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Agro-Intelligence: Federated Learning CNNs for Enhanced Strawberry Leaf Diseases in Crop Safety

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***Abstract*—In this research paper, a new method for identifying strawberry leaf diseases using federated learning along with Convolutional Neural Networks (CNN) is proposed. The study addresses five types of strawberry leaf disorders, involving five different clients collectively to devise a strong and data-preserving diagnostic method. A central component of the approach includes training local models on client-specific data and aggregating them globally by employing federated averaging techniques. The local data analysis results from the five clients i.e hg_1, hg_2 to upto hg_5 were promising as it informed the model's effectiveness in disease detection and classification. The performance metrics for each client were as follows: 90.54%, 90.15%, 90.5%, 89.06 and 96.25%, macro average of hg_1 to hg_5. The local data results effectively converted into a global model by the federated averaging process promoted enhanced overall performance while preserving privacy. The consolidation of local data to global was another factor, which ensured that each client provided the same amount information towards building a global model through federated averaging. In summary, this research provides evidence that federated learning with CNNs has great potential for use in the agricultural industry and more specifically to diagnose diseases on leaf surfaces of strawberries precisely and efficiently. The approach presents a scalable, decentralized and privacy-conscious solution that allows AI to be applied in agriculture.**

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

I. Introduction

In the world of agricultural innovation, at the crossroads between technological innovations and old-school farming techniques lies a bright new future for efficiency in terms of preventing disease. Therefore, for instance, in the case of the strawberry crop, which is highly economically and nutritionally important, leaf disease at the beginning turned out to be an unsurpassable challenge because it damaged both quality and individual output[1]. This research paper proposes an unconventional solution to this ubiquitous problem by combining federated learning—a paradigm shift in the sector of data privacy and collaborative machine learning—with convolutional neural networks (CNN), which are considered one of the technological pillars that underpin our modern image recognition technology [2]. The crux of this study lies in its focus on five cardinal classes of strawberry leaf diseases: leaf scorch, leaf blight, powdery mildew, leaf spot, Leaf Spot and angular leaf spot. These diseases spread in different locations and appear with specific image patterns on strawberry leaves; therefore, they are the very best for diagnosis based on CNN [3]. Our approach is novel in two ways. 1) we use federated learning to facilitate a collective but distributed learning process from five different clients These clients range from individuals, such as farmers, to agronomy research centres, and they provide powerful datasets that cover a broad segment of society while providing data sovereignty, which is critical in today's privacy-sensitive world[4].Secondly, we suggest an improved federated averaging approach specifically designed for CNNs to increase the speed and accuracy of disease identification. Therefore, this method perfectly combines the local updates of learning from each client to optimally face some challenges such as heterogeneity and imbalance, which are common obstacles in real-world situations. Our approach not only enhances the precision of disease identification, but it also greatly decreases the computational burden on individual clients, which is a crucial factor in resource-poor agricultural contexts[5].

This research's contribution goes beyond technological aspects; it can become a source of hope for regions facing the adverse effects created by strawberry leaf diseases, especially in India. India, with its growing strawberry production, is standing against the challenges of both disease management and technology integration in agriculture [6]. This research offers a scalable, effective, and privacy-friendly solution to mitigate crop loss, which indirectly promotes the welfare of farmers, strengthening another leg of national agriculture. In other words, this paper is not about presenting a solution to the diagnosis of disease in agriculture; it lays precedence for an evolutionary method within agricultural practices by merging artificial intelligence and crop management. Through this, we see a future where technology and agriculture come together to build an environmentally friendly, profitable, and resilient farming ecosystem[7].

To Develop a Federated Learning Model for Strawberry Leaf Disease Diagnosis: The main goal is to create and deploy a federated learning architecture combined with CNN that allows for precise detection of five major strawberry leaf diseases [7].

