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Lightweight Federated Learning for Rice Leaf Disease Classification Using Non Independent and Identically Distributed Images

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Abstract: Rice (*Oryza sativa* L.) is a vital food source all over the world, contributing 15% of the protein and 21% of the energy intake per person in Asia, where most rice is produced and consumed. However, bacterial, fungal, and other microbial diseases that have a negative effect on the health of plants and crop yield are a major problem for rice farmers. It is challenging to diagnose these diseases manually, especially in areas with a shortage of crop protection experts. Automating disease identification and providing readily available decision-support tools are essential for enabling effective rice leaf protection measures and minimising rice crop losses. Although there are numerous classification systems for the diagnosis of rice leaf disease, no reliable, secure method has been identified that meets these needs. This paper proposes a lightweight federated deep learning architecture while maintaining data privacy constraints for rice leaf disease classification. The distributed client–server design of this framework protects the data privacy of all clients, and by using independent and identically distributed (IID) and non-IID data, the validity of the federated deep learning models was examined. To validate the framework's efficacy, the researchers conducted experiments in a variety of settings, including conventional learning, federated learning via a single client, as well as federated learning via multiple clients. The study began by extracting features from various pre-trained models, ultimately selecting EfficientNetB3 with an impressive 99% accuracy as the baseline model. Subsequently, experimental results were conducted using the federated learning (FL) approach with both IID and non-IID datasets. The FL approach, along with a dense neural network trained and evaluated on an IID dataset, achieved outstanding training and evaluated accuracies of 99% with minimal losses of 0.006 and 0.03, respectively. Similarly, on a non-IID dataset, the FL approach maintained a high training accuracy of 99% with a loss of 0.04 and an evaluation accuracy of 95% with a loss of 0.08. These results indicate that the FL approach performs nearly as well as the base model, EfficientNetB3, highlighting its effectiveness in handling both IID and non-IID data. It was found that federated deep learning models with multiple clients outperformed conventional pre-trained models. The unique characteristics of the proposed framework, such as its data privacy for edge devices with limited resources, set it apart from the existing classification schemes for rice leaf diseases. The framework is the best alternative solution for the early classification of rice leaf disease because of these additional features.

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1. Introduction

Agriculture is essential for human survival because it supports and regulates the food chain. Previously, farmers relied on frequent field visits to check on crop growth, which frequently resulted in food shortages because of calamities caused by nature and human error [1]. Traditional farming practices are often less profitable because they require a lot of human labour. Along with meeting consumer demand, the food production industry has a duty to combat poverty, prevent malnutrition, and protect freshwater resources. Grains, such as wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), and maize (*Zea mays* L.) are frequently used as a primary food source and give people the energy they need for daily activities [2]. The production of these three grains, which is the biggest in the world, is incredibly plentiful [3]. Wheat has the most area harvested each year with 214 million ha, followed by rice with 154 million ha and maize with 140 million ha. Human consumption accounts for 85% of total production for rice, compared with 72% for wheat and 19% for maize [4]. Rice is a vital food consumed globally and is produced almost entirely domestically. In Asia, rice is a well-liked and reasonably priced nutrient source. According to FAOSTAT, rice is grown in five continents: Asia, Africa, America, Europe, and Oceania [5].

Rice crop fields are vulnerable to damage from diseases and pests every year, and inexperienced young farmers may struggle to identify the exact disease affecting their crops. The majority of the time, rice diseases are found using carefully supervised techniques, such as a visual inspection of the crops or lab tests [6]. A skilled person is needed for visual inspection, which can take a lot of time. Laboratory experimentation, on the other hand, involves a lengthy process and the use of chemical reagents. In most nations, the demand for rice is anticipated to increase more quickly than the supply. Damage to the rice crop is unacceptable for this reason, regardless of the cause. It is necessary to automate the detection of rice leaf diseases to reduce crop losses [7]. By continually scanning crops for potential infections, this automated method of disease identification will also lower labour costs. For automatically identifying rice leaf diseases, numerous researchers have put forward fascinating ideas [8]. There are many machine learning (ML)/deep learning (DL) and internet of things (IoT) approaches available for early rice leaf diseases identification and they have proven successful in a number of different fields. However, for the past ten years, applying ML to decentralised data has been a difficult task [9]. To enable a decentralised approach, a framework that integrates multiple methods of deep learning in real-time to support the data privacy, lessen communication costs, and provide a distributed framework for training and testing is required. Lightweight federated learning is in demand right now to address important issues such as data privacy, security, access rights, and heterogeneous data access [10].

Federated learning (FL) is extremely valuable for maintaining privacy while performing deep learning tasks, particularly in the domain of classifying diseases that affect rice leaves. Its potential is based on its ability to effect fundamental changes in fields of distributed ML/DL, particularly in terms of privacy and security. Since 2018, more researchers have become interested in running FL experiments across many important industries, including healthcare and finance [11–14]. It accomplishes this without requiring data transfer from the participants' individual client nodes. Researchers at Google came up with this method, which entails training distributed datasets in a centralised parameter server [15]. Lightweight FL refers to the development of algorithms and methods that reduce the amount of computational and communication resources needed for model training on edge devices or distributed systems. In environments with limited resources, such as those involving mobile devices, IoT devices, or networks with constrained bandwidth, it is intended to make federated learning effective and scalable. It could be put to use in a variety of applications that call for quick analytics on widely dispersed data. To classify the diseases of rice leaves, there is still a dearth of research in the area of FL. For the successful application of FL in real-world scenarios, these issues must be resolved. Figure 1 illustrates the three steps that make up the FL process.

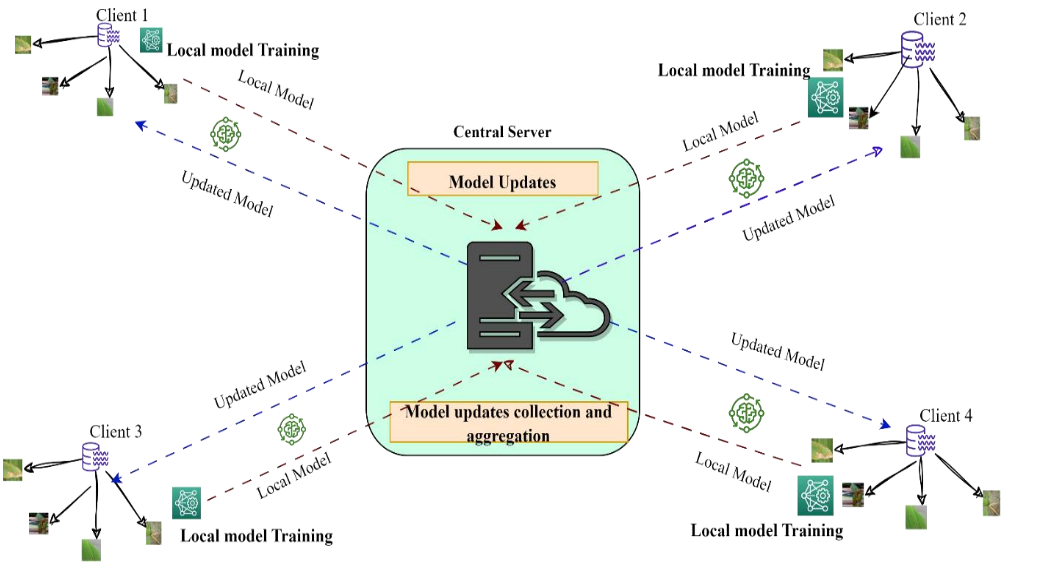

Figure 1. Federated deep learning system for rice leaf disease classification.

i. Every client trains the model locally at their respective local site using their own data set (images of rice leaf disease), then uploads the locally trained model to the main server;
ii. The central server integrates local models, updates, trains a global model, then provides access to the updated model for all clients;
iii. Every client uses the parameters received by the globally trained model from the central server to both inform their own decisions and take part in the next cycle of model updates.

