

Democratizing Species Identification: Deep Learning Approach for Image-Based Mangrove Species Classification

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Abstract

Mangrove ecosystems are essential to coastal resilience and biodiversity, yet accurate species identification remains limited by traditional, expert-dependent methods. This study introduces a machine learning-based approach for automated mangrove species identification via a user-friendly web application that allows users to upload images of mangrove features, such as leaves or flowers, for analysis. Focusing on three dominant species found in Pulau Kukup, Johor—*Bruguiera cylindrica*, *Bruguiera gymnorhiza*, and *Rhizophora apiculata*—the system employs advanced image recognition models to classify species from uploaded images. A custom object detection model based on YOLO-NAS, a state-of-the-art convolutional neural network architecture, was trained using a curated and augmented dataset hosted on Roboflow. Uploaded images are processed through an image preprocessing pipeline and passed through the trained model for prediction. Model performance was evaluated using precision metrics across varying confidence thresholds. The resulting average precision (maP) of 54.6% – 89% demonstrates the model's capability to identify mangrove species with moderate accuracy, minimizing false positives. This work highlights the potential of integrating deep learning and computer vision into biodiversity monitoring tools. By enabling automated species identification from user-submitted images, the system supports broader participation in mangrove research and conservation while laying the groundwork for scalable, AI-driven ecological applications.

Highlights

- Developed a YOLO-NAS model for automated mangrove species identification.
- Focused on three dominant species in Pulau Kukup, Johor, Malaysia.
- Achieved mean average precision (mAP) of 54.6%-89% with curated image dataset.
- Integrated predictions into a user-friendly web application for accessibility.
- Demonstrates AI potential in scalable, citizen-driven biodiversity monitoring.

1.0 Introduction

Mangrove ecosystems play a critical role in coastal resilience by serving as natural buffers against storm surges and erosion while also providing habitats for a wide range of species. Effective conservation and management of these ecosystems require accurate identification of mangrove tree species. However, current identification practices largely depend on expert-based, manual methods, which are time-consuming, invasive, and often inaccessible to the broader public due to their complexity and technical nature.

Existing taxonomic resources, while informative, are often not user-friendly for non-specialists. This creates a significant barrier to community engagement and broader participation in conservation efforts. Moreover, challenges in fieldwork—such as difficult terrain, dense canopy structures, and species

similarities—further complicate data collection and classification efforts. Remote sensing techniques, though promising, face limitations such as the need for high-resolution, low-altitude data acquisition, which can be logistically challenging (Kuenzer et al., 2011). Furthermore, the distinctive physical characteristics of mangrove ecosystems pose practical challenges for species identification. Dense canopies, overlapping species, and muddy or waterlogged terrain can hinder field access and make precise measurements difficult. While modern remote sensing techniques offer potential solutions, their application in mangrove environments is constrained by several limitations. Accurate species-level classification often requires high spatial resolution imagery, typically obtained through low-altitude aerial surveys or unmanned aerial vehicles (UAVs). These methods, however, are resource-intensive and may face logistical barriers in complex mangrove habitats. Additionally, the spectral signals captured in remote sensing imagery are frequently mixed due to the presence of leaves, stems, water, and soil within a single pixel, reducing the accuracy of species differentiation (Kuenzer et al., 2011; Fatoyinbo et al., 2018).

The current gap in accessible, scalable, and accurate identification tools highlights the need for a technology-driven solution. This research proposes the development of a web-based application that utilizes machine learning to automate the identification of mangrove species. Users can upload images of mangrove leaves, flowers, or other features, which are then analyzed using a trained deep learning model for species classification.

This approach directly contributes to multiple United Nations Sustainable Development Goals (SDGs), including SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land). By democratizing access to identification tools, it also supports SDG 4 (Quality Education) and SDG 11 (Sustainable Cities and Communities). Ultimately, this work aims to enhance mangrove conservation through accurate, efficient, and accessible species identification powered by artificial intelligence.

2.0 Related studies

There are few closely related studies found with parallel objective with this research. Villamor et. al., (2025) uses deep learning specifically YOLOv8 to classify 10 mangrove species through leaf images. 4311 images have been used as training dataset and the results was magnificent at 97–98%. Still on applying deep learning, Sang et. al., (2025) applies YOLOv10 to enhances the mangrove's leaf morphology recognition for species identification. The typical process on labelling was conducted and PSA attention mechanism was used to enhance the leaf details features extraction. Sang uses SCDOWN to downsample the trained images in order to preserve the key characteristics to ensure accurate classification. Total of 4000 images, approximately 500 images per species with uniform resolution of 224 x 224 pixels has been used in this study. Through these processes, the accuracy of 92.4% has been obtained by comparing the testing dataset accuracy to the baseline model. Besides YOLO, another type of deep learning which famously used for image classification is MobileNetV3. Viodor et. al., (2023) has applied MobileNetV3 for mobile-based mangroves species identification and achieving 98.4% of

accuracy. In this study, Viodor et. al., (2023) trained 5000 mangrove's leaf images uses the transfer learning method to achieve such performance.

3.0 Study area

The research was conducted on Pulau Kukup (Fig. 1), an entirely mangrove-covered, uninhabited island located approximately 1 km off the southwestern coast of Pontian District, Johor, Malaysia. The island spans an area of approximately 6.47 km² (647 hectares), making it one of the largest intact mangrove islands in Peninsular Malaysia (Ramsar Convention Secretariat, 2008). It is surrounded by about 8 km² of intertidal mudflats that provide critical feeding grounds for migratory waterbirds (BirdLife International, 2022). Pulau Kukup was officially gazetted as a Johor State Park on 27 March 1997 under the Johor State Park Corporation Enactment 1989, and later designated as a Ramsar Wetland of International Importance on 31 January 2003 (Johor National Parks Corporation, 2024).

