Lemon Leaf Disease Detection Using CNN and MobileNet

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***Abstract*—Leaf diseases significantly impact agricultural yield, necessitating robust detection methods for early intervention. This paper presents a comparative analysis of two deep learning approaches for leaf disease detection using a publicly available Kaggle dataset comprising images of nine lemon leaf types, categorized into two classes: healthy and diseased. A custom Convolutional Neural Network (CNN) model, tailored for leaf disease classification, achieved an accuracy of 87.41%. In contrast, a transfer learning approach utilizing the MobileNet model yielded a superior accuracy of 99.22%. The results demonstrate the effectiveness of transfer learning in handling diverse lemon leaf types and complex disease patterns, offering higher accuracy with reduced computational overhead. This study highlights the potential of deep learning for precision agriculture and provides valuable insights into model optimization for scalable, real-world applications.**

***Index Terms*—Leaf Disease Detection, Convolutional Neural Network (CNN), MobileNet, Transfer Learning, Deep Learning.**

I. INTRODUCTION

The agricultural sector plays a pivotal role in ensuring global food security, yet it is continually challenged by biotic stressors, notably plant diseases that compromise crop yield and quality. Leaf diseases, in particular, pose a significant threat due to their rapid spread and potential to devastate entire harvests. Conventional diagnostic methods, reliant on manual inspection by agronomists, are labor-intensive, susceptible to subjective errors, and impractical for large-scale agricultural systems. Consequently, there is a pressing need for automated, accurate, and scalable solutions to facilitate early detection and management of leaf diseases.

Recent advancements in deep learning have transformed the landscape of precision agriculture, offering robust tools for automated disease detection. Convolutional Neural Networks (CNNs) and transfer learning frameworks have demonstrated remarkable success in image-based classification tasks, making them well-suited for identifying disease symptoms in plant imagery. This paper investigates the efficacy of two deep learning approaches for lemon leaf disease detection using a publicly available dataset from Kaggle, comprising images of nine leaf types categorized into healthy and diseased classes. We propose a custom-designed CNN model, engineered to extract disease-specific features, which achieves a classification accuracy of 87.41%. Additionally, we employ MobileNet, a lightweight architecture optimized through transfer learning, attaining a superior accuracy of 99.22%. This study aims to compare the performance of these models, elucidate the benefits of transfer learning in resource-constrained settings, and provide actionable insights for deploying deep learning solutions in real-world agricultural applications.

II. RELATED PAPERS

We evaluated and summarized pertinent research related to our study in this section. A wide variety of publications on different aspects of machine learning, particularly in the domain of plant disease detection using convolutional neural networks (CNNs) and transfer learning models. The key findings from these investigations, which have considerably advanced the field, are reviewed in detail below:

The paper [1] presents a method for classifying lemon leaf diseases using CNN models and transfer learning. Models like DenseNet-201, ResNet-50, ResNet-152V2, and Xception were tested, with Xception achieving the highest accuracy of 94.34%. This approach outperforms prior methods by addressing challenges like small datasets and limitations in methodology. The research contributes to more effective disease detection in citrus plants, potentially reducing production losses.

The paper [2] explores the detection of citrus leaf diseases using CNN models and transfer learning, leveraging a PaaS cloud platform for mobile applications. It classifies five leaf conditions: black spot, melanose, canker, greening, and healthy. The study employs models like ResNet152V2, InceptionResNetV2, and DenseNet201, achieving a 98% precision and recall, with an F1 score and ROC-AUC of 0.99. An augmented dataset enhanced model performance. Additionally, a compact 15-layer CNN was deployed on the cloud, enabling real-time disease identification through smartphones. This research offers a practical and efficient approach to early disease detection in agriculture.

The paper [3] introduces the CLTN model, a hybrid of CNN and LSTM, for detecting and classifying Lemon Citrus Canker (LCC) disease. Using a dataset of 3,000 images, the model achieves 94.2% accuracy in binary classification and 98.43% accuracy in multi-classification of disease severity levels. This approach enhances lemon disease detection and classification, addressing challenges in agricultural productivity.

