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Evalution of Pretrained CNN Models for Medicinal Leaf Classification

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Abstract - **The paper aims to develop a framework that can classify medicinal plant leaves using deep learning techniques. The classification of medicinal plant leaves was done on a large database, which consisted of 30 different plant species with around 62,770 images. The classification of leaves was done by using six different pre-trained models, namely MobileNetV2, DenseNet121, NASNetMobile, ResNet50, EfficientNetB0, and In-ceptionV3, using transfer learning techniques. Out of all six models, the MobileNetV2 model showed the maximum accuracy of 94.64% as compared to other models on the basis of precision, recall, and F1-score values.**

Index Terms - **Classification of leaves from medicinal plants, deep learning, comparative analysis, CNNs, transfer learning, image classification, MobileNetV2, ResNet50, EfficientNetB0, InceptionV3, DenseNet121, NASNet.**

I. INTRODUCTION

Medicinal plants are the center of medicine, offering concrete contributions to medicine. They form a link between traditional medicine and modern medicine, supporting herbal medicine as well as natural medicine, while at the same time supporting pharmaceutical research and development. Therefore, it is imperative that we correctly identify the real medicinal plants from the fake ones. If we get this wrong, we are looking at real risks here. Experts, including botanists, have been trying to distinguish between medicinal plants by looking at the leaves, their shape, texture, structure, and even the patterns on the leaves, but this is wide, time-consuming, and not very effective.

There has been good traction in the tech space lately, especially around AI and computer vision. There is a lot of buzz in the developer community about creating an automated system that is capable of identifying plants from an image, i.e., identifying a plant by taking an image of its leaves.

Although the plant ID tools that utilize automation are fairly accurate, they may not necessarily work well when considering the vast diversity of plant life that we have on this planet. The advantages of using transfer learning are quite obvious, as we have many pre-trained models that are known to perform well on image classification tasks, such as MobileNetV2, DenseNet121, NASNetMobile, ResNet50, EfficientNetB0, InceptionV3, etc.

This study indicates the need to include the concept of deep learning in the classification of medicinal leaves by exploring the models using the transfer learning technique. In the study, the researchers used 30 different medicinal plants, totaling 62,770 images. The pre-processing techniques were used in the study to improve the performance of the models in the generalization of the results. In the study, the accuracy, precision, recall, and F1 score were used as the evaluation metrics. The study was also tested using the confusion matrix and ROC curve as the evaluation metrics. The study indicated the potential of the MobileNetV2 model to perform better than other models by learning the essential features.

II. RELATED WORK

Today, with computer vision and deep learning technologies, the identification of medicinal plants is gaining momentum. In the past, experts used to look at each plant based on their leaves' features, texture, and color, etc., and then make an identification. Although this approach was based on experts' knowledge, it was a time-consuming and error-prone process. But today, with the latest advancements in deep learning and computer vision technologies, it is possible to identify medicinal plants based on their leaves..

Researchers Sharrab *et al.* [1]. developed a model of deep learning that utilizes the images of leaves in the identification of medicinal plants. The study shows that the computer is capable of automatically selecting the meaningful features of the images, as well as differentiating between various kinds of plants. Dileep and Pournami [2] presented the AyurLeaf system, which utilizes deep learning techniques in the accurate identification of medicinal plants.

Recent studies in medicinal plant research show the development of two trends, namely, the enhancement of plant identification using deep learning techniques, and the simplification of the identification process without compromising the accuracy. On the other hand, Raina *et al.* [3]. discussed various deep learning techniques for herbal leaves classification. In addition, Alebel *et al.* [4] . presented various digital image processing techniques for traditional medicinal plants classification in Ethiopia. Regarding the simplification trend, Gautam *et al.* [5]. presented a classification method for medicinal leaves using deep learning techniques, while Pushpa *et al.* [6]. presented a ”hybrid deep neural network” for plant identification.

Other than that, machine learning has opened several other fronts for research in medicinal plants. Dastres *et al.* [7] and his team used ML algorithms for forecasting habitat suitability for medicinal plants. In another work, Latif and Nawaz [8] presented an extensive review of medicinal plants and their numerous applications. This review emphasizes their significance for healthcare and pharmaceutical research. Bouakkaz *et al.* [9] and his team used optimized CNN models for enhancing classification of medicinal plants.

Research on the comparison of various deep learning models has also been carried out. An evaluation of various architectures of deep convolutional neural networks for the automated identification of medicinal plants was carried out by Dey *et al.* [12]. An ensemble model of convolutional learning with fine-tuning was proposed by Hajam *et al.* [13].

There is an increasing interest in the automatic recognition of plants in their native environment itself. In this context, Malik *et al.* [16]. presented a method that employs a real-time technique of deep learning to recognize medicinal plants in their native environment. Azadnia *et al.* [17] . presented a method that employs the CNN along with GAP technique to distinguish between different plant species. Ok textitet al. [18]. presented a comprehensive survey on the applications of deep learning techniques in the identification of medicinal plants.

In the field of research, works have been conducted for the identification of medicinal plants using deep learning techniques. In most of the research works, the efficiency has been evaluated for the efficiency of one or two models of the hybrid approach. In the present work, the efficiency of six different models, namely MobileNet V2, ResNet 50, EfficientNet B0, Inception V3, DenseNet 121, and NASNet, has been evaluated for the classification of medicinal plant leaves, and the best model has been identified for the purpose of plant identification.

III. Dataset Description

The project uses an image database, which is accessible for free. It uses digital images of leaves related to the medicinal value of various plants and those leaves differ in shape, size, and orientation. The project has 62,770 images, which are enough for training a deep learning model. The images are divided into three sets for proper evaluation. The images for training are 54,507, for validation, they are 4,231, and for testing, they are 4,088.

