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Detection of Neem Leaf Disease Using Deep Learning Models

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Abstract — Neem is a medicinal plant known for its antibacterial and antifungal properties. However, various leaf diseases affect its growth and medicinal value, making early and accurate detection crucial. Traditional manual inspection methods are time-consuming and error-prone. This research proposes an automated neem leaf disease detection system using deep learning. Five Convolutional Neural Networks (CNNs)—ResNet50, DenseNet, MobileNet, GoogleNet, and AlexNet—were evaluated for classifying seven neem leaf categories: Alternaria, Dieback, Leaf Blight, Leaf Miners with Powdery Mildew, Powdery Mildew, and Healthy leaves. A dataset of 1862 images was split into 80% training and 20% testing. Images were pre-processed using resizing, normalization, and augmentation to improve model performance. K-Means clustering segmentation was applied to assess its impact on classification by enhancing diseased region detection. Among the tested models, DenseNet achieved the highest accuracy of 90%. This study highlights the potential of deep learning for neem leaf disease detection. Future work will focus on hybrid models and advanced segmentation to enhance classification accuracy and robustness.

Keywords—Neem leaf diseases, Deep Learning, k-means image segmentation, Smart Farming

I. INTRODUCTION

Agriculture is a core sector sustaining food security, economic growth, and sustainable livelihoods worldwide. The health of crops plays a critical role in defining agricultural productivity, and plant diseases are an extreme danger to the quality and quantity of crops. Immediate disease detection is necessary in order to avoid losses and guarantee successful management of diseases. plant disease detection techniques are based primarily on visual observation employed by farmers or agricultural specialists are time-consuming. With advancements in artificial intelligence (AI) and deep learning, automated plant disease detection has gained attention for its accuracy, efficiency, and scalability. Neem is a medicinal crop widely cultivated in tropical and subtropical areas due to its antimicrobial, antifungal and insecticidal in nature. Neem trees are prone to a variety of leaf diseases that affect their development and medical significance. Diseases common with neem leaves as noted in Figure 1 and Figure 2 are Alternaria, Dieback, Leaf Blight, healthy, Leaf Miners with Powdery Mildew, and Powdery Mildew. The capability to properly classify these diseases is required for neem development and disease control. Thus, creating an automatic system for neem leaf disease detection can help in early diagnosis and control measures that reduce economic loss and ensure plant health. Deep learning algorithms such as ResNet50, DenseNet, MobileNet, GoogleNet, and AlexNet have been used extensively in the detection of plant diseases because they can extract complex patterns from leaf pictures. This work examines the effectiveness of these deep learning models in classifying neem leaf diseases. A data set of 1862 images were employed in model training and evaluation, and within for them, DenseNet performed best at 90% Accuracy. make it the best-performing model for this task. To further examine the effect of image preprocessing on classification performance, K-Means clustering segmentation was employed to the data set. K-Means is an unsupervised machine learning algorithm widely employed for image segmentation. The objective of including K-Means segmentation in this research was to determine its impact on disease categorization accuracy by enhancing the separation of diseased and healthy regions in leaf images However, while K-Means segmentation was integrated, its success in enhancing classification outcomes were strictly analyzed. The primary objectives of this research are to develop an automated deep neem leaf disease detection learning-based system.

II. RELATED WORKS

Traditional Deep learning techniques have been extensively applied in plant disease detection, utilizing convolutional neural networks (CNNs) and image segmentation to improve classification accuracy. This study introduced the Leaf Disease Transfer Learning Algorithm (LDTLA), leveraging CNNs for classification. While neither study focused on neem leaf disease, the methodologies employed could be adapted for neem leaves [1].

Another study utilized DenseNet-121 on the Plant Village dataset to classify various plant diseases but did not specifically investigate neem leaf disease [2]. A study on ResNet-based models achieved high classification accuracy but did not address neem-specific diseases [4]. Image segmentation plays a crucial role in identifying affected leaf areas before classification. One study employed a lightweight multi-scale extended U-Net (LWMSDU-Net) for crop [26] disease segmentation, achieving 92.17% accuracy. Though the study did not focus on neem leaves, its segmentation approach could be applicable for neem leaf disease detection [6].

