Neem Leaf Disease Detection Using Hybrid Deep Learning Models

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Abstract: Neem is well-known for its medicinal value however; neem yields are highly affected by various leaf diseases. Management and control of the diseases requires timely and accurate detection. This paper introduces a mobile hybrid deep learning framework based on MobileNet and DenseNet that has high accuracy of 90.5% compared to other hybrid models. The proposed framework consists of image processing, feature extraction model, and ensemble learning model to improve accuracy and robustness. The dataset includes 1862 images of neem leaf diseases in six classes; a split of an 80-20 training to testing ratio was used for the dataset. The proposed MobileNet DenseNet framework is an enhancement from existing framework and illustrates the feature extraction and classification capabilities. Empirical results support our model has the highest accuracy and is an effective approach for neem leaf disease detection. The current paper provides precision agriculture with an automated framework for accurate neem leaf disease detection and timely disease management programs.

1 INTRODUCTION

Neem, one of the highly recognized medicinal trees, possesses antibacterial, antifungal, and insecticidal characteristics. Nevertheless, various leaf diseases have a huge impact on its health and productivity, hence restraining its growth capacity and medicinal qualities. Some of the most prevalent neem leaf diseases are Alternaria, Dieback, and Leaf Blight. These diseases not only diminish the natural resistance of the tree against insects but also decrease the overall vigor of the tree, resulting in massive agricultural and economic losses. A timely and accurate diagnosis of these diseases is indispensable for the proper implementation of control measures. Traditional approaches for detecting neem leaf diseases rely on manual inspection performed by agricultural professionals. These methods are subjective in nature, time-consuming, and not ideal for large-scale surveillance. Moreover, most of the neem leaf diseases have the same visual symptoms, which poses a challenge to differentiate between them through human observation. This makes it absolutely crucial to devise an automated, accurate, and efficient method for proper classification of neem leaf infections.

Deep learning models have shown promising performance in plant disease diagnosis, with the ability to extract complex information and precisely identify images. These architectures, such as DenseNet, ResNet, MobileNet, AlexNet, and GoogleNet, have shown promising performance in image classification. However, single models are prone to failure in handling intra-class variability problems and limitations on feature extraction, which results in decreased classification accuracy. In an attempt to address these problems, hybrid models have become increasingly popular in the area of recent work. This work introduces a hybrid deep learning model that combines the strengths of MobileNet and DenseNet for neem leaf disease classification (Elakiya, E et al., 2024). MobileNet, with its lightweight architecture and computational aspect, enhances feature extraction, while DenseNet, with its dense connection and deep feature propagation, enhances classification accuracy. We compare the MobileNet-DenseNet model with other hybrid frameworks, such as DenseNet-AlexNet, DenseNet-ResNet, and DenseNet-GoogleNet, to

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determine the best architecture to apply in the classification of neem leaf diseases. To evaluate the performance, a dataset of 1,862 images of neem leaves was used, classified into six classes: Alternaria, Dieback, Leaf Blight, Leaf Miners with Powdery Mildew, Powdery Mildew, and Healthy. From the experimental results, the proposed MobileNet-DenseNet model contributions are proposing a hybrid deep learning model (MobileNet-DenseNet) for accurate neem leaf disease classification (R. Kanagaraj et al., 2023). Compares the performance of the other three hybrid models to select the optimal architecture. Demonstrates the proposed model's practical application for the diagnosis of neem leaf diseases automatically, which is beneficial for precision agriculture and sustainable neem tree cultivation.

2 RELATED WORKS

This paper explores a set of hybrid deep learning architectures for plant disease detection, emphasizing their effectiveness in the field of precision agriculture. One of the commonly used methods involves combining EfficientNetB0 with MobileNetV2, both light-weight mobile architectures, with an accuracy rate of 98.44%. This hybrid system is more effective compared to other conventional CNN-based architectures like ResNet and AlexNet and, therefore, is a promising candidate for plant disease diagnosis in real-time (Vamshi et al., 2024). Another method involves combining Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) for differentiation between different types of plant diseases and achieves 98% accuracy, 97% precision, and 96% recall (Vellela et al., 2024).

