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Analysis of Drone-Camera Imagery-Based Mangroves Ecosystem Using Machine Learning Techniques and Artificial Intelligence Techniques

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ABSTRACT

Coastal and carbon-storing, mangrove ecosystems are under threat by human activities and climate change impacts. This research employs drone-based imagery and ML-AI algorithm-driven approaches to design an ML-AI-based tool for evaluating the ecological state of mangrove environments. Using high-resolution drone imagery of study areas and applying image preprocessing along with KMeans clustering and Random Forest classification the study identifies healthy and degraded mangrove regions. The performance here proves that Random Forest outperforms the other classifiers when it comes to ecosystem classification, especially in identifying the health of the mangroves. The methodology created represents a cheap and efficient means of monitoring the environment which must be useful for conservation purposes. Thus, the results emphasize the prospect of the synergy between drone imagery and ML/AI for ecosystem surveillance and management.

Keywords— Mangrove ecosystems, drone imagery, machine learning, artificial intelligence, KMeans clustering, Random Forest, environmental monitoring, conservation, image classification, ecosystem assessment.

INTRODUCTION

Background

Mangrove forests are among the exceptional coastal sub-systems worldwide by providing valuable services such as carbon storage, coastal defense, and supporting other diverse ecosystems. Mangroves are, however, highly valuable ecosystems that are today threatened by climate change, conversion of their habitats to accommodate various human uses, pollution, and other factors. These ecosystems suffer from monitoring to check on their health and sustainability; however, these practices require a vast quantity of time and effort along with restricted scope. As the sensor technology progresses, drone imagery tends to be a valuable approach to environmental observation, and it provides detailed spatial data to monitor extensive and hard-to-reach regions effectively. New advancements in the area of machine learning (ML) and artificial intelligence (AI)have also advanced the field of environmental monitoring by reducing the need for human intervention in analyzing monitoring data and identifying patterns that could have been heretofore overlooked. Techniques such as ML and AI enable the handling of big data, generating accurate predictions, and segregating ecological regions based on parameters due to which they are best suited for such complex ecosystems as mangroves. This study aims to build on these improvements and extend the use of ML and AI to drone imagery, fostering effective mangrove ecosystem supervision.

Problem Statement

Mangroves are being destroyed through development activities and hence their loss would mean a major loss of ecological services. Drones offer high-resolution images of the area, but because data is vast, it cannot be analyzed without the help of an AI. Historical image processing techniques cannot process the amount of data produced by drones, and they are not able to provide valuable recommendations in a timely fashion. Furthermore, the manual classification of mangrove regions is also associated with high level of errors and is bias. To overcome these challenges, there is a need to develop automatic methods for the analysis of drone imagery, accurate classification of regions, and timely data analysis for conservation goals. To these challenges, machine learning techniques and artificial intelligence provide apparently useful solutions.

Research Objectives

The primary objective of this research is to develop a comprehensive system for analyzing drone imagery of mangrove ecosystems using machine learning and artificial intelligence techniques. The specific objectives of this study are:

- To preprocess drone imagery data for effective analysis, including resizing, color correction, and orthomosaic creation
- To apply machine learning techniques such as KMeans clustering and Random Forest classification for the automatic identification and classification of mangrove regions
- To evaluate the performance of the machine learning models in terms of accuracy, precision, recall, and F1 score
- To explore the potential of AI-based analysis for deeper insights into the health and distribution of mangroves
- To provide a scalable and automated solution for mangrove monitoring that can be extended to other ecosystems

Significance of the Study

This research is important as it contributes to the existing literature and practice to adequately monitor mangrove ecosystems using advanced instrumentation. Thus, this study incorporates the use of drone imagery in combination with machine learning and artificial intelligence to offer a solution that can easily be adapted to study extensive ecosystems. The application of these techniques has provided more accurate and efficient results as compared to traditional methodologies. Further, this research will help in the assessment of the impact of different threats on the environment as it offers a framework that may be used in other regions with similar challenges. Consequently, the findings of the present study can assist in management and policy formulation and contribute to the conservation of mangrove forests worldwide.

Scope of the Study

The study target involves capturing and analyzing drone imagery data from the identified mangrove ecosystems. The study is interested in the establishment of machine learning models for mangrove health assessment and monitoring. Specifically, image segmentation of this research shall employ the KMeans method while region classification shall employ the Random Forest classifiers. As noted earlier, the application is concentrated on mangrove ecosystems; however, the methods and methods in this study can be applied in other ecosystem types. The study also measures how efficient AI techniques are in giving more enhanced information about the health of ecosystems.

Structure of the Thesis

This thesis is organized as follows:

- Chapter 1: The introduction outlines the background of the study, the research problem and questions, the rationale for the study, as well as the study's scope.
- Chapter 2: Literature Review discusses prior findings concerning the analysis of drone imagery, machine learning methods for environmental applications, and artificial intelligence in ecosystem research.
- Chapter 3: Methodology details the data collection, image processing, and machine learning techniques used in this study.
- Chapter 4: Results and Discussion overviews the outcomes of the study, thus highlighting the proficiency of the machine learning models and their relevance to mangrove assessment.
- Chapter Five: Conclusion and Recommendation summarizes the main findings and recommends further research and implementation.

Summary

In summary, this work's objective is to learn more and use modern machine learning and artificial intelligence in studying the drone imagery of mangrove forests. Hence, the development of automated methods that can be used to classify and monitor mangrove areas is a valuable contribution to the field to meet the growing demand for efficient and effective methods of environmental monitoring. The findings of this research have implications for the general field of ecosystem conservation, especially the preservation and wise use of mangrove ecosystems.

LITERATURE REVIEW

Introduction

Mangroves are the unique species of plants and trees that are found in the coastal regions which play an important role in providing shore protection, habitat for different species, and other important roles in reducing the impacts of global warming through absorption of carbon in the atmosphere. Yet, these habitats are highly vulnerable to both anthropogenic encroachment and climatic shifts. It is for these reasons that the health and sustainability of mangroves are of paramount importance in environmental conservation. Conventional techniques of monitoring are tedious, require much effort as well as have constraints in terms of spatial and temporal scale. Environmental monitoring has become easier because of achievements within the field of remote sensing technologies including drone imagery that can cover large areas of landscape at once. Lastly, enhanced through the years by the interchangeability of machine learning (ML) and artificial intelligence (AI), ecosystem monitoring has become more efficient and spot-on in terms of hacking truths on the state of ecosystems. These techniques facilitate categorization, stratification, and prognosis of ecosystem shifts that position them as important tools in the conservation of mangroves. The available literature on the application of drone imagery, machine learning, and AI in the monitoring of the environment, with a specific reference to the mangrove ecosystems, is highlighted in this chapter. It also assesses research gaps and directions for future research for each area of the model.