Federated learning, which protects clients' privacy during the training process, is better suited for data-sensitive applications than the current ML/DL approaches. Since a node participating in federated learning has access to a local model, intermittent connectivity problems have little effect on its performance [16]. The communication overhead is also addressed which is a significant drawback of conventional ML/DL approaches.

Agriculture plays an important role in supporting the growing population and serving as an essential energy source. Plant diseases present a serious risk to crop quality and yield, which has an effect on agricultural development. Expert manual observation, which takes time and requires a lot of work, has traditionally been the standard method for identifying rice leaf disease. A model for automatic disease detection in rice leaves has been created to address these issues [17]. Deep learning (DL), a powerful image processing technique, has demonstrated remarkable success in various tasks such as scene analysis, disease detection, and object detection [18]. Specifically, in the context of rice diseases, DL can be effectively utilized for leaf diagnosis, allowing farmers to make informed decisions on whether to apply crop treatments based on the detected diseases affecting the leaves.

In this study, an FL-based model was proposed for the classification of rice leaf diseases due to the several advantages that make it suitable for the requirements of rice leaf disease classification. Firstly, it addresses data privacy concerns by allowing the training process to be performed directly on users' devices, without the need to transfer sensitive agricultural data to a central server. When working with sensitive data, this is especially crucial. Second, distributed datasets from various sources can be handled by federated learning [19]. Since different regions or nations may have a variety of diseases or environmental factors influencing the growth of rice plants, this is helpful in the context of classifying rice leaf diseases. The classification models can be more reliable and accurate by utilising data from different sources [20]. Federated learning plays a crucial role in reducing communication costs, which is particularly important for agricultural applications where internet connectivity can be unreliable or limited in certain areas. By enabling localized model training, federated learning enhances productivity and minimizes the necessity for extensive communication. Due to these benefits, federated learning is a desirable method for categorizing rice leaf diseases while addressing data privacy issues, allowing for a variety of datasets and improving communication in resource-constrained settings. The proposed work focuses on rice leaf disease classification as it can significantly help farmers and agricultural researchers to identify crop diseases. The paper's main contributions are:

i. Implementing a lightweight federated learning approach for rice leaf disease classification;
ii. Implementing an improved distributed training model using federated learning with IID and non-IID datasets;
iii. The proposed procedure has demonstrated effectiveness compared to present techniques with data privacy for rice leaf diseases classification.

2. Related Study

In several studies, different ML/DL techniques were used to identify and categorise rice leaf diseases. Jiang et al. [21] devised an approach using a deep learning Convolutional Neural Network (DCNN) model and a Support Vector Machine (SVM) classifier, with an impressive testing accuracy of 96.8% on a dataset of 8911 images. In a similar vein, Krishnamoorthy et al. [22] proposed two different CNN architectures, Simple CNN and InceptionResNetV2, and used transfer learning techniques to achieve an astounding accuracy of 95% for disease recognition. Furthermore, Rallipali et al. [23] used CNN models, particularly AlexNet and M-Net, to identify various rice leaf diseases with an accuracy of 71.98% using a dataset of 120 images. On the other hand, Prajapati et al. [24] used the K-means clustering algorithm and morphological operations to segment diseases, which resulted in a classification accuracy of 73.33% using an SVM classifier on a dataset containing 40 images for each disease. Kumar et al. [25] suggested pre-trained models, such as MobileNet and InceptionNetV2, with validation accuracies of 70.31% and 76.56%, respectively, for the identification of rice leaf disease. In addition, Azim et al. [26] proposed a model for classifying brown spot, leaf smut, and bacterial leaf blight diseases that combined saturation and hue threshold segmentation techniques with a gradient boosting decision tree algorithm, achieving accuracies of 86.58% with XGBoost and 81% with SVM. In contrast to earlier techniques, Pallathadka et al. [27] developed a comprehensive machine learning framework that made use of histograms for image processing, principal component analysis for extracting features and SVM, Naive Bayes, and CNN models for classification. Finally, Bhartiya et al. [28] used a quadratic SVM classifier for extracting shape features and classified rice leaf disease with an accuracy of 81.8%. In Table 1 different algorithms that have been utilized for identifying various rice leaf diseases are discussed. However, the compromise between accuracy and data privacy is a significant concern. While algorithms can achieve high accuracy in disease detection, there may be potential implications for data privacy.

Table 1. Comparative study of various techniques.

Reference	Area of Study	Algorithm	ML/DL	FL	Data Privacy	Evaluation Parameters
[21]	Rice leaf diseases	DCNN, SVM	√	X	Not implemented	Accuracy = 96.8%
[22]	Rice leaf diseases	CNN InceptionNetV2	√	X	Not implemented	Accuracy = 95%
[23]	Rice leaf diseases	CNN, AlexNet M-Net	√	X	Not implemented	Accuracy = 71.9%
[25]	Rice leaf diseases	MobileNet InceptionNetV2	√	X	Not implemented	Validation Accuracies 70.31%, 76.56%
[26]	Rice leaf diseases	XGBoost, SVM	√	X	Not implemented	Accuracies 86.5%, 81%
[27]	Rice leaf diseases	CNN, SVM, Naïve Bayes, PCA	√	X	Not implemented	better
[24]	Rice leaf diseases	KMeans, SVM	√	X	Not implemented	Accuracy = 73.33%
[28]	Rice leaf diseases	Quadratic SVM	√	X	Not implemented	Accuracy = 81.8%
[10]	Driver Behaviour	Bi-LSTM, CNN-Bi-LSTM, LSTM, CNN-LSTM	√	√	Implemented	Validation Accuracy = 89%
[29]	Disaster prediction	VGG16, DenseNet, ResNet, InceptionRes-NetV2	√	√	Implemented	Validation Accuracy = 74%
[16]	Fake News	Bi-LSTM, CNN-Bi-LSTM, LSTM, CNN-LSTM	√	√	Implemented	Validation Accuracy = 90–92%
[9]	Analyse Milk Quality	CNN, LSQR, PLSR, NNPLS	√	√	Implemented	Mean Accuracy LSQR = 82% PLSR = 84% CNN = 87% NNPLS = 89%

Researchers have acknowledged the use of enhanced ML/DL for the classification of diseases affecting rice leaves. However, they frequently shared the raw or processed data across distributed system environments to improve the accuracy of these algorithms. These methods increased the accuracy but also brought up issues with data privacy and communication costs. Given the situation, a perfect solution is required that guarantees data security, lowers communication costs, and offers a decentralised environment for developing and testing AI models. Federated learning can meet these needs by making it possible to train models collaboratively while protecting data privacy and cutting down on communication costs [19,30,31]. Researchers can accurately identify rice leaf diseases while maintaining significant data security and lowering communication costs in a decentralised training and testing environment by using a federated learning approach. The federated learning approach proposed by [10,16,29] offers a framework for dealing with the detection of fake news, driver behaviour analysis, and disaster prediction. This method gives different stakeholders the ability to create accurate and secure models in these domains while maintaining data privacy, enhancing decision-making and reducing the potential risks.

