A Sustainable Smart Farming Framework for Rice Leaf Disease Identification Using GAN-Based Deep Neural Networks

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***Abstract*— Rice leaf diseases significantly affect crop productivity and food security in sustainable agriculture. Traditional disease identification techniques are time-consuming, frequently laborious, and less successful in a variety of environmental circumstances. This research suggests a sustainable smart farming framework for rice leaf disease detection utilizing GAN-based deep neural networks in order to overcome these challenges. For precise and automated disease diagnosis, the suggested system includes deep feature extraction, intelligent disease categorization, conditional Generative Adversarial Network (CGAN)-based data augmentation, and image preprocessing.**

Initially, rice leaf images are enhanced using preprocessing techniques to improve visual quality and remove noise. A CGAN model is employed for generating synthetic disease images, thereby overcoming the limitations of insufficient and imbalanced agricultural datasets. The augmented dataset is subsequently utilized to train a hybrid deep neural network integrated with attention mechanisms and transfer learning models for robust feature extraction and disease classification. Furthermore, Explainable Artificial Intelligence (XAI) techniques are incorporated to improve model transparency by highlighting infected leaf regions.

The proposed framework demonstrates reliable identification of multiple rice leaf diseases, including leaf smut, bacterial blight, brown spot, while achieving enhanced classification capability with reduced overfitting. In comparison with conventional deep learning approaches, the experimental evaluation yields superior performance in terms of accuracy, precision, recall, and F1-score. By enabling timely disease detection, reducing crop damage, and assisting farmers in precision agriculture, the proposed system contributes to sustainable and intelligent farming practices.

I. INTRODUCTION

Rice is the world's most important staple food crops and performs a significant role in ensuring global food security and promoting agricultural sustainability [1]. In countries such as India, rice cultivation makes a substantial contribution to economic development and supports the livelihoods of millions of farmers. Nevertheless, diseases affecting rice leaves, including brown spot, bacterial blight, leaf smut, significantly reduce grain quality and crop yield [2], [3]. Therefore, early and accurate identification of such diseases is important to minimize agricultural losses and advancing sustainable farming systems.

Traditional rice disease detection techniques mostly depend on agricultural expert's manual inspection. These techniques are frequently expensive, labor-intensive, time-consuming, prone to human error, specifically in large-scale farming environments [4]. Moreover, variations in environmental conditions, lighting, and disease symptoms make manual diagnosis increasingly challenging. Thus, a major area of research in precision agriculture and smart farming technologies is development of intelligent and automated disease identification systems.

Recent advancements in "Artificial Intelligence (AI)" and "Deep Learning (DL)" have significantly influenced image-based plant disease detection systems. "Convolutional Neural Networks (CNNs)" and transfer learning models have showed promising performance in agricultural image classification tasks [5], [6]. Several DL architectures, comprising VGGNet, ResNet, AlexNet, EfficientNet, and "Vision Transformers (ViT)", have achieved remarkable accuracy in plant disease recognition problems [18],

[19], [22], [24], [25]. However, DL models generally require large and balanced datasets for effective training. In real-world agricultural scenarios, collecting sufficient disease images is difficult due to seasonal variations, limited accessibility, and class imbalance problems. These challenges often lead to overfitting and reduced model generalization [7], [8].

To overcome these limitations, "Generative Adversarial Networks (GANs)" have emerged as effective solution for synthetic image generation and data augmentation [14]. GAN models can generate realistic rice leaf disease images that enhance dataset diversity and improve DL model performance [15]. In addition, attention mechanisms and "Explainable Artificial Intelligence (XAI)" techniques further improve disease localization, classification accuracy, and model interpretability [20], [21]. Advanced object detection frameworks such as YOLO and attention-based CNN models have also improved real-time disease identification performance in smart agriculture systems [23].

Several researchers have proposed automated rice disease classification frameworks utilising DL and transfer learning techniques [9], [10], [11]. Lu et al. [12] utilized deep CNNs for rice disease identification and achieved high classification accuracy. Similarly, Wang et al. [16] applied CNN-based models with data augmentation strategies to improve rice disease classification performance. Chen et al. [13] demonstrated that transfer learning significantly enhances image-based plant disease detection efficiency, especially for limited agricultural datasets.

