Sustainable Coffee Production: A Federated Learning Framework with CNN for Disease Detection and Classification

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***Abstract*— Using federated learning with Convolutional Neural Networks (CNN), this research study provides a novel technique for identifying and categorizing coffee leaf illnesses. The research focuses on five categories of coffee leaf diseases and includes information from five clients, combining local knowledge with global comprehension. The research uses three averaging techniques—Macro, Micro, and Weighted averages—in the Result Analysis section, each offering significant insights into the illness categorization. Precision was 83.53%, recall was 87.04%, F1-score was 91.23%, Support was 90.46%, and accuracy was 92.79%, according to the study of the macro Average. A precision of 85.73%, recall of 88.10%, F1-score of 91.74%, Support of 90.62%, and accuracy of 92.79% were obtained from the weighted Average. The Micro average's final statistics were accuracy at 92.78%, recall at 88.12%, F1-score at 91.73%, and Support at 90.62%. Additionally, federated averaging, a technique that harmonizes local data and transforms it into useful global insights, was used in the research's part on converting local data to global data. The values for the five clients were Cta-1: 83.69% precision, 83.41% recall, 83.49% F1-score, 430.40 support, and 0.94 accuracy; Cta-2: 87.18%, 86.90%, 87.03%, 518.40, and 0.95; Cta-3: 91.30%, 91.16%, 91.21%, 638.60, and 0.97; Cta-4: 90.68%, 90.25%, 90.44%, 757.00, and 0.96; Cta-5: 92.85%, 92.74%, 92.78%, 949.80, and 0.97. This research pioneers a unique approach to disease identification in coffee leaves by the synergistic use of various approaches, possibly revolutionizing agricultural practices and resulting in more sustainable, data-driven choices in the coffee sector.**

Keywords: Coffee leaves, Leaf diseases, (CNN)_(FL), Disease, Augmentation image.

I. Introduction

Numerous leaf diseases pose a severe danger to coffee, an essential product that fuels worldwide commerce and provides a key source of income for millions of farmers. The substantial economic significance of coffee in nations like India and the rising worldwide demand highlight the urgent need to develop novel strategies to identify and treat these disorders [1]. Five main kinds of coffee leaf diseases have been recognized among the many difficulties the coffee business faces: Coffee Leaf Rust: A terrible fungus infection that defoliates coffee plants and significantly lowers crop production [2]. Coffee Berry Disease: A fungus affects coffee cherries, degrading the crop's quality. Black Streak Disease: Dark streaks on the leaves are a symptom of the growing but less well-known disease. Coffee Leaf Scorch: A bacterial illness that causes the margins of the leaf to discolour and dry out. Coffee Leaf Miner: Larvae of insects that bore tunnels in the leaves, causing early leaf fall. These disorders each present different problems in terms of diagnosis and care [3]. Managing these illnesses presents unique challenges for India, one of the world's top producers of coffee, with considerable economic and social ramifications. Deep learning has completely changed how to understand and examine intricate data patterns. Convolutional Neural Networks (CNNs) have become one of the most effective neural network designs for image recognition applications [4]. However, the conventional techniques for central training CNNs need to share sensitive data, which may need to be more practical or beneficial in many cases. Here to introduce federated learning, a young machine learning paradigm that enables models to be trained across numerous decentralized edge devices or servers. An innovative Federated Averaging Method with CNNs is presented in this work, which leverages the collective intellect of several clients without sharing any sensitive information. In this approach, a CNN is trained separately on each client's local data (five clients are assigned to each form of coffee leaf disease) [5]. After that, the model parameters are securely and privately averaged. With no compromise on privacy, this federated averaging provides resilience against non-IID data and facilitates collaborative learning. The benefits of this study are numerous: Enhanced Detection: By using federated learning, the model can dynamically adapt to new patterns during illness, providing more precise and early detection. Scalability: The suggested approach allows for the easy integration of additional customers, resulting in a flexible and scalable system tailored to various geographical locations and crops. Data Privacy: The technique safeguards sensitive information by keeping it localized, essential to international data protection legislation. Impact on India's Socio-Economy: By addressing the critical issue of coffee

