agronomy

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Federated Transfer Learning for Rice-Leaf Disease Classification across Multiclient Cross-Silo Datasets

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Abstract: Paddy leaf diseases encompass a range of ailments affecting rice plants' leaves, arising from factors like bacteria, fungi, viruses, and environmental stress. Precision agriculture leverages technologies for enhanced crop production, with disease detection being a vital element. Prompt identification of diseases in paddy leaves is critical for curtailing their propagation and reducing crop damage. However, manually diagnosing paddy diseases in regions with vast agricultural areas and limited experts proves immensely difficult. The utilization of machine learning (ML) and deep learning (DL) for diagnosing diseases in agricultural crops appears to be effective and well-suited for widespread application. These ML/DL methods cannot ensure data privacy, as they involve sharing training data with a central server, overlooking competitive and regulatory considerations. As a solution, federated learning (FL) aims to facilitate decentralized training to tackle the identified limitations of centralized training. This paper utilizes the FL approach for the classification of rice-leaf diseases. The manuscript presents an effective approach for rice-leaf disease classification with a federated architecture, ensuring data privacy. We have compiled an unbalanced dataset of rice-leaf disease images, categorized into four diseases with their respective image counts: bacterial blight (1584), brown spot (1440), blast (1600), and tungro (1308). The proposed method, called federated transfer learning (F-TL), maintains privacy for all connected devices using a decentralized client-server setup. Both IID (independent and identically distributed) and non-IID datasets were utilized for testing the F-TL framework after preprocessing. Initially, we conducted an effectiveness analysis of CNN and eight transfer learning models for rice-leaf disease classification. Among them, MobileNetV2 and EfficientNetB3 outperformed the other transfer-learned models. Subsequently, we trained these models using both IID and non-IID datasets in a federated learning environment. The framework's performance was assessed through diverse scenarios, comparing it with traditional and federated learning models. The evaluation considered metrics like validation accuracy, loss as well as resource utilization such as CPU and RAM. EfficientNetB3 excelled in training, achieving 99% accuracy with 0.1 loss for both IID and non-IID datasets. MobilenetV2 showed slightly lower training accuracy at 98% (IID) and 90% (non-IID) with losses of 0.4 and 0.6, respectively. In evaluation, EfficientNetB3 maintained 99% accuracy with 0.1 loss for both datasets, while MobilenetV2 achieved 90% (IID) and 97% (non-IID) accuracy with losses of 0.6 and 0.2, respectively. Results indicated the F-TL framework's superiority over traditional distributed deep-learning classifiers, demonstrating its effectiveness in both single and multiclient instances. Notably, the framework's strengths lie in its

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Citation: Aggarwal, M.; Khullar, V.; Goyal, N.; Gautam, R.; Alblehai, F.; Elghatwary, M.; Singh, A. Federated Transfer Learning for Rice-Leaf Disease Classification across Multiclient Cross-Silo Datasets. *Agronomy* **2023**, *13*, 2483. https://doi.org/10.3390/agronomy13102483

Academic Editor: Peng Fu

Received: 2 September 2023
Revised: 20 September 2023
Accepted: 23 September 2023
Published: 27 September 2023

cost-effectiveness and data-privacy assurance for resource-constrained edge devices, positioning it as a valuable alternative for rice-leaf disease classification compared to existing tools.

Keywords: federated learning; transfer learning; resource utilization; IID and non-IID

1. Introduction

The agricultural sector plays a vital role in the economic advancement of any country. It provides fundamental raw materials, which act as the foundation for numerous industries. The production of agriculture is significantly impacted by rice, a crop that is grown all over the world. Over 50% of the global population, mainly in Asia, Africa, and America, relies primarily on rice as a food source. It provides about 13% of the protein consumed per person daily and about 20% of the daily caloric intake. Sadly, pests and diseases cause significant losses in the rice harvest for farmers every year, with an estimated average loss of 37%. It is cultivated in more than a hundred nations around the world, with an annual harvest that covers about 158 million hectares and yields about 700 million tons of rice [1]. Asia outperforms other continents in terms of rice cultivation, producing most of the world's supply.

Several methods and strategies are available to address the challenges posed by rice diseases. These include implementing effective equipment and field cleaning practices between growing seasons, adopting disease-resistant seed varieties obtained from clean sources, employing appropriate fertilization techniques, promoting the presence of natural predators to control pests, ensuring proper grain storage, and judiciously using insecticides [2]. Out of the strategies outlined, many are categorized as preventative measures. However, the utilization of insecticides is a critical and immediate requirement to address rice-leaf diseases. It is important to note that various types of rice-leaf diseases exist, and each specific disease necessitates a distinct type of insecticide for effective eradication. Hence, the choice of insecticides should be tailored to the specific rice-leaf disease at hand, initiating treatment with the relevant insecticide for the majority of rice-leaf diseases encountered in paddy fields [3]. Subsequently, a rotation of insecticides is implemented, switching to suitable options for different rice-leaf diseases present in the field. The duration of this process can vary, contingent on the number and severity of rice-leaf disease types. This situation is projected to ameliorate with the advancement of precision agriculture techniques, allowing for the real-time monitoring of rice-leaf diseases and the precise application of appropriate insecticides, therefore streamlining the treatment process [4].

To address this constraint, Artificial Intelligence (AI) methods enable the creation of smart applications designed to assist in the diagnosis of crop diseases [5]. Machine-learning (ML) approaches, particularly supervised learning, necessitate access to data both centrally and locally during the training process [6]. Nonetheless, computing and storage assets are distributed across various geographical areas, prompting organizations to adopt distributed training methods to leverage these resources effectively. Nevertheless, the presence of diverse and dispersed computing resources gives rise to concerns regarding privacy and security. As a solution, the concept of (FL) has emerged, presenting a method to harness the capabilities of distributed resources through collaborative training of a shared machine model. FL has already demonstrated its potential in various domains, including but not limited to medicine [7], industrial engineering [8], and mobile devices [9] in recent practical implementations. This study illuminates the viability of federated learning (FL) as an appropriate strategy for distributed machine learning within the realm of rice-leaf diseases. The research emphasizes the utilization and assessment of FL in the context of diagnosing ailments in rice leaves, leveraging transfer learning (TL), and adopting a centralized learning framework, which necessitates the data's central presence on a server for training purposes. In the FL methodology, data dispersal across training clients is possible, operating in a distributed and asynchronous manner to construct a central model.

The proposed work focuses on the classification of diseases in rice leaves, which could provide valuable assistance to farmers and agricultural researchers in the identification of crops. The main contributions of this paper are:

i. Implementing a federated transfer learning approach for rice-leaf disease classification;
ii. Implementing an enhanced distributed training approach through federated learning, involving both IID and Non-IID datasets;
iii. The proposed method has shown its efficacy while addressing data privacy and resource utilization concerns in the classification of rice-leaf diseases.

The proposed federated transfer learning technology shows immense potential for transforming the agriculture sector. By harnessing data from a variety of sources, including farms, agricultural experts, and industry stakeholders, this innovation allows for the creation of highly precise and localized predictive models. Farmers stand to gain personalized guidance for crop management, pest control, and efficient resource allocation, resulting in higher yields and cost savings. Agricultural experts can draw upon the collective knowledge embedded in the federated model to make data-informed decisions and offer tailored advice to farmers. Additionally, stakeholders in the agriculture industry can access valuable insights into market trends and supply chain dynamics, facilitating improved planning and risk management. Overall, federated transfer learning technology can boost productivity, sustainability, and profitability within agriculture, all while upholding the integrity of data privacy and security.

2. Related Study

Over the years, the field of identifying rice-leaf diseases through image analysis has witnessed the development of numerous approaches. Petchiammal et al. [10] Introduced a visual dataset called Paddy Doctor, designed to detect paddy diseases. The comprehensive dataset comprises 16,225 annotated images of paddy leaves, distributed among 13 categories encompassing 12 disease types and a category for healthy leaves. The authors subsequently employed this dataset to conduct the classification of rice-leaf diseases with Convolutional Neural Network (CNN) as well as with VGG16, ResNet34, Xception, MobileNet, and four transfer learning models and achieved the highest F1-score value, i.e., 97.50%. Sudhesh et al. [11] introduced a method for identifying rice-leaf diseases, which leverages a combination of the Dynamic Mode Decomposition technique and an attention-driven preprocessing approach. Their study focuses on four distinct classes of rice-leaf diseases, specifically bacterial blight, blast, brown spot, and tungro, encompassing a total dataset of 3416 images. The authors proceed to employ ten distinct transfer-learned deep Convolutional Neural Network (CNN) models, integrating them with three machine-learning classifiers for disease classification. Their analysis concludes that the XceptionNet model achieves the highest accuracy, notably 94.33%, surpassing the performance of other transfer-learned models. Haruna et al. [12] developed a specialized model called StyleGAN2-ADA, which stands for Style-Generative Adversarial Network Adaptive Discriminator Augmentation. This model was designed to detect diseases in rice leaves.

Patil et al. [13] introduced an innovative AI model for grading rice, which employs an enhanced strategy employing the faster-region-based convolutional neural network (FR-CNN). This method is utilized to accurately determine the sizes of individual leaf instances and identify regions affected by infections. The model's effectiveness was evaluated in comparison to other CNN architectures. The backbone of the system, the EfficientNet-B0 architecture, was chosen due to its exceptional accuracy performance, achieving an impressive accuracy rate of 96.43%. Furthermore, Patil et al. [14] introduced an innovative multimodel approach called Rice-Fusion to effectively diagnose rice diseases. This method involved combining data from two distinct sources: agro-meteorological sensors and a camera. By extracting numerical characteristics from the agro-meteorological sensor data, and visual attributes from images of the rice, they achieved an impressive testing accuracy of 95.31% using the Rice-Fusion framework. In comparison, other approaches that relied solely on a single source of data achieved lower accuracies: 82.03% using a Convolutional Neural Network (CNN) and 91.25% using a Multi-Layer Perceptron (MLP) architecture. This showcases the superior performance of the Rice-Fusion method in diagnosing rice diseases. Salamai et al. [15] have presented a lesion-aware visual transformer approach designed to enhance the precise and dependable detection of paddy leaf diseases. This innovative method focuses on identifying distinct lesion features that play a crucial role in the process. They have introduced a novel network for multi-scale contextual feature extraction, which effectively captures both local and global contextual representations of disease-related features across various scales and channels. Remarkably, their approach achieved remarkable results, attaining an accuracy of 98.74% along with an impressive F1-score of 98.18%. Gulzar et al. [16] employed five deep-learning models, including AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNet, for the classification of sunflower disease detection. Their findings revealed that the EfficientNetB3 model achieved the highest accuracy, reaching 97.9%. Mamat et al. [17] implement an automatic image annotation system to classify the ripeness of oil palm fruit. The approach utilizes deep learning in combination with the You Only Look Once (YOLO) algorithm. The mean Average Precision (mAP) achieved for oil palm fruit classification was 98.7%, while for other fruit, it reached 99.5%. The proposed technique effectively and accurately annotated a substantial number of images.