A hybrid optimization model combining Black Widow Optimization and Cat Swarm Optimization improved CNN-based classification in mango leaf disease detection, although it did not specifically address neem leaf diseases [3]. Several studies integrated autoencoders with CNNs to achieve 99.82% accuracy on the Plant Village dataset, showcasing potential for neem leaf disease classification when applied to a specialized dataset [9]. Additionally, a study using autoencoders for pepper and cherry leaf disease detection highlighted unsupervised learning techniques that could be adapted for neem leaf diseases [10].

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The DIR-BiRN approach combined residual networks without image segmentation, optimizing disease detection accuracy while reducing computational overhead [5]. A study on pre-trained models for plant disease segmentation and classification demonstrated their applicability across various datasets, which could be extended to neem leaf diseases [11]. Another research introduced CACPNET, integrating channel pruning and attention mechanisms for efficient leaf disease detection but did not include image segmentation or neem leaf disease detection [15]. YOLO V5-CAcT achieved an average recognition accuracy of 94.24% across 59 disease categories, suggesting its potential for neem leaf disease detection [17].

Lightweight CNN models incorporating local binary patterns for feature fusion demonstrated high accuracy in apple, tomato, and grape leaf disease classification. These models could be adapted for neem disease detection by training them on neem-specific datasets [13]. Unsupervised deep learning methods, such as autoencoders for multispectral image anomaly detection, have been investigated for cucumber leaf diseases, though they did not focus on neem leaves [14]. Another study explored unsupervised autoencoders for leaf disease detection and anomaly screening, which could be useful for neem leaf diseases [10]. SE-VRNet, utilizing an attention mechanism and a deep residual network, demonstrated success in leaf disease detection and could be adapted for neem [16]. Furthermore, studies on image-based plant disease identification using enhanced SinGAN and ResNet34 suggest that these methodologies could be applied to neem leaf disease detection [12].

Although numerous deep learning techniques exist for plant disease detection, specific research on neem leaf disease remains scarce. The reviewed studies highlight the effectiveness of CNNs, transfer learning, and hybrid models in classifying various plant diseases. However, the absence of neem leaf-specific datasets and tailored image segmentation techniques presents a significant gap. A study using a dataset of 54,306 images demonstrated deep learning models achieving 99.35% accuracy, suggesting potential for neem leaf disease detection if appropriate datasets and training methodologies are developed [7]. Another research emphasized the need for diverse training data to enhance overall model performance, which is essential for neem disease identification [8]. Future research should focus on developing a robust neem leaf disease dataset incorporating multiple disease types. Enhancing image segmentation can improve disease localization and severity assessment. Leveraging hybrid deep learning techniques may enhance classification accuracy and generalization. Exploring lightweight and optimized CNN architectures can contribute to real-time detection. By addressing these gaps, neem leaf disease detection can be improved, ultimately benefiting agricultural productivity and disease management strategies.

III. MATERIALS AND METHODS

A. Dataset Description

A dataset of 1,862 neem leaf images was collected from Mendeley Data [24], as shown in TABLE I. Alternaria, Dieback, Leaf Blight, Leaf Miners with Powdery Mildew, Powdery Mildew, and Healthy leaves were the six classes that were included in the dataset and displayed images of each class is shown in Figure 1 and Figure 2. Image augmentation was used to ensure an equal distribution across all classes because the dataset was extremely unbalanced. This improved the ability of the model to generalize across various disease types. Preprocessing methods were used to ensure consistency and enhance the dataset's quality prior to training. Each image was resized to ensure uniformity in dimensions by matching the input size required by the CNN architectures. In order to stabilize the training process and speed up convergence, pixel values were normalized to a range of 0 to 1. In order to allow the model to concentrate on relevant leaf features, background interference was also eliminated using noise reduction techniques. During preprocessing, images were converted into NumPy arrays and their associated class labels were appended to arrays to enable efficient processing in deep learning frameworks.

