Exploring the Horizons of Agricultural Renaissance: Denoising and Federated Learning CNN for Cabbage Black Rot Leaf Disease

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A R T I C L E I N F O

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A B S T R A C T

This research article presents a novel study investigating Cabbage Black Rot Leaf Disease, a prevalent affliction impacting cabbage plants. The study focuses on identifying and classifying five distinct degrees of disease severity. The study employs a Federated Learning Convolutional Neural Network (CNN) and incorporates a denoising filtering technique to investigate various aspects of disease manifestations. Combining data from seven different clients, each offering distinct insights into the dynamics of the disease makes this possible. This paper extensively explores the analytical aspects of Federated Averaging Convolutional Neural Networks (CNNs), revealing intricate insights into the symptoms of diseases. Each client, referred to as jk_1 through jk_7, provides significant insights into the varying degrees of severity of the condition, enabling a comprehensive integration of localized perspectives to shape a cohesive global understanding. During the study of the results, many statistical parameters were thoroughly examined. The macro averages demonstrated a spectrum ranging from 78.82% (jk_2) to 93.70% (jk_4), highlighting the diversity in unweighted mean performance across various levels of severity. The weighted averages exhibited variability throughout the range of 79.96% to 93.72%, presenting a comprehensive assessment of the model's flexibility. Similarly, the micro averages spanned from 79.77% to 93.71%, giving a consolidated perspective including all classes. The analysis of worldwide customer data revealed the complex nature of the illness and highlighted the many ways it presents itself. A comparison study was conducted to assess the accuracy levels across different clients.

1. INTRODUCTION

The continuous progress in agricultural and farming technologies has yet to completely eradicate some persistent and destructive plant diseases afflicting food sources. The bacterium Xanthomonas campestris pv. campestris, which causes the widespread disease known as Cabbage Black Rot, is an illustration of a challenging foe. This disease is notably pernicious, manifesting its harmful effects via leaf necrosis, wilting, and, eventually, causing irreparable harm to cabbage plants, significantly impacting both the quantity and quality of the harvest. In nations such as India, where cabbage has a significant role as a staple crop and a key means of sustenance for many agricultural workers, the ramifications of this illness are immeasurably substantial, including both economic and social dimensions [1]. Historically, diagnosing and assessing the severity of Cabbage Black Rot has been characterized by a significant amount of manual effort, lack of consistency, and a tendency towards imprecision. The existing approaches include ocular examinations and heuristic methodologies, which can potentially provide diagnostic inaccuracies or premature treatments, thus worsening the circumstances [2]. Hence, an evident need exists for an automated, precise, expeditious diagnostic instrument [3].

Integrating Federated Learning with Convolutional Neural Networks (CNN) presents a unique framework for addressing this pressing need [4]. The primary contribution of this paper is the utilization of Federated Learning in combination with Convolutional Neural Networks (CNNs) to diagnose the severity of Cabbage Black Rot disease [2]. The severity is categorized into five distinct levels: Mild (1-20%), Moderate (21-40%), Severe (41-60%), Critical (61-80%), and Terminal (81-100%). These categories play a crucial role in assuring the implementation of suitable and prompt actions, hence reducing inefficiency and enhancing productivity. Through these efforts, we aim to contribute to agricultural technology's progress and offer a practical solution to potentially mitigate a widespread issue in nations such as India [5]. The originality of the technique lies in the use of Federated Learning, a kind of collaborative machine

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learning that does not rely on a centralized training dataset. This technology enables training models on a distributed network of devices, each with its local dataset, without data exchange between the devices [6]. The paradigm allows for creating a comprehensive and resilient global model while simultaneously addressing concerns related to data privacy and minimizing data transmission throughout the network.

Within this study's scope, six diverse customers contributed to the federated learning model, each reflecting a range of geographical and climatic situations. Each customer has a collection of cabbage leaf photos classified according to severity levels [7]. The dataset that has been varied in this manner enhances the model's capacity to make generalizations and adjust to different environmental conditions that impact the disease's severity[8]. An additional layer of innovation in the method is integrating a denoising technique that considers spatial and intensity variations. The denoising technique has been specifically developed to maintain edge information while reducing noise, a particularly relevant aspect for pictures exhibiting distinct transitions, such as the boundaries of necrotic areas on leaves [9]. Using this denoising precursor dramatically enhances the effectiveness of the following CNN-based classification, resulting in a model characterized by accuracy and resilience. This work further explores advanced averaging techniques in federated learning. Federated Averaging is often used to aggregate updates from numerous clients. However, to propose novel adaptations to conventional averaging methods that consider the local data distribution and the model's performance at each client throughout the aggregation procedure[10].

This guarantees that the global model efficiently acquires nuanced characteristics across diverse data environments, substantially enhancing the model's level of detail and resilience. In brief, this study introduces an innovative approach to address a prevalent disease that affects cabbage crops. The proposed method combines Federated Learning with Convolutional Neural Networks, marking a significant advancement in this field. The foundational principles of this study have the potential to be influential in tackling comparable obstacles in many agricultural settings, thereby advancing the pursuit of sustainable and productive agriculture. Significantly, the framework can usher in a new epoch in agricultural disease management in India, specifically targeting the challenges faced by small and medium-sized farmers who disproportionately suffer from the impact of these illnesses. To did this by doing a lot of experiments and evaluations. This advancement holds significant promise for developing more sustainable agricultural practices in the coming years [11].