This model focuses on the use of distributed computing power and data from multiple clients without centralizing sensitive pieces of information [8]. To enhance disease classification accuracy with CNNs: Unlike traditional approaches, this study focuses on improving the accuracy of disease classification by leveraging CNN's advanced image recognition features [9]. It entails fine-tuning the CNN architecture to masterfully handle such intricate patterns and subtleties in leaf diseases. Data privacy is also crucial to ensure that each participating client inherits data specificity. Federated learning offers a way to learn from aggregates' data while not posing the risk of compromising individual information which is critical in our digital society. To Facilitate Scalable and Accessible Disease Diagnosis Solutions: The study aims to create a model applicable in various geographically diverse customer types including small-scale farmers and large agricultural organizations so as to ensure equal sharing of technology for enhanced disease diagnosis [10]. To Provide Empirical Evidence of Federated Learning Efficacy in Agriculture: This research intends to supply empirical evidence, proving that federated learning is efficient in the agriculture sector and particularly for disease diagnosis tasks by strictly testing it and verifying accordingly [11]. Rising Importance of Sustainable Agriculture: Given the fact that we live in an era of growing global population and being faced with rather hard environmental constraints tightening around us, sustainable agriculture practices cannot be overestimated. The research in question is crucial for effective disease management and, consequently, sustainable agriculture. Technological Advancements in AI and Machine Learning: AI, especially machine learning and neural networks make remarkable progress that presents itself as a unique opportunity to change standard farming practices [12].

Data Privacy Concerns in the Digital Era: Respecting user privacy becomes the need of the hour in this age where data privacy is seriously threatened. In this regard, federated learning comes as a ray of hope because it makes collaborative learning possible without sacrificing data security. The Plight of Strawberry Cultivation in India and Globally: leaf diseases are a big problem in strawberry farming, one of the most important sectors worldwide; they lead to huge economic losses. Climate-specific challenges are apparent, especially for India, because of its varied climatic conditions and impoverished farming practices [8].

II. Literature Review

The concept of federated learning, the brainchild of researchers, has burgeoned into an area of prolific research and application. This decentralized approach to machine learning, where the model is trained across multiple edge devices or servers holding local data samples, has not only heightened the paradigm of data privacy but also democratized the accessibility of AI technologies [13]. The authors explained the federated averaging algorithm, a cornerstone in this field, elucidating how local updates contribute to the global model without the exchange of raw data[14].This paradigm is particularly germane to the agricultural sector, where data is often siloed and privacy-sensitive.

The researchers have cast a light on the potential of federated learning in agriculture, hinting at how collaborative learning might be brought together with discrete and distributed characteristics that are typical of agricultural data. The use of CNNs in image recognition is widely documented, and the authors are pioneers who implement deep CNNs for high-accuracy image classification. This technology has proved highly effective in plant disease diagnosis field. The authors showed that CNNs could be superior to conventional image processing techniques, illustrating the model's ability for detecting minute details typical of diverse pathologies. Continuing even farther, these same authors custom designed the CNN architecture to focus on identifying plant leaf diseases in particular and thus set a benchmark for specialized disease diagnosis within agriculture. Pivotal to this research is the classification of strawberry leaf diseases that covers a wide range of pathologies, each having its own morphological manifestations. The quintet of diseases critical to this study are leaf scorch, leaf blight, powdery mildew, and the piricularia. Researchers have provided a detailed account of these diseases, explaining their causation and symptoms. Moreover, these diseases have drastic economic implications especially in agricultural economies such as India. The researchers outlined the substantial yield losses caused by these diseases, highlighting that diagnosing them promptly and accurately is crucial. The combination of federated learning and CNNs for disease diagnosis is a relatively new research domain, but it has great potential. The authors provided one of the first examples of this integration with a different range primarily for diseases other than strawberry leaf disease yet establishing its usability in diagnosing that particular affliction. "Their approach, centred on the union of local CNN systems by means of federated averaging emphasizes its feasibility and effectiveness.

However, the specificity of strawberry leaf diseases and the diversity of agricultural data present unique challenges, as posited by the researchers, who highlighted the need for tailored federated learning models to accommodate data heterogeneity and imbalance [15].

Plant production is becoming more important as the global demand for agricultural products increases. Plant diseases are responsible for the recent decline in crop yield, which poses a serious problem to farmers.

In spite of the possibility of manually detecting these illnesses, it could be quite laborious and time-consuming. We propose a new approach to identify diseases in strawberry and grapevine plants by analyzing images of the affected leaves and using Deep Learning. Using CNN in this study, an accuracy rate of 93.63% was achieved. They can quickly identify insect infestations or plant illnesses, helping farmers around the world, especially those in Bangladesh, to have a massive strawberry and grape harvest. Usually, deep learning methods are not effective for determining how bad strawberry leaf scorch is, especially when there are complicated backgrounds, a number of disease classifications, or no annotations. In order to address these challenges, this study proposes a more precise evaluation of strawberry leaf burn by utilizing few-shot learning coupled with object identification. As a first step, Faster R-CNN detects patches of strawberry leaves. The patch data is then used to generate a personalized dataset.