A hybrid stacking learning approach that integrates pre-trained models with image processing technology has demonstrated improved performance. With ensemble CNNs trained on the Plant Village dataset that contains images of healthy and diseased leaves, this approach achieves a classification accuracy range of 99.75% to 100% (Sheneamer et al., 2024). A hybrid approach integrating wavelet analysis, autoencoder denoising, and SVM classification has been reported to be effective for a range of plant species but is not specifically neem leaf disease (Huddar et al., 2024). A hybrid model integrating EfficientNetB7 enhances image segmentation and classification with an Adaptive and Attention-aided Mask R-CNN (AAM-RCNN), which is further optimized by the Boosted Random Parameter-based Golden Tortoise Beetle Optimizer (BRP-GTBO). This approach significantly improves plant disease detection and classification accuracy (Patil et al., 2025). Another hybrid model involving Convolutional Neural Networks (CNNs) and K-means clustering clocks 98.38% accuracy on a database of 7,771 leaf images, which suggests its application in the automatic diagnosis of diseases (Mallma et al., 2021). Comparison of deep learning architectures such as VGG16, VGG19, and ResNet50 has stated that limitations in datasets are a significant challenge, thus resulting in the application of hybrid models that combine deep learning and machine learning methods in a bid to improve classification performance (Kumar, S., & Singh, S. R. (2023). Traditional image processing techniques such as histogram equalization, K-means clustering, and feature extraction via methods such as the Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Gray-Level Co-occurrence Matrix (GLCM) have also been tried, with CNNs performing consistently better than Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) classifiers in disease identification (Kanabur et al., 2019).

A hybrid AlexNet+SVM model was discovered to have 99.9986% accuracy in large-scale plant disease classification of 38 leaf diseases on 12 crop species, though this approach is not particularly designed for neem leaf infections (Kawatra et al., 2020). A CNN-DenseNet hybrid model was employed in another research to enhance feature extraction to an accuracy of 98.79% and may potentially be employed as a precision agriculture tool (Dari et al., 2023). Hybrid models with K-means clustering to mark disease area and CNNs for classification had a mean accuracy of 92.6%, which is higher than conventional classification methods (Devi, N., et al., 2025). The fusion of ViTs and CNNs has also been employed for the detection of plant diseases. A VGG16, Inception-V3, and DenseNet20-based model as the CNN feature extractors attained 99.24% accuracy in apple leaf disease detection and 98% accuracy in the classification of corn leaf diseases, signifying the effectiveness of hybrid models in multi-scale feature extraction (Aboelenin et al., 2021). Transfer learning techniques incorporating DenseNet201 and VGG16 and SVM have also significantly enhanced the performance of disease classification with high F-scores and improved performance over individual deep learning models (Sharma et al., 2023).

3 MATERIALS AND METHODS

3.1 Dataset Description

The dataset, which includes 1,862 neem leaf photos, was collected from Mendeley Data, as shown in Table 1. It is divided into six categories: Alternaria, Dieback, Leaf Blight, Leaf Miners with Powdery Mildew, Powdery Mildew, and Healthy leaves, with examples shown in Figures 1 and 2. Due to a considerable class imbalance, image augmentation techniques were used to obtain a uniform distribution across every classes, hence improving the model's capacity to generalize across different diseases. Several pre-processing processes (E. Elakiya, 2017) were performed prior to training to ensure consistency and increase dataset quality. Each image was resized to fit the input dimensions of the CNN architectures. Pixel values were also adjusted within the 0 to 1 range to help with training stability and convergence. To improve the model's emphasis on key leaf properties, noise reduction techniques were used to reduce background interference.

3.2 Data Augmentation

Augmentation techniques were employed prior to dataset splitting to rectify class imbalance. A balanced dataset was achieved by augmenting each class with 565 images. The augmentation techniques included brightness correction, zooming (±20%), rotation (0° to 360°), horizontal and vertical flipping, and the insertion of Gaussian noise. These adjustments reduced the likelihood of overfitting while also supporting models in learning more robust and generalized properties through changes in scale, illumination, and orientation.