The author of this [4] applies the DenseNet121 model to automate lemon quality detection, classifying lemons as ”Good Quality” or ”Bad Quality.” Using a dataset of 2,076 images, the model achieved 96% accuracy after preprocessing techniques like resizing, normalization, and data augmentation. This study demonstrates the potential of deep learning in optimizing agricultural and supply chain processes.

The paper [5] utilizes the Inception ResNet V2 model for citrus disease detection and classification. It focuses on identifying diseases like black spot, canker, and melanose, achieving high accuracy and efficiency. The study emphasizes the importance of deep learning in agricultural disease management, offering a robust solution for early detection and prevention.

The studies reviewed highlight advancements in disease detection and classification but reveal gaps in lemon leaf disease research. This paper addresses these with a focused, practical approach for improved detection.

III. PROPOSED METHODOLOGY

The development of an effective leaf disease detection system requires a robust methodology that encompasses data preparation, model design, and evaluation. This section outlines the approach adopted to classify lemon leaf images into healthy and diseased categories using deep learning techniques. The methodology leverages the Lemon Leaf Disease Dataset (LLDD) from Kaggle, which is preprocessed to ensure compatibility with the proposed models. Two models are evaluated: a custom Convolutional Neural Network (CNN) designed for feature extraction and classification, and MobileNet, a pre-trained architecture fine-tuned via transfer learning. The dataset is split into training and validation sets to train and assess the models, with performance metrics derived from the validation phase. This structured methodology ensures that the models are optimized for accuracy and practical deployment in precision agriculture.

A. Figures of the Dataset

The Lemon Leaf Disease Dataset (LLDD) properties are summarized in Figure I, providing an overview of its structure and composition. The dataset includes 1354 images of nine types of lemon leaves, categorized into healthy and diseased classes, which forms the foundation for training and validating the proposed models.

Name:	**Lemon Leaf Disease Dataset (LLDD)**	
Categories:	**Healthy**	**Diseased**
Images:	**Total: 1354**	**Format: JPG**
Types	['Bacterial Blight', 'Curl Virus', 'Healthy Leaf', 'Dry Leaf', 'Deficiency Leaf', 'Spider Mites', 'Anthracnose', 'Sooty Mould', 'Citrus Canker']	
Source:	Kaggle	

Fig. 1. Dataset Properties

B. Dataset Collection and Properties

The Lemon Leaf Disease Dataset (LLDD), sourced from Kaggle, was utilized for this study. The dataset comprises 1354 images in JPG format, featuring nine types of lemon leaves categorized into two classes: healthy and diseased. The diseased category includes eight distinct conditions: Bacterial Blight, Curl Virus, Dry Leaf, Deficient Leaf, Spider Mites, Anthracnose, Sooty Mould, and Citrus Canker, alongside the Healthy Leaf category. This diverse dataset provides a comprehensive representation of lemon leaf conditions, enabling robust model training and evaluation for disease detection in precision agriculture.

C. Data Prepossessing

To ensure compatibility with deep learning models, the LLDD was preprocessed using Keras. Images were resized to a uniform dimension of 224x224 pixels to match the input requirements of both the custom CNN and MobileNet models. The pixel values were normalized using the level-mode technique to scale intensities between 0 and 1, enhancing model convergence. The dataset was then split into 80% for training (1083 images) and 20% for validation (271 images). During training, a batch size of 32 was used, with data shuffling enabled and a fixed seed value to ensure reproducibility. These preprocessing steps standardized the input data, mitigating biases and improving model performance.

D. Proposed Models

This study proposes two deep learning models for leaf disease detection: a custom Convolutional Neural Network (CNN) and a transfer learning-based MobileNet. The custom CNN was designed with a sequential architecture, comprising three convolutional layers with ReLU activation, each followed by max-pooling layers to extract spatial features, and two dense layers for classification. Dropout regularization (0.5) was applied to prevent overfitting. The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss, achieving an accuracy of 87.41

