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Deep Learning-Based Detection of Mango Leaf Diseases Using CNN Architecture

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Abstract: Mango leaf diseases pose a significant threat to mango production, impacting yield and quality. Accurate and early detection of these diseases is critical for effective management and sustainable agriculture. This research presents a deep learning-based approach for automatic mango leaf disease detection using convolutional neural network (CNN) architectures, including VGG16, VGG19, ResNet50, DenseNet121, and AlexNet. A comprehensive dataset of mango leaf images, representing various diseases such as Anthracnose, Bacterial Canker, and Powdery Mildew, was preprocessed and categorized. Each model was trained and evaluated using image data augmented for improved generalization, with class labels converted to categorical formats. Results indicate that DenseNet121 achieved the highest accuracy, with consistent precision and recall across disease classes, suggesting it as an optimal model for this application. This study highlights the potential of deep learning for precise and scalable plant disease detection, offering a promising tool for automated agricultural disease management. Future work will explore model deployment in mobile applications to support real-time disease detection in the field.
Keywords: Convolutional Neural Networks (CNNs), Deep Learning Mango Leaf Diseases, Detecting Disease, Accuracy, Dataset, Models/Architectures (e.g., VGG16, ResNet50, DenseNet121, AlexNet), Anthracnose, Powdery Mildew, Bacterial Canker, Precision Agriculture, Plant Disease Detection, Image Classification, Transfer Learning, Mobile Applications, Tunneling, IoT Devices, Sustainable Agriculture, Automation, Generalization.

I. INTRODUCTION

Mangoes are a staple crop in tropical and subtropical regions, contributing significantly to global agricultural output. However, various diseases severely affect mango production, leading to considerable economic losses. Early detection and effective management of these diseases are critical for sustainable farming. Traditionally, manual inspection has been the primary method for identifying leaf diseases, but this is labor-intensive and prone to inaccuracies. Recent advancements in deep learning have opened new opportunities for automating disease detection in plants. Specifically, (CNNs) have shown great promise in classifying and diagnosing plant diseases based on images, offering higher efficiency and accuracy compared to manual methods.

Several studies have explored the use of deep learning for mango leaf disease detection. For example, a study by Kumari et al. (2023) demonstrated the use of CNNs to accurately identify diseases such as powdery mildew and anthracnose, achieving high classification performance. In another study, the MobileNetV3 architecture was applied to mango leaf disease classification, providing a lightweight solution suitable for real-time applications in precision agriculture.

Additionally, research by Shad et al. (2024) highlights the potential of transfer learning, where pre-trained models like ResNet50 and VGG16 were fine-tuned on mango leaf datasets to achieve impressive results in disease detectionper proposes a deep learning-based approach using CNN models to detect and classify mango leaf diseases, aiming to provide an automated solution for farmers and researchers. The system leverages a dataset of 4200 images of mango leaves, categorized into various disease classes, to train multiple models and evaluate their performance in terms of accuracy, precision, and recall.

II. LITERATURE REVIEW

In recent years, machine learning and deep learning have gained considerable attention in plant disease detection for their ability to automate diagnostics and improve crop management. While traditional image processing methods were initially employed in this field, the introduction of deep learning, especially Convolutional Neural Networks (CNNs), has significantly enhanced both accuracy and efficiency. In the domain of agricultural disease detection, various studies have explored CNN architectures for identifying diseases in crops such as tomatoes, grapes, and potatoes. For instance, Ferentinos (2018) proposed the use of deep learning models, specifically CNNs, to detect diseases in tomato plants with high accuracy, demonstrating the potential of CNNs in plant pathology. Similarly, (Mohanty et al., 2016) showed that CNN-based approaches could surpass traditional image classification techniques in accuracy when applied to datasets of plant diseases, including leaf blight and rust diseases in maize and other crops.