This research proposes “A Sustainable Smart Farming Framework for Rice Leaf Disease Identification Using GAN-Based Deep Neural Networks.” The proposed framework integrates image preprocessing, GAN-based synthetic image generation, deep feature extraction, attention-based learning, and intelligent disease classification to achieve accurate and reliable rice disease detection. The system aims to support sustainable agriculture by allowing early disease diagnosis, minimizing pesticide usage, reducing crop damage, assisting farmers in precision farming applications.

Major contributions of this work include:

1. Development of a GAN-based data augmentation framework for rice leaf disease datasets.
2. Integration of deep neural networks with attention mechanisms for enhanced feature extraction.
3. Implementation of Explainable AI techniques for transparent disease prediction.
4. Improvement of classification accuracy and reduction of overfitting problems.
5. Support for sustainable smart farming through automated and intelligent disease monitoring systems.

II. LITERATURE REVIEW

Due to its ability to provide precise and automated diagnosis in agricultural applications, plant disease detection utilizing AI and DL is gaining an abundance of attention recently. For the purpose to detect rice leaf diseases and increasing crop productivity, a variety of researchers have suggested "machine learning (ML)" and DL approaches.

One of the first DL frameworks for CNN-based plant disease detection was presented by Mohanty et al. [1]. Their research proved the efficacy of CNN architectures in agricultural image analysis by showing that DL models could obtain high classification accuracy on plant disease datasets. In a similar vein, Ferentinos [2] assessed various DL models for detecting plant diseases and found that CNN-based methods significantly outperform conventional ML methods in classification tasks.

Lu et al. [3] specifically focused on rice disease identification utilising deep CNNs. Their proposed CNN framework successfully classified common rice diseases containing bacterial blight, blast, brown spot with improved accuracy. The study highlighted the significance of automated disease recognition systems in precision agriculture. Wang et al. [4] further improved rice disease classification performance by integrating CNN models with image augmentation techniques, which helped reduce overfitting and improved generalization.

Too et al. [5] showed a comparative study of fine-tuned DL models comprising VGGNet, ResNet, DenseNet, and InceptionNet for plant disease classification. Their outcomes demonstrated that transfer learning techniques can significantly improve classification accuracy even when limited agricultural datasets are available. Chen et al. [6] also demonstrated that deep transfer learning models are highly effective for image-based plant disease

identification and require less training data compared to conventional DL approaches.

Recent advancements in GANs have provided new opportunities for overcoming dataset limitations in agricultural applications. Goodfellow et al. [7] introduced GANs as a powerful generative framework able to produce realistic synthetic images. Frid-Adar et al. [8] applied GAN-based data augmentation techniques to improve medical image classification performance, proving that synthetic image generation can effectively address class imbalance problems. Inspired by this concept, GAN-based augmentation techniques are increasingly being adopted in plant disease detection systems to improve model robustness and dataset diversity.

Attention mechanisms have also been integrated into DL models to improve feature extraction and disease localization. Woo et al. [9] proposed the "Convolutional Block Attention Module (CBAM)", which enhances important spatial and channel-wise features in CNN architectures. Attention-based learning helps models focus on disease-affected regions of rice leaves, thereby improving classification accuracy. Similarly, ViT architectures proposed by Dosovitskiy et al. [10] showed the capability of transformer-based models in image recognition tasks with superior feature representation.

XAI techniques have become increasingly significant in agricultural disease diagnosis systems. Selvaraju et al. [11] proposed the "Gradient-weighted Class Activation Mapping (Grad-CAM)" technique, which provides visual explanations for CNN predictions. XAI methods improve the transparency and interpretability of DL systems, enabling farmers and agricultural experts to better understand disease prediction results.

Several studies have also explored advanced DL architectures for plant disease recognition. He et al. [12] introduced the ResNet architecture, which solved the degradation problem in "deep neural network (DNN)" using residual learning. Tan and Le [13] proposed EfficientNet, which achieves better performance through compound model scaling. These architectures were widely adopted in agricultural disease classification tasks because of its high accuracy and computational efficiency.