The island supports approximately 18 species of true mangroves, including *Rhizophora apiculata*, *Bruguiera cylindrica*, and *Bruguiera gymnorhiza*—the focal species in this study—contributing significantly to regional biodiversity (Ramsar Convention Secretariat, 2008). Pulau Kukup is also designated as an Important Bird Area (IBA) due to the presence of globally threatened species such as the Lesser Adjutant stork (*Leptoptilos javanicus*) (BirdLife International, 2022). The island's protected status, coupled with existing boardwalks and viewing platforms, allows non-invasive access for field studies. Its proximity to the Kukup mainland enhances logistical feasibility. Additionally, engaging with local communities supports the integration of traditional ecological knowledge into mangrove species research (Johor National Parks Corporation, 2024).

4.0 Methodology

The methodology of this research started with the literature analysis on past studies and reference book on mangrove species identification. Chintala (2008) stated that combination of vegetative characters (leaves) and reproductive features (flower and fruit) able to distinguish closely related species such as *Avicennia alba* and *Avicennia marina* by pairing leaf characteristic with fruit shapes and colours. Hence in this research, dual parameters of leaves and fruits or flower has been adapted in deep learning train dataset.

The workflow can be divided into four phases; begins with data collection, data preparation, deep learning development and finally performance testing. Figure 2 shows the overall workflow involved in this research.

4.1 Data Collection

The workflow begins with on-site data collection at Pulau Kukup and data mining from the internet. There are two reasons of photo data mining; to enrich the training dataset and to increase the flexibility

variety of image data format in training dataset, since this web app supposed to be used by variety types of users. Since this study only focus on three mangrove species, *Rhizophora apiculata*, *Bruguiera gymnorhiza* and *Bruguiera cylindrica*. All the sample collected on-site has been verified by experience mangrove species identifier from Johor National Park Corporation and also with reference to Mangrove Guidebook for Malaysia by Lee et. al., (2015). The close-up image data is just managed to be collected at 200 images. Early testing with the developed machine learning finds that this data is too small to achieve an acceptable precision. Figure 3 shows the morphology features of leaves and flower/fruits of three corresponding species.

4.2 Data Preparation

Hence, the data augmentation has been applied to increase the number of images. Data augmentation involves creating modified versions of the existing photos by applying transformations such as rotation, flipping, hue, saturation and brightness. These techniques simulate various real-world conditions, helping the model become more adaptable to different viewing angles and environmental factors. By augmenting the data, the model could better generalize from the training set to real-world scenarios, enhancing its accuracy and reliability. This process also helped to mitigate the risk of overfitting, ensuring that the model performed well not only on the training data but also on new, unseen images. Data augmentation thus played a crucial role in enhancing the effectiveness and generalization capability of the machine learning model in. The total number of photos originally was at most 200 only per species which consists both leaves and flowers. After undergoing data augmentation process, the images were artificially increased to 700 images per species. Data augmentation steps also allow the images in the datasets to be standardized. The steps include resizing images to standard resolution, noise reduction and brightness and contrast adjustment. Figure shows the settings and the augmented process outcome.

4.3 Image-based data training and machine learning development

The basis of this machine learning is supervised classification. To make the identification of mangrove species more accurate and specific, the model was designed to extract and combine features from both leaves and flowers. This dual-parameter approach allowed the machine learning algorithm to identify species with higher precision, leveraging the distinct patterns and structures present in each type of image. There are two processes occurring during the training phase; differentiation of features from background features in the photo and labelling of photos (leaves and flowers/fruits) to the species. Some images with complicated background require tracing of features, meanwhile less complicated images just required marking of square boundary. These trained library of image – mangrove species were developed in Roboflow. The process of species identification by object detection was later conducted by YOLO-NAS (You Only Look Once - Neural Architecture Search) with the reference to the developed library. The training process was improvised several times by improving the number of trained

images, the tracing of boundary and adjusting hyperparameter until the acceptable performance were achieved.

4.4 Web User Interface Development

After training the model, the development of a user-friendly website UI was initiated to make the research accessible and interactive for a broader audience. The website serves as a platform for researchers, conservationists, and the public to upload images of mangrove species for identification. The UI was designed with simplicity and efficiency in mind, ensuring that users could easily navigate the site and use its features. Key functionalities include the ability to upload photos and view the identified species. It also comprises all the information about the study, so that future developers and researchers can use this as a platform or a base to start. The integration of the machine learning model with the website allows users to get real-time species identification results, making the tool practical for both educational purposes and field research.

The website for mangrove species identification was developed using HTML and JavaScript, creating a responsive and interactive user interface. HTML structured the content and defined page elements such as images, text, and forms, while JavaScript added interactivity and dynamic features. JavaScript handled user inputs, dynamically updated content, and integrated with the machine learning model for species identification. Users could upload images of leaves and flowers, and JavaScript managed asynchronous requests to the server where the YOLO-NAS model processed the images and returned predictions. The website featured drag-and-drop image uploads, and real-time feedback, ensuring a seamless user experience with instant results from the model. By combining HTML's structural capabilities with JavaScript's interactivity, the website effectively facilitated accurate mangrove species identification using both leaf and flower images.