Federated learning is important to detect rice leaf diseases because it makes possible to combine distributed datasets from various farmers and regions, giving researchers a thorough understanding of how diseases behave in various environments. Federated learning has become known as a promising solution to the privacy and distributed data challenges in ML/DL systems. It introduces a new concept for secure learning that allows multiple devices or edge devices to collectively train a shared model without sharing raw data. Google has been at the forefront of developing and implementing federated learning techniques. They recognized the limitations of centralized architectures that rely on data sharing and devised FL as a solution. FL ensures that these devices can contribute to the learning process without compromising their privacy. Additionally, FL minimizes data loss by enabling local training on edge devices, thereby reducing the need for extensive data transmission [32].

The traditional ML-based approach obtains raw data for predicting rice leaf diseases. Because of the exponential growth of data, machine learning has grown in popularity within agriculture. Many ML systems, however, suffer from a lack of training data [15]. This is primarily due to growing data privacy concerns, such as restrictions on sharing information with other systems. Data analytical frameworks need to be combined with incorporated services in order to provide such services [9]. FL is highly suitable for resolving data privacy concerns in such environments by facilitating the sharing of trained models instead of raw data between resources. Truong et al. [12] proposed a novel FATRAF (FL-based auto encoder transformer Fourier anomaly detection architecture) was introduced, demonstrating its remarkable ability to achieve superior anomaly detection performance for time series data in industrial control systems (ICSs). This lightweight model is particularly beneficial for ICS security, as it allows for frequent updates in changes detected in the normal behaviours of smart devices used in a smart factory environment. Khullar and Singh [16] introduced a federated-Fake News Classification (f-FNC) framework, which leverages a distributed client–server architecture to ensure data privacy for all connected edge devices or clients. The framework utilizes LSTM, BiLSTM, CNN-LSTM, and CNN-BiLSTM deep learning algorithms with both independent and non-independent identically distributed (IID and non-IID) datasets. By adopting a multi-client federated learning approach, the framework achieved an impressive maximum accuracy range of 90–92% for fake news classification.

3. Materials and Methods

The methods and algorithms used in the suggested work are illustrated in this section. This paper presents a federated deep learning architecture to address data privacy constraints in the classification of rice leaf diseases. The framework employs a distributed client–server design, ensuring the privacy of all client data through the utilization of both identically and non-identically distributed (IID and non-IID) data.

3.1. Federated Learning

Federated learning is a disseminated optimisation ML technology developed in 2017 by Google researchers to train remote datasets on a centralised parameter server. The training of a shared predictive model is carried out without the need to transfer data from client nodes such as mobile phones and gateway devices, thus preventing data drift [17]. As a result, this technique offers a greater potential for use in a broader range of applications where rapid analytics based on widely distributed data is required. Since many client devices are involved in federated learning, it can be thought of as a comprehensive distributed systems [30].

In a federated learning (FL) system, there are three main components: the server, the communication background, and the clients. The prescribed definition of FL involves M clients (M1, M2... MN) that have their own datasets (D1, D2... DN), and the complete dataset is represented as DN = D1 ∪ D2 ∪ ... ∪ DN. Further description mentioned in Algorithm 1.

Algorithm 1 (FedAvg: Federated Learning)

M- Clients from 1 to n
F- fractions of clients used per round
B- Mini batch size (local)
E- Epoch number (local)

Server() //At Global Server
Initialize global weights: φ_0
for t = 1,2,3. . . **do**
  T ← max (F.M,1)
  R_t←(random sets of T clients)
  for client m ∈ R_t **do parallel**
  ClientUpdate(m, φ_t)
  $\varphi_{t+1} \leftarrow \sum^{M}{}_{m=1} \varphi^{m}{}_{t+1}$
  end
end
Client () // At Client site
ClientUpdate (m, φ): // on client site
SS ← Split data into B Batches
for each t from 1 to E **do**
  for batch b ∈ SS **do**
    Update client with weights φ
  end
end
return φ to server

3.2. Data Collection and Pre-Processing

The entire dataset contains 5932 images of rice diseases such as bacterial leaf blight, blast, brown spot, and tungro. Some of the images were collected from the rice field of western Odisha and some are collected from an agricultural pest and insect pests picture database [33]. Figure 2 depicts four types of rice diseases. The images are all properly labelled and are kept in JPG format. As shown in Table 2, there are 5932 images, 1584 of which are of bacterial leaf blight, 1440 of blast, 1600 of brown spot, and 1308 of tungro. Each image depicts a different rice disease. In order to simulate a federated environment for a dataset (i.e., the total rows in dataset divided by the total clients), the data collected were randomly divided into equal parts based on the number of clients participating in the simulation. Each client was then assigned a random partition of the dataset. This distribution was meant to mimic a scenario where each client had their own unique and diverse dataset.

Table 2. Particulars of images available in data set.

Leaf Disease Name	Original Images	Training Data (80%)	Testing Data (20%)
Bacterial leafblight	1584	1267	317
Blast	1440	1140	300
Brown spot	1600	1290	310
Tungro	1308	1048	260
Total	5932	4745	1187

The dataset has been pre-processed by resizing the images to meet the deep learning model's requirements, such as 75 × 75 size, and applying grayscale. The pre-processed data was then partitioned at random for distribution to N clients, each of which had their own pre-processed data to use as training and evaluation for federated learning at their end. The data distribution was done to simulate a situation in which each client had a portion of a dataset.

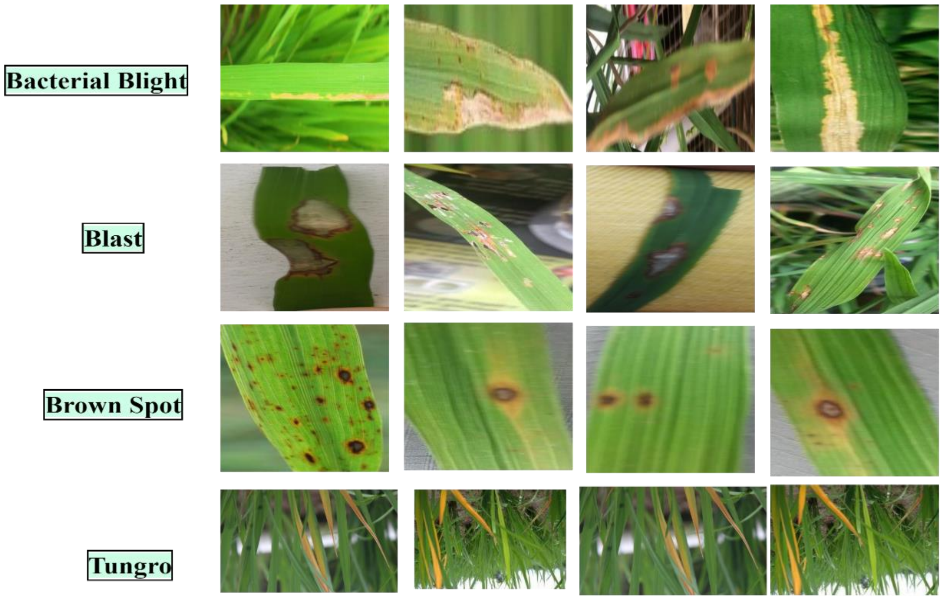

Figure 2. Rice leaf disease sample images.