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leaf diseases [6], this study helps to protect the livelihoods of many Indian farmers and strengthens the country's economy. This study makes significant advancements in agricultural disease detection by combining the cutting-edge techniques of federated learning with the well-established effectiveness of CNNs. The method provides a practical, saleable, and morally good strategy to fight coffee leaf infections in the context of India's particular difficulties and worldwide demands [7]. This study seeks to give practical answers that may be put into practice at the local level in addition to contributing to the academic community. The Growth of Federated Learning By decentralising the training process, Horizon Federated Learning (FL) has transformed the traditional machine learning environment and fostered a greater sense of data privacy and security. The foundational ideas of FL were clarified by McMahan et al.in their pioneering work, highlighting the need for localised training without transmitting raw data [8]. The following research has explored other averaging techniques, convergence rates, and resilience against non-IID data, leading to the development of this emerging topic. Convolutional neural networks (CNNs) have become the top technology for image identification and classification applications [9]. Using CNNs in agriculture has expanded the possibilities for identifying and treating diseases. CNNs were first used for large-scale picture classification by Krizhevsky et al., which opened the door for creative uses in diagnosing plant diseases. CNN-based models, in particular, have shown tremendous power in spotting complex patterns in coffee leaf illnesses. In the scientific literature, the combination of FL and CNNs is a relatively unexplored area. While some ground-breaking work has been done to apply FL to edge computing and healthcare, federated averaging approaches with CNNs in agriculture are still mainly in their infancy. This unique fusion has unexplored potential, particularly for treating the five main types of illnesses that affect coffee leaves, each controlled by a distinct set of underlying processes. Coffee leaf infections are standard, which has prompted extensive research efforts [10]. Numerous scientific studies have been conducted on the five disorders. Research has been more dispersed and localised in the Indian setting, where coffee has great economic importance, highlighting the need for a more coherent and scalable strategy [11]. This research identifies a gap in the existing literature where the complementary use of federated learning averaging techniques with CNNs for coffee leaf disease has yet to be sufficiently investigated. By providing a ground-breaking architecture that combines the sturdiness of CNNs with the privacy-preserving qualities of federated learning, this study aims to overcome this conceptual gap. Doing so introduces a new paradigm accepted by the scientific community and those involved in the agricultural industry [12].