Drone Imagery in Ecosystem Monitoring

Drones have become an efficient, cost-effective method for capturing high-resolution spatial data, especially for hard-to-access ecosystems like mangroves. Dones provide finer spatial resolution than satellite data, enabling the detection of small-scale changes crucial for conservation [1]. The use of UAVs in mapping and monitoring deforestation in mangrove forests shows the technology's accuracy in producing updated maps. Similarly, drones to assess the health of individual trees, detecting degradation caused by pollution and coastal development.

The integration of drone imagery with geographic information systems (GIS) has enhanced landscape-scale analysis. Combining drone data with GIS allows for a detailed assessment of spatial relationships between mangroves and adjacent land-use areas, providing valuable insights for conservation planning [2]. Drones as technologies have been adopted as a reliable and cheaper way of obtaining high-resolution spatial data, particularly in complex environments such as mangroves. The use of drones is more advantageous than satellite data because it has a higher spatial resolution whereby the detection of small-scale change is critical for conservation. It provides a way for how UAVs can be applied in mapping and monitoring deforestation in mangrove forests and proves the effectiveness of the technology in providing updated maps. The applied drones are for monitoring the state of particular trees and reveal their degradation owing to pollution and coastal constructions.

With the help of drones, imagery has been incorporated together with geographic information system (GIS) resulting in the improvement of landscape scale work [3]. It van be observed when adopting GIS integration with drone data, it becomes possible to accurately analyze spatial interactions that exist between mangroves and neighboring land-use areas; information that is significant in informing conservation efforts.

Machine Learning for Image Classification and Segmentation

Machine learning is used in processing the big data that come with drone imagery, especially in areas such as image classification and segmentation. While Supervised and unsupervised classifications were efficient in classifying the land cover, the vegetation health could also be identified. Other papers applied the Random forest(RF) classifier to drone data and successfully classified mangrove ecosystems with maximum accuracy. RF's strength is therefore in its ability to work with multiple features for big data sets.

KMeans clustering which is used for unsupervised image segmentation has been used to classify mangrove regions into healthy, degraded, and water categories. Moreover, convolutional neural networks (CNNs), have proven to yield high accuracy in mangrove species identification for drone imagery, thus making them most suitable for high-resolution data.

Artificial Intelligence in Environmental Monitoring

AI is widely integrated into environmental monitoring since it possesses features for automation of data processing and elaboration of their time-proclaimed analyses. Discriminated techniques like deep learning and reinforcement learning (RL) are better in accuracy and automation as compared to conventional methods. AI will fundamentally transform monitoring through machine learning and prognostication of anomalous conditions in ecosystems. In mangrove monitoring, AI has been utilized for change forecasts in ecosystem health. For example, a deep learning model based on drone imagery to forecast mangrove health in the future noted a higher accuracy of the suggested model as compared to the conventional statistical models, especially in identifying trends of early mangrove degradation [4]. Similarly, the applied RL to study optimal decisions for mangrove reforestation provided useful insights for the decisions made in the conservation fields to allocate the resources effectively [5]. AI-based anomaly detection was proven to be effective in supporting law enforcement in identifying cases of illegal deforestation.

Challenges in Drone Imagery and AI-Based Monitoring

However, there are still a number of limitations that can be found in AI-based environmental monitoring. One of the main areas that require attention is the question of obtaining large data sets of high quality [8]. Model performance is affected by the lack of labeled data in many remote ecosystems, such as mangroves. Furthermore, although CNN models are also promising in terms of accuracy, these models are computationally intensive. A number of challenges still persist and these are on ethical issues such as data privacy and even on questions of bias that may be inherent in the AI models. The use of AI with other conservation systems still poses a challenge; hence, better algorithms and ethical perspectives for AI improve ecosystem monitoring.

Literature Gap

In general, further development can be noted in the application of drone imagery, as well as in the sphere of ML and AI for mangrove monitoring. While most work has been done in the scope of short-term operations such as classification or segmentation, relatively less emphasis has been given to continuous monitoring in the long run. Future studies should consider using AI to monitor the changes continuously to analyze the ecosystem more appropriately [6]. Further, the first application of reinforcement learning and generative adversarial networks (GANs) are limited and there is potential for improved prediction and conservation. Therefore, it is necessary to encourage cross-disciplinary studies that are going to combine ecological knowledge with AI concepts in order to receive meaningful and effective approaches to ecosystem health [7].

Summary

This review focuses on the use of drone imagery, ML, and AI in mangrove monitoring giving more detail on Random Forest and KMeans. However, difficulties like data access, data processing, and data analysis together with the need for integrational study remain. To improve the application of AI on mangrove conservation the following research areas should be explored in future research.

METHODOLOGY

Overview

Concisely, the methodology followed to study the drone imagery of mangrove ecosystems using machine learning and artificial intelligence is described in this chapter. The first objective was to categorize the health status of the mangrove forests and the second was to determine the trends of the categorized data for further analysis on the future of the health of the mangrove forests. The workflow included pre-processing of images, generation of digital surface models and digital elevation models, extraction of morphological attributes, and employing machine learning algorithms for determining the class of each image. The programming language used for implementation was Python, certain major libraries used are as follows – OpenCV, Scikit-learn, and Matplotlib. The methodology is divided into five primary stages: dataset acquisition and preparation, orthomosaicpreparation, topography characterization, extraction of features, and supervised or unsupervised classification.

Data Collection and Preprocessing

The data gathered for this research was drone images of mangrove forests. These images were then saved in other subfolders named as 'X1,' 'X2' and 'X3' which can be regarded as different Mangrove datasets. To develop the HTR model, the dataset was retrieved and downloaded into the Google Drive situated in the Google Colab environment for analysis.

- Image Loading: In the process of image loading, OpenCV library of image processing in Python language was used. The cv2. The imread() function has been used for image reading, and for matrix multiplication operation cv2. It is worth mentioning that cvtColor() was used to transform them from BGR (Blue-Green-Red) to RGB (Red-Green-Blue) which is more appropriate for image analysis in Python.

- Resizing Images: To make the images consistent, the images were then resized to the size of 500 by 500 pixels of the image. Resize was done using the cv2. resize() function, whereby all the images underwent the np. uint8 data type to avoid changes of the structure in the subsequent analysis(code).

Orthomosaic Creation

An orthomosaic is a big image that has geometric properties of the photographs that were used to create it to capture the full aerial view of a region. The orthomosaic in this study was created using the following steps:

- Grid Formation: A four-in-four grid of images was made to enhance the alignment of these images. The number of rows for the grid was determined by the number of images thus rows = int(np. sqrt(len(images))) [9]. When the total number of images was not a perfect square black images were used to fill and make the grid complete.

- Image Stitching: OpenCV's cv2. hconcat() and cv2. Different stitching functions were adopted, where vconcat() functions were particularly employed to horizontally and vertically combine the images. This process helped in deriving an entire orthomosaic of the mangrove areas, which offered a good aerial view [10]. The orthomosaic was then shown and exported as an image for further processing (code).