To ensure that the deep learning workflow is smooth, all images were resized to 160 by 160 pixels. The standard image processing techniques were used, implying that all images were subjected to normalization. To increase the initial dataset of 700 images, various image augmentation techniques were used.

The leaf images were taken under varying lighting conditions, backgrounds, and angles. These represent the various environments that leaves are exposed to in nature. The leaves, especially the medicinal ones, look very similar to one another.

The images of the leaves are clicked in different lighting conditions, different backgrounds, and different angles. This is because the leaves are exposed to different environments. The leaves, especially the medicinal leaves, look quite similar with regards to their appearance.

The medicinal leaf dataset is the best place where the capability of the deep learning-based machine learning system could be tested for distinguishing one species from another. The availability of more than one image of each species and the variety of leaves make it the best place for developing the transfer learning-based system.

Fig. 1. Sample Images from Medicinal Leaf Dataset

TABLE I
Dataset Distribution

Dataset Split	Number of Images
Training subset	54,470
Validation subset	4,214
Test subset	4,086
Total Images	62,770
Number of Classes	30

IV. METHODOLOGY

A. System Overview

This starts with the acquisition of the image of the leaf. Then comes feature extraction and classification. The classification is performed through the pre-trained CNN model. The performance of the model is evaluated through different parameters. The parameters include accuracy, precision, recall, F1 score, confusion matrix, and ROC curve.

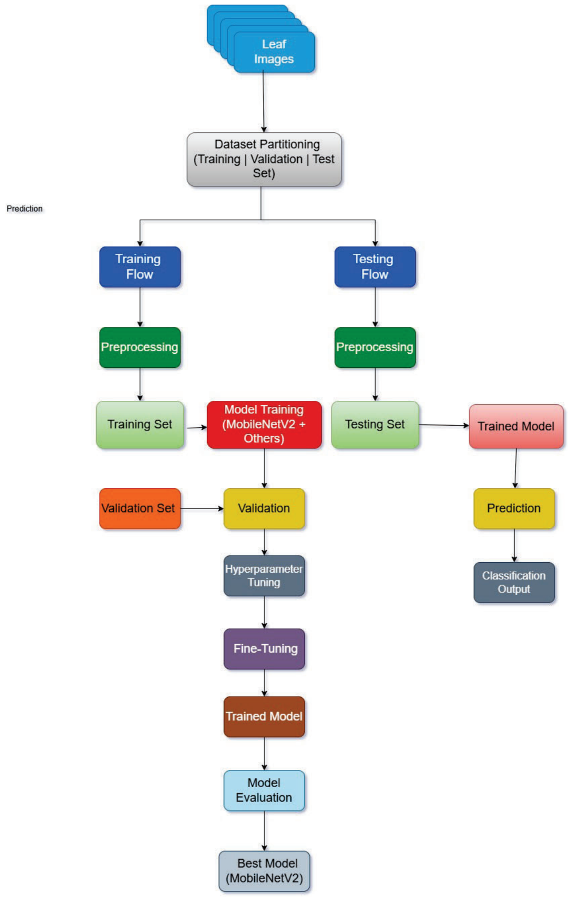


Fig. 2. Transfer Learning Architecture

B. Data Preprocessing

Data preprocessing is considered an essential step prior to the training of the actual deep learning models. For the purpose of this research, different techniques were used for data preprocessing. It was found to be beneficial for the learning potential of the deep learning models. The techniques used for data preprocessing were:

- Resizing the images to 160×160 pixels in size, ensuring all models are presented with consistent data.
- Normalizing the pixel data by scaling down the original range of $[0, 255]$ to $[0, 1]1$, achieved by applying a rescaling operation.
- Loading the data in batches, as it is a large-scale image dataset.

C. Data Augumentation

We expand the data that the model is exposed to, which helps the model become better at generalizing, preventing the problem of overfitting. The model is able to recognize the same features in the images, even though the conditions under which the images were taken were different from the original conditions. This is done by using data augmentation techniques, including flipping, rotating, zooming, and adjusting the image brightness and contrast.

The original dataset has 30 different medicinal plant species, with 54,507 images in the dataset. On average, we get 54,528 images per epoch, with 32 images per batch, making 1,704 batches per epoch.

All augmentations are done in real-time, with no data being saved. It would take up a lot of space to save the images used during augmentations, as depicted in Figure 3.

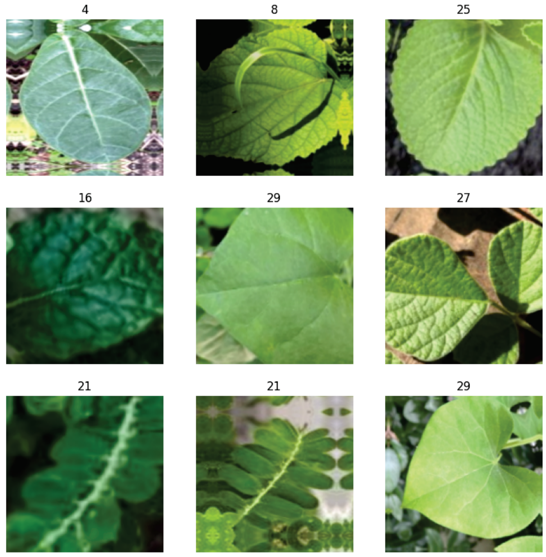


Fig. 3. Example of data augmentation applied to medicinal leaf images.

D. Transfer Learning Models

We used transfer learning to improve the ability of the model to classify images of medicinal leaves and to decrease training time. The idea behind using transfer learning was based on the fact that pre-trained CNN models are effective in recognizing basic features such as edges, texture, and form in images of leaves. We fine-tuned them by replacing the last layer with a new one.