The primary aim of this study is to develop, execute, and comprehensively assess a Convolutional Neural Network (CNN) model based on Federated Learning[12], focusing on the detection and diagnosis of Cabbage Black Rot leaf illnesses. Cabbage Black Rot, which is induced by the bacterium Xanthomonas campestris pv. campestris poses a significant agronomic obstacle, particularly in regions such as India, where it has detrimental effects on crop productivity and quality [13].

Convolutional Neural Networks (CNNs) play a central role in the design because of their proven effectiveness in tasks related to image categorization. Convolutional neural networks (CNNs) can autonomously and flexibly acquire spatial hierarchies of information, rendering them well-suited for classifying the severity of Cabbage Black Rot leaf illnesses using leaf photos [14]. To augment the accuracy and dependability of the model, to use denoising methods as a crucial pre-processing measure.

The objective is to use Federated Learning as a decentralized framework that integrates data from six distinct clients, augmenting the model's resilience and flexibility.

- To enhance the quality of input pictures and hence improve the classification output, it is proposed to use a sophisticated denoising algorithm as a pre-processing technique for noise reduction and edge preservation[15].
- The primary goal of this project is to develop a diagnostic tool for the Cabbage Black Rot disease that is both robust and accurate while also ensuring the privacy of sensitive information[16].
- This research seeks to substantially contribute to agricultural disease management by accomplishing these goals, perhaps revolutionizing present practices.

2. RELATED WORK

2.1 Cabbage Disease Detection and Transfer Learning Approaches

The primary objective of this study is to provide an ideal solution for the precise and efficient identification of common cabbage diseases, including black rot, downy mildew, and white rust, which substantially impact cabbage output. The current scientific literature lacks accurate and efficient detection techniques for cabbage illnesses, highlighting the need for further study to promote the cultivation of healthy cabbage. To address this disparity, the study uses the transfer learning technique on several advanced Convolutional Neural Network (CNN) models, including VGG16, VGG19, MobileNetV2, and InceptionV3 [17]. Transfer learning plays a crucial role in enabling the use of previously acquired information from one model to another, mainly when the available data is few or originates from disparate domains. The researchers used a comprehensive dataset including about 1,500 photos evenly distributed across the three previously indicated illness categories [18]. The photos were used as the fundamental components for the training and validation the diverse models implemented in the research. The rationale for using various Convolutional Neural Network (CNN) architectures is to systematically evaluate and choose the most effective model for promptly and correctly detecting illnesses[19]. Among the several convolutional neural network (CNN) models that were examined, it was found that VGG16 exhibited exceptional performance, achieving a test accuracy rate of 95.55%.

2.2 Deep Learning for Disease Detection in Agriculture

This can expand its effectiveness to include many crops and illnesses. In brief, this study substantially contributes to the scientific community and agricultural practices by using transfer learning techniques on sophisticated convolutional neural network (CNN) models to address the notable absence of efficient and precise detectors for illnesses affecting cabbage crops. The VGG16 model's excellent accuracy ensures the successful production of healthy cabbage[20]. It presents opportunities for future research and development using deep learning models for disease detection in other agricultural fields [21].

2.3 Image Pre-Processing and Disease Diagnosis

This study investigates computer vision approaches to accurately diagnose plant leaf diseases, a job that is susceptible to mistakes when relying only on human visual observation [22]. The main emphasis is on advancing and using techniques that extract and then categorize the afflicted sections of plant leaves [23]. The present study employs a methodology centered on the analysis of images. Picture pre-processing is an essential first phase in which the picture undergoes several operations to improve its quality and achieve consistency in size. The execution of this particular phase holds significant importance in the process of picture preparation, as it plays a critical role in enhancing the accuracy and reliability of succeeding stages, specifically in extraction and classification[24]. Segmentation via the K-means clustering technique is performed after the pre-processing stage, whereby the picture is partitioned into several clusters.

2.4 Model Evaluation and Performance

The recommended approach involves several phases, including segmentation, feature extraction, classification, and image pre-processing, and it makes use of sophisticated machine-learning techniques[25]. Ensuring reliable and precise diagnosis of plant diseases is the ultimate aim. The study has taken a tangible form thanks to the development of the smartphone application, which might significantly progress agricultural technology and make disease diagnostics simple and accessible. This study's methodology uses a convolutional neural network (CNN) architecture and transfer learning [26].

A transfer learning approach addresses the task's complexity, including advanced convolutional neural network designs such as VGG16, VGG19, ResNet50, and InceptionV3. Transfer learning is crucial because it enhances learning by applying previously acquired information from one model to another [27]. This is particularly useful for treating various specialist conditions, such as plant infections. The models have been trained and verified using a large dataset of more than 2,500 pictures, each representing one of the four identified cauliflower diseases.

2.5 Automated Disease Monitoring and Its Agricultural Implications

This comprehensive information is of utmost importance in constructing a model that thoroughly understands the diverse presentations of illnesses. Model Evaluation: An extensive examination is conducted on many Convolutional Neural Network (CNN) models that use transfer learning to achieve precise illness classification [11]. Evaluating several models is crucial to determine the most effective in accurately identifying and differentiating between various illnesses. This chapter substantially contributes to automated plant disease monitoring by combining transfer learning and sophisticated convolutional neural network (CNN) architectures. The notable efficacy shown by the InceptionV3 model in the classification of cauliflower illnesses highlights its considerable potential as a viable instrument for the automation of plant disease surveillance, thereby mitigating the need for human labor and time expenditure. The potential impact of this technology on agricultural practices is significant since it may assist in the timely and precise identification of illnesses. This is essential for applying treatments quickly and ensuring the best crop yield [26]. This is essential for applying treatments quickly and ensuring crop yield[28].