All the aforementioned research endeavors employed traditional machine-learning methodologies, wherein an aggregated server or computing device handled both the storage of data and the training of the model. Consequently, the requirement emerged for all data to be centralized before commencing the training process. Traditional ML methods necessitate a model designed to learn from an extensive set of training samples, a task that can prove challenging at times due to privacy concerns that hinder the collection of such data [18], However, in the FL framework, models undergo individual training on local sites, and updated weights are subsequently transmitted to a central server for aggregation. As a consequence, the central server remains unaware of raw data, solely receiving model characteristics such as parameters, gradients, and weights [19].

Antico et al. [20] presented a study showcasing how FL effectively addresses challenges while also emphasizing the obstacles that demand attention. Their research involved the implementation of a federated learning framework utilizing five Convolutional Neural Network (CNN) models. This framework was employed to accurately identify diseases affecting Maize crops, all while maintaining data privacy across varied domains. Kabala et al. [21] delved into the utilization of federated learning (FL) for the categorization of crop diseases through image analysis. They devised and examined Convolutional Neural Network (CNN) models that incorporated attention mechanisms, including vision transformers, within a federated learning framework, leveraging an accessible plantvillage dataset platform, they determined that ResNet50 exhibited superior performance in multiple experiments compared to alternative models. Additionally, ResNet50 was identified as an ideal and well-suited choice within the context of a federated learning scenario. Khullar and Singh. [22] Presented a federated framework termed f-FNC, aimed at classifying fake news. This framework functions using a decentralized client-server structure, emphasizing the privacy of data for all interconnected clients or edge devices. The methodology involves the application of LSTM, BiLSTM, CNN-LSTM, and CNN-BiLSTM DL algorithms. These algorithms were employed on datasets exhibiting both IID and non-IID characteristics. Through the adoption of a multiclient FL approach, the framework achieved notable accuracy, ranging between 90% and 92%, for the classification of fake news. Table 1 demonstrates the comparative study for rice-leaf disease image classification using ML, DL, and FL techniques.

Table 1. Comparative analysis of related technique.

Reference	Study Area	Approach Used	Training Place	Accuracy	Privacy Support
[10]	Rice Diseases	DL	Centralized	F1-Score = 97.50%	No
[11]	Rice Diseases	DL	Centralized	Accuracy = 94.3%	No
[12]	Rice Diseases	DL	Centralized	mean Average Precision (mAP) = 0.93% and 0.91%	No
[13]	Rice Diseases	DL	Centralized	Accuracy = 96.4%	NO
[14]	Rice Diseases	DL	Centralized	Accuracy = 95.3%	NO
[15]	Rice Diseases	DL	Centralized	Accuracy = 98.7%	NO
[16]	Sunflower Diseases	DL	Centralized	Accuracy = 97/9%	NO
[17]	Oil Palm Fruit Ripeness	DL	Centralized	mean Average Precision (mAP) = 98.7%	NO
[20]	Maize Diseases	FL	Distributed	Accuracy = 96.87%	YES

3. Methods and Materials

The conventional machine-learning technique collected and processed the data in a centralized manner for rice-leaf disease prediction. The process involves gathering a dataset of rice-leaf images, where each image is labeled with the corresponding disease category.

The centralized nature of data collection and processing is the major disadvantage of conventional machine-learning techniques [23]. Federated learning can mitigate this issue by allowing models to be trained on data distributed across multiple clients or data sources. This distributed nature enables a more diverse and representative dataset to be used for training, as each client may have its own unique data distribution. By aggregating the model updates from multiple clients, federated learning can capture a more comprehensive understanding of the underlying data distribution and improve the model's generalization performance [24]. This section describes the techniques and computational processes utilized in the research study. The F-TL framework, as proposed, comprises three primary steps: (1) Data preprocessing involves resizing images to a 75×75 dimension and converting them to grayscale. (2) Model training and analysis encompass the utilization of CNN and eight transfer learning models, including DenseNet201, EfficientNetB3, InceptionNetResNetV2, MobileNetV2, VGG16, VGG19, Xception, and ResNet152V2, to identify the best-performing model. (3) The implementation of the federated learning approach with both IID and non-IID datasets is executed to address concerns related to data privacy and computational resource usage. The steps followed in the proposed approach is shown in Figure 1. The paper introduces a federated transfer learning framework designed to tackle concerns regarding data privacy and resource utilization in rice-leaf diseases image classification.

3.1. Federated Learning

FL is an ML approach that permits the training of a shared model through multiple decentralized devices or servers without the need to directly transfer or centralize their data. In FL, instead of sending raw data to a central server for the training of the model, training occurs directly on the devices or servers at a local level [25]. The models are then updated collaboratively by aggregating the locally trained model parameters or gradients. The fundamental principle of federated learning is to bring the model training process closer to the data sources while preserving data privacy and security. Federated Learning ensures data privacy by enabling devices to collectively improve a global model without disclosing raw data. Instead of sharing data, it aggregates model updates, and privacy-enhancing methods such as differential privacy or secure aggregation bolster the protection of individual data privacy, rendering it a dependable solution for privacy-conscious applications. This is particularly valuable in scenarios where data are sensitive, distributed, or reside on devices with limited resources or unreliable network connectivity [26]. The main principle of FL is the minimize-loss function.

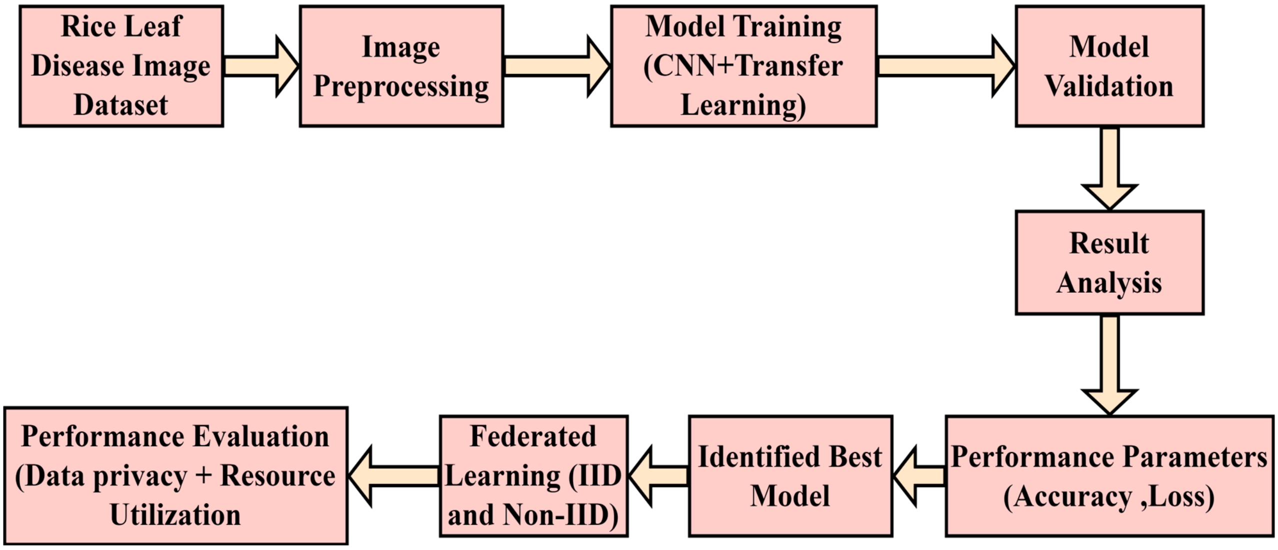

Figure 1. Steps followed in the proposed method for rice-leaf disease classification.

In federated learning, the overall process typically consists of three main steps.

1. Training task and global model initialization: During this preliminary stage, the central server outlines the training task and delineates the intended application. The server generates an initial global model, by setting the hyperparameters and determining the objective function i.e., represented by $J(\theta, D\_i)$ for each client i. Subsequently, the server disseminates this initialized global model to the chosen local participants who will play a role in the training procedure.

The mathematical representation of the objective function is as follows:

$$J(\theta, D\_i) = \sum(L(f(\theta, x), y)) \tag{1}$$

where global model parameters represented by θ and D_i denote the local dataset for each client. The objective function quantifies the difference between the model's predicted outputs and the actual labels for the local dataset. $f(\theta, x)$ represents the model's prediction for input x using the global model parameters θ, and y represents the true label. L denotes the loss function.

2. Local model training: During the FL process, each participating client within the network holds its own individual set of data. These clients perform local model updates using their respective data. For each training round, select a subset of clients or devices, C_i, where i = 1, 2,. . . , M, and M is the number of selected clients for the round. For each selected client C_i, perform local model training using its local dataset D_i. This involves optimizing the client's local model parameters θ_i to minimize the objective function $J(\theta\_i, D\_i)$. This can be achieved through iterative optimization algorithms, such as stochastic gradient descent (SGD), represented as:

$$\theta\_i(k + 1) = \theta\_i(k) - \eta \times \nabla J(\theta\_i(k), D\_i) \tag{2}$$

Here, η is the learning rate, k denotes the iteration or epoch, and ∇J represents the gradient of the objective function with respect to the client's local model parameters θ_i.

3. Aggregation of Local Model Updates: After local training, the local model updates from the selected clients are aggregated to obtain an updated global model. This can be achieved through techniques such as weighted averaging or simple averaging, represented as:

$$\theta\_global(k + 1) = (1/N) \times \sum(\theta\_i(k + 1)) \quad (3)$$

Here, θ_global represents the updated global model parameters after aggregation.

