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Coconut Leaf Disease Analysis: Merging Distributed Client Data using Federated Learning CNNs

Krishan Kumar
Department of Electronics and Communication Engineering, BPS Mahila Viswavidyalaya, India
Krishan.bpsmv@gmail.com

Rajender Kumar
Department of Electronics and Communication Engineering, BPS Mahila Viswavidyalaya, India
rajender.mtech@gmail.com

Seema Jangra
Department of Computer Science, IP College for Women, Delhi University India
seema.mtech@gmail.com

***Abstract*—Within the broad field of agricultural research, the prompt and precise identification of diseases affecting coconut leaves has become a critical issue, particularly when guaranteeing long-term crop yields. To determine the severity of coconut leaf illnesses over four gradations, this research explores a unique technique that uses Federated Learning in conjunction with Convolutional Neural Networks (CNN) and data from six clients. The federated paradigm prioritizes data privacy and allows for decentralized, collaborative model training that draws insights from various data sources. Our approach uses a sophisticated architecture with many convolutional layers that can extract complex disease patterns. The disease's presentation is shown across four severity levels in each client's local dataset, giving the model a thorough grasp of the disease's course. Through the combination of local updates, the federated framework produces a comprehensive model with improved generalization skills, using the many subtleties each client dataset offers. The study of the results demonstrates the model's effectiveness using many statistical standards. Our CNN model uses federated averaging approaches to distinguish client performance indicators. The macro average results showed the model's adaptability, ranging from 80.01% (fs_4) to a respectable 88.02% (fs_2). The micro averages were between 80.74% and 88.24%, while the weighted average scores varied from 80.82% to 88.26%. These measures provide evidence of the model's resilience and flexibility in the face of possible discrepancies in the datasets of individual clients.**

Keywords:Chilli_leaf_diseases, Convolutional neural networks (CNNs), Federated learning, Disease classification, Severity levels.