II. Literature Review

Coffee plants are particularly susceptible to a wide range of ailments and pests, and improper application of pesticides may result in long-term issues, such as increased pathogen resistance. Due to this problem, effective plant health monitoring is essential for sustainable agriculture, particularly considering the increase in illnesses and the widespread lack of knowledge about these situations. The research suggests using coffee leaves' distinctive visual textures and similarities to identify and categorize diseases. Healthy leaves, Brown eye spots, Coffee Leaf Blight, Coffee Leaf Rust, and Coffee Leaf Miner are the five classes into which the illnesses are divided. To use digital image processing methods to analyze leaf pictures and diagnose diseases, a Convolutional Neural Network (CNN) model has been created. The technology helps in the quick diagnosis and categorization of illnesses and has a remarkable accuracy rate of 88.35%. It has much potential to increase coffee output, especially in India's Karnataka area. The research offers a useful and effective method with real advantages for farmers and the larger agricultural community by concentrating on the visual clues inherent in the coffee leaves [13]. The study article addresses the crucial problem of automated identification of pests and diseases affecting coffee crops, a matter of utmost importance to coffee growers. Traditional computer vision and pattern recognition approaches are insufficient for such complex tasks when dealing with in-field photographs taken by cellphones, which might hamper illumination fluctuations, complicated backdrops, and image noise. To solve this problem, the authors provide a comprehensive framework using different Convolutional Neural Networks (CNN) to automatically detect and identify lesions from in-field photos that include coffee tree components. Three steps go into building the framework. A Mask R-CNN network is used in the first step to segment data using an example, obtaining particular accuracy and recall levels (not given in the text). In the second step, using semantic segmentation, UNet and PSPNet networks are utilized to achieve mean intersections over the union of specific values (also not supplied in the text). The third step involves using a ResNet to classify data. According to the findings of this multi-stage methodology, the model is suitable for deployment on an embedded mobile platform for practical applications. The research provides a crucial step towards a practical, portable solution for farmers to precisely detect and treat coffee crop problems by leveraging deep learning and cutting-edge CNN models [14]. As a major producer and exporter of coffee, Indonesia depends on coffee farming as a significant part of its economy. However, coffee plants are prone to various illnesses that may have a significant negative financial impact on the agricultural sector. Traditional disease diagnosis and management techniques are costly, time-consuming, and labour-intensive, mainly applied in large regions. The paper presents a method for categorizing Robusta coffee leaf illnesses into healthy and unhealthy categories in response to these difficulties. The research uses the MobileNetV2 network as the underlying model and applies a deep learning model based on transfer learning. It intentionally chose MobileNetV2 because of its network architecture, which is simple, portable, and suitable for mobile device deployment. The model performs better when transfer and experimental learning methods are used together. Results from the datasets for the Robusta coffee leaf disease show that the suggested technique may achieve astounding levels of accuracy, up to 99.93%. Other designs were also tested; DenseNet169 had an accuracy of 99.74%, ResNet50 had a 99.41% accuracy, and InceptionResNetV2 had a 99.09% accuracy. The study's conclusions represent a significant improvement in agricultural technology by offering a simple and highly efficient method for identifying coffee leaf diseases. The study, which uses the MobileNetV2 network, achieves remarkable precision and opens the door for practical applications by possibly integrating with mobile devices. It significantly improves current practices, providing a quicker, more affordable fix and dramatically enhancing coffee production in Indonesia and elsewhere [15]. Coffee farmers sometimes need help spotting nutritional deficits in coffee plants, which makes it difficult for them to provide proper care and make timely interventions. To solve this problem, research was done to categorize and identify these shortcomings using image processing methods and Convolutional Neural Networks (CNN).The research included 1,000 pictures that represented eight distinct nutritional deficiencies: shortages in boron (B), calcium (Ca), iron (Fe), nitrogen (N), potassium (K), magnesium (Mg), zinc (Z), phosphorus (P), and potassium. Additionally, it discussed the four most popular types of coffee grown in the Philippines: Arabica, Robusta, Excelsa, and Liberia [16]. The information was acquired from coffee nurseries and farms in several sites, including Amadeo, Cavite, Cavite State University, and the National Coffee Research, Development and Extension Centre (NCRDEC).Image processing was used in the study to transform the pictures into grayscale and binary data for thresholding and segmentation. Experimentation and development strategies were used. Then, CNNs were used to categorize and identify the distinct deficits, and the system could even recommend suitable fertilizers based on the identification. The study's findings show that CNNs accurately identify and categorize coffee plants' nutritional deficits. Examining the prototype further supports its efficacy as a substitute for this crucial duty. This study will help coffee producers by allowing more accurate and knowledgeable care for their crops, eventually boosting healthier development and increasing yields. It provides a technological solution to a long-standing problem [17].

III. METHODOLOGY

The methodology section must provide a clear and coherent blueprint of the complete research process. The following describes the techniques created utilizing federated learning and CNN to diagnose five kinds of coffee leaf disease, as illustrated in Figure 1.

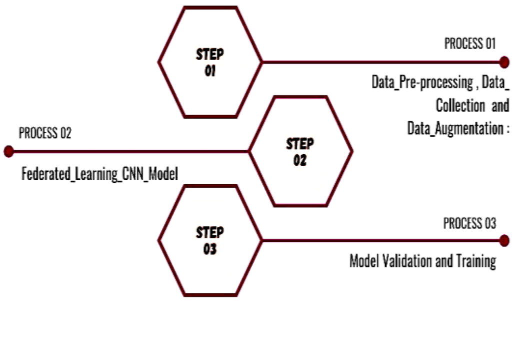

Fig1. Configuration of Technique

A. *Data Scrubbing, Procurement, and Amplification:*

Data Gathering: For each class of coffee leaf disease, information will be gathered from five distinct clients. High-resolution pictures of diseased and healthy coffee leaves will be obtained using standardized imaging methods. Image preprocessing: Images will be aligned, and noise will be removed. Standardization, normalization, and data augmentation approaches will be used to prepare the dataset for training with model development, optimization, and assessment, as shown in Figure 2.