TABLE I. Neem Leaf Disease Dataset

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

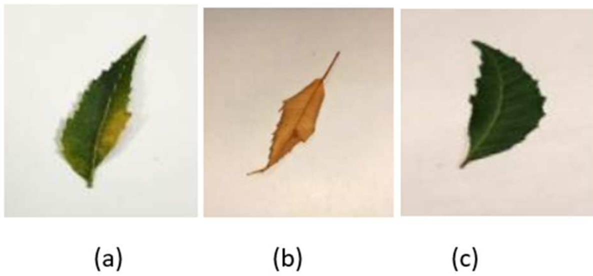

Fig. 1. (a) Alternaria (b) Dieback (c) Healthy

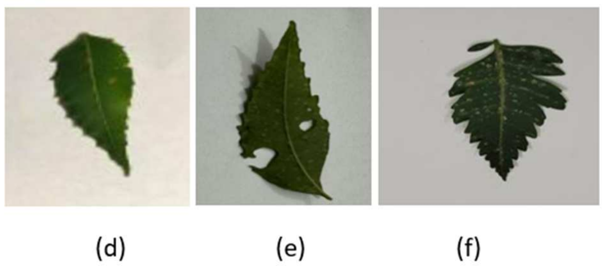

Fig. 2. (d) Leaf blight (e) Leaf miners Powdery mildew (f) Powdery mildew

B. Data Augmentation

Augmentation techniques were used before dataset splitting in order to address class imbalance. A balanced dataset was ensured by augmenting each class with 565 images. Among the augmentation techniques were brightness adjustment, zooming (±20%), rotation (0° to 360°), flipping horizontally and vertically, and Gaussian noise addition. These changes reduced the chance of overfitting while assisting the models in learning more robust and generalized features by introducing changes in scale, lighting, and orientation.

C. 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 made sure the models had enough data for learning. The training set was used to optimize model parameters, while the testing set provided an objective assessment of classification accuracy.

D. Image segmentation

K-Means clustering-based image segmentation was used to improve disease detection by segmenting infected areas of neem leaves and minimizing background interference. The process started with loading the image, changing it from BGR to RGB format, and reshaping it into a two-dimensional array where every pixel was represented as a three-dimensional RGB vector. These pixel intensities were then passed through the K-Means algorithm with K = 7 to segment the image into seven prominent color regions by pixel intensity. The algorithm terminated either after 100 iterations or when there was less than 0.2 movement in centroids, thereby ensuring convergence. Cluster centers were initialized randomly to introduce variation in the output. After clustering, pixel labels were mapped back to their respective cluster colors, and the segmented image was reconstructed to its original shape. This method sought to highlight diseased areas by collecting similar color intensities, allowing the model to target relevant patterns and suppress background noise. As Figure 3 indicates, this enhanced the visual contrast between healthy and affected areas. K-Means segmentation, however, had shortcomings in segregating diseases such as Powdery Mildew, which exhibited vague, diffuse infection patterns akin to healthy tissue. Due to its inherent dependency on color similarity alone, without taking spatial or textural information into account, it failed to correctly separate diseased areas. Although providing some visual improvement, K-Means did not enhance overall classification accuracy [25]. In some cases, segmentation introduced artifacts that interfered with feature extraction [27]. Therefore, while it served as a basic preprocessing step [29], more advanced segmentation techniques could be considered in future work. Methods such as U-Net, Mask R-CNN, or attention-based models could provide more robust and precise segmentation by learning complex spatial and contextual features and can expect the high accuracy.

