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Detection and Categorization of Rice Leaf Diseases through Federated Learning and Improved Vision Transformer Models

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Abstract

Rice (Oryza sativa L.) is an important food source for people worldwide. In Asia, where it is mostly grown and eaten, it provides 14% of protein and 22% of calories per person. Microbial diseases like viral, bacterial, fungal, and other illnesses are bad for health and food production, which is a big problem for rice farmers. It is hard to tell if these diseases are present physically, especially in places that do not have crop safety specialists. Managing disease detection and making decision-making tools easy is important for making Rice Leaf (RL) protection techniques work and lowering damage to rice crops. Unfortunately, there is not yet a reliable and safe way to diagnose RL disease, even though many options exist. Federated Learning (FL) is an appealing and effective way to deal with these issues. The study suggested using FL and improved Vision Transformers (VT) models to find and classify RL diseases. Highly specified transfer learning (TL) models and the suggested design that uses the Self-Attention Mechanism (SAM) have been tested. These models are then combined into a decentralized learning method based on FL. The suggested architecture utilizes the advantageous interactions of VT models, CoAtNets, and the improved Swin Transformer (ST) V2, leading to a superior representation of features. The suggested model in the FL system markedly surpasses all previously evaluated TL models, attaining accuracies of 99% for RL disease categorization.

Keywords: Rice, Leaf Diseases, Federated Learning, Vision Transformers, Self-Attention Mechanism, Swin Transformer, Disease Categorization.

1 Introduction to RL Disease, FL, and VT

Agriculture is vital for human existence since it sustains and governs the food chain. Historically, farmers depended on regular field inspections to monitor crop development, often leading to food shortages due to natural disasters and human mistakes (Wani et al., 2022). Conventional agricultural methods are less lucrative due to their high need for manual labor. The food production business must address customer demand while combating poverty, preventing hunger, and safeguarding freshwater resources. Cereals, including wheat, rice, and maize, are often used as a fundamental food source,

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providing essential energy for everyday activities (Poornappriya & Gopinath, 2022). The global output of these crops is very abundant. Wheat occupies the largest harvesting area annually, totaling 215 million hectares, next to rice at 158 million hectares. Consumption by people constitutes 86.5% of the overall rice output, in contrast to 72.3% for wheat (Rice as a global staple food). Rice is an essential food eaten worldwide and is mostly produced locally. In Asian countries, rice is a popular and economical source of nutrition (Mohandas et al., 2024).

Rice farms are susceptible to annual loss from insects and diseases, and amateur farmers may find it challenging to diagnose the specific illness impacting their harvests accurately. Rice infections are mostly identified by meticulously monitored methods, including visual crop inspections or laboratory analyses (Pothen & Pai, 2020). A proficient individual is required for visual examination, which may be time-consuming. Conversely, laboratory testing entails an extensive procedure and the utilization of synthetic reagents. In several countries, the requirement for rice is projected to rise faster than its availability. Destruction of the rice crop is intolerable, irrespective of the source. Automating the diagnosis of RL diseases is essential to mitigate crop losses (Bari et al., 2021). This automatic disease diagnosis approach will save labor expenses by consistently monitoring crops for possible infections. Many researchers have proposed intriguing methods for the automated identification of RL diseases (Altınbilek & Kızıl, 2021).

Numerous machine learning (ML) or deep learning (DL) methodologies exist for the early detection of RL diseases, demonstrating efficacy across many domains (Cao & Jiang, 2024). Nonetheless, throughout the last decade, the application of ML to decentralized data has posed significant challenges (Vimalajeewa et al., 2021). A framework is needed to provide a decentralized approach by integrating several DL algorithms in real time, ensuring data security, reducing communication expenses, and offering a distributed system for training and validation. Advanced DL schemes like VT with FL are needed to tackle critical concerns in detecting RL diseases (Chhabra et al., 2023).

