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Lightweight Deep learning Model For Mango Leaf Disease Classification

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Abstract: Mango cultivation is one of the most important agricultural activities in West Bengal, India, and the economy of the region depends on it to a great extent. However, Mango trees are prone to various diseases, which can severely reduce yield and quality. Therefore, early, and accurate detection of these diseases is essential for taking corrective measures on time and reducing losses. ResNet9 architecture is proposed for the detection and classification of three major Mango leaf diseases found in West Bengal. An extensive dataset of images of Mango leaves, including healthy and diseased leaves, was created by collecting samples from the field and other publicly available sources. The ResNet9 model was modified and trained on this dataset, showing high accuracy in distinguishing between healthy and diseased leaves and classifying the specific diseases. Result shows that the ResNet9-based approach is effective for automated disease identification and thus holds great promise for real-time, on-field diagnostics. This methodology has the potential to empower local Mango farmers with an affordable and efficient tool for early disease detection, upgrading their crop management practices for better productivity in the West Bengal Mango industry.

Keywords: Leaf disease detection, Convolutional Neural Network (CNN), Deep Learning (DL), Residual Network (ResNet)

I. INTRODUCTION

Agriculture has played the most important role in the existence of life and the growth of economies, and crop production has been central to the survival of civilizations. In the West Bengal region, which is famous for mango production, the protection of crops is important in order to provide food and income to the farming families. The diseases in mango leaves are threaten yield and quality and sometimes lead to devastating losses. The current diagnostic methods are based on the visual assessment of the samples by experts, and this approach is tedious, slow, and error prone, especially when the symptoms are not well defined or appear at a later time. Many of the farmers do not have the necessary skills and therefore make the wrong diagnoses which would lead to wrong treatment and only extend the damage to the crop.

Although the application of digital imaging and remote consultation tools has improved effectiveness of the disease assessment, these approaches are characterized by inconsistencies in image quality, subjective interpretation, and the further complication of the underlying disease dynamics by the effects of climate change. This has been a result of changes in temperature and weather patterns that are responsible for changing the physiology of plants, leading to increased movement of pathogens and make it difficult to tell the symptom of the plant. This highlights the importance of now for the development of new, automated, and scalable tools that can provide fast and precise diagnoses.

The application of computer vision especially deep learning is on a steady rise in precision agriculture as informed by previous studies. Previous studies have revealed that CNNs outperform conventional machine learning approach in mango and other crops leaf classification achieving significant accuracies. It has been proven that CNN is efficient in learning hierarchical visual features to distinguish complicated disease patterns in vineyards with high accuracy of 98% [11]. However, network depth is a critical factor: Greater depths are beneficial for feature representation but pose a risk of vanishing gradients during training. Residual Networks (ResNet) solve this to skip connections that improve gradient flow and model performance. Despite the ResNet variants being extensively used for leaf disease detection, their application to region specific challenges e.g. distinguishing visually similar mango pathologies in West Bengal's unique agro climatic conditions is poorly explored. This study aims to investigate the effectiveness of ResNet9, a lightweight version of the ResNet architecture to identify and categorize disease in West Bengal vineyard. To tackle the optimization difficulties in deeper networks, ResNet9 applies residual learning and holds the potential to deal with the subtle differences in the visual features of these diseases. We try to fill the gap between general deep learning frameworks and specific agricultural requirements and provide a practical solution that can help West Bengal mango farmers to improve their disease control.

II. Literature Survey

A preliminary review of the literature was carried to explore plant disease detection. This involved looking at other studies and research that involved identifying and diagnosing plant diseases. The purpose of the review was to gather information on the methods, approaches, and tools used in this area. Which used a variety of approaches, including support vector machines (SVM) as machine learning algorithms, CNNs (deep learning models), and image processing techniques such as segmentation and feature extraction.