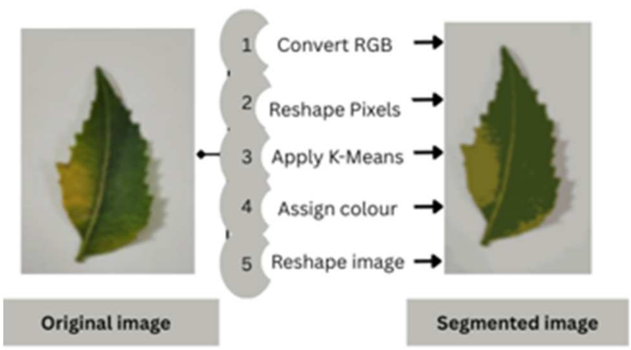

Fig. 3. K-Means image segmentation

E. Architecture Design

TensorFlow and Keras were used to implement the models, and ImageNet-pretrained weights were used for transfer learning. To address class imbalance, the dataset was preprocessed by applying data augmentation, normalizing pixel values, and resizing images to 224×224 pixels. To maximize training efficiency, early stopping was enabled, and the models were trained on 80% of the dataset and validated on the remaining 20%. The proposed model utilizes five state-of-the-art deep learning architectures—DenseNet121, ResNet50, AlexNet, MobileNet, and GoogleNet—for neem leaf disease classification. In order to extract deep hierarchical features from neem leaf images, each model was put into practice using transfer learning and pretrained weights from ImageNet. In order to predict six disease categories, the classification pipeline used feature extraction, global pooling, fully connected layers, and SoftMax classification. The whole process is shown in Figure 4. The working principles of each model are explained in detail below.

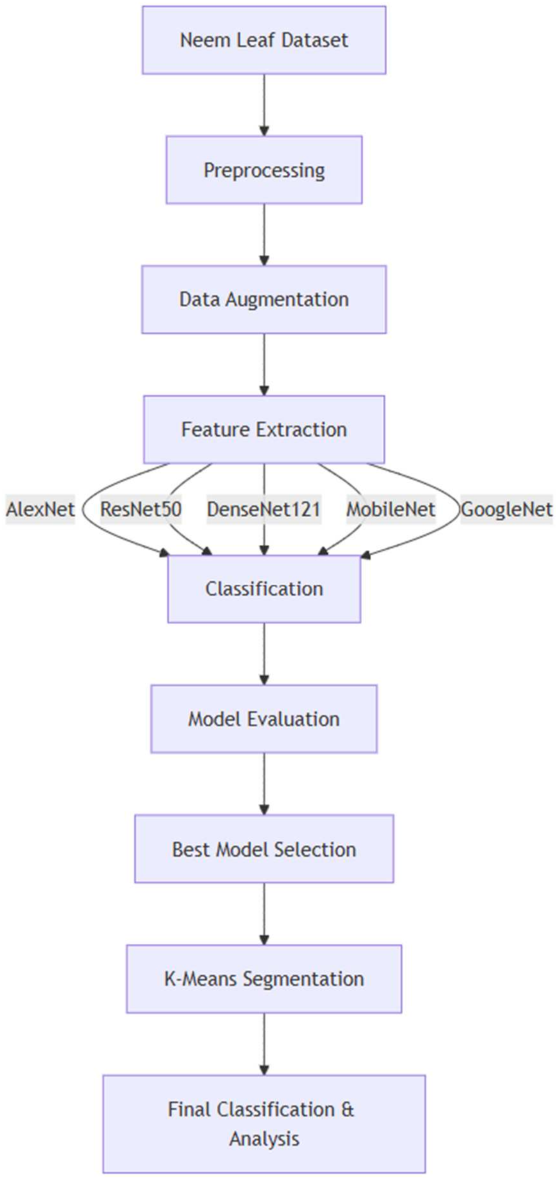

Fig. 4. System Architecture

IV. Models Description

A. DenseNet121

DenseNet121 is an advanced CNN architecture that introduces dense connectivity, where each layer receives input from all preceding layers. Gradient flow, feature reuse, and effective parameter learning are all improved by this method [19] Deep feature extraction is made easier by the dense blocks, and computing performance is maximized by bottleneck layers. The transition layers reduce dimensionality while maintaining crucial information by down sampling feature maps using pooling procedures. A fully connected layer with SoftMax activation is used for the final classification, allocating probabilities to each disease type [20]. DenseNet121 is the best model for disease identification because it successfully recognizes intricate patterns in neem leaf images, with a 90% classification accuracy

B. ResNet50

ResNet50 addresses the vanishing gradient problem in deep networks by incorporating residual connections, allowing information to flow across multiple layers without significant degradation [21]. Convolutional layers, batch normalization, residual blocks, and global average pooling layers constitute the design. Key aspects are preserved through direct information transfer between layers made possible by the skip connections in residual blocks. The model extracts low-level and high-level characteristics for classification by processing input images through a number of convolutional filters. Probabilistic outputs for illness categories are produced by the softmax classifier and the final fully connected layers. ResNet50 is appropriate for disease classification tasks because it successfully strikes a compromise between computational efficiency and depth.