FL is beneficial for preserving privacy during DL tasks, especially in classifying diseases impacting RL. Its promise lies in its capacity to induce significant transformations in distributed ML and DL domains, especially regarding privacy and security. Since 2018, many academics have shown interest in conducting FL trials across significant sectors, like healthcare and agriculture (Islam et al., 2023). Agriculture is crucial for sustaining the increasing population and providing a vital energy source. Plant diseases significantly threaten crop productivity and quality, impacting agricultural growth. Typically, skilled human observation, which is time-consuming and labor-intensive, has been the usual approach for diagnosing RL disease. A model for the automated identification of diseases in RL has been developed to tackle these challenges.

2 Related Works

Research studies have used distinct ML/DL methodologies to detect and classify RL diseases. In (Jiang et al., 2020), authors developed a methodology using a DL-based Convolutional Neural Network (DCNN) model, achieving a notable validation accuracy of 97.7% on an ensemble of 9002 images. Similarly, authors in (Krishnamoorthy et al., 2021) introduced two distinct CNN architectures, basic CNN and InceptionResNetV2, using TL approaches to get an impressive accuracy of 95.4% in leaf disease detection. Additionally, authors in (Rallapalli & Saleem Durai, 2021) used CNN models, namely AlexNet and M-Net, to detect many RL diseases, achieving an accuracy of 72.02% using a collection of 125 RL images (Sethy et al., 2020).

Authors in (Zhu et al., 2023) introduced MSCVT, a compact, hybrid VT model for crop disease recognition that integrates CNN and VT characteristics using multiscale SAM, achieving excellent identification accuracy on real-world disease samples. Nonetheless, the authors did not include any pre-processing network to assess the model's resilience and adaptability with real-world data. In (Zeng et al., 2023), authors created the Squeeze-and-Excitation VT (SEVT) model for extensive and detailed plant illness categorization, integrating ResNet with an external SAM for pre-processing and VT for feature categorization; however, it demonstrated reduced accuracy in field conditions, highlighting the challenges of field recognition. Nevertheless, the authors did not seek to implement this concept in practical settings while preserving the size and efficacy of the service.

Pang et al., (2023) developed a new method termed Dense CNNs and VT Network for precise detection of RL diseases, employing a multi-head SAM on their database and a freely accessible dataset, demonstrating its robustness against outside influence in real-field conditions. Therefore, it is essential to emphasize the efficacy of the innovative DL algorithms that enhance model effectiveness within a decentralized FL network context, which was absent in these studies. Conventional TL techniques may lack efficiency in the contemporary landscape due to their dependence on several features, which, despite their diversity, may provide less accurate classification capabilities.

3 Proposed Method

3.1 Data Gathering and Pre-processing

This database (Rice Leaf Diseases Dataset) comprises 120 JPG photos of RL affected by disease. The images are categorized into three types according to the kind of illness. The categorizations consist of the following RL diseases: Leaf Smut (25 images), Brown Spot (35 images), and Bacterial Leaf Blight (60 images).

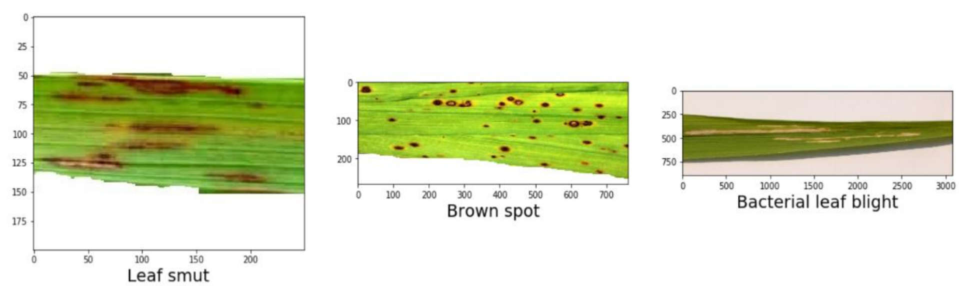

Figure 1: Sample RL Disease Images in the Database (Rice Leaf Diseases Dataset)

Figure 1 shows the sample images in the database. The database has been pre-processed by downsizing the images to 75 × 75 pixels and converting them to grayscale to satisfy the proposed FL model's specifications.