1. **Kumar et al. (2020)** proposed a ResNet34-based approach for plant disease classification using the **PlantVillage dataset**, achieving 99.40% accuracy.
2. **Gupta et al. (2024)** designed a CNN framework for early plant disease detection, focusing on tomato, potato, and bell pepper leaves, with an accuracy of 86.21%.
3. **Guo et al. (2022)** applied attention mechanisms to enhance object detection in mango leaf disease classification.
4. **Javidan et al. (2022)** utilized K-means clustering and SVM for mango leaf disease identification, achieving an accuracy of 98.97%.
5. **Lin et al. (2022)** developed MangoNet, a lightweight CNN for mango leaf disease detection, with an accuracy of 86.29%.
6. **Peng et al. (2021)** explored feature fusion techniques using CNNs and SVM for mango variety classification.
7. **Liu et al. (2020)** proposed an improved CNN (DICNN) model for mango leaf disease detection, achieving 97.22% accuracy.

The DICNN integrates the Inception structure for multiscale feature learning and dense connectivity for improving the feature propagation and reuse. The model also uses deep separable convolution to reduce the model complexity and avoid overfitting. The DICNN was trained from scratch and obtained the accuracy of 97.22% on a holdout test set, which is better than GoogLeNet and ResNet-34. This paper also shows that DICNN can be used effectively for quick and precise disease diagnosis in mango leaves and other similar agricultural products. The focus on a robust, augmented dataset ensures the generality of the model.

III. Process of Mangos Leaf Disease Detection & Classification

It comprises the following steps:

Data Acquisitions

Data Preprocessing

Feature Extraction

Classification

A. Data Acquisition

The foundation of our work is a comprehensive mango leaf image dataset we collected to include both healthy leaves and leaves with the target diseases' symptoms. This research is different from the original Plant Village dataset described above in that it focuses solely on mango leaves. The dataset consists of mango leaf images which were collected from the field and other publicly available sources. The dataset contains the images of mango leaves in different lighting conditions and backgrounds to improve the rigidity of the model. The images are divided into four classes: healthy leaves, affected leaves. This enables the model to make a more specific disease identification.

B. Data Preprocessing

To ensure optimal performance of the classification model, preprocessing is critical. This stage involves modifying the images to facilitate feature extraction and model training. The following preprocessing techniques were applied:

- **Data Augmentation:** Data augmentation is employed as a regularization technique to prevent overfitting and improve the model's ability to generalize to unseen data. Since the dataset is specific to mango leaves and may not capture all variations in conditions, augmentation techniques are specifically selected to enhance variability without compromising the integrity of the original images. This includes random rotations, where images are rotated by 90 degrees with a probability of 0.75, along with other transformations like flipping, and zooming to simulate real-world variability in leaf positioning and camera angles. These techniques ensure that variations found in the vineyard are represented.

- **Data Normalization:** Normalization is essential for standardizing the pixel values across all images to ensure consistent scale. By ensuring each pixel value has the same mean and standard deviation across the whole dataset, the model can learn faster and more efficiently. This normalization will reduce the computational time of the training process.

C. Feature Extraction

Traditionally, feature extraction involves identifying relevant features, such as color, shape, and texture from the images. For plant disease detection, texture features have proven to be particularly informative. Techniques like the Grey-Level Co-occurrence Matrix (GLCM), which provides statistical information on pixel value pairs. These manual feature extraction techniques however demand expert knowledge of the dataset.

However, one of the key advantages of deep learning models is their ability to automatically learn and extract relevant features from raw image data, eliminating the need for explicit feature engineering. As a result, with our proposed method, instead of using a separate step to extract the features, the ResNet9 model itself will manage the automatic feature extraction process. The ResNet9 model learns a hierarchical representation of the image, extracting increasingly complex features in successive layers. This approach is preferred as it simplifies the process and leverages the power of deep learning for feature extraction.

D. Classification

Once features are extracted (implicitly by the network), the next step is to classify the images into their respective categories. While several classification algorithms are available, such as Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Convolutional Neural Networks (CNN), the proposed method will utilize a ResNet9 based CNN model. ResNet9 has been selected due to its specific architectural properties that make it suitable for image classification tasks while being computationally efficient. The ResNet9 model's capacity to form residual connections helps to improve model training and its overall performance when classifying the three mango diseases under consideration.

