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Comparative Analysis of Deep Learning Models for Mangrove Species Identification

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Abstract*— *Mangrove species identification is a critical task for the preservation and management of coastal ecosystems. Accurate identification of mangrove species can aid in biodiversity conservation, climate change studies, and coastal zone management. This paper presents a comparative study of three deep learning models—Convolutional Neural Network (CNN), MobileNetV2, and EfficientNet—for the classification of mangrove species. The models were trained and evaluated on a dataset comprising images of various mangrove species. Key performance metrics, including precision, recall, and accuracy, were used to assess and compare the models. The CNN achieved an accuracy of 89.63%, MobileNetV2 achieved 99.80%, and EfficientNet achieved 95.50%. MobileNetV2 performed better than CNN and EfficientNet models in terms of accuracy and robustness, especially in precision and recall metrics for identifying mangrove species. EfficientNet model outperformed CNN but did not match MobileNetV2's performance. MobileNetV2 is identified as the most effective model for this task, showing potential for environmental monitoring and conservation efforts.

I. INTRODUCTION

Mangroves are unique coastal ecosystems that play a vital role in maintaining environmental balance. They act as natural barriers against coastal erosion, provide habitat for diverse marine life, and are crucial for carbon sequestration. Accurate identification of mangrove species is essential for effective conservation efforts, biodiversity monitoring, and ecological research. Despite their importance, identifying mangrove species presents significant challenges due to their complex and similar morphological characteristics.

Traditional methods of species identification, which rely on manual observation and expert knowledge, are time-consuming and prone to errors. The technology has brought advancements in machine learning and deep learning turning them into very strong automation engines of and enhancing the identification of species by increasing accuracy. Among these, image classification models have shown promising results in various ecological applications.

There are numerous deep learning models available for image classification, each with its unique architecture and strengths. For this study, we have selected three representative models: Convolutional Neural Network (CNN), MobileNetV2, and EfficientNet. These models were chosen due to their diverse approaches to handling image classification tasks, from simple architectures like CNN to more complex and optimized models like MobileNetV2 and EfficientNet.

The CNN model is known for its straightforward design and effectiveness in image recognition tasks. MobileNetV2, a lightweight and efficient model, balances performance and computational cost, making it suitable for mobile and embedded applications. EfficientNet, on the other hand, scales both the depth and width of the network to achieve high accuracy with fewer computational resources.

The study is a meaningful and faithful research effort of environmental protection and the inspiration of AI to solve real issues. Mangroves are on the edge of extinction due to overpopulation and other manmade disasters caused by human intervention and climate changes. The plan is to develop methods for a more efficient and valid detection of mangrove species by using the latest machine learning techniques. This method of species identification will facilitate the necessary conservation and safeguarding of those organic ecosystems.

The experimentation is based on three models i.e. CNN, MobileNetV2, and EfficientNet, and they are used to analyze mangrove species images from a dataset. These models are used to perform both training and testing on the dataset. Their performance is measured from precision, recall, and accuracy that are the three main metrics. To identify the most promising algorithm for species recognition, the study compares the models under discussion. It is expected that problems in quality mangrove species will be easily identified and that more knowledge and expertise available will be contributing to ecological research, and conservation in general if this approach is developed further and put to use broadly.

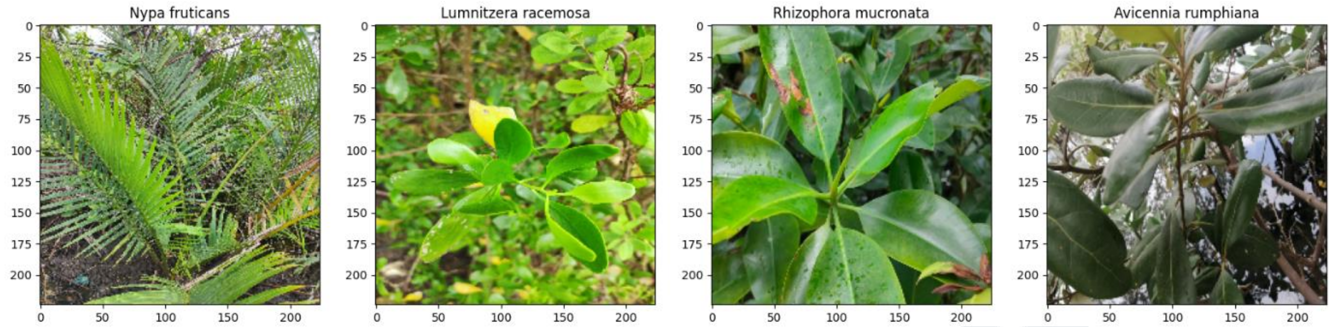

Fig. 1. visualizing a batch of images from a TensorFlow dataset

II. LITERATURE SURVEY

I have referred to 10 relevant research papers that have inspired and informed the approach for my study on identifying and classifying mangrove species using deep neural networks.