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In recent years, attention has shifted towards applying deep learning for a more extensive range of plant species. For example, Kamilaris and Prenafeta-Boldú (2018) conducted a comprehensive review of deep learning applications in precision agriculture, concluding that CNNs were the most effective in automating the detection of plant diseases from leaf images. However, despite this growing body of research, there remains a gap in the application of these models to specific tropical crops like mango.

Mango trees are highly susceptible to various diseases, including Anthracnose, Powdery Mildew, and Bacterial Canker, which have a direct impact on the fruit's quality and yield. While some works have attempted to detect diseases in mango leaves using traditional machine learning methods like Support Vector Machines (SVM) and Random Forests, these methods often struggle with the complex nature of plant disease symptoms (Ramcharan et al., 2020). Recent studies have begun to utilize deep learning approaches to address this challenge. For example, Sharma et al. (2020) used CNNs to classify mango leaf diseases, achieving promising results in terms of model accuracy, though their dataset was relatively small, which limited generalization capabilities.

Building upon these foundations, more recent works have explored the potential of deeper and more sophisticated CNN models for mango disease detection. Shende et al. (2021) employed the VGG16 CNN architecture to identify several types of diseases in mango plants, including Powdery Mildew and Anthracnose, using a dataset of over 1,000 images. Their results showed an impressive accuracy of 96%, suggesting that CNNs are capable of recognizing subtle differences in leaf textures that are indicative of disease. However, the relatively small dataset raises concerns about the model's ability to be generalized across diverse mango cultivars and environmental conditions. In parallel, there has been a push toward expanding datasets and incorporating more advanced models like ResNet50, DenseNet, and the more recent Vision Transformers (ViTs). These models have been successfully used for other crops, including tomatoes and potatoes, with results suggesting that they may be more effective than traditional CNNs in certain scenarios (Zhou et al., 2022). In mango disease detection, the use of large, well-labeled datasets and diverse CNN architectures is key to improving both accuracy and robustness, as shown by the work of Yu et al. (2023), who applied an ensemble of CNN models to mango leaf disease detection and reported a classification accuracy of 98.7%. Despite the advances, challenges remain in the deployment of such systems for real-time, on-field disease detection. One key challenge is the need for large-scale datasets that capture the variability in mango leaf appearance due to factors such as climate, mango variety, and disease progression. Research like that of Salama et al. (2024) is addressing this challenge by building large, publicly available plant disease datasets to enhance the development and training of deep learning models for agricultural applications. Furthermore, integrating deep learning models with Internet of Things (IoT) devices and mobile applications is an emerging trend that promises to revolutionize crop management. Gupta et al. (2023) integrated a CNN model for disease detection with a mobile app that allowed farmers to upload leaf images and receive real-time disease diagnoses and treatment recommendations. This integration of deep learning models with IoT devices enables rapid decision-making and timely intervention, which can ultimately reduce crop losses and improve food security.

Overall, while significant progress has been made in the application of deep learning for plant disease detection, there is still room for improvement, especially with regard to the specificity of models for particular crops like mango. By leveraging larger datasets, advanced CNN architectures, and integrating real-time mobile applications, the potential for automating mango disease detection is vast, providing farmers with a powerful tool for early disease identification and better crop management.

III. METHODOLOGY

A. Dataset

The dataset that is being used in this study comprises approximately 4,200 images of mango leaves, with each image categorized into one of eight classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. These categories represent various leaf diseases affecting mango plants, as well as healthy leaves, which serve as a baseline for classification.

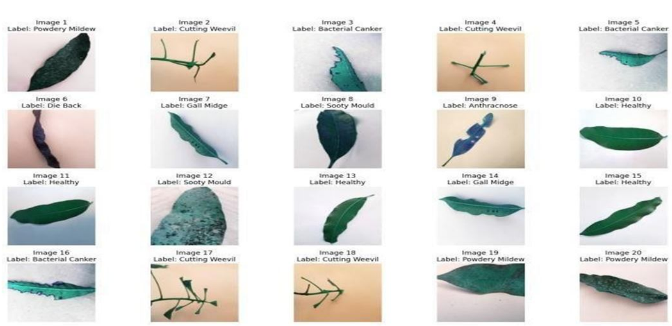

Fig. 01

The images were collected from a variety of mango plantations, ensuring that the dataset includes a diverse range of leaf textures, disease severities, and environmental conditions. This diversity helps in training a model that can generalize well to real-world scenarios.