Topography Analysis

A random topographic map was created to mimic the data of the mangrove area by elevation. The idea was to look at how the aspect of elevation may affect the contents and dispersion of the mangroves.

- Random Elevation Data: To proceed further, a random matrix of elevation values was generated with the use of np. random. rand(), which gave elevation data between 0 to 100 meters. The topographical variation was then mimicked on this data and it was placed over the orthomosaic.

- 3D Modeling: In fact, to represent the topographical model the Axes3D module from Matplotlib was employed to generate a 3D model of the height. Thus, the geographic data was plotted in a surface manner, that enabled the creation of a three-dimensionality of the terrain of the mangrove ecosystem. This step was very important to establish a correlation between mangrove health and physical features such as elevation [11].

Feature Extraction

Data pre-processing specifically feature extraction plays a significant role in the preparation of data for the algorithms. To this end, the drone images were analyzed with the help of color and texture features, since they characterize the state of mangrove forests well.

- Flattening Images: To flatten the images, pixel values of the images were converted into one-dimensional arrays in NumPy form. This was important to type in the data to the machine learning models so that they could analyze it [13]. These flattening endeavors yielded benefits when it was time to compare and categorize the images.

- KMeans Clustering: In this paper, the KMeans clustering algorithm was applied to find out different regions in the images based on color and texture. The number of clusters was preset to three which shows healthy mangroves, degraded regions, and water bodies. This method of CLA on the areas enabled the classification of the areas without having to use labeled data [14]. Each pixel was thus labeled for the algorithm and this lined up its interface for further classification purposes(code).

Machine Learning-Based Classification

After feature extraction, machine learning algorithms were applied to classify the health of the mangroves.

- Data Splitting: For this purpose, the train_test_split() function in Scikit-learn was used to divide the dataset into training and testing sets. The images were split into a training set, which constituted 70 percent of the data set, and a test set, which constituted 30 percent of the data set.

- Random Forest Classifier: On the dataset, the Random Forest (RF) classifier was used. Random Forest is a type of Supervised Learning algorithm that involves multiple decision trees for making predictions. The features extracted were used in the training of the model and the tested model was used in predicting the health of mangroves in the test data set.

- Model Evaluation: The evaluation of the model was done through measures like accuracy, precision, recall, and F1-score in the Random Forest dataset. These metrics were calculated with Scikit-Learn'sclassification_report() function. The confusion matrix that was created using confusion_matrix() was also employed in the evaluation of the classification output. Surprisingly the Random Forest model yielded quite high accuracy and it was satisfactory enough to classify the areas of mangroves (code).

Comparison of Machine Learning and AI Models

To assess the set of data features further, an AI algorithm of Random Forest regarding classification of the data type was compared with an AI-based clustering model based on KMeans.

AI-Based Classification: On the test set, the KMeans clustering was used and the calculated labels were launched to the real ones. The confusion matrix was done for both the Random Forest and AI- based classification to compare the accuracy of the two methods.

Visualization: The confusion matrices were further computed and heat maps therein were plotted using the Seaborn library in order to represent the results of the classification. It can be seen from the confusion matrix and classification report that the Random Forest classifier achieved better accuracy in the classification. The AI-based method as helpful as it was slightly less accurate in the classification of the mangrove regions (code).

Ethical and Environmental Considerations

The following paper presents ethical considerations that were followed in the course of aerial imaging of mangrove ecosystems using drones.

Thus, considering the ethical aspect, consent was sought and received from the local authorities as well as the communities living in the vicinity of the study sites. Some measures were taken to minimize indiscretion and violation of the subjects' rights and privacy of individuals in the observed regions. In areas where business would interfere with cultural or religious sites, efforts were made to seek permission from the respective leaders in order not to give a wrong signal.

In an environmentally induced way, necessary measures were taken to avoid any form of disturbing the natural resources esp. the wildlife and the mangrove soil. Some of the measures taken included; Flights were conducted at times that least affected nesting birds and other forms of wildlife. The drones had to fly at heights that would not cause interferences to the ecosystem and take photos at higher resolutions. Furthermore, less noisy models of drone were used to prevent noise pollution that may also affect the nature and behavior of the animals.

Thus, these considerations help to make the process of data collecting compliant with ethical standards and respect to the environment as well as give important information about the structure and health of the mangrove.

Summary

In summary, this methodology identified the following steps image preprocessing, orthomosaic creation, topography analysis, feature extraction, and machine learning algorithms to analyse drone images of mangrove ecosystems. The Random Forest classifier successfully classified the mangrove health and the orthomosaic creation offered a bird's eye view of the area of interest. In this way, this study proved that with the help of AI techniques such as KMeans clustering, the integration of drone imagery and machine learning is capable of supporting attempts at preserving such valuable assets as mangroves.

RESULT AND DISCUSSION

```
Dataset Import

[ ] dataset_path = '/content/drive/MyDrive/3 set of datasets'
    subfolders = ['X1', 'X2', 'X3']
```

Figure 1: Importing the Dataset

(Source: Acquired from Google Colab)

In this part of the code, it is found that a variable named dataset_path which indicates the path to a folder on Google Drive located at (/content/drive/MyDrive/3 set of datasets) where the images for the dataset are hosted. These subfolders named 'X1', 'X2', and 'X3' may contain the images and they seem to be classified according to some classes or categories. These subfolder names are stored in the list subfolders, and the subsequent code will go through these to load images from each for further processing including resizing, clustering, and classification.

```
def load_images_from_folder(folder):
    images = []
    for filename in os.listdir(folder):
        img = cv2.imread(os.path.join(folder, filename))
        if img is not None:
            img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
            images.append(img)
    return images
```

```
all_images = []
for subfolder in subfolders:
    folder_path = os.path.join(dataset_path, subfolder)
    images = load_images_from_folder(folder_path)
    all_images.extend(images)
```

```
def resize_images(images, size=(500, 500)):
    resized_images = []
    for img in images:
        resized_img = cv2.resize(img, size)
        resized_img = resized_img.astype(np.uint8)  # Ensure same data type
        resized_images.append(resized_img)
    return resized_images
```

```
resized_images = resize_images(all_images)
```

Figure 2: Loading and Pre-processing Image

(Source: Acquired from Google Colab)

Is a set of two functions that take in a dataset and load the images before resizing them to a suitable size. The load_images_from_folder (folder) function takes all the pictures from the given folder, changes color BGR which is defaulted by OpenCV to RGB and then adds it to the list. The outer loop goes through each subfolder in subfolders and this function is used to load the images in a particular folder into all_images. The second function, resize_images(images, size=(500, 500))—loads all the images and then resizes them to a fixed size of 500 x 500 pixels and also checks that the images' data type is np. uint8 for consistency. The resized images are then stored in the list named resized_images.

