Bridging AI and Ethnobotany: A Deep Learning Approach for Medicinal Plant Identification and Real-World Deployment

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Abstract. Precise identification of medicinal plants is relevant to pharmacological studies and proper use of species, but most currently used image-based methods are tested on small-scale data and do not provide much information on the extrapolation of models. The paper examines how deep learning can be used to classify ten medicinal plant species, which are commonly used in rural and semi-urban areas in Bangladesh. An augmented subset of 5,000 images was augmented to 10,000 and divided into training, validation and test subsets. A variety of convolutional neural networks models, such as EfficientNetB3, InceptionV3, MobileNetV2, and VGG19 were trained and compared. The highest accuracy (99.00%) was attained by Efficient- NetB3 as compared to the other models. Nevertheless, such high accuracy shows that it is necessary to further validate it, including cross-validation and external dataset testing, to determine how well it works in the real world. A web-based prototype that was lightweight was created as well to illustrate that it can be used in practice. Comprehensively, the paper gives a comparative review of the current CNN models and explains the capabilities and their constraints to automated recognition of medicinal plants.

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1 Introduction

Medicinal plants are of critical importance in the modern and traditional health care systems as they are concentrated with a high level of bioactive compounds. In areas like Bangladesh where the use of herbal remedies is commonplace, correct identification of species of medicinal plants is important to influence the safe use of herbs, as well as pharmacological research. Nevertheless, manual detection is slow, knowledge- based and can be inaccurate especially where species have similar features. The development of artificial intelligence and, in particular, deep learning has changed the way species recognition by images is performed: now, it can be carried out automatically, extracting the features and classifying them with high accuracy. The use of CNNs as plant recognizers has become popular, and has shown great improvements over the previous feature-engineering methods. Nevertheless, much of the current research work is based on small or unrepresentative datasets, does not assess model generalize ability, or does not discuss computational theory in many details (related to practical implementation).

There is still an evident research gap in creating a balanced assessment of state- of-the-art architectures based on a varied dataset regarding medicinal plants and also with regard to model efficiency and deploy ability. The current paper bridges these gaps by assembling a curated list of ten medicinal plants species that are usually found in Bangladesh and conducting a comparative evaluation of some of the most popular models of deep learning, compared, such as EfficientNetB3, InceptionV3, MobileNetV2, and VGG19. Moreover, a light web-based prototype is deployed to show that the most suitable model is practically applicable. The proposed research will facilitate the achievement of a methodological contribution as well as a deployable tool on the identification of medicinal plants by connecting the diversity of datasets, architectural comparison, and real-time usability. The results are added to the current work on digital herbarium systems, biodiversity surveillance, and education on plants on the community level and reveal the existing limitations and opportunities to improve them in the future.

2 Literature Review

Initial studies on medicinal plant recognition were based on handcrafted characteristics and traditional machine learning. Begue et al. [21] applied morphological and color descriptors to Random Forest whereby they attained an accuracy of 90.1% and Kumar et al. [8] attained an accuracy of up to 99% with feature-based classifiers. Though these studies have shown that even manual engineered features can be efficient, their functioning is greatly determined by what descriptors are used and do not tend to perform well in diverse environmental situations. The introduction of deep learning saw CNNs take over as the market leader in plant image classification. The first studies by Akter et al. [1] and Bhuiyan et al. [6] revealed middle results that formed the baseline of 71.3% and 84.58. Later researches used more sophisticated architectures. Khatun et al. [4] employed the Xception to predict five species; whereas Habiba et al. [5] obtained a 96% accuracy when employing VGG16 with transfer learning.