3.2 Proposed Framework

This work presents the model framework for the challenging task of RL disease categorization inside the FL system, effectively integrating the diverse features of two fundamental models: ST and CoAtNet. These two VT approaches extract features by integrating layers inside their architectural framework, as seen in Figure 2. The abstraction, capability, and efficiency of the CoAtNet model are greatly improved due to the systematic vertical layering of convolutional and attention layers. On the other hand, the ST V2 model incorporates three essential strategies to improve flexibility and capacity for efficiency. A residual-post-norm approach in conjunction with cosine attention is used to improve learning equilibrium and address key problems typical of big VT models. Additionally, it presents a log-spaced permanent position bias approach, making it easier to migrate pre-trained models from lower-resolution tasks to high-quality jobs, hence increasing flexibility across various resolution configurations.

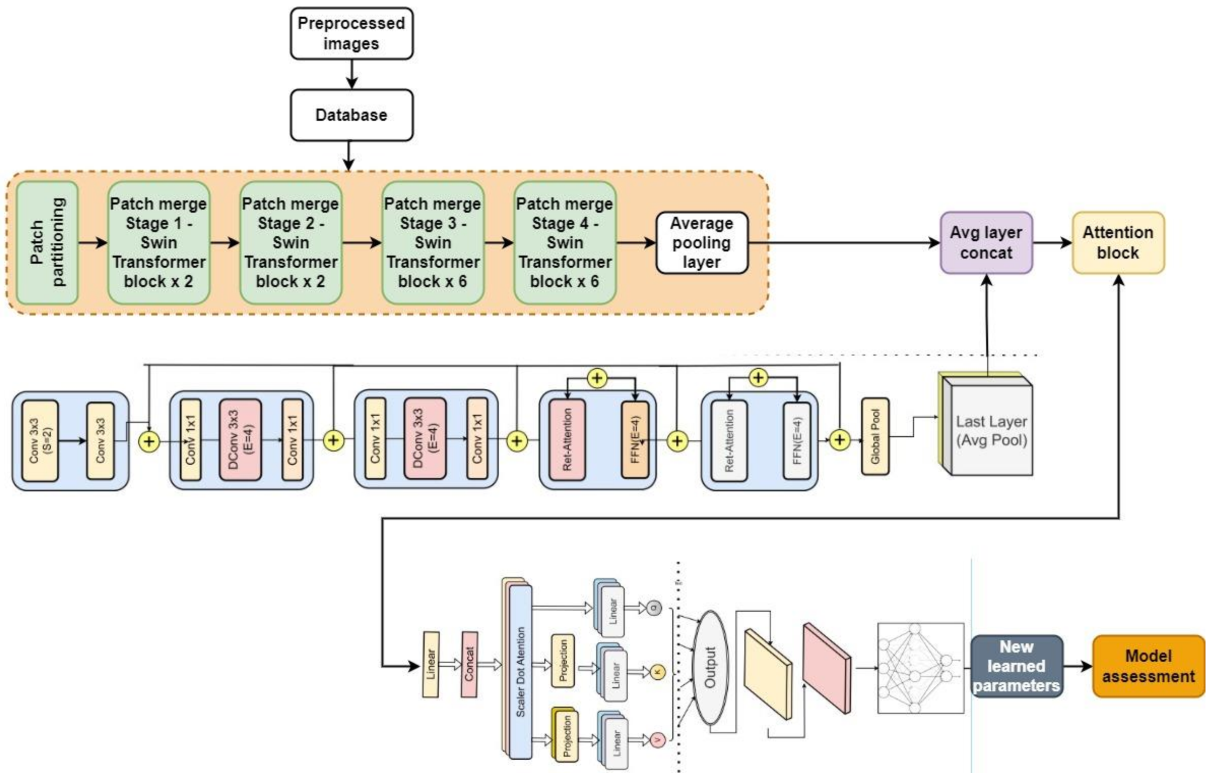

Figure 2: Proposed Framework for Classifying RL Diseases Using Improved VT (CoAtNet and ST) to Extract Features