Table 1: Neam Leaf Disease Dataset.

Diseases	Number of images
Alternaria	191
Dieback	174
Leaf blight	231
Leaf miners' Powdery mildew	203
Powdery mildew	544
Healthy	519
Total	1862

Figure 1: (a) Alternaria (b) Dieback (c) Healthy.

Figure 2: (d) Leaf blight (e) Leaf miners' Powdery mildew (f) Powdery mildew.

3.3 Data Splitting

The final dataset size after augmentation was 3,390 images, of which 80% were used for training (2712 images) and 20% were used for testing (678 images). In addition to preserving an independent test set for unbiased evaluation, this ensured that the models had enough data to train. The training set was utilized to optimize model parameters, while the testing set gave an objective evaluation of classification accuracy.

3.4 Architecture Design

The proposed hybrid deep learning model improves neem leaf disease classification through a structured pipeline that includes data preparation, augmentation, model implementation, compilation, and training. The dataset was preprocessed by scaling all images to 224×224 pixels for compliance with pretrained models. Pixel normalization was the dataset was class imbalance further, we apply data augmentation techniques to the dataset where they are rotation, flipping, zooming, brightness modifications, and translations were used to avoid overfitting. The hybrid model design is built on feature fusion, which involves two deep learning models extracting distinct feature representations that are then concatenated for classification. The MobileNet+DenseNet hybrid model, which performed best, combines MobileNetV2's lightweight and efficient feature extraction (Elakiya et al., 2024) with DenseNet121's hierarchical feature propagation. Additionally, DenseNet+AlexNet, DenseNet+ResNet, and DenseNet+GoogleNet hybrid models were created for comparative analysis using a similar methodology. Transfer learning was used in all models, with ImageNet-pretrained weights to utilize learnt feature representations while freezing the basic model layers. Each model retrieved deep hierarchical features from neem leaf images, then used Global Average Pooling (GAP) to convert the feature maps into one-dimensional vectors. The concatenation of these feature vectors formed a compounded representation that was used to increase classification accuracy. The features went through a fully connected dense layer of 128 neurons with ReLU activation before the last SoftMax classification layer. This layer allowed for the classification of input images into six different neem leaf disease groups. TensorFlow and Keras were used to create the models, which were trained using an 80-20 train-validation split across 60 epochs, with early pausing to prevent overfitting. Figure 3 illustrates the full workflow. A full explanation of each model's operating principles is given below.

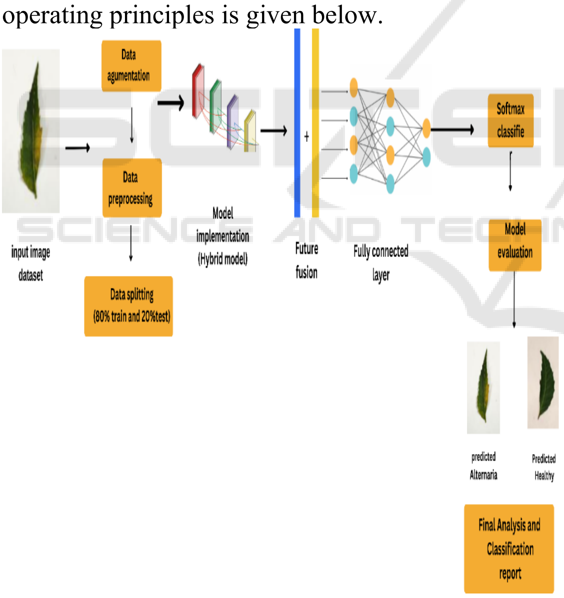

Figure 3: Functional Diagram of the Proposed Model.