More comprehensive comparative studies, like the one by Dey et al. [7], compared several architectures and found DenseNet201 as the most resilient, and the researchers by Hassan et al. [10] proved the superiority of MobileNet in comparison with InceptionV3 and Xception in their data. Another strategy that was considered was fine-tuning, and Ayuki et al. [23] attained 96.02 percent accuracy with optimized MobileNetV2. The recent trends in research are hybrid and ensemble approaches to enhance the performance. Uddin et al. [2] achieved 97% to 99% with ensemble learning whereas Pushpa et al. [15] proposed HybNet that utilized squeeze and excitation mechanisms with 94.24. Swarm intelligence applied with ResNet50 yielded 99.9% accuracy by Renukaradhya et al. [16], and with a number of architectural innovations, Chetia et al. [17], Sekharamantry et al. [18] and Azadnia et al. [20] reported similarly high accuracies.

Similar studies have paid attention to actual implementation. Putri et al. [9] and Sasikaladevi et al. [19] created mobile applications to facilitate the day-to-day plant identification with their work, and Islam et al. [12] expanded the scope of the work by introducing the object localization with the use of YOLOv2. Irrespective of these improvements, systematic reviews like the one by Sourov et al. [13] note that there are still several limitations, such as dependence on proprietary datasets, not being evaluated in real-world settings, and not focusing on computational efficiency to run on low-resource devices. In general, the currently available literature shows significant advances and at the same time displays obvious gaps: numerous works present extremely high accuracy values without thorough cross-validation, use small datasets, or fail to compare different current architectures with identical conditions. Furthermore, not many studies combine the issues of dataset diversity, model efficiency, and applicable deployability. To resolve these gaps, the current study offers a filtered collection of ten of these medicinal plant species, a comparative analysis of some of the current state-of-the-art CNN models, and an assessment of the performance of these models in terms of generalization and practicality to be applied in real-time. This makes the work a methodological contribution as well as a step towards practical accessible medicinal plant identification systems.

3 Methodology

The methodology (Fig. 1) is a combination of consecutive stages of data collection, preprocessing, augmentation, model development, and evaluation. Training current convolutional neural networks (CNNs) based on high-resolution images of ten botanically validated species is used to automatically extract features of a discriminative nature, thus removing the manual feature engineering process. An extensive analysis based on several performance indicators and visualization tools is done to measure model effectiveness. Lastly, the best model is implemented as a web application to show that it is actually practical. This dataset has been built by taking images of ten medicinal plant species, and a sequence of augmentation methods was performed, including horizontal and vertical flipping, changing the brightness and contrast, shifting, and rotating to enhance the diversity of the datasets. The dataset was then divided into training (70%), validation (15%), and testing (15%) sets to provide equal balance in model evaluation. The augmented dataset was trained and tested on 4 deep learning architectures, i.e. EfficientNetB3, InceptionV3, MobileNetV2 and VGG19. The classification reports, confusion matrices, and the accuracyloss curves were used to evaluate the model performance. EfficientNetB3 was the most accurate architecture among the examined ones, thus it was chosen as the proposed model. This model was later implemented as a web application (Flask based) written in HTML, CSS, and JavaScript to allow real time recognition of medicinal plants.