I. INTRODUCTION

As a multipurpose crop, coconuts are important to rural economies and ecological components, especially in Asia and the Pacific, where India is one of the major producers[1]. However, the incidence of illnesses affecting coconut leaves presents grave risks to coconut production and, therefore, to the financial security of the dependent populations[2]. The prevalence of these diseases in recent times has highlighted the need for creative and effective detection techniques to prevent agricultural yield and quality losses[3]. To develop a more sophisticated method for identifying and evaluating the severity of coconut leaf illnesses, this study takes a novel approach by combining Federated Learning with Convolutional Neural Networks (CNN)[4]. Federated Learning facilitates machine learning models' ability to learn efficiently from many data points spread across many places[5]ss. This allows our six customers to protect the confidentiality and integrity of their sensitive data, only disclosing the necessary updates to the models. This combination of global model refinement and localized learning highlights the learning paradigm and makes it suitable for dispersed data situations seen in real life[6]. Additionally, our method extrapolates the disease severity in coconut leaves into four meticulous levels: Moderate (26–50%), which indicates that the disease is progressing and needs to be monitored; Severe (51–75%), which suggests that the disease has advanced and needs to be treated immediately; and Critical (76–100%), which indicates that there is significant damage to the leaves and that urgent remediation may be necessary[7]. This fine-grained classification facilitates sophisticated comprehension and focused action, which maximizes resource distribution and improves the effectiveness of illness management. Because coconut leaf infections are a serious problem in India and worldwide, our study helps alleviate this urgent agricultural issue by providing a sophisticated diagnosis method. This is essential not only to protect the financial interests but also to maintain ecological equilibrium. Our study expands on the conventional federated learning technique by including Federated Averaging approaches, focusing on model averaging to obtain improved model stability and performance. To provide effective learning from various decentralized and heterogeneous data sources, this offers a strong answer to the variable data distributions across distinct clients. Our study serves as a shining example of creative intervention against the growing problems associated with illnesses of the coconut leaf. It offers fresh perspectives and innovative solutions essential for India, which is struggling to deal with the ever-increasing effects of chronic diseases on its rural environment[8]. It also gives a global framework for resolving similar issues in other ecological and geographical settings. With this paradigm, we expect to considerably lower yield loss and make great progress in managing illnesses that affect coconut leaves, which will benefit the world's agricultural economy and ecological subsistence. To sum up, this study clarifies a novel strategy by combining CNN with Federated Learning, providing a ray of hope for areas plagued by the consequences of coconut leaf illnesses. The keystones of this study are the careful severity classification and federated averaging methodologies, which will usher in a new era of illness identification and management with significant ramifications for India and the global community. First, this study aims to develop a sophisticated, privacy-preserving diagnostic model using Convolutional Neural Networks (CNN) and Federated Learning. This goal includes the idea of a decentralized learning framework that enables many customers to participate in model improvement without giving up the privacy of their personal information. The key component of this goal is to ensure strict data privacy regulations are followed while using the dispersed datasets from the six enrolled customers to improve the model's diagnostic ability to identify ailments of the coconut leaf.The second aim focuses on integrating and using federated averaging techniques inside the federated learning framework. This target is to improve model stability and performance by concentrating on advanced averaging approaches, which address the intrinsic problems caused by diverse clients having varied data distributions. To achieve this goal, improving model convergence and prediction accuracy is essential. This allows for the effective fusion of knowledge from several decentralized data domains.This study's third goal is to carefully classify coconut leaf illnesses according to their severity, which ranges from Mild (1–25%) to Critical (76–100%)[9]. To enable focused and timely responses, this granular stratification seeks to provide nuanced insights into the various phases of leaf diseases. This goal facilitates a comprehensive knowledge of disease dynamics by identifying the various disease symptoms. This helps to preserve coconut production and quality and optimizes remedial resources and procedures.The ultimate goal is to thoroughly assess and carefully validate the created model in various agroecological settings, guaranteeing its resilience and adjustability. The evaluation of the model's diagnostic competence and prediction accuracy against a range of coconut leaf diseases and in various situations is highlighted by this goal. This purpose examines the model's universality and flexibility to provide a globally applicable solution that will be especially helpful for places like India, where the occurrence of coconut leaf diseases has significant ecological and economic ramifications. While each objective is a crucial component of the research apparatus, they all work together to form a cohesive and comprehensive research trajectory that aims to mitigate the complex challenges of coconut leaf diseases by applying cutting-edge technological interventions and sophisticated methodological approaches[10].