3.3. Feature Extraction

The process of changing raw data into a set of significant characteristics that can be used for evaluation or machine learning tasks is referred to as feature extraction. Feature extraction is a technique used in many fields, including artificial intelligence, natural language processing, and signal processing, to identify significant patterns, characteristics, or representations in input data. This process helps to simplify and enhance the subsequent analysis or modelling tasks. The feature extraction process plays a crucial role in deep learning networks, which consist of pooling and convolutional layers. These layers are designed to extract image features that are useful for tasks such as target identification and positioning [34]. Deep features were obtained by extracting information from the fully connected layer, and these features were then utilized as input for the training process of the classifier.

Different configurations can be experimented with to enhance the performance of models in rice leaf disease detection, such as incorporating layers, modifying the learning rate, or altering the amount of neurons per layer, also accelerate this process by using pre-trained models [35]. These models offer significant time and computational resource savings.

In this research, 13 pre-trained models were utilized to extract features. These models, such as VGG, ResNet, and Inception, have been trained on large datasets such as ImageNet and have learned to extract useful features from images. These extracted features serve as inputs for subsequent processes such as object recognition, segmentation, and classification, enabling the accurate identification of rice leaf diseases. By modifying each segment for the feature extraction process, the accuracy of these features can be enhanced even with limited data. This method significantly accelerates training and improves accuracy by utilising specific model architectures with various layers, such as reshape, flatten, dense, dropout, and activation functions [23]. Table 3 provides details of the feature extractors, including their size, parameters, depth, input shape, and feature layer.

Table 3. Feature extractor with weights.

Pre-Trained Model	Input Shape	Size (MB)	Parameters	Depth	Feature Layer
DenseNet201	(224-224-3)	80	20.2M	402	2D Global average pooling
EfficientNetB3	(300-300-3)	48	12.3M	210	Dropout
EfficientNetB4	(380-380-3)	75	19.5M	258	Dropout
EfficientNetB5	(456-456-3)	118	30.6M	312	Dropout
EfficientNetB6	(528-528-3)	166	43.3M	360	Dropout
InceptionResnetV3	(229-229-3)	215	55.9M	449	2D Global average pooling
ResNet101	(224-224-3)	171	44.7M	209	2D Global average pooling
ResNet101V2	(224-224-3)	171	44.7M	205	2D Global average pooling
ResNet152	(224-224-3)	232	60.4M	311	2D Global average pooling
ResNet152V2	(224-224-3)	232	60.4M	307	2D Global average pooling
VGG16	(224-224-3)	528	138.4M	16	Dense
VGG19	(224-224-3)	549	143.7M	19	Dense
Xception	(229-229-3)	88	22.9M	81	2D Global average pooling

3.4. IID and Non-IID Data

In FL, IID and non-IID data refer to different distribution patterns of data across the participating devices or clients.

In IID data each client or device in the federated learning setup possesses a similar distribution of data. The data across clients is independent and follows the same statistical distribution. For example, if the task is image classification, IID data would mean that each client has a similar proportion of images from different classes [15]. On the other hand, non-IID means the distribution of data across clients is not identical or independent. The data may have different statistical properties, such as varying class distributions, different feature representations, or imbalanced data [36]. For example, in image classification, each client may have a different set of classes or an imbalanced distribution of classes.

Figure 3 represents how the IID and non-IID data sets are distributed among different famers' sites. The IID data set is equally distributed, and the non-IID data set is distributed randomly among different farmers' sites.

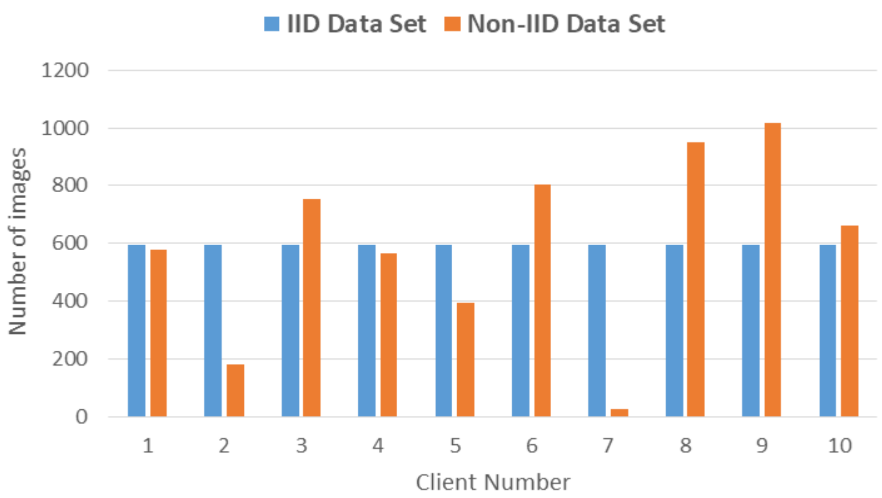

Figure 3. IID and non-IID data distribution of rice leaf disease images.

3.5. Proposed Federated Learning Framework for Rice Leaf Disease Images Classification

The need for rice leaf disease images classification arises from the desire to safeguard rice crops, enhance agricultural productivity, and ensure food security. By leveraging technology to develop accurate and efficient detection methods, farmers can be empowered with the necessary tools to effectively manage and mitigate the impact of rice leaf diseases. Farmers and researchers collect sensitive information related to their crops, such as images of infected rice leaves, geographic locations, and farming practices. This data may contain proprietary information or personally identifiable information (PII) that needs to be protected. In this section, the proposed work focuses on implementing and analysing the performance of federated learning for rice leaf disease classification. The proposed framework for classification of rice leaf disease is discussed in Figure 4.

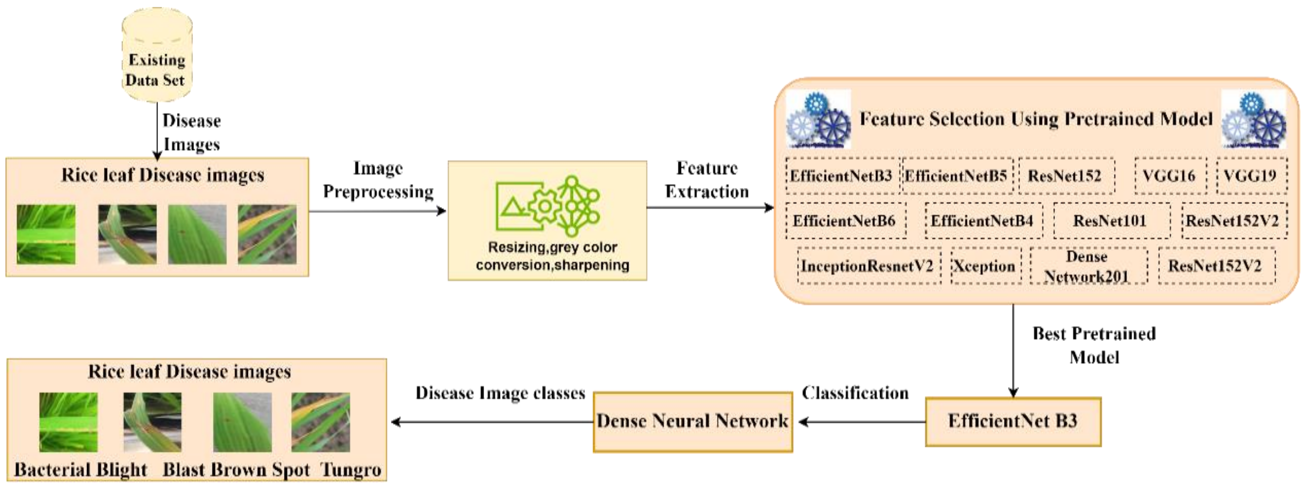

Figure 4. Methodology for baseline pre-trained model for rice leaf disease classification.