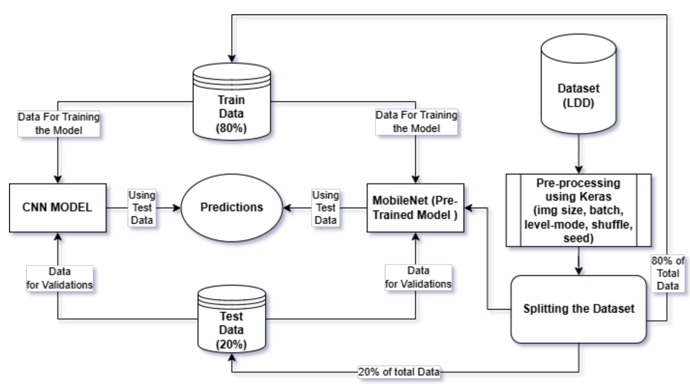

Fig. 2. Proposed Method

MobileNet, a lightweight architecture pre-trained on ImageNet, was fine-tuned for this task via transfer learning. The base layers were frozen to retain pre-trained features, while the final layers were retrained on the LLDD with a softmax output for binary classification (healthy vs. diseased). The model was optimized using the Adam optimizer with a learning rate of 0.0001, achieving a superior accuracy of 99.22

E. How CNN Works and Implementation

A Convolutional Neural Network (CNN) operates by processing images through a series of layers to extract and classify features. It starts with convolutional layers, which apply filters to the input image to detect low-level features like edges and textures, producing feature maps. These maps are passed through an activation function (e.g., ReLU) to introduce non-linearity. Pooling layers (e.g., max-pooling) then downsample the feature maps, reducing spatial dimensions while retaining important information, which lowers computational complexity. The process repeats across multiple convolutional and pooling layers to capture increasingly complex patterns. The resulting feature maps are flattened into a vector and fed into dense (fully connected) layers, which integrate the features for final classification. The output layer typically uses an activation function (e.g., softmax) to produce class probabilities. During training, the model optimizes its weights by minimizing a loss function (e.g., cross-entropy) using an optimizer like Adam, adjusting weights via backpropagation based on the error between predicted and actual labels.

In this study, the custom CNN was implemented to classify lemon leaf images into healthy and diseased categories. The architecture includes three convolutional layers with ReLU activation and max-pooling layers, followed by two dense layers with dropout (0.5) to prevent overfitting. As per the code, the model is compiled using the Adam optimizer, sparse categorical cross-entropy loss (suitable for integer-encoded labels), and accuracy as the metric. It was trained on 80% of the Lemon Leaf Disease Dataset (LLDD) (1083 images) and validated on 20% (271 images), achieving an accuracy of 87.41%. This implementation leverages the CNN's ability to learn disease-specific patterns directly from the dataset, though its performance is limited by its simpler design and lack of pre-trained knowledge.

F. How MobileNet Works and Implementation

MobileNet is a lightweight deep learning model designed for efficiency, using depthwise separable convolutions to reduce computational cost. It splits traditional convolution into two steps: depthwise convolution, which applies a single filter per input channel to capture spatial features, and pointwise convolution (1x1 convolution), which combines these features across channels. This factorization significantly reduces parameters and computations, making MobileNet ideal for resource-constrained environments.

The model, pre-trained on ImageNet, leverages transfer learning by reusing learned features (e.g., edges, shapes) and fine-tuning them for a specific task. The pre-trained layers are often frozen to retain general features, while later layers are retrained to adapt to the new dataset. The output is typically processed through global average pooling to reduce spatial dimensions, followed by dense layers for classification, with a softmax activation for class probabilities. The model is optimized using a loss function (e.g., cross-entropy) and an optimizer like Adam.

In this study, MobileNet was fine-tuned for leaf disease detection using transfer learning. The base model was loaded with ImageNet weights, excluding the top layer, and configured for an input shape of 224x224x3. As per the code, the first 80 layers were frozen to preserve pre-trained features, while layers beyond the 80th were made trainable to adapt to the LLDD. The base model's output was processed with GlobalAveragePooling2D to reduce dimensions, followed by a dense layer with 1024 units and ReLU activation, and a final dense layer with softmax activation for classification into the dataset's classes (healthy and diseased). The model was compiled using the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy loss (for one-hot encoded labels), and accuracy as the metric. Trained and validated on the same dataset split as the CNN, MobileNet achieved an accuracy of 99.22%. This implementation highlights MobileNet's efficiency and ability to leverage pre-trained features, resulting in superior performance for leaf disease detection.