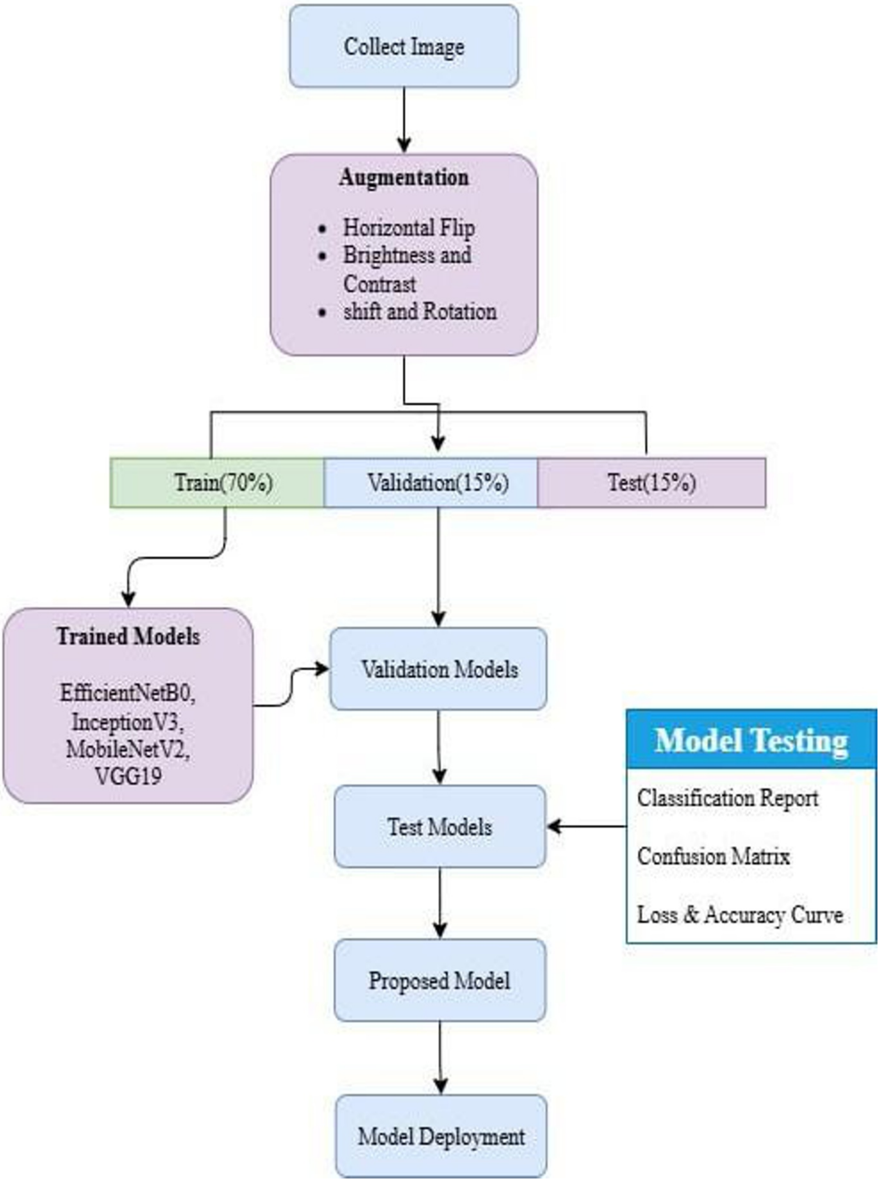

Fig. 1. Work Flow Diagram

3.1 Dataset Description

Data applied in this study were gathered from an open-source dataset on Kaggle [25], including high-resolution photos of ten various classes of medicinal plants. Each class has around 500 images, meaning that the total number of raw samples is 5,000. The selected plant species are among the most common medicinal herbs in South Asian traditional medicine, particularly those endemic to Bangladesh. These include Bhibitaki, Candelabra Plant, Chebulic Myrobalan, Gotu Kola, Holy Basil, Indian Borage, Lemongrass, Longevity Spinach, Madagascar Periwinkle, and Neem tree (Fig.2). The visual acquisition process focused on capturing visual variation in shape, texture, and coloration under varying lighting and environmental conditions so that the model could learn from an enormous diversity of visual situations in the real world. In order to further enrich the dataset and improve the generalization ability of the models, data augmentation was applied. Each original image was artificially transformed using augmentation techniques, effectively doubling the dataset to 10,000 images virtually. The augmentation was applied so that the dataset would encompass variations in plant orientation, size, lighting, as well as other natural variations, which are typically encountered in real-life scenarios.

Fig. 2. Sample Image of each class.

3.2 Data Preprocessing

A number of preprocessing operations were conducted before the models were trained to guarantee that there was consistency and quality of data. The data was categorized into three subsets namely, 70% training, 15% validation and 15% testing. To ensure that all subsets had equal proportions of classes, a stratified sampling method was used. In order to enhance the dataset and reduce overfitting, data augmentation was performed with the help of Albumentations library. Local contrast and emphasizing of plant patterns and edges was augmented with contrast limited adaptive histogram equalization (CLAHE). Besides, the geometric transformations such as horizontal and vertical flips, rotations (40 and -40), and scaling (20 and -20) were used to model different acquisition conditions. Alterations in the brightness and contrast were also added to achieve the effect of the variations in the illumination. The size of all images was reduced and standardized to the input requirements of the neural networks. These preprocessing measures did not only enhance the diversity of the data, but also made the models more resilient to spatial and photometric differences.

