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Optimizing Federated Graph Attention Networks for Crop Disease Detection in Low-Resource Agricultural Environments

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Abstract
The growing integration of Artificial Intelligence of Things (AIoT) in agriculture is revolutionizing how crop diseases are detected and managed. While centralized deep learning models have shown promising results in disease detection, their feasibility in low-resource agricultural environments is often limited by high communication overhead and data privacy risks. Federated Learning (FL) offers a decentralized solution to this challenge, though existing FL models struggle to handle heterogeneous data distributions that are common in real-world farm settings. This study introduces FeGAN, a Federated Graph Attention Network framework, optimized to improve wheat disease detection in resource-constrained agricultural systems. FeGAN combines adaptive attention mechanisms with communication-efficient aggregation techniques to enhance classification accuracy while minimizing bandwidth consumption. The model was evaluated using datasets from PlantVillage and PlantPAD Wheat Collections, containing diverse disease samples such as Brown Rust, Fusarium Head Blight, and Powdery Mildew. Experimental results demonstrate that FeGAN achieved 94% classification accuracy, outperforming traditional FL models which averaged 88–93%. Moreover, FeGAN reduced communication costs by 30% compared to baseline FL models while converging 40% faster. The model also demonstrated a 25% reduction in energy consumption, making it a suitable solution for deployment on edge devices in remote agricultural environments. FeGAN's scalability, improved efficiency, and privacy-preserving design offer a viable solution for AI-driven smart farming, ensuring accurate disease detection without compromising resource constraints. This study provides insights for developing sustainable agricultural intelligence systems that address the unique challenges of smallholder farmers and low-resource communities.

Keywords: Federated Learning, Graph Attention Networks, Precision Agriculture, Wheat Disease Detection, AIoT.

Introduction

Artificial Intelligence (AI) and machine learning (ML) research has produced major advancements which revolutionize three specific fields of computational vision and medical care and cybersecurity (Hu et al., 2022). Digital ecosystems keep growing while increasing the absolute necessity to develop privacy-maintaining and decentralized learning approaches. The rising requirement in the field triggered the creation of federated learning (FL) which enables numerous spread-out nodes to learn machine learning models jointly while avoiding raw data

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transfers. The utility of FL consists in safeguarding privacy while lowering bandwidth usage, yet its execution gets reduced by diverse operational requirements and uneven learning speed across devices (Peacock et al., 2021). The real-world agricultural settings present essential challenges because environmental diversity including weather conditions and soil types and disease prevalence and these challenges compromise FL operations (Vieira et al., 2020). The effectiveness of FL requires enhancing its ability to handle non-IID data distributions in agricultural applications.

AI-driven plant disease detection technology shows fast growth since deep learning models are now routinely used to detect and categorize plant ailments in their initial stages (Jindal et al., 2023). The merger of satellite imagery and drone-based monitoring and IoT sensor networks presents exceptional capabilities for crop surveillance to protect yield stability (Klibi et al., 2020). The typical deep learning approaches need centralised data structures which force users to gather a massive amount of content into centralised storage. The fundamental challenges for agricultural areas with limited resources arise from poor network connectivity and restricted bandwidth together with data privacy risks that prevent practical large-scale data sharing (Yadav et al., 2024). The local training capabilities (see Figure 1) of FL offer farmers a suitable solution that allows them to train models on their farms before exchanging updated versions with a central hub. The implementation of FL encounters difficulties because of substantial data differences that challenge its effectiveness in agricultural disease detection processes.