4.5 Performance Testing

The results of this research are evaluated using quantitative measures to ensure the accuracy and reliability of the machine learning model in identifying mangrove species. The primary metrics used for this evaluation were the Mean Average Precision (mAP) and precision graph.

The Mean Average Precision (mAP) is a crucial metric for assessing the performance of object detection models. It quantifies the model's ability to correctly identify and localize the objects of interest. In this case, the 3 focused mangrove species. The mAP values were calculated based on the validation set, which comprised 30% of the total dataset. The results revealed decent mAP values, indicating that the model had a strong detection capability. Specifically, the mAP values ranging more than 50% – 89%, suggesting that the model was highly effective at correctly identifying and localizing the mangrove species based on the input images. This high performance demonstrated the model's robustness and its ability to generalize well from the training data to new, unseen data. The metric would have been higher if there was more data.

In addition to mAP, the precision graph from Roboflow was also utilized to further assess the model's performance. Precision measures the proportion of true positive predictions among all positive predictions, providing insight into the model's accuracy in identifying mangrove species without producing false positives. The precision graph displayed a consistently high precision across different confidence thresholds, reinforcing the model's reliability in accurately detecting mangrove species. The combination of favourable mAP values and a high precision graph reinforced the reliability of the machine learning model in accurately identifying mangrove species.

5.0 Results and Discussion

The tangible results of this research can be divided into two main features; the machine learning for image-based mangrove species identification and the web user interface that enables the user interaction with the machine learning codes. The machine learning is connected to the web UI using API. Web UI serves as interaction platform for user to upload the data and finally received the results of identification, along with the precision percentage. Figure 6 shows the flow of the interaction between UI and machine learning model backend.

The accuracy of mangrove species identification was found around the range of 0.54 to 0.89 depending on the visibility of the leaves on images. The confidence level of prediction was calculated individually for each leaf or flower that identified in each image by YOLO-NAS. Hence, angle and visibility of each feature in the image also contributes to these percentages. This is the advantages of using YOLO architecture for object identification. Instead of adapting individual image labelling as other CNN classifier, YOLO extracts features using bounding box coordinates, scores the objectness and finally class the probability. Figure 7 shows the results of identification of each species with the corresponding precision value for these studies.

5.1 Comparative performance analysis: CNN vs YOLO

For sake of experiment, the dataset is also trained in Convolutional Neural Network (CNN) to investigate the possibility in accuracy improvement with classifier machine learning. CNN processed each image through multiple layers, identifying and learning the unique characteristics of each species. Similarly, dual-parameters of both leaf and flower images has been used in the CNN model, but unfortunately the performance testing only achieved 0.47 confidence level of accuracy when validated against test results, which was quite low, and the graphs were unstable.

5.2 Performance Testing for YOLO-NAS

To address this challenge and improve accuracy, the YOLO-NAS model was later used as the machine learning algorithm. The YOLO-NAS model is known for its better performance in object detection tasks, providing better accuracy and efficiency compared to traditional CNNs. Roboflow was used for the training of the dataset using the YOLO-NAS model, making the process simpler and ensuring the model could accurately identify mangrove species with the highest possible precision. This switch to YOLO-

NAS not only saved time but also resulted in a more robust and accurate identification model, highlighting the advantages of using advanced machine learning frameworks for complex image analysis tasks.

The Mean Average Precision (mAP) and the Precision Graph of the YOLO-NAS model indicate its strong detection capabilities. The mAP values, calculated on the validation set, approached 50%, demonstrating the model's effectiveness in accurately detecting objects. Furthermore, the precision graph from Roboflow showed consistently high precision across different confidence thresholds, with an average precision of 54.6% – 89%. To further increase this accuracy, it is essential to have more data in the future. In machine learning, the richness of the dataset significantly impacts the model's accuracy. Precise image and data labelling are crucial for improving the model's learning process and enhancing its performance.

The class_loss (Top-left) graph shows the classification loss over epochs. The blue line represents the actual loss values, and the orange dotted line is a smoothed version of the loss. Initially, the classification loss starts high (~ 2.75) and decreases sharply within the first few epochs, then stabilizes around 1.25, indicating the model quickly learns to classify. The box_loss (Top-center) graph shows the bounding box regression loss over epochs. The loss starts around 0.45 and increases slightly over time, stabilizing around 0.50 to 0.55. The increase in loss might suggest some overfitting or difficulties in accurately predicting bounding boxes as training progresses. The obj_loss (Top-right) graph shows the objectness loss over epochs. The objectness loss starts high (~ 0.775), decreases sharply, then fluctuates between 0.65 and 0.80. The fluctuations suggest variability in the model's ability to determine the presence of objects in different epochs. The precision (Top-far-right) graph shows the precision metric over epochs. Precision starts lower (~ 0.25), increases sharply, and then stabilizes around 0.60 to 0.65. This indicates the model's improving accuracy in correctly identifying objects as training progresses. The recall (Bottom-left) graph shows the recall metric over epochs. Recall starts low (~ 0.20) and increases over time, stabilizing around 0.35 to 0.40, with some fluctuations. This indicates an improvement in the model's ability to detect objects over time, though with some instability. The mAP (Bottom-center) graph shows the mean Average Precision (mAP) over epochs. The mAP starts around 0.10 and increases steadily, stabilizing around 0.30 to 0.35. This metric indicates an overall improvement in the model's performance in terms of precision and recall over time. The mAP_50_95 (Bottom-right) graph shows the mean Average Precision at IoU thresholds from 50% to 95% over epochs. The mAP_50_95 starts very low (~ 0.02) and increases significantly, stabilizing around 0.20 to 0.25. This shows the model's improved performance across different IoU thresholds, though it remains lower than the overall mAP, indicating more stringent evaluation criteria.