4 HYBRID MODELS

4.1 Mobile Net-DenseNet

The hybrid model between MobileNet-DenseNet combines the excellence of MobileNetV2, a light-weight and computation-efficient convolutional neural network, and DenseNet121, a deep learning network with better feature propagation. MobileNetV2 is particularly optimized for mobile and embedded vision tasks, providing the optimal performance-computation trade-off. DenseNet121 helps in efficient reuse of features, thus enhancing the performance of the model with a reduction in the number of total parameters at the same time compared to normal convolutional networks. The hybrid model accepts an input image of size 224×224×3 by simultaneously utilizing MobileNetV2 and DenseNet121, both pre-trained on the ImageNet database. For pre-learned representation integrity maintenance, the layers are frozen. After feature extraction, Global Average Pooling (GAP) layers transform feature maps into one-dimensional vectors, thus reducing the dimension without losing essential spatial information. The output feature vectors of both models are concatenated to produce a single representation that combines MobileNet's efficient spatial feature learning with DenseNet's hierarchical feature propagation. The concatenated feature vector is then fed into a fully connected dense layer of 128 units with ReLU activation followed by a softmax classifier, which classifies the image into one of the six neem leaf disease classes. Figure 4 shows the end-to-end process.

4.2 DenseNet-AlexNet

DenseNet121 is the base deep feature extractor within the DenseNet-AlexNet hybrid model, with AlexNet offering supplemental feature learning potential within its plain but effective convolutional layers. Five convolutional and three fully connected layers comprise AlexNet, successfully extracting principal textures and low-level spatial information to enhance DenseNet's deeper feature representations. Again, as with the initial model, both networks compute an input image in parallel, and feature maps generated from both networks are reduced to one-dimensional feature vectors using Global Average Pooling (GAP). Concatenation at this point is where both these feature vectors, taking the strength of each network, are concatenated before moving through a fully connected layer. The concatenation here takes feature vectors, borrowing strength from each network, before moving through a fully connected layer. The final classification uses the softmax activation function. The combination of AlexNet's simplicity and DenseNet's deep connections yields a model that adequately balances computation with deeper feature extraction.

4.3 DenseNet-ResNet50

The hybrid DenseNet-ResNet50 architecture integrates the useful features of DenseNet's feature reuse mechanism with the residual connections of ResNet, which stabilize deep neural networks by avoiding the vanishing gradient issues. The ResNet50 deep residual learning architecture improves the gradient flow between layers, resulting in better extraction of deep features. Under this setup, DenseNet121 and ResNet50, pre-trained on ImageNet, both forward an input image in parallel. After the feature extraction process, Global Average Pooling (GAP) is used to transform the output of both networks into one-dimensional feature vectors. These vectors are concatenated to form a combined feature representation that captures ResNet's hierarchical learning benefits with connectivity of DenseNet. The resulting merged feature vector then passes through a fully connected layer with 128 neurons followed by classification through a softmax layer. This hybrid model benefits from ResNet's capacity to retain learned information in deep networks and, simultaneously, exploits the efficient feature sharing between layers by DenseNet.

4.4 DenseNet-GoogleNet

The DenseNet-GoogleNet model combines GoogleNet's inception modules with DenseNet's densely connected layers to improve multi-scale feature extraction. GoogleNet (InceptionV3) is widely used for its parallel convolutional filters with different kernel sizes, which allow the model to collect information at different scales. This is very useful in the detection of complex patterns of disease. In this hybrid design, DenseNet121 and GoogleNet (InceptionV3) process the input image separately, so each network extracts features independently. GoogleNet's inception modules can recognize fine-grained features as well as larger structural information. The feature maps extracted from each network are then fed to Global Average Pooling (GAP) to get compact feature vectors. These concatenated feature vectors leverage the best of both designs before being passed to a fully connected dense layer followed by a final softmax classifier. Where entire working process of hybrid model is depicted in Figure4. GoogleNet's capability of processing input at different scales complements DenseNet's hierarchical feature extraction, so this hybrid model is extremely successful in recognizing neem leaf diseases of varying intensities.