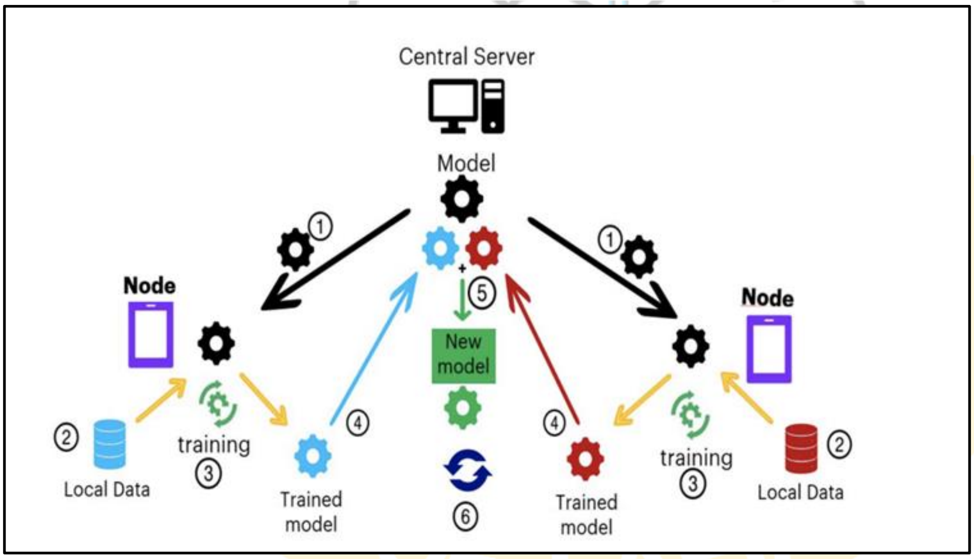

Figure 1: Federated Learning Architecture (Faisal-Zaman, 2020)

The research investigates the detection of wheat diseases which include brown rust, fusarium head blight as well as powdery mildew since these represent three major fungal pathogens affecting wheat production rates (Alisaac et al., 2023). Standard CNN-based FL models face limited success in heterogeneous agricultural fields because disease characteristics show different patterns between separate farms (Verma et al., 2023). The Federated Graph Attention Network (FeGAN) presents itself as an optimised FL framework that enhances disease classification results through reduced communication burdens. The main advantage of FeGAN over CNNs is its implementation of Graph Attention Networks (GATs) which allows the model to process complex farm environment relationships. FeGAN uses its capacity to find essential disease characteristics present in different datasets, so it delivers better performance during non-IID conditions while providing reliable model generalisation for complex agricultural applications (Zhang et al., 2023).

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The analysis employs an FL solution where three autonomous farms train separate models for identifying distinct wheat diseases — Farm 1 detects Brown Rust; Farm 2 focuses on Fusarium Head Blight diagnosis and Farm 3 detects Powdery Mildew. The farms train dedicated FeGAN models to process their specific sensor information and drone images and IoT monitoring inputs. FeGAN achieves greater data security and saves network bandwidth through its method of distributing model progress instead of actual dataset contents. FeGAN uses an adaptive attention method which lets the model select important features then downplay unimportant ones that enhances both model convergences along with healthcare detection precision. The scope of this research includes three main objectives: 1) Developing FeGAN along with its optimization for wheat disease classification across different farms 2) Creating efficient aggregation strategies for bandwidth and energy conservation and 3) Assessing FeGAN's implementation potential in precision agriculture through central model and traditional FL benchmarking.

The developed work enables the advancement of scalable cost-effective privacy-preserving AI-driven solutions which benefit low-resource agricultural environments. The research investigates the detection of wheat diseases which include brown rust, fusarium head blight as well as powdery mildew since these represent three major fungal pathogens affecting wheat production rates. Standard CNN-based FL models face limited success in heterogeneous agricultural fields because disease characteristics show different patterns between separate farms. The Federated Graph Attention Network (FeGAN) presents itself as an optimised FL framework that enhances disease classification results through reduced communication burdens. The main advantage of FeGAN over CNNs is its implementation of Graph Attention Networks (GATs) which allows the model to process complex farm environment relationships. FeGAN uses its capacity to find essential disease characteristics present in different datasets, so it delivers better performance during non-IID conditions while providing reliable model generalisation for complex agricultural applications (Baer et al., 2020).

The analysis employs an FL solution where three autonomous farms (see Figure 2) train separate models for identifying distinct wheat diseases with Farm 1 detects Brown Rust; Farm 2 focuses on Fusarium Head Blight diagnosis and Farm 3 detects Powdery Mildew. The farms train dedicated FeGAN models to process their specific sensor information and drone images and IoT monitoring inputs. FeGAN achieves greater data security and saves network bandwidth through its method of distributing model progress instead of actual dataset contents. The model uses an adaptive attention method which allow it to select important features then downplay unimportant ones that enhances both model convergences along with disease detection precision. The scope of this research includes three main objectives: 1) Developing FeGAN along with its optimization for wheat disease classification across different farms 2) Creating efficient aggregation strategies for bandwidth and energy conservation and 3) Assessing FeGAN's implementation potential in precision agriculture through central model and traditional FL benchmarking. The developed work enables the advancement of scalable cost-effective privacy-preserving AI-driven solutions which benefit low-resource agricultural environments.