The model shows significant improvement in classification loss, precision, and object detection performance (mAP and recall) over the epochs. The fluctuations in box_loss and obj_loss suggest some instability or potential overfitting, which might require further investigation or regularization techniques. Precision and recall both improve over time, indicating better accuracy and completeness in object

detection. Overall, the model's performance improves as indicated by increasing mAP and recall, though there is room for further optimization to stabilize losses and improve performance metrics.

The results shows that the integration of mobile technology for the identification of mangrove species proves a significant advancement in mangrove research and conservation efforts. Traditional methods of species identification, while effective, are often limited by the availability of expert knowledge and the accessibility of detailed taxonomic resources. This project leverages the widespread use of technology and the capabilities of machine learning, specifically YOLO-NAS model, to ease the access to species identification tools.

To compare the performance of this finding with another related research such as Viodor et. al., Sang et. al., (2025) and Villamor et. al., (2025), it is evidence that the accuracy can be improve with the incremental in trained images. This study only used 490 photos in training dataset for each species, meanwhile the rest of the aforementioned studies are using 4000–5000 images in training the deep learning.

6.0 Conclusion

The introduction of a web application for the identification of mangrove species using advanced image recognition and machine learning techniques is a promising step forward in the field of mangrove conservation. By replicating the expert process of species identification in a user-friendly method, this project makes the identification process accessible to a wider audience. The initial focus on the mangrove species of Pulau Kukup, Johor, provides a targeted starting point for the development and refinement of this technology.

This innovative approach has the potential to transform how mangrove species are identified and understood by both specialists and the general public. By enhancing the accuracy and ease of species identification, the application supports informed conservation practices and raises awareness about the importance of mangrove ecosystems. As a result, it contributes to the long-term preservation of these critical habitats, promoting sustainable management and restoration efforts.

Ultimately, the success of this project could serve as a model for similar initiatives in other regions and ecosystems, further bridging the gap between scientific expertise and public engagement in environmental conservation. This existing model can be taken in as a pretrained model in the future to further expand the number of species it can support. Crowdsourcing can be considered as one of the initiatives in expanding the current training dataset to achieve a higher accuracy rate.

Declarations

Author Contribution

S.S.V. developed the machine learning code and curated the data-training library. S.N.A. conceptualized and designed the research methodology, and drafted the manuscript. N.H. provided guidance on validation procedures and performance assessment. L.T. contributed expertise on species identification and verified taxonomic accuracy.