Some of the pre-trained CNN models that the study implemented and tested are as follows:

- **MobileNetV2:** It is a light-weight CNN that makes use of depth-wise separable convolution and inverted residual blocks in order to ensure that the computation is minimal without compromising the learning of the features of the image.

- **DenseNet-121:** This model is unique in that it has dense connectivity, which allows smooth information flow during training.
- **NASNet-Mobile:** This model is part of the NAS family and is designed to optimize performance with minimal computational cost.
- **ResNet50:** This model is a deep CNN that uses residual connections to facilitate easier training of deep networks
- **EfficientNet-B0:** This model is designed to optimize performance with minimal efficiency.
- **InceptionV3:** This model is designed to maximize performance using multiple filter sizes in convolution operations.

In order to improve how well the leaves used for medication classification are identified, the network was improved at the convolutional stage by adding a dense layer, batch normalization, dropout, global pooling, and softmax activation.

E. MobileNetV2-Proposed CNN Architecture

MobileNetV2 is a lightweight convolutional neural network The system utilizes MobileNetV2 to extract the necessary feature information, as depicted in Figure 4. The input is resized to 160x160 before normalization. MobileNetV2 is a light-weight CNN that is specifically designed for feature extraction, keeping the computation light with the help of depthwise separable convolutions. The architecture of the proposed system starts with the initial convolutional layer of MobileNetV2, followed by a series of bottleneck layers. These bottleneck layers assist the network in learning discriminative feature information, including texture, vein, and shape information, without compromising the computational complexity of the network.

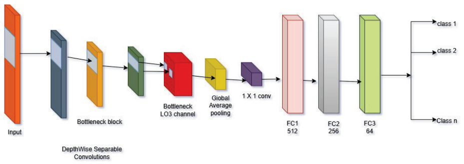


Fig. 4. MobileNetV2 Architecture

Finally, the feature representation is reduced again using a 1x1 convolution. Next, global average pooling is used to reduce the spatial dimensions of the feature map, resulting in a single feature vector.

The classification head of the model comprises a dense layer with ReLU activation followed by dropout for regularization purposes. The model concludes with a softmax classifier, which predicts probabilities for all 30 classes of medicinal plants.

In this paper, MobileNet V2 is used as a feature extractor, and the weights of this model have been pre-trained using ImageNet. The convolutional base of this model is kept frozen during initial training, and only the classification head is trained. For fine-tuning, the top of this model is unfrozen and retrained at a low learning rate to capture more details of images of medicinal leaves.

F. Model Training and Fine Tuning

The optimizer used was Adam, with a learning rate of 0.0003. The loss function used was sparse categorical cross entropy, batch size was 32, and epochs were set to 15.

All of the pre-trained model convolutional base layers were frozen during this initial run, so that only the new layers were being trained. This approach enables the models to take advantage of general visual features that were pre-trained from ImageNet.

Fine-Tuning In the second approach, we unfroze the final model layers and trained for an additional 5 epochs with a reduced learning rate. This approach enables pre-trained models to relearn features that are more suitable for medicinal leaf datasets, hence enhancing classification.

V. EXPERIMENTAL SETUP

The study made use of TensorFlow and Keras, which are popular toolkits for deep learning. The medicinal leaf dataset used in this study contains 62,770 images. The dataset used in this research is divided into different plant classes. The dataset used in this study is divided into training, validation, and testing data. The dataset used in this study contains 54,507, 4,231, and 4,088 images for training, validation, and testing. Before feeding the images into the network, they are resized to (160 × 160).

The study made use of a batch size of 32 in this research. Adam is used as an optimizer in this study. The study used sparse categorical cross-entropy as the loss function. To prevent overfitting, this study made use of a technique known as early stopping. The study makes use of a technique in which the pre-trained layers are trained for a maximum of 15 epochs. The last layers are then trained for 5 epochs. The study makes use of different models for transfer learning. The models used in this study are MobileNet V2, DenseNet 121, NASNet Mobile, ResNet50, EfficientNet B0, and Inception V3. The performance of the models is measured using different metrics such as accuracy, precision, recall, F1 score, confusion matrices, and ROC curve.

TABLE II
TRAINING CONFIGURATION AND EXPERIMENTAL PARAMETERS

Parameter	**Value**
Dataset Classes	30 medicinal plants
Training Images	54,507
Validation Images	4,231
Test Images	4,088
Image Size	160 × 160
Batch Size	32
Optimizer	Adam
Initial Training Epochs	15
Fine-Tuning Epochs	5

VI. RESULTS AND DISCUSSION

The performance of each model is also validated using accuracy, loss curve, confusion matrix, and classification reports. The accuracy and loss curve for the training and validation of the MobileNetV2 model are as follows:

- MobileNetV2
- DenseNet121
- NasNetMobile
- ResNet50
- EfficientNetB0
- InceptionV3

A. *MobileNetV2 Results*

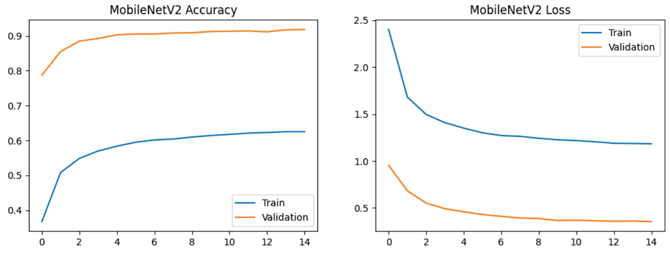


Fig. 5. MobileNetV2 accuracy and Loss

Fig. 5 Accuracy and loss curve for the training and validation of the MobileNetV2 model. The convergence of the model is clear in the accuracy and loss curve.