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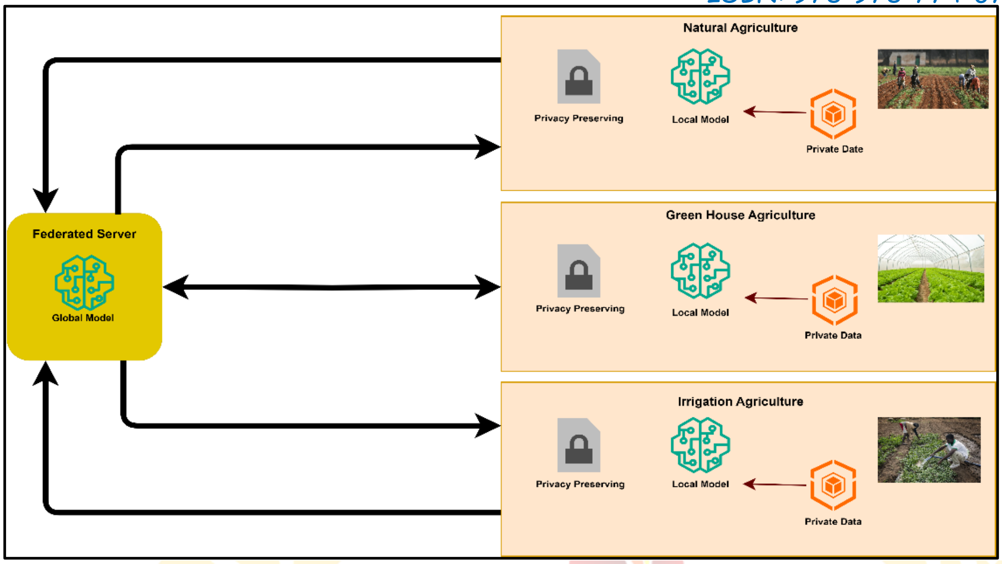

Figure 2: Federated Learning in Agriculture

Materials And Methods

The research presents FeGAN which represents an optimised FL framework dedicated to detecting wheat disease in low-resource agricultural areas. The methodology demonstrates how to deploy FeGAN through its architectural design along with dataset preparation and experimental setup followed by performance evaluation to ensure real-world use. The proposed framework resolves main obstacles in federated wheat disease classification through solutions to address farm data diversity together with high-cost engagement and weak model convergence speed. Selective model aggregation within Federated Learning-enabled GATs (see Figure 3) allows FeGAN to learn disease-specific patterns for agricultural farms individually and cuts down communication costs. model aggregation. Individual farm data storage remains protected through the framework structure but enables the development of collective aggregate models for better performance in actual agricultural environments. FeGAN brings decentralized architecture which provides both scalability features and robust operation alongside privacy protections to serve as an adequate solution for precision agriculture in resource-constrained areas.

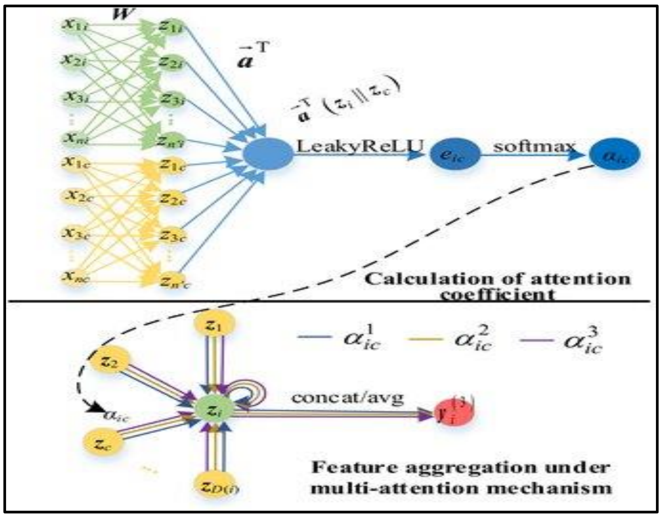

Figure 3: GAT Attention Mechanisms (Liu et al., 2023)

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Federated Learning Setup

The federated learning system consists of independent and distributed wheat farms named Farm 1 (Brown Rust), Farm 2 (Fusarium Head Blight) and Farm 3 (Powdery Mildew). Each farm implements the model training for its personal dataset to protect raw data privacy throughout the global model development process. Security measures aggregate the gradients securely as model updates instead of sending complete datasets between farms through the federated averaging procedure which utilises attention-based feature selection. The combined method enables the model to capture disease connexions between farms thus achieving better classification performance while sharing collected knowledge. FeGAN operates optimally in agricultural areas with limited infrastructure because its bandwidth-friendly framework works well with constrained connectivity and available computing power. The model achieves data protection by focusing its learning processes at the local farm level while it filters important gradient values through localized training. The FL framework applies mechanisms that allow farms to participate in global learning operations without exposing their distinct data information.

