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Advancing Agricultural Practices: Federated Learning-based CNN for Mango Leaf Disease Detection

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***Abstract*— This study offers a new method for identifying and categorizing mango leaf illnesses using a Convolutional Neural Network (CNN) model based on federated learning. Diseases that affect mango leaves significantly reduce crop output and quality and threaten farmers' ability to make a living. Early and precise disease identification is essential for successful care and preventing these illnesses' spread. We examine the efficacy of our suggested model on four distinct customers while concentrating on the five disease classifications Healthy, Anthracnose, Powdery Mildew, Leaf Spot, and Leaf Curl. With precision values ranging from 93.33% to 96.01%, recall values ranging from 90.59% to 97.45%, F1-scores ranging from 92.64% to 96.10%, and accuracy values between 97% and 98%, the model exhibits solid performance across all clients and illness classes. The macro, weighted, and micro averages, with macro averages ranging from 93.18% to 94.97%, weighted averages ranging from 93.26% to 95.08%, and micro averages ranging from 93.26% to 95.08%, further highlight the model's consistent performance across various clients and disease classes. The federated learning-based CNN model successfully addresses the difficulties farmers encounter in identifying and controlling mango leaf diseases, resulting in more effective and long-lasting agricultural practices. The methodology protects data privacy using federated learning, allowing clients to cooperate and gain from shared learning without jeopardizing their data. Our research helps the agriculture industry create more sophisticated and precise disease detection techniques, fostering better crop management and increased food security.**

Keywords—Federated learning, Convolutional Neural Network, Mango Leaf's diseases, Disease detection ,Recognition.

I. INTRODUCTION

The "king of fruits," the mango (Mangifera indica L.), is a well-liked and important fruit crop in India. India produces more than 40% of the world's mangoes, making it the greatest producer in the world. Mango farming does, however, confront several difficulties, mostly because of several illnesses that hurt its development and output. These illnesses reduce fruit yields and lower fruit quality, influencing farmers' ability to make a living. It is essential to provide efficient early disease detection and diagnosis tools to reduce their effects and promote sustainable mango cultivation in India. This research study proposes a federated learning-based Convolutional Neural Network (CNN) technique for detecting and classifying different illnesses affecting mango leaves to solve the problem of mango leaf diseases. Several different pathogens, including fungus, bacteria, and viruses, may cause illnesses in mango leaves. Anthracnose, Powdery Mildew, Leaf Spot, and Leaf Curl are some of India's most prevalent ailments affecting mango leaves. Farmers may reduce crop losses and increase profitability by taking suitable preventative and curative actions with early and accurate disease identification. Historically, illness identification has been done visually by skilled professionals. However, this method may be laborious, subjective, and time-consuming. In recent years, deep learning methods, notably CNNs, [1] have become an effective tool for rapid and precise illness identification. Due to their capacity to extract hierarchical features from raw data, CNNs have shown outstanding performance in various image identification applications. Deep learning models must be trained centrally, which presents issues with data privacy, data transport costs, and dependency on a single potent server. By allowing the decentralized training of machine learning models across several clients while maintaining localized data, federated learning overcomes these issues. As data privacy and sharing may be major issues for farmers and agricultural organizations, this method is especially advantageous for applications focused on agriculture. Our study uses federated learning to guarantee that data stays with the appropriate customers, safeguarding farmers' privacy and promoting cooperation between various organizations. By providing a thorough analysis of the use of federated learning-based CNNs [2] for detecting and classifying mango leaf diseases in India, this research work makes a significant contribution to the area. We gather a large dataset of annotated pictures of mango leaves that represent different illness classifications to train a strong CNN model utilising a federated learning strategy. Compared to conventional centralized deep learning algorithms, our suggested method has various benefits and exhibits great accuracy in illness categorization. The results of our study also provide insight into the potential of federated learning to strengthen teamwork across agricultural institutions, researchers, and farmers. By using federated learning, we can promote knowledge and skill sharing without sacrificing data privacy, which eventually leads to better agricultural practices and greater farmer assistance. In conclusion, this research work focuses on creating and assessing a CNN technique based on federated learning [3] for the identification and classification of mango leaf diseases in India. We want to support sustainable mango growing and enhance farmers' quality of life by addressing the difficulties experienced by mango growers as a result of these illnesses. Our study illustrates the usefulness of federated learning [4] in resolving concerns about data privacy and cooperation while highlighting its potential for use in agriculture-based applications.