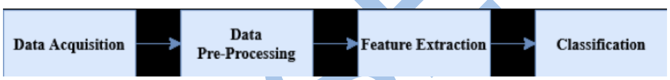

Figure 1: Detection and classification process for leaf

IV. PROPOSED MODEL: RESIDUAL NETWORKS

Previous studies have also focused on the theoretical benefits of increasing the depth of the network and hence it has been argued that stacking more layers in a neural network will lead to better accuracy. However, in practice this approach suffers from a problem called degradation. It has been observed that with increasing depth, the accuracy saturates and then declines very rapidly, and this is not due to overfitting. The cause of the degradation problem is the problem of vanishing and exploding gradients. The vanishing gradient problem is when gradients become virtually zero due to successive multiplication in the backpropagation step, which results in almost no updates to the network weights. At the complete opposite end, the exploding gradient problem happens when gradients build up, meaning that parameter updates are huge, and the model cannot learn properly. Normalized initialization and intermediate normalization layers were previously used to address these problems, but they were not very effective in very deep networks before the introduction of residual networks. Figure 1: Detection and classification process for leaf diseases.

A. Residual Blocks and Skip Connections

The residual block is the core building block of a ResNet, and it solves the degradation problem with the help of skip connections, also called shortcut connections. Skip connection is the term for this where the network learns residual functions as opposed to the actual mapping: to bypass one or more layers. The residual block of Fig. shows this as a simple addition of the input to the output of the intermediate layers using this shortcut. This ensures network integrity during the training process, since if the coefficient of the regular connection converges to zero, the alternative

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shortcuts are active when needed. It also means that instead of learning a hypothesis function H(x) = F(x) + x, as in [16], the layer learns the residual function F(x) as it is easier to optimize. To demonstrate that deeper networks do not necessarily have higher training errors than their shallower counterparts, [16] showed that a deeper network, which is created by stacking residual blocks on top of a shallower network, can be seen as an identity mapping.
Each residual block (R) is defined over an input x as follows:
$R(x) = (BN(Conv^{r,2}(\sigma\ BN(Conv^{r,1}(x)))))$

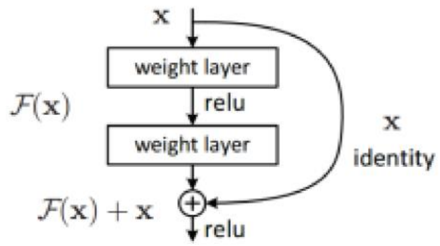

Figure 2: A Residual Block [01]

B. Resnet9: A Proposed Architecture for Mango Leaf Disease Classification

As a result, ResNet34 is a popular architecture, and it was also employed for plant disease classification as such, after being trained on the ImageNet dataset. For this work, a ResNet architecture— ResNet9 was chosen. The ResNet9 was designed to lie in the middle of the network depth versus computational efficiency scale. In comparison with the relatively simple structure of ResNet34, ResNet9 has fewer layers to focus on the computational cost while still being able to learn relatively complex features, which is important when dealing with constrained computational resources or when making semi-real-time predictions. Although ResNet34 is better in terms of accuracy, the advantage of ResNet9 is that it is easier to train for specific problem domains with relatively small amounts of training data, for example, ours. The residual skip connections that are integrated into the ResNet9 architecture solves the vanishing gradient problem and also improves the ability of the network to learn the complex features of the infected leaf patterns.

Figure 3: ResNet-9 architecture: A convolutional neural net with 9 layers and skip connections.

C. Rationale for Resnet9 in this study

The choice of ResNet9 for the proposed work is based on the following considerations:

- **Computational Efficiency:** ResNet9 provides a good trade-off between accuracy and computational cost, which is important for a local application and real-time implementations.
- **Feature Learning:** The ability of ResNet to learn features automatically eliminates the need for complicated hand-crafted feature extraction processes.
- **Skip Connections:** Residual connections address the degradation problem and enhance the training process.