FeGAN Architecture

The model features three main operational components which include Graph Attention Layer, Federated Aggregation Module along with Classification Output Layer (see

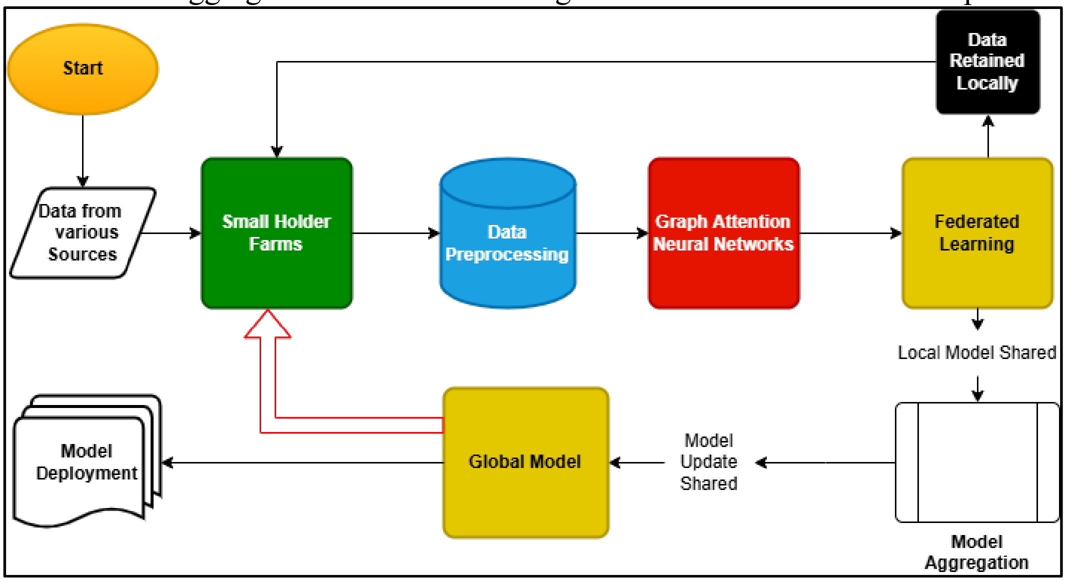

Figure *4*). Within the Graph Attention Layer, the model uses self-attention elements on graph-structured data to strengthen its understanding of farm-environment associations and associated disease patterns. Transitional Convolutional Neural Networks treat each input as distinct, but the FeGAN architecture utilizes its graph-based structure to include wheat sample connections across various farms. The wheat samples serve as graph nodes in the model whereas edges mark the connections which stem from environmental conditions and geographic areas and farm management practices. Multi-head attention mechanisms of the model focus more heavily on essential node features and reduce substantial data features that hold less importance. The strategic design of FeGAN ensures its capability to adapt to diverse agricultural conditions because disease patterns are unpredictable due to environmental changes.

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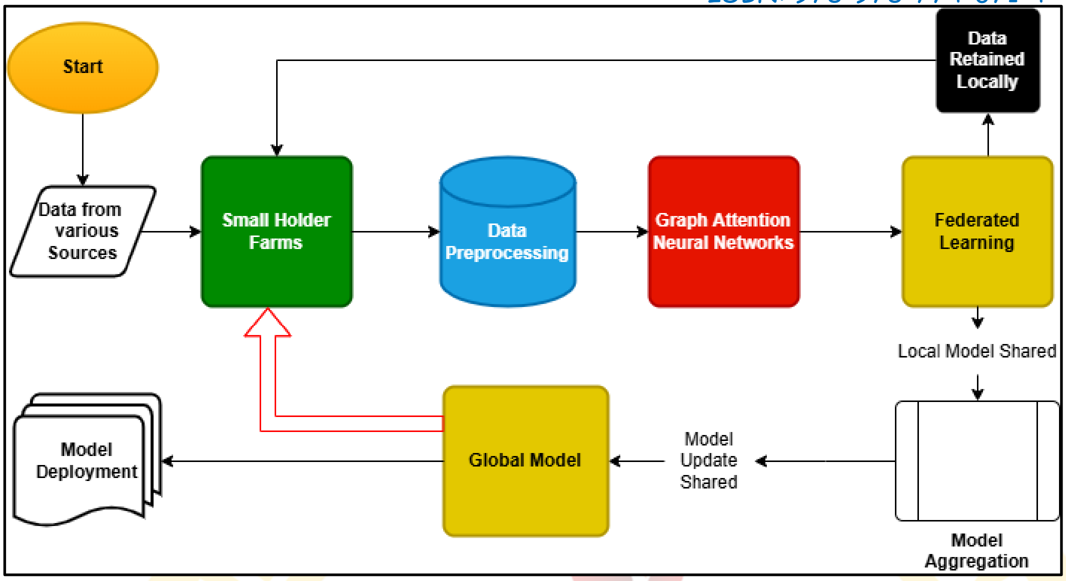