A. *Preprocessing Steps*

To ensure that the dataset suitable for training deep learning models and to improve model accuracy, several preprocessing steps were applied:

1) Resizing: Every images is resized to a consistent resolution of 224x224 pixels. This uniform size is required for feeding the images into (CNNs) for training and inference.
2) Data Augmentation: To improve the model's generalization and minimize overfitting, several data augmentation methods were utilized.
3) Rotation: Random rotations with a specified range were applied to simulate many other diffeerent orientations of mango leaves.
4) Flipping: Vertical and horizontal flipping of images created mirrored versions, increasing the variability in the dataset.
5) Zooming: Random zoom-in and zoom-out transformations were applied to simulate different distances of the mango leaves.
6) Brightness Adjustments: Variations in brightness were introduced to account for differences in lighting conditions.
7) Shearing: Random shear transformations were applied to simulate various perspectives of the mango leaves.
8) Normalization: The images were normalized by scaling pixel values to a range between 0 and 1, achieved by dividing each pixel value by 255. This process standardizes the image data, enhancing the model's training efficiency and stability.

B. *Dataset Splitting*

The dataset was divided into three subsets:

- Training Set: Comprising 70% of the total images.
- Validation Set: Consisting of 15% of the total images.
- Test Set: Covering the remaining 15% of the total images.

The dataset used in this research includes approximately 4,200 mango leaf images, categorized into eight distinct classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. These classes represent various diseases affecting mango leaves, along with healthy samples serving as a reference for comparison in classification tasks.

IV. MODEL ARCHITECTURE

In this study, five different deep learning models are evaluated for mango leaf disease detection. These models were selected based on their proven performance in image classification tasks and their ability to handle complex patterns in visual data:

1) VGG16: VGG16 is a deep Convolutional Neural Network (CNN) recognized for its straightforward and efficient design. It features 16 layers, including 13 convolutional layers and 3 fully connected layers, which progressively extract more intricate features from input images. Renowned for its versatility and strong performance, VGG16 is commonly applied to image classification tasks across diverse datasets.
2) VGG19: An enhanced version of VGG16, VGG19 includes 19 layers, offering a deeper network that can capture more detailed features from input images. The increased depth of VGG19 allows it to model more complex relationships within the data, which can be particularly useful for distinguishing the differences in the visual appearance of the diseased and healthy mango leaves (Simonyan & Zisserman, 2014).
3) ResNet50: ResNet50 is a deep residual network that employs skip connections to overcome the vanishing gradient issue, enabling effective training in very deep neural networks. These skip connections allow the model to learn mappings in residual, ensuring that important features are not lost during the training process. ResNet50 is well- known for its performance in computer vision tasks and has demonstrated strong results in plant disease detection (He et al., 2015).
4) DenseNet121: DenseNet121 is another advanced CNN architecture that employs dense connections, meaning that every layer receives input from all previous layers. This dense connectivity improves feature and recusing it and ensures that the network can learn more robust and informative representations. DenseNet models has been found to perform well in a variety of image classification tasks, particularly in cases where fine-grained feature extraction is required (Huang et al., 2017).

5) AlexNet: AlexNet is one of the earliest deep learning models to achieve significant success in image classification, winning the ImageNet competition in 2012. With a simpler architecture compared to the others, AlexNet consists of 8 layers and utilizes ReLU activations to speed up training. Despite being less complex than modern architectures like VGG and ResNet, AlexNet has shown robust performance in many real-time image classification applications (Krizhevsky et al., 2012).