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Figures

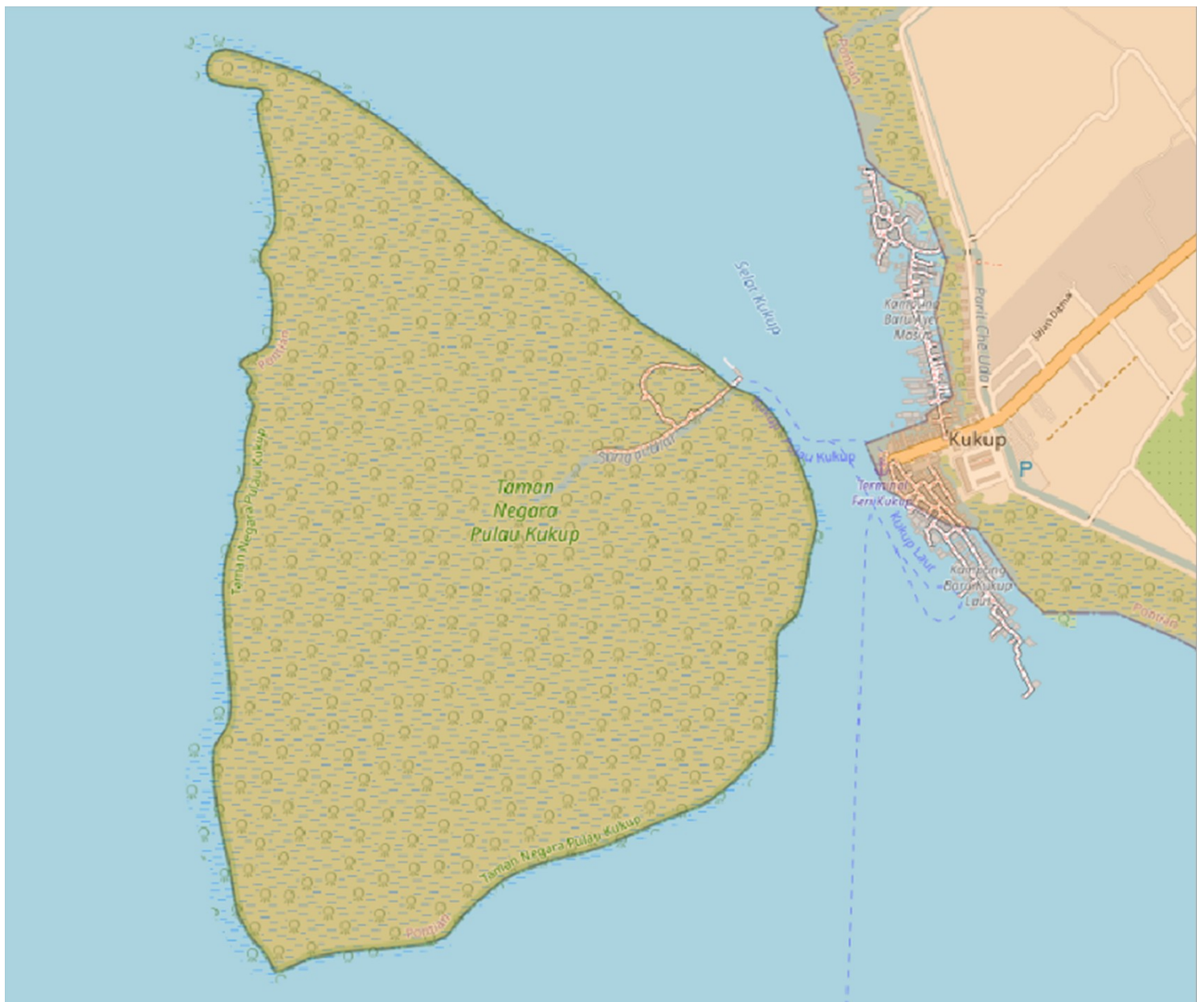


Figure 1

Study area – Pulau Kukup, Johor

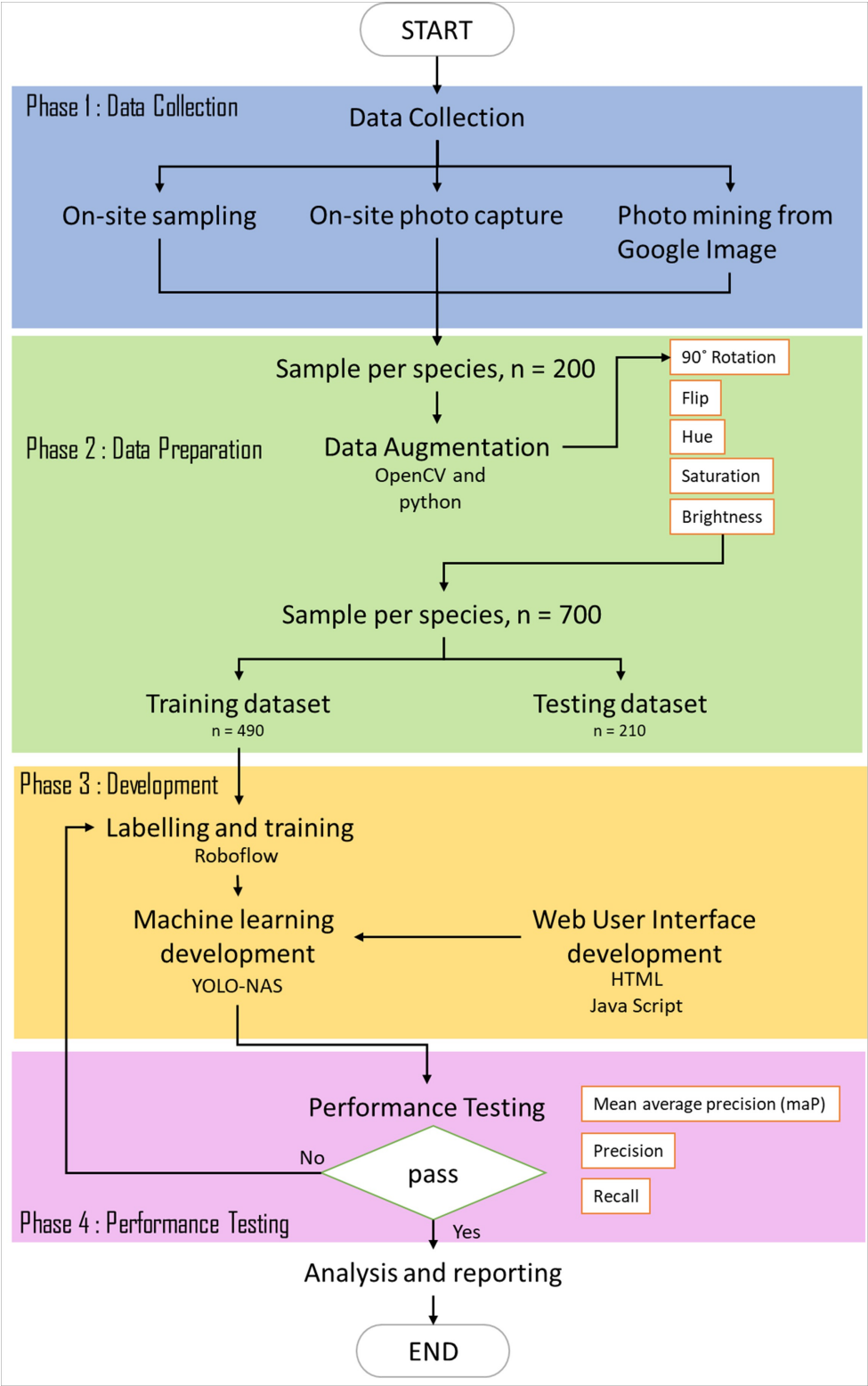


Figure 2

Research workflow