RESULT ANALYSIS

This section includes all essential figures and tables, as well as a thorough discussion of the Lemon Leaf disease detection using Train-Val Accuracy, Train-Val loss Graphs as well as confusion matrix.

G. Performance Graphs

The evaluation of deep learning models for leaf disease detection requires a comprehensive analysis of their performance across various metrics to ensure reliability and practical applicability. This section presents a visual assessment of the custom Convolutional Neural Network (CNN) and MobileNet models using performance graphs, which provide insights into their classification capabilities on the Lemon Leaf Disease Dataset (LLDD). The custom CNN achieved an accuracy of 87.41%, while MobileNet, leveraging transfer learning, attained a superior accuracy of 99.22%. To understand their behavior in detail, we analyze key visualizations, including the confusion matrix, which highlights class-wise prediction accuracy, and accuracy vs. loss graphs, which illustrate the models' training and validation dynamics over epochs. These graphs collectively offer a clear perspective on the models' strengths, potential limitations, and suitability for real-world deployment in precision agriculture, enabling a deeper understanding of their performance beyond aggregate metrics.

H. Analysis of Accuracy and Loss Graphs for CNN Model

The accuracy and loss graphs illustrate the performance of the custom CNN model for leaf disease detection over 14 epochs. The accuracy graph shows training accuracy (blue) rising from 0.3 to 0.9, stabilizing by epoch 14, while validation accuracy (orange) peaks at 0.9 by epoch 5 but fluctuates between 0.85 and 0.9, indicating good generalization with mild overfitting (gap 0.05).

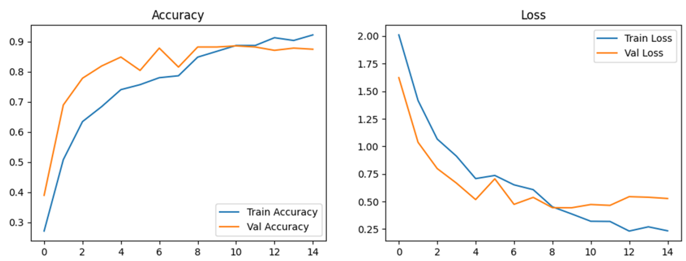

Fig. 3. Accuracy and Loss Graph of CNN

The loss graph reveals training loss (blue) dropping from 2.0 to 0.25, and validation loss (orange) decreasing from 1.75 to 0.5, with fluctuations between 0.4 and 0.6, suggesting some instability on unseen data. These trends align with the reported 87.41% accuracy, but the variability in validation metrics and slight overfitting indicate potential improvements through regularization or data augmentation for better handling of visually similar disease classes, as seen in the confusion matrix.

I. Analysis of Accuracy and Loss Graphs for MobileNet Model

The accuracy and loss graphs depict the performance of the MobileNet model for leaf disease detection over 30 epochs. The accuracy graph shows training accuracy (blue) and validation accuracy (orange) starting at 0.4 and 0.5, respectively. Both metrics rise sharply within the first 5 epochs, reaching 0.95, and stabilize near 0.98 by epoch 30, with minimal gap between them, indicating excellent generalization and negligible overfitting.

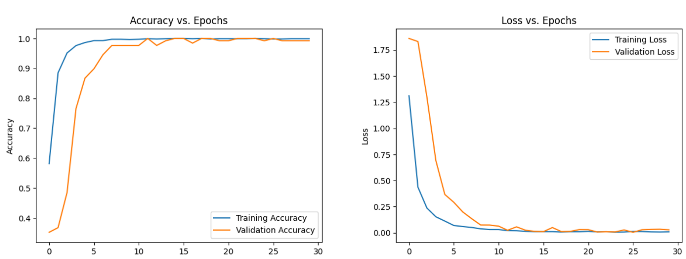

Fig. 4. Accuracy and Loss Graph of Mobilenet

The loss graph shows training loss (blue) and validation loss (orange) starting at 1.75 and 1.5, respectively, and decreasing rapidly to 0.25 by epoch 5. Both losses continue to decline, stabilizing near 0.05 by epoch 30, with slight fluctuations in validation loss. This suggests the model effectively minimizes errors on both datasets. Compared to the custom CNN (87.41% accuracy), the MobileNet model demonstrates superior performance, likely due to its efficient architecture, making it well-suited for mobile-based leaf disease detection despite challenges with visually similar classes, as noted in the confusion matrix.