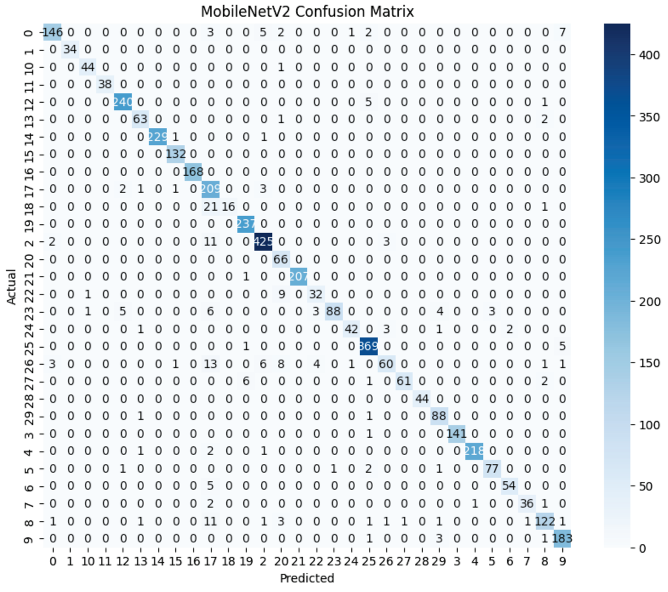


Fig. 6. Confusion Matrix MobileNetV2

Fig. 6 depicts the confusion matrix for the MobileNetV2 model using the test dataset. The presence of prominent diagonal lines in the confusion matrix indicates that the classification of the medicinal plant classes is done with minimum error.

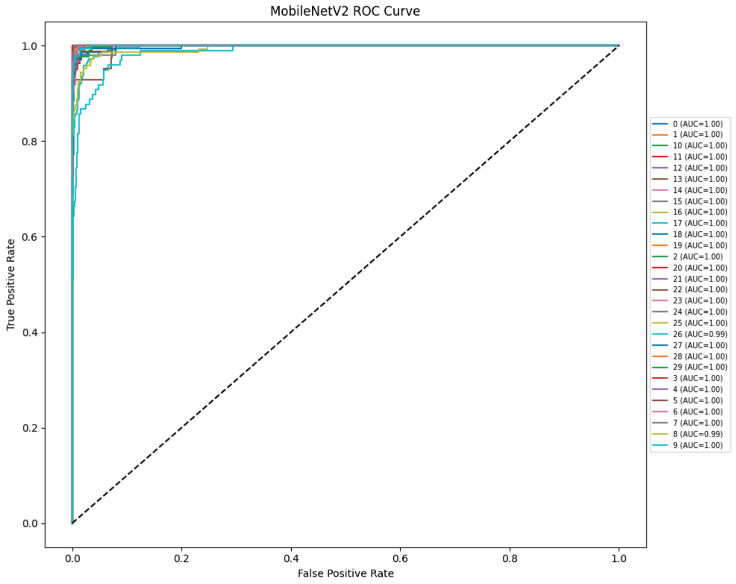


Fig. 7. Roc Curve of MobileNetV2

Fig. 7 depicts the ROC curve for the MobileNetV2 model for various classes. The high value of the AUC value close to 1.0 indicates the accuracy of the classification of the classes of medicinal plants.

The performance of the classification of the MobileNetV2 model was better when compared with all the models. The model has classified the test data with an accuracy of 94.64% in total. The confusion matrix shows that the medicinal plant classes are well classified by the model, as all the diagonal values are prominent in the matrix. The values are not much confused with each other, but they are similar in their visual appearance. The values of the leaves are confused with each other.The ROC curve analysis shows that the performance of the classification of the model is good, as all the values are high.

B. *DenseNet121 Results*

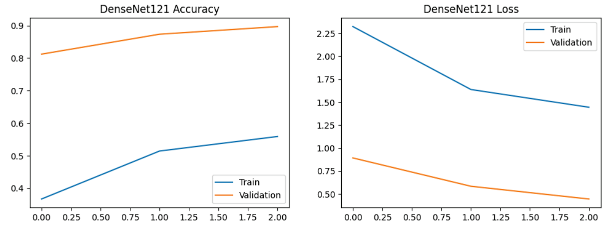


Fig. 8. DenseNet121 accuracy and Loss

As shown in Fig. 8, the accuracy and loss of the DenseNet121 model during the training process. It is clear that the learning process is smooth, as shown by the increase of accuracy and loss during the training process.

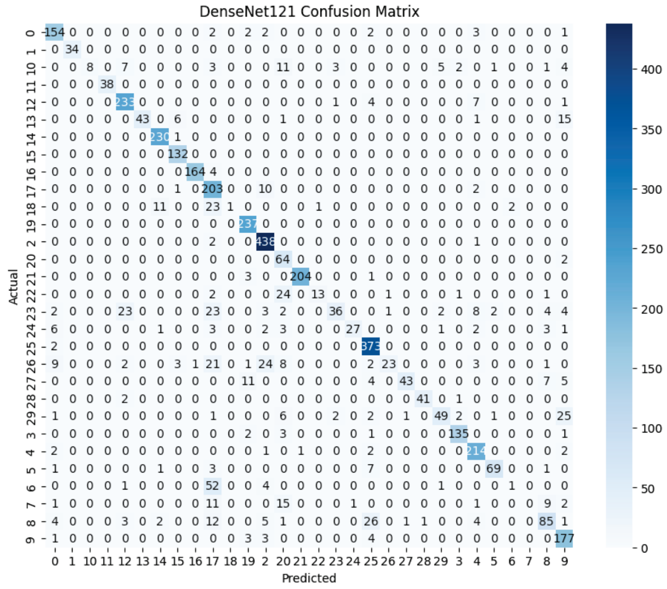


Fig. 9. Confusion Matrix of DenseNet121

The confusion matrix of the DenseNet121 model is shown in Fig. 9, indicating that all classes are correctly classified, as shown by the prominent diagonal line in the confusion matrix, apart from those classes that look similar, such as leaves.