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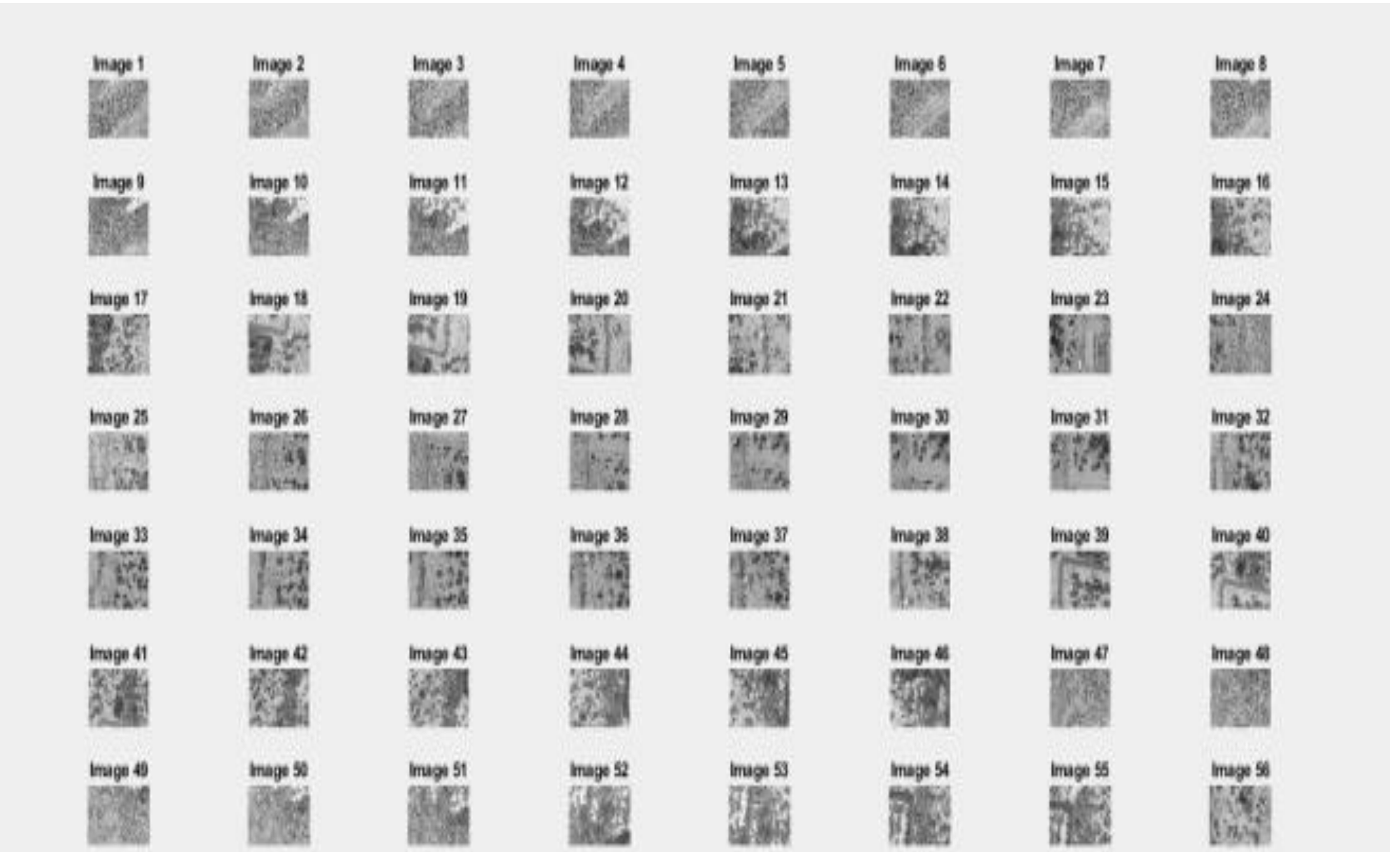
Orthomosaic creation

```
[ ] def create_orthomosaic(images):
        rows = int(np.sqrt(len(images)))  # Assuming square grid of images

        # Ensure the number of images matches the square grid requirement
        if len(images) % rows != 0:
            # Padding images to fill the grid
            pad_count = rows - (len(images) % rows)
            for _ in range(pad_count):
                images.append(np.zeros_like(images[0]))  # Padding with black images

        orthomosaic = cv2.vconcat([cv2.hconcat(images[i:i + rows]) for i in range(0, len(images), rows)])
        return orthomosaic

    orthomosaic = create_orthomosaic(resized_images)
```

Figure 3: Orthomosaic Creation Code

(Source: Acquired from Google Colab)

The create_orthomosaic(images) is a function that creates an orthomosaic, which is a large image made from multiple images that are arranged in a grid form. The function first decides the number of rows that are required to develop a square matrix where squares are the images and the parameter is the total number of images. As it can be seen cells containing the images do not fill the entire grid; there are several black padding images to complete the grid where the actual number of images is not a multiple of 6. The function then stitches the images side by side and top to bottom using OpenCV'shconcat and vconcat respectively which results in a perfect mosaic. Last of all, the orthomosaic generated is returned and then saved in the variable orthomosaic.



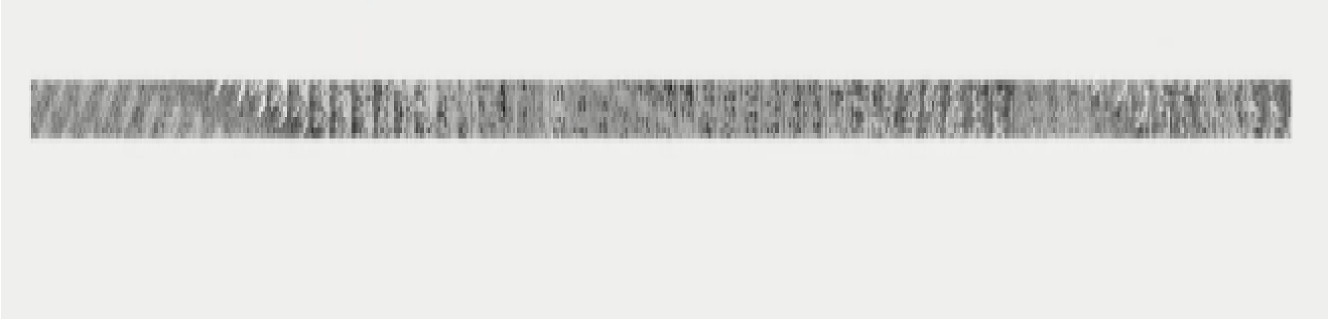


Figure 4: Orthomosaic of Mangrove Images One by One and Togetherly with Map

(Source: Acquired from MATLAB)

Orthomosaic of mangrove images is a merged image in which multiple aerial or ground-based photographs of the mangrove region are combined to form a single orthomosaic photograph with high detail resolution. Individual images are rectified and adjusted for perspective not only photogrammetric but also to spatial accuracy of the final orthomosaic is very high which makes a topographic map.