Firstly, the features from the given classes of rice leaf diseases were extracted using various pre-trained models. A comparison was made between different trained models based on their training and validation accuracies to determine which model performed the best, and EfficientNetB3 was found to be the best-performing model. When implementing a federated learning (FL) system, one of the challenges is ensuring that the learning model can run efficiently on the edge devices, which act as the monitors of each zone. This requires the learning model to be lightweight, allowing it to feasibly operate on these devices. The lightweight nature of the model becomes crucial in the design of any FL-based system [37]. That is why we used a dense neural network for classification, which is a 3-layer model, instead of using another heavy and highly trained model. Each neuron in a layer of this kind of network is linked to every neuron in the layer below it, enabling the transmission of computation and data through multiple layers. EfficientNetB3 was chosen as a baseline model because it performed the best overall and had been implemented in a federated environment.

The proposed framework for federated learning in rice leaf disease classification presented in Figure 5 utilised a client–server architecture. Python programming libraries such as Keras and TensorFlow supported the implementation of the framework. Every network client had a dedicated processing and storage system to manage their unique structured data and produce model training and weights. The federated global weights of the trained models of the clients were processed by the remote server. Compared to traditional distributed machine learning and deep learning frameworks, the proposed federated framework reduces communication overhead and data privacy issues by transmitting only trained models between the client and server.

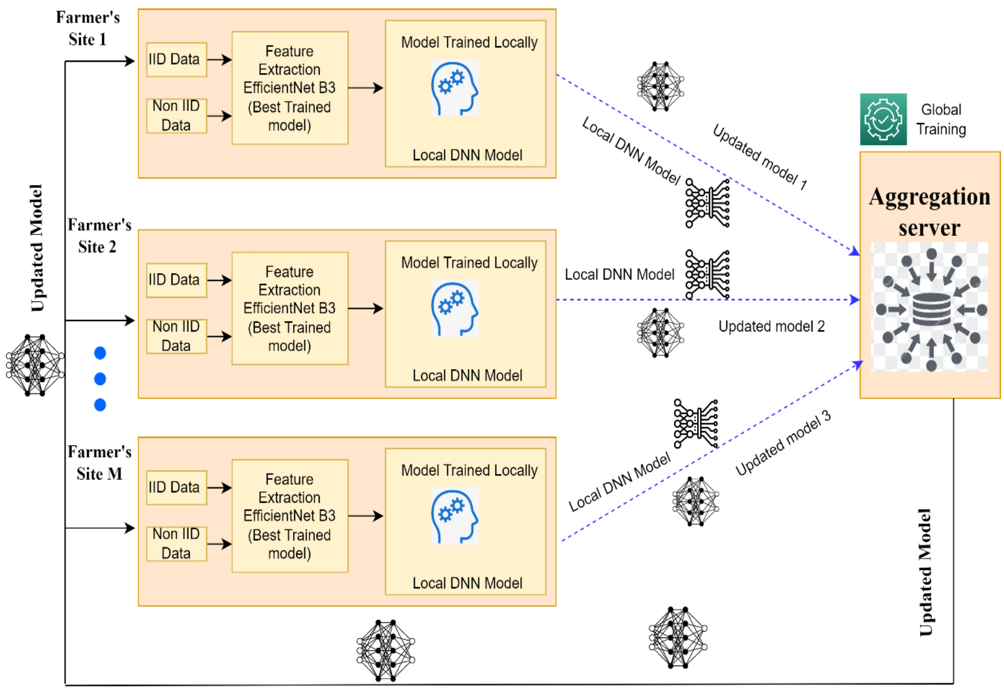

Figure 5. Methodology for federated deep learning approach for classification of rice leaf disease images.

The full implementation procedure was as follows:

Step 1: Every client within the M-clients system independently collected data on rice leaf disease and stored it in its corresponding storage system.

Step 2: The collected datasets of rice leaf disease images underwent individual cleaning and pre-processing by every client within the M-clients system.

Step 3: Next, the dataset was prepared at the edges of the M-clients system for the rice leaf diseases classification using federated learning.

Step 4: In the classification process, features were extracted using 13 pre-trained models on both IID and non-IID data to identify the best trained model, i.e., EfficientNetB3 as a baseline model.

Step 5: Each client trained the baseline model locally with Dense Neural Network (DNN).

Step 6: The federated learning process was initiated by the server, starting with the initial weights. The server shared the available initial weights with the M-clients in the aggregation server.

Step 7: Each client initialised their individual training and validation using their own datasets after receiving the weights. Every client delivered their updated weights to the server after the training process was complete in order to determine the federated average weights.

Step 8: The weights collected from all connected clients were used by the server to calculate the federated average (FedAvg) weights.

Step 9: The federated server then sent all connected clients the resultant federated average (FedAvg) weights from Step 8 again for processing.

3.6. Model Validation

The suggested pre-trained models were trained by the labelled data, which were classified into two different classes. The "bacterial leaf blight" had 1584 images, "Blast" had 1440 images, "Brownspot" had 1308 images, and" Tungro" had 1308 images of rice leaf diseases. The model was built using Keras and Tensorflow 2.0 and used RTX 2080Ti as GPU for this experimental setup. The segmented images with a 3 × 3 filter helped the models to learn key features of the rice leaf diseases. The actual shape of the images was 256 × 256, but it was resized into 75 × 75 to train our model. Further, the data was split into training and testing data in the ratio 80:20. Twenty percent of data (1187) were kept in the validation set for testing the models' performance. While training the models, it was needed to estimate how well our model was learning per each iteration.

4. Results

This section provides a discussion of the results obtained from comparing the performance of conventional DL algorithms, namely VGG16, VGG19, Resnet152, DenseNet, InceptionResnetV2, Xception, EfficientNetB3, etc., for rice leaf disease classification. The best-trained model was determined through a comparative analysis based on training-evaluated accuracies. The conclusion of the study indicates that the pre-trained model EfficientNetB3 achieved the highest training and evaluated accuracy, reaching 99%. Table 4 and Figure 6 show the results of traditional machine learning with dense architecture.

Table 4. Baseline results with dense neural network.