J. Confusion matrix Scores

A confusion matrix is a table used to evaluate the performance of a classification algorithm. It compares the actual (true) values to the predicted values, providing insights into the accuracy of the model.

K. MobileNet

The MobileNet model's performance was evaluated using a confusion matrix, which revealed perfect classification across all nine classes of the Lemon Leaf Disease Dataset (LLDD) on a subset of validation data (128 samples).

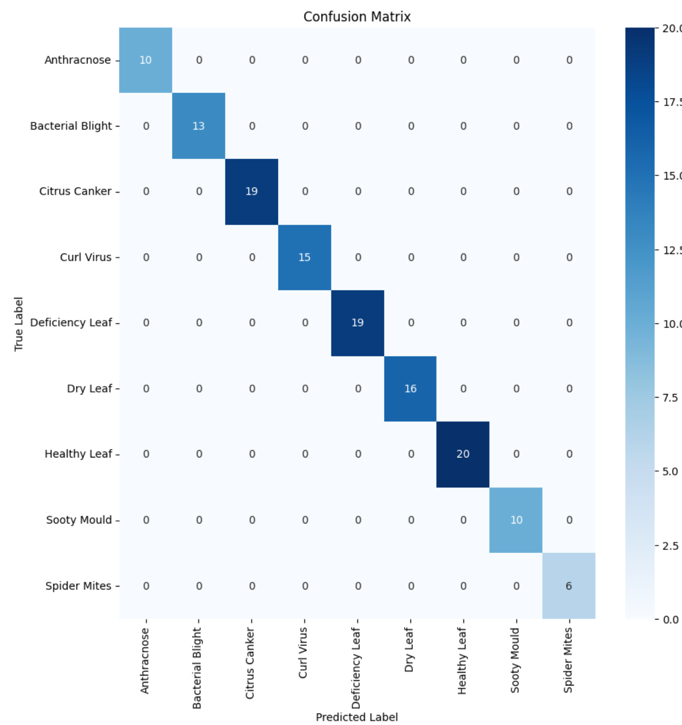

Fig. 5. MobileNet Confusion Matrix Result

The matrix's diagonal values indicated accurate predictions for each class: 10 for Anthracnose, 13 for Bacterial Blight, 19 for Citrus Canker, 15 for Curl Virus, 19 for Deficiency Leaf, 16 for Dry Leaf, 20 for Healthy Leaf, 10 for Sooty Mould, and 6 for Spider Mites. This flawless performance aligns with the model's overall validation accuracy of 99.22%, highlighting its ability to differentiate healthy leaves from diseased ones, as well as distinguishing among various diseases. However, the absence of misclassifications in this subset suggests the need for evaluations with more challenging and diverse data to assess the model's robustness and generalizability.

L. Custom CNN

The confusion matrix reveals the custom CNN model achieved an overall accuracy of 87.41% for leaf disease detection, with strong diagonal performance indicating accurate predictions for most classes. True positive rates were highest for ”Deficiency Leaf” (40), ”Healthy Leaf” (36), ”Dry Leaf”

(31), and "Sooty Mould" (32). "Citrus Canker" (27) and "Curl Virus" (26) also performed well, despite minor misclassifications like Citrus Canker being predicted as Deficiency Leaf (4 instances) and Curl Virus as Anthracnose (2 instances).