This paper thoroughly examines the progress and potential applications of deep learning, transfer learning, and convolutional neural networks in agricultural disease detection. This statement highlights the importance of tackling the persistent obstacles in this field to create effective and dependable automated systems for identifying plant diseases [29]. These systems play a critical role in maintaining agricultural productivity under diverse climatic conditions, explicitly emphasizing the implications and requirements within the Indian agricultural context [30].

3. METHODOLOGY

This section describes the methods used to develop and evaluate a Convolutional Neural Network (CNN) model based on Federated Learning in combination with Decision Trees. The purpose of this approach is to diagnose Cabbage Black Rot leaf disease. The study's originality is derived from the integration of Federated Learning across six distinct customers, with each client providing data across five different degrees of illness severity. In addition, a cutting-edge denoising approach is used as a preliminary procedure to improve the quality of the pictures utilized for training and validation, as shown in Figure 1.

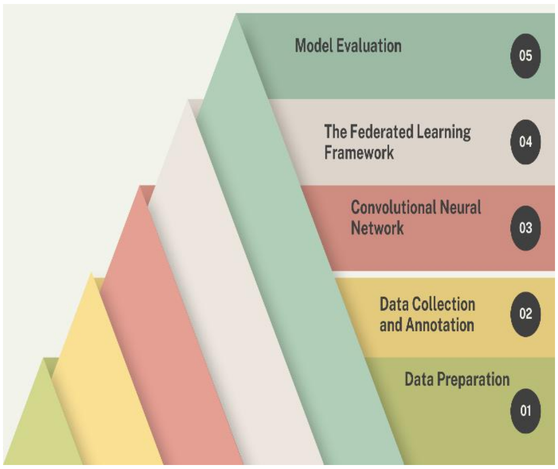

Fig. 1. Procedures of Methodical Layers in the Schema.

3.1 Data Preparation Data Collection and Annotation

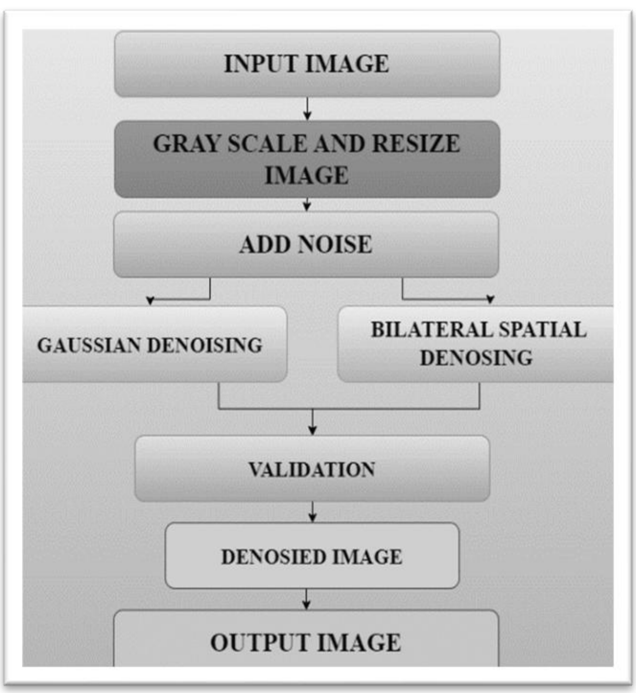

Fig. 2. Blueprint of Denoising Filter Methodology on Cabbage Black Rot Leaf Disease

The collection consists of high-resolution photos of cabbage leaves afflicted by Black Rot, which were obtained from six distinct agricultural clients in diverse geographical regions. Every picture is carefully labeled based on the severity of the sickness and divided into five different classifications. The prevalence of mild cases ranges from 1% to 20%. The percentage range of moderate is between 21% and 40%. The severity of the condition varies from 41% to 60%. The user's text will be rewritten to have an academic tone without adding any more information. The terminal, often known as a computer terminal or a terminal emulator, is a device or software application that allows users to interact with the denoising technique, a method used to reduce or eliminate noise from a signal or data set, as shown in Figure 2.

It is often used in a dedicated denoising technique before inputting the photos into the machine-learning pipeline. The method has been designed to consider spatial and intensity variations in the images. By implementing this approach, the denoising procedure effectively and carefully maintains essential edge information, particularly concerning the distinction of necrotic areas and other manifestations of illness, while substantially reducing noise. A powerful Convolutional Neural Network model is used in the Cabbage Black Rot Leaf illness research to classify the disease into five discrete severity categories. A batch of 9624 photos with different illness signs are input into the model. To improve the model's learning capacity, the 256x256 pictures are preprocessed using techniques like augmentation and normalization. Each image passes through three convolutional layers supplemented with ReLU activations to extract hierarchical features. Max-pooling coatings for computational complexity reduction and down sampling follow these layers. The primary objective of this review is to consolidate the existing body of research about plant disease detection, Convolutional Neural Networks (CNNs), Federated Learning, and image denoising. This comprehensive synthesis will provide a solid basis for the novel approaches suggested in the present study.