C. AlexNet

AlexNet is a classical CNN architecture consisting of five convolutional layers followed by three fully connected layers. The model uses max pooling to reduce spatial features, dropout regularization to avoid overfitting, and ReLU activation for non-linearity [18]. While the fully connected layers convert this information into class probabilities, the convolutional layers extract fine-grained visual features. A probability distribution is assigned to each disease class by the last softmax layer. AlexNet is a useful part of the suggested model because of its comparatively straightforward architecture, which enables effective feature extraction.

D. MobileNet

MobileNet is designed for efficient deep learning on mobile and edge devices using depth wise separable convolutions, which reduce the number of parameters while maintaining classification accuracy [22]. Convolutional layers, global average pooling layers, batch normalization, and ReLU activation are all included in the model. By providing a width multiplier, MobileNet enables model complexity to be customized according to resource limitations. The classification probabilities for diseases categories are produced by the last fully linked softmax layer. Real-time disease diagnosis is made possible by MobileNet's lightweight design, which also reduces computing expenses.

E. GoogleNet

GoogleNet, also known as Inception v1, incorporates Inception modules, where multiple convolutional filters (1×1, 3×3, and 5×5) operate in parallel to extract multi-scale features [23]. Convolutional layers, pooling layers, fully connected layers, and softmax activation for classification [28] make up the design. GoogleNet is very helpful for collecting variations in neem leaf diseases because of its capacity to extract a variety of hierarchical aspects.

V. Results and Discussion

The performance of different deep learning models was evaluated using metrics such as accuracy, loss, precision, recall, F1-score, sensitivity, specificity, AUC (Area Under Curve), and MUC (Mean Under Curve), as shown in Table 2. Among all tested models, DenseNet achieved the highest accuracy of 90%, demonstrating superior performance in neem leaf disease detection. MobileNet followed closely with 89% accuracy, offering a balance between performance and computational efficiency. Other models, including ResNet, GoogleNet, and AlexNet, showed comparatively lower accuracy, as illustrated in Figure 15. To enhance classification, K-Means clustering was applied as a preprocessing step. However, it did not improve model accuracy. This limitation is due to K-Means' reliance on color similarity, which proved inadequate in distinguishing subtle disease patterns—particularly in Powdery Mildew and failed to account for texture or spatial features. Although K-Means offered slight visual enhancement, it was not effective for deep learning-based classification. Future work may consider advanced segmentation techniques like U-Net or Mask R-CNN for better localization of diseased areas.

TABLE II. Comparison of used models Accuracy and Error

Parameter	ResNet50	GoogleNet	AlexNet	MobileNet	DenseNet
Accuracy	75.22	78.76	80.82	89.68	**90.2**
Precision	77.11	79.81	80.59	88.70	**89.20**
Recall	74.93	77.07	79.57	88.48	**88.56**
F1score	74.86	77.30	79.18	88.55	**88.75**
Sensitivity	74.93	77.07	79.57	88.48	**88.56**
Specificity	95.11	95.79	96.20	97.91	**97.90**
MCC	70.67	74.89	77.32	87.22	**87.25**
AUC	95.38	95.19	96.25	98.64	**98.26**
Loss	0.3	0.3	0.2	0.2	**0.2**