Algorithm 1: DenseNet-MobileNet Hybrid Model.

```
Input:    X → Dataset,d → Preprocessed dataset and resized images,l → Corresponding labels for the images
Output: Final classification performance on the test dataset
For each and every epoch:
    Feature Extraction using MobileNet:
    For each convolution layer in MobileNet:
        For each input image in X:
            Extract feature map aij from MobileNetV2 convolutional layers.
        End for
    End for
    Apply Global Average Pooling (GAP) for obtaining compact feature representation.
    Final MobileNetV2 feature vector: (1, num_filters)
    Feature Extraction using DenseNet121:
    For each convolution layer in DenseNet121:
        For each input image in X:
            Extract feature map aij from DenseNet121 convolutional layers.
        End for
    End for
    Use Global Average Pooling (GAP) to generate a compact feature representation.
    Final DenseNet121 feature vector: (1, num_filters)
Hybrid Feature Fusion:
    Define feature set fet from dataset d.
    For each image in dataset:
        Preprocess the image before inputting it into the models.
    End for
    Split dataset into train_fet, test_fet, train_labels, test_labels.
Train & Evaluate MobileNetV2:
```

27. M_MobileNet ← Train MobileNetV2 on train_fet, train_labels.
28. Extract training features: MobileNet_train ← M_MobileNet.predict(train_fet).
29. Extract testing features: MobileNet_test ← M_MobileNet.predict(test_fet).
30. Train & Evaluate DenseNet121:
31. M_DenseNet ← Train DenseNet121 on train_fet, train_labels.
32. Extract training features: DenseNet_train ← M_DenseNet.predict(train_fet).
33. Extract testing features: DenseNet_test ← M_DenseNet.predict(test_fet).
34. Hybrid Model Construction:
35. Combine extracted features:
36. model_train ← Concatenation of MobileNet_train and DenseNet_train.
37. model_test ← Concatenation of MobileNet_test and DenseNet_test.
38. Train a fully connected neural network on the merged feature set.
39. Evaluate performance on test data.

5 RESULTS AND DISCUSSION

The performance of proposed hybrid deep learning models was checked through various measures of performance, i.e., accuracy, loss, precision, recall, F1-score, sensitivity, specificity, AUC (Area Under the Curve), and MUC (Mean Under curve), which are displayed in Table 2.

Table 2: Comparison of Used Models Accuracy and Error.

Parameters	Densenet- GoogleNet	DenseNet-AlexNet	DenseNet-Resnet50	DenseNet-MobileNet
Accuracy	88.20	88.50	88.79	90.56
Precision	87.68	87.82	87.97	89.71
Recall	87.09	87.43	86.96	89.36
F1score	87.29	87.47	87.13	89.42
Sensitivity	87.09	87.43	86.96	89.36
Specificity	97.63	97.68	97.57	97.95
MCC	85.50	85.86	85.23	87.64
AUC	98.25	98.46	98.14	97.64
Loss	0.1	0.1	0.1	0.09

Among the evaluated models, DenseNet-MobileNet achieved the highest performance, attaining an accuracy of 90.56%., because of MobileNet's fast feature extraction and DenseNet's hierarchical connection. The DenseNet-ResNet model followed with 88.79% accuracy, because of residual learning, while DenseNet-AlexNet and DenseNet-GoogleNet showed lower accuracy in Fig 12. Despite the fact that GoogleNet's inception modules allow for multi-scale feature extraction, the decreased accuracy shows feature redundancy in neem leaf disease diagnosis. The training and validation accuracy and loss curves give a better understanding of the performance of the model. The accuracy graph indicates a steady increase with the epochs, with DenseNet-MobileNet having the highest stability level, while the loss graph indicates effective convergence, which depicts decreased classification errors. Figure 4 to 11 shows the Accuracy, Loss and Confusion Matrix of various models.