II. LITERATURE REVIEW

In Sri Lanka, coconut production is significant since it is a major source of money and a vital part of the country's economy. However, a growing worry is the increasing frequency of illnesses that damage coconut trees[11]. These include insect diseases and nutritional deficiencies that affect the leaves, weakening the coconuts' vigour and total production. Within this framework, this study aims to support the health of coconut leaves by making it easier to identify illnesses early on, allowing farmers to get the most rewards from their coconut harvest. Using cutting-edge machine learning and image processing methods, the suggested solution takes a sophisticated approach to identifying insect infestations and nutritional deficits in coconut leaves. It entails careful analysis and monitoring after the administration of pesticides and fertilizers. The program highlights the shift in detecting diseases in coconut leaves from depending on human specialists to automated recognition systems, leading to a faster and more effective approach. An Android smartphone application has been created to make this a reality. It is intended to identify pests, their feeding habits, pest illnesses, and nutritional deficits in coconut palms. The technique included basic pre-processing on the datasets, essential for image processing technologies, including filtering, scaling, flipping the data horizontally and vertically, and converting RGB to greyscale. Following these procedures, many algorithms were analyzed thoroughly to accomplish classification. As a result, SVM and CNN were determined to be the best classifiers, with accuracies of 93.54% and 93.72%, respectively[12]. With early, accurate disease identification and control, this novel project hopes to increase coconut output and empower farmers to bring about revolutionary change in the agricultural industry. This project's integration of cutting-edge technology with approachable user interfaces is expected to revolutionize agriculture, especially helping Sri Lanka's coconut sector [13]. Plant diseases greatly reduce the amount of food that is produced. Therefore, early and precise diagnosis and identification are essential to reducing production losses. Deep learning techniques have become increasingly popular, and as a consequence, creative applications for plant disease diagnosis have emerged, giving reliable instruments with very accurate outcomes. To outline current trends and highlight knowledge and application gaps, this work conducts a thorough systematic review of the literature to define the state-of-the-art applications of Convolutional Neural Networks (CNN) in identifying and classifying plant diseases[5]. To provide a comprehensive picture of the developments and difficulties associated with using CNNs to identify plant diseases, 121 publications from the last ten years are examined in this study. These publications cover a wide range of topics, such as methods for detecting diseases, features of datasets, and the diversity of crops and pathogens that are investigated. This comprehensive analysis offers an informative overview of creative developments in using CNNs for plant disease diagnosis, emphasizing the complexities and diverse methods of plant disease detection[3]. The systematic review's findings help to clarify the areas that need further investigation and attention from the scientific community to understand better how CNNs are being used to identify plant diseases. This study greatly helps direct future research paths and improve the creation of more complex and precise CNN-based plant disease detection models by illuminating the state-of-the-art and unmet requirements in the area [14]. Although coconut is a major and lucrative crop worldwide, several pests and illnesses often reduce its output[15]. As a healthy coconut tree has healthy leaves, the main goals are to increase the vitality of coconut leaves and identify problems early on to maximize farmer output. The suggested approach, which uses DenseNet-121 architecture to classify photos of coconut leaves and invents a disease identification model, is an example of contemporary automation progressing while offering farmers an affordable option. This model shows extraordinary accuracy, nearly 99%, surpassing previous approaches. It uses a carefully selected dataset of 526 healthy and ill pictures. It reduces the required features by improving feature propagation and mitigating the vanishing gradient issue. By providing high-precision detection and classification of diseases in coconut leaves, this project's automation can replace the need for specialized labour in identifying ailments in coconut leaves. It also addresses the difficulties encountered in gathering datasets at different stages of illness in coconut plantations and significantly contributes to agricultural technology [16]. This study suggests a computerized approach that uses a Modified Inception Net-based Hyper Tuning Support Vector Machine classification technique, often known as MIN-SVM, to help laypeople and dendrologists identify coconut trees. Three morphological criteria—height, inclination, and orientation—are analyzed by this novel system to classify coconut trees. These factors are critical in determining the health and development characteristics of the trees, which in turn affects the design and use of harvesting robots. This model effectively uses deep learning, which removes fine details from photos and improves feature extraction. The research uses four Convolutional Neural Network models to extract features from pre-processed pictures of coconut trees: Visual Geometry Group, Inception Net, ResNet, and MIN-SVM. After that, the Support Vector Machine (SVM) machine learning model is used to classify these characteristics. To its surprise, MIN-SVM performs better than the others, with an accuracy of 95.35% against Visual Geometry Group's (91.90%), Inception Net's (81.66%), and ResNet's (71.95%). The improved compatibility of characteristics taken from the Modified Inception Net with the SVM classifier shows the system's effectiveness. The encouraging experimental results highlight MIN-SVM's potential as a potent automated system that can precisely identify coconut trees based on the important variables of height, inclination, and orientation. This marks a major advancement in computerized dendrology and the management of coconut trees [17].

III. METHODOLOGY

The setting includes six customers, each of whom has a distinct dataset that includes cases of illnesses of coconut leaves classified into four severity categories: mild (1-25%), moderate (26–50%), severe (51–75%), and critical (76–100%). These clients follow the fundamental privacy rules of federated learning by autonomously training a Convolutional Neural Network (CNN) model on their separate datasets while maintaining the localization of the data, as shown in Figure 1.