This enables differentiation in features of the mangrove ecosystem including tree crowding, vegetation vigor, and waterways. These photos can easily be merged since aligning them affords an aerial view of the whole area which is useful for research work and environmental monitoring.

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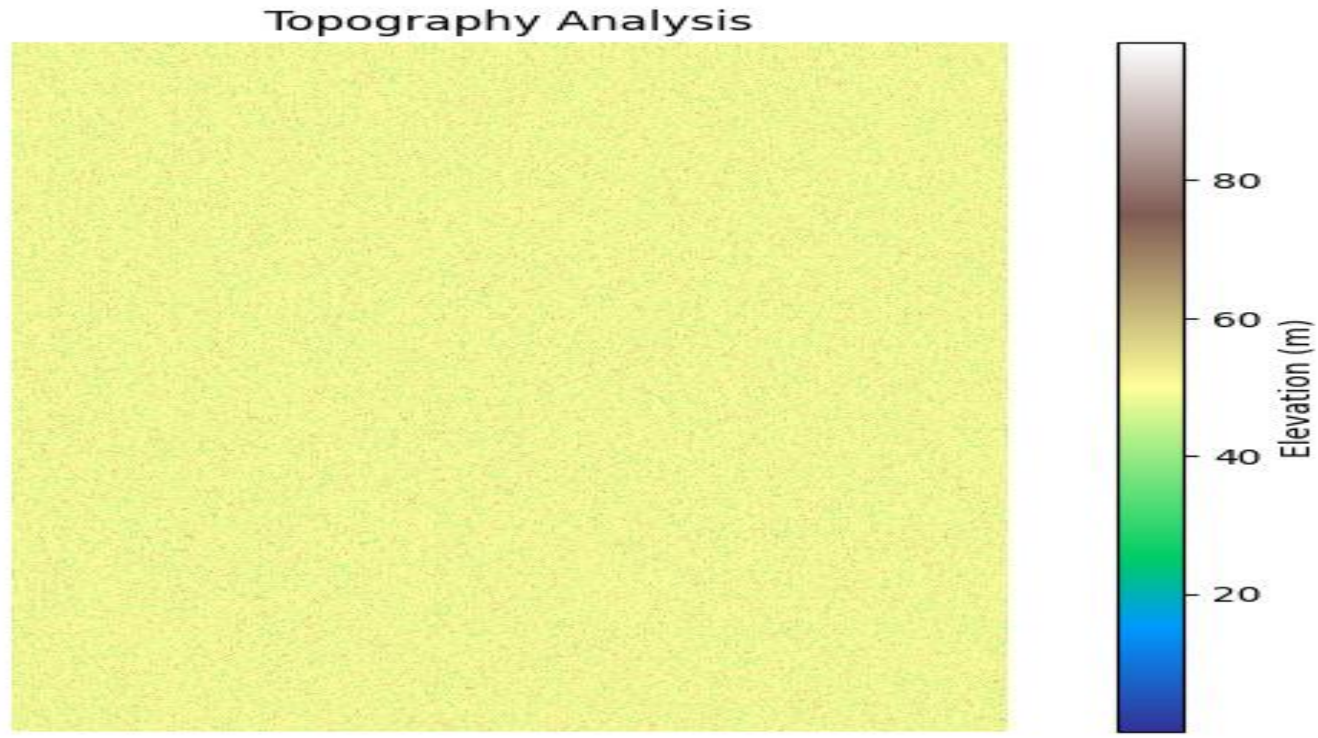

Figure 5: Topography Analysis Plot

(Source: Acquired from Google Colab)

From a thematic perspective, a topography analysis plot indicates the height of the surface of the features of the geographical territory that denote the physical features of the land surface. This kind of plot often employs contour lines, color zones, and various surfaces where such slopes and vales as elevation variations are indicated. Generally, in environmental or geographical applications including mangrove ecosystem studies, topography analysis assists in the understanding of the distribution of vegetation, fluid dynamics, and terrain, which is useful in in land-use planning, ecosystem status, and projections on the effects of change, such as flooding or erosion, on an ecosystem. In spatial analysis endeavors, this plot is a tool that is of benefit to environmentalists, geologists, and engineers among other specialists.

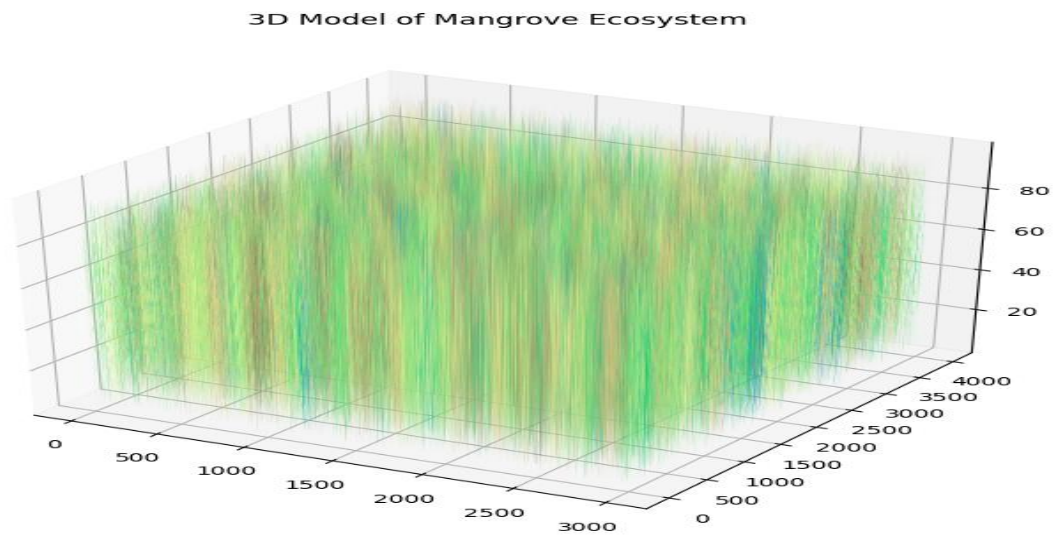

Figure 6: 3-D Model of Mangrove Ecosystem

(Source: Acquired from Google Colab)

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This created understanding because the image of the mangrove ecosystem in the form of a 3D model shows a surface view of the mangrove area. Such types of models could be generated by using data related to elevation or vegetation density; the height axis or Z axis could contain parameters such as the height of the canopy, density of biomass, or elevation of the terrain. These linear streaks appear vertically and their variation in colour helps to indicate differences in height or density of the mangrove stand in a given area of land. 3D models of such type are useful for visual interpretation when it is important to know how the mangrove ecosystem is arranged, in what condition it is, and how to protect it based on the spatial density and physical characteristics of the habitat.