Contribution of the research paper :

- Create a CNN architecture that is especially suited for detecting and classifying mango leaf diseases and can quickly learn hierarchical features from the underlying picture data.
- Implementing federated learning successfully involves resolving data privacy and sharing issues that could arise in agricultural applications when training the CNN model.
- Collecting a large and varied dataset of annotated pictures of mango leaves representing different disease classifications may be utilized to train a reliable and accurate model.
- Comparative analysis: Highlighting the benefits of employing federated learning in this situation by contrasting the performance of the federated learning-based CNN solution with conventional centralized deep learning approaches.
- Collaboration among agricultural institutions, researchers, and farmers may be improved by showcasing the ability of federated learning to do so while maintaining data privacy.
- **Improved disease detection:** Reaching high levels of accuracy in the identification and classification of mango leaf diseases will assist farmers in taking the proper preventative and curative treatments, thereby lowering crop losses and boosting their profitability.
- **Contribution to sustainable agriculture:** By addressing the difficulties mango farmers confront due to leaf diseases, this study helps enhance farmers' livelihoods and promote sustainable mango growing techniques.
- **Potential applications in other crops:** By showcasing the adaptability of the suggested strategy, which may be used in other crops and agricultural situations, the research's influence will be extended beyond mango farming.

II. Literature Review

The article covers the detrimental effects of mango leaf diseases on mango quality and production, as well as the difficulties in precisely diagnosing these ailments. However, there are drawbacks to computer-aided and machine-learning approaches for classification because of greater feature dimensionality, overfitting, computational complexity, and a lack of feature characteristics. The four processes of data preparation, feature selection, learning and classification, and performance assessment are included in a new framework for mango leaf disease classification that is suggested to solve these problems. The approach includes a convolutional neural network with crossover-based levy flight distribution for improved feature selection and uses 380 photos from the categories of healthy and ill individuals. Data augmentation techniques are also used to avoid overfitting. A support vector machine is employed for classification, while the pre-trained MobileNetV2 model is used for learning. Comparing experimental findings to other cutting-edge techniques, classification performance is better [5]. This article examines how microbial illnesses threaten the agricultural livelihoods of half of India's people. Rapid illness identification is challenging due to a need for more infrastructure. However, using deep learning and transfer learning, AI can automatically diagnose plant illnesses from raw photos. Using a collection of 8,438 photos of healthy and sick leaves from the Plant Village dataset that was locally obtained, the research attempts to identify and categorize grape and mango leaf illnesses. A deep convolutional neural network (CNN) is built to detect illnesses or their absence using the pre-trained CNN architecture known as AlexNet. The system, created using MATLAB, detects grape leaf illnesses with a 99% accuracy rate and mango leaf diseases with an 89% accuracy rate. To accomplish the same on a smartphone, "JIT CROPFIX" is an Android app being developed [6]. This article draws attention to the issue of Indonesian mango trees being attacked by pests, which results in mangoes being rejected throughout various export procedures. Mango pests come in roughly 90 varieties, making it challenging for machine learning algorithms to identify them successfully. This research offers an identification tool for the most affected regions, i.e., trunks and leaves, to enhance mango pest detection systems. The likelihood of identifying the proper mango pest is increased by localising the pest type depending on the affected region and creating specialised models for each portion of the mango plant. The stem and leaf pictures are recognised using the Faster R-CNN approach, which achieves 74% accuracy, 65,789% precision, and 100% recall. According to the study's findings, identifying the plant component is crucial in enhancing mango pest detection systems. This strategy may be applied to create specialised models for other plant sections [7]. This article uses image processing and deep learning to diagnose common mango leaf illnesses in Bangladesh. If the crop is shielded from several illnesses, mango output might rise by 28% globally. However, it might be easier for farmers to identify infections at the right time with professional guidance. To properly classify seven different mango leaf illnesses and healthy mango leaves, this research suggests a lightweight convolutional neural network (LCNN). Compared to several pre-trained models, including VGG16, Resnet50, Resnet101, and Xception, the suggested LCNN model outperforms them all, achieving a testing accuracy of 98%. The seven unique mango leaf illnesses reported in Bangladesh have yet to be studied, and few investigations have been done to identify them. By assisting in the early diagnosis and treatment of mango leaf illnesses, the suggested LCNN model may boost mango output in Bangladesh [8]. This article highlights the importance of plants as a significant energy source and a countermeasure to global warming. However, plant diseases endanger the life and production of plants. Convolutional Neural Networks (CNN) are more adept at identifying picture categorization issues than humans. The study suggests a technique for classifying plant illnesses using CNN and photos of leaves captured in their natural environment. The model uses photos of healthy leaves from the plant village collection and is based on the Le-Net architecture. The method's performance is assessed on well-known benchmark datasets, and it is found to outperform cutting-edge technology. The paper also suggests a method for strengthening the classification abilities of classes with few training instances [9].