3.3 Model Selection

The models of four state-of-the-art convolutional neural networks, including EfficientNetB3, InceptionV3, VGG19, and MobileNetV2, were tested in the same experimental environment in the aim of finding the most suitable architecture to classify medicinal plants. The same preprocessed dataset, training protocol, hyperparameters, image resolution, hardware environment, and data augmentation pipeline were used to train and test all the models. Such rigorous homogeneity provided an equal and impartial comparison of architectures.

Of the tested models, the EfficientNetB3 showed the best overall performance with 99.0% accuracy and better precision, recall, and F1 scores on all classes. Its good performance is due to the compound scaling strategy of EfficientNet, which scales uniformly network depth, width, and input resolution, allows achieving an optimal tradeoff between accuracy and computational efficiency. InceptionV3 also reported the best performance of 98.13% accuracy but it is comparatively more expensive and contains a higher number of parameters, which reduces its application in real-time or systems with limited resources. The parameter-intensive and deep architecture of VGG19 was less accurate (96.33) and even more computationally intensive than the historical VGG19, which is less deep. The least accurate model (91.64) was MobileNetV2, which was advantageous by its lightweight nature; it, however, showed unpredictable results among some of the classes.

According to these predetermined and detailed assessments, EfficientNetB3 was chosen as the ultimate model. It offered optimum trade-off between accuracy, robustness and computational efficiency thus best applicable in real world deployment. As a result, EfficientNetB3 became the main structure of the real-time medicinal plant classification system.

3.4 Model Architecture

EfficientNet-B3 architecture (Fig.3) receives an input image of a medicine plant and sends it through a sequence of convolutional layers and Mobile Inverted Bottleneck Convolution (MBConv) blocks [24]. The initial stage is a Conv 3x3+BN layer, which transforms the input to produce an output of 112×112×40. The network's core operations are driven by consecutive MBConv blocks, specifically MBConv1 and MBConv6 with 3×3 and 5×5 kernels, respectively, that efficiently extract features while spatial sizes are progressively reduced. The blocks, optionally with an "Inverted Residual Connection" (IRC), are staged to successively shrink the size of the feature maps from

112×112 to 7×7. After this feature extraction, the network's classification head takes over, utilizing a Conv1x1 layer to expand channels to 1536, followed by a Global Average Pooling (GAP) layer, a fully connected (FC) layer, and, finally, a softmax activation function to produce a probability distribution for the classification task. The model's classification head is configured to classify different types of medicinal leaves.

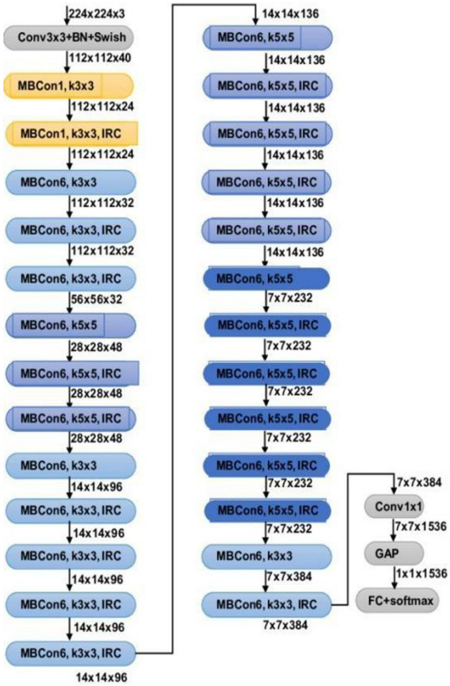

Fig. 3. Architecture of Efficient-NetB3

3.5 Model Deployment

The system was implemented as a web application called MediPlant AI based on client server architecture. The backend was written using Flask and handles the HTTP requests and model inference, whereas the frontend is created using HTML5, CSS3, and JavaScript, which allows it to have a responsive and accessible interface regardless of the device used. With the help of this design, users can recognize plant species and access information about their medicinal properties in real-time.