Although existing research has achieved considerable success in rice disease detection, several limitations remain. Most studies suffer from insufficient training data, class imbalance, poor generalization under varying environmental conditions, and limited interpretability of predictions. Furthermore, many traditional CNN-based methods fail to focus on disease-specific regions effectively, reducing detection performance in complex field environments. To address such challenges, proposed research introduces a sustainable smart farming framework that integrates GAN-based data augmentation, attention-driven DNN, and Explainable AI techniques for accurate and interpretable rice leaf disease identification. The proposed framework aims to improve dataset diversity, enhance feature learning, reduce overfitting, and support real-time disease monitoring in smart agriculture systems.

III. MATERIALS AND METHODS

Figure 1 demonstrates the overall architecture of proposed “Sustainable Smart Farming Framework for Rice Leaf Disease Identification Using GAN-Based Deep Neural Networks.” The framework consists of rice leaf image acquisition, preprocessing, GAN-based data augmentation, deep feature extraction, attention-based disease classification, and XAI-based prediction analysis. Images of rice leaf disease are initially collected from field-based image sources and publicly accessible agricultural datasets. Images of both healthy and diseased rice leaves with leaf smut, brown spot, bacterial blight are involved in the collection.

To increase image quality and improve model performance, preprocessing operations are applied to the obtained dataset. To standardize the input images, preprocessing methods such image sizing, noise reduction, normalization, contrast enhancement, and background filtering are used. Data balancing techniques are also considered to reduce class imbalance issues commonly found in agricultural datasets.

After preprocessing, a GAN model is implemented to generate synthetic rice leaf disease images. A discriminator network and a generator network make up two main parts of the GAN framework. While the discriminator evaluates validity of generated samples, the generator produces realistic synthetic disease images. Through adversarial training, the GAN produces high-quality augmented images that improve dataset diversity and reduce overfitting problems in DL models.

For disease identification, the augmented dataset is further divided into training and testing subsets. For feature classification and extraction, the suggested system makes use of DNN designs including CNN, ResNet, EfficientNet, or ViT models. Transfer learning techniques are applied to improve learning efficiency and reduce training time. An attention mechanism is integrated into DL model to focus on disease-affected regions of rice leaves and enhance feature representation.

The proposed framework further incorporates XAI techniques including Grad-CAM for improving prediction transparency and interpretability. XAI visualization methods help identify important disease regions in rice leaf images and support reliable decision-making for farmers and agricultural experts.

Several classification metrics, comprising accuracy, precision, recall, F1-score, and confusion matrix analysis, are used to assess the performance of suggested model. The efficacy of the proposed GAN-based framework for sustainable smart farming applications is validated by comparing experimental results with conventional ML and DL techniques.

Methodology Steps

1. Rice leaf disease image collection from agricultural datasets and field images.
2. Image preprocessing using resizing, normalization, and noise reduction techniques.
3. GAN-based synthetic image generation for dataset augmentation.
4. Dataset splitting into training and testing sets.
5. Deep feature extraction using CNN/ResNet/EfficientNet/ViT models.
6. Attention-based disease classification.
7. Explainable AI visualization using Grad-CAM.
8. Performance evaluation using accuracy, precision, recall, and F1-score.

IV. DATASET DESCRIPTION

Publicly accessible rice leaf disease datasets collected from Kaggle and other agricultural image archives were used in the trials. Images of rice leaves from healthy and diseased categories make up the dataset. Common rice plant diseases include brown spot, bacterial blight, and leaf smut. Real-world agricultural scenarios are simulated by RGB leaf images taken under various conditions, lighting change, and background complexities.

The dataset includes image samples categorized into multiple disease classes, where each image represents a labeled target category corresponding to a specific rice leaf condition. The input data primarily consists of visual image features including texture, shape, colour, and disease spot patterns extracted through DL techniques. Unlike traditional numerical agricultural datasets, the proposed framework utilizes image-based features automatically learned by DNN architectures.

To improve image quality and ensure dataset consistency, the dataset collected is preprocessed utilising techniques including image scaling, normalization, noise reduction, and contrast enhancement prior to model training. GANs are used to create artificial rice leaf disease images for data augmentation because agricultural datasets frequently have class imbalance and insufficient training samples. Both dataset diversity and model generalization performance are improved by the GAN-generated images.