In conclusion, the model uses a self-supervised initial training strategy called SimMIM. This approach significantly reduces the need for labeled input throughout the training process, which in turn makes it easier to have a more efficient use of the available resources. These strategies, when combined, improve the efficiency, productivity, and adaptability of the ST V2 model across a wide range of activities and applications.

$$B = \sqrt{\frac{\pi}{2e}}\left(\sum_{j=1}^{N} f_{1j} + \sum_{j=1}^{N} f_{2j}\right) \quad (1)$$

The proposed framework uses a feature merging to combine the results of two network frameworks. These frameworks serve as the basis for this model for feature extraction. These frameworks are, respectively, labeled as $f1\ and\ f2$, and they correspond to the outputs of CoAtNet and ST. $f1\ and\ f2$ are both matrices that are $N \times 772$, where N is the number of entries in the matrix. The calculation of the element-wise mean, which results in the production of a new matrix B, is what is required to achieve the feature merging, as shown in Equation (1). Feature extraction has been the primary application of the merging of features, which has served as the essential underpinning for this model.

$$E(S,K,V) = B(SK^{T}W)V \quad (2)$$

For the goal of classification, the linear attention (LA) layer proved to be an effective tool. By lowering the size of the characteristic vector from 772 to 64, the LA layer improves computing performance, reduces the danger of excessive fitting, and provides a more concise portrayal of data. With this reduction, the LA layer makes it easier to analyze the model. Equation (2) reveals that the letter S represents the search matrix, K represents the key matrix, V represents the value matrix, W represents the learnt weight matrix, and E represents the number of input factors.

3.3 Clipping Method

This research uses the Layer-based Weight Frosting technique for weight clipping. This technique includes storing the weights of certain layers in the artificial neural network to decrease the number of parameters that can be learned. The model immobilizes the final 30 levels of every attribute extraction system (CoAtNet and ST V2) in the proposed methodology. The final 30 levels of CoAtNet are immobilized, hence decreasing the number of parameters for training. Similarly, the final 30 levels of ST V2 are immobilized, reducing the parameter pool for training from around 28 million to 18,987,457. The mean pooling layer aggregates the outcomes of the feature extraction systems. This layer contains parameters that can be trained. The output layer is a dense layer including three output categories, containing 135 parameters for training.

Frosting layers substantially decreases the parameters requiring updates during training, reducing computing and storage demands. Reducing parameters to optimize expedites the learning process, allowing swifter system iterations and adjustments. This approach efficiently employs previously trained weights, so stabilizing the learning procedure for new assignments is especially advantageous when the new database is limited. Lowering the model's dimensionality using stored layers mitigates excessive fitting, hence improving the model's conversion capabilities on unidentified information. This approach utilizes the resilience of models that have been trained previously, providing benefits in processing speed and normalization, necessitating meticulous layer choice to optimize effectiveness and speed. Identifying each layer to freeze requires meticulous evaluation and testing within the model framework of the regional and global nodes in the FL framework. Excessive frosting of layers may impede the training process.

However, frosting an insufficient number may not provide substantial computing advantages. Consequently, we maintain the freeze on the last 30 levels. This clipping technique utilizes the identical deep ensemble methodology as the proposed model, integrating model mean forecasts to achieve high accuracy and reliable uncertainty estimates while aggregating its forecasts. Consequently, this methodology adeptly encompasses both evidentiary and computational ambiguity.