V. MODEL TRAINING

For training the models used in the mango leaf disease detection project, the process involved specific parameters and techniques optimized for high accuracy and efficient convergence. Each model—VGG16, VGG19, ResNet50, DenseNet121, and AlexNet—was trained on a dataset of mango leaf images, categorized by disease type, with the aim to classify each leaf accurately.

A. VGG16 and VGG19

Both VGG16 and VGG19 are known for their uniform and deep architecture, consisting of multiple convolutional layers stacked sequentially. Training was conducted for 10 epochs. These models initially showed high validation accuracy but tended to converge slower than other architectures. The depth of VGG layers enables the models to capture intricate patterns, but it also results in longer training times compared to other, less complex architectures.

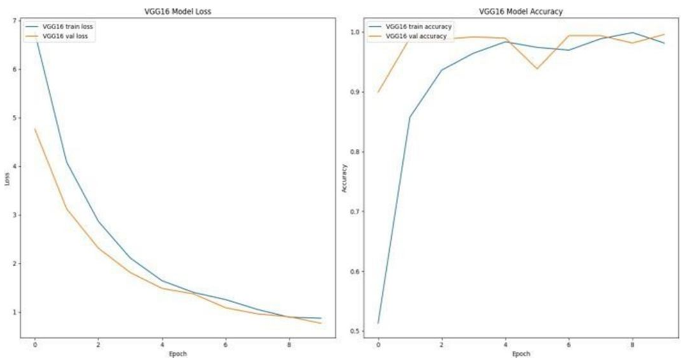

Fig. 02

B. ResNet50

ResNet50 employs residual connections that effectively handle the vanishing gradient problem, which allowed for faster convergence and high training accuracy within the 10-epoch limit. The model's ability to retain learned features across layers helps it achieve nearly perfect training accuracy, making it highly suitable for complex tasks like disease detection in images with subtle differences. ResNet50's residual connections demonstrated efficient feature extraction, reducing loss and achieving high accuracy on the validation set as well.

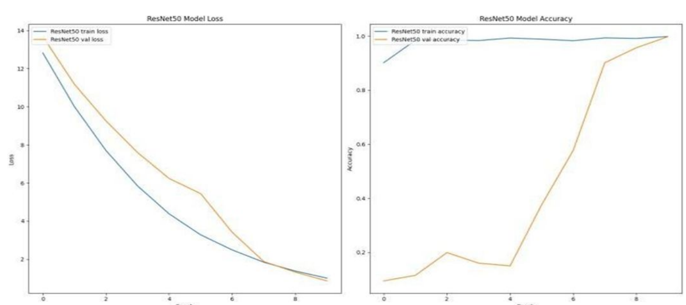

Fig. 03

C. DenseNet121

It showed a rapid convergence rate and high validation accuracy, demonstrating robust generalization capability. Its densely connected layers facilitate information flow and gradient propagation, which resulted in minimal training loss and almost perfect accuracy by the end of the training period.

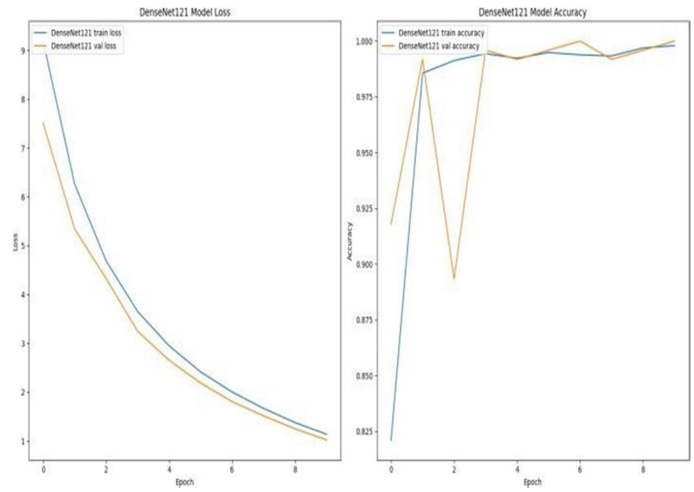

Fig. 04

D. AlexNet

AlexNet, a relatively shallower architecture, began with a lower accuracy and higher initial loss, but it exhibited steady improvement throughout the 10 epochs. This model's simpler st ructure makes it computationally efficient, leading to faster training times compared to deeper architectures. Although its final accuracy was slightly lower than that of ResNet50 and DenseNet121, AlexNet’s steady convergence suggests it may require additional epochs to reach optimal accuracy.