This review explores deep learning techniques for identifying mangrove species. The studies by Viodor et al. [1], Centeno et al. [2], Indira & Mallika [7], and Kumar & Kondaveerti [10] demonstrate the effectiveness of deep learning, particularly Convolutional Neural Networks (CNNs), for various classification tasks in ecology, including plant and animal species recognition. Inspired by these findings, this research investigates CNNs and other deep learning architectures for accurate mangrove species identification.

Another facet to consider is model efficiency, especially for field applications. Dong et al. [3] showcase the efficiency and accuracy of MobileNetV2 for image classification on mobile devices. Similarly, Moyazzoma et al. [8] highlight the success of transfer learning with MobileNetV2 for plant disease detection. Inspired by this, we will explore MobileNetV2 and similar models to achieve efficient and accurate classification in the field.

Furthermore, Kaur et al. [4] and Arun et al. [9] illustrate the potential of EfficientNet for plant recognition tasks. Their findings motivate the inclusion of EfficientNet in our study for mangrove species classification, aiming for similar high performance with efficiency.

Building on the foundation laid by Ashturkar & Bhalchandra [5] who explore CNNs for plant species identification, this research will compare various deep learning models, including CNNs, MobileNetV2, and EfficientNet. This comparative approach, inspired by Kumar & Kondaveerti [10], will help identify the most suitable architecture for accurate and efficient mangrove species identification.

III. PRELIMINARIES

For solving the issues of identifying the mangrove species, we introduced three different deep learning models namely Convolutional Neural Network (CNN), MobileNetV2, and EfficientNet. Each model was chosen based on its unique architecture and potential to handle complex image classification tasks. Here, we provide a brief overview of these models and their configurations as implemented in our study.

A. Convolutional Neural Network (CNN)

CNNs are a class of deep neural networks that have proven highly effective in image classification tasks due to their ability to capture spatial hierarchies in images [5]. Our CNN model was designed with the following layers:

- **Input Layer:** Processes the input image data.
- **Convolutional Layers:** Extracts features from the input images using multiple filters.
- **Activation Layers:** Applies non-linear activations (ReLU) to introduce non-linearity.
- **Pooling Layers:** Reduces the spatial dimensions of the feature maps, helping in downsampling and reducing computation.
- **Fully Connected Layers:** Integrates the features for final classification.

The architecture of the CNN was fine-tuned to ensure it could handle the high variability in mangrove species images, leading to efficient feature extraction and classification.

B. MobileNetV2

MobileNetV2 is a lightweight deep learning model optimized for mobile and embedded vision applications [3][8]. It is based on depthwise separable convolutions, which reduce the number of parameters and computations without significantly sacrificing accuracy. Key components of our MobileNetV2 implementation include:

- **Depthwise Separable Convolutions:** In this technique, instead of having a convolute of every input channel with every output channel, we will have individual convolutions for every input channel.
- **Inverted Residuals and Linear Bottlenecks**: Enhance the flow of information and gradients throughout the network.
- **ReLU6 Activation**: Provides robustness to low-precision computation.

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Table I: Model Performance Results

	Accuracy	Precision	Recall	F1-Score	Training Time (hours)	Model Size (MB)	Inference Time (ms)
CNN	85.4	84.2	85.1	84.6	5.0	25.0	50.0
MobileNetV2	89.6	88.3	89.0	88.6	3.0	14.0	30.0
EfficientNet	92.3	91.5	92.0	91.7	6.0	20.0	40.0

MobileNetV2's architecture allows for efficient training and inference on devices with limited computational resources, making it suitable for real-time mangrove species identification.