3.4 ATQ Integration

It has been used after-training quantization (ATQ) inside FL. The process has four primary steps: model learning, centralized server optimization, framework dissemination, and consolidation (Kivrak et al., 2020).

- The first model is learned on the existing centrally stored information at the primary server. This stage serves as the foundation for the following optimization methods.
- After the preliminary learning of the regional nodes, level-wise weight clipping is performed on the suggested framework to eliminate excessive or less relevant parameters. Subsequently, ATQ is used, which diminishes the accuracy of modeling weights and triggers, lowering storage and computing demands.
- The improved framework, which includes clipped and quantized variables, is disseminated to all FL nodes to receive additional regional training.

- Following regional training on every FL node, changes to the model, including weights and slopes, are sent to the centralized server. The centralized server consolidates these changes, implements essential optimization methods such as clipping and ATQ, and redistributes the revised model to the nodes.

Upon concluding comprehensive training on the universal model, we diminish the level of complexity of the NN through ATQ clipping procedures. The ATQ approach has been used to maximize and reduce learned models, therefore minimizing memory usage and enhancing inference time. PTQ has been employed to transform modeling weights and triggers from higher to lower levels of accuracy post-training. This method lowers the model's size and improves computational effectiveness without markedly sacrificing performance. PTQ offers substantial savings in sample size, rendering them appropriate for devices with constrained storage, and accelerates inference via less accurate calculations.

Furthermore, quantized models exhibit reduced power consumption, which is advantageous for battery-powered devices and extensive data center implementations. Nonetheless, PTQ may result in a degradation in accuracy, particularly in models that are sensitive to variations in precision. The proposed models have been meticulously calibrated and refined to solve this issue.

4 Results and Discussion

The present section depicts the findings derived from assessing the effectiveness of traditional DL algorithms, including VGG16, VGG19, ResNet152, DenseNet, Xception, and EfficientNet, with the proposed FL and VT model for categorization of RL diseases. The categorizations consist of the following three RL diseases: Leaf Smut, Brown Spot, and Bacterial Leaf Blight.

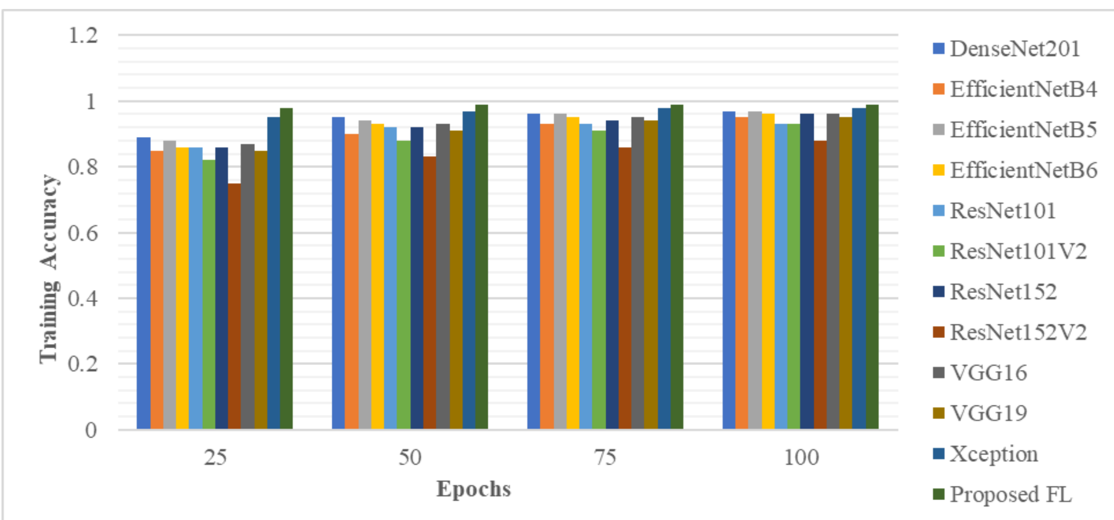

Figure 3: Training Accuracy Versus Epochs for Various DL Models in RL Disease Categorization