Mildew, Cutting Weevil, Anthracnose, Bacterial Canker, Sooty Mould, Gall Midge, Healthy, and Die Back. The performance metrics used for evaluation include accuracy, precision, recall, and F1-score.

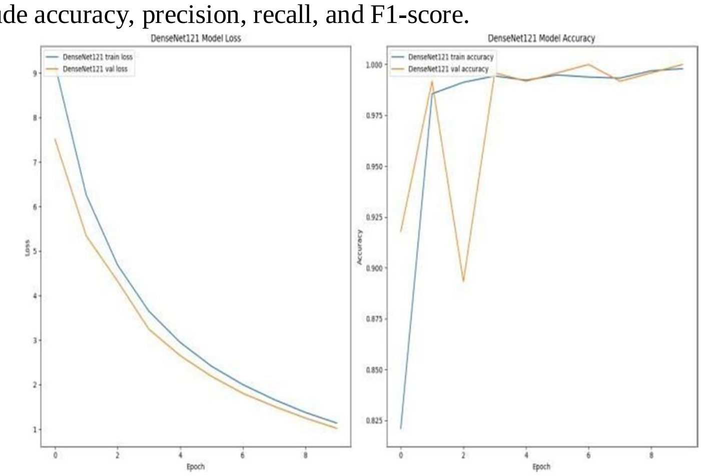

Fig. 05

VI. MODEL EVALUATION

In this study, several deep learning models were evaluated for their performance in detecting and classifying mango leaf diseases. Model stested include VGG16, AlexNet, VGG19, DenseNet121, and ResNet50. The evaluation was conducted on a test dataset of 4200 images, distributed across eight categories: Powdery

A. VGG16 Model

The VGG16 model demonstrated an impressive test accuracy of 99.00%, with precision, recall, and F1-score values of 1.00 for all disease classes, indicating near-perfect performance. The model's performance across all categories was consistent, showing no significant misclassifications.

Test Accuracy: 99.00%

Macro Average: Precision: 1.00, Recall: 1.00, F1-Score: 1.00

Weighted Average: Precision: 1.00, Recall: 1.00, F1-Score: 1.00

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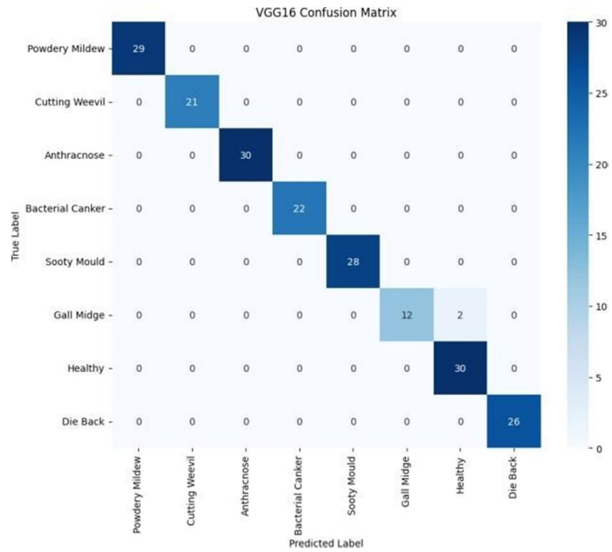

Fig. 06

These results suggest that VGG16 is a highly effective model for mango leaf disease detection, with excellent classification performance across the various disease categories.