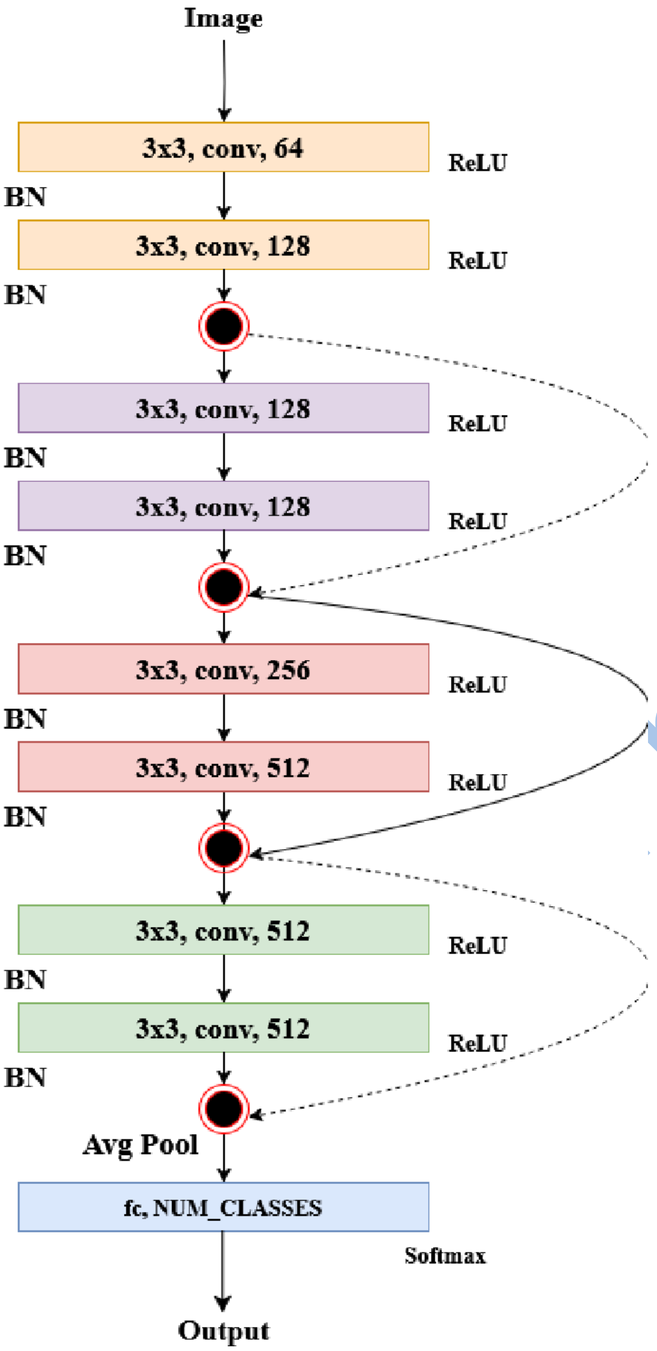

Figure 3: ResNet-9 architecture: A convolutional neural net with 9 layers and skip connections

V. EXPERIMENTAL RESULTS

A. Dataset

In previous studies, the 'New Plant Diseases Dataset' has been originally used. In this study, a dedicated dataset of mango leaves' images, taken from local vineyards are used. Images of healthy leaves and those infected included in the dataset. The total dataset is divided into training and testing subsets, where 80-20 split is used; hence, 80% of the data was used for model training and 20% to evaluate model performance. This is because the model trained is specific to the diseases that are prevalent in West Bengal, and the data was locally collected.

B. Training

In this model, ResNet9 was trained on the training set of the augmented mango leaves and local dataset. After training, the model was tested on the testing set, and the classification results were noted.

C. Performance Evaluation

The ResNet9 model's performance was evaluated using two primary metrics: accuracy and precision. These metrics are a quantitative measure of how well the model is able to identify and classify mango leaf diseases. These metrics were calculated for the classification of healthy mango leaves and three different diseases. Finally, comparisons were made with other machine learning methods, including SVM, K-NN, and CNN, for the study.