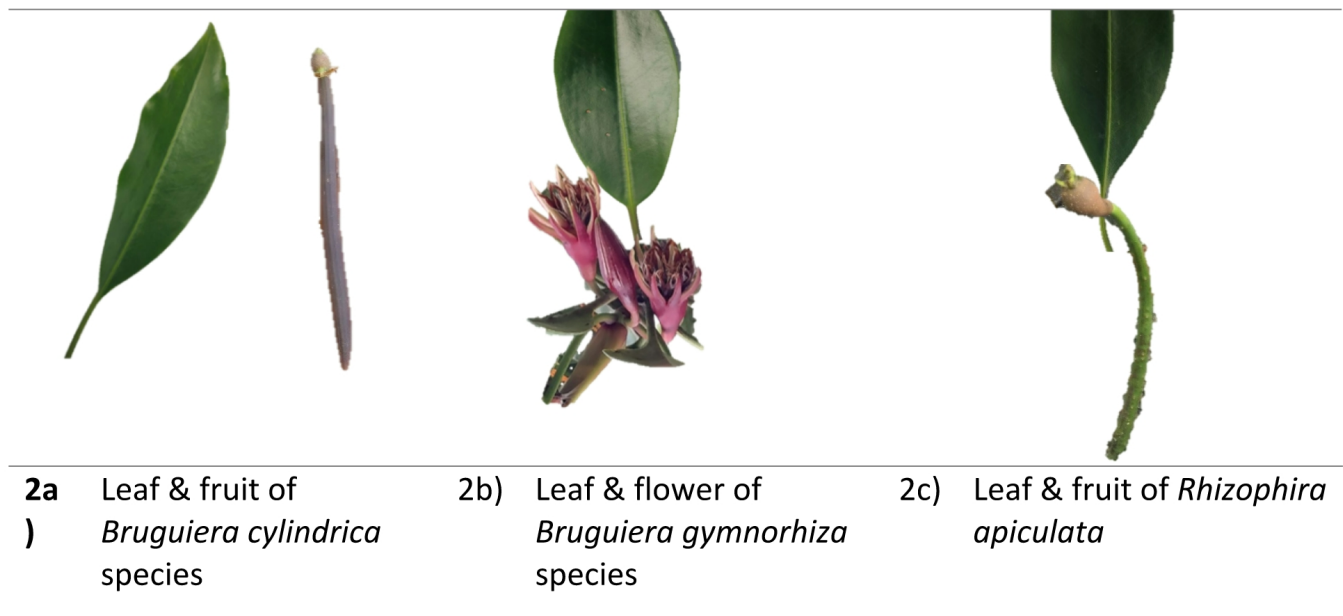


Figure 3

The sampling features taken from site.

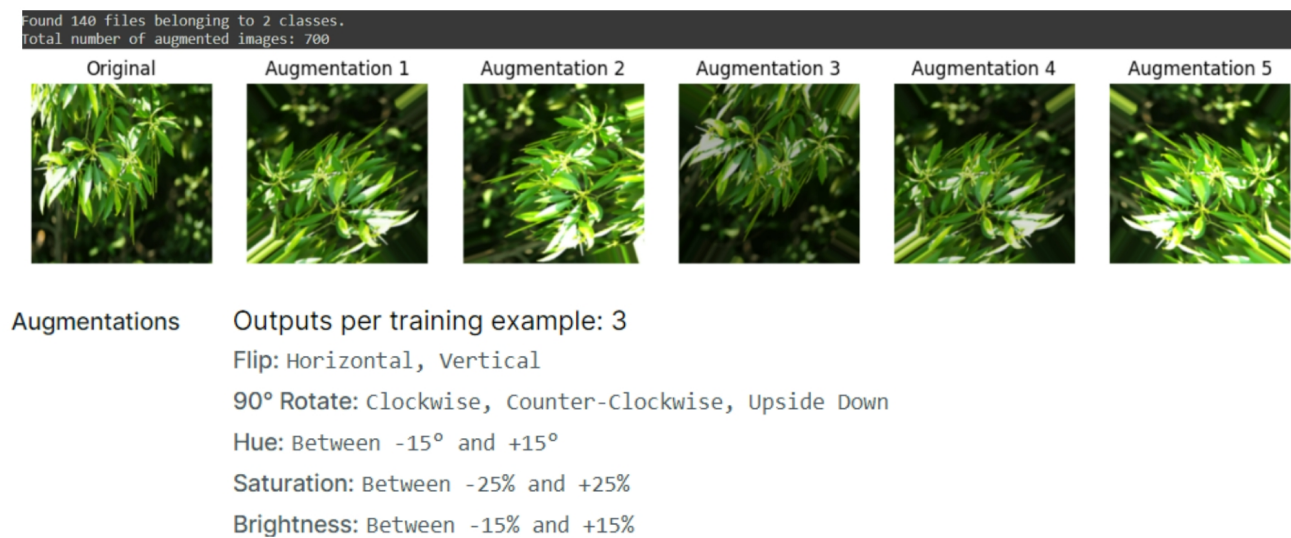


Figure 4

The augmented photo and the augmentation settings applied.