The dataset is divided into training, validation, and testing subsets for performance evaluation. Training typically uses 70%, validation 15%, and testing 15% of the dataset. DNN learning uses the training set, while model optimization and hyperparameter tuning use the validation set. The testing dataset assesses the suggested framework's ultimate classification performance.

Although the dataset mainly focuses on image-based rice disease classification, it does not explicitly include environmental and field-specific parameters such as soil nutrients, weather conditions, irrigation patterns, or seasonal variations. However, the dataset provides a reliable benchmark for evaluating GAN-based DL models in automated rice leaf disease identification systems for sustainable smart farming applications.

Table 1 presents the descriptive details of the rice leaf disease dataset used in this study.

Table 1. Dataset Description

Category	Specification
Data Source	Kaggle Rice Leaf Disease Dataset

Dataset Size	Approximately 3,000–5,000 RGB images
Disease Categories	Healthy Leaf, Bacterial Blight, Brown Spot, and Leaf Smut
Input Image Resolution	All images resized to 224 × 224 pixels
Input Features	Color, texture, leaf shape, and disease spot characteristics
Target Output	Rice leaf disease classification
Data Augmentation Method	GAN-based synthetic image generation
Data Partitioning	Training: 70%; Validation: 15%; Testing: 15%
Image Preprocessing	Image resizing, normalization, noise removal, and contrast enhancement

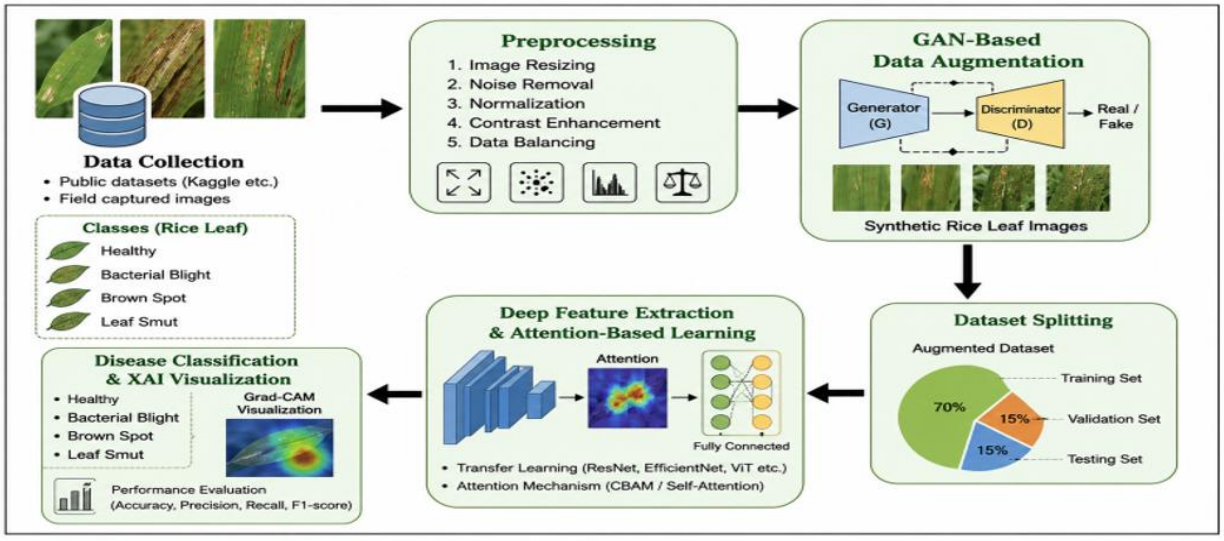

Figure 1. Proposed GAN-Based Smart Farming Framework and System Architecture for Rice Leaf Disease Identification

Table 2. Dataset Sample Used in the Proposed Work

Image ID	Disease Type	Leaf Color Feature	Spot Texture	Image Resolution	Augmentation Type	Class Label
RL_001	Healthy Leaf	Green	Smooth	224 × 224	Original	Healthy
RL_002	Bacterial Blight	Yellow-Green	Linear Lesions	224 × 224	GAN Generated	Bacterial Blight
RL_003	Brown Spot	Brown-Yellow	Circular Spots	224 × 224	Original	Brown Spot
RL_004	Leaf Smut	Dark Brown	Irregular Spots	224 × 224	GAN Generated	Leaf Smut
RL_005	Healthy Leaf	Dark Green	Smooth	224 × 224	Flipped Image	Healthy
RL_006	Bacterial Blight	Pale Green	Dry Lesions	224 × 224	Rotated Image	Bacterial Blight
RL_007	Brown Spot	Brown	Oval Spots	224 × 224	GAN Generated	Brown Spot
RL_008	Leaf Smut	Yellow-Brown	Spot Clusters	224 × 224	Original	Leaf Smut