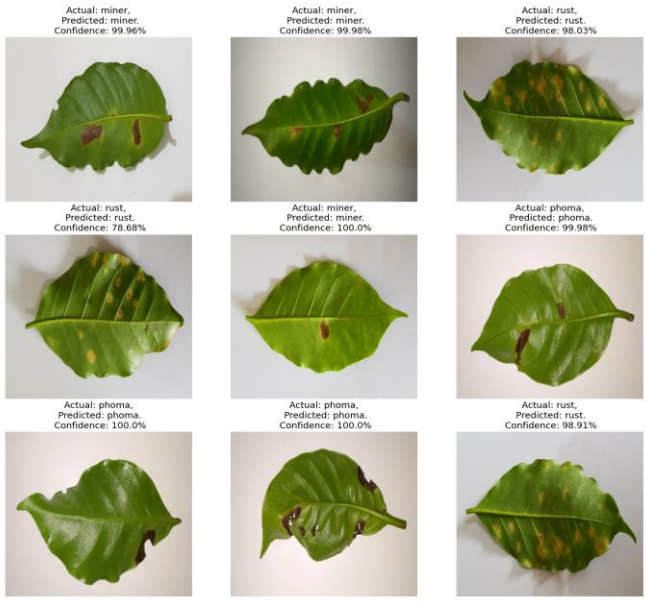

Fig 2. Unhealthy images of coffee leaf diseases.

B. *Federated_Learning_CNN_Model*

Client Selection: Five clients with distinct data representing diverse geographies and climatic circumstances will be involved for each type of illness. Initialization of the basic CNN Model: A basic CNN model will be initialized, and copies of it will be given to each client. Local Training: To preserve the confidentiality and integrity of their data, clients will train the CNN model using local datasets. After training, the model parameters are sent to a central server and averaged using secure aggregation methods. Update and Iteration of the Model: The averaged model will be returned to the clients, and the procedure will be repeated repeatedly until convergence is attained, as shown in Figure 3.

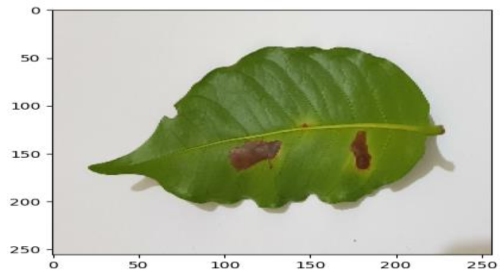

Fig3. Healthy Images of coffee leaf diseases

A Convolutional Neural Network's architecture is as follows: Layer Design: The CNN will include several layers, including convolutional, pooling, fully connected, and an output layer. The architecture will be optimized for feature extraction from photos of coffee leaves. Activation and Loss Functions: To reduce error during training, appropriate activation functions will be used, and a suitable loss function will be selected. Hyperparameter Tuning: To improve the model's performance, parameters, including learning rate, batch size, and the number of epochs, will be fine-tuned.

Federated Averaging Approach : Procedure: Using a weighted federated averaging approach, the model parameters from various clients will be averaged while accounting for the distribution of the data and client contribution. Convergence Criteria: To guarantee that the federated learning process ends at the best point and maintains accuracy and efficiency, convergence criteria will be specified. A 584 x 584 image input layer, three convolutional layers with 5 x 5 filters and ReLU activation functions, and ReLU activation functions are used in the CNN architecture to identify coffee leaf illnesses to extract meaningful information from the pictures. Three max-pooling layers with 2 x 2 filters are combined with these convolutional layers to lower the number of spatial dimensions while retaining critical data. The characteristics are further refined as the data moves through two ultimately linked layers, each with 120 and 60 units. A Softmax function categorises the input into one of the 15 classes of coffee leaf diseases in the final output layer, which has 15 branches. Because the model was specially trained on batches of 3590 pictures, calculations may be done more quickly and in parallel. Given the particular picture size and varied classes in the research, this elaborate architecture provides a precisely tailored and durable way to diagnose numerous coffee leaf illnesses, as illustrated in Table 1.