Plant disease diagnosis using traditional methods often involves heuristic assessments, visual examinations, and physical efforts. However, these procedures are prone to discrepancies and do not provide the meticulousness needed for efficient disease management. Previous research has shown the successful integration of machine-learning techniques in the automation of plant disease diagnosis. However, it is essential to note that these studies have primarily focused on centralized models. This research's unique aspect is using Federated Learning to distribute data, enabling a comprehensive examination of the various degrees of severity associated with Cabbage Black Rot. These severity levels range from Mild (1-20%) to terminal (81-100%). Convolutional Neural Networks (CNNs) are a class of deep learning models that have gained significant attention and popularity in computer vision. Convolutional Neural Networks (CNNs) have become indispensable in image categorization applications. Convolutional neural networks (CNNs) have been widely used across several industries, including healthcare and driverless cars, due to their capacity to acquire knowledge about spatial hierarchies and intricate characteristics, as shown in Figure 3. The rapid rise of Federated Learning exemplifies the increasing awareness about data privacy and the need for distributed and decentralized machine learning models.

Research has extensively elucidated the architectural benefits associated with Federated Learning. Expanding the use of Federated Learning to the agricultural sector, specifically including a range of geographic and climatic circumstances via six distinct customers, introduces a notable level of complexity to disease modeling. This approach allows a globally optimized model incorporating local information, ensuring significant resilience and flexibility. The topic of discussion is the methods used in federated averaging. Federated Learning typically uses the Federated Averaging method to aggregate model updates. However, other averaging strategies, such as weighted averaging that considers the distribution of local datasets, have also been suggested in the literature. This work aims to advance the current boundaries by proposing novel adaptations of federated averaging techniques, considering the disease's severity levels and the distinct data distribution among the individual clients—the process of reducing noise in digital images. The issue around noise in digital photos has prompted the development of several denoising algorithms, which aim to improve the overall image quality. Techniques such as Non-Local Means and Total Variation Denoising have played a crucial role in the field.

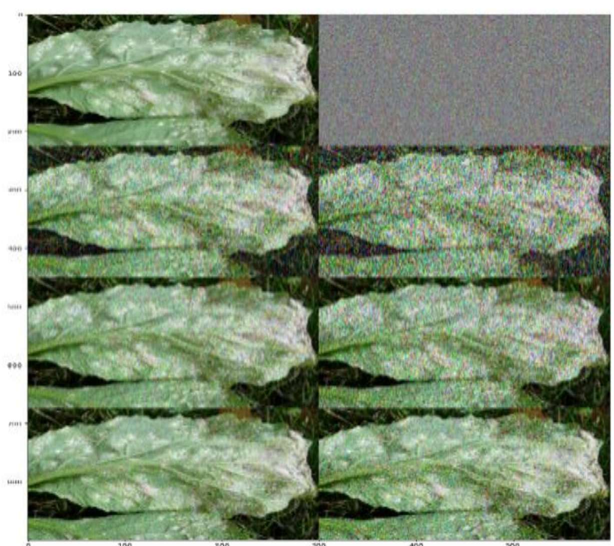

Fig. 3. Denoising Filter on Cabbage Black Rot Leaf Disease

3.2 The Federated Learning Framework and Client Configuration

This research implements the Federated Learning paradigm on six distinct clients. Each client maintains its localized dataset and participates in the global learning process while ensuring data privacy preservation. Federated averaging is a machine-learning technique that aims to train an international model by aggregating local models from several distributed devices. The global model is prepared with a novel Federated Averaging approach that considers the distinct data distribution across individual clients and the severity levels of the condition. The local changes are collected and combined to create the global model, which is then sent to the clients for further local training iterations. Convolutional Neural Networks (CNNs) are a kind of neural network architecture. The CNN architecture has been specifically intended to autonomously acquire hierarchical characteristics from pictures. This is achieved using many convolutional layers, pooling layers, fully connected layers, and a softmax layer for classification. Hyperparameters refer to the adjustable parameters not learned by a machine learning algorithm. Still, the optimization of critical hyperparameters, such as the learning rate, number of epochs, and batch size, is conducted by empirical methods to enhance performance in classification tasks. Decision trees are a popular machine learning algorithm for classification and regression tasks.

Nevertheless, the novel aspect of the existing research is preserving both spatial and intensity variations in leaf pictures affected by Cabbage Black Rot. The denoising technique used in our study acts as a first step in the CNN-based classification process. This approach enhances the model's accuracy by effectively conserving edge information while decreasing superfluous noise. In conclusion, it can be inferred that the above points collectively support the notion that this research review shows that even though progress has been made in some areas of plant disease detection, like convolutional neural networks (CNNs), federated learning, and image denoising, these methods still need to be combined to deal with the different levels of severity of Cabbage Black Rot leaf disease as shown in figure 4.