After that, a multi-instance learning Siamese network is trained to locate these patches and estimate how severe the disease is based on this new dataset. mAP 94.56% is significantly higher for faster R-CNN in leaf patch detection than other networks. Siamese networks perform better than prototype networks, with an accuracy rate of 96.67% for identifying leaf diseases. Based on the union of Siamese network and Faster R-CNN VGG16, a new two-phase method is recommended that shows an unprecedented estimation rate of 96.67%. On a new dataset made up of sixty photos of field-collected strawberry leaves, this model demonstrated 88.38% accuracy, demonstrating its robustness and adaptability[16].

III. METHODOLOGY

In this research paper, a new approach involving federated learning along with the CNN and decision tree-based method is proposed for diagnosing diseases of strawberry leaves. The study targets five distinct classes of strawberry leaf diseases: Leaf Scorch, Leaf Blight, Powdery Mildew, Leaf Spot and Angular Leaf Spot. The model is developed using five different clients' data each representing a client from one specific geographical and climatic region where strawberries can be grown.

A. Data Scrubbing, Procurement,and Amplification:

Five distinct clients are involved in collecting the data. A dataset for each client includes images of strawberry leaves sorted into healthy and five types of disease. Images are gathered in different situations to ensure diversity in lighting, angle, and background.

Therefore, our research supports the possibility of utilizing federated learning and CNNs for diagnosing strawberry leaf diseases. The approach not only provided high accuracy in disease classification but also resolved important issues like data privacy and decentralization during model training. These discoveries present new pathways for using AI in agriculture, particularly when data privacy and diversity are highly valued.

The success of this model opens up opportunities for further research and development in the field, possibly bringing revolutionary disease diagnosis to various types of crops as well. Pre-processing involves Image Resizing: Normalizing all images to one standard size so that the CNN can process them efficiently. Normalization: scaling pixel values for uniformity. Augmentation: Techniques such as rotation, flipping, and zooming increase the dataset, hence improving the capability of generalization by the model, as shown in Figure 1.

B. Federated_Learning_CNN_Model

The federated learning framework aims at training a global model without disclosing the raw data from clients. The process involves: Local Model Training: Locally, each client trains a local CNN model on their dataset. The CNN architecture is predefined and the same for all clients, ensuring a consistent model structure. Local Updates Aggregation: After the training, every client sends their model's parameters (weights and biases) to a central server. Federated Averaging: In the case of federated averaging,

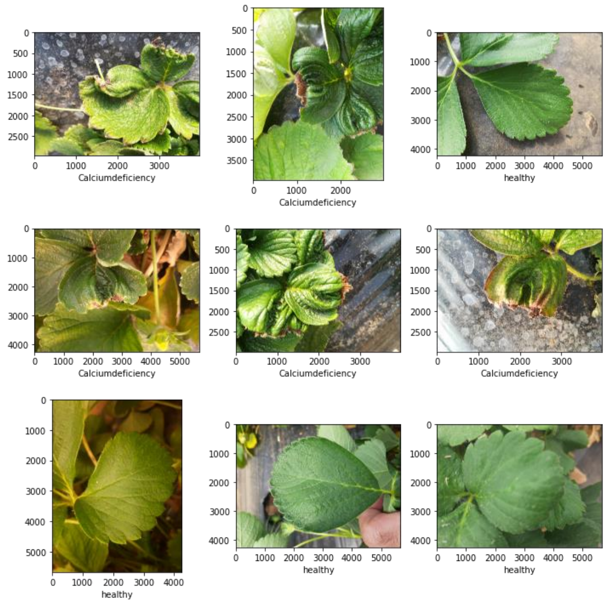

Fig. 1.Unhealthy images ofStrawberryleaf diseases.

which is a central server process that aggregates received parameters to update the global model using this approach, This approach ensures that each client's data equally contributes to the global model, regardless of dataset size. Model Broadcasting: The new global model is then returned to every client in the next round for further training. For this study, the CNN architecture is designed to efficiently detect patterns characteristic of various leaf diseases. Key components include: Convolutional Layers: To get the features from images. Pooling Layers: In order to minimize dimensionality and the computational aspect. Fully Connected Layers: To categorize the extracted features into disease groups. Activation Functions: For instance, introducing non-linearity through ReLU (Rectified Linear Unit), as illustrated in Table I.