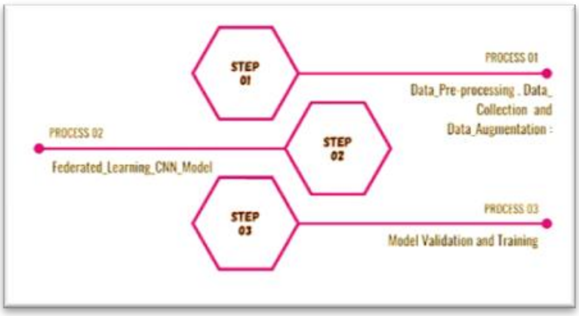

Fig1. Phases in the Process Approach

A. *Information Compilation and Preliminary Processing*

The dataset comprises a wide range of coconut leaf photos showing various disease severity stages. Preprocessing techniques, including scaling, normalization, and augmentation, are applied to these pictures to guarantee consistency and provide a variety of representations to enhance the model's learning ability. On a different test dataset, the models' prediction accuracy, sensitivity, specificity, and F1 score are assessed. These metrics provide information on the model's dependability in various operating circumstances and its capacity to detect the severity levels of illnesses affecting coconut leaves accurately, as shown in Table1.

TABLE 1. LEVELS OF SEVERITY IN COCONUT LEAF DISEASES

Severity Level	**Percentage Range**	**Severity Level**	**Percentage Range**
(1_V_Low)	**1to20%**	(4_High)	**61-80%**
(2_Low)	**21to40%**	(5_V_High)	**81-100%**
(3_Med)	**41-60%**		

Identifying and classifying plant diseases depending on their severity has proven crucial in developing targeted intervention plans. Such gradational assessment, which is differentiated on a scale from Mild (1-25%) to Critical (76-100%), offers a sophisticated knowledge of illness development and enables resource-optimized therapies [3] in agricultural environments such as coconut plantations where different degrees of severity call for other management methods to maintain quality and productivity,as shown in Figure 2.

Fig 2.Pictures of the illnesses that affect coconut leaves

B. *Model Aggregation*

In the federated learning paradigm, every client uses their dataset to train the model separately. The global model that contains the generalized learning from every client is then created by combining the model weights using federated averaging techniques. The clients are then given access to this global model again for training and improvement, iterating through many rounds until convergence is reached.Federated Averaging: Federated Averaging is a valuable technique for effectively aggregating model updates from several clients. By computing the average and considering the model's weights from each client, it helps to create a reliable and broadly applicable global model that integrates various learning vantage points.Iterative Learning and Refinement: After averaging, the global model is sent to the clients for further training and improvement using their localized data. Iteratively carrying out this procedure enables the model to continuously learn and adapt until a predetermined degree of convergence and accuracy is reached.

C. *Federated Learning CNNModel*

The preprocessed photos of coconut leaves displaying various illness signs at varying degrees of severity are sent to the input layer. For the sake of uniformity and best learning, these photos are normalized. Several convolutional layers are used to extract hierarchical characteristics from the input pictures, spaced out by pooling layers. Convolutional layers scan the input picture using various kernel sizes to identify complex patterns correlating to sickness symptoms. The pooling coatings maximize computing efficiency by reducing the dimensionality and keeping the essential characteristics.The fully linked layers are categorised by interpreting the hierarchical features retrieved by the layers before them. The output layer uses the softmax function to provide probability distributions for the four coconut leaf disease severity levels. Decision Tree Classifier: Based on the retrieved characteristics, a Decision Tree Classifier is created and combined with the CNN model to generate interpretive and hierarchical choices. This classifier is essential for practical implementations as it helps determine the severity of illnesses affecting coconut leaves and offers clear insights into the components that influence the condition.