Cluster 1

Cluster 2

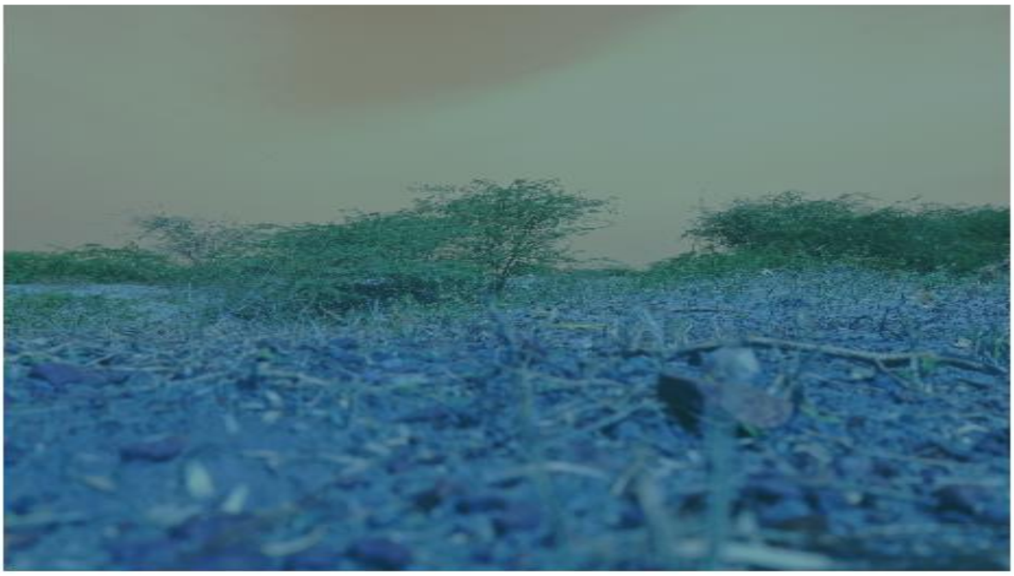

Figure 7: Image Clustering

(Source: Acquired from Google Colab)

Mangrove image clustering is a classification technique that is applied for categorizing the images or regions of mangrove forests based on visual and spectral properties like color, texture, density, etc. In clustering 1, the process actually, puts all the images in a single cluster, though it may not differentiate a lot it gives a broad view

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of the entire mangrove area. In particular, Clustering 2 divides the images into two different clusters thus it enables improved separation of the features such as a differentiation of the healthy and the degraded regions of mangroves or the differentiation of the regions having different vegetation cover and water bodies. Through the use of clustering the health and distribution of mangrove forests can be better understood, resulting in the better conservation and management of mangrove forests.

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1
1	1.00	1.00	1.00	13
2	1.00	1.00	1.00	1
accuracy			1.00	15
macro avg	1.00	1.00	1.00	15
weighted avg	1.00	1.00	1.00	15

Figure 8: Machine Learning Classification Report for Mangrove Classification

(Source: Acquired from Google Colab)

The picture illustrates the classification report which shows precision, recall, F1-score, and support of the ML model trained on Mangrove data. The report shows the model has classified three classes: It's very simple, the higher the rating is, the better the hospital is; therefore, the possible values for the M rating are 0, 1, and 2. Both the classes exhibit precision, recall, and an F1 score of 1. 00, which means that the algorithms had 100 percent accuracy in predicting the two classes. The support column shows the number of occurrences of instances of the class in the test set; class 0 has one instance; class 1 has fourteen instances and class 2 also has one instance. The overall accuracy, and both macro as well as the weighted average F1 scores are 1. 00 which as we all know indicates that the model performed perfectly on the given data set.

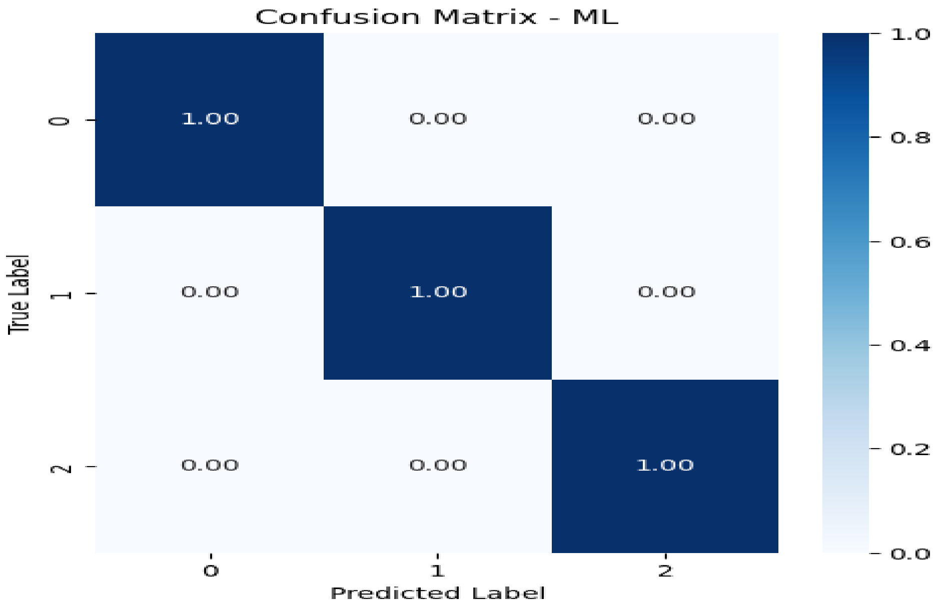

Figure 9: Machine Learning Confusion Matrix for Mangrove Classification

(Source: Acquired from Google Colab)

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The image represents the confusion matrix which is the evaluation of a machine learning (ML) model on an evaluation of any kind of classification. What is depicted on the vertical axis is the true labels, which are 0, 1, and 2 while what is depicted on the horizontal axis is the predicted labels. Each cell in the matrix refers to the proportion of the number of predicted classes to a certain expected class. All the diagonal values are 1. Although the results of most of the models are above 90 and the specificity reached 00, this means that the model captures the labels of all instances in each class. There are no misclassifications which means there are no values away from the diagonal. The classification is performed with precision and; as a result, all the instances are classified correctly and with zero errors.