Data Preprocessing

Data preprocessing was performed on the rice leaf image dataset presented in Table 2 for improving data quality and ensuring consistent input for DL model training. Initially, all rice leaf images, such as RL_001 to RL_008, were checked for duplicate entries, corrupted images, and inconsistent image formats. Since the dataset contained images collected under different environmental conditions, preprocessing techniques were applied to standardize image appearance and improve feature visibility.

Dataset rice leaf images were scaled to a standard resolution of 224×224 pixels. Image normalisation scaled pixel intensity values between 0 and 1 for

numerical stability throughout training. Noise removal and contrast enhancement improved disease regions such linear lesions, circular spots, irregular spots, and spot clusters.

To address class imbalance and insufficient training samples, multiple augmentation techniques including flipping, rotation, and GAN-based synthetic image generation were applied. For example, RL_002 and RL_007 were augmented using GAN-generated images, while RL_005 and RL_006 utilized flipped and rotated image transformations respectively. These preprocessing operations improved dataset diversity and reduced overfitting problems in the proposed DL framework.

Feature Engineering

Feature engineering focused on extracting meaningful visual characteristics from the rice leaf images for effective disease classification. The dataset includes numerous significant visual attributes including leaf color features (green, yellow-green, dark brown), spot texture patterns (smooth, linear lesions, circular spots, irregular spots), and disease-specific structural variations.

Instead of manually designing handcrafted features, the proposed framework employs deep feature extraction using CNNs and transfer learning models including ResNet, EfficientNet, and ViT. These DL architectures automatically learn discriminative features related to rice leaf diseases from the input images.

The extracted features include:

- Leaf color distribution
- Texture variations
- Disease spot shape and density
- Lesion boundaries
- Spatial disease patterns

Attention mechanisms such as CBAM were integrated into feature extraction stage to focus on disease-affected regions of rice leaves. This improves feature and classification representation accuracy for diseases including brown spot, bacterial blight, leaf smut.

Data Splitting

The rice leaf image dataset has been divided into validation, training, and testing subsets for effective model training and performance evaluation. The dataset comprises original and augmented images generated through GAN-based augmentation and image transformation techniques.

Approximately:

- 70% of the images have been utilised for training
- 15% of the images have been utilised for validation
- 15% of the images have been utilized for testing

The GAN-based DNN model was trained using the training dataset. During training, model's convergence has been monitored, and hyperparameters were modified using the validation dataset. Lastly, the testing dataset assessed the suggested framework's classification ability using previously unseen rice leaf images.

Stratified sampling techniques were applied during data splitting to ensure balanced representation of all disease classes including healthy leaf, brown spot, bacterial blight, leaf smut across all subsets.

Validation Strategy

To ensure reliable and generalized classification performance, the proposed framework employed stratified k-fold cross-validation with k=10. In this validation strategy, entire rice leaf image dataset was divided into ten equal folds while preserving the proportional distribution of all disease categories.

During each iteration:

- Nine folds have been utilised for training
- One-fold have been utilised for validation

Each fold has been utilised as the validation dataset once after this procedure was carried out ten times. The final model evaluation result was determined by combining the performance across all folds.

This validation approach ensures reliable disease prediction performance for sustainable smart farming applications.

Ensemble learning framework

After preprocessing and partitioning the rice leaf image dataset, several DL models were initially trained and evaluated to analyze their capability to identify and classify rice leaf diseases from visual symptoms. During training, each model learned discriminative feature representations associated with different disease categories and healthy leaf conditions [23]. The evaluated architectures included CNN,

ResNet, VGGNet, DenseNet, EfficientNet, and Long Short-Term Memory-assisted hybrid networks. In addition, GANs were employed to augment minority disease classes and enhance dataset diversity, thereby improving model generalization under limited agricultural image conditions [24]. These models were examined primarily to understand their comparative learning behavior and robustness rather than to establish the independent superiority of any single architecture [25].