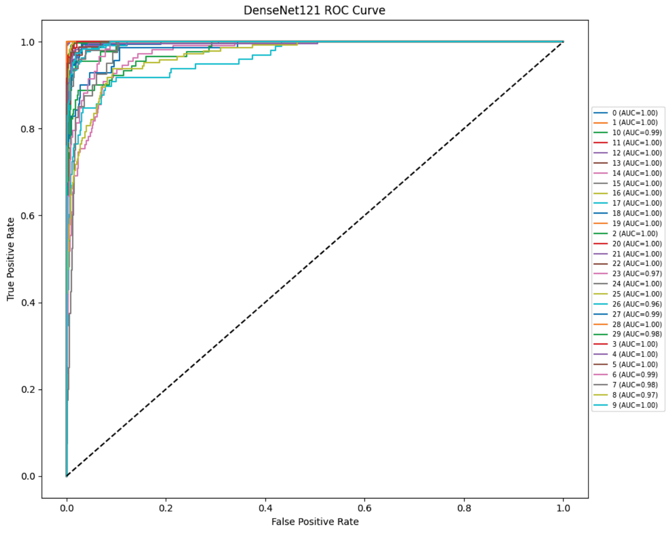


Fig. 10. Roc Curve of DenseNet121

The ROC curve of the DenseNet121 model for all classes is shown in Fig. 10, indicating that the DenseNet121 model has good classification ability for the medicinal leaf dataset, as shown by the increase of the value of the AUC, close to 1.

The DenseNet121 model was able to classify the data with an accuracy of 84.85% for the test dataset. The dense connectivity between the layers allows the model to reuse the representations of features.From the confusion matrix, it is clear that all the classes were correctly classified, and there was some level of confusion for certain classes. DenseNet121 was able to classify the data slightly less than MobileNetV2, but it was able to classify the data reliably for medicinal leaves.

C. *NASNetMobile Results*

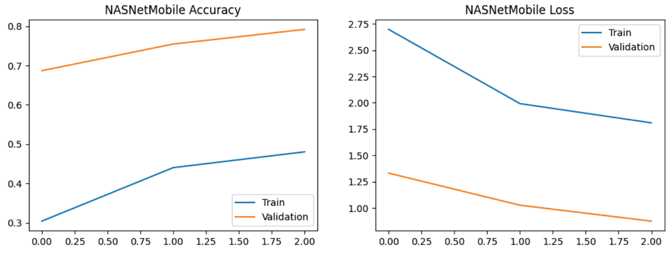


Fig. 11. NASNetMobile accuracy and Loss

In addition, Fig. 11 indicates the accuracy and loss of the NASNetMobile network on the validation set. It is clear that the network is learning at a gradual pace, but with a certain level of accuracy compared to other models.

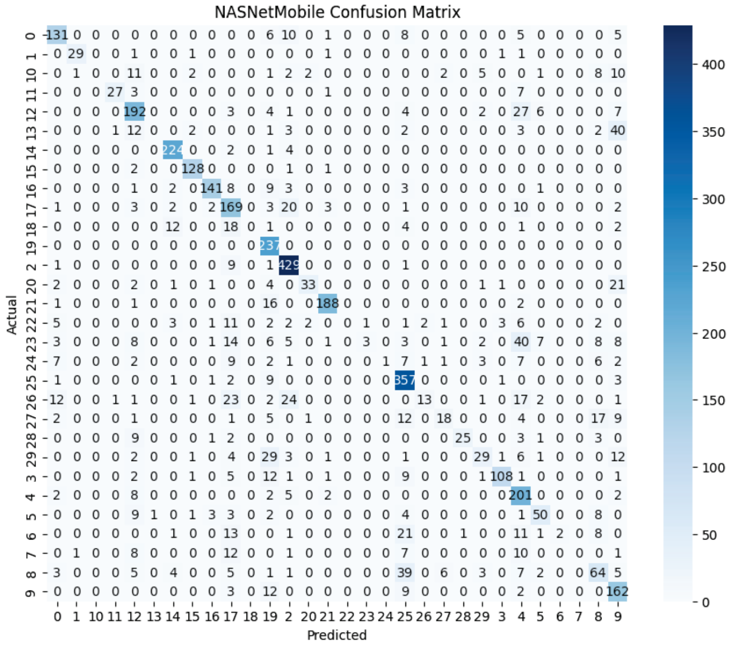


Fig. 12. Confusion Matrix of NASNetMobile

The confusion matrix of the NASNetMobile network is demonstrated in Fig. 12. It is clear that the network has classes that are correctly classified, but with significant levels of misclassification in the various plant classes.

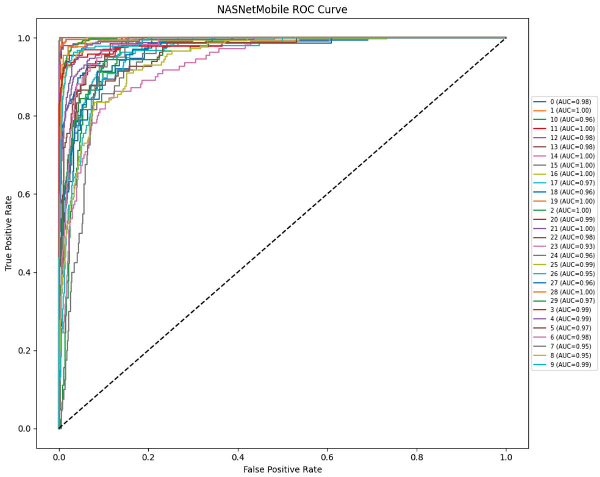


Fig. 13. Roc Curve of NASNetMobile

The ROC curves of all classes in the NASNetMobile network are demonstrated in Fig. 13. It is clear that the network has a moderate level of classification concerning the medicinal leaves.