The process of minimizing the training function in federated learning includes going through these steps across several training rounds. During each round, the global model parameters are adjusted using the combined updates from local models, continuing until convergence or a predetermined stopping condition is reached. Table 2 presents a comparative analysis of federated learning with traditional approaches [27]. It emerges as a promising approach, offering respectable learning accuracy while prioritizing privacy preservation and maintaining minimal communication overhead.

Table 2. Comparative analysis of federated learning with other approaches.

	Centralized Learning	**Centralized Distributed Learning**	**Decentralized Distributed Learning**	**Federated Learning**
Definition	Data are collected at the central server and processed.	Data are shared between multiple servers and processed in parallel.	There is no central server. Multiple clients process the data locally and then share training updates between all clients.	Multiple clients trained their model with local data and then shared this local model with the aggregation server.
Communication Overhead	Large, as all data are collected at the server.	Large, as raw data are shared between servers.	Large, as compared to FL as it needed a synchronization between multiple clients.	Smaller, as compared to other approaches as no raw data are shared between clients and server.
Data privacy	All data are aggregated at a central server, so data privacy is a concern.	All data are shared with a central server, so data-privacy risk exists.	Data privacy is maintained through the avoidance of raw data-sharing.	
Accuracy	High	Moderate	Moderate	Low

3.2. Data Collection and Preprocessing

We collected a heterogeneous dataset for rice-leaf disease images. The dataset contains a total of 5932 images. There exist 1584 images depicting bacterial leaf blight, 1440 images portraying blast, 1600 images illustrating brown spot, and 1308 images showcasing tungro [28]. All images are saved in JPG format and properly labeled. Figure 2 shows some samples of our collected dataset. The dataset was split into training and testing subsets at an 80:20 proportion. To create a simulated federated environment for both IID and non-IID datasets, the data were normalized to standard input values and shuffled to prevent sequential bias. In non-IID scenarios, additional steps may involve careful data partitioning to create balanced client datasets. Each client received an exclusive and varied portion of the dataset. This allocation was structured to replicate a situation in which each client holds a distinct dataset of their own, therefore enhancing the diversity within the overarching federated learning environment.

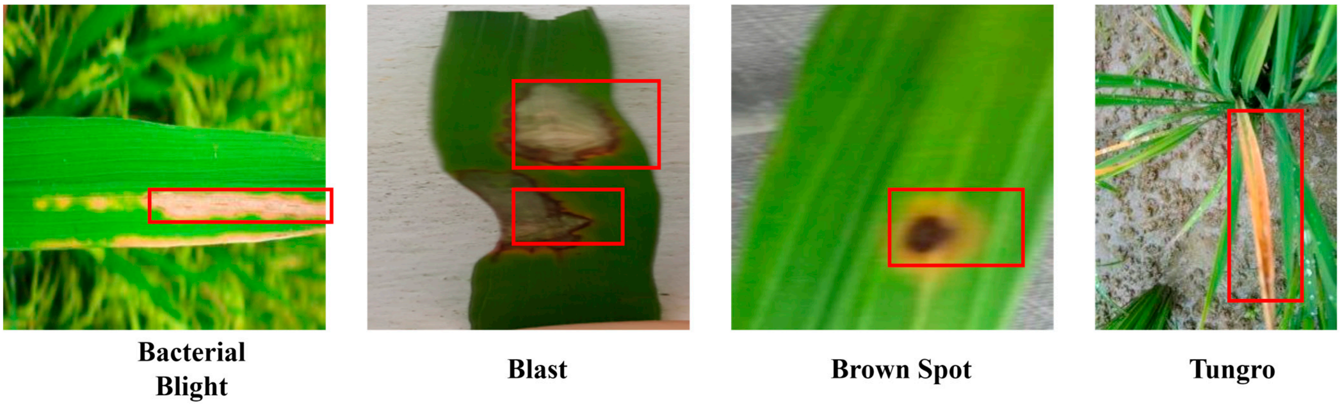

Figure 2. Image samples of rice-leaf diseases.

Each client performs local preprocessing on its assigned data partition. This preprocessing step can involve various tasks, such as data cleaning, normalization, resizing, and augmentation. The preprocessing procedures carried out by each client can vary based on the characteristics of the data and the demands of the federated learning assignment [19]. To meet the requirements of the model, the dataset underwent preprocessing steps. The images underwent resizing to achieve a standardized dimension of 75 $\times$ 75 pixels, ensuring uniformity in the input dimensions for the model. Additionally, the images were converted to grayscale, which reduces the color channels from RGB to a single grayscale channel. These preprocessing steps were performed to prepare the dataset for training the federated learning model effectively.

3.3. Transfer Learning

A powerful deep-learning technique known as transfer learning leverages the insights gained from pretrained models to address new and related tasks. It entails applying a pretrained model—typically trained on a large dataset—to a task or dataset that is different but related and that contains fewer labeled examples. This method achieves high performance on the target task while using fewer computational resources and less training time. This approach is adopted due to the extensive time and computational resources required to train complex parameters in deep-learning architectures. Acquiring a substantial labeled dataset for model training poses a significant challenge. Consequently, transfer learning has emerged as a favored strategy and is naturally integrated into practical applications. This involves utilizing a pretrained network, where only the parameters of the final classification layers are retrained from scratch using the training set [29].

The current study uses CNN along with transfer learning models for rice-leaf disease classification as shown in Figure 3. CNNs are a specialized type of deep neural network architecture that effectively processes and analyzes visual data. By leveraging convolutional layers, pooling layers, Dropout layers, and fully connected layers, CNNs can acquire hierarchical representations and extract significant features from images [30,31]. Their ability to capture local patterns and spatial relationships has made them a go-to choice for image classification, object detection, and other computer vision tasks.

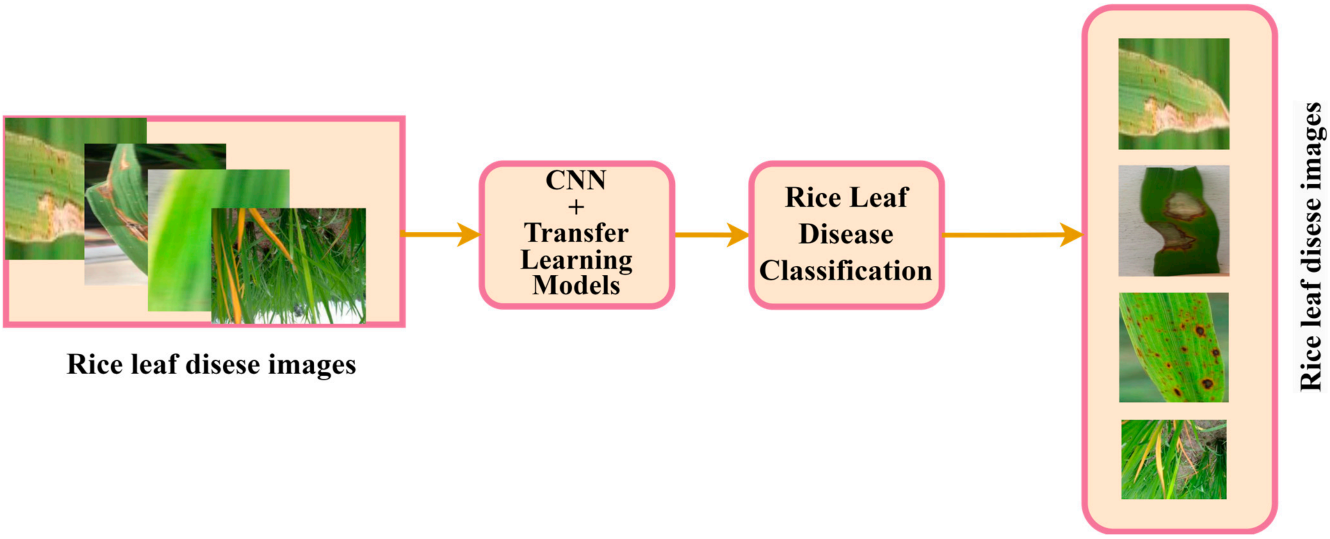

Figure 3. Rice-leaf disease classification using CNN and transfer learning.

3.4. IID and Non-IID Data

In federated learning, the distribution of data among participating clients can be categorized into two main types: IID (Independent and Identically Distributed) and non-IID data. IID data pertains to a situation in which the distribution of data among the clients is similar, and each client's data are representative of the overall dataset. This assumption simplifies the federated learning process as the global model can be trained on local updates from clients without any additional considerations. On the other hand, non-IID data describes a situation where the data-sharing among the clients is heterogeneous or imbalanced. This implies that each client could have a distinct data arrangement, and the data samples within each client might not accurately represent the entire dataset [24]. The reasons for non-IID data can vary, such as variations in data collection sources, different demographics of clients, or variations in local data distributions [32].

Figure 4 illustrates two scenarios: an IID dataset and a non-IID dataset distributed among four Farmer's sites.

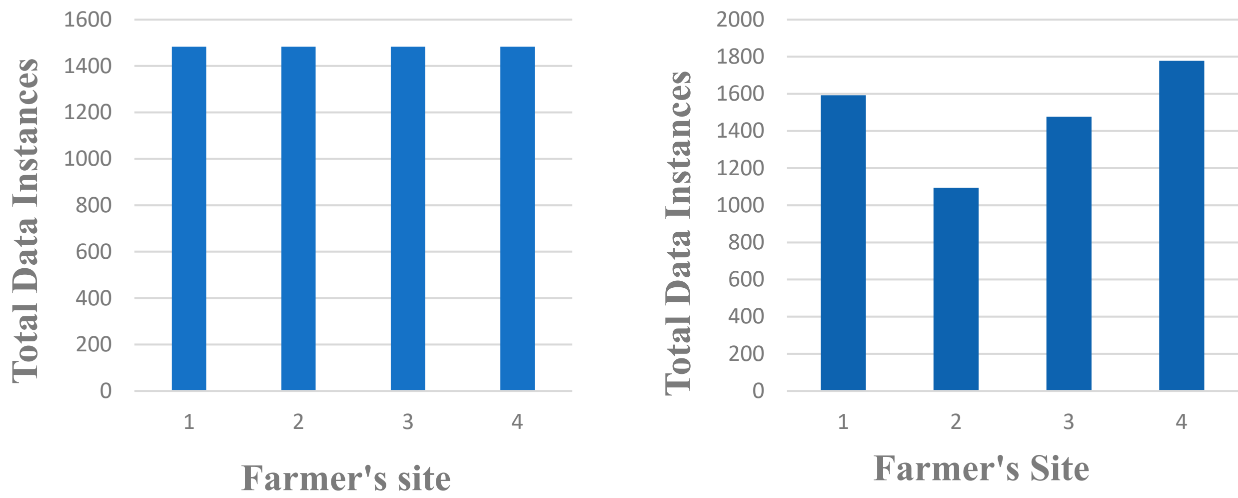

Figure 4. Data distribution in IID and non-IID datasets.