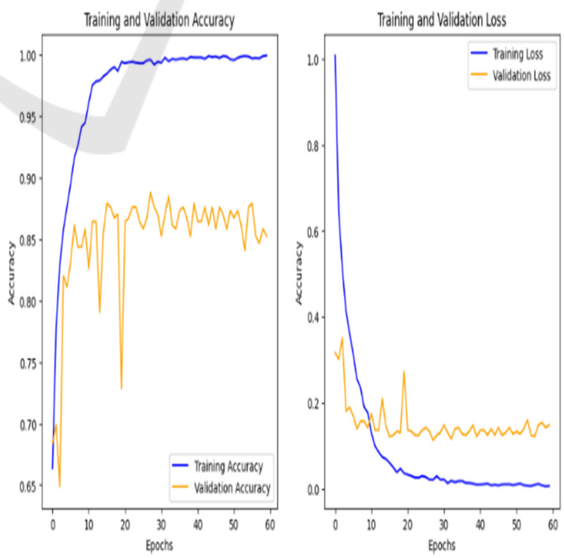

Figure 4: Accuracy and Loss Graph for DenseNet-MobileNet.

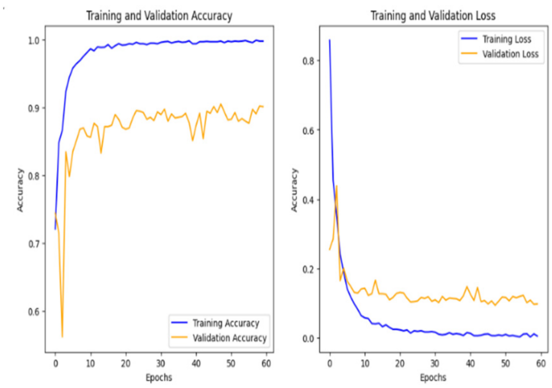

Figure 5: Accuracy and Loss Graph for DenseNet-ResNet5.

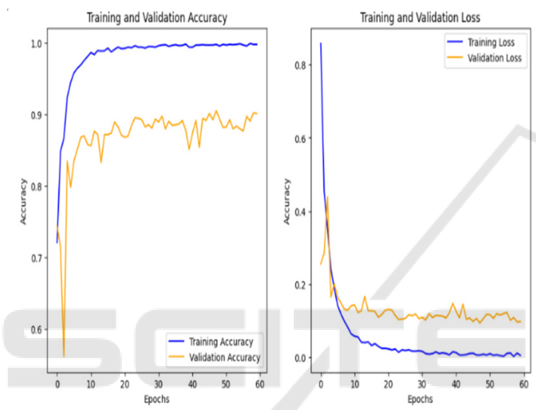

Figure 6: Accuracy and Loss Graph for DenseNet-GoogleNet.

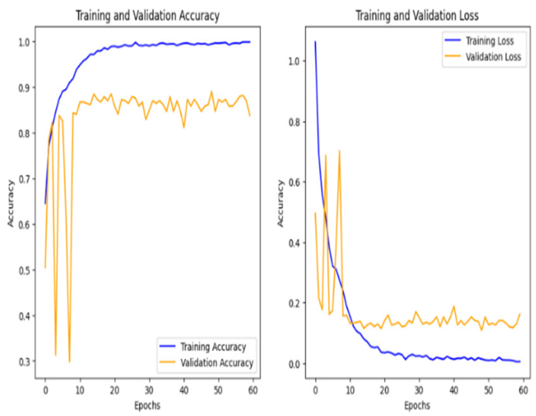

Figure 7: Accuracy and Loss Graph for DenseNet-AlexNet.

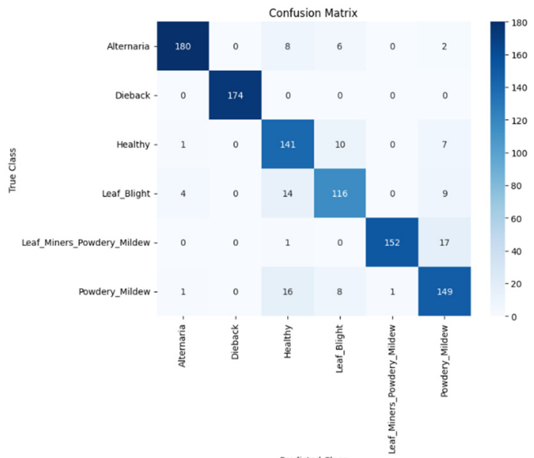

Figure 8: Confusion Matrix of DenseNet-MobileNet.