The accuracy of this network is 72.43% when this network is used along with the medicinal leaves dataset.

Optimization techniques were used for the optimization of this network using the neural search algorithm optimization technique. The accuracy of this network is less when this network is compared with the accuracy of the MobileNetV2 and DenseNet121 network.

From the confusion matrix, it is observed that the classification of the plants is being done in an improper manner using this network because this network is not using the finer features of the leaves as accurately as the other two networks.

D. ResNet50 Results

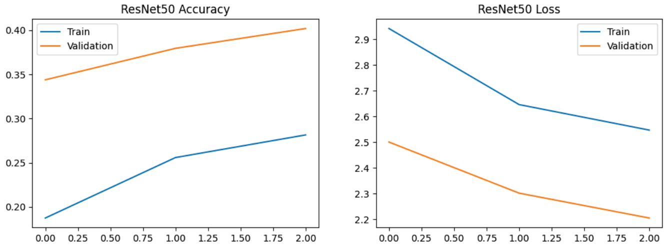
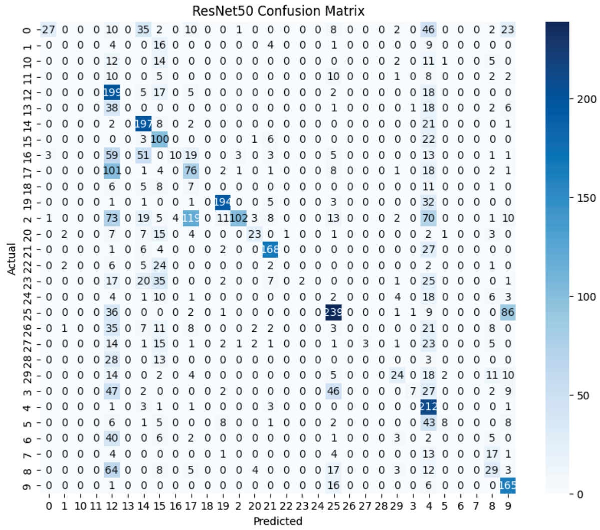


Fig. 14. ResNet50 accuracy and Loss

The results obtained by the ResNet50 model indicate a sluggish learning process with low accuracy on the used dataset, as shown in Figure 14. It can be noted that the ResNet50 model underperforms when compared to the other models used in this research.



	0	1	10	11	12	13	14	15	16	17	18	19	2	20	21	22	23	24	25	26	27	28	29	3	4	5	6	7	8	9
0	27	0	0	0	10	0	35	2	0	10	0	0	1	0	0	0	0	0	8	0	0	0	2	0	46	0	0	0	2	23
1	0	0	0	0	4	0	0	16	0	0	0	0	0	0	4	0	0	0	1	0	0	0	0	0	9	0	0	0	0	0
10	0	0	0	0	12	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	11	1	0	0	5	0
11	0	0	0	0	10	0	0	5	0	0	0	0	0	0	0	0	0	0	10	0	0	0	1	0	8	0	0	0	2	2
12	0	0	0	0	199	0	5	17	0	5	0	0	0	0	0	0	0	0	2	0	0	0	0	0	18	0	0	0	0	0
13	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	18	0	0	0	2	6
14	0	0	0	0	2	0	197	8	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0	1
15	0	0	0	0	0	0	3	100	0	0	0	0	0	1	6	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0
16	3	0	0	0	59	0	51	0	10	19	0	0	3	0	3	0	0	0	5	0	0	0	0	0	13	0	0	0	1	1
17	0	0	0	0	101	0	1	4	0	76	0	2	1	0	1	0	0	0	8	0	0	0	1	0	18	0	0	0	2	1
18	0	0	0	0	6	0	5	8	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	1	0
19	0	0	0	0	1	0	1	0	0	1	0	194	0	0	5	0	0	0	3	0	0	0	0	0	32	0	0	0	0	0
2	1	0	0	0	73	0	19	5	4	119	0	11	102	3	8	0	0	0	13	0	0	0	2	0	70	0	0	0	1	10
20	0	2	0	0	7	0	7	15	0	4	0	0	0	23	0	1	0	0	1	0	0	0	0	0	2	1	0	0	3	0
21	0	0	0	0	1	0	6	4	0	0	0	2	0	0	168	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0
22	0	2	0	0	6	0	5	24	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0
23	0	0	0	0	17	0	20	35	0	0	0	2	0	0	7	0	2	0	0	0	0	0	1	0	25	0	0	0	0	1
24	0	0	0	0	4	0	1	10	0	1	0	0	0	0	0	0	0	0	2	0	0	0	4	0	18	0	0	0	6	3
25	0	0	0	0	36	0	0	0	0	2	0	1	0	0	0	0	0	0	239	0	0	0	1	1	9	0	0	0	0	86
26	0	1	0	0	35	0	7	11	0	8	0	0	0	2	2	0	0	0	3	0	0	0	0	0	21	0	0	0	8	0
27	0	0	0	0	14	0	1	15	0	1	0	2	1	2	1	0	0	0	1	0	3	0	1	0	23	0	0	0	5	0
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29	0	0	0	0	14	0	0	2	0	4	0	0	0	0	0	0	0	0	5	0	0	0	24	0	18	2	0	0	11	10
3	0	0	0	0	47	0	2	0	0	0	0	2	0	0	0	0	0	0	46	0	0	0	0	7	27	0	0	0	2	9
4	0	0	0	0	1	0	3	1	0	1	0	0	0	0	3	0	0	0	0	0	0	0	0	0	212	0	0	0	0	1
5	0	0	0	0	6	0	1	5	0	0	0	8	0	0	1	0	0	0	2	0	0	0	0	0	43	8	0	0	0	8
6	0	0	0	0	40	0	0	6	0	2	0	0	0	0	0	0	0	0	1	0	0	0	3	0	2	0	0	0	5	0
7	0	0	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	4	0	0	0	0	0	13	0	0	0	17	1
8	0	0	0	0	64	0	0	8	0	5	0	0	0	4	0	0	0	0	17	0	0	0	3	0	12	0	0	0	29	3
9	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	6	0	0	0	0	165