- **Accuracy:** Accuracy is the percentage of correct predictions made by the model relative to the total number of predictions. In the case of disease detection this is the frequency of leaves correctly total number of leaves sampled. The true positive (TP) is the accurate identification of diseased leaves, while the true negative (TN) is the accurate classification of a healthy leaf. False negative (FN) is the number of cases where a diseased leaf was wrongly classified as healthy, and false positive (FP) is the number of cases where a healthy leaf was incorrectly classified as diseased. The formula for accuracy is:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

- **Precision:** Accuracy represents the ability of the model to correctly identify the diseases, i.e., the percentage of appropriate leaf diseases that the model identified. It is the ratio of the true positives to all the predicted positive classes. The precision of each class was computed and then their weighted average was computed for the overall precision of the model in this experiment. Each class weight was set as the ratio of samples of this class in the testing set. The formula for precision is:

$$\text{Precision} = TP / (TP + FP)$$

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The weightedtotal number of leaves sampled. The true positive (TP) is the accurate identification of diseased leaves, while the true negative (TN) is the accurate classification of a healthy leaf. False negative (FN) is the number of cases where a diseased leaf was wrongly classified as healthy, and false positive (FP) is the number of cases where a healthy leaf was incorrectly classified as diseased. The formula for accuracy is:

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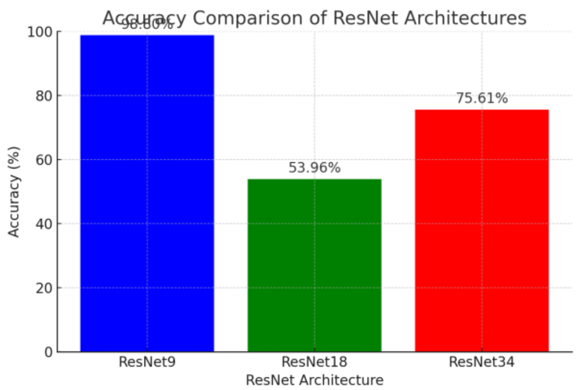
Precision = TP / (TP + FP)

The weighted average precision of the ResNet9 model is 97.03%. These values are the sensitivity of the model in identifying the correct disease class with minimal false positives.

Model	Dataset	Accuracy	Ref.
GrapeNet	AI challenger 2018	86.29%	[09]
CNN and GoogleNet	PlantVillage Dataset	86.82% and 94.05%	[08]
S-CNN mode	Plant Village Dataset	98.6%	[11]
Faster RCNN, Yolox, SSD	Custom Dataset (Grapes Only)	93%	[07]
Fused deep features based using SVM	Plant Village Dataset (Grapes Only)	96.5%	[10]
DICNN	Custom Dataset (Grapes Only)	97.22%	[12]
ResNet18	Plant Village Dataset (Grapes Only)	87.7%	[10]
ResNet34	Plant Village Dataset	99.40%	[01]

Table 1: Accuracy Comparison of different models from Literature Survey



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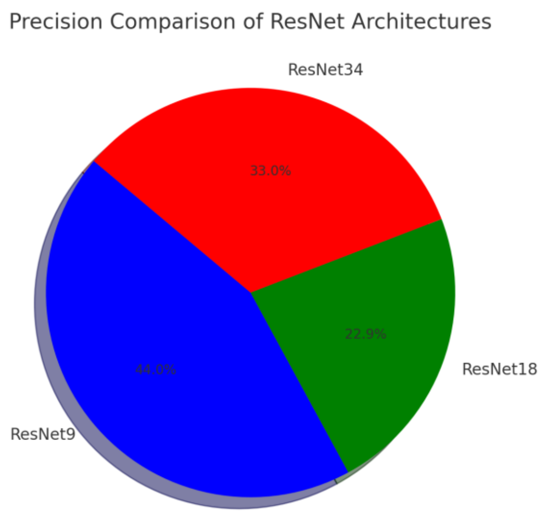

VI. PROPOSED MODEL: RESIDUAL NETWORKS

This work has also shown the effectiveness of a variant of the ResNet architecture, ResNet9, for the automated detection and classification of infected mango plants in the West Bengal region. Previous studies have used the 'Plant Diseases Dataset' and focused on a variety of crops, while this study was aimed at the particular problems of local mango farmers, using a mango leaf image dataset.