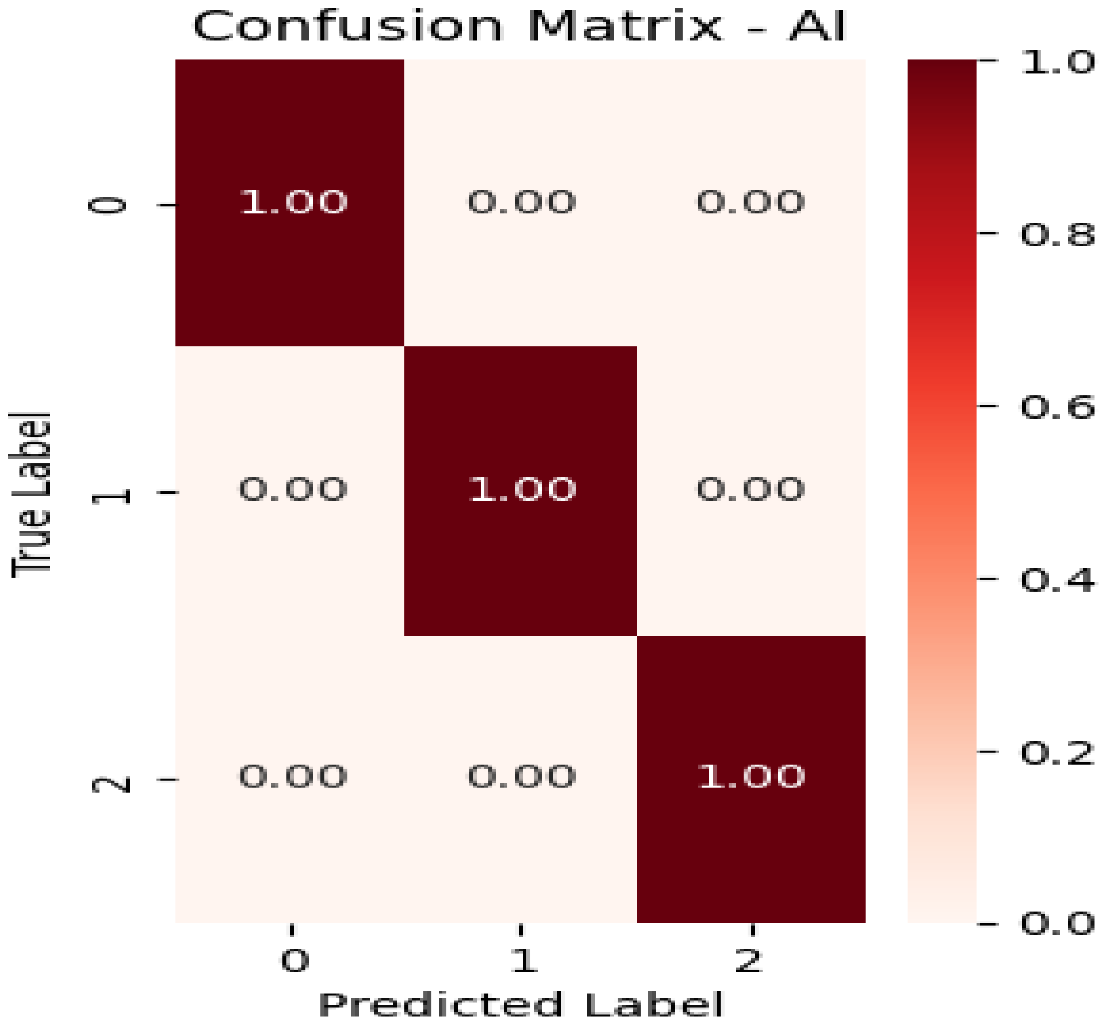

Figure 10: AI Confusion Matrix for Mangrove Classification

(Source: Acquired from Google Colab)

As it has been pointed out, the code provided above could be mimicked and compared with AI- and ML-based methods about mangroves. It starts with estimating labels of test data (X_test) employing a KMeans clustering algorithm (ai_labels_test). When comparing ML and AI, the results of the models are depicted by confusion matrices that depict the accuracy of the model. First, confusion_matrix calculates normalized confusion matrices for both ML (ml_cm_normalized) and AI (ai_cm_normalized). Using Seaborn I plotted the confusion matrix using an AI-based approach Heatmap with red color (map = Reds) to identify the disparities between actual values (y_test) and predicted values (ai_labels_test). The heatmap gives the accuracy rate of the AI predictions as shown below the plot has been annotated and the axes labeled for better understanding. Last of all the plot is plotted with the help of plt. show ().