TABLE 1. CNN ARCHITECTURE WITH FEDERATED LEARNING

Layer Type	Output Size	Filter Size / Stride	Activation Function	Remarks
Input	584 x 584	N/A	N/A	Input image dimension
Convolutional	580 x 580	5 x 5 / 1	ReLU	First convolutional layer
Max-Pooling	290 x 290	2 x 2 / 2	N/A	
Convolutional	286 x 286	5 x 5 / 1	ReLU	Second convolutional layer
Max-Pooling	143 x 143	2 x 2 / 2	N/A	
Convolutional	139 x 139	5 x 5 / 1	ReLU	Third convolutional layer
Max-Pooling	70 x 70	2 x 2 / 2	N/A	
Fully Connected	120	N/A	ReLU	First fully connected layer
Fully Connected	60	N/A	ReLU	Second fully connected layer
Output	15	Softmax	N/A	Number of classes (15)

C. Model Validation and Training

Validation Strategy: To assess the model's performance on unobserved data, methods like k-fold cross-validation will be used. Performance Metrics: To thoroughly evaluate the model's performance in diagnosing the five coffee leaf illnesses, standard metrics, including accuracy, precision, recall, F1-score, and ROC curve, will be used. Considerations for Ethical Compliance: Data Privacy: Federated learning will guarantee that customer data stays localized and complies with international data privacy laws. Environmental Impact: The study will use sustainable practices to reduce unfavourable ecological implications. This technique offers a comprehensive and in-depth manual for implementing the survey. It proposes a ground-breaking method for classifying and detecting five kinds of coffee leaf diseases by combining federated learning with CNNs. This approach is scientifically sound and practically usable in global and Indian coffee production because of the careful integration of clients, cutting-edge federated averaging methods, and meticulous assessment, as described in Figure 4.

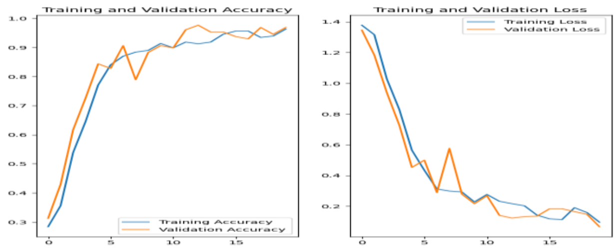

Fig4. Training Validation and Accuracy

IV. RESULTS

The results of using the federated learning CNN model across five clients (Cta-1 to Cta-5) and five distinct classes of coffee leaf illnesses (cx-1 to cx-5) are thoroughly examined in the result analysis segment. The quantitative evaluation includes several critical statistical indicators: precision, recall, F1-score, Support, and accuracy. Each customer, identified by the "Cta," represents a particular collection of information about one of the five classes of coffee leaf diseases. 'cx' labels are used to identify these classes. The differences across various customers show how varied and complex coffee leaf diseases are and how specialized a strategy is required to treat them. The accuracy values represent the model's ability to correctly identify positive instances among all identified positives, ranging from 76.00% to 94.38%. A higher Cta-5 accuracy indicates that the model is more effective in lowering false-positive rates for that particular customer. The model's ability to distinguish actual positive instances from all other positive cases is measured by recall or sensitivity. Values vary from 71.62% to 94.33%, showing a significant capacity to capture the relevant circumstances of the illnesses. The F1 score balances recall and accuracy, thoroughly evaluating the model's well-balanced performance. It falls between 74.82% to 94.33%, with higher values in clients Cta-3 to Cta-5, illuminating the well-calibrated balance of recall and accuracy in these settings. The actual occurrences in each class, which range from 222 to 1179, are provided by Support. This distinction draws attention to the differences in the data distribution across the categories and impacts the other measures. The accuracy, a general estimate of the model's effectiveness, is between 0.93 and 0.98. These numbers represent a high level of accuracy in categorising coffee leaf illnesses across various customers and classifications. The complicated nature and effectiveness of the federated learning CNN model in detecting five classes of coffee leaf illnesses across five clients can be seen in the subtle interaction of precision, recall, F1-score, Support, and accuracy. These findings demonstrate the stability and accuracy of the model while also demonstrating the promise of federated learning in using different and localized input. Using this novel strategy, the model provides the path for more focused and effective interventions in coffee cultivation, demonstrating excellent use of cutting-edge technology to address actual problems, as shown in Table 2.