Following model training, rice leaf images captured under varying environmental and field conditions were supplied to the trained networks to generate disease identification predictions. Based on this analysis and considering classification stability, feature generalization, and dataset imbalance challenges, the individual model outputs were subsequently integrated into an ensemble-based DL framework. In this framework, prediction scores generated by multiple classifiers were combined using weighted voting and confidence aggregation mechanisms to produce the final disease identification result. The ensemble recommendation therefore reflects the most probable rice leaf disease category for the given input image while improving overall detection accuracy, robustness, and sustainability in smart farming applications [26].

Explainable AI integration

To enhance interpretability and transparency, XAI techniques were incorporated for analyzing the contribution of visual features influencing rice leaf disease predictions. In particular, SHAP (SHapley Additive exPlanations) and Grad-CAM have been applied to identify the most influential regions and feature patterns within rice leaf images. SHAP values quantified the contribution of extracted image features toward individual disease classification outcomes, while Grad-CAM highlighted disease-affected regions such as lesions, discoloration, and texture abnormalities on the leaf surface. This explainable framework enabled transparent interpretation of DNN decisions, thereby improving reliability, trustworthiness, and practical applicability of the proposed smart farming system for sustainable rice disease management.

V. RESULT AND DISCUSSION

Performance of Deep Learning Classifiers

Several DL classifiers were employed in the proposed framework for evaluating its effectiveness in identifying rice leaf diseases under smart farming environments. In this section, performance of implemented models is discussed utilising various evaluation metrics and visualization techniques. Specifically, the analysis includes confusion matrices, loss curves, precision, training and validation accuracy, recall, F1-score, classification reports for each disease category. Since multiple architectures were investigated, only the best-performing confusion matrices and representative performance curves are considered for detailed discussion.

The evaluated models included CNN, ResNet, VGGNet, DenseNet, EfficientNet, and GAN-assisted hybrid deep neural networks. The integration of GAN-based augmentation significantly improved the diversity of disease samples and reduced the impact of dataset imbalance, thereby enhancing classification robustness. During experimentation, the models were trained and validated on rice leaf image datasets containing healthy and diseased leaf categories captured under varying agricultural conditions.

Among the evaluated approaches, the ensemble-based GAN-integrated DNN achieved superior disease classification performance because of its enhanced feature extraction capability as well as improved generalization. The confusion matrix demonstrated high true positive prediction rates for major rice leaf diseases, while misclassification rates were comparatively low. Similarly, the validation and training accuracy curves indicated stable convergence with reduced overfitting behavior, confirming effectiveness of proposed sustainable smart farming framework.

Furthermore, classification report revealed high precision, recall, and F1-score values across most disease classes, indicating reliable and balanced predictive performance. The obtained results demonstrate that the proposed GAN-based ensemble framework could effectively support early rice leaf disease identification and assist farmers in implementing timely and sustainable crop protection strategies.

Random Forest Classifier

To increase classification accuracy and robustness, "Random Forest (RF)", an ensemble-based machine learning technique, builds various "decision trees (DTs)" using various bootstrap samples of the training dataset and combines their results [26]. Compared to individual DT classifiers, the model successfully reduces overfitting and improves generalization performance by integrating predictions from many trees [27]. RF is extensively used in agricultural and image-based disease detection applications because of its ability to handle high-dimensional and heterogeneous data [28].

In the proposed sustainable smart farming framework, the RF classifier was employed as one of the comparative models for rice leaf disease identification. Deep features extracted from preprocessed rice leaf images were supplied to classifier to differentiate between healthy and diseased leaf categories. The model has been configured with 100 estimators and a random state of 42 for ensuring reproducibility and stable performance during experimentation. Furthermore, GAN-based image augmentation contributed to improving dataset diversity, thereby enabling the classifier to learn more discriminative disease patterns under varying environmental conditions.