Training Accuracy													
Epochs	**DN201**	**ENB3**	**ENB4**	**ENB5**	**ENB6**	**IRV2**	**RN101**	**RN101V2**	**RN152**	**RN152V2**	**VGG16**	**VGG19**	**Xception**
25	0.89	0.98	0.85	0.88	0.86	0.94	0.86	0.82	0.86	0.75	0.87	0.85	0.95
50	0.95	0.99	0.9	0.94	0.93	0.96	0.92	0.88	0.92	0.83	0.93	0.91	0.97
75	0.96	0.99	0.93	0.96	0.95	0.97	0.93	0.91	0.94	0.86	0.95	0.94	0.98
99	0.97	0.99	0.95	0.97	0.96	0.98	0.93	0.93	0.96	0.88	0.96	0.95	0.98
Validation Accuracy													
Epochs	**DN201**	**ENB3**	**ENB4**	**ENB5**	**ENB6**	**IRV2**	**RN101**	**RN101V2**	**RN152**	**RN152V2**	**VGG16**	**VGG19**	**Xception**
25	0.91	0.98	0.87	0.91	0.84	0.92	0.87	0.81	0.85	0.79	0.88	0.86	0.92
50	0.94	0.98	0.91	0.94	0.95	0.95	0.91	0.88	0.91	0.83	0.94	0.91	0.96
75	0.96	0.99	0.87	0.91	0.96	0.96	0.94	0.91	0.93	0.84	0.96	0.91	0.97
99	0.97	0.99	0.93	0.97	0.96	0.96	0.91	0.93	0.95	0.87	0.96	0.96	0.97

Further, a federated learning approach was implemented using the trained model EfficientNetB3 as a baseline model. The dataset was distributed to local machines for training, and the trained models were shared at the aggregated server end. The process was repeated for ten communication rounds with 10 epochs per round, and a validation was conducted after each round. The federated architecture consisted of one server and 10 clients with different data chunks. In federated learning, the data set is distributed to each local machine itself. Individual local machines use 10 epochs to complete one training cycle and train the model and to share their trained model with an integrated system as well. The federated average (FedAvg) function at the server end was used to train the collected models from different clients. The global model is then shared with the connected clients. Individual clients retrained the machine using the global model as a baseline after receiving the global model. The distributed data is both of type IID, i.e., identical and independent, and non-IID. In Tables 5 and 6, the results of federated learning with IID data and non-IID data are discussed.

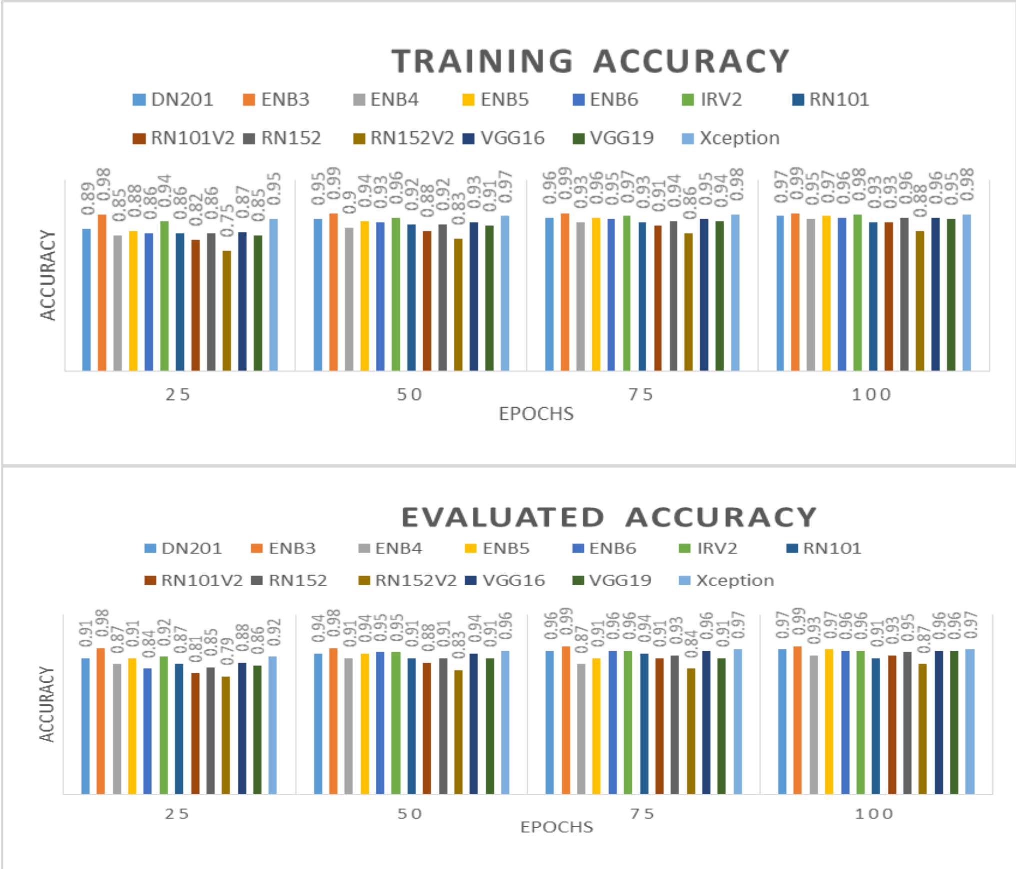

Figure 6. Training and evaluated accuracies for baseline results.

Table 5. EfficientNetB3 deep learning's training-evaluated accuracy and loss comparison of FL (IID).

Federated Learning (IID)							
Comm.Round	**Epoch**	**Training Accuracy**	**Change (+/−)**	**Training Loss**	**Change (+/−)**	**Validation Accuracy**	**Validation Loss**
1	1	0.99	0.0	0.023	−0.009	0.96	0.2
	10	0.99		0.014			
2	1	0.98	0.01	0.031	−0.02	0.98	0.1
	10	0.99		0.011			
3	1	0.98	0.01	0.051	−0.035	0.95	0.2
	10	0.99		0.016			
4	1	0.99	0.0	0.041	−0.033	0.99	0.06
	10	0.99		0.008			
5	1	0.98	0.01	0.039	−0.034	0.99	0.08
	10	0.99		0.005			

Table 5. *Cont.*

Federated Learning (IID)							
Comm.Round	**Epoch**	**Training Accuracy**	**Change (+/−)**	**Training Loss**	**Change (+/−)**	**Validation Accuracy**	**Validation Loss**
6	1	0.99	0.01	0.024	−0.02	1	0.009
	10	1		0.004			
7	1	0.98	0.0	0.113	−0.094	0.98	0.01
	10	0.98		0.019			
8	1	0.97	0.01	0.06	−0.04	0.97	0.33
	10	0.98		0.02			
9	1	1	−0.01	0.009	−0.001	0.97	0.19
	10	0.99		0.005			
10	1	0.98	0.01	0.05	−0.004	0.99	0.03
	10	0.99		0.006			

Table 6. EfficientNetB3 deep learning's training-evaluated accuracy and loss comparison of FL (non-IID).

Federated Learning (Non-IID)							
Comm.Round	**Epoch**	**Training Accuracy**	**Change (+/−)**	**Training Loss**	**Change (+/−)**	**Validation Accuracy**	**Validation Loss**
1	1	0.95	0.02	0.11	−0.03	0.94	0.13
	10	0.97		0.08			
2	1	0.96	−0.01	0.15	−0.04	1	0.02
	10	0.95		0.11			
3	1	0.93	0.07	0.19	−0.13	1	0.01
	10	0.99		0.06			
4	1	1	−0.04	0.02	0.03	0.96	0.1
	10	0.96		0.05			
5	1	0.95	0.02	0.12	−0.04	0.97	0.15
	10	0.97		0.08			
6	1	0.97	0.01	0.09	−0.04	0.96	0.18
	10	0.98		0.05			
7	1	0.97	0.01	0.08	−0.02	0.92	0.33
	10	0.98		0.06			
8	1	0.95	0.02	0.22	0.08	0.94	0.17
	10	0.97		0.14			
9	1	0.95	0.01	0.16	−0.05	0.95	0.12
	10	0.96		0.11			
10	1	0.97	0.02	0.07	−0.03	0.95	0.08
	10	0.99		0.04			

Figure 7 shows the accuracy and loss results for ten communication rounds, i.e., C-0 to C-9. After ten communication rounds, the training accuracy was 0.99 and the training loss was 0.006 when the data were distributed identically and independently. For non-IID training, accuracy and loss were 0.99 and 0.04, respectively. The evaluated accuracy and loss were 0.99 and 0.03 for IID data, and for non-IID data, the maximum evaluated accuracy was 0.95 and the maximum evaluated loss was 0.08. The performance of federated deep learning was found to be comparable to that of traditional single or baseline machine learning approaches as both achieved similar levels of validation accuracy, i.e., 99.9%, despite differences in their implementation.