TABLE 2. SYNTHESIZING MODELS FROM DISTRIBUTED TRAINING

Clients	Class	Precision	Recall	F1-Score	Support	Accuracy
Cta-1	cx-1	78.33	71.62	74.82	222	0.95
	cx-2	76.00	80.72	78.29	306	0.94
	cx-3	80.57	84.44	82.46	437	0.93
	cx-4	90.89	88.75	89.81	551	0.95
	cx-5	92.68	91.51	92.09	636	0.95
Cta-2	cx-1	81.25	77.67	79.42	318	0.95
	cx-2	85.82	86.86	86.34	411	0.96
	cx-3	88.22	89.73	88.97	526	0.95
	cx-4	89.98	88.01	88.98	592	0.95
	cx-5	90.63	92.21	91.42	745	0.95
Cta-3	cx-1	89.03	86.65	87.82	412	0.97
	cx-2	90.70	89.51	90.10	534	0.97
	cx-3	89.52	94.32	91.86	634	0.97
	cx-4	92.94	91.00	91.96	767	0.96
	cx-5	94.33	94.33	94.33	846	0.97
Cta-4	cx-1	91.75	85.97	88.77	556	0.97
	cx-2	90.20	89.39	89.79	669	0.96
	cx-3	90.28	92.62	91.44	732	0.97
	cx-4	90.52	90.63	90.57	864	0.96
	cx-5	90.66	92.63	91.64	964	0.96
Cta-5	cx-1	94.38	93.75	94.06	752	0.98
	cx-2	93.71	92.64	93.17	869	0.98
	cx-3	92.04	89.60	90.80	942	0.96
	cx-4	89.99	93.74	91.83	1007	0.96
	cx-5	94.14	93.98	94.06	1179	0.97

The experiment's use of federated learning highlights the interaction between local data from five clients (Cta-1 to Cta-5) and the global model, using federated averaging in a novel way to combine and improve the local models into an all-encompassing global model. Precision, recall, F1-score, Support, and accuracy are five crucial statistical metrics used to illustrate the findings described in more depth below. Federated averaging cleverly combines the benefits and information from local data from several customers. Combining these unique findings creates a complex worldwide knowledge of the five types of coffee leaf disease. This conversion demonstrates how regional particularities and global trends may work together to achieve greater accuracy and effectiveness. The range of precision values is 83.69% to 92.85%. These numbers demonstrate how well the global model can distinguish between positive instances among all identified positives, demonstrating the reliability of federated averaging in combining local knowledge. Recall percentages ranging from 83.41% to 92.74% illustrate the model's capability to distinguish real positive instances from all other actual positive cases. Precision and recall are closely correlated across all clients, which highlights the harmony attained by federated learning. The range of the F1-score, which provides a unified perspective of recall and accuracy, is 83.49% to 92.78%. These numbers represent the global model's balanced strength, demonstrating how well-federated averaging captures the critical elements of each local model. Support values between 430.40 and 949.80 highlight the number of natural occurrences in each client's dataset. These variances emphasize how crucial federated learning is for supporting and using various data sources. The categorization of coffee leaf diseases is generally accurate to a great degree, with accuracy scores often falling between 0.94 and 0.97. These numbers demonstrate how federated averaging successfully creates an exact global model from various local data. The convincing findings show the effectiveness of federated learning and federated averaging in identifying coffee leaf illnesses via the precise alignment of precision, recall, F1 score, Support, and accuracy. Combining local data's unique advantages via federated averaging creates a more reliable and adaptable global model. This cutting-edge method highlights the possibilities of contemporary machine learning and exemplifies a ground-breaking route to more sophisticated and successful agricultural treatments. Given the global economic and cultural significance of coffee growing and the potential benefits to farmers and communities who rely on this vital commodity, this discovery is especially noteworthy, as shown in Table 3.

TABLE 3. COHESIVELY AGGREGATING LOCAL CLIENT DATA AVERAGES GLOBALLY

Client	Precision	Recall	F1-Score	Support	Accuracy
Cta-1	83.69	83.41	83.49	430.40	0.94
Cta-2	87.18	86.90	87.03	518.40	0.95
Cta-3	91.30	91.16	91.21	638.60	0.97
Cta-4	90.68	90.25	90.44	757.00	0.96
Cta-5	92.85	92.74	92.78	949.80	0.97