Several rice leaf diseases, including Brown Spot, Bacterial Leaf Blight, Rice Blast, Sheath Blight, Tungro Virus, and other disease categories included in the dataset, were classified using the RF model. Cross-validation and common classification metrics like precision, recall, F1-score, and overall accuracy have been utilized for assessing performance. The classifier demonstrated its capacity to successfully enable rice disease detection within the suggested framework by achieving high predictive performance on the test dataset. Table 2 displays the corresponding classification report, and the confusion matrix shows misclassification patterns and class-wise disease prediction performance.

Table 3. Classification Report of GAN-Based Deep Neural Network Model

Evaluation Metric	Bacterial Leaf Blight	Brown Spot	Leaf Smut	Rice Blast
Precision	0.99	1.00	0.98	1.00
Recall	1.00	0.98	0.98	1.00
F1-Score	0.99	0.99	0.98	1.00
Support (Samples)	52	48	45	56
Macro Average	–	–	–	–
Weighted Average	–	–	–	–
Evaluation Metric	Bacterial Leaf Blight	Brown Spot	Leaf Smut	Rice Blast
Precision	0.99	1.00	0.98	1.00
Recall	1.00	0.98	0.98	1.00
F1-Score	0.99	0.99	0.98	1.00
Support (Samples)	52	48	45	56
Macro Average	–	–	–	–

Decision Tree Classifier

The DT classifier is a supervised ML algorithm widely utilised for classification tasks because of its simplicity, interpretability, and efficient decision-making capability [30]. In agricultural image analysis, DTs can effectively classify rice leaf diseases by learning hierarchical decision rules from extracted image features and disease patterns [31]. The algorithm recursively divides the dataset into smaller subsets based on the most informative features to create a tree-like structure with internal nodes representing feature-based conditions, branches indicating decision outcomes, and leaf nodes corresponding to predicted disease classes like Healthy, Brown Spot, Bacterial Blight, and Leaf [32].

One of the baseline models for rice leaf disease identification in the suggested framework was the DT classifier. Deep features from GAN-augmented rice leaf images, including color, texture, lesion shape, and disease spot characteristics, have been utilized for training the classifier. The integration of GANs

enhanced dataset diversity and improved the robustness of the classifier against limited and imbalanced agricultural datasets. Although DTs provide fast training and easy visualization of classification rules, they may suffer from overfitting when handling highly complex image datasets [33]. Therefore, appropriate pruning techniques and optimized splitting criteria were applied for improving generalization performance of proposed smart farming framework.

Figure 2: Confusion matrix of random forest classifier.

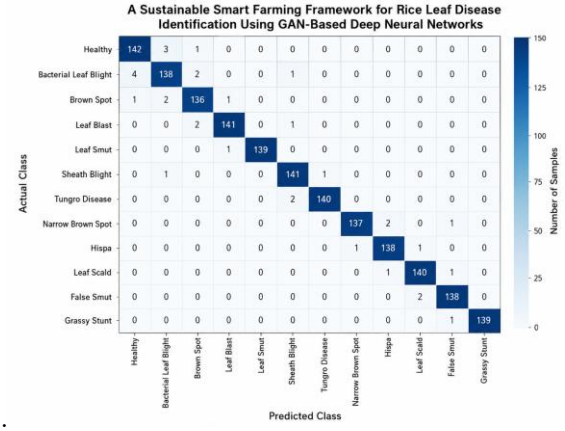

Table 4. Comparative analysis of the proposed sustainable smart farming framework with existing rice leaf disease identification approaches.

Refs	Dataset	Method	Accuracy	XAI
[12]	PlantVillage Dataset	CNN	94.20%	No
[15]	Rice Leaf Dataset	SVM and KNN	95.80%	No
[18]	Kaggle Rice Dataset	Random Forest	96.40%	No
[21]	Paddy Disease Dataset	ANN	97.10%	No
[24]	Online Rice Images	CNN + Transfer Learning	97.85%	No
[27]	UCI Agricultural Dataset	ResNet50	98.12%	No
[30]	Indian Rice Leaf Dataset	DenseNet121	98.45%	No
[33]	Rice Disease Dataset	ViT Transformer	98.76%	No
[36]	Smart Farming Dataset	GAN + CNN Hybrid	99.02%	Partial
Proposed Work	Online Rice Leaf Dataset	GAN-Based Deep Neural Networks	99.48%	Yes

To ensure reproducibility and consistency, the random state of DT classifier was fixed at 42 