3.5. Resource Utilization

Resource utilization in federated learning refers to the efficient allocation and usage of computational resources during the training process across multiple clients or devices. It aims to optimize resource utilization to achieve effective and scalable federated learning while minimizing overhead and ensuring efficient communication. Efficient resource utilization in federated learning is crucial to ensure scalability, reduced training time, and effective utilization of computational resources across distributed clients and servers. By optimizing resource allocation, minimizing communication overhead, and employing efficient model optimization techniques, federated learning can achieve high performance while utilizing resources efficiently [33]. To determine the cost efficiency of a system, one of the measures taken into consideration is the efficient utilization of available resources. In this case, the analysis focused on the utilization of CPU and RAM in both the traditional system and the proposed system [22]. By examining the CPU and RAM utilization, the goal was to assess how efficiently the system utilized these resources in comparison to the proposed system.

3.6. Model Training

The model was implemented utilizing Keras and Tensorflow 2.0. The results were executed on a laptop equipped with an Intel Core i7 CPU, 32 GB of RAM, and a solid-state drive.in our proposed system we used CNN, DenseNet201, EfficientNetB3, Inception-NetResNetV2, MobileNetV2, VGG16, VGG19, Xception, and ResNet152V2. To expedite the training convergence process, we leveraged pretrained weights from these models, which were originally trained on a vast dataset of over a million images sourced from the ImageNet database. Although the fully connected layers in the model's final section were excluded, the convolution layers retained their default architecture without modification. Table 3 summarizes the architecture of a Convolutional Neural Network (CNN) model, showcasing the sequence of layers and their configurations used in our implementations. It starts with the input layer, processing $75 \times 75 \times 3$-dimensional images, followed by a series of Conv2D layers employing 256, 128, and 64 filters, each with a 3×3 kernel size, ReLU activation, 'same' padding, and He Uniform kernel initializer. MaxPooling2D layers reduce spatial dimensions by 2×2 pooling, while Dropout layers introduce regularization with a rate of 0.1. After the convolutional layers, a Flatten layer reshapes the data into a 1D vector. Finally, a Dense layer with a SoftMax activation serves as the output layer with the number of neurons corresponding to the class count. This concise representation offers insight into the CNN's structure and critical parameters for image classification tasks.

Table 3. Convolutional neural network layer description.

Layer	Type	Parameters
1	Input ($75 \times 75 \times 3$)	-
2	Convolutional (2D)	Filters: 256, Kernel size: (3, 3) Activation function (ReLU)
3	Maxpooling (2D)	Pool size: (2, 2)
4	Dropout	Dropout rate (0.1)
5	Convolutional (2D)	Filters: 128, Kernel size: (3, 3) Activation function (ReLU)
6	Maxpooling (2D)	Pool size: (2, 2)
7	Dropout	Dropout rate (0.1)
8	Convolutional (2D)	Filters: 64, Kernelsize: (3, 3) Activation function (ReLU)
9	Maxpooling (2D)	Pool size: (2, 2)
10	Dropout	Dropout rate (0.1)
11	Flatten	-
12	Dense layer	Activation: SoftMax

4. Proposed Federated Transfer Learning (F-TL) Framework for Rice-Leaf Disease Identification

Early detection of rice-leaf diseases is of utmost importance as they can significantly impact crop yield and quality. Rice plants are susceptible to a range of diseases, including those that affect the leaves. Identifying these diseases at an early stage is crucial for effective disease management and minimizing the negative consequences on rice production [34]. The use of DL in rice-leaf disease identification has the potential to revolutionize agricultural practices, enabling timely and accurate detection of diseases, precise management strategies, and improved crop health monitoring. It can empower farmers with valuable tools to mitigate the impact of diseases, optimize resource utilization, and enhance overall crop productivity [35]. Deep learning, being a centralized approach, introduces concerns regarding data privacy and communication costs. This is precisely why the federated learning approach is employed. Federated learning mitigates these issues by enabling decentralized training on distributed devices or servers [36]. In this section, the emphasis is placed on the execution and evaluation of FL techniques for the classification of rice-leaf diseases. The proposed work aims to analyze the performance of FL in accurately categorizing different types of rice-leaf diseases. Figure 5 illustrates the suggested framework for rice-leaf disease classification.

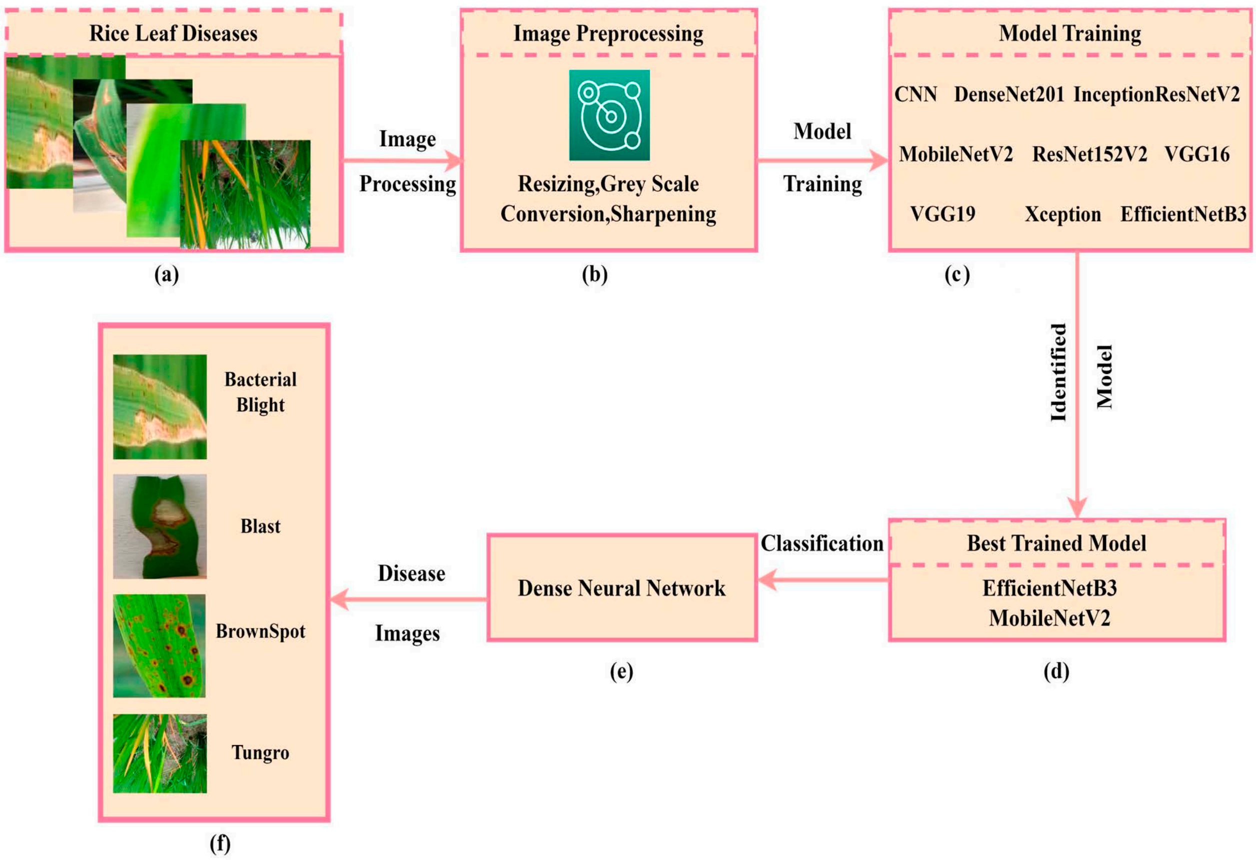

Figure 5. Proposed transfer learning framework for classification of rice-leaf diseases. (**a**) The rice-leaf disease dataset. (**b**) Image processing approach. (**c**) Model training with c1.CNN, c2–c9: pretrained models. (**d**) Identified the best models (EfficientNetB3 and MobileNetV2) as they produced the best results for classifying rice-leaf diseases. (**e**) Classification using Dense Neural Network. (**f**) Rice-leaf disease classification.

First, the images from the provided dataset are processed using image processing techniques such as resizing, sharpening, and converting to grayscale. Models are trained using CNN and various transfer learning approaches. Various trained models were assessed by comparing their training and validation accuracies to identify the most proficient model. According to our implementation results the analysis indicated that EfficientNetB3 and MobileNetV2 models performed well. When setting up an FL system, a key obstacle is guaranteeing the efficient execution of the learning model on edge devices, acting as monitors in each zone. This necessitates the learning model to be of minimal weight, enabling its practical functioning on these devices. The lightweight attribute of the model assumes significant importance in the blueprint of any FL-driven system [37]. That is why, for model training in decentralized systems, we used mobilenetV2 which is a lighter model than EfficientNetB3 along with Dense Neural Network.

Figure 6 depicts the process of employing federated learning for the identification of rice-leaf diseases, utilizing the EfficientNetB3 and MobileNetV2 models. The dataset containing rice-leaf images is distributed to the models for training. This training occurs at individual farmers' sites, involving both IID and non-IID datasets. Upon the completion of a training cycle, each farmer's site shares its locally trained model with an aggregation server. This aggregation server plays a pivotal role. It combines the models received from various farmers' sites and updates the model weights. The updated global model is then communicated back to all the individual farmers' sites. The federated learning approach involves the participation of farmers as federated clients, each equipped with either the EfficientNetB3 or MobileNetV2 transfer learning models. These models were selected due to their proven success in past classification tasks. The process ensures that the models learn from decentralized data sources while still benefiting from a shared, improved global model. The proposed approach uses four clients and 5932 images to classify rice-leaf diseases in a federated learning environment. Increasing the dataset or the number of clients does not significantly impact our approach because the models are trained individually. Increasing the dataset enhances model performance, but if we increase the number of clients, it will mainly involve adding a bit more work to incorporate additional sites.