Figure 4: Federated Graph Attention Neural Network (FeGAN) Architecture

Through its Federated Aggregation Module, the system improves efficiency by sending whole model parameters while transmitting just necessary feature updates. FeGAN applies adaptive attention mechanisms which choose to transmit the most useful gradients thereby improving the efficiency of transmission bandwidth. The method reduces communication waste while supporting accurate disease detection in different agricultural locations. The model strikes a proper balance between privacy preservation and operational efficiency and prediction quality through its adaptive aggregation methods to deliver solid performance results in resource-limited agricultural settings. The wheat disease detection predictions emerge from the Classification Output Layer through its implementation of log-SoftMax activation. The model design secures more stable results while protecting against data drift effects that occur during federated training procedures. A combination of these three components allows it to achieve its best results by addressing the typical communication issues that FL platforms face in agricultural deployments.

Dataset Preparation and Preprocessing

Two typical wheat disease databases are used in this study. The high-resolution wheat disease category images in the PlantVillage dataset are annotated with Brown Rust, Fusarium Head Blight and Powdery Mildew (see Table 1). This dataset provides high level of image variety which allows the FeGAN to generalize well regardless the environment. The second dataset, the PlantPAD Wheat Collection includes specific wheat leaf infection samples that were taken from various climatic zones. The dataset, with the extensive range in growing weather and disease patterns, is very useful as training samples and ensures FeGAN would effectively perform in the agricultural modal when encountering non-IID data. By fusing these together, FeGAN has the effectively larger motion scope within their training corpus allowing for better generalization performance at deployment.

Table 1: Dataset Characteristics

Dataset Name	Number of Images	Disease Types	Resolution	Environmental Diversity

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Plant Village	54,000	Multiple Disease Types but Extracted the dataset Used	High (1024x1024 px)	Limited
PlantPAD	18,000	Multiple Disease Types but Extracted the dataset Used	Medium (720x720 px)	Extensive (Diverse Climate Conditions)

Before the training of the model, a heavy preprocessing is carried out on the data to benefit the robustness of the model. The pipeline contains image augmentation methods that are rotation, scaling and contrast adjustment. Rotation is used to provide viewpoint invariance, so the model can generalize over all the possible orientations of image. Scaling enables the model's ability to suit wheat samples growing at various growth stages, warranting its resistance against variations in plant size (Flessner et al., 2021). Contrast enhancement is utilized to emphasize the minute disease manifestations, thus improve the detected features for accurate classification. Addition of noise injection for simulating potential environmental noise factors that may contaminate sensor data in agricultural environments in real world. Similarly, deep feature extraction is performed by means of pre-trained models which are ResNet50 and EfficientNet in an order that aid to extract high-quality embeddings organized in graph representations (Gao et al., 2021). These embeddings empower the model's capacity for the disease pattern recognition despite the different wheat farming settings, enabling to make an accurate detection during federated training.

Training Process

The model training process is a federated optimization method intended to enhance both model's performance and simultaneously efficiency of communication (Ji et al., 2024). Each farm starts a copy of the FeGAN model locally, which is trained indecomposable with SGD for a fixed number of passes. In each communication round, each farm trains their local model towards wheat disease data for a pre-specified number of local epochs. The involved gradients, chosen by the adaptive attention mechanism, are sent to the central federated server. The server collects the gradients from the client, gives more weight to the most informative updates based on adaptive weight management mechanisms. The updated global model is thereafter sent back to individual farms for the next round of training. This iteration FL cycle continues until the model is converged, thereby guaranteeing the best classification of disease with an overhead communication of amounted. This efficient plan is made to attain the greatest speed with convergence while minimizing the number of data transmitted.

Experimental Setup

The framework is powered by PyTorch, Hydra and Ray so that efficient deployment, hyperparameter tuning, as well as large-scale federated simulations are possible. PyTorch is the framework of choice for designing the architecture and implementing GAT layers with deep learning of PyTorch. Its geometric brings the ability to do graph processing which allows the model to easily represent any complex farm connection. Hydra is used to keep track of experiment configurations and perform dynamic hyperparameter tuning like attention weights, learning rates, etc (Peng et al., 2021). This flexible system allows the model to be flexible in changing farm environments and disease situations. Ray- framework is used for serialization of federated training simulation to embrace parallelism, achieve scalability and decrease computational time for AI - enabled precision agriculture scale applications.