Figure 3 shows the training accuracy versus epochs for various DL models in RL disease categorization. The results demonstrate that the "Proposed FL" model regularly attains the maximum accuracy (0.98-0.99), surpassing all alternatives. DenseNet201, versions of EfficientNet, and Xception demonstrate robust accuracy (reaching 0.97-0.98) as the number of epochs increases. ResNet models (e.g., ResNet101, ResNet152V2) display reasonable performance, while VGG models show consistent but somewhat worse accuracy. Accuracy increases with epochs, with "Proposed FL" demonstrating superior efficacy.

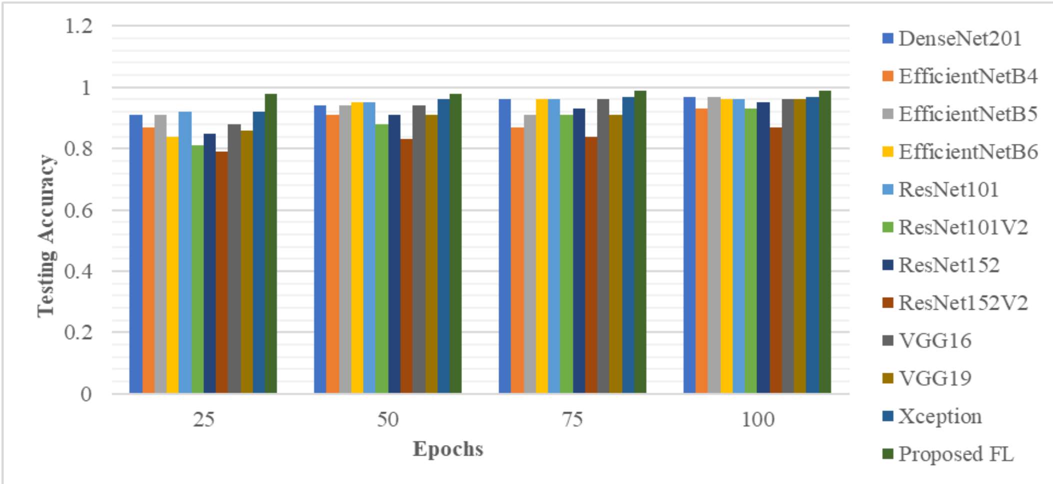

Figure 4: Testing Accuracy Versus Epochs for Various DL Models in RL Disease Categorization

Figure 4 illustrates the testing accuracy versus epochs for various DL models in RL disease categorization. Figure 4 illustrates the efficacy of several DL models throughout 25, 50, 75, and 100 training epochs. The suggested FL model with VT (CoAtNet and ST) consistently attains the maximum accuracy throughout all epochs, achieving 0.99 by the 75th epoch, surpassing competing models such as DenseNet201, EfficientNet variations, and ResNet families. The Xception and VGG models demonstrate commendable performance; nonetheless, they fall short compared to the suggested FL model, underscoring its enhanced proficiency in precise RL disease categorization.

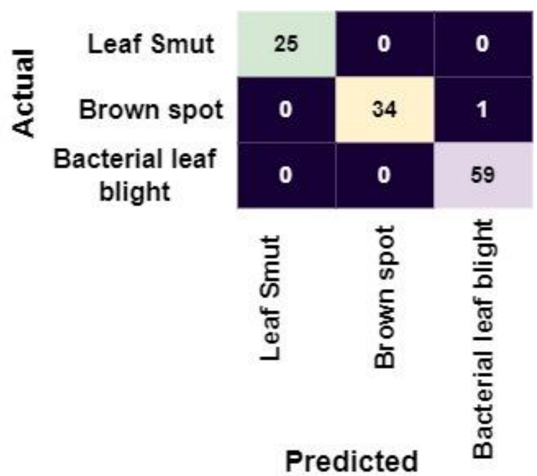

Figure 5: Confusion Matrix of Proposed FL Model with VT (CoAtNet and ST) for RL Disease Categorization