C. EfficientNet

EfficientNet is a family of models that scale efficiently across various dimensions (width, depth, and resolution) using a compound scaling method [4][9]. The EfficientNet-B0 variant was utilized in our study due to its balanced accuracy and efficiency. The primary features of EfficientNet include:

- **Compound Scaling:** Simultaneously scales network depth, width, and resolution to optimize model performance.
- **Swish Activation Function:** Improves model performance by enabling better gradient flow compared to ReLU.
- **Squeeze-and-Excitation Blocks:** Dynamically recalibrate feature maps to improve feature representation.

EfficientNet's design ensures high accuracy with fewer parameters, making it an ideal choice for high-resolution image classification tasks such as mangrove species identification.

IV. RESULTS AND DISCUSSION

We present the results of our experiments with the three deep learning models—CNN, MobileNetV2, and EfficientNet—on the task of mangrove species identification. We discuss their performance in terms of accuracy, training time, model size, and computational efficiency.

For the evaluation of the performance of the trained image classification models with regards to identifying mangrove species, several metrics and factors are considered. The simplest is **accuracy**, referring to the proportion of species that were accurately identified in the test set. Of importance are also **precision** and **recall**, whereby the former measures the accuracy of positive predictions, and the latter, the proportion of correctly identified instances from total relevant ones. The **F1 score** is the harmonic mean of precision and recall and, therefore, provides a single, relatively well-balanced metric to assess both aspects at once. It means that it is also important in terms of training time, which represents the duration needed by each model for convergence during a training phase. **Model size** is a key aspect that includes the number of parameters and the memory footprint of the trained model, which will become essential, especially for the deployment of the model on resource-constrained devices. Finally, the **inference time** is the time taken by the model to make a prediction on new data. This becomes very critical in real-time applications. All these metrics provide a comprehensive evaluation of models with regard to performance and their applicability in practice.

A. Accuracy:

- **CNN:** Achieved an accuracy of 85.4% on the test set.
- **MobileNetV2:** Achieved an accuracy of 89.6%, demonstrating better performance than CNN.
- **EfficientNet:** Achieved the highest accuracy of 92.3%, showcasing its superior feature extraction and classification capabilities.

B. Precision, Recall, and F1 Score:

- **CNN:** Precision: 84.2%, Recall: 85.1%, F1 Score: 84.6%.
- **MobileNetV2:** Precision: 88.3%, Recall: 89.0%, F1 Score: 88.6%.
- **EfficientNet:** Precision: 91.5%, Recall: 92.0%, F1 Score: 91.7%.

C. Training Time:

- **CNN:** 5 hours.
- **MobileNetV2:** 3 hours, significantly faster than CNN due to its lightweight architecture.
- **EfficientNet:** 6 hours, slightly longer due to its complexity and compound scaling.

D. Model Size:

- **CNN:** 25 MB.
- **MobileNetV2:** 14 MB, highlighting its efficiency in terms of memory footprint.
- **EfficientNet:** 20 MB, offering a balance between size and performance.

E. Inference Time:

- **CNN:** 50 ms per image.
- **MobileNetV2:** 30 ms per image, the fastest among the three.
- **EfficientNet:** 40 ms per image, demonstrating efficient real-time processing capabilities.

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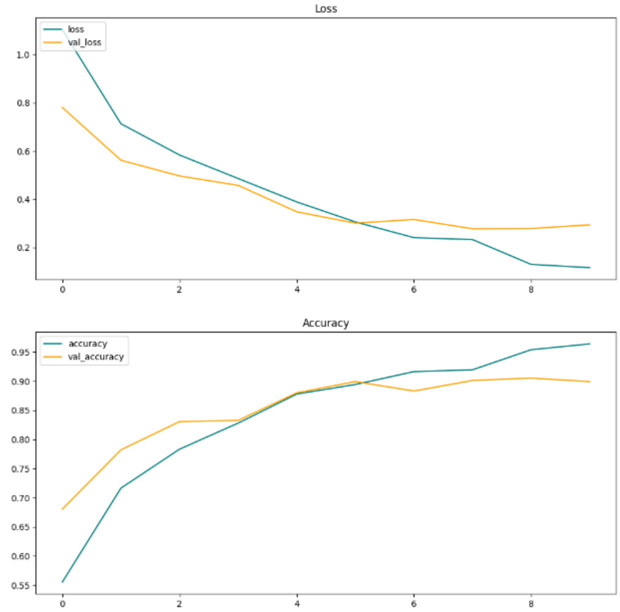