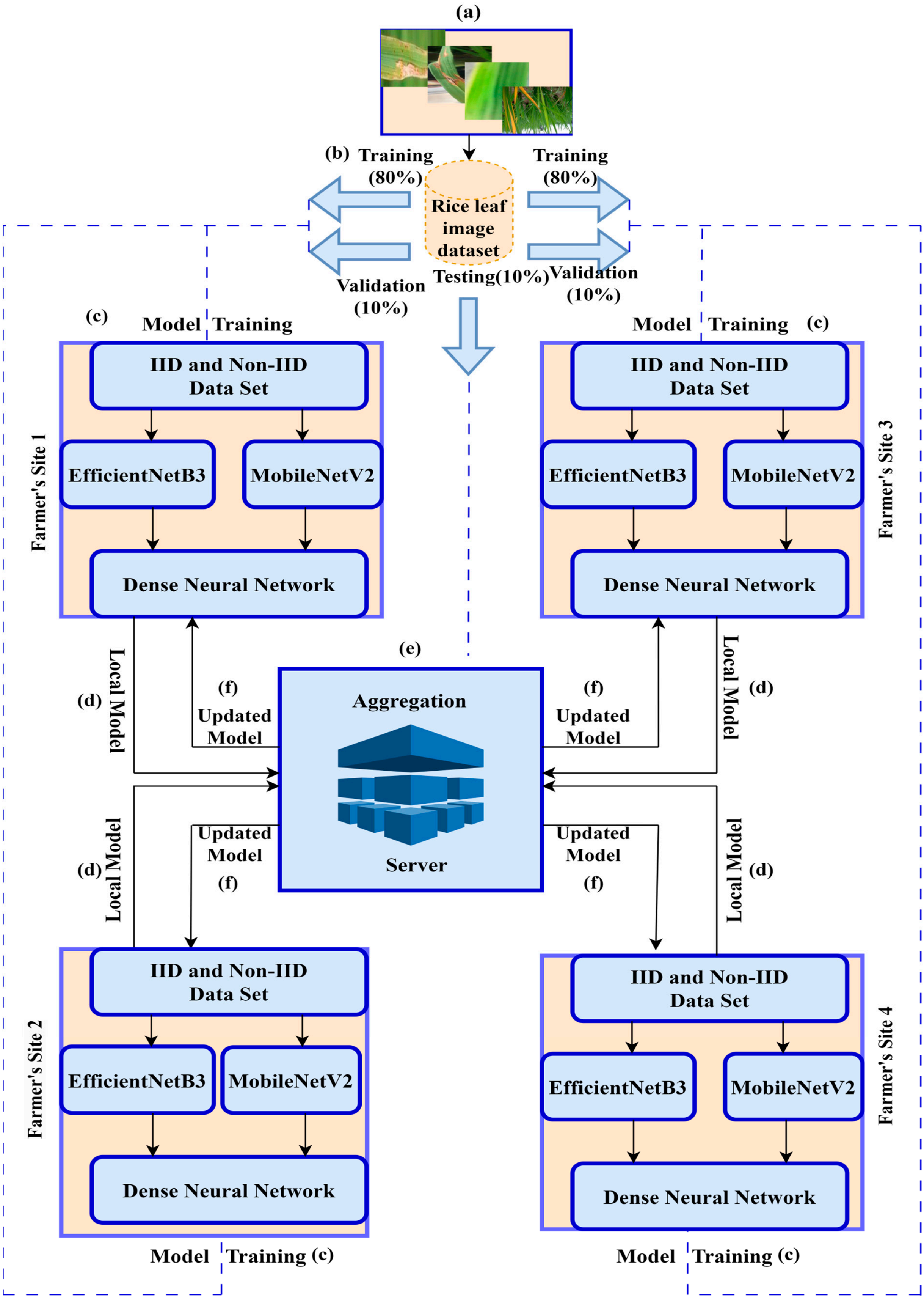

Figure 6. Federated learning approach for the proposed framework. (a) rice-leaf image dataset. (b) Splitting the data into training (80%), validation (10%), and testing (10%) datasets. (c) Trained the model locally at each farmer's site. (d) Send local trained model to aggregated server. (e) Trained aggregated server. (f) Shared updated model with each farmer's site.

5. Results Analysis

This section presents the final results of the implementation and evaluates the efficacy of various models in detecting rice-leaf diseases. For each attempted model, training, and validation accuracy, as well as loss, are provided to assess their classification performance. Training accuracy, also known as categorical accuracy, measures how well the models classify the training dataset. The loss function of the model is a crucial component of deep neural networks [38]. It indicates the extent to which the models deviate from the actual results, allowing us to determine how well the CNN models predict rice-leaf diseases from the dataset. Following training and evaluation, the best-performing transfer learning model(s) were selected according to their outcome values. The main objectives were to achieve higher test accuracy and lower loss function of the model [39]. These metrics are essential in gauging the effectiveness of the models in accurately identifying and classifying rice-leaf diseases.

5.1. Classification Results of CNN and Transfer Learning Models

The provided Table 4 displays the training and validation accuracy as well as the loss values for various CNN and eight transfer learning models, including DenseNet201, EfficientNetB3, InceptionNetResNetV2, MobileNetV2, VGG16, VGG19, Xception, and ResNet152V2. All models performed exceptionally well, achieving excellent results. Upon reviewing the accuracy, it was found that DenseNet201, EfficientNetB3, MobileNetV2, VGG16, and ResNet152V2 demonstrated the highest accuracy, reaching an impressive 100% and 99% training accuracy along with the lowest validation loss values. Conversely, other models such as DenseNet201, VGG19, and Xception achieved strong results with validation accuracy ranging from 98% to 99%, alongside training accuracy, and exhibited validation loss values of 0.08 and 0.12. The CNN model achieved a validation accuracy of 90% and a training accuracy of 91%, with corresponding validation and training loss values of 0.38 and 0.24. However, InceptionResNetV2, despite achieving high training accuracy at 99%, exhibited notably lower validation accuracy at 26%.

Table 4. Classification results of CNN and other transfer learning models.

	CNN	DN201	ENB3	IRV2	MNV2	RN152V2	VGG16	VGG19	Xception
Accuracy	91.82	98.47	99.39	99.05	99.60	99.37	99.22	99.03	99.73
Validation Accuracy	90.56	99.10	100.00	26.64	100.00	100.00	100.00	99.33	98.65
Loss	0.24	0.10	0.11	0.13	0.09	0.11	0.12	0.13	0.06
Validation Loss	0.38	0.08	0.06	-	0.08	0.09	0.09	0.12	0.12

5.2. Training, Validation Accuracy, and Model Loss of CNN and Transfer Learning Models

Figures 7 and 8 illustrate a comparison of training and validation accuracy as well as training and validation loss for various models, including CNN and eight different transfer learning architectures. Notably, the lines representing the models show a consistent upward trend in every epoch, indicating that these models learned rapidly from the training data.

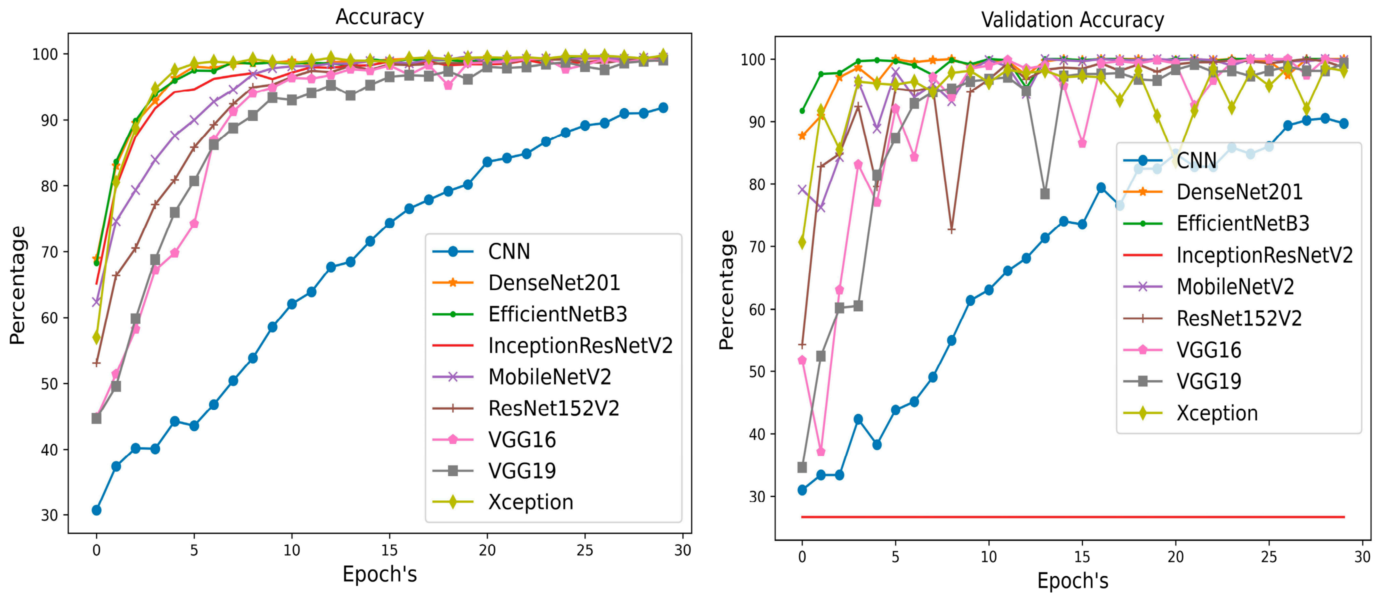

Figure 7. Training and validation accuracy.