An input picture with the dimensions 264x264x3, which indicate the width, height, and three RGB channels, is given to the model.Layers for Max Pooling and Convolution: The corresponding 32, 64, 128 and 256 filters are consecutively placed on top of four convolutional layers. Each convolutional layer uses the same padding, a stride of 1, and a kernel size of 3x3 to maintain the spatial dimensions. The most significant characteristics are captured, and computational complexity is decreased by applying a max pooling layer with a pool size of 2x2 and a stride of 2 after each convolutional layer. This reduces the spatial dimensions by half. The two fully connected layers of the model, each with 512 and 256 neurons, are used to interpret and make sense of the hierarchical properties that the earlier levels had retrieved. Twelve neurons comprise the output layer, corresponding to the twelve disease severity classifications. A softmax activation function is used to transform the outputs into probability distributions across the 12 classes. Batches of the dataset are fed into the model as part of the model training procedure. In this instance, 8436 photos of coconut leaves with varying degrees of disease severity are included in the collection. The images are separated into batches, and the model is fed to these batches one after the other. By modifying its weights throughout each training session, the model gains knowledge of the innate patterns and traits of the illnesses, improving its ability to classify coconut leaf diseases into their corresponding severity categories with ever-increasing precision. With careful attention to detail, this CNN architecture for coconut leaf disease detection and classification effectively learns the finer points of the diseases by repeatedly running through the batched dataset and adjusting its weights. This allows it to produce precise predictions about disease severity levels across various cases, as shown in Table 2.

TABLE 2. CNN MODEL IN COCONUT LEAF DISEASES

Layer Type	Layer Details	Output Dimension
Input	Dimension: 264x264	264x264x3
Convolutional	Filters: 32, Kernel: 3x3, Stride: 1, Padding: Same	264x264x32
Max Pooling	Pool Size: 2x2, Stride: 2	132x132x32
Convolutional	Filters: 64, Kernel: 3x3, Stride: 1, Padding: Same	132x132x64
Max Pooling	Pool Size: 2x2, Stride: 2	66x66x64
Convolutional	Filters: 128, Kernel: 3x3, Stride: 1, Padding: Same	66x66x128
Max Pooling	Pool Size: 2x2, Stride: 2	33x33x128
Convolutional	Filters: 256, Kernel: 3x3, Stride: 1, Padding: Same	33x33x256
Max Pooling	Pool Size: 2x2, Stride: 2	16x16x256
Fully Connected	Neurons: 512	512
Fully Connected	Neurons: 256	256
Output	Classes: 12, Activation: Softmax	12

IV. RESULTS

The findings show how well the federated learning CNN can differentiate between four degrees (v_1 to v_4) of Coconut leaf disease severity for six clients (fs_1 to fs_6). The illness identification performance metrics by client and severity level are shown in this extensive table.Five performance parameters are shown in detail in the table: accuracy, precision, recall, F1-score, support, and accuracy. These indicators provide a comprehensive view of the model's performance for every client and illness severity level.Overall, accuracy scores for different clients and severities are relatively stable, usually falling between 0.86 and 0.95, which shows how resilient the model is.Prominent differences in recall, F1-score, and accuracy scores, particularly across customers, highlight the distinct data distribution and difficulties presented by each client's local dataset.fs_1: Generally speaking, this client performed consistently at all severity levels. From v_1 through v_4 severity levels, the maximum accuracy of 0.93 is seen, suggesting a solid model for this client.fs_2: This client's data shows a positive trend, with accuracy levels routinely exceeding 0.93. The F1-scores of the v_1 and v_3 severities, in particular, reveal a good balance between recall and accuracy.fs_3: The precision and recall figures show slight fluctuation despite the admirably consistent accuracy. Further training data or tweaking might benefit this client's model.fs_4: Compared to other severities, this client's v_1 severity level has a somewhat lower accuracy of 0.86. This suggests that there may be difficulties in differentiating this specific severity level for the fs_4 dataset.fs_5: The data indicates a strong showing, particularly in the v_2 and v_3 severities. These levels have the highest accuracy, at 0.95, making them the best-performing categories for this client.fs_6: The data indicates that the model has a balanced performance for this client, with low fluctuation across the severities and a steady accuracy that hovers around 0.91-0.93.Federated Education CNN has shown to be an impressive resource for identifying different Coconut Leaf Disease severity levels in a wide range of patients. On the other hand, the fact that each client's dataset presents various issues highlights the need for ongoing training data expansion and refinement to address the client-specific heterogeneity in accuracy, recall, and F1 scores.This thorough analysis, which includes many performance metrics, provides priceless insights. It establishes the foundation for iterative model improvements. It guarantees the successful implementation of this federated learning model in practical settings, assisting in promptly and accurately detecting Coconut leaf disease,as shown in Table 2.