In the case of the classification engine, an EfficientNetB3 model with a finetuned version, which has reached 99 percent accuracy on the test set, was trained using PyTorch. The model was made deployable, and a pipeline of inference was implemented, which preprocesses images that were uploaded by users. This pipeline, which uses Python Imaging Library, standardizes the input images to a 224×224 size and balances them using ImageNet statistics and then into the model to be predicted.

When the image is uploaded, the system takes the input and runs the model inference, which then returns the name of the predicted species name and its medicinal uses (Fig. 4) in 500 milliseconds on average. This is an efficient and modular system that bridges the gap between a deep learning research and practice, which can be useful in the education of people and the conservation of botanicals. The deployment of the proposed model is shared in the reference section [26].

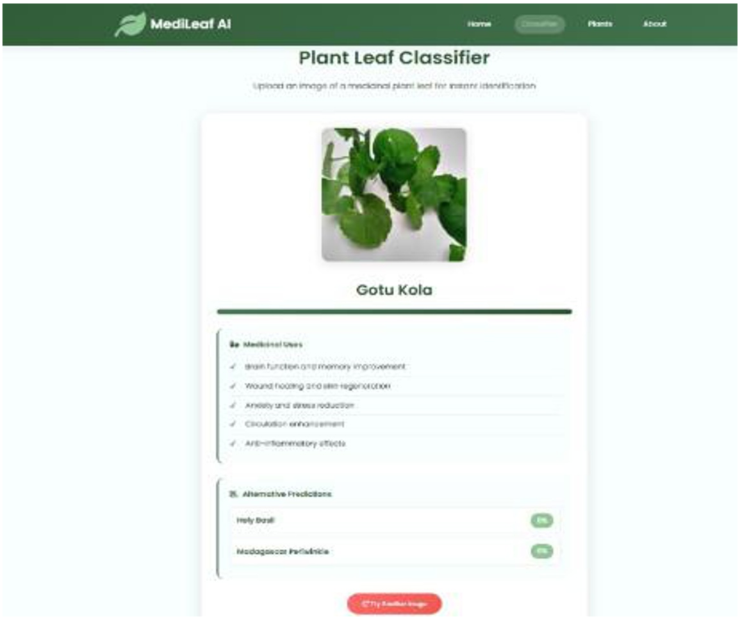

Fig. 4. Web Based Application's Classified Result

4 Methodology

The findings suggest that EfficientNetB3 is more efficient in terms of trading. The key performance measures applied in the study are accuracy, precision, recall, and F1-score. These measures have been selected with the aim of fully assessing the extent to which each of the models is effective in classification tasks especially in multiclass problems. The measures of accuracy and precision and recall are concerned with the false positives and false negatives, but the measure of accuracy refers to the overall accuracy of the model predictions. F1-score, a harmonic product of both precision and recall, will provide a moderate perspective of effectiveness of the model.

EfficientNetB3 was the most accurately classified model with 99.00% accuracy, which is significantly more accurate than the other models in all the metrics used in evaluation. The model was well generalized across the classes and highly robust even in the morphological similarity amongst plant species. InceptionV3 was ranked second with the accuracy of 98.13, which is stable but not very stable. A more mature but deeper model, vgg19, achieved a consistent 96.33 percent accuracy one, though, was limited in its potential by a higher computation cost and slower convergence. MobileNetV2 is a light yet powerful model with a 91.64%. It was a powerful trade-off on this high-variability data set, especially in its relatively lower F1-score and recall values. The detailed evaluation results for all models are summarized in Table 1.