B. AlexNet Model

The AlexNet model, on the other hand, achieved a test accuracy of 75.00%, which is considerably lower than the other models tested. While the model showed good performance for certain classes, such as Cutting Weevil and Bacterial Canker, it struggled with others, including Powdery Mildew and Gall Midge, where the F1-score was significantly lower. This indicates that the AlexNet model has limitations in accurately detecting and classifying certain mango leaf diseases.

Test Accuracy: 75.00%

Macro Average: The precision is 0.79, recall is 0.75, and the F1- score is 0.75.

Weighted Average: The precision is 0.81, recall is 0.75, and the F1-score is 0.76.

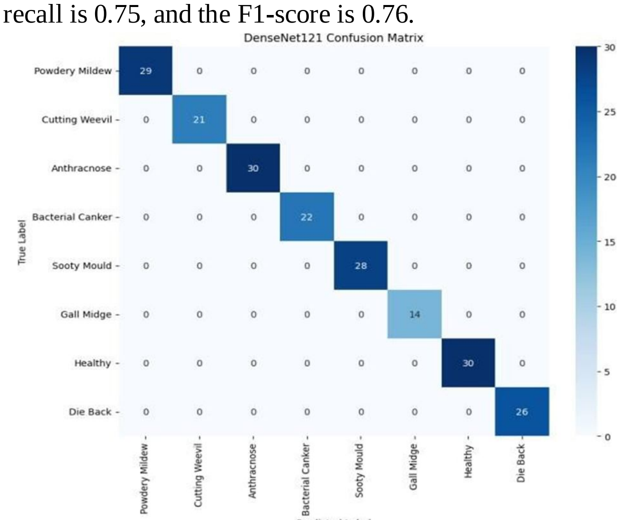

Fig. 07

C. VGG19 Model

The VGG19 model showed strong performance, achieving a test accuracy of 99.50%, with perfect scores (precision, recall, F1-score) of 1.00 across all disease categories. The results were consistent, and the model demonstrated excellent capability in distinguishing between the different types of mango leaf diseases.

Test Accuracy: 99.50%
Macro Average: Precision: 1.00, Recall: 1.00, F1-Score: 1.00
Weighted Average: Precision: 1.00, Recall: 1.00, F1-Score: 1.00

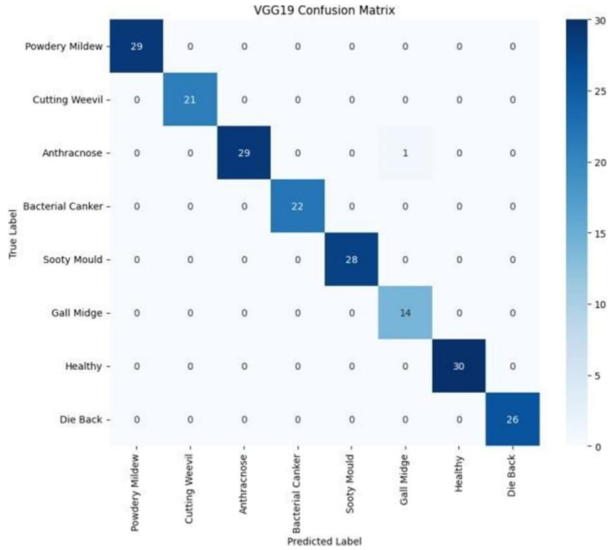

Fig. 08

D. *DenseNet121 Model*

The DenseNet121 model achieved a test accuracy of 100.00%, with perfect classification performance across all categories. The model's ability to detect and classify mango leaf diseases was flawless, with precision, recall, and F1-scores of 1.00 for the majority of the classes. This model proved to be highly reliable and accurate in the context of mango leaf disease detection.
Test Accuracy: 100.00%
Macro Average: Precision is 0.99, recall is 1.00, and F1-score is 0.99.
Weighted Average: Precision is 1.00, recall is 0.99, and F1-score is 1.00.