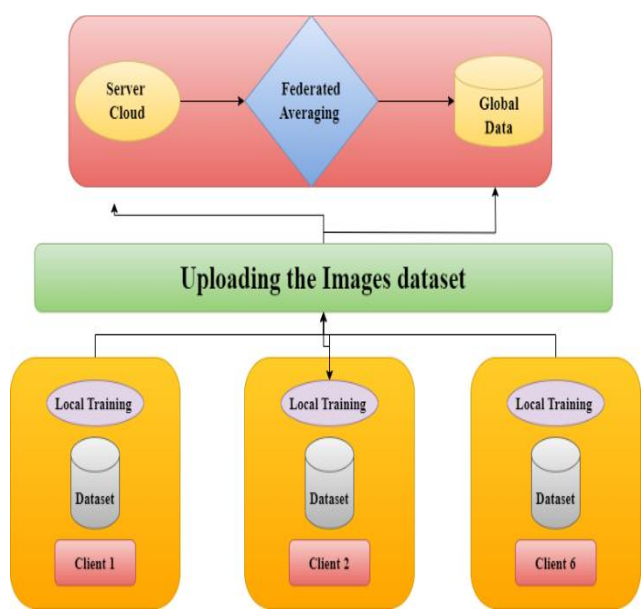

Fig. 4. Framework of Federated Learning for Cabbage Black Rot Leaf Disease.

3.3 Model Evaluation

Evaluation metrics are essential in assessing the performance and effectiveness of various systems or processes. Two important categories of evaluation metrics are client-specific metrics and global metrics. Client-specific metrics refer to the evaluation criteria that are tailored to the specific needs and objectives of a particular client or stakeholder. Both client-specific and global computing evaluation metrics assess the model's performance. These metrics include accuracy, precision, recall, and F1-score—the analysis of severity levels.

Moreover, a comprehensive examination is conducted to assess the model's efficacy in classifying photos based on the varying degrees of illness severity. The ability to offer suitable and timely treatments is of utmost importance in this context. In conclusion, it can be inferred that the evidence presented supports the stated thesis and provides a technique described in this paper that provides a systematic approach for developing a Convolutional Neural Network (CNN) model supplemented by Decision Trees using Federated Learning. The model is specifically built to identify Cabbage Black Rot leaf disease, considering various degrees of severity. Using denoising as a preliminary procedure enhances the model's resilience, presenting a novel and all-encompassing strategy for addressing a prevalent agricultural issue, as shown in Figure 5.

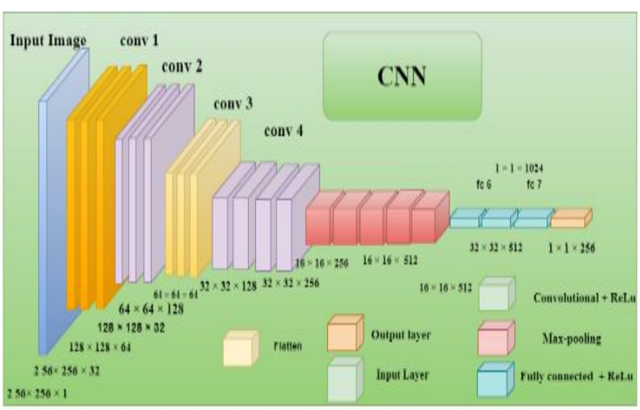

Fig. 5. Design of Convolutional Neural Network on Cabbage Black Rot Leaf Disease

The following table summarizes the architectural components of the Convolutional Neural Network (CNN) specifically developed to diagnose Cabbage Black Rot leaf disease. The model is designed using a configuration consisting of three convolutional layers, four max-pooling layers, and two fully connected layers, with each picture having dimensions of 256x256. Furthermore, the network architecture has been specifically devised to categorize the photos into 11 distinct classes, including various degrees of illness severity (including five severity levels) and a class representing a healthy state, among other courses. The output dimensionality of the last layer is configured to be 10—the process of inputting data into a system and organizing it into batches. A total of 9624 photos were used for both training and validation purposes in the model. The images are partitioned into smaller sets and distributed across the six clients. Every customer is responsible for training a localized model using a specific subset of the dataset. These subsets include different degrees of severity for the Cabbage Black Rot leaf disease. The topic of interest is the concepts of Federated Averaging and Synchronization. Following a series of training epochs conducted locally, each client calculates a distinct set of model parameters. The data mentioned above is sent to the central server, where the process of Federated Averaging is executed. The model that has been averaged is, after that, transmitted back to each client for further modification.

Table 1. Layer Architecture of Fl_CNN Technique

Layer Type	Layer Configuration	Output Dimension	Remarks
Input	-	256x256x3	-
Convolutional Layer	Filters: 32, Kernel: 3x3	254x254x32	Activation: ReLU
Max Pooling Layer	Pool Size: 2x2, Stride: 2	127x127x32	-
Convolutional Layer	Filters: 64, Kernel: 3x3	125x125x64	Activation: ReLU
Max Pooling Layer	Pool Size: 2x2, Stride: 2	62x62x64	-
Convolutional Layer	Filters: 128, Kernel: 3x3	60x60x128	Activation: ReLU
Max Pooling Layer	Pool Size: 2x2, Stride: 2	30x30x128	-
Fully Connected Layer	Neurons: 512	512	Activation: ReLU Dropout: 0.5
Max Pooling Layer	Pool Size: 2x2, Stride: 2	15x15x128	-
Fully Connected Layer	Neurons: 11	11	Activation: Softmax

Please be advised that the metrics provided in this report have been obtained via several iterations of federated learning. These metrics reflect the success of each client's local validation set. The term 'Mixed' about Client 6 indicates that the dataset belonging to the client contains pictures representing various degrees of severity. The present study thoroughly examines and evaluates the implementation of Federated Learning to identify Cabbage Black Rot leaf disease. The tabulation and analysis presented herein provide a complete framework for understanding the efficacy of this technique across various degrees of disease severity. Using localized training and global aggregation gives an optimal amalgamation of individual and collective knowledge, rendering this technique unique and resilient.