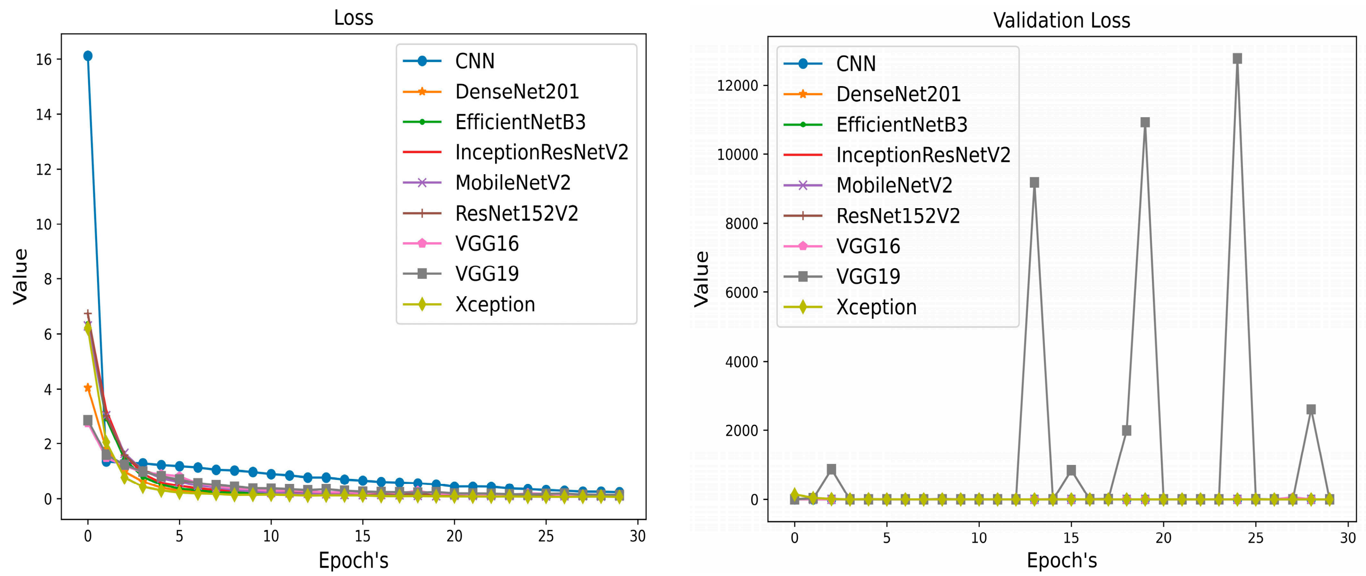

Figure 8. Training and Validation Loss.

Among the transfer learning architectures, DenseNet201, EfficientNetB3, and MobileNetV2, represented by the orange, green, and purple lines, respectively, achieved the highest accuracy, reaching a remarkable 100% training accuracy. On the other hand, the InceptionResNetV2 model, denoted by the red line, had the lowest validation accuracy, only reaching 26%. This discrepancy in performance suggests that transfer learning models, particularly DenseNet201, EfficientNetB3, and MobileNetV2, demonstrated superior learning capabilities compared to the traditional CNN architecture in this scenario. We trained our model for 30 epochs because it yielded the best results during this period. The applied callback ended the mobilenet model at 30 epochs. Our validation accuracy and loss became stable after 30 epochs in mobilenet, indicating that further training might have introduced overfitting or not provided significant improvements.

The analysis of the Training and Validation loss functions is presented in Figure 8. It is evident that as the models underwent more training, their loss functions consistently decreased. This indicates that the models effectively learned from the rice-leaf disease images during the training process. As the models underwent more training time, they achieved reduced values for the loss functions [40]. The figures provide compelling evidence that our models were accurately trained on the rice-leaf disease images. They were able to strike a balance between capturing the intricacies of the data without being overly simplistic (underfitting) or memorizing the training data without generalizing well (overfitting). Moreover, when these well-trained models were tested on the rice-leaf disease dataset, they performed exceptionally well. They successfully detected rice-leaf diseases in the test dataset with high precision and recall, showcasing their ability to generalize their knowledge and make accurate predictions on previously unseen data.

5.3. Performance Evaluation of FL

After the previous comparison, it was noted that the transfer learning models DenseNet201, EfficientNetB3, MobileNetV2, ResNet152V2, and VGG16 performed very well. From these models, we chose EfficienetNetB3 and MobileNetV2 for implementing a federated learning approach. The dataset was made available to numerous local machines for training, and at the server end, the trained models from each machine were combined and shared. In federated architecture, there was a single server and four clients, each of which had its own set of datasets. Data are kept on the local machines themselves in federated learning. Each local machine used the number of epochs to train its model using EfficientNetB3 and mobileNetV2 as well as the Dense Neural Network, and it shared its trained models with the aggregation server. The federated average (FedAvg) function was employed on the server side to train the accumulated models obtained from diverse clients. The resultant global model was distributed among the linked clients. Upon receiving the global model, individual clients retrained their local models using the global model as the standard model. The distributed dataset consisted of two types: IID (Identical and Independent) and non-IID.

Table 5 and Figures 9 and 10 showcase the outcomes of employing the FL approach with IID and non-IID datasets using EfficientNetB3 and MobileNetV2 models. For the IID dataset, EfficientNetB3 achieves a remarkable training and validation accuracy of 99%, while MobileNetV2 records a training accuracy of 98% and a validation accuracy of 90%. Conversely, the non-IID dataset yields even more promising results: EfficientNetB3 attains 100% training accuracy and 99% validation accuracy, while MobileNetV2 demonstrates a training accuracy of 99% and a validation accuracy of 97%.

Table 5. FL results with IID and non-IID dataset(s).

Baseline Model(s)		**EfficientNetB3**				**MobileNetV2**			
Train/Valid	**Data**	**Accuracy**	**Loss**	**Precision**	**Recall**	**Accuracy**	**Loss**	**Precision**	**Recall**
Training	IID	99.75	0.1	99.75	100	98.65	0.47	96.29	99.82
Training	Non-IID	100	0.1	100	100	99.93	0.17	99.93	100
Validation	IID	99.47	0.13	99.83	99.18	90.96	0.63	93.77	88.2
Validation	Non-IID	99.41	0.13	99.74	99.16	97.95	0.22	98.77	97.35

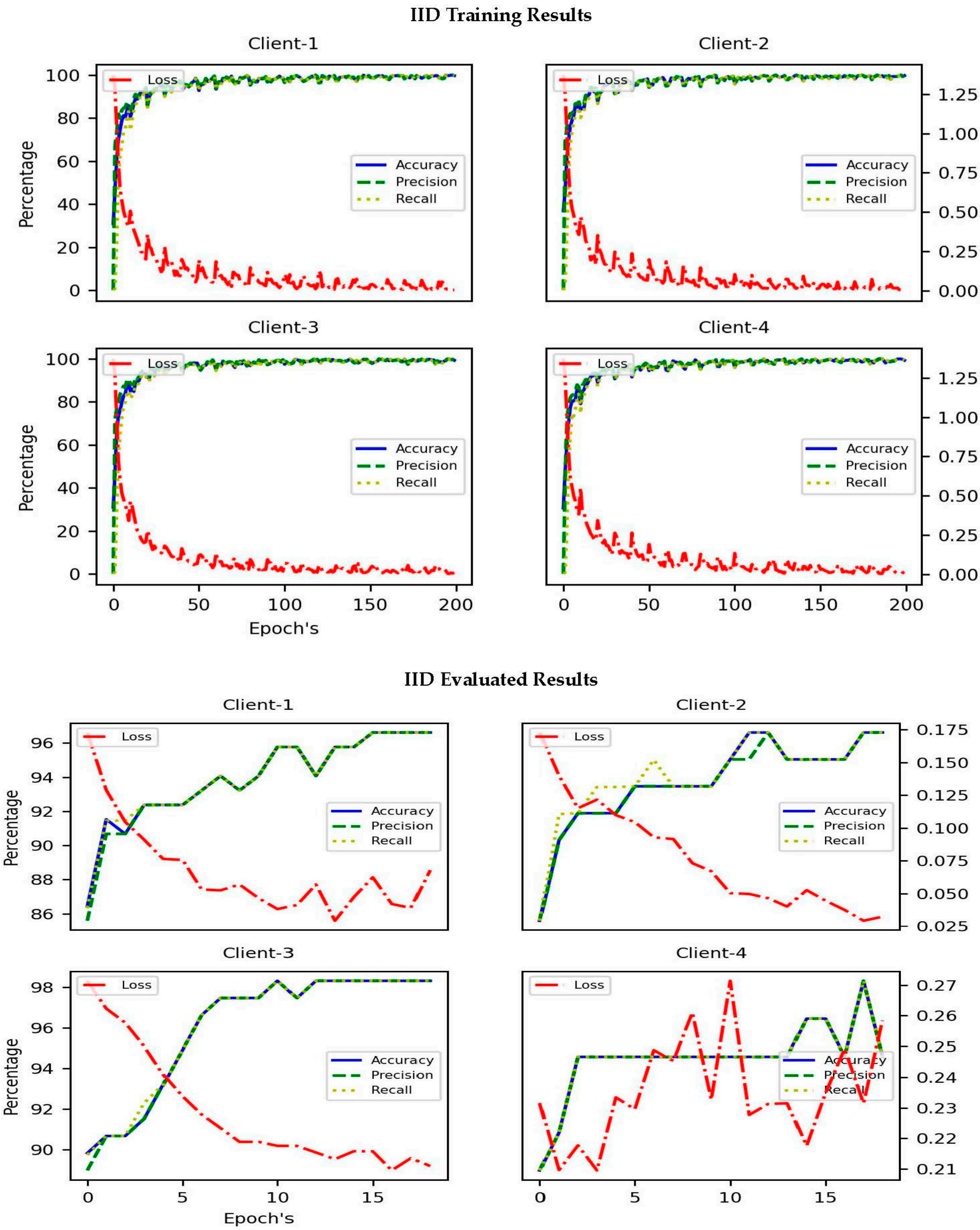

Figure 9. Federated learning training and evaluated results with IID Dataset.