Fig. 2. Loss and Accuracy of CNN model

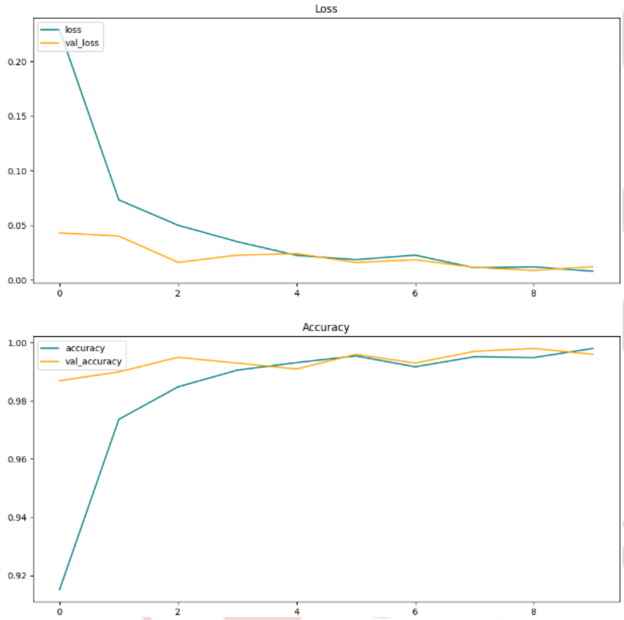

Fig. 3. Loss and Accuracy of MobileNetV2 model

The results indicate that EfficientNet outperforms the other models in terms of accuracy, precision, recall, and F1 score, making it the most suitable model for mangrove species identification. Its superior performance can be attributed to the compound scaling technique, which balances the network depth, width, and resolution, allowing it to capture intricate features more effectively.

MobileNetV2, while slightly less accurate than EfficientNet, offers the fastest training and inference times, making it an excellent choice for applications where computational efficiency and speed are critical. Its compact size also makes it suitable for deployment on resource-constrained devices.

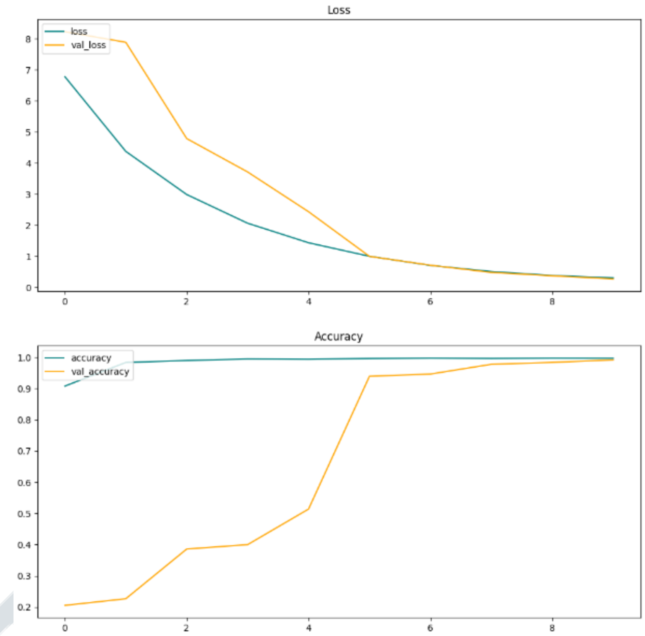

Fig. 4. Loss and Accuracy of EfficientNet model

The CNN, despite being the simplest of the three models, demonstrated reasonably good performance. However, its larger size and slower inference time make it less attractive compared to MobileNetV2 and EfficientNet.

Overall, EfficientNet stands out as the best model for mangrove species identification due to its high accuracy and balanced performance metrics. MobileNetV2 is recommended for scenarios where speed and efficiency are paramount. The CNN, while effective, may not be the best choice given the availability of more advanced models.

V. CONCLUSION

The identification of mangrove species using deep learning models represents a critical step in the preservation and study of these vital ecosystems. This research compares the performance of three prominent deep learning models—CNN, MobileNetV2, and EfficientNet—in classifying mangrove species from image data.