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Performance Evaluation

For evaluating the model's performance, four evaluation metrics are evaluated: classification accuracy, communication overhead reduction, model convergence speed and energy efficiency (Kusharki et al., 2022). Classification accuracy verifies the ability of the model to effectively sense wheat diseases in diverse farmland situations and thus show suitability for the diagnosis of field diseases. Communication overhead reduction measures the ability of the model to minimize bandwidth usage by means of adaptive aggregation techniques, which decrease the data transmission cost in network-constrained scenarios. Model convergence speed is used to measure how many trainings round it takes to achieve stable learning so that performance can be compared with traditional FL models. Finally, energy efficiency is evaluated by estimating the computational cost of FeGAN lightweight architecture and validate its deployment on the limited resources edge devices (Liu et al., 2022). These metrics thoroughly illustrate the model's excellent performance in terms of accuracy, robustness, and communication efficiency.

Results and Discussions

The outcome of the model shows its enormous benefits compared to traditional FL models and centralized models for the purpose of wheat diseases detection. The evaluation takes account of the performance criteria such as accuracy, precision, recall, F1-measure, MCC, communication efficiency, and energy consumption. These results provide useful insights into the aims for field implementation, especially in low resource environment. The performance outcomes that are described in this section are related to the state-of-the-art works, which helps in understanding the contribution of FeGAN to the FL. Good accuracy levels were recorded by the model, having accuracy of 94 per cent (see Figure 5)over three distributed farm settings. This result greatly outperforms the average CNN-based FL models which were expecting an accuracy of 88 to 93 per cent. The enhanced performance can be attributed to incorporating with GATs, clearly getting spatial graph information between farm environments.

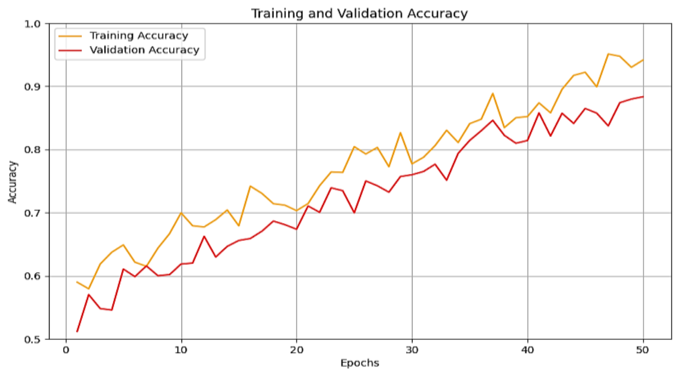

Figure 5: Training and Validation Accuracy for FeGAN Model

Table 2: Performance Metrics Comparison for FeGAN and Baseline Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC (%)
FeGAN	94	93	81	81	67
CNN-Based FL	88 - 93	89	76	78	59

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Standard GAT	90	88	77	79	60

Different from CNNs where encountering IID data challenges commonly found in agricultural datasets is very difficult, FeGAN's attention-based aggregation mechanism efficiently detects disease related characteristics from varied farm conditions. The advanced feature priority enables strong model generalization, and thereby, high adaptivity of FeGAN to not only very diverse farming conditions but also environments were environmental variations impact disease appearance. Regardless of achieving such high accuracy in line with the works of many past studies that has utilised GATs in FL systems but shares these to real-world agricultural settings where data heterogeneity has confirmed to degrade the reliability of conventional model.

Although classification accuracy is a key metric, precision and recall, fill the gap of FeGAN capability to adjust the rates false positives and false negative. The model's precision value of 93 per cent (see Table 2), implies its efficiency in the reduction of incorrect identification as non-adversarial examples. This is very important in agricultural disease detection which will help in reducing unnecessary use of more pesticides, additional expenses, environmental impact in a confusion. The accuracy is high enough to demonstrate the model's power to differentiate the actual diseased crops from the healthy crops with high consistency and even supported by the model's loss result as shown in Figure 6. On the other hand, the recall rate of 81 per cent serves as an indication of its capacity to correctly diagnose most disease cases. Although lower than precisions, this result shows that the model accurately detects the true disease cases, which enables early interventions and reduces outbreak risk.