The findings suggest that EfficientNetB3 is more efficient in terms of trading off between the predictive performance and the model complexity. Its performance justifies the efficacy of scaling the compound in learning fine-grained pattern of the leaves and averting the intra-class variation and inter-class variation of the data set. EfficientNetB3 has shown an excellent performance in all the measurements hence it was chosen as the model that can be deployed to a real-time medicinal plant identification system. This outcome justifies the strength of data design, the data augmentation process, and the training procedure as well.

Overall, the comparative analysis points out that while base and light-weight architectures such as VGG19 and MobileNetV2 work just as well, more recent scalable architectures such as EfficientNet and Inception decisively perform better with high-precision classification on real-world noisy image data.

Table 1. Classification Performance of Models

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB3	99.00	0.99	0.99	0.99
InceptionV3	98.13	0.98	0.98	0.98
VGG19	96.33	0.96	0.96	0.96
MobileNetV2	91.64	0.92	0.91	0.91

4.1 Model Evaluation

To thoroughly analyze the performance of our proposed EfficientNetB3 model for medicinal plant classification, we employed a combination of evaluation tools like the confusion matrix, training vs. validation accuracy and loss curves, and comprehensive classification metrics. This multi-modal assessment is a robust representation of the model's learning patterns, generalization capability, and per-class performances To further evaluate the performance of the proposed EfficientNetB3 model, a detailed classification report was generated, which includes precision, recall, F1-score, and support for each of the ten medicinal plant classes. These metrics provide a deeper understanding of the model's behavior across different species, ensuring that performance is not skewed toward particular classes.

As shown in Table 2, the model achieved consistently high results across all plant categories. Most classes, including Bhibitaki, Chebulic Myrobalan, Gotu Kola, Holy Basil, Indian Borage, Lemongrass, Longevity Spinach, and Neem Tree, attained perfect scores of 1.00 in precision, recall, and F1-score, indicating flawless classification. For the Candelabra Plant and Madagascar Periwinkle classes, the model achieved slightly lower precision values of 0.99, though the recall remained at 0.99–1.00, ensuring reliable identification with negligible misclassifications.

These results demonstrate that EfficientNetB3 is highly reliable and effective for medicinal plant classification, achieving near-perfect performance across all ten species. The minimal variations observed in precision for Candelabra Plant and Madagascar Periwinkle suggest that future work may incorporate additional samples or feature refinement for these specific categories. Nonetheless, the overall outcome confirms the suitability of EfficientNetB3 for real-world deployment in automated medicinal plant identification systems.

Table 2. Classification Report of Proposed Model

Class	Precision	Recall	F1-Score
Bhibitaki	1.00	1.00	1.00
Candelabra Plant	0.99	0.99	0.99
Chebulic Myrobalan	1.00	0.99	1.00
Gotu Kola	1.00	1.00	1.00
Holy Basil	1.00	1.00	1.00
Indian Borage	1.00	1.00	1.00
Lemongrass	1.00	1.00	1.00
Longevity Spinach	1.00	1.00	1.00
Madagascar Periwinkle	0.99	1.00	1.00
Neem Tree	1.00	1.00	1.00

4.2 Confusion Matrix

The confusion matrix shown in Fig. 5 indicates the actual vs. predicted label distribution for all 10 plant classes. The model is nearly perfect with the majority of classes being 100% correctly predicted. Minor misclassifications occur only in the Chebulic Myrobalan and Candelabra plant classes, and one sample each get misclassified. The rest of the classes such as Bhibitaki, Holy Basil, Gotu Kola, and Neem Tree have no misclassification. This indicates that the model is highly effective in distinguishing between plant species which are morphologically highly similar.