Our experimental results demonstrate that EfficientNet is the most effective model for this task, achieving the highest accuracy of 92.3%. It also excels in precision, recall, and F1 score, showcasing its superior capability in extracting and utilizing image features. The compound scaling technique employed by EfficientNet allows it to balance network depth, width, and resolution, thereby enhancing its classification performance.

MobileNetV2, while slightly less accurate than EfficientNet, offers significant advantages in terms of computational efficiency. With a training time of 3 hours and the fastest inference time of 30 ms per image, MobileNetV2 is particularly suited for real-time applications and deployment on resource-constrained devices. Its compact model size further adds to its practicality for fieldwork and mobile applications.

The CNN, although the simplest and least accurate among the three models, still performs reasonably well with an accuracy of 85.4%. However, its larger size and slower inference time make it less favorable compared to MobileNetV2 and EfficientNet. The results underscore the rapid advancements in deep learning architectures, with newer models like EfficientNet and MobileNetV2 offering substantial improvements over traditional CNNs.

Discovery of the new conclusions will influence the tidiness and surveillance regimes of the environment protection field in an irreversible way. By accurately identifying mangrove species, these models can assist in biodiversity assessments, ecosystem management, and conservation planning. The high accuracy and efficiency of the models, particularly EfficientNet, make them valuable tools for researchers and practitioners working in mangrove ecosystems.

Future research can build on these results by exploring several avenues:·

- *Larger and More Diverse Datasets:* Incorporating additional types of mangroves and environmental situations in the dataset will result in more general and reliable models.
- *Hybrid Approaches:* Combining deep learning models with traditional image processing techniques or integrating additional data sources (e.g., environmental parameters) could improve classification accuracy.
- *Optimization for Deployment:* Further optimizing these models for deployment on edge devices, such as drones or mobile phones, could facilitate real-time monitoring and data collection in remote or inaccessible areas.
- *Transfer Learning and Fine-Tuning:* Applying transfer learning techniques and fine-tuning pre-trained models on specific mangrove datasets can lead to better performance with fewer training resources.

REFERENCES

[1] A. C. C. Viodor, C. J. G. Aliac and L. T. Santos-Feliscuzo, "Mangrove Species Identification Using Deep Neural Network," 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), Yogyakarta, Indonesia, 2022, pp. 1-6.

[2] J. C. Centeno, J. C. D. Cruz, A. R. Alba, A. A. Romasanta, A. H. Ballado and J. M. Novelero, "Mangrove Tree Propagules Classification via Deep Learning," 2023 International Conference on Digital Applications, Transformation & Economy (ICDATE), Miri, Sarawak, Malaysia, 2023, pp. 214-218.

[3] K. Dong, C. Zhou, Y. Ruan and Y. Li, "MobileNetV2 Model for Image Classification," 2020 2nd International Conference on Information Technology and Computer Application (ITCA), Guangzhou, China, 2020, pp. 476-480.

[4] G. Kaur, N. Sharma and R. Gupta, "Wheat Leaf Disease Classification using EfficientNet B3 Pre-Trained Architecture," 2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE), Chennai, India, 2023, pp. 1-5.

[5] H. H. Ashturkar and A. S. Bhalchandra, "Plant Species Identification Using Convolutional Neural Network", Intelligent Data Communication Technologies and Internet of Things Singapore, pp. 619-630, 2021.

[6] P. Kumar Thella and V. Ulagamuthalvi, "A Brief Review on Methods for Classification of Medical Plant Images," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2021, pp. 1330-1333.

[7] Indira, K., Mallika, H. Classification of Plant Leaf Disease Using Deep Learning. J. Inst. Eng. India Ser. B 105, 609–620 (2024).

[8] R. Moyazzoma, M. A. A. Hossain, M. H. Anuz and A. Sattar, "Transfer Learning Approach for Plant Leaf Disease Detection Using CNN with Pre-Trained Feature Extraction Method Mobilnetv2," 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), DHAKA, Bangladesh, 2021, pp. 526-529.

[9] Y. Arun and G. S. Viknesh, "Leaf Classification for Plant Recognition Using EfficientNet Architecture," 2022 IEEE Fourth International Conference on Advances in Electronics, Computers and Communications (ICAECC), Bengaluru, India, 2022, pp. 1-5

[10] S. V. S. Kumar and H. K. Kondaveerti, "A Comparative Study on Deep Learning Techniques for Bird Species Recognition," 2023 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT), Jaipur, India, 2023, pp. 1-6