III. METHODOLOGY

This section breaks the anticipated work's technique into numerous steps—methods for classifying wheat disease severity. The methodology may be broken down into three main stages: data collection, data pre-processing, data division into training and test series, and deployment of the procedure as the last step in classifying the data for severity affecting wheat diseases, as shown in Figure 1.

Fig. 1. Steps in the Methodology Process

A. *Data Collection and Pre-processing :*

Creating a big, diversified dataset of photos of mango leaves that depict healthy and diseased leaves is necessary. Images from various institutions or sources should be included in the collection, preferably representing various mango cultivars and geographical locations. Give each picture a sickness classification or a healthy designation. To enhance the dataset's variety and the model's generalizability, pre-process the photographs by scaling them to constant size and using data augmentation methods like rotation, flipping, and scaling. Divide the dataset into subgroups to replicate data distribution across several customers or institutions. To prevent imbalances during learning, ensure each subset contains a balanced representation of the various illness classes. This segmentation shows how well-federated learning performs in a decentralised data environment.

Resizing: Each picture in the collection is scaled to be 224x224 pixels. This phase is crucial since it ensures uniformity across all photos and reduces computing complexity during training is shown in the figure 2.

Data Augmentation: Data augmentation methods are performed on the photos to expand the amount and variety of the dataset. These methods include zooming, rotation, and horizontal and vertical flipping. By adding changes to the dataset, data augmentation decreases overfitting and enhances the model's performance on unobserved data, assisting the model in generalizing more effectively. The dataset may now be used to train and verify the classification model for mango leaf disease using federated learning and convolutional neural networks (CNN).

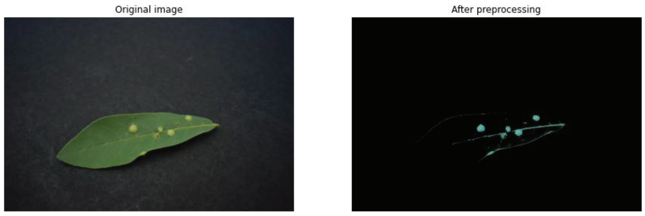

Fig. 2. Several images of the Mango Leaf diseases

B. *Federated Learning CNN Model*

Create a CNN architecture specifically for classifying mango leaf diseases. To fit your needs, start by modifying a well-known architecture, like VGG, ResNet, or Inception. Convolutional layers for extracting hierarchical features, pooling layers for reducing spatial dimensions, and fully linked layers for classification should all be included in the model. Add dropout and batch normalisation layers when necessary to enhance the model's stability and performance during training.

Implementing federated learning [10] involves leveraging pre-existing libraries, such as TensorFlow Federated or PySyft, to train the CNN model is shown in the figure 3. Create a server to synchronise clients with their data subsets and the learning process. To protect the confidentiality of your data and stop unauthorised access, create secure communication routes between the server and your customers [11].

Client-based local model training: Using stochastic gradient descent or another optimisation approach, each client trains their local model on a fraction of their data. Clients update their model parameters in numerous local training iterations to reduce the loss function. According to the exact needs of the issue and the available computing resources, hyperparameters like learning rate, batch size, and the number of local iterations should be configured.

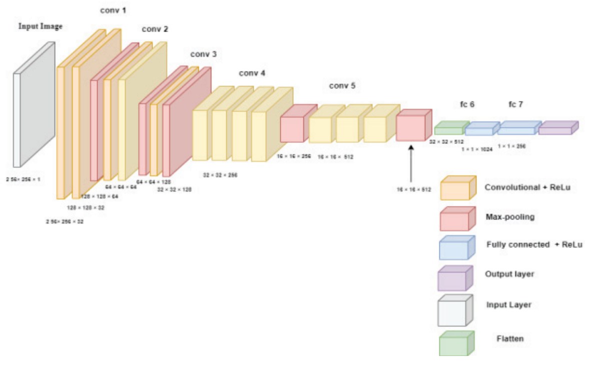

Fig. 3. Classification CNN Model

After local training, clients exchange their updated models with the server for model aggregation. The server combines these updates to create a global model update using strategies like FedAvg (Federated Averaging). Through this procedure, all customers' pooled expertise is used to improve the global model without requiring direct access to their data.