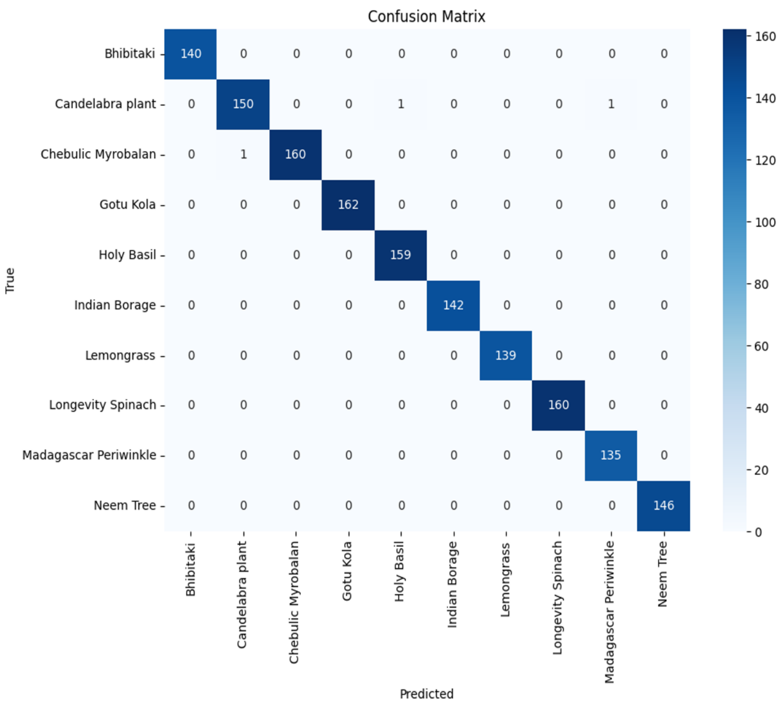

Fig. 5. Confusion Matrix of EfficientNetB3

4.3 Training Loss and Validation Loss

Accuracy and loss curve shown in Fig. 6 indicates that the model rapidly converges to high accuracy, achieving over 99% validation accuracy within the first few epochs and maintaining stability throughout training. There is no significant gap between training and validation accuracy, suggesting low variance and excellent generalization. A sharp decline in both training and validation loss is observed during early epochs, followed by a plateau at minimal values. This consistent downward trend without divergence suggests that the model is neither underfitting nor overfitting.

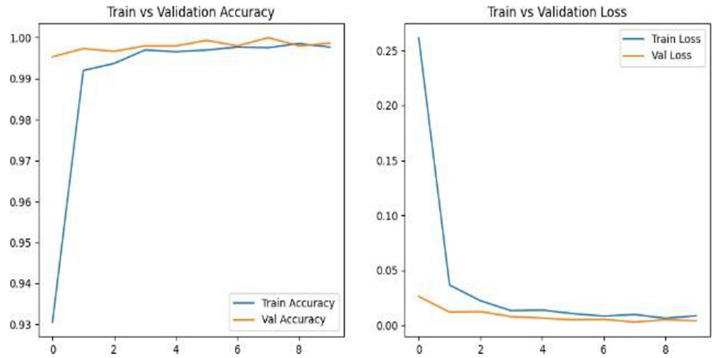

Fig. 6. Accuracy and Loss Curve of EfficientNetB3

4.4 Cross Validation

In order to ensure that the final model is robust, a 5-Fold Cross-Validation was conducted using a Stratified full dataset. The stratification was a measure that ensured that each of the folds retained the original class distribution giving fair assessment of all the medicinal plant categories. The model was fitted on four subsets in each fold and validated on the remaining on, so that any sample was only validated once.

The cross validation showed a high degree of stability and good generalization, with an average of 0.99 using very low standard deviation of 0.000349. The small folds variance means that the model was consistent in its performance irrespective of the data split and that it was not overfitting and therefore confirms the validity of the chosen EfficientNetB3 architecture even further.

4.5 Ablation Study

In order to test the strength and the capacity to generalize the proposed Efficient- NetB3 model, an ablation experiment was performed based on an external dataset [27] [28] [29] [30] of 20 real-world images per class that are gathered in various online sources. These samples had large differences in illumination, camera angle, and texture of the leaves, occlusion, and background clutter- the conditions that were not included in the original training set. The full-fine-tuned, heavily data-augmented, and 300x300 input resolution baseline model showed good generalization and consistently recognized most of the external samples on par to the 0.99 accuracy on the primary test set. The results have been added in Fig. 7.