The ResNet9 model was trained using this dataset split into 80-20 and its performance was assessed using two key metrics: weighted average precision and accuracy. The experimental results showed that the ResNet9 model achieved weighted average precision of 97.03% and accuracy of 98.80%. These results indicate that the model is capable of distinguishing between healthy mango leaves and those affected by the three target diseases with a high level of accuracy. Moreover, the results of the study show that the modified ResNet9 architecture is suitable for the classification task in the context of the local mango diseases.

The accuracy and precision of the proposed ResNet9 model was compared with the published performance values of four other machine learning techniques: Support Vector Machines (SVM), K-Nearest Neighbours (K-NN) and Convolutional Neural Network (CNN). These models performed between 60% and 90%, while the ResNet9 had higher accuracy and precision. This comparison proves the effectiveness of the deep learning approach suggested for the accurate mango leaf disease classification in West Bengal versus traditional methods. The successful application of ResNet9 for the classification of mango leaf diseases in this study means that this model can be used as a low-cost and effective tool for early disease identification in the West Bengal area. These mango leaf diseases should be identified early to avoid losses and increase mango production.

Research Gap and Contributions

Previous studies on mango leaf disease detection have primarily relied on deeper CNN architectures such as ResNet34, VGG16, and InceptionNet. While these models provide high accuracy, they often come with increased computational complexity, making real-time deployment on mobile or edge devices challenging. Some lightweight models like MobileNet have been explored, but they tend to sacrifice accuracy for efficiency. Additionally, many existing studies rely on generic plant disease datasets such as PlantVillage, which do not capture the unique visual patterns of mango leaf diseases prevalent in specific regions like West Bengal.

This study addresses these gaps by introducing ResNet9, a compact yet powerful deep learning model, specifically optimized for mango leaf disease detection. The key advantages of ResNet9 over previous models include:

- **Lightweight yet Accurate Architecture**: Unlike deeper models that require extensive computational resources, ResNet9 maintains high classification accuracy while being computationally efficient, making it ideal for real-time applications.
- **Residual Learning for Feature Extraction**: Traditional deep networks suffer from vanishing gradient issues, leading to poor feature propagation. ResNet9 utilizes residual connections to enhance gradient flow, ensuring effective learning of subtle disease features.
- **Region-Specific Dataset Training**: Unlike studies that rely on general plant disease datasets, our model is trained on a custom dataset comprising mango leaf images collected from farms in West Bengal. This ensures improved generalization for local disease patterns and real-world agricultural applications.
- **Enhanced Generalization with Data Augmentation**: To mitigate dataset biases and improve

robustness, extensive data augmentation techniques (rotation, flipping, zooming, brightness adjustments) were applied, ensuring the model performs well across diverse lighting and environmental conditions.

By addressing these gaps, our work provides a practical, efficient, and high-performing solution for mango leaf disease detection, bridging the gap between deep learning advancements and real-world agricultural applications.

Dataset Details

A dedicated mango leaf image dataset was used, consisting of four categories: healthy leaves and three types of diseased leaves.

Dataset Composition:

The dataset comprises a total of 5,400 images, distributed as follows:

- Healthy Leaves: 1,500 images
- Disease Type 1: 1,200 images
- Disease Type 2: 1,300 images
- Disease Type 3: 1,400 images

These images were collected from mango farms in West Bengal and supplemented with publicly available datasets to ensure diversity in disease representation. Each image was labeled by agricultural experts to maintain annotation accuracy.