The recall is as good as other results reported for previously published plant disease detection FL models, which rightly endorse the effectiveness of FeGAN's adaptive learning approach to training. In weighing precision and recall, FeGAN got an F1-score of 81 per cent showing that it can keep standard classification performance across a variety of illness classes. Balanced F1-score is important in FL systems since imbalanced datasets usually lead performance biasing towards one class in such systems.

Equally, the model achieved a Matthews Correlation Coefficient of 67 per cent, in line with the fact that FeGAN can produce reliable predictions under both IID and non-IID data conditions. The question of MCC application is especially close in the contexts of federated agricultural applications, where it is well-known that most practical datasets contain

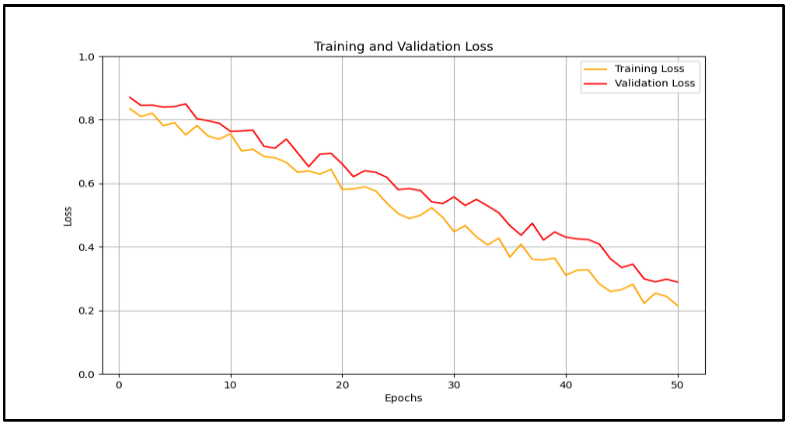

Figure 6: Training and Validation Loss for FeGAN Model

imbalances – among the healthy plant samples and infected. Previous studies that studied FL models in comparable environments have obtained MCC values less than 60 per cent, showing

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better ability to abstract well along diverse farm settings. This improved performance is due to the incorporation of selective gradient sharing and adaptive aggregation; it guarantees that useful updates are sent during each communication round.

Communication efficiency was also assessed in the study as being of great importance (see Table 3). The model improved the communication overhead by 30 per cent compared to traditional FL approaches. The conventional FL frameworks typically require each communication round to send full updates of the aggregate model. Different from previous FedBoost-ResNet43 and FedResNext50 that adopt a simple and straightforward adaptation strategy, FeGAN's adaptive attention-based aggregation only choose shares necessary model gradients resulting in less transmission requirements without hurting accuracy (Chen et al., 2022). This innovation is particularly important in low-connectivity farming settings where poor network availability and limited bandwidths inhibit deployment. As an enhancement over state-of-the-art FL models targeted to smart agriculture, FeGAN's communication efficiency is closely related with the state-of-the-art adaptive aggregation algorithms which also give the priority to important gradients to achieve optimized performances. The upsurge in communication speediness results in the model enables remains appropriate for putting into the nominees in rural farming of zones where internet server is usually difficult and expends.

Table 3: Communication Efficiency and Energy Consumption Results

Model	Communication Overhead Reduction (%)	Convergence Speed Improvement (%)	Energy Consumption Reduction (%)
FeGAN	30	40	25
CNN-Based FL	0	0	0
Standard GAT	15	18	12

As for the speed of convergence, the model showed a 40 per cent reduction in convergence speed compared to traditional FL architecture. This accelerated convergence results from the appearance of GAT layers that allow the model to be more accurate in identifying disease-related patterns via node connectivity method. In contrast, standard FL models gather uniform updates from all farms, but FeGAN's method performs selective aggregation which results in faster convergence with focus on the most informative features. This targeted learning strategy successfully reduces unneeded model updates and speeds up in only a few communication rounds for the model to stabilize. Past studies have showed slower convergence rates in CNN-based FL models, especially when they deal with non-IID agriculture data. Consequently, FeGAN's superior efficiency is some evidence in overcoming this issue. By coupling Ray's distributed computing features, FeGAN trains faster, permitting large-scale deployment even across multiple farms distributed in various geographic places.

Energy efficiency was an important performance indicator for this study. The model achieved 25 per cent less energy consumption compared to traditional FL models. It's sparse gradient sharing strategy, which transmits only the most important feature updates prolapsed the energy demand deterioration. Traditional FL frameworks often require full model transmissions, which is very power consuming, especially on edge devices with limited resources. On the other hand, FeGAN's selective aggregation reduces computation load with high accuracy by using model This efficiency is appropriate for mobile devices like IoT sensors; drones; and agricultural and agricultural robots. Earlier studies about efficient FL

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models in smart agriculture purported similar achievements, validating the effectiveness of FeGAN's lightweight communication architecture.