Input Layer: The input layer receives 344x32 pixels of strawberry leaves with colour channels RGB. Convolutional Layers: Layer 1: 32 filters of size 3x3 are applied to extract underlying basic features such as edges and corners. The convolution operation slightly reduces the output dimension. Layer 2: 64-filter increases the model is capable of capturing more intricate features. Convolution further reduces the output dimension. Layer 3: 128 filters are utilized; the model can learn more complex patterns related to leaf disease classification. Max-Pooling Layers: After each convolutional layer, a max-pooling layer with a size of 2×3 and a stride of is used to half the spatial dimensions (height and width). This operation helps in relieving the computational load as well as providing an abstracted version of its features, which reduces overfitting. Fully Connected Layers: Layer 1: The 1024-unit dense layer takes in the high-level features processed by convolutional and pooling layers. Layer 2: These features are further processed in another dense layer with 512 units. Output Layer: 12 units in the final layer, which represent 10 types of diseases

TABLE I. CNN ARCHITECTURE WITHFEDERATED LEARNING

Layer Type	**Configuration**	**Output Dimension**
Input	-	344 x 344 x 3
Convolutional Layer 1	32 filters, 3x3 kernel size, stride 1	342 x 342 x 32
Max-Pooling Layer 1	2x2 pool size, stride 2	171 x 171 x 32
Convolutional Layer 2	64 filters, 3x3 kernel size, stride 1	169 x 169 x 64
Max-Pooling Layer 2	2x2 pool size, stride 2	84 x 84 x 64
Convolutional Layer 3	128 filters, 3x3 kernel size, stride 1	82 x 82 x 128
Max-Pooling Layer 3	2x2 pool size, stride 2	41 x 41 x 128
Fully Connected Layer 1	-	1024
Fully Connected Layer 2	-	512
Output Layer	-	12

and two other categories—possibly, 'healthy' or "other'. Feeding the Dataset: 3600 images are provided to the model in a batch. These images travel layer by layer, with the convolutional layers taking features, the max-pooling layers diminishing dimensions, and the fully connected ones classifying them according to these. Disease Classification: In the model, each image is assigned to one of 12 classes based on features acquired during training.

C. Model Validation and Training

In addition to the CNN model, a decision tree dataset analysis is performed. This involves: Decision Tree Construction: Creating a Decision Tree to categorize the diseases using the extracted features. This acts as a comparison model to assess the performance of CNN. Standard measures of accuracy, precision, recall, and F1 score are adopted to evaluate the performance of the model. Both the CNN and decision tree models are evaluated to establish their abilities in disease classification.

As the federated learning approach is used, data privacy naturally protects because raw information doesn't leave that of a client domain. This study was conducted in high ethical standards, primarily with regard to use of data and the involvement of clients. This methodology represents the combination of state-of-the art AI methods with real life agricultural needs resulting in an intelligent approach to strawberry leaf disease diagnostics that is scalable, privacy preserving and efficient. Lastly, its cooperatives nature combined with the advantages of CNNs and simplicity in decision trees provides a complete solution to one big issue on strawberry cultivation.