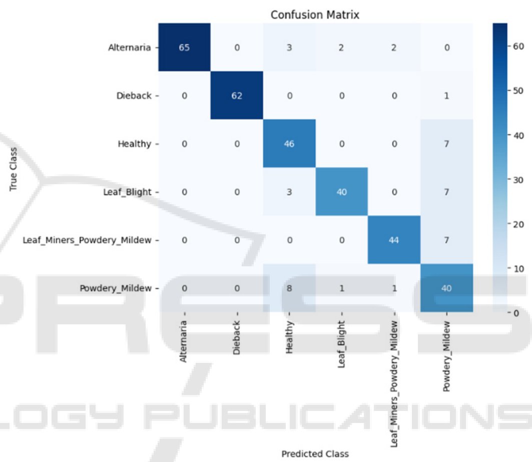

Figure 9: Confusion Matrix of DenseNet-ResNet50.

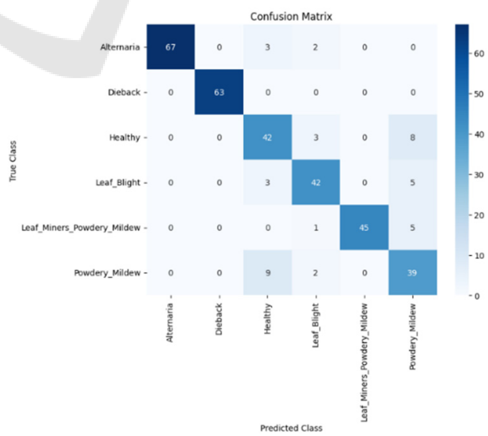

Figure 10: Confusion Matrix of DenseNet-GoogleNet.

Figure 11: Confusion Matrix of DenseNet-AlexNet.

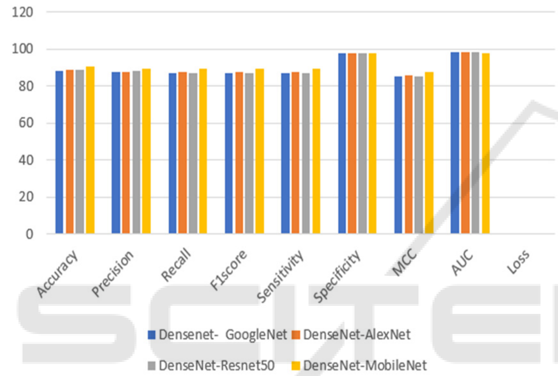

Figure 12: Comparison of used Models.

6 CONCLUSIONS

This study proposed a hybrid deep learning approach for neem leaf disease detection by integrating DenseNet with MobileNet, ResNet, AlexNet, and GoogleNet. Among these models, DenseNet-MobileNet had the highest accuracy of 90.5%, making it the most effective for neem leaf disease classification. Other hybrid models, including DenseNet-ResNet (88.7%), DenseNet-AlexNet (88.5%), and DenseNet-GoogleNet (88.2%), also performed well but were slightly less accurate. The study of model performance utilizing criteria such as accuracy, loss, precision, recall, and AUC revealed that hybrid models outperform independent architectures. The accuracy and loss graphs showed stable training and convergence, confirming the reliability of the proposed models for automated disease prediction. For future work, tribrid models integrating three deep learning architectures shall be explored to further enhance classification accuracy. In addition, a new neem disease dataset will be compiled to increase model generalization and robustness. To improve model performance, attention mechanisms, explainable AI approaches, and hyperparameter tuning will be combined. Furthermore, efforts will be made to create lightweight models for real-time disease identification in mobile and edge computing settings. These developments will help precision agriculture (S. Banerjee et al., 2024) by enabling early and efficient disease identification.

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