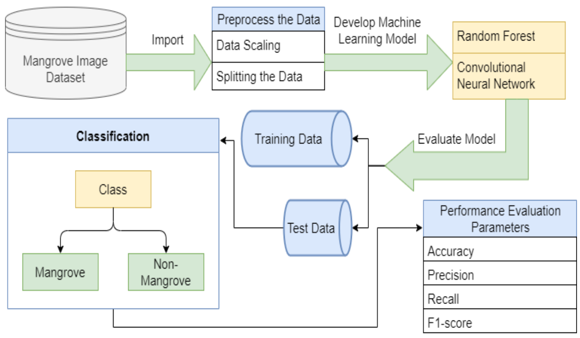

Figure 5. Classification of Mangroves using Machine Learning and Deep Learning method

E. Model Evaluation

Model evaluation provides a comprehensive analysis of the performance of the CNN model developed as described earlier for the image classification task of mangroves and non-mangroves. It can be done by computing the following:

- **Accuracy**

  Accuracy of the model on the test data. Accuracy is

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the proportion of correctly classified images out of the total number of images in the test set.

- **Confusion Matrix**

  Generate a confusion matrix to analyze the model's performance in terms of true positives, true negatives, false positives, and false negatives. A confusion matrix helps to identify which classes the model is having difficulty with.

- **Precision and recall**

  Calculate the precision and recall of the model. Precision measures the proportion of true positives out of all positive predictions, while recall measures the proportion of true positives out of all actual positives.

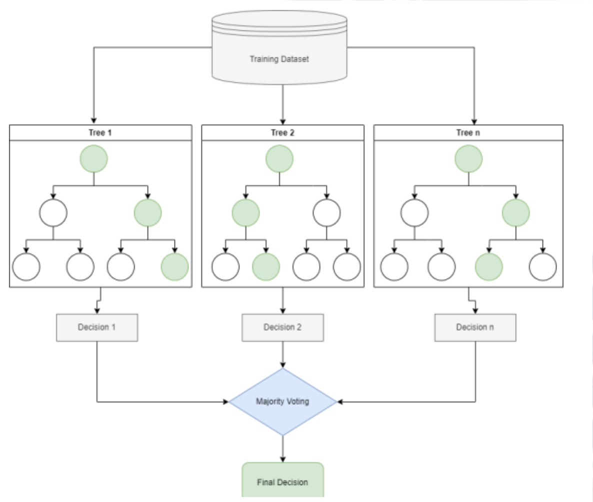

Figure 6. Random Forest classifier

- **F1 score**

  Calculate the F1 score, which is the harmonic mean of precision and recall. The F1 score provides a balanced measure of precision and recall.

IV. Result Analysis

In this study, we applied two popular machine learning algorithms, Random Forest and Convolutional Neural Network (CNN), to classify images of mangroves and non-mangroves. The performance of each algorithm was evaluated using various metrics, including accuracy, F1 score, confusion matrix, precision and recall.

The Random Forest algorithm achieved an accuracy of 76.47% on the test data. The confusion matrix revealed that the model correctly classified 110 out of 145 mangrove images and 98 out of 127 non-mangrove images. The precision and recall were calculated as 0.79 and 0.76 for the mangrove class, and 0.74 and 0.77 for the non-mangrove class, respectively. The F1 score was 0.77 for the mangrove class and 0.75 for the non- mangrove class.

The CNN model achieved an accuracy of 84.926% on the test data, outperforming the Random Forest model. The Precision, Recall and F1 score for the CNN model is 1.0, 0.8492 and 0.9184 respectively. The comparative result analysis is shown in table IV.

V. Conclusion

The creation of an image dataset using Landsat 8 images and processing them in ArcGIS Pro allowed for the implementation of both the Random Forest and CNN algorithms.

The results of this study indicated that the CNN algorithm achieved higher accuracy in the classification of mangroves and non-mangroves compared to the Random Forest algorithm. These findings suggest that CNN could be a useful tool for the accurate and efficient classification of mangroves and non-mangroves, which is important for their conservation and management.

This study utilized Google Colab, which provided access to GPU resources, to implement the Random Forest and CNN algorithms for the classification of mangroves and non-mangroves. The use of GPU resources allowed for faster processing of the algorithms, which improved the efficiency of the study. These findings suggest that the use of GPU resources in machine learning applications can enhance the speed and accuracy of classification tasks.

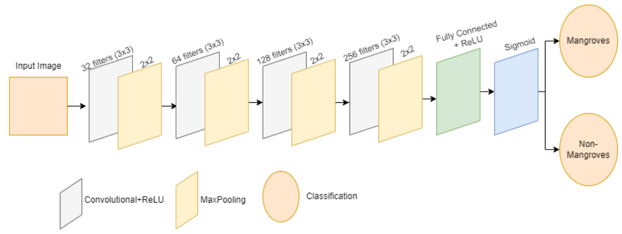

Figure 7. Convolutional Neural Network architecture

Table IV. Comparative Result Analysis

Evaluation Parameter	Algorithm Used	
	Random Forest	***Convolutional Neural Network***
Accuracy	76.47%	84.926%
Precision	0.77	1.0
Recall	0.76	0.8492
F1-score	0.75	0.8943

VI. Future Scope

The future scope of the research can include expanding the dataset to cover larger areas, including more diverse mangrove ecosystems, and using different remote sensing datasets to improve accuracy. Additionally, the use of other machine learning and deep learning techniques can be explored to further improve the accuracy of mangrove mapping. Furthermore, an investigation of the potential of integrating the mapped mangrove data with other geospatial datasets can be done to enhance the analysis of mangrove ecosystem dynamics and the impact of anthropogenic activities. Thus, there are many exciting possibilities for further research in this area, and the results of this study provide a strong foundation for future investigations into the use of remote sensing and machine learning for mangrove mapping and monitoring.

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