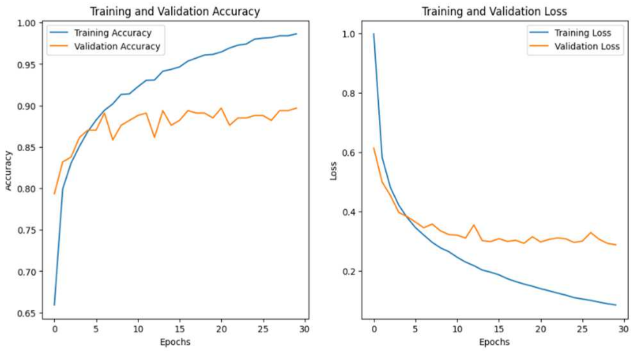

Fig. 5. Loss and Accuracy Graph for DenseNet

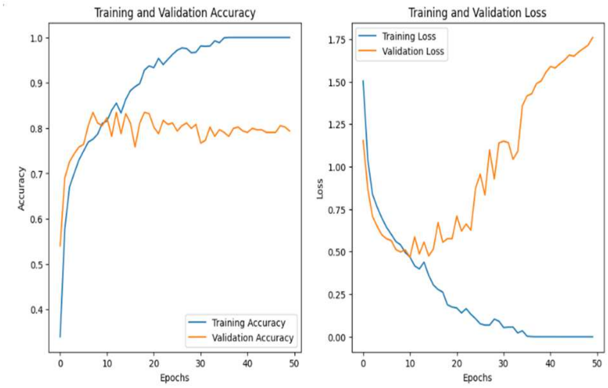

Fig. 6. Loss and Accuracy Graph for AlexNet

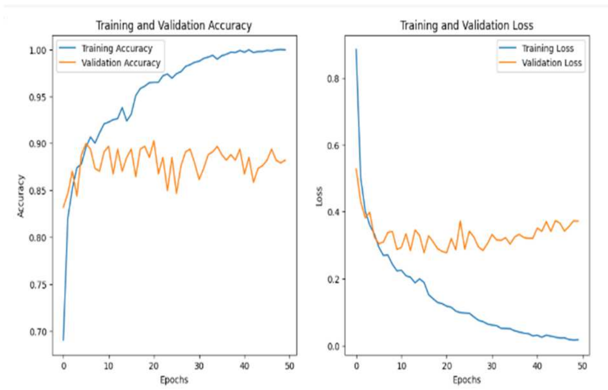

Fig. 7. Loss and Accuracy Graph for MobileNet

Fig. 8. Accuracy and Loss Graph for ResNet

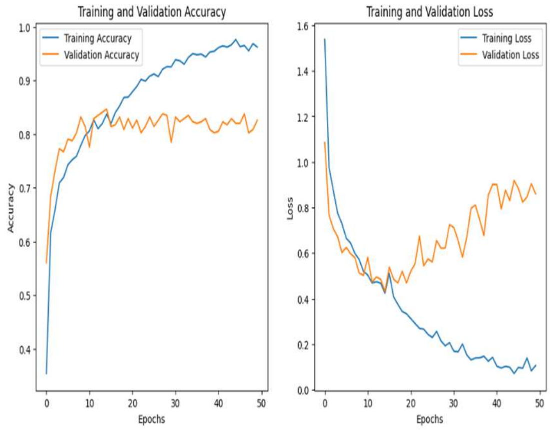

Fig. 9. Loss and Accuracy Graph for GoogleNet

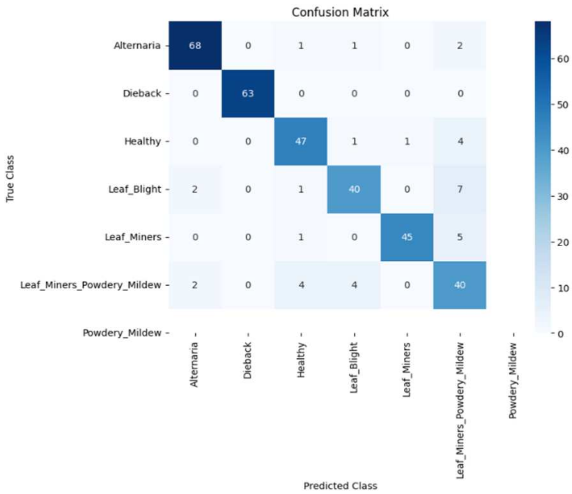

Fig. 10. Confusion Matrix for DenseNet

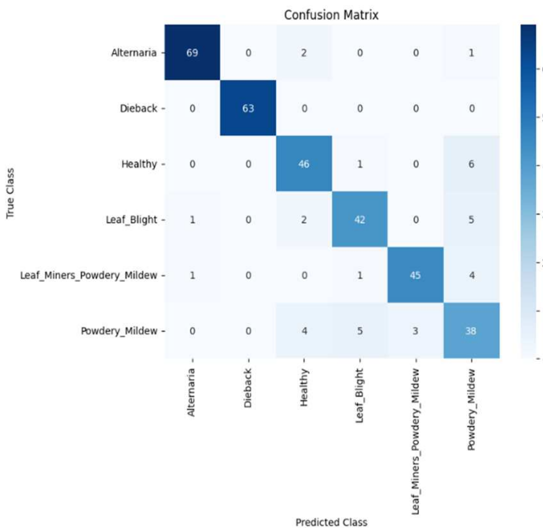

Fig. 11. Confusion Matrix for MobileNet

Fig. 12. Confusion Matrix for AlexNet

Fig. 13. Confusion Matrix for ResNet

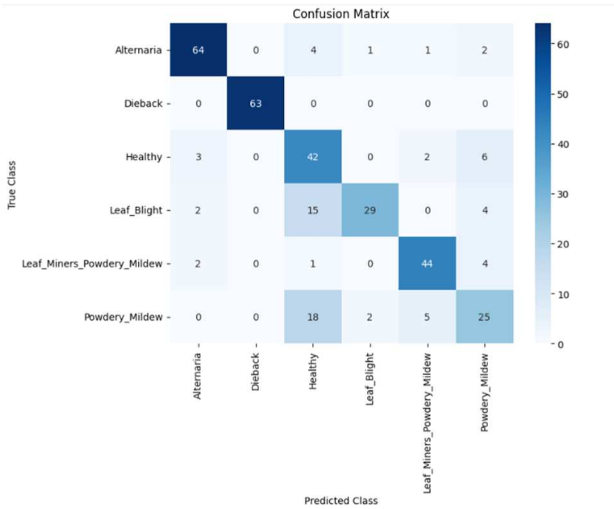

Fig. 14. Confusion Matrix for GoogleNet

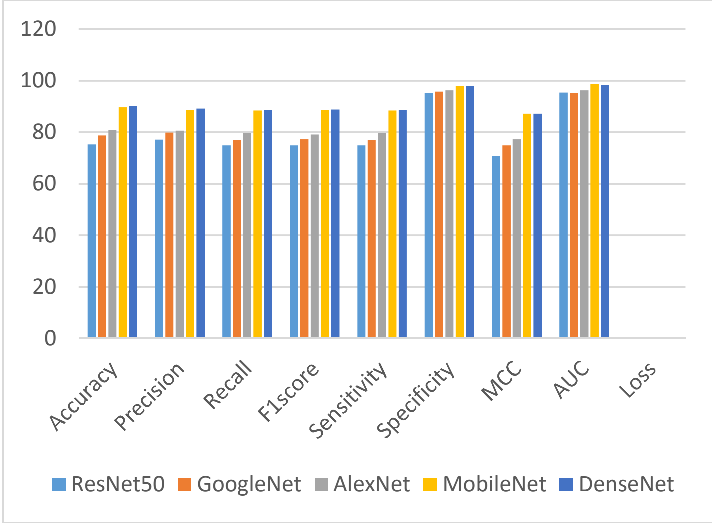

Fig. 15. Comparison of used Models

CONCLUSION

The various deep learning models, including AlexNet, ResNet50, MobileNet, DenseNet, and GoogleNet, were evaluated for Neem leaf disease detection. Among these models, DenseNet achieved the highest accuracy of 90.2%, outperforming other architectures. While MobileNet demonstrated a lightweight structure with relatively high accuracy (89.68%), DenseNet was chosen for its superior classification performance despite its computational complexity. The results indicate that DenseNet effectively captures intricate leaf disease patterns, making it the most suitable model for this task. Furthermore, K-Means segmentation was explored to analyse its impact on accuracy, but it did not lead to significant improvements. For future work, efforts will focus on improving segmentation techniques to enhance disease classification, considering factors such as texture, lighting conditions, and complex leaf features. Advanced image segmentation techniques like U-Net or Mask R-CNN for better localization of diseased areas. Additionally, hybrid models combining the strengths of different CNN architectures could be explored to achieve even higher accuracy and robustness in disease classification.

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