TABLE II. ATTRIBUTES AND VALUES OF LOCAL CLIENT'S DATA

Clients	Class	Precision	Recall	F1-Score	Support	Accuracy
fs_1	v_1	74.78	86.00	80.00	300	0.93
	v_2	81.46	80.04	80.74	461	0.91
	v_3	87.79	85.80	86.78	486	0.93
	v_4	91.65	88.05	89.81	661	0.93
fs_2	v_1	87.54	87.12	87.33	621	0.95
	v_2	89.84	81.55	85.49	802	0.93
	v_3	85.33	92.57	88.80	848	0.94
	v_4	90.04	90.45	90.24	1089	0.94
fs_3	v_1	72.80	74.71	73.74	344	0.91
	v_2	87.53	82.21	84.79	444	0.93
	v_3	83.85	91.04	87.30	502	0.93
	v_4	92.78	89.20	90.95	648	0.94
fs_4	v_1	65.97	66.74	66.36	427	0.86
	v_2	89.54	76.03	82.23	484	0.92
	v_3	82.37	86.91	84.58	527	0.92
	v_4	83.71	89.27	86.40	587	0.92
fs_5	v_1	83.84	79.44	81.58	934	0.92
	v_2	89.99	88.11	89.04	959	0.95
	v_3	86.63	95.69	90.93	1022	0.95
	v_4	86.51	83.89	85.18	1254	0.91
fs_6	v_1	80.92	81.64	81.28	561	0.93
	v_2	83.52	82.99	83.25	623	0.93
	v_3	84.50	83.63	84.06	782	0.91
	v_4	86.43	87.13	86.78	855	0.92

This paper presents the detailed findings obtained using a CNN technique to federated learning for determining the severity of coconut leaf diseases at four levels using data from six customers in the area. The federated learning architecture generates a global model that leverages heterogeneous, dispersed data without direct access by averaging the local updates.Five critical performance indicators are included in the table: accuracy, precision, recall, F1-score, support, and accuracy. These standards provide a deep insight into each client's model's competency.The accuracy metrics are generally consistent and oscillate in the range of 0.90 to 0.94, which is evidence of the effectiveness and generalizability of the model.The model correctly recognizes the infected coconut leaves and catches the majority of actual illness incidences, as seen by the near alignment of accuracy and recall values for most customers.fs_1: This client exhibits almost equal recall and accuracy performance, suggesting a well-balanced detection capacity. A 0.93 accuracy indicates a well-performed model determination for this specific customer dataset.fs_2: With an accuracy of 0.94, fs_2 has the highest rating among the clients on the list. The accuracy and recall values' harmonic alignment highlight the model's balanced detection ability for this client.fs_3: The findings show a praiseworthy balance between recall and accuracy. It is clear from the accuracy of 0.93 that the model performs steadily for the third customer.fs_4: While somewhat lower than other customers, fs_4's accuracy and recall are tightly interwoven. An accuracy of 0.90 indicates possible areas where the dataset for this specific customer might be improved.fs_5: This client's data shows a strong model performance, further supported by an accuracy measure of 0.93 and almost equal precision and recall values. fs_6: The client fs_6 has a steady performance, with metrics for accuracy, recall, and precision ranging from 0.83-0.92. This consistency shows how flexible and capable the model is in making balanced predictions for this client. The process of averaging local client updates to generate a global model that is more broadly applicable highlights the intrinsic nature of federated learning. The many subtleties that each client dataset provides to this global model help it become more resilient and flexible in various real-world situations. This investigation clearly shows that the federated learning CNN respects data privacy and decentralization while showing potential in detecting coconut leaf diseases. The model's accuracy and recall values are almost the same between customers, which bodes well for its ability to provide accurate and well-balanced forecasts. This thorough research opens the door for the federated learning model's ongoing development, guaranteeing that it stays at the forefront of precise and privacy-preserving illness detection—a significant benefit to the world's coconut sector, as illustrated in Table 3.