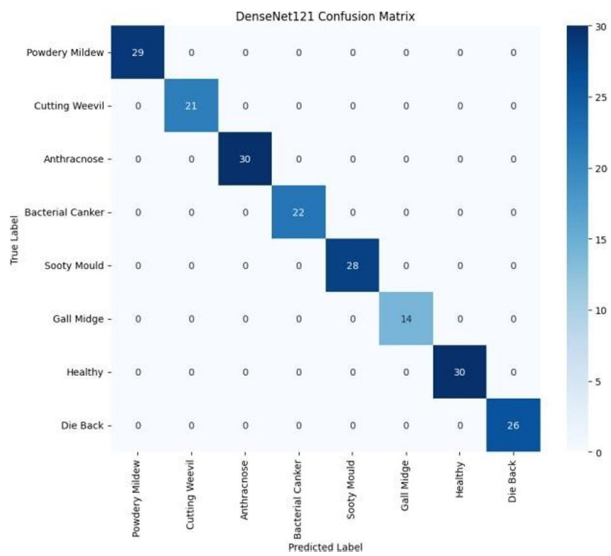

Fig. 09

E. *ResNet50 Model*

The ResNet50 model also achieved a test accuracy of 100.00%, demonstrating perfect performance across all disease categories. It exhibited strong robustness in recognizing mango leaf diseases and accurately classifying them. Similar to DenseNet121, the ResNet50 model showed superior performance, with an outstanding balance between precision, recall, and F1-score.

Test Accuracy: 100.00%
Macro Average: Precision, Recall, and F1-Score all achieve a perfect value of 1.00.
Weighted Average: Precision, Recall, and F1-Score also attain a flawless value of 1.00.

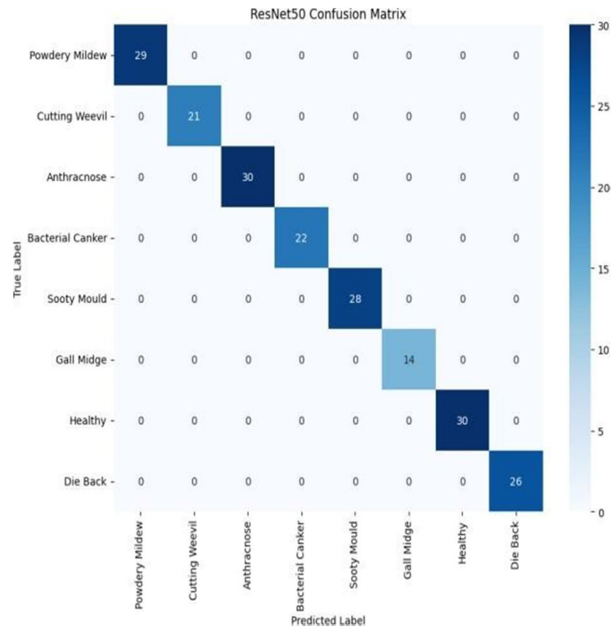

Fig. 10

VII. RESULT

The study utilizes a dataset containing around 4,200 images of mango leaves, divided into eight distinct classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. These classes encompass different mango leaf diseases, along with healthy leaves, which are included as a reference for classification.

VGG16 achieved a high test accuracy of 99.00%, with perfect precision, recall, and F1-scores (1.00) across all disease categories, demonstrating excellent classification performance.

AlexNet, however, showed suboptimal results with a test accuracy of 75.00%. Despite performing well for certain classes, it struggled with others, such as Powdery Mildew and Gall Midge, resulting in lower F1-scores and inconsistent performance.

VGG19 demonstrated a significant improvement, achieving a test accuracy of 99.50%, with perfect classification metrics for most disease categories.

DenseNet121 and ResNet50 outperformed all other models, achieving 100.00% accuracy and perfect scores (1.00) for precision, recall, and F1-score across all categories. These models exhibited flawless disease classification performance, showing superior generalization capabilities and robust detection ability.