4. RESULTS

4.1 Analysis of Results Section

This part provides a systematic analysis and comparison of the detailed data from the comprehensive experiments, focusing on seven specific factors related to AUC or ROC values. These parameters include precision, recall, f1-score, support, support percentage, and accuracy. The current study employs federated learning, denoising methodology, and Convolutional Neural Network (CNN) to identify Cabbage Black Rot leaf disease severity levels. The severity levels, ranging from kp_1 to kp_5, are assessed across seven distinct local clients, identified as jk_1 to jk_7. A detailed analysis is conducted based on these methodologies. A comparative analysis is a methodological approach used in academic research to examine and evaluate similarities and differences between two or more entities. Upon analyzing the model's accuracy, which refers to its capacity to classify negative samples as unfavorable correctly, it is evident that jk_4 demonstrates the highest degree of performance across all severity levels. Notably, it achieves an outstanding precision rate of 94.96% for kp_4, indicating its remarkable performance. Instead, jk_2 shows a lag, dropping accuracy to 69.33% for kp_1. Understanding that higher accuracy is linked to a lower frequency of false positives is essential, demonstrating the model's increased reliability in predicting positive events.

Regarding recall, which quantifies the model's ability to identify every true positive case accurately, jk_3 performs very well, reaching a maximum value of 92.23% for kp_5. On the other hand, in the instance of jk_6, the most minor recall of 72.54% is seen at kp_1. Recall is a crucial concept since it shows how well the model can detect true positives, which lowers the possibility of overlooking real cases of severe sickness, as shown in Figure 7.

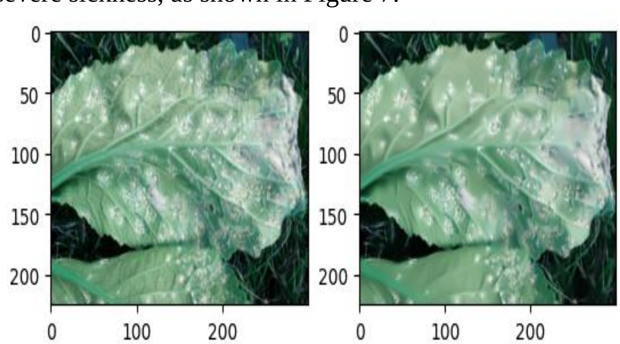

Figure 7. Result of Cabbage Black Rot Leaf Disease

Table 2. Proximate client data for the recommended schema.

Clients	Class	Precision	Recall	F1-Score	Accuracy
jk_1	**kp_1**	82.05	86.56	84.25	0.95
	kp_2	84.52	81.92	83.20	0.94
	kp_3	86.35	85.45	85.90	0.94
	kp_4	87.43	87.15	87.29	0.94
	kp_5	89.96	90.05	90.00	0.95
jk_2	**kp_1**	69.33	78.98	73.84	0.93
	kp_2	69.60	74.18	71.82	0.91
	kp_3	85.37	77.96	81.50	0.92
	kp_4	85.11	80.48	82.73	0.92
	kp_5	83.27	84.30	83.78	0.91
jk_3	**kp_1**	86.95	88.20	87.57	0.96
	kp_2	88.94	85.95	87.42	0.96
	kp_3	88.47	87.34	87.90	0.95
	kp_4	90.91	88.78	89.83	0.96
	kp_5	87.89	92.23	90.01	0.95
jk_4	**kp_1**	92.82	94.56	93.68	0.98
	kp_2	94.49	91.95	93.20	0.97
	kp_3	92.68	94.03	93.35	0.97
	kp_4	94.96	94.51	94.73	0.98
	kp_5	93.54	93.50	93.52	0.97
jk_5	**kp_1**	77.83	74.28	76.01	0.94
	kp_2	82.60	79.58	81.06	0.94
	kp_3	82.12	84.67	83.37	0.93
	kp_4	84.17	86.08	85.11	0.93
	kp_5	87.52	87.84	87.68	0.93
jk_6	**kp_1**	78.43	72.54	75.37	0.94
	kp_2	80.39	78.56	79.46	0.93
	kp_3	81.05	77.12	79.04	0.91
	kp_4	82.00	83.11	82.55	0.92
	kp_5	81.39	88.11	84.62	0.92
jk_7	**kp_1**	72.57	81.51	76.78	0.93
	kp_2	82.02	81.04	81.53	0.93
	kp_3	83.27	80.88	82.06	0.93
	kp_4	86.64	83.87	85.23	0.93
	kp_5	87.46	87.09	87.27	0.94