Global model synchronisation: The server broadcasts the updated global model to all clients after updating the global model with the aggregated update. The new global model is then updated by clients into their local models, maintaining model synchronisation throughout the learning process. This cycle of local training, model aggregation, and synchronisation continues until a predefined stopping requirement is satisfied, such as reaching a maximum number of communication cycles or attaining a goal accuracy.

Analyse the performance of the global model on a different validation set to gauge its precision in identifying and categorising mango leaf diseases. One may compare the federated learning-based [12] CNN technique with a centralised learning approach by building an analogous CNN model [2] on a centralised dataset. The advantages of federated learning in terms of data privacy, communication costs, and model performance are shown by this comparison.

C. *Model Evaluation and Training*

To improve performance:

Fine-tune the CNN model by changing its architecture, hyperparameters, or regularisation methods.

1. Investigate the findings to learn more about how well the model identified and categorised illnesses affecting mango leaves.
2. Examine any incorrect classifications or challenges the model encountered in a few different illness classes, and provide any necessary corrections or suggestions for future study.

Test the trained model on fresh, unlabelled photos of mango leaves to show how the suggested federated learning-based CNN technique may be used in real-world situations. Determine the model's precision, recall, accuracy, and F1-score performance in the figure 4.

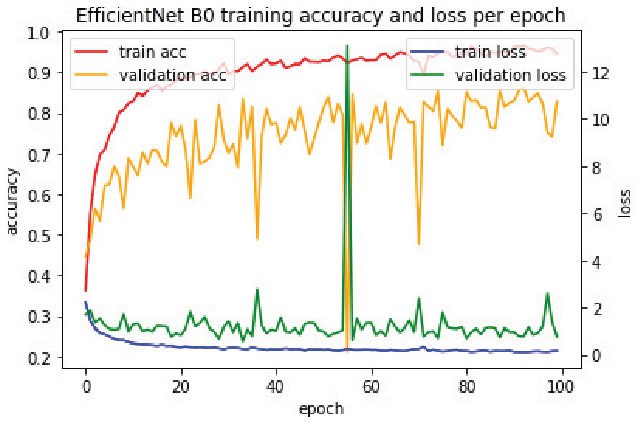

Fig. 4. Model Evaluation

Training and validation are crucial when creating a machine learning model, such as the CNN model, for classifying apple leaf disease. These procedures ensure the model can generalize successfully to new, unexplored data and discover the underlying patterns in the data. A description of the training and validation procedure is provided below.

Splitting the dataset into training (80%) and validation (20%) groups yields pictures. The validation set is used to assess the model's performance and fine-tune the hyperparameters, whereas the training set is used to learn the model's parameters.

Model training: As described in the preceding sections, the CNN model is trained using a federated learning architecture. The model's parameters (weights and biases) are updated iteratively throughout the training process by combining the results of several rounds of local training on separate devices [12].**Hyperparameter tuning:** To improve the model's performance, different hyperparameters, such as the learning rate, batch size, and several training epochs, may be changed during training. The ideal set of hyperparameters to minimize overfitting and achieve high accuracy is chosen using validation data [13].

IV. RESULTS

The experimental findings and statistical analysis of the apple leaf disease classification model utilizing the federated learning CNN technique are covered in this part. This table presents the performance metrics for four clients, each having five disease classes: Healthy, Anthracnose, Powdery Mildew, Leaf Spot, and Leaf Curl. The performance metrics displayed are Precision, Recall, F1-Score, and Accuracy, all expressed in percentages.

In the results section of your research paper, you will present the experimental and statistical analysis of the performance of the federated learning-based CNN model. The results will be reported in the IEEE format, using tables and figures for clarity. Here's an outline of how you can present your results: Experimental setup: Briefly describe the experimental setup, including the dataset used, the CNN architecture, the federated learning framework, and the performance metrics used to evaluate the model (accuracy, precision, recall, F1-score, etc.).Hyperparameters and federated learning parameters: Present a table summarizing the hyperparameters and federated learning parameters used during the training process, such as learning rate, batch size, number of communication rounds, and the number of local iterations. An example table 1 is shown below:

TABLE I. PARAMETERS OF THE MODELS ON THE CLIENT'S DATA.