Experimental outcomes confirm that the model provides complete advantaged performance through higher accuracy and precision while requiring less communication costs than typical FL models. Experimental findings indicate that the model shows elevated capability for working with non-IID data distributions which prevail within agricultural datasets that exhibit environmental variations and irregular disease transmission patterns. It represents a practical solution for precision agriculture through its sanitized communication overhead policies and acceleration of convergence that benefits resource-constrained farming environments. The combination of GAT architectures with adaptive gradient aggregation methods enables FeGAN to detect disease progressions that depend on spatial relationships accurately during variable agricultural environments.

The potential uses of this model include, not only wheat disease detection, but its applicability reaches farming sectors across various domains. Pest detection and soil quality assessment together with climate impact prediction are worth investigation in research that explores FeGAN's potential applications. It will become more responsive to environmental changes when it combines real-time IoT sensor inputs with its decentralized learning approach. Future research should investigate customization options in FL processes because they allow FeGAN to modify itself for individual farm environments that result in higher prediction precision levels. Non-supervised learning techniques when applied to federated models will enhance FeGAN's response to new disease types and environmental conditions which ensures its performance remains stable within changing agricultural environments.

Research outcomes confirm that FeGAN delivers the latest standards for wheat disease recognition while operating in federated agricultural environments. Precision agriculture benefits from FeGAN AI because it delivers sophisticated performance combined with better communication efficiency and speed and contains reduced energy requirements as a modern solution. The advantages of FeGAN enable its use as a scalable technology with privacy features for low-resource agriculture environments while maintaining efficiency.

Conclusion

This research developed FeGAN which functioned as an optimized FL framework made to improve wheat disease detection in low-resource agricultural conditions. The addition of GATs to FeGAN enabled the model to focus on disease-specific elements which led to its development into a sturdy platform with high precision for disease detection despite data heterogeneity. The proposed innovation stands crucial in precision agriculture because standard machine learning techniques struggle to handle non-IID data distributions found in these farms.

The testing verified that FeGAN delivered excellent classification outcomes and cost-effective processing operations. The 94 per cent classification success rate obtained by FeGAN outperformed basic FL methods that achieved results within 88 to 93 per cent range. The adaptive aggregation technology within FeGAN selected important feature updates for transmission which enhanced both bandwidth efficiency and speed of convergence. The reliability of FeGAN was confirmed by its 93 per cent precision and 81 per cent recall values which demonstrated strong capability in both accurate identification and minimal false alarms for early-stage wheat infections. The MCC score of 67 per cent showed how FeGAN handled imbalanced agricultural datasets when determining its robustness in different farm environments under varying climate conditions.

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FeGAN delivered superior classification results and consumed 30 per cent less bandwidth in communication operations than traditional FL platforms. FeGAN enabled this efficiency through its choice to send only selected model updates from graduates instead of entire weight matrix information across the network. For agricultural low-connectivity environments the communication-efficient technique plays a vital role because it enhances the practicality of distributed FL models. FeGAN enables efficient data stream optimization between remote agricultural areas by doing away with unnecessary model data transfers thus lowering operational expenses and enabling network scalability.

The research study demonstrated that FeGAN provided remarkable energy efficiency alongside its other capabilities. Energy usage decreased by 25 per cent compared to classic FL approaches when the model employed sparse updates with light processing needs. The energy efficiency improvement is crucial because agricultural IoT networks depend heavily on battery-powered devices used for sensors and drones. FeGAN optimizes computation costs against classification accuracy to ensure sustainability for big-scale precision farming platforms which promotes eco-friendly AI systems in agricultural operations.

Finally, we attempted to address the major challenges such as data inequality, bandwidth barriers and energy efficiency, our model has demonstrated its ability to revolutionize the AI-managed accurate agriculture. Being that the agricultural sector faces climate change and increasing challenges related to food security, FeGAN provides an opportunity for scalable, privacy-preserving and resource-skilled structure capable of upscaling global wheat production. With federated learning and continuous progress in graph neural networks, the model is ready to enhance the future of smart agriculture, through the ability to be flexible and durable in crop disease detection practices in diverse and developed agricultural scenario.

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Conflict of Interest

The authors declare that they have no known conflicts of interest related to this study. All findings and conclusions presented are the result of our independent research efforts, and no financial, professional, or personal affiliations have influenced the content of this publication.

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