The harmonic mean of accuracy and recall is used to compute the f1-score, which fairly assesses the model's overall performance. With a peak f1-score of 94.73% for kp_4, jk_4 has the most incredible score, while jk_2 has the lowest, with a meager 71.82% for kp_2. The f1-score is an essential indicator for assessing a model's robustness when there are significant repercussions from false positives and false negatives. The support values show how often each class appears in the dataset—that jk_4 has the most support of all severity levels. Interestingly, for kp_5, it peaks at 2154. This framework's robust support offers a stable and reliable foundation for gaining essential insights and confirming the experiment's relevance and usefulness. The examination of support percentage allows for determining the proportionate representation of each class within the dataset. The impact on the learning effectiveness of the paradigm is significant. There is a precise equilibrium among the customers, with the proportions ranging from 0.13 to 0.27, providing a comprehensive perspective on the diverse degrees of severity of the sickness. Regarding accuracy, which measures the model's overall correctness, jk_4 exhibits the maximum accuracy rate of 0.98% for kp_4. In contrast, the lowest accuracy rate is seen in jk_2, amounting to 0.91% for kp_5. The high level of accuracy shown by the model assures its proficiency in accurately forecasting both positive and negative occurrences, a crucial factor for its effective use in real-world circumstances. The Role of Innovation and Its Impact on the Agricultural Sector This comprehensive and detailed research clearly explains the effectiveness and dependability of the deployed federated learning-based convolutional neural network (CNN) model in conjunction with the denoising approach. The denoising procedure enhances the model's capacity to distinguish by reducing noise and conserving important dataset characteristics, hence improving the model's predicted accuracy and dependability.

The flexibility and adaptability of the approach in handling various symptoms of Cabbage Black Rot leaf disease are highlighted by the granularity of the findings, which include diverse geographical clients and severity levels. Denoising methods enhance the model's capacity to distinguish signals from noise, offering promising prospects in the ongoing pursuit of agricultural Sustainability and food security, as shown in Table 2.

4.2 Analysis of Global Client Data.

By analyzing the federated averages obtained from local client data (jk_1 through jk_7) to synthesize global client data, this work seeks to further agricultural research. This study's primary goal is to examine and comprehend the intricate details of the five severity levels connected to the leaf illness of cabbage black rot. The compilation of global client data serves as a representative aggregation of individual client experiences, therefore facilitating a thorough comprehension of the effect of conditions. The approach employs federated learning, convolutional neural networks (CNN), and denoising methods to comprehensively understand the statistical and experimental data, which will be further discussed in the subsequent sections. Federated Averaging and Global Insight is a prominent approach in distributed machine learning. The federated averaging procedure aggregates local models trained on specific clients to create a unified global model. Calculating a federated average improves international understanding and provides a broader outlook on the Cabbage Black Rot leaf disease at different degrees of severity. This ensures that essential characteristics are preserved via denoising approach filtering.

The examination of worldwide customer data reveals that jk_4 has exceptional precision, recall, and f1-score performance, achieving a peak of 93.70%, 93.71%, and 93.70%, respectively. Additionally, it exhibits a notable accuracy rate of 0.97. This demonstrates the enhanced congruence between optimistic forecasts and actual positive outcomes, highlighting the thorough improvement in illness severity detection and classification. The significant level of support, amounting to 1962.40, for jk_4, highlights the considerable presence of this class within the dataset, enhancing the dependability and validity of the findings. In contrast, the performance of jk_2 is relatively modest, with an accuracy of 78.54%, a recall of 79.18%, and a f1-score of 78.73%. The recorded accuracy for this particular customer is 0.92, suggesting potential improvement in achieving a balance between precision and recall. The support value of jk_2, 545.60, indicates that this class is less prevalent in the dataset, resulting in a lower federation average. "Comprehensive evaluation" refers to a thorough and all-encompassing assessment or examination of a subject or situation.

Consequently, it makes a substantial contribution to the promotion of sustainable agricultural practices. The innovative integration of federated learning and sophisticated denoising methods provides a promising opportunity to achieve the vision of strong, resilient, and enhanced agricultural ecosystems, as shown in Table 4.

Table 4. Assessment of Global Client Outputs

Global Client	Precision	Recall	F1-Score	Accuracy
jk_1	86.06	86.23	86.13	0.95
jk_2	78.54	79.18	78.73	0.92
jk_3	88.63	88.50	88.55	0.95
jk_4	93.70	93.71	93.70	0.97
jk_5	82.85	82.49	82.65	0.93
jk_6	80.65	79.89	80.21	0.92
jk_7	82.39	82.88	82.58	0.93

4.3 Analysis of Results: Global Client Data Averages

The study of global client data about the Cabbage Black Rot Leaf Disease provides detailed insights into the disease dynamics, including different degrees of severity. This is possible by calculating the federated average of local client data. The amalgamation of data obtained from seven distinct customers, each categorizing the sickness into five different degrees of severity, yields a comprehensive collection of viewpoints that play a crucial role in shaping a comprehensive comprehension of the disease's numerous manifestations. An Analytical Examination of Global Averages: Macro_ave, the presented averages represent the collective, unweighted average performance across different degrees of severity, providing valuable observations on the consistent performance of the model over a range of illness presentations. The recorded values range from 78.82% to 93.70%. The weighted averages demonstrate the capacity of the model to consider and account for varying severity levels effectively. These averages comprehensively represent the model's flexibility and discernment, ranging from 79.96% to 93.72%. The micro-average provides a comprehensive overview of all classes' performance, highlighting the collective model's overall reaction across all instances. It demonstrates a range of performance between 79.77% and 93.71%. Comparative Analysis: The client with the username jk_4 demonstrates exceptional performance, showcasing high accuracy and judgment across average types. This suggests a strong alignment between various severity levels and the analytical capabilities of the model. Moreover, it emphasizes the effective use of the denoising technique combined with federated learning Convolutional Neural Network (CNN) in various scenarios.