TABLE III. CLIENT DATA'S GLOBAL MEAN COMPUTATION FRAMEWORK

Client	Precision	Recall	F1-Score	Support	Accuracy
fs_1	83.92	84.97	84.34	477.00	0.93
fs_2	88.18	87.92	87.97	840.00	0.94
fs_3	84.24	84.29	84.19	484.50	0.93
fs_4	80.40	79.74	79.89	506.25	0.90
fs_5	86.74	86.79	86.69	1042.25	0.93
fs_6	83.84	83.85	83.84	705.25	0.92

The table comprehensively analyses the federated averages using three different averaging techniques—Macro, Weighted, and Micro—across six other local clients (fs_1 to fs_6). These averages provide a brief picture of how well the federated learning model performed for different customers. Macro Average (Macro_ave): It treats all classes equally by computing the metric for each class individually and then averaging the results. This averaging works well when you want to provide equal weight to each class or when your datasets are balanced. Weighed_ave, or the weighted average, accounts for label imbalance while computing the measure. It assigns greater weight to the prevalent class by weighting the calculation according to the number of true cases for each label. Micro Average (Micro_ave): To calculate the metric, it combines the contributions from each class. This strategy might be helpful if you think there may be an imbalance in class. fs_1: There is consistent class performance since the weighted and micro averages are similar. Even if it is a little lower, the macro average is still quite high, showing that all courses performed very evenly. fs_2: This client exhibits the highest values out of the three averages, indicating a better model performance. Even after accounting for class imbalances, a strong performance is implied by the proximity of the weighted and micro averages. fs_3: Micro and weighted averages are closely linked, showing a similar tendency to that seen in fs_1. The performance of the model seems consistent and well-rounded. fs_4: Despite having averages lower than those of the other customers, the model can maintain a steady performance for this client despite possible class imbalances, as shown by the closeness between the micro and weighted averages. fs_5: The values of the three averages are almost in line with one another, suggesting that the model has a balanced detection capacity for this client over a range of classes. fs_6. Using these insights, the federated learning model can be skillfully adjusted to meet the unique needs of every customer, ultimately improving its overall effectiveness in identifying coconut leaf disease, asshown in Table 4.

TABLE IV. GLOBAL SYNTHESIS OF LOCAL AVERAGES MEASURES

Averages	fs_1	fs_2	fs_3	fs_4	fs_5	fs_6
Macro_ave	84.41	88.02	84.24	80.01	86.74	83.84
Weighted_ave	85.36	88.26	85.59	80.82	86.72	84.15
Micro_ave	85.22	88.24	85.50	80.74	86.76	84.15

V. CONCLUSION

The goal of reducing the harmful effects of coconut leaf diseases is central to the complex web of agro-based research. By combining Federated Learning with Convolutional Neural Networks (CNN), this study explored previously unexplored areas to effectively detect the various stages of coconut leaf illnesses using six customers' data. The datasets for each client provide an unmatched depth of knowledge, reflecting a microcosm of the disease's complex nature across four severity levels.Our research path resulted in a model deeply rooted in a multi-layered convolutional architecture designed to detect even the most subtle illness signs. Federated Learning leverages the collective knowledge contained in each client's dataset in a decentralized manner while maintaining data sovereignty. A global model with better discrimination skills is the result of this method of operation, as the statistical benchmarks demonstrate.The federated average findings provide an instructive image when delving further into the empirical measurements. The macro average numbers showed how flexible the model was in various data environments, ranging from 80.01% (for fs_4) to an astounding 88.02% (for fs_2). Notably, the weighted average, which varied from 80.82% to 88.26%, showed the model's awareness of possible class imbalances. Concurrently, the micro averages, essential for summarising overall performance, ranged from 80.74% to 88.24%.

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