Table 7 and Figure 8 depict the results based on various performance parameters such as accuracy, loss, precision, and recall-rate for IID and non-IID data. This suggests that federated deep learning can achieve comparable results to traditional approaches while preserving the fundamental principles of deep learning.

Table 7. Average of training/evaluation IID/ non-IID results.

	Data	Accuracy	Loss	Precision	Recall-Rate
Training	IID	98.22	0.13	98.22	98.22
Training	Non-IID	96.17	0.13	96.1	96.54
Evaluation	IID	99.79	0.01	99.79	99.79
Evaluation	Non-IID	97.48	0.09	97.74	97.2

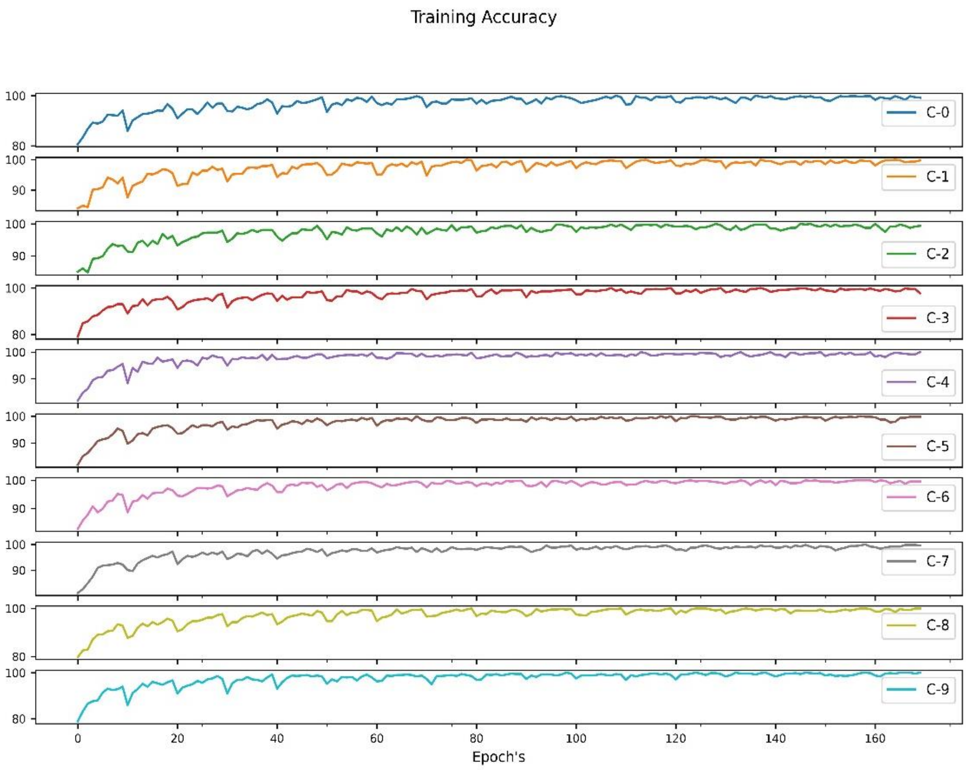

Figure 7. *Cont*.

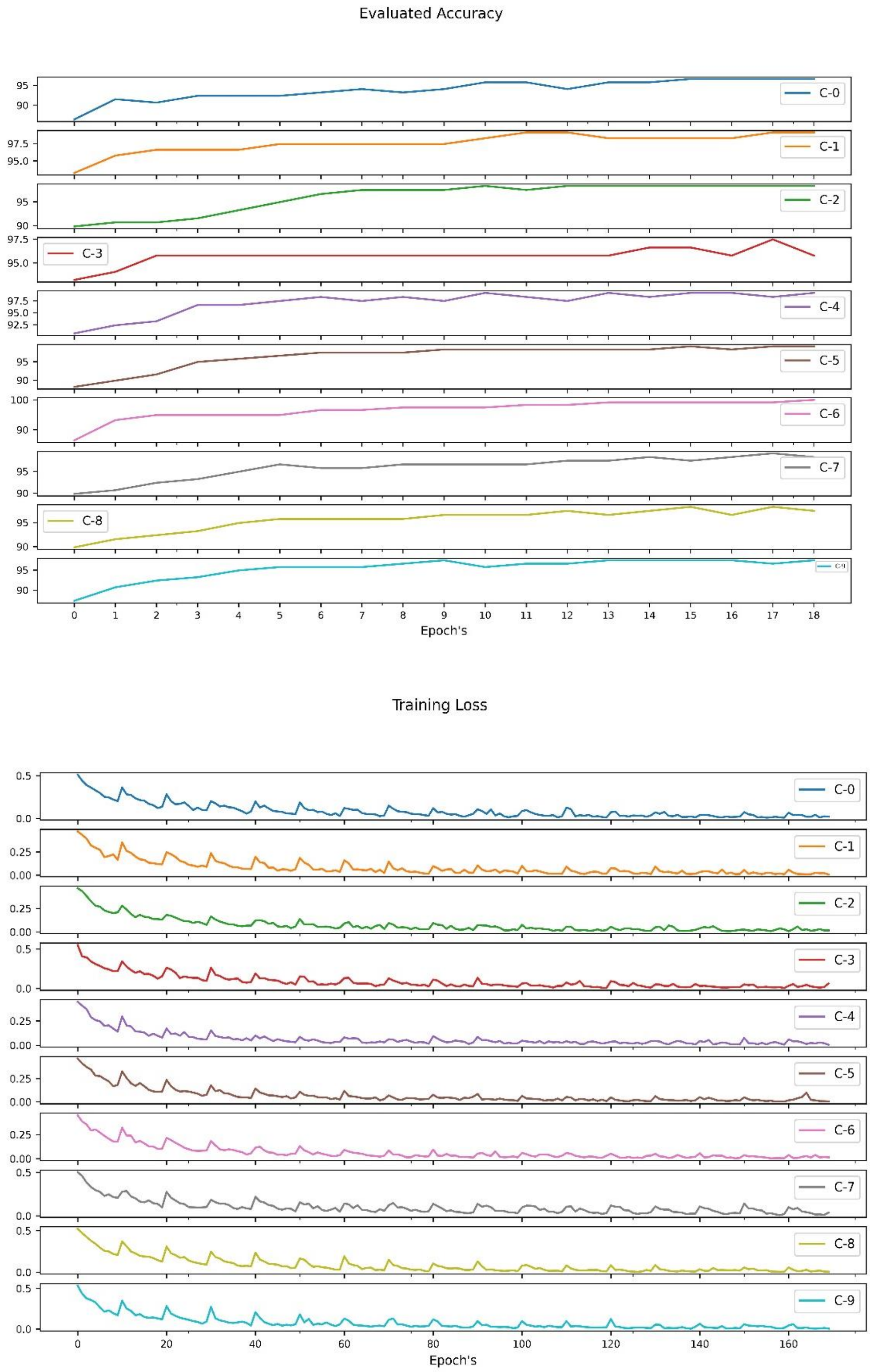

Figure 7. *Cont*.