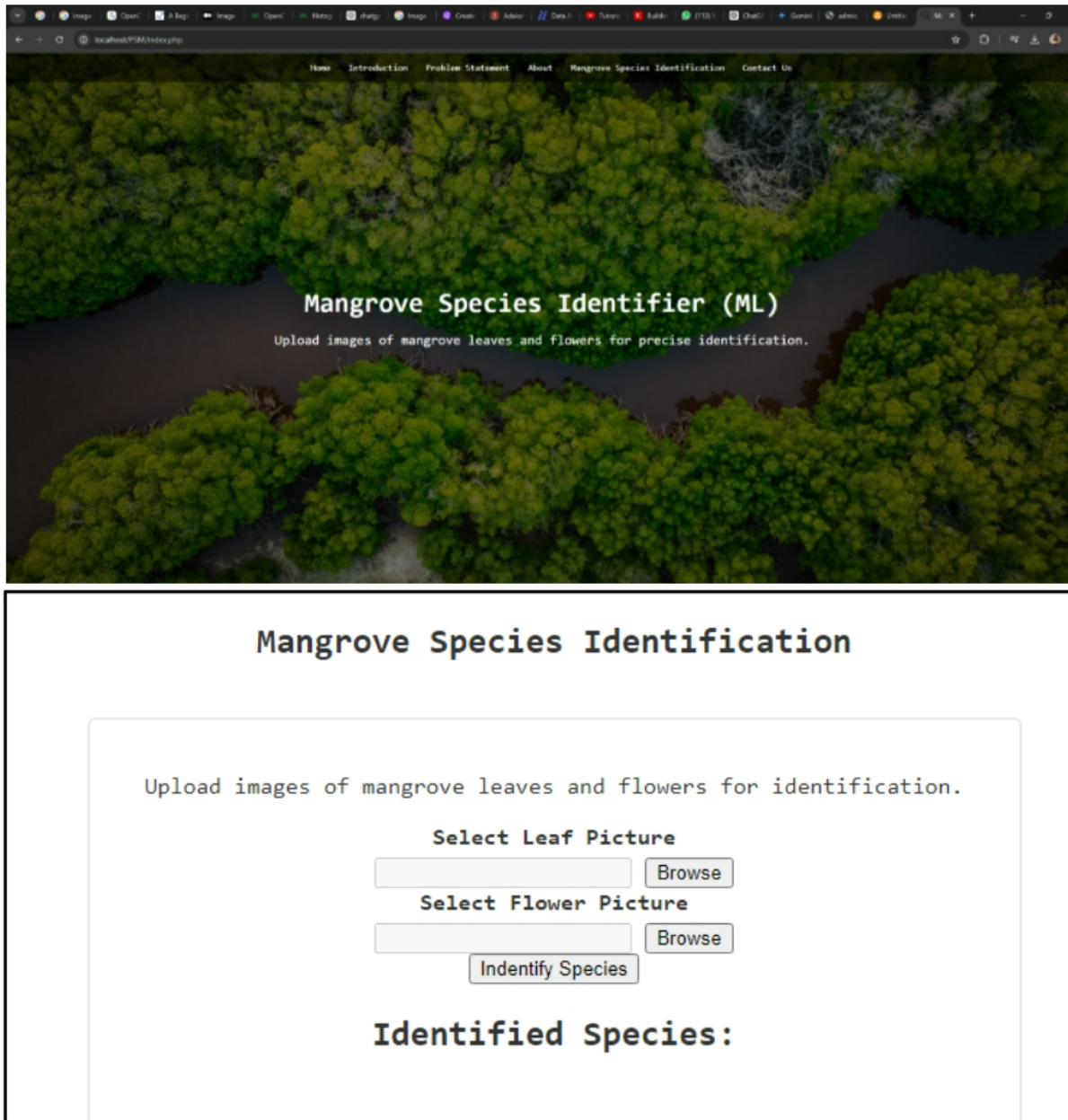


Figure 5

Website UI

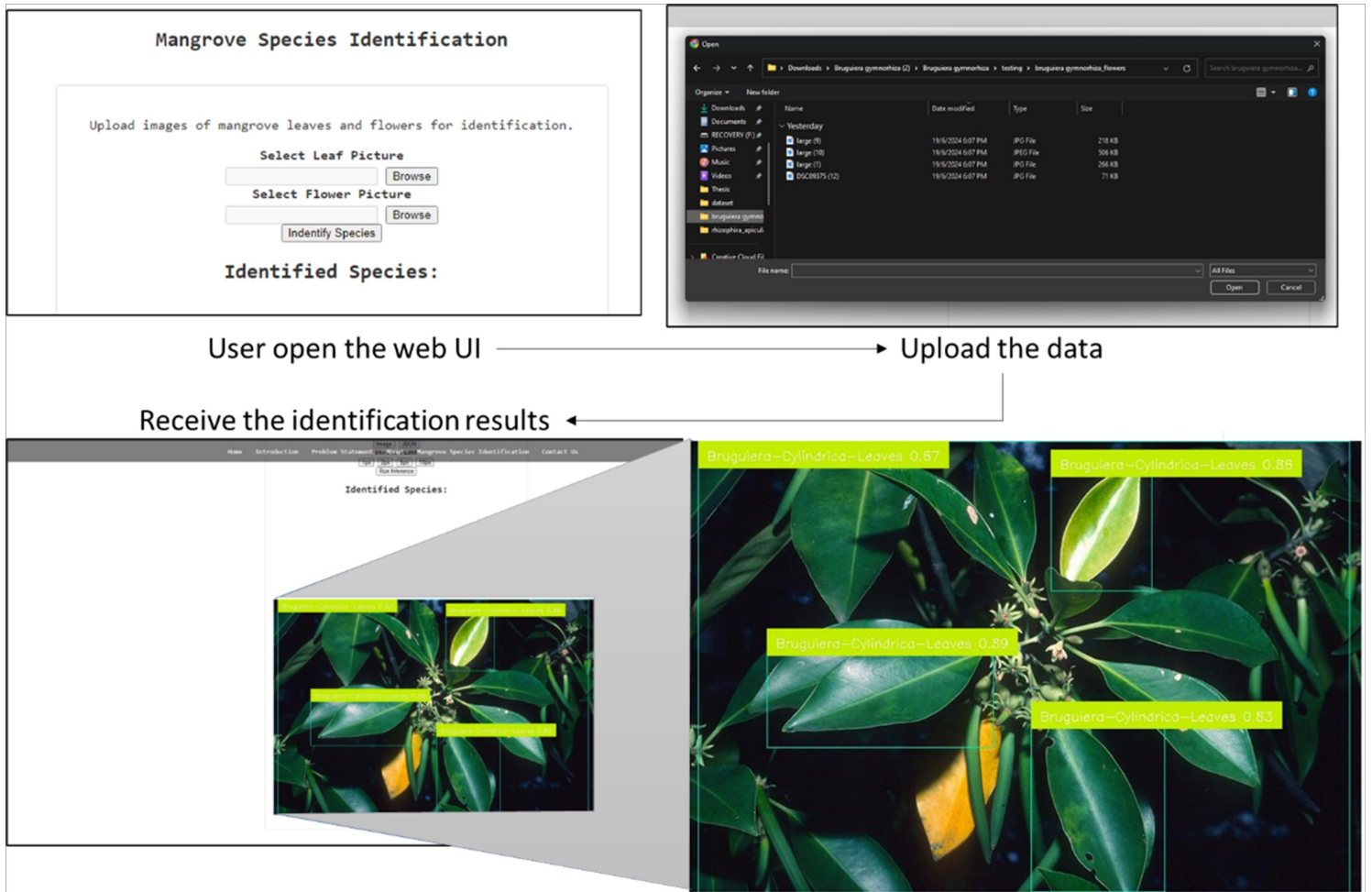


Figure 6

The simple interaction of UI and machine learning model



Species: *Bruguiera Cylindrica*
 Precision range: 0.67 – 0.89
 Average precision: 0.81



Species: *Bruguiera Gymnorhiza*