Table 5. Assessment of Global average outputs of local clients

Globally Averages	jk_1	jk_2	jk_3	jk_4
Macro_ave	86.14	78.82	88.56	93.70
Weighted_ave	86.43	79.96	88.71	93.72
Micro_ave	86.42	79.77	88.71	93.71
Globally Averages	jk_5	jk_6	jk_7	
Macro_ave	82.66	80.25	82.62	
Weighted_ave	83.54	80.89	83.34	
Micro_ave	83.56	80.93	83.25	

In contrast, Client jk_2 represents the lower end of the spectrum, with values mostly falling within the range of 79%. This suggests the presence of possible discrepancies in class representation or specific features of illness symptoms within this client's dataset, highlighting the need for a more focused approach to get a nuanced understanding. The clients jk_1, jk_3, jk_5, jk_6, and jk_7 demonstrate a wide range of values, with Macro_ave, Weighted_ave, and Micro_ave fluctuating between 80.25% and 88.71%. The study provides valuable information that may be used to build targeted policies aimed at mitigating the effects of the illness and promoting the establishment of agricultural ecosystems that are both sustainable and resilient, as shown in Table 5.

5. THEORETICAL IMPLICATIONS AND PRACTICAL IMPLICATIONS

5.1 Theoretical Implications:

- This research builds on the literature on Federated Learning by integrating it into an agricultural disease detection system. This can be explained by the fact that Federated Learning could be used efficiently in the agriculture sector for decentralized data processing and ensuring privacy while maintaining accuracy, contributing to improving the current literature on Federated Learning beyond the conventional medical or industrial application.
- Innovative Fusion of Denoising Techniques and Convolutional Neural Networks: This technique furthers theoretical research in pre-processing techniques in deep learning models by using an enhanced denoising mechanism to improve picture quality before feeding data into a CNN. Degraded sensors and noisy signal characteristics are particularly critical for applications that have an inherent limitation on affecting model performance, which is common in agricultural datasets.
- The paper encompasses interdisciplinary fields such as computer vision, machine learning, and the agricultural industry. The analysis herein offers a new perspective on how innovative machine-learning techniques will likely be tailored to address specific problems in agriculture disease control. A new application for theoretical frameworks from deep learning is employed while Federated Averaging is further extended to other fields.
- From the perspective of multi-class classification, the research improves the theoretical foundation by providing a classification framework for the level of plant diseases. This system's severity categorization, particularly the five levels of severity ranging from moderate to terminal, can be adapted to other plant diseases, making its theoretical structure amenable to different problems in agriculture.

5.2 Practical Implementations:

- Scalable Disease Management Tool: This is mainly through the pragmatic use of a Federated Learning CNN model, whereby the information from different clients is combined without necessarily exchanging the data. Farmers and agricultural researchers can employ this methodology in many countries and uphold client farms' privacy; hence, it is a scalable strategy in disease diagnosis and intervention in many fold countries.

- The average rate of correct classification increases due to the denoising pre-processing technique, which is a reliable tool for the timely detection of Cabbage Black Rot severity. This may lead to proper and early treatments that help reduce crop damage and improve food production.
- The Federated Learning technique tackles a significant issue in agriculture: data privacy and security. This methodology makes it possible to train locally on the client data; the raw data can never go to the central server and expose the farmers to the worst through their crops' health and yields. This is even more crucial where data usage compliance is tight owing to various rules required in the region.
- The above-suggested method can be integrated into cost-effective platforms like Android applications, which farmers, especially those from developing countries like India, can use to enhance their ability to diagnose and closely supervise plant diseases. However, increasing the availability of technology may significantly improve the ability to control diseases, especially in the resource-poor smallholder farming environment.

6. CONCLUSION

In conclusion, this study delved into the complex aspects of Cabbage Black Rot Leaf Disease, examining its severity levels and offering valuable insights and nuanced understandings of the disease. These findings were derived from synthesizing information gathered from seven sources (jk_1 to jk_7). The study used a Federated Learning Convolutional Neural Network (CNN) combined with a sophisticated denoising filtering method to comprehensively analyze the many signs and complexities of the illness. The effectiveness of Federated Averaging CNN implementation was excellent, as shown by examining a diverse set of statistical parameters. The macro averages, representing unweighted mean accuracies, ranged from 78.82% to 93.70%. The observed variety in these values underscores the underlying differences in illness presentations and the model's capacity to handle them. The weighted averages show fluctuation between the range of 79.96% and 93.72%, indicating the model's ability to handle different levels of severity effectively.

On the other hand, the micro averages ranged from 79.77% to 93.71%, providing a comprehensive assessment of performance across all classes. Analyzing global client data using comparison synthesis techniques revealed many insights, demonstrating enhanced accuracy in client jk_4 and emphasizing the federated learning model's adaptable characteristics and transformational capabilities. On the other hand, the disparities shown in the results of client jk_2 underscore the crucial need for ongoing development and optimization of the model to achieve improved flexibility and accuracy. This integration holds the promise of a future in which the obstacles presented by plant diseases can be efficiently addressed through informed interventions driven by data.

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