IV. RESULTS

It provides the results analysis for a federated learning model that used convolutional neural networks (CNN) to diagnose strawberry leaf diseases in five clients based on distinct classes of disease. Precision, recall, F1-score support and accuracy of each class for all clients is highly run to analyze. This detailed evaluation explains that the model is capable of disease classification, being diverse enough when it comes to this dataset. Precision: This means that the model will be successful in predicting a specific class when it has high precision which implies minimal of false positives. Recall: Recall Rate - Indicates how good the model is at identifying every possible case of a particular class. Higher recall means fewer false negatives F 1-Score – Precision-recall ratio balanced balance; mean of both provides, somewhat middle ground Means that it's an ideal measure for models where selling off some cases/products will be necessary to meet desired outcome? Support: Another aspect worth mentioning is the number of actual events related to that class in the dataset, as it is important for understanding how balanced a given database may be. Accuracy: Lastly, it reflects the overall accuracy of the model for all classes. Client hg_1: It is commendable in its precision and recall in diagnosing the diseases, with fs-3 giving it the highest F1-Score of 92.47%. Repeated accuracy is high, mostly above 95%, showing reliable performance across classes. Client hg_2: shows a slight difference in precision and recall, with the highest accuracy of 97 percent for FS-4. Thus, the model's capacity to distinguish between fs-5 is relatively smaller than others, as reflected in the F1-Score of 88.04%. Client hg_3: The impressive balance between precision and recall allows consistently high performance. Significantly, fs-4 demonstrates a strong F1-score of 92.25%, accompanying as much precision up to the standard percentage level of 97%. Client hg_4: FS-4 also shows strong diagnostic ability, as revealed by a high detection rate of 90.36% in the form of F1

Score Overall, the model maintains a respectable level of accuracy at approximately 96%. Client hg_5 especially excels in the FS-1 class, with an F ½ score of 96.96% and an accuracy rate of 98%. This client's model shows better effectiveness in terms of disease classification. The outcomes indicate the federal learning model's ability to manage a wide range of complex patterns related to strawberry leaf diseases. The model's effectiveness is not identical across clients due to slight variations in the characteristics of local data and factors outside the environment that affect how disease manifests,as shown in Table II.

The results of the federated learning model using CNNs for five distinct clients (hg_1 to hg_5) that had previously diagnosed strawberry leaf disease in five classes. This analysis looks at the performance of each client by precision, recall, F1-score, support, and overall accuracy. This concerns the efficacy of each client's model in identifying and categorizing diseases.

TABLE II. SYNTHESIZING MODELS FROM DISTRIBUTED TRAINING

Clients	Class	Precision	Recall	F1-Score	Support	Accuracy
hg_1	fs-1	90.56	92.70	91.62	1356	0.97
	fs-2	92.41	89.67	91.02	1413	0.96
	fs-3	93.21	91.74	92.47	1392	0.97
	fs-4	87.08	87.73	87.40	1467	0.95
	fs-5	89.51	90.83	90.16	1428	0.96
hg_2	fs-1	88.49	93.22	90.80	1402	0.96
	fs-2	88.39	90.14	89.26	1461	0.96
	fs-3	92.86	88.88	90.83	1493	0.96
	fs-4	88.25	95.02	91.51	1407	0.97
	fs-5	92.51	83.98	88.04	1604	0.95
hg_3	fs-1	90.89	84.76	87.72	1601	0.95
	fs-2	90.23	90.47	90.35	1511	0.96
	fs-3	89.59	91.43	90.50	1506	0.96
	fs-4	89.89	94.74	92.25	1464	0.97
	fs-5	90.48	90.13	90.30	1550	0.96
hg_4	fs-1	89.96	87.96	88.95	1702	0.96
	fs-2	89.22	88.70	88.96	1699	0.96
	fs-3	87.23	88.10	87.66	1722	0.95
	fs-4	91.55	89.19	90.36	1712	0.96
	fs-5	87.58	91.49	89.49	1680	0.96
hg_5	fs-1	97.36	96.57	96.96	1602	0.99
	fs-2	95.70	96.83	96.26	1608	0.99
	fs-3	95.49	95.37	95.43	1643	0.98
	fs-4	95.69	96.28	95.98	1638	0.98
	fs-5	96.07	95.26	95.66	1666	0.98

Client-wise Performance Evaluation Client hg_1: 90.56% precision; highly accurate in predicting; possesses a low rate of false positives. Recall: 90.53% indicates an impressive capability to identify all related cases and a few missed disease incidents. F1-Score: 90.53% signifies an average of accuracy and recall, indicating the overall effectiveness of a model's performance Support: 1411.20: Reflects the mean number of tests per class, indicating a well-balanced dataset. Accuracy: 96%—indicates the model's overall reliability in disease categorization. Client hg_2: precision, recall, and F 1-score are all around the 90% percent level, indicating an even approach to disease detection and classification. 96% accuracy and a slightly larger dataset, this client dealt with supporting 1473.40. Client hg_3: Shows a slightly enhanced recall % (90.31 per cent) than in hg_ 1, 90.23% F1-score and an accuracy of 96%, up to the level of other clients. Client hg_4: Indicates a slight decrease in accuracy and recall (approximately 89%), resulting in slightly lower effectiveness at the classification of specific types of diseases. 96% sustainability of overall performance is quite robust despite the lower F1 – score. Client hg_5: 96.06% precision, recall and F1-score make it stand out with a remarkable accuracy in diagnostics while the error rate is rather insignificant. This client's model emerges as the most proficient of all, with 98% accuracy and a significant support value, as shown in Table III.