 Precision range: 0.51 – 0.84
 Average precision: 0.70



Species: *Rhizophora Apiculata*
 Precision range: 0.67 – 0.80
 Average precision: 0.74

Figure 7

The results of species identification

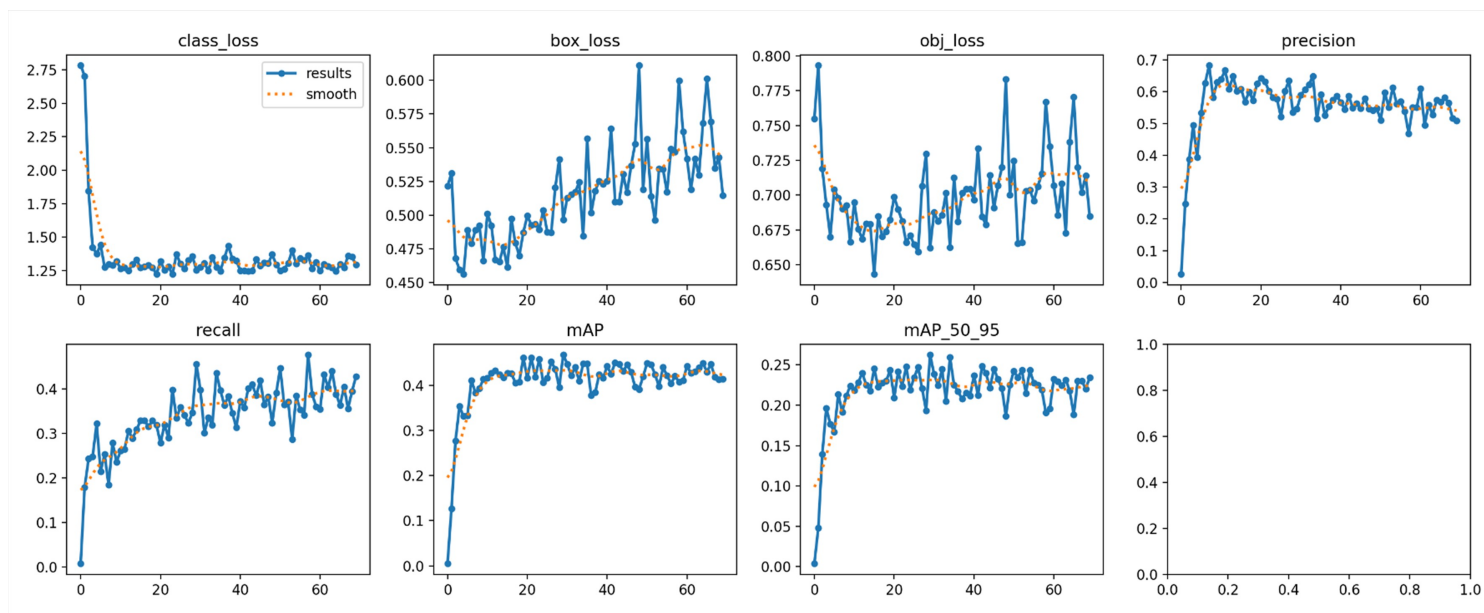


Figure 8

Generated graph results of mAP based on validation set