Figure 5 shows the confusion matrix of the proposed FL model with VT (CoAtNet and ST) for RL disease categorization. The results are obtained for the dataset (Rice Leaf Diseases Dataset) containing 120 images of RL impacted by disease. The images are classified into three categories based on the kind of disease. The classifications include the following RL diseases: Leaf Smut with 25 images, Brown Spot (35 images), and Bacterial Leaf Blight (60 images).

The confusion matrix for the proposed FL model using VT (CoAtNet and ST) exhibits outstanding efficacy in classifying RL diseases. The model achieved flawless categorization for Leaf Smut (25 accurate predictions) and virtually impeccable results for Brown Spot (34 right predictions with one misclassified as Bacterial Blight). Each of the 59 eligible identifications for bacterial Blight was a correct classification. The results demonstrate that the model has exceptional accuracy and recall, enabling it to be both practical and reliable in accurately identifying RL illnesses.

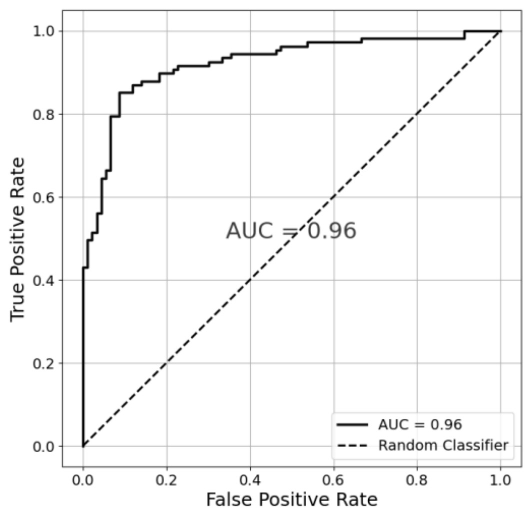

Figure 6: ROC Curve of the Proposed FL Model with Improved VT (CoAtNet and ST) for RL Disease Categorization

The Area Under the Receiver Operating Characteristic (ROC) curve is the area under the curve that visually depicts the efficacy of the suggested framework as the detection threshold changes. The AUC score is the area under the ROC curve scoring system. It assesses the system's overall capability to discern between the two categories (positive and negative) at several different threshold levels. An AUC of 0.5 indicates stochastic performance, whereas an AUC of 1.0 signifies flawless categorization. Figure 6 illustrates the ROC curve of the proposed FL model with VT (CoAtNet and ST) for RL disease categorization. The proposed model gave improved performance with AUC=0.96.

5 Conclusion

The study proposes identifying and categorizing RL diseases using federated learning and vision transformers. This study experiments on highly parameterized transfer learning models, including the proposed architecture using the Self-Attention Mechanism. It integrates these models into a decentralized learning framework based on federated learning. The proposed architecture leverages the beneficial interactions of VT models: CoAtNets and the enhanced Swin Transformer (ST) V2, resulting in enhanced feature representation. Furthermore, we include weight clipping into our framework, which is then categorized by an enhanced LA mechanism to reduce output dimensionality. The model achieved flawless categorization for Leaf Smut (25 accurate predictions) and virtually impeccable results for Brown Spot (34 right predictions with one misclassified as Bacterial Blight). Bacterial Blight was accurately categorized with 59 valid identifications. The suggested FL model with VT (CoAtNet and ST) consistently attains the maximum accuracy throughout all epochs, achieving 0.99 by the 75th epoch, surpassing competing models such as DenseNet201, EfficientNet variations, and ResNet families in RL disease categorization. In the future, IoT technology will be used to detect RL diseases. Furthermore, encryption methods may be used to mitigate privacy issues inside the FL environment during the dissemination of learned models.

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