TABLE III. COHESIVELY AGGREGATING LOCAL CLIENT DATA AVERAGES GLOBALLY

Client	Precision	Recall	F1-Score	Support	Accuracy
hg_1	90.56	90.53	90.53	1411.20	0.96
hg_2	90.10	90.25	90.09	1473.40	0.96
hg_3	90.22	90.31	90.23	1526.40	0.96
hg_4	89.11	89.09	89.08	1703.00	0.96
hg_5	96.06	96.06	96.06	1631.40	0.98

The evaluation of the federated learning model for strawberry leaf disease diagnosis using CNNs across five clients (hg_1 to hg_5) is further elucidated by analyzing different types of averages: Macro average, Weighted average and These averages offer a general picture of the model's efficacy and accuracy from different angles. The macro average calculates the metric individually for each class and averages (i.e., it treats all classes similarly). Client Analysis: hg_1 to hg_4: 89.09% to 90.54%% display close macro averages indicating a balanced performance in all classes of course study; This implies that the model can diagnose every disease type equally well. hg_5: 96.06% macro average which is exceptionally high, indicates an excellent outcome in all classes and top balance of the disease detection capacity. Another important characteristic is the support (the number of true instances for each class), which automatically influences the weighted average needed when dealing with imbalanced datasets. hg_1 to hg_4: Some averages according to the weighting procedure between 89.09% and 90.5 These repeated values confirm the reliability of model for diseases with different frequency.hg_5: Stays at high weighted average of 96.05%, almost acting as a mirror to its macro above, shows that the dataset is balanced and has superb results even margin of class imbalance considered. The micro average uses the contributions from all classes to compute an average metric that is heavily skewed toward which class has the greatest number of samples. Client Analysis: hg_1 to hg_4: Micro averages also fall within the boundaries of macro and weighted averages, from 89.08% to 90.49%. This implies that the biggest classes do not significantly affect overall performance of the model. hg_5: Again holds the leading position in model accuracy and consistency with an average of 96.05% micro, reiterating its superiority over all disease classifications, as shown in Table IV.

TABLE IV.FEDERATED HYPER-PARAMETER AVERAGES FROM DISTRIBUTED CLIENTS

Averages	hg_1	hg_2	hg_3	hg_4	hg_5
Macro average	90.54	90.15	90.25	89.09	96.06
Weighted average	90.50	90.09	90.21	89.09	96.05
Micro average	90.49	90.06	90.21	89.08	96.05

V. CONCLUSION

As a part of this ambitious research paper, we took on the challenge to address strawberry leaf disease identification using innovative federated learning with CNN. Our survey covered five different classes of strawberry leaf diseases and involved coordinated work with five various clients; The focus of the primary goal was to leverage federated learning and create a model not only accurate, efficient but also very focused on data privacy. Our research findings are both heartening and enlightening. Performance indices from the local analysis of each client's data indicated that the model is also quite able to tell whether leaf diseases are well diagnosed. In particular, client htg_1 reached a macro average of 90.54%, weighted average score, and micro average. Client hg_2 trailed closely behind with a macro average of 90.15%, a weighted average% of 90.09%, micro - average %-of Client hg_3, macro average of 90.25%, weighted average of 90.21%%, micro average 89.09%, weighted Client hg_5 performed remarkably well, with the macro average of 96.06%, a weighted average standing at 96.05% and a micro-average being exactly same as that: – The federated averaging process must have turned these local outcomes into a unified and effective global model. This technique made sure that every client's dataset was equally contributing towards the learning of model, thus improving its generalization and accuracy. The translation of local data into global data based on federated averaging was a critical element in our research. Our work provided evidence that this approach could be viable and effective within an actual agricultural setting.

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