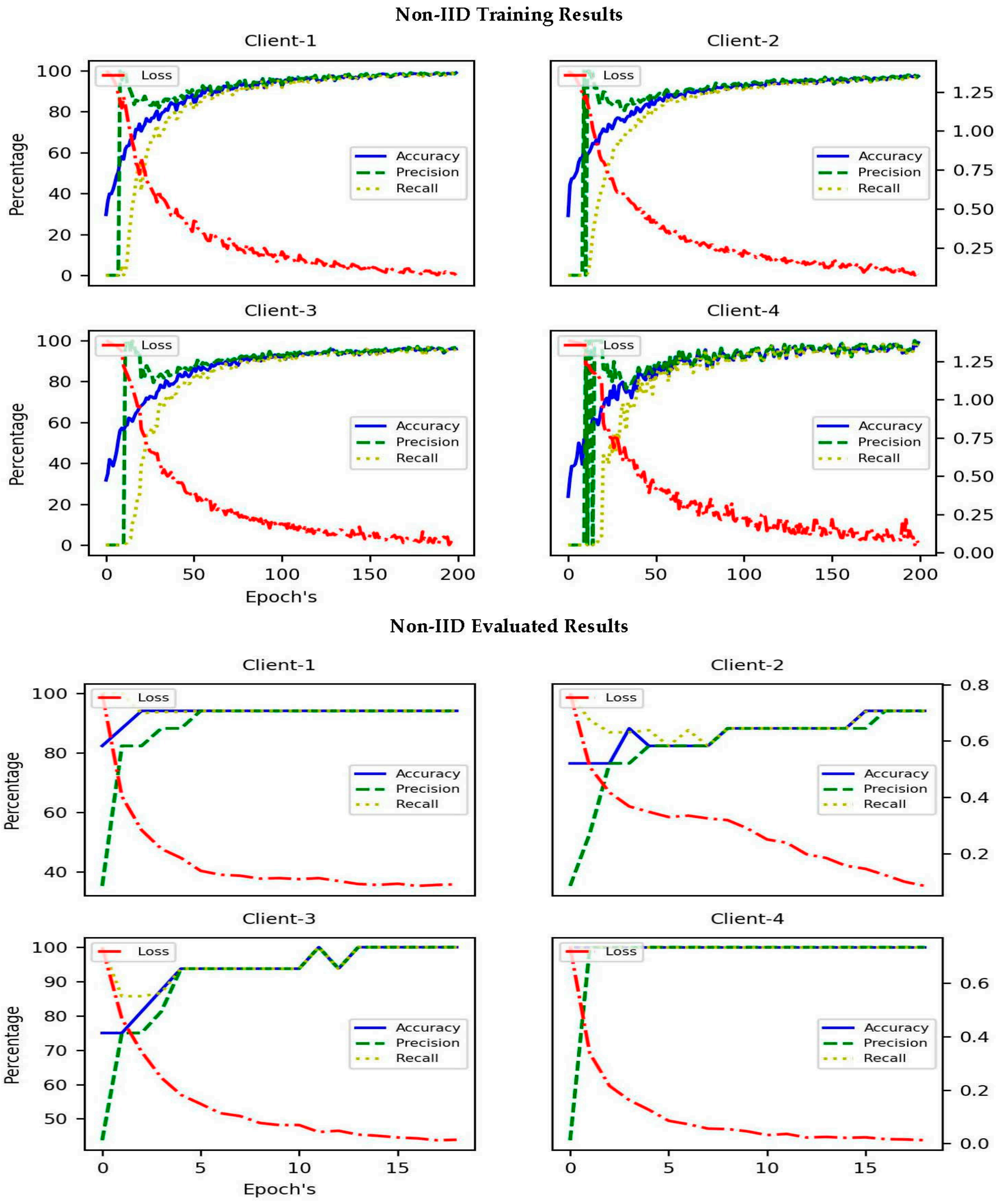

Figure 10. Federated learning training and evaluated results with non-IID Dataset.

5.4. Performance Evaluation with Resource Utilization

Effective utilization of resources within federated learning entails the careful distribution of computational power, memory, and bandwidth among participating devices or servers. This optimization process guarantees productive model training while upholding device limitations, curtailing energy use, overseeing data privacy, and managing parallelism and scheduling intricacies.

The overarching goal of this optimization is to attain model convergence while considering each device's distinct capacities and limitations, thus facilitating collaborative training without the need to centralize sensitive data. In the proposed F-TL system, an analysis was conducted on the utilization of CPU, RAM, and GPU for the EfficientNetB3 and MobilenetV2 models. The analysis of resource utilization is presented in Figures 11 and 12. As depicted in Figure 11, the CPU utilization within the EfficientNetB3 model exhibited fluctuations ranging from 10% to 20%, while RAM and GPU usage remained consistently between 90% and 100%. Conversely, in the context of a non-IID dataset, CPU utilization spanned from 40% to 60%, showcasing an improvement compared to the IID dataset, and RAM usage spanned from 80% to 100%. GPU utilization approached 100%. Shifting to the MobilenetV2 model, as illustrated in Figure 12, the IID dataset demonstrated CPU utilization levels ranging from 20% to 40%, coupled with RAM utilization persistently between 95% and 100%. For the non-IID dataset, CPU utilization extended from 20% to 60%, RAM usage reached up to 80%, and GPU utilization ranged from 95% to 100%. The results indicate that MobileNetV2 displayed more efficient resource utilization compared to EfficientNetB3.

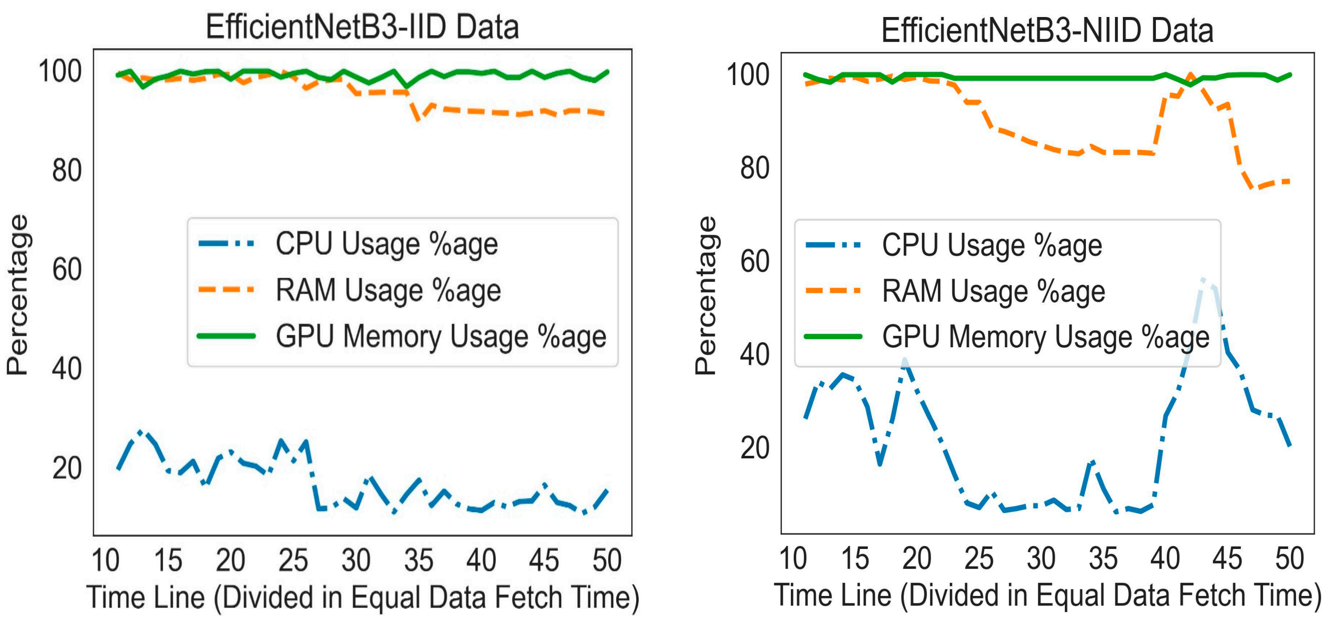

Figure 11. Resource Utilization results with EfficientNetB3(IID and non-IID dataset).

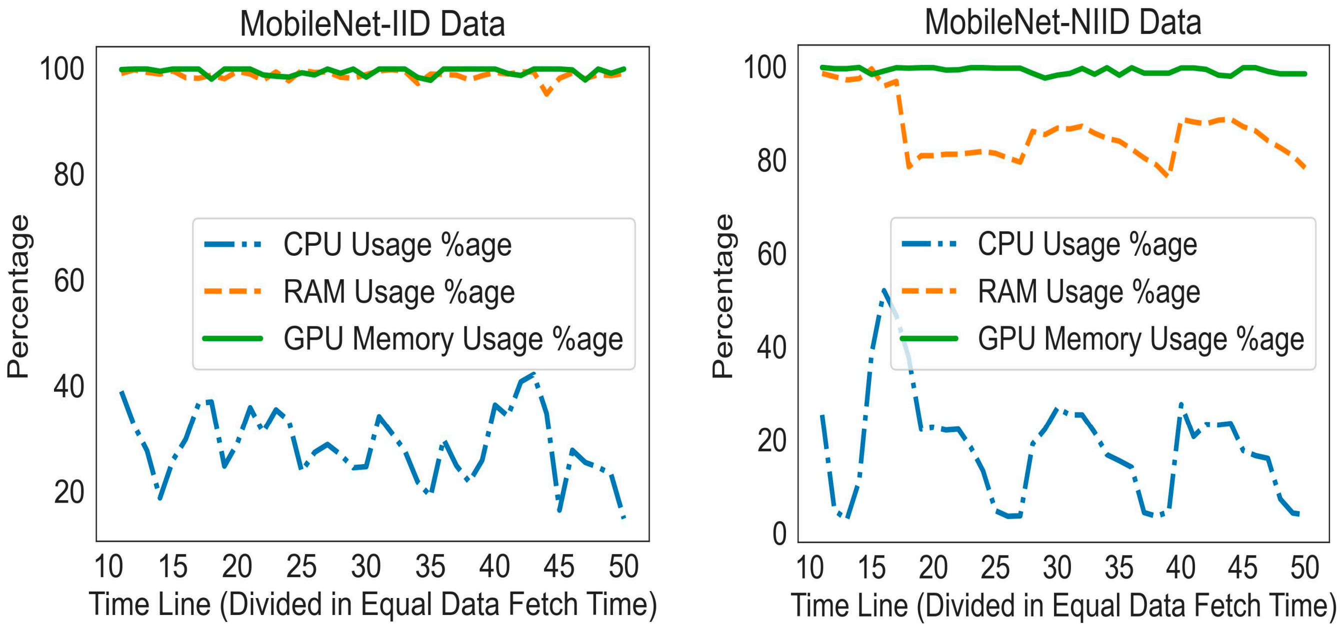

Figure 12. Resource Utilization results with MobileNetV2 (IID and non-IID dataset).