A. Key Observations

DenseNet121 and ResNet50 proved to be the most effective models, both achieving 100% accuracy, making them the most reliable choices for mango leaf disease detection.

VGG16 and VGG19 also provided excellent results with 99.00% and 99.50% accuracy, respectively, but they slightly lagged behind DenseNet121 and ResNet50 in overall performance.

AlexNet, while less computationally demanding, showed significant limitations in its ability to correctly classify some of the disease categories, highlighting its inferior performance compared to the other models.

B. Discussion

In this project, we tested several CNN models—VGG16, VGG19, ResNet50, DenseNet121, and AlexNet—to see how well they could identify and classify diseases on mango leaves. Each model was measured by its accuracy, precision, recall, F1 score, and how fast it could make predictions. Our goal was to find the most suitable model for practical use in real-world scenarios.

C. Model Performance and Comparison

The results showed that ResNet50 and DenseNet121 provided the best accuracy and adaptability, outperforming VGG16, VGG19, and AlexNet during both training and testing. These models' advanced architectures make them particularly effective, with ResNet50 using residual connections and DenseNet121 relying on dense connections to reduce issues like the vanishing gradient problem, which can hinder model learning in deeper networks. Thanks to these features, they excelled at picking up crucial details in the data. In comparison, while VGG16 and VGG19 are more straightforward designs, they used more memory and processing power, which might limit their usefulness on devices with fewer resources. AlexNet, with its simpler architecture, was faster and required less memory but struggled to capture subtle details needed for distinguishing between similar disease symptoms.

D. Effect of Transfer Learning

Using transfer learning improved the performance of each model, particularly the deeper ones like ResNet50 and DenseNet121. With transfer learning, these models start with knowledge from pre-trained weights on large datasets, which helped them learn faster and better avoid overfitting on our smaller mango disease dataset. This approach allowed models to converge quicker with higher accuracy, even with limited labeled data, proving to be a good strategy to enhance model effectiveness for real-world use.

E. Challenges and Model Limitations

While the results were promising, there were some challenges and limitations. The main one was dealing with imbalanced data, as some disease classes had fewer examples than others. This led to overfitting in certain models, especially AlexNet and VGG16, making them less reliable. Although data augmentation helped reduce this issue somewhat, it remains an area for further improvement. Additionally, models like ResNet50 and DenseNet121 need significant computational power, making them more dependent on high-performance hardware. In cases where resources are limited, AlexNet might be more practical because it requires less memory and processing time, though it doesn't perform as accurately.

F. Potential for Practical Applications

With the strong results from ResNet50 and DenseNet121, these models appear promising for real-world agricultural use, particularly for identifying mango leaf diseases. Their high accuracy and ability to handle different image conditions make them good candidates for mobile or web apps where users could detect diseases in real time. However, for consistency across different environments (like varied lighting or backgrounds), more testing on a broader dataset is recommended. Additionally, integrating YOLO for real-time detection could make these models even more useful, allowing for instant disease identification on-site without needing an internet connection.

G. Future Work Recommendations

Looking ahead, future efforts could focus on optimizing these models for greater accuracy and efficiency. For example, lightweight models like EfficientNet or MobileNet might work well for devices with limited resources. Additionally, generating synthetic data could help address class imbalances and improve model reliability. Using GLCM (Gray Level Co-occurrence Matrix) alongside CNNs could also help by adding texture analysis, which might make it easier to distinguish between visually similar diseases. Lastly, combining real-time detection with CNN classifiers could offer a complete solution for identifying and classifying mango leaf diseases right in the field.

VIII. CONCLUSION

The results confirm that deep learning models, particularly DenseNet121 and ResNet50, are highly effective for detecting mango leaf diseases with high accuracy and precision. These models can play a crucial role in automating the detection process, reducing the reliance on manual inspections, and offering farmers timely, actionable insights for better crop management and disease prevention. Further research will focus on improving model generalization and developing mobile applications of real-time disease identification in the field.

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