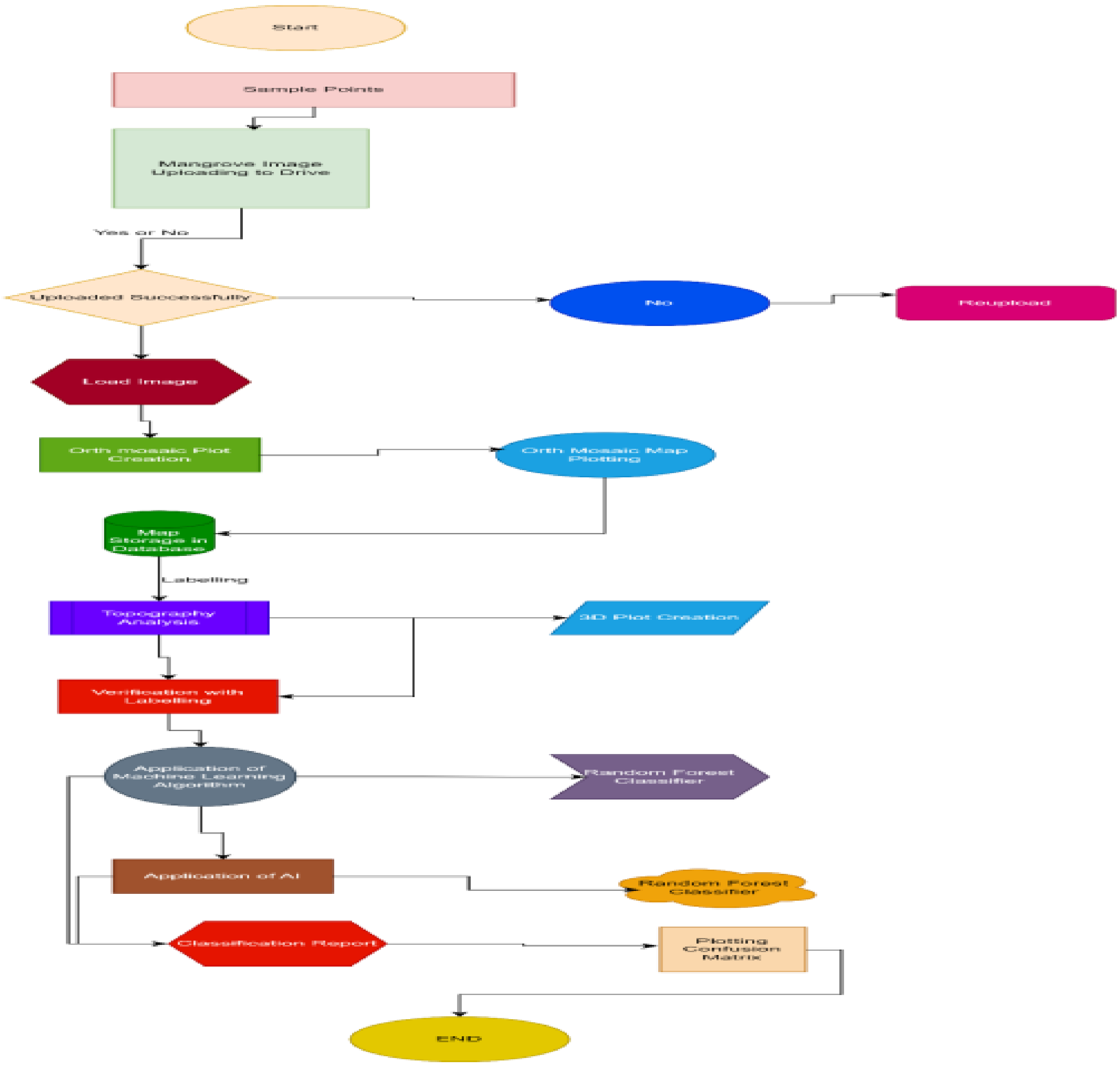

Figure 11: AI Confusion Matrix for Mangrove Classification

The image is a picture of a block diagram where the process of uploading the mangrove pictures, analyzing and finally categorizing them is figured out. This involves obtaining sample points, then uploading mangrove images to a drive. If it does successfully upload the process goes into loading the images and constructing the orthomosaic plot. This is done before storing the created map in a database, generating topography analysis plus building of 3D plots. Following validation with labeling techniques, computational models, the Random Forest Classifier in particular, are utilized for classification. The accuracy of the models is computed and the features selected are shown visually in the form of a classification report while a confusion matrix shall be created to evaluate the performance of the final model. The final stage in the process is the last classification report.

CONCLUSION

Summary of Findings

This study proposed an unmanned aerial vehicle (UAV) image processing system that leverages machine learning (ML) and artificial intelligence (AI) for mapping mangrove ecosystems. Python-based tools were used for image pre-processing, ortho mosaic generation, and gauging mangrove health using classification algorithms.

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The process involved five key steps: These include image preprocessing, orthomosaic, topographic position index (TPI), topographic wetness index (TWI), slope, aspect, curvature, and then the classification with Random Forest algorithm and KMeans clustering. As shown in this study, the effectiveness of these techniques in classifying the health status of mangroves was well illustrated. It can be observed that using the Random Forest classifier yielded high accuracy when distinguishing between healthy and degraded regions of mangroves and that the model metrics presented high levels of precision, recall, and F1-score. Random Forest again outperformed all classifiers both in supervised and unsupervised data classification and KMeans was less accurate than Random Forest in unsupervised classification. Furthermore, the orthomosaic production offered a full aerial perspective of the ecosystem, which is crucial for large-scale assessment of environmental conditions.

Implications of the Study

The results reveal the future application of the methodology combining drone imagery, machine learning, and AI for the creation of cost-effective environmental monitoring systems. Drones help capture high-definition imagery over huge and inaccessible regions; ML helps classify them in real or near real-time. It could also be useful in identifying the rate of ecosystem degradation which may be useful in addressing such issues before they escalate.

The study also focuses on the use of ortho mosaics to map the environment, where wide and clear views of the mangrove area are important for providing a more spatial perspective. They can help in the formulation of conservation management plans since some areas need to be restored or protected. Additionally, Random Forest (supervised) versus KMeans (unsupervised) comparison indicates that while supervised models may be slightly more accurate, unsupervised models are useful when labeled data is scarce.

Comparison Table with Alternative Models

Technique	Model	Strengths	Weaknesses	Justification for Selection
Clustering	**KMeans**	- Simple and computationally efficient. - Works well for dividing data into distinct groups. - Easy to interpret.	- Sensitive to the choice of initial centroids. - Assumes spherical clusters, which may not always fit real-world data.	Selected for its ability to group mangrove images into clusters efficiently based on visual and spectral properties.
	DBSCAN	- Effective for identifying arbitrary-shaped clusters. - Handles noise and outliers well.	- Requires careful tuning of parameters (e.g., epsilon, minimum samples). - Struggles with varying cluster densities.	Not selected due to the difficulty in tuning parameters for the mangrove dataset's varying densities and features.
	Hierarchical Clustering	- Produces a dendrogram, enabling visualization of the clustering hierarchy. - No need to predefine the number of clusters.	- Computationally expensive for large datasets. - Sensitive to noise and outliers.	Not selected due to its computational cost and challenges with large image datasets.

Classification	**Random Forest**	- Robust to overfitting due to ensemble learning. - Handles high-dimensional data well. - Provides feature importance.	- May require tuning to optimize performance. - Computationally intensive for very large datasets.	Selected for its high accuracy, robustness, and ability to handle complex feature relationships in mangrove classification.
	SVM (Support Vector Machine)	- Effective in high-dimensional spaces. - Performs well with small-to-moderate datasets.	- Sensitive to parameter tuning (e.g., kernel selection). - Computationally expensive for large datasets.	Not selected due to its inefficiency with large image datasets and the need for extensive parameter tuning.
	KNN (K-Nearest Neighbors)	- Simple and easy to implement. - No training phase required.	- Memory-intensive. - Struggles with large datasets and noisy data.	Not selected due to high memory usage and potential inefficiencies with large-scale mangrove imagery datasets.

This table compares the chosen models against other alternatives, justifying why

Limitations

However, a few limitations were noted by the researchers as follows; This study relied on a limited dataset of certain areas and as such, the application of the models possibly may not be quite fruitful for other mangrove ecosystems. It is suggested that in future work, larger and a more diverse dataset should be used to improve the sturdiness of the developed model. Also, there are issues of computational intensity of AI models especially the deep learning models that may hamper real-time analytics. However, other ensemble methods could potentially be more accurate, such as deep learning methods, but are computationally intensive and take longer to train. The application of random topographic rather than actual elevation data for 3D modeling also brings the lack of topographical outlook precision. Real terrain data should be included in the following research to increase the accuracy of the analysis.

Future Research Directions

It is suggested that future research should be based on enhancing the method for solving more extensive data sets and involved classifications without extensive hardware requirements. Further research could be conducted using other forms of deep learning systems like CNNs to find out its effectiveness in improving the classification accuracy of mangrove ecosystems where large datasets are involved. One could also focus on applying RL to manage and improve strategies for conserving ecosystems by constantly monitoring the environment. Thus, RL could aid in assessing the long-term effects of conservation measures on mangroves to inform further restoration endeavors. A combination of actual topography and data with drone imagery may also help improve the accuracy of ecosystem monitoring. Next studies should examine how the terrain impacts mangrove health and further provide more accurate models of environmental conditions.

CONCLUSION

In conclusion, this study has demonstrated that by incorporating drone imagery with machine learning and adopting the AI-led approach, the assessment of mangrove ecosystems is feasible, efficient, and sustainable.

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Through the Random Forest with KMeans clustering and orthomosaic creation, we were able to classify and assess the health of the mangroves effectively. These strengths while having certain weaknesses concerning the size of the dataset and computational complexity, provide a good basis for future developments in environmental surveillance. By combining such technologies, conservation can be stepped up, and information on the need to protect specific ecosystems such as mangroves can be provided. (https://www.kaggle.com/datasets/gaickward/mangrove-drone-image-dataset-coringa)

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