6. Ethical Implications

Several significant ethical issues are brought up by the growing use of AI in agriculture. A sustainable and morally sound future for the agricultural industry depends on taking data privacy, algorithmic bias, and the equitable distribution of benefits into account as AI technologies become increasingly important in optimizing farming practices, resource allocation, and decision-making. Fair and unbiased models have the potential to enhance the precision of crop disease forecasts, yield projections, and sustainable agricultural methods, leading to overall advancements in crop production and the well-being of farming communities. Additionally, ensuring fair access to these technologies can help narrow the digital gap, promoting innovation and cooperation among farmers and researchers [41,42]. Through the elimination of biases and the promotion of fairness in machine-learning models applied in agriculture, we grant farming communities the ability to access advanced technology and valuable information resources [43,44] Latin America and South Asia are characterized by their abundant agricultural variety, with small-scale farmers serving as pivotal contributors to food production in these regions. The consideration of bias and fairness in machine-learning research related to tropical crops in Latin America presents substantial social benefits [45]. Ethical issues related to our study are:

i. Data privacy: Federated learning is a privacy-preserving machine-learning technique in which models are trained on decentralized data sources without the necessity to centralize or share raw data. This approach is particularly pertinent in sensitive sectors such as agriculture. Agricultural data can yield valuable insights but may also encompass personally identifiable information or sensitive business data. To safeguard data and privacy while harnessing the advantages of federated learning in agriculture, it is imperative to establish suitable security measures and enhance awareness among stakeholders in the agricultural sector regarding potential risks.

ii. Bias and fairness: In the framework of federated transfer learning (F-TL) for rice-leaf disease classification in agriculture, addressing concerns related to bias and fairness is of utmost importance to ensure that the model performs equitably and accurately. To achieve fairness, strategies for data sampling and distribution are thoughtfully designed to maintain representativeness among different clients. Data preprocessing techniques are consistently applied and utilized to mitigate bias during the model training process. Furthermore, privacy-preserving techniques are integrated to enhance fairness.

iii. Deployment in Resource-Constrained Areas: Deploying federated learning models in resource-constrained areas presents a multitude of challenges. Limited internet connectivity, inadequate infrastructure, device diversity, data quality issues, and the high cost of implementation can hinder accessibility and affordability. Furthermore, ensuring data privacy and security in such contexts can be complex, and there may be a lack of skills and training to set up and maintain federated learning systems. The availability of training data and adherence to local regulations also pose significant hurdles. Addressing these challenges requires a context-specific approach, collaboration with local stakeholders, and a commitment to inclusivity and equity to prevent disparities in access to technology and its benefits.

iv. Data source and ownership: The dataset of rice-leaf disease images used in this study was sourced from open sources available on the Mendeley database [28]. The dataset owner collected some images from the fields of Odisha, while others were obtained from the Agricultural and Insect Pest Database.

7. Discussion

The efficiency of the proposed federated transfer learning (F-TL) for the rice-leaf disease classification system involved an examination of resource utilization and encompassed both an Independent and Identically Distributed (IID) dataset, as well as a randomly distributed non-IID database, as illustrated in Figures 7–12. The results from Figures 7 and 8 demonstrate that the transfer learning models, namely EfficientNetB3 and MobilenetV2, outperformed the other suggested models. Both EfficientNetB3 and MobileNetV2 attained impressive training accuracy levels of 99%, with validation accuracy scores reaching a perfect 100%. EfficientNetB3 had a training loss of 0.1, while MobileNetV2's training loss was slightly lower at 0.09. As a result, these two models were chosen as the baseline models for the federated learning paradigm. The training and evaluation accuracies in the federated learning approach are depicted in Figures 9 and 10. When considering the IID dataset, the training accuracy achieved using EfficientNetB3 was 99%, accompanied by a loss value of 0.1. For MobilenetV2, the training accuracy was 98%, with a loss value of 0.4. However, in the case of the non-IID dataset, the training accuracy for EfficientNetB3 reached 100%, while for MobilenetV2, it was 90%. The corresponding loss values were 0.1 for EfficientNetB3 and 0.6 for MobilenetV2.Turning to the evaluated accuracy, EfficientNetB3 achieved a 99% accuracy with a loss value of 0.1 for IID and non-IID datasets. For MobilenetV2, the evaluated accuracy was 90% with a loss value of 0.6 for the IID dataset, and for the non-IID dataset, the accuracy was 97% with a loss value of 0.2.

These superior results underscore the efficacy of the proposed model while preserving data integrity. However, the implementation of a federated learning system faces a noteworthy challenge: ensuring the operational efficiency of the learning model on edge devices, which function as monitors for distinct zones. This necessitates a lightweight model design to enable effective functioning on these devices. This lightweight characteristic is pivotal in shaping FL-based architectures [37,46]. Thus, we chose a Dense Neural Network design, employing a 3-layer model with density in its structure [47]. This choice was driven by the intention to veer away from resource-intensive models, ensuring compatibility within edge device limitations. Consequently, we advocate for the adoption of MobileNetV2 due to its lightweight nature. MobileNetV2 is a streamlined CNN architecture curated for efficient deployment on mobile and embedded devices. Its efficiency stems from strategies like depth-wise separable convolutions, inverted residuals, and linear bottlenecks, collectively reducing computations while maintaining information flow. The model's adaptability via width multiplier and resolution reducer parameters allows control over complexity and resources. Ultimately, MobileNetV2 strikes a harmonious balance between size, speed, and accuracy, rendering it an optimal choice for resource-constrained edge devices and applications. Furthermore, it was deduced from Figures 10 and 11 that MobileNetV2 exhibited notably efficient CPU utilization, RAM usage, and GPU consumption in comparison to EfficientNetB3. The comparison between the proposed F-TL framework under Independent and Identically Distributed (IID) and non-IID scenarios and conventional distributed deep learning is displayed in Table 6.

Table 6. Performance analysis.

Performance Parameters	Federated Learning EfficientNetB3 (IID)	Federated Learning EfficientNetB3 (Non-IID)	Federated Learning MobileNetV2 (IID)	Federated Learning MobileNetV2 (Non-IID)	Traditional Transfer Learning
Validation Accuracy	99%	99%	98%	90%	99–100%
Validation Loss	0.1	0.1	0.4	0.6	0.06–0.08
CPU Utilization	10–20%	40–60%	20–40%	20–60%	-
RAM Utilization	90–100%	80–100%	95–100%	80%	-
GPU Utilization	90–100%	Upto 100%	95–100%	95–100%	-
Data Privacy	Yes	Yes	Yes	Yes	No
Data Processing	Federated Weights	Federated Weights	Federated Weights	Federated Weights	Dataset

Table 6 presents the performance of both models, demonstrating their competence. However, we opt for MobileNetV2 in the federated learning environment due to its lightweight design, which aligns with the requirements of the federated learning approach. This choice is motivated by the need for models that can efficiently operate in a decentralized setup, where computational resources may be limited, and data privacy is a priority. MobileNetV2's efficiency and suitability make it a preferred candidate for this specific context, ensuring that federated learning can be conducted effectively and securely.

8. Conclusions and Future Work

Machine-learning methods have demonstrated their effectiveness in various applications, including predicting diseases using images of agricultural crops. This study aims to assess how federated learning (FL) can address the issue of the data-privacy gap that is present in centralized machine-learning approaches. Therefore, in this manuscript, we implement the federated transfer learning (F-TL) framework to classify rice-leaf diseases. First, we implement and analyzed the CNN and transfer learning models such as DenseNet201, EfficientNetB3, InceptionResNetV2, MobileNetV2, VGG16, VGG19, Xception, ResNet152V2 and select the two best models EfficientNetB3 and MobilenetV2 based on validation and training accuracy and loss. EfficientNetB3 and MobileNetV2 both achieved high training accuracy at 99%, and their validation accuracy reached 100%. The training loss for EfficientNetB3 was 0.1, while for MobileNetV2, it was 0.09. In terms of validation loss, both models exhibited low values, with EfficientNetB3 at 0.06 and MobileNetV2 at 0.08, respectively. Further FL was executed using EfficientNetB3 and MobilenetV2 with IID and non-IID datasets for the classification of rice-leaf diseases. According to the evaluation of the federated transfer learning system, both the EfficientNetB3 and MobileNetV2 models demonstrated strong performance. However, given the requirement for a lightweight model in federated learning technology, we opted for the MobileNetV2 transfer learning model to classify rice-leaf diseases. This choice allows us to maintain data and computational resources efficiently.

The outcomes evident from the contrastive analysis displayed in Table 6 make it evident that the newly introduced federated transfer learning (F-TL) framework yielded significantly improved results in validation accuracy and validation losses, all without necessitating any additional resources. The primary standout aspect of the proposed F-TL framework revolved around data privacy, in conjunction with similar accuracy, reduced losses, and minimal processing resource that was overlooked within the conventional DL framework. To sum up, the suggested economical approach for rice-leaf disease classification using federated learning proved notably superior and secure compared to conventional frameworks. However, a constraint of this proposal appears to be the alignment of existing federated learning programming libraries, potentially requiring heightened efforts. In subsequent endeavors, the suggested methodology could be expanded through the incorporation of hyperparameter optimization and innovative averaging techniques to enhance effectiveness. Furthermore, to tackle privacy apprehensions in the federated setup, encryption methods could be applied during the exchange in trained models.

Author Contributions: Study conception and design: M.A., V.K., N.G., R.G. and F.A.; data collection: M.A., V.K., N.G., M.E. and A.S.; methodology: M.A., V.K., N.G., F.A. and M.E.; analysis and interpretation of results: M.A., V.K., N.G., R.G. and A.S.; draft manuscript preparation: M.A., V.K., N.G., R.G. and A.S.; Supervision, V.K. and N.G.; Project Administration, V.K., N.G., R.G., A.S., F.A. and M.E.; Funding Acquisition: R.G., F.A., M.E. and A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the Researchers Supporting Project Number (RSPD2023R564), King Saud University, Riyadh, Saudi Arabia.

Data Availability Statement: Data are available as open source.

Acknowledgments: This work was funded by the Researchers Supporting Project Number (RSPD2023R564), King Saud University, Riyadh, Saudi Arabia.

Conflicts of Interest: The authors declare no conflict of interest.

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