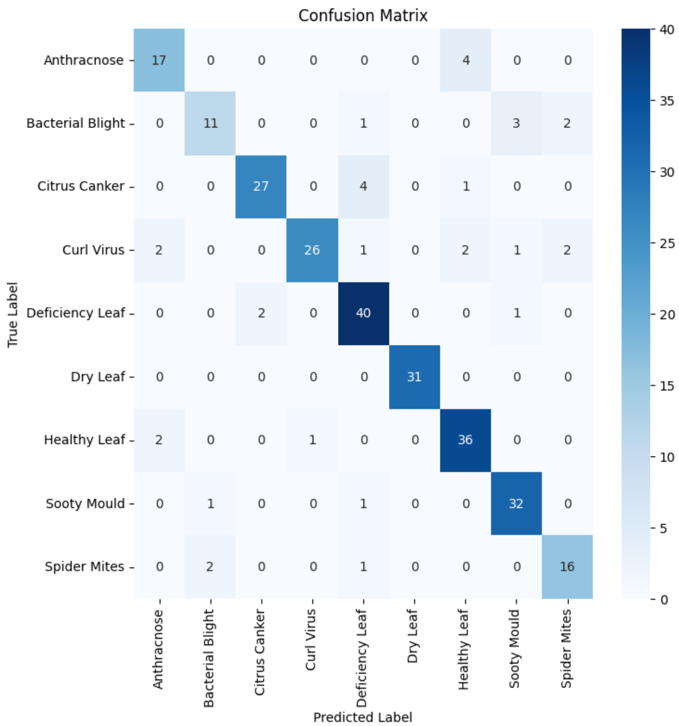

Fig. 6. Custom CNN Confusion Matrix Result

Challenges arose for "Anthracnose" (17) and "Spider Mites" (16), with Anthracnose misclassified as Healthy Leaf (4 instances) and Spider Mites as Bacterial Blight (2 instances). "Bacterial Blight" (11) had the weakest performance, with various misclassifications, including 3 instances as Spider Mites and 2 as Deficiency Leaf. While the model shows robust overall performance, improvements in distinguishing similar or underrepresented classes could enhance reliability.

M. Comparisons

This table provides a direct comparison of two distinct models, our Custom CNN and MobileNet, for the image classification task. Their respective strengths and weaknesses are highlighted through key performance metrics.

Metric	**Custom CNN**	**MobileNet**
Overall Accuracy	87.41%	∼98%
Training Accuracy	0.9 (epoch 14)	0.98 (epoch 30)
Validation Accuracy	0.85–0.9, fluctuating	0.98, stable
Training Loss	2.0 to 0.25	1.75 to 0.05
Validation Loss	1.75 to 0.5, fluctuating	1.5 to 0.05
Overfitting	Mild (∼0.05 gap)	Negligible
Bacterial Blight	11/17 (3 misclassified)	Expected better

TABLE I
COMPARISON OF CUSTOM CNN AND MOBILENET MODELS

IV. Conclusion and Future Works

This study successfully demonstrates the application of deep learning for lemon leaf disease detection using the Lemon Leaf Disease Dataset (LLDD). Two models were evaluated: a custom Convolutional Neural Network (CNN) and a transfer learning-based MobileNet. The custom CNN, designed to extract disease-specific features, achieved an accuracy of 87.41%, showcasing its capability to learn patterns directly from the dataset. However, MobileNet, leveraging pre-trained weights and fine-tuning, outperformed the CNN with an accuracy of 99.22%, highlighting the effectiveness of transfer learning in enhancing classification performance. The lightweight nature of MobileNet also makes it suitable for deployment in resource-constrained environments, such as mobile devices used by farmers. These results underscore the potential of deep learning in precision agriculture, providing a scalable and accurate solution for early leaf disease detection.

A. Future Work

Future research can build upon this study by expanding the dataset to include a broader variety of leaf types and diseases, improving model generalizability across different crops. Incorporating real-time data augmentation and advanced preprocessing techniques, such as image segmentation, could further enhance model robustness. Additionally, integrating the models into a mobile application with an intuitive user interface would facilitate on-field deployment, enabling farmers to access diagnostic tools seamlessly. Exploring other lightweight architectures, such as EfficientNet, and comparing their performance with MobileNet could provide deeper insights into optimizing for both accuracy and computational efficiency. Finally, deploying the models on edge devices with IoT integration could enable automated, real-time monitoring of crop health, advancing the adoption of smart agriculture practices.

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