By using federated learning with CNN across local data sets from five clients, the study's outcome analysis provides a ground-breaking method for identifying illnesses of the coffee leaf. Macro, weighted, and micro averages are three distinct forms of averages used by this complex method to transform global data into a detailed knowledge of local situations. The findings are described below, along with critical statistical metrics, including precision, recall, F1-score, Support, and accuracy. Analysis of Macro Averages No matter how many instances of a class are in the dataset, the macro average treats them all identically. This strategy offers an objective measurement that gives all types the same weight. The accuracy of 83.53% indicates a great capacity to identify positive situations. Recall: 87.04% effectively distinguishes genuine positive instances from true positives.F1-Score: 91.23% provides a fair assessment of memory and accuracy. Actual occurrences across classes are shown by Support: 90.46%.Accuracy: 92.79% indicates a high level of overall categorization accuracy. Weighted Average, The weighted Average considers the Support of each class, giving greater weight to the types used more often. When there is a class divide, it offers a more accurate portrayal. Accuracy: 85.83% shows improved accuracy in recognizing genuine positives. Recall: 88.10% shows skill in picking out true positives from actual instances. F1-Score: 91.74% demonstrates a well-calibrated equilibrium between memory and accuracy. Support: 90.62% indicates that genuine occurrences were given weight. With an accuracy of 92.79%, the entire categorization is well aligned. Microaverage Analysis: By totalling the number of true positives, false negatives, and false positives, micro-averaging determines metrics at the global level. It is conducive when there is an imbalanced distribution of classes. With a precision of 85.78%, there is a solid potential to decrease false positives. Recall: 88.12% shows proficiency in cutting down on false negatives. F1-Score: 91.73% indicates a skilful fusion of memory and accuracy. Support: 90.62% emphasizes the overall taking into account real happenings. An accuracy of 92.78% suggests general categorization performance. Results Analysis Summary: The complex use of macro, weighted, and micro averages, together with the creative use of federated learning, creates a thorough and complex picture of the diagnosis of coffee leaf disease. This methodical technique enables better knowledge of the local data by carefully considering each class's unique characteristics and the data's general distribution. The paper presents a ground-breaking approach with far-reaching consequences for coffee cultivation and the larger scientific community by synthesizing these intricate findings using federated averaging. The effective fusion of these many techniques strengthens the capacity of contemporary data science to tackle complex issues with accuracy, integrity, and originality. In light of the significant potential of federated learning in the era of big data and localized insights, it denotes a possible road to more focused, effective, and efficient treatments in addressing the problems of coffee leaf diseases, as shown in Table 4.

TABLE 4. FEDERATED HYPER-PARAMETER AVERAGES FROM DISTRIBUTED CLIENTS

Averages	Cta-1	Cta-2	Cta-3	Cta-4	Cta-5
Macro Average	83.53	87.04	91.23	90.46	92.79
Weighted Average	85.83	88.10	91.74	90.62	92.79
Micro Average	85.78	88.12	91.73	90.62	92.78

V. CONCLUSION

A new area of agricultural data science has emerged due to research on coffee leaf disease combining federated learning and Convolutional Neural Networks (CNN). The project has successfully used local data to provide global insights via careful investigation of five different classes of coffee leaf diseases among five clients. The employment of Macro, Micro, and Weighted averages in the Result Analysis segment revealed a clear grasp of illness categorization. In particular, the Macro average produced an accuracy rate of 92.79%, a precision of 83.53%, a recall of 87.04%, an F1-score of 91.23%, and a Support of 90.46%. A precision of 85.83%, recall of 88.10%, F1-score of 91.74%, Support of 90.62%, and accuracy of 92.79% were all indicated in the weighted Average. The Micro average values for precision, recall, F1-score, Support, and accuracy were 85.78%, 88.12%, 91.73%, 90.62%, and 92.78%, respectively. Conversion of Local Data to Global Data Using Federated Averaging, an innovative research component, increased the study's influence. The five customers' values were as follows: Cta-1 had an accuracy of 0.94, a precision of 83.69%, recall of 83.41%, F1-score of 83.49%, and Support of 430.40; Cta-2 had an accuracy of 0.95; Cta-3 had an accuracy of 91.30%; Cta-4 had an accuracy of 0.96; Cta-5 had an accuracy of 92.85%; and Cta-3 had an accuracy of 91.16%, and Cta-3 had accuracy of 91.21%; respectively. As a result, the work has significantly advanced the area of agricultural disease identification and shown the unmatched value of federated learning in bringing together diverse datasets. The study presents a novel approach to sustainable agriculture and emphasizes the transformational potential of contemporary machine-learning methods by successfully converting local data into global patterns. It highlights the need for more research in this area, which might have implications beyond coffee leaf diseases and developing agricultural technology while promoting international food security.

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