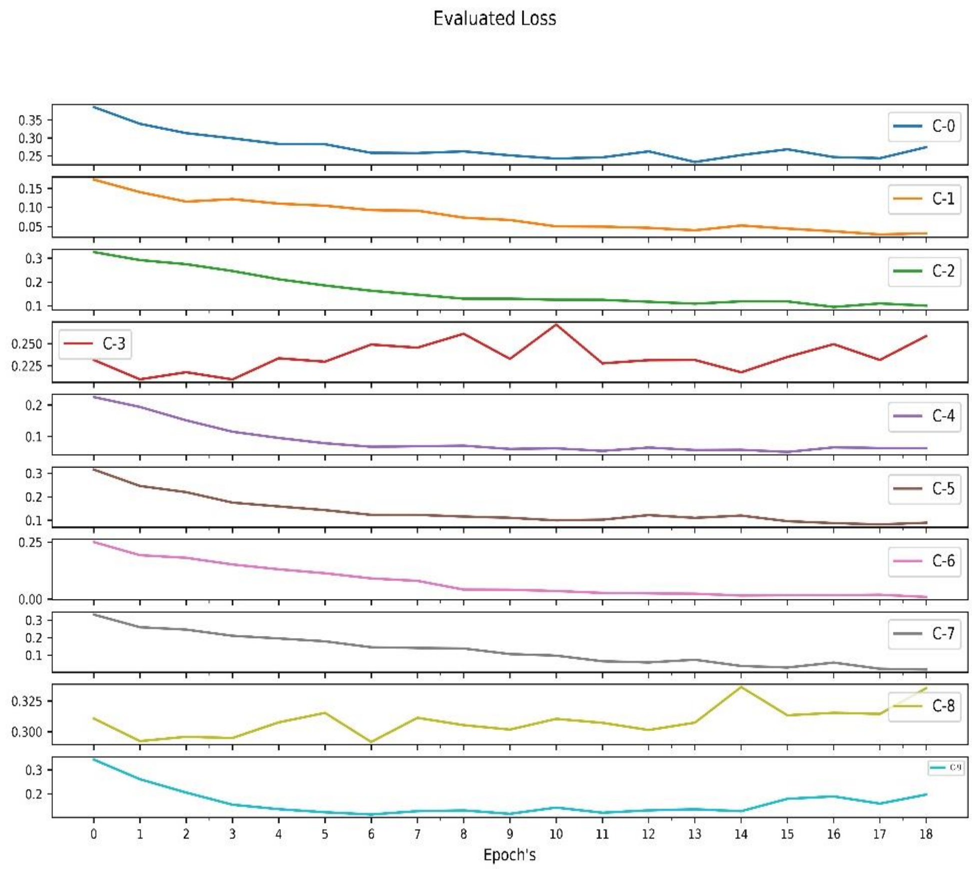

Figure 7. Training–evaluated accuracy and loss comparison of FL-implemented EfficientNetB3 pre-trained model.

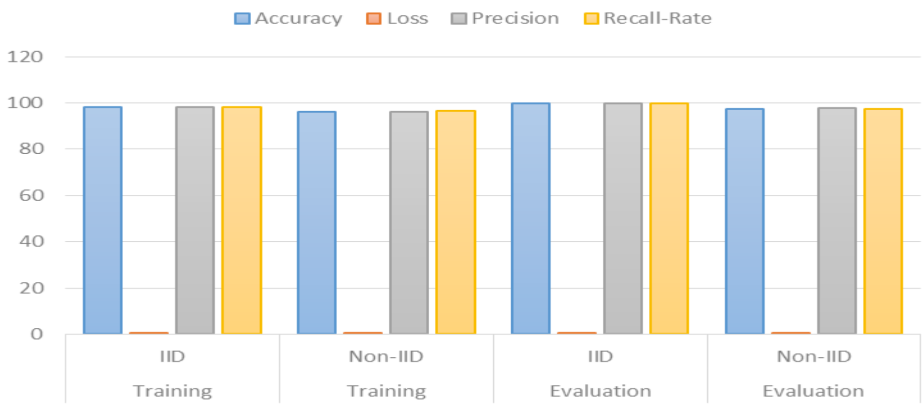

Figure 8. Training/Evaluated IID and non-IID results comparison.

5. Discussion

The proposed model exhibits a superior performance compared to other related studies using the same dataset. In this section, we compared our suggested model with previously published techniques using the same rice leaf disease image dataset. We presented the results of the federated learning (FL) technique on both IID and non-IID datasets, employing various pre-trained models for rice leaf disease classification while maintaining data privacy at the farmer's site. Table 8 illustrates that several researchers have developed suitable frameworks for the early detection of rice leaf disease with high accuracy parameters; however, none of them focused on data preservation at the client's site. Sethy et al. [33] and Sharma et al. [38] achieved results similar to ours, but they did not prioritize data preservation. In contrast, our proposed model achieved an impressive 99% accuracy while ensuring data preservation.

Table 8. Comparison of the proposed model using the same dataset as other studies in the field.

Researchers	Technology	Performance in Accuracy	Data Privacy
Sethy et al. [33]	ML/DL	98%	No
Sharma et al. [38]	ML/DL	99%	No
Haruna et al. [39]	ML/DL	91%	No
Sudhesh et al. [40]	ML/DL	93%	No
Proposed Model	DL + FL	99%	Yes

6. Conclusions and Future Work

In the modern era, it is essential to classify rice leaf disease while preserving data privacy. This manuscript discusses the use of lightweight federated deep learning to implement rice leaf disease classification. Firstly, pre-trained models such as EfficientNet, VGG19, Resnet152, VGG16, and Xception were implemented and analysed. As compared to the other mentioned algorithms, the evaluated accuracy of EfficientNetB3 is 99%. Once the best-performing model is identified, i.e., EfficientNetB3, consider this the baseline model for federated learning. Further, federated learning was implemented using EfficientNetB3 for rice leaf disease classification. As per the analysis of the federated deep learning ecosystem, EfficientNetB3 resulted in 99% training and evaluated accuracies with minimum losses of 0.006 and 0.03 for IIDs (when data is identically distributed to all clients) and for non-IIDs (data is not identically distributed), respectively. The training accuracy was 99% with a minimum loss of 0.04, and the evaluated accuracy was 95% with a loss of 0.08. The results obtained in the federated deep learning ecosystems were found to be very similar to those obtained in the baseline machine learning ecosystem. Based on the analysis, it was concluded that the proposed system performs better in terms of resource utilisation and data privacy in the federated deep learning ecosystem and also achieves classification results that are very similar to those of the baseline machine learning system. In the future, the results will be implemented using IoT technology to identify rice leaf diseases [41]. Additionally, to address privacy concerns in the federated ecosystem, encryption techniques could be implemented when sharing trained models.

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