Fig. 15. Confusion Matrix of ResNet50

Figure 15 shows the confusion matrix of the ResNet50 model, indicating a high rate of misclassifications and poor feature learning during the classification of medicinal leaves.

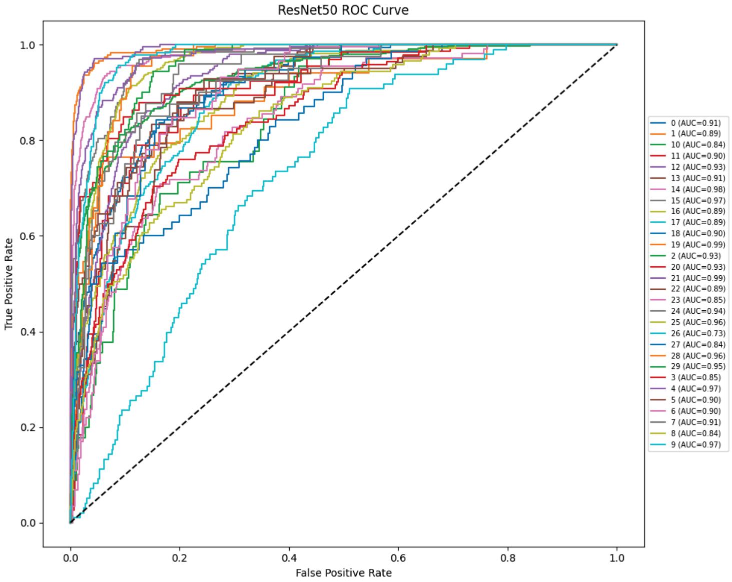

Fig. 16. Roc Curve of ResNet50

Figure 16 shows the ROC curve of the ResNet50 model with all classes combined. The classification accuracy of the model is very poor, as indicated by the AUC values.

The accuracy of the ResNet50 model on the test set was 43.66%. Even though deep neural networks are good at identifying fine-grained features, the ResNet50 model was not good at differentiating between the medicinal leaves, as shown in the confusion matrix.

E. EfficientNetB0 Results

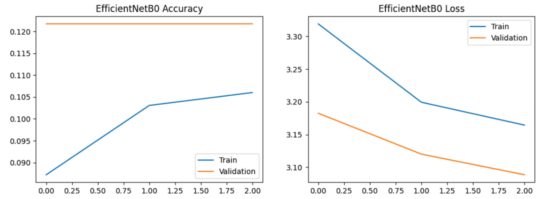

Fig. 17. EfficientNetB0 accuracy and Loss

Figure 17 illustrates how the training of EfficientNetB0 has turned out. It has not taken off as expected, as the accuracy is still on the lower side.

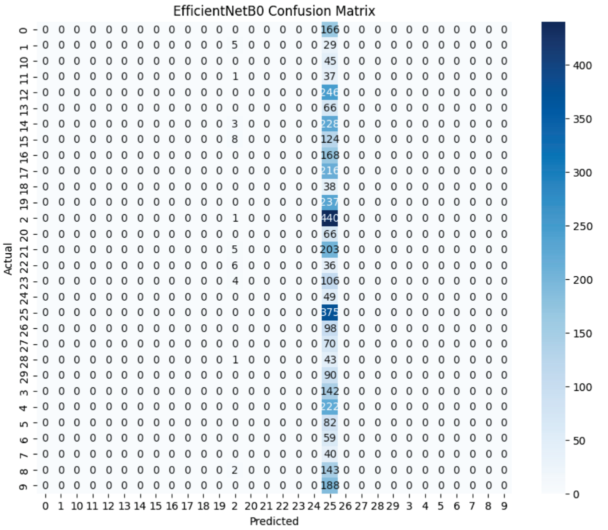

Fig. 18. Confusion Matrix of EfficientNetB0

Figure 18 illustrates the confusion matrix for EfficientNetB0. It is clear that the classes are not being recognized as expected, as there is a lot of overlapping, especially for the medicinal leaf.

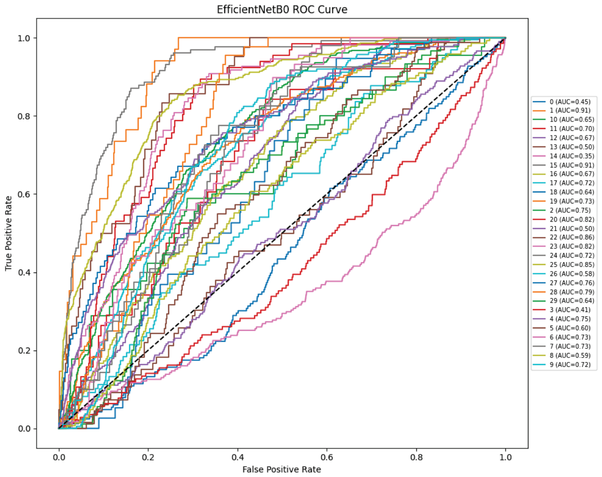

Fig. 19. Roc Curve of EfficientNetB0

Figure 19 illustrates the ROC curves for all the classes. It is clear that the results are poor for all the classes, especially for the medicinal leaf.