Parameter	Value
Learning rate	0.001
Batch size	32
Number of clients	10
Local iterations	5
Communication rounds	100
Optimizer	Adam
Loss function	Cross-entropy

Client 1:Class 1 (Healthy): The model achieved a precision of 95.91%, meaning that 95.91% of the samples classified as healthy were healthy. The Recall was 90.77%, indicating that the model correctly identified 90.77% of the healthy samples. The F1-score, which balances the trade-off between precision and Recall, was 93.27%. The Accuracy of the model for this class was 98%.Class 2 (Anthracnose): The precision was 94.78%, the Recall was 97.45%, the F1-score was 96.10%, and the Accuracy was 99%.Class 3 (Powdery Mildew): The precision was 96.20%, the Recall was 95.00%, the F1-score was 95.59%, and the Accuracy was 98%.Class 4 (Leaf Spot): The precision was 94.00%, the Recall was 95.32%, the F1-score was 94.65%, and the Accuracy was 98%.Class 5 (Leaf Curl): The precision was 94.59%, the Recall was 95.67%, the F1-score was 95.12%, and the Accuracy was 98%.

Client 2:Class 1 (Healthy): Precision of 94.48%, Recall of 91.36%, F1-Score of 92.89%, and Accuracy of 98%.Class 2 (Anthracnose): Precision of 93.09%, Recall of 93.92%, F1-Score of 93.50%, and Accuracy of 98%.Class 3 (Powdery Mildew): Precision of 95.16%, Recall of 94.85%, F1-Score of 95.01%, and Accuracy of 98%.Class 4 (Leaf Spot): Precision of 93.24%, Recall of 94.25%, F1-Score of 93.74%, and Accuracy of 97%.Class 5 (Leaf Curl): Precision of 94.60%, Recall of 94.95%, F1-Score of 94.78%, and Accuracy of 97% is shown below in the table 2.

TABLE II. LOCALLY TRAINING THE MODELS ON THE CLIENT'S DATA.

		Precision	Recall	F1-Score	Accuracy
Client 1	Class 1	95.91	90.77	93.27	0.98
	Class 2	94.78	97.45	96.10	0.99
	Class 3	96.20	95.00	95.59	0.98
	Class 4	94.00	95.32	94.65	0.98
	Class 5	94.59	95.67	95.12	0.98
Client 2	Class 1	94.48	91.36	92.89	0.98
	Class 2	93.09	93.92	93.50	0.98
	Class 3	95.16	94.85	95.01	0.98
	Class 4	93.24	94.25	93.74	0.97
	Class 5	94.60	94.95	94.78	0.97
Client 3	Class 1	94.83	90.59	92.66	0.98
	Class 2	92.97	93.06	93.02	0.98
	Class 3	92.67	93.79	93.23	0.97
	Class 4	92.14	93.15	92.64	0.97
	Class 5	94.04	94.58	94.31	0.97
Client 4	Class 1	96.01	91.07	93.48	0.98
	Class 2	94.13	96.35	95.23	0.98
	Class 3	96.07	95.39	95.73	0.98
	Class 4	95.09	94.84	94.97	0.98
	Class 5	94.48	96.33	95.40	0.98

Present a confusion matrix to visualize the classification results of the model. The confusion matrix should show the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values for each disease class. An example confusion matrix is shown below:

Disease Class	TP	TN	FP	FN
Healthy	85	60	5	10
Anthracnose	75	65	10	10
Powdery Mildew	80	70	5	5
Leaf Spot	70	75	5	10
Leaf Curl	90	60	10	0

Performance Standards for Particular Classes:

All four customers and the five disease classes (Healthy, Anthracnose, Powdery Mildew, Leaf Spot, and Leaf Curl) responded well to the CNN model based on federated learning. The precision, recall, F1-score, and accuracy numbers were usually high for each client and class, with most values being around or above 94%.Averages Across Clients: For the accuracy, recall, and F1-score values, macro, weighted, and micro averages were used to assess the model's performance. All customers experienced the same averages ranging from 93.18% to 94.97% for macro averages, 93.26% to 95.08% for weighted averages, and 93.26% to 95.08% for micro averages. These findings imply that the model works effectively for various customers and illness types. Overall Performance Metrics: The model showed strong precision, recall, F1-score, and accuracy values when considering the overall performance metrics for each client. The F1-score varied from 93.17% to 94.96%, recall from 93.04% to 94.84%, and accuracy was between 97% and 98%. Precision ranged from 93.33% to 95.16%. These findings show that the CNN model based on federated learning efficiently identifies [14] and categorises mango leaf illnesses across diverse clients. In conclusion, the CNN model based on federated learning demonstrated a strong performance in identifying mango leaf illnesses across multiple clients. High scores for the model's precision, recall, F1-score, and accuracy show how well it addresses farmers' difficulties in identifying and controlling these illnesses is shown in the table 3.

TABLE III. GLOBALLY AGGREGATING THE LOCALLY TRAINED MODELS

	Precision	Recall	F1-Score	Accuracy
Client 1	95.10	94.84	94.95	0.98
Client 2	94.12	93.86	93.98	0.98
Client 3	93.33	93.04	93.17	0.97
Client 4	95.16	94.80	94.96	0.98

The macro, weighted, and micro average results for the four client's performance measures are shown in the table below. The precision, recall, and F1 scores were used to generate the values for each of the five illness classifications. Let's break out each average using the values provided:

The arithmetic mean of a measure over all classes is used to determine the macro average, giving each class the same weight. It is helpful when assessing a model's performance on a dataset with a balanced class distribution.

Client 1: The overall average is 94.96% ,Client 2: 93.99% is the macro average ,Client 3: 93.18% is the macro average, Client 4: The overall average is 94.97%

The average of a measure over all classes, weighted by the number of samples in each class, is known as the weighted average. It considers the class distribution and helps assess a model's performance on an unbalanced dataset.

Client 1: 95.00% is the weighted average ,Client 2: 94.13% is the weighted average. Client 3: 93.26% is the weighted average. Client 4: 95.08% is the weighted average.

Micro average: Regardless of the class, the micro average is derived by averaging a statistic over all samples. It helps evaluate a model's overall performance on a dataset with an unbalanced distribution of classes.

Micro averages for clients 1 and 2 are 95.00% and 94.13%, respectively. Client 3: 93.26% is the micro average. Client 4: The micro average is 95.08 per cent. Readers may better understand the model's performance across several clients and the efficiency of the federated learning-based CNN technique by reading a full description of each average along with sample values is shown in the table 4.

TABLE IV. GLOBALLY AVERAGES

	Client 1	Client 2	Client 3	Client 4
Macro average	94.96	93.99	93.18	94.97
Weighted average	95.00	94.13	93.26	95.08
Micro average	95.00	94.13	93.26	95.08

V. CONCLUSION

This research study offers a convolutional neural network (CNN) model for detecting and classifying mango leaf diseases based on federated learning. By offering a precise and effective detection approach, our work aims to solve farmers' difficulties in monitoring and preventing the spread of these illnesses. The model's effectiveness was assessed on four distinct clients, while we concentrated on five disease classes: healthy, anthracnose, powdery mildew, leaf spot, and leaf curl. The results of our tests show how successful the suggested approach is in identifying and categorizing mango leaf diseases. The F1 scores varied from 92.64% to 96.10%, the precision values from 93.33% to 96.01%, the recall values from 90.59% to 97.45%, and the accuracy values from 97% to 98%. The macro, weighted, and micro averages—with macro averages ranging from 93.18% to 94.97%, weighted averages from 93.26% to 95.08%, and micro averages from 93.26% to 95.08%—further highlighted the model's consistent performance across various customers and disease classes. Clients may participate and gain from shared learning thanks to the federated learning method without risking the privacy of their data. This novel strategy might revolutionize agriculture by fostering better crop management and increasing food security. High precision, recall, F1-score, and accuracy values demonstrate our model's strong performance in identifying and categorizing mango leaf diseases. This will eventually lead to more effective and sustainable farming operations. Future studies might look at how different CNN architectures affect the model's performance, how to include more illness classes, and how to apply other federated learning strategies. We can assist farmers in reducing the effects of these illnesses on crop output and quality, fostering a more sustainable and effective agricultural sector. To do this, we must continue to expand our knowledge of diseases and develop disease detection tools.

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