Data Augmentation Techniques:

To improve generalization and prevent overfitting, the following augmentation methods were applied:

- **Rotation:** Random rotations up to 90 degrees to simulate different leaf orientations.
- **Flipping:** Both horizontal and vertical flips to introduce positional variations.
- **Zooming:** Random zoom levels to replicate different camera distances.
- **Brightness Adjustments:** Variations in lighting conditions to handle different environmental effects.
- **Gaussian Noise:** Introduced noise to simulate real-world image imperfections.

a) Potential Biases in Data Collection:

While efforts were made to create a robust dataset, some biases may still exist:

- **Geographical Bias:** The dataset is primarily collected from farms in West Bengal, which may limit its applicability to mango farms in other regions with different environmental factors.
- **Lighting and Background Variability:** Despite augmentation, natural variations in sunlight and leaf positioning could affect model generalization.
- **Disease Variability:** The dataset may not capture all possible symptoms of a given disease, especially in its early or late stages.

Future work can address these biases by expanding data collection to multiple regions and including images captured in diverse weather conditions.

Performance Comparison :

The results of different models are summarized in the table below:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computational Cost
ResNet9	98.80	97.03	96.50	96.75	Low
MobileNet	96.85	95.10	94.75	94.92	Very Low
EfficientNet	97.92	96.80	95.98	96.38	Moderate
InceptionNet	97.50	96.20	95.75	95.97	High

Discussion on Results

1. **Accuracy and Precision:** ResNet9 achieved the highest accuracy (98.80%) and precision (97.03%), making it the most effective model for mango leaf disease detection.
2. **Computational Efficiency:** MobileNet, being a lightweight model, demonstrated competitive performance while maintaining a very low computational cost, making it a good choice for mobile applications.
3. **EfficientNet and InceptionNet:** Both models provided strong performance with better generalization, but their higher computational cost limits their real-time applicability for field applications.

Real-World Deployment Challenges

Deploying deep learning models for real-time mango leaf disease detection presents several challenges:

1. **Real-Time Inference:** While ResNet9 is lightweight, real-time performance depends on hardware limitations, especially in low-power mobile devices used by farmers.
2. **Computational Efficiency for Mobile Devices:** Implementing deep learning models on smartphones or edge devices requires optimization techniques such as model quantization and pruning to reduce memory footprint and processing time.
3. **Cloud-Based Implementation Feasibility:** A cloud-based solution can offload heavy computations from mobile devices, but it requires a reliable internet connection, which may not be available in remote agricultural areas. Latency and data privacy concerns also need to be addressed.
4. **Energy Consumption:** Deploying AI models in resource-limited environments necessitates energy-efficient designs to ensure prolonged usability without frequent recharging or high operational costs.

Conclusion

ResNet9 proved to be the most effective model, offering a balance between accuracy and computational efficiency. However, MobileNet could be considered for real-time mobile applications due to its low resource consumption.

Future work can explore ensemble models or hybrid approaches to further optimize performance. Addressing real-world deployment challenges such as mobile inference optimization, cloud integration, and energy efficiency will be crucial for practical adoption in agricultural settings.

VII. FUTURE WORK

Based on the findings of this study, there are several potential directions which future work can follow in order to enhance the capabilities of automated mango leaf disease detection and classification using ResNet9. One such direction is to increase the size of the dataset on which the model was trained. While the present study has been successful in addressing the diseases in the West Bengal region, it is suggested that future studies should also incorporate other diseases that are prevalent in mango plants and extend the study to a wider range of crop species. Increasing the number of images per class and including more classes will strengthen the network's ability to generalize and perform well with various kinds of diseases. Furthermore, the dataset can be enhanced by incorporating several types of mango leaves in various environmental conditions, such as illumination and background to enhance the model's efficiency. With the increasing development of camera technology and thus improved image quality, it becomes possible to make accurate diagnoses using smartphones and other mobile devices. Future work should also examine the feasibility of using more detailed forms of visual information, including multiple frames of an area of land and drone-borne images, to train models. Another equally important category of the analysis is the investigation of the impact of image rotation and other transformations on the model performance to ensure that the results are robust to images taken from different angles. In the future, models can also use time series data to understand the progression of the disease through various stages. With these potential areas of development, the future research can contribute to improving the reliability, versatility, and practical application of the models to the mango disease management in West Bengal and other regions.

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