To appreciate the input of various components of the training pipeline, they were one by one removed and the effect of their absence studied. With exclusion of augmentation, there was a significant decrease in performance to about 0.95 accuracy which is how augmented variability is relevant in enhancing robustness. Further freezing of the backbone during training also decreased the accuracy to almost 0.93, which indicated that complete fine-tuning was required to achieve the best learning of features. Likewise, a drop of input resolution by 300x300 to 224x224 reduced accuracy to approximately 0.96 indicating that increased input resolution refines the finer leaf structures that are useful in medicinal plant identification.

All these findings confirm that data augmentation, full model fine-tuning and an increased input resolution are synergistic to improve the reliability of a model in unseen settings. Moreover, practical application of the system via a Flask-based web application confirmed the feasibility of the system: the model produced correct predictions on all inputs that were tested and showed consistent inference accuracy. It proves that the suggested EfficientNetB3 architecture is not only efficient when examined in a controlled setting but also quite reliable to be used in the real-time identification of medicinal plants.

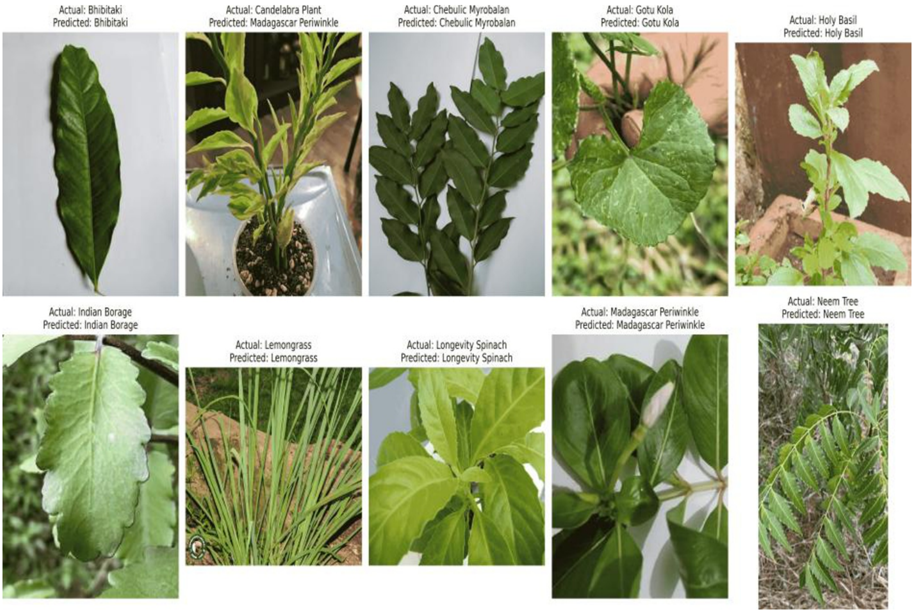

Fig. 7. Ablation Sample Data

5 Conclusion & Discussion

This study underscores the transformative potential of deep learning in the automated classification of medicinal plants, a task traditionally dependent on manual expertise. Among the evaluated architectures, EfficientNetB3 exhibited superior performance, achieving an impressive 99.0% accuracy while maintaining strong generalization across diverse image conditions. The integration of this model into a web-based recognition system built with Flask, HTML, CSS, and JavaScript extends its utility beyond laboratory experimentation, enabling real-time identification and information retrieval about medicinal properties. Such an intelligent framework not only supports healthcare professionals and researchers in accurate plant identification but also contributes to biodiversity conservation, ethnobotanical documentation, and digital herbal education. The outcomes affirm that deep learning-driven recognition systems can bridge the gap between traditional medicinal knowledge and modern computational intelligence, paving the way for sustainable and accessible plant-based healthcare innovations.

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