EfficientNetB0 underperformed compared to the other models, achieving an accuracy of 9.19% due to the insufficient fine-tuning and possible mismatch between the pretrained weights and the medicinal leaf dataset characteristics. The confusion matrix indicates that only a small number of classes were correctly predicted. This implies that the network failed to adapt to the medicinal leaf dataset. The low performance of the network could be attributed to inadequate feature learning or fine-tuning on the medicinal leaf dataset.

F. InceptionV3 Results

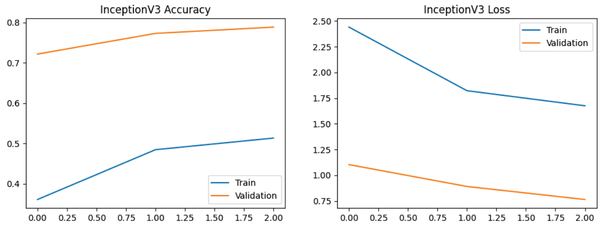

Fig. 20. InceptionV3 accuracy and Loss

Figure 20 illustrates the performance of the InceptionV3 model over time, including accuracy and loss.

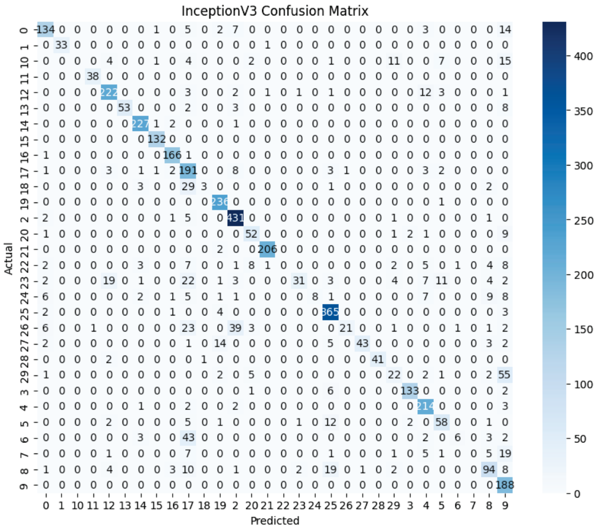

Fig. 21. Confusion Matrix of InceptionV3

Figure 21 illustrates the confusion matrix for the InceptionV3 model.

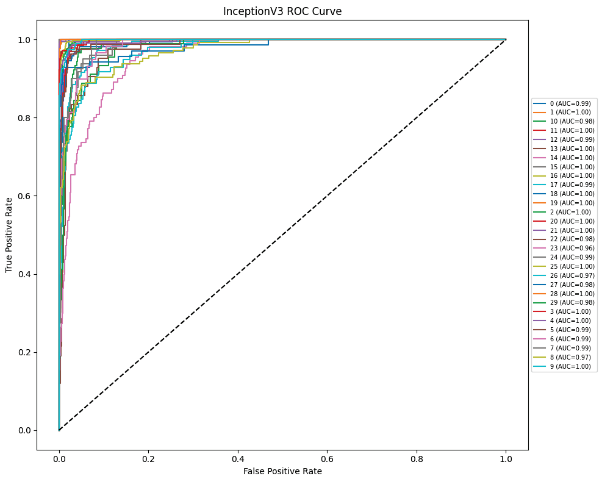

Fig. 22. Roc Curve of InceptionV3

Figure 22 shows the ROC curve for the InceptionV3 model.

Overall, the model can differentiate the classes, but some classes, such as the leaves, are easily confused with one another as they look quite similar.

When the model is run on the test set, it has an accuracy of 81.89%. By using filters of various scales, the model can detect various features in the images. The model has higher accuracy than the NASNetMobile and ResNet50 models but less than the DenseNet121 and MobileNetV2 models.

G. Model Comparison

To evaluate the performance of various deep learning models in medicinal leaf classification, we tested six different CNN models against each other. The results of each tested model on the test set are given in Table III.

TABLE III
PERFORMANCE COMPARISON OF DEEP LEARNING MODELS

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
MobileNetV2	0.9464	0.9513	0.9464	0.9453
DenseNet121	0.8486	0.8569	0.8486	0.8246
InceptionV3	0.8190	0.8150	0.8190	0.7888
NASNetMobile	0.7243	0.7109	0.7243	0.6763
ResNet50	0.4366	0.5377	0.4366	0.3776
EfficientNetB0	0.0920	0.0115	0.0920	0.0160

It was observed that MobileNetV2 had the highest accuracy of 94.64%, followed by DenseNet121 with an accuracy of 84.86%, and then InceptionV3 with an accuracy of 81.90%. Although NASMobile had an acceptable performance, ResNet50 and EfficientNetB0 had disappointing results. The former had the lowest accuracy among all these CNNs.

VII. CONCLUSION

A framework is proposed that relies on deep learning, specifically transfer learning, in classifying medicinal leaves with top-notch accuracy. It is based on a substantial amount of data with 62,770 images of 30 different plant species.

In this paper, different CNN architectures are used in classifying medicinal leaves. Pre-processing is also included in the framework for better accuracy.

Out of the six transfer learning architectures used in leaf classification, MobileNetV2 resulted in the highest accuracy at 94.64%. The precision, recall, and F1 score were also quite promising.

The results prove that medicinal leaves can be classified using this framework. Also, the framework is capable of learning highly accurate features, which is a great advantage. This framework can be improved and made available to botanists and doctors. Suggestions:

The framework can be improved using better approaches such as ensemble learning. Also, the framework can be run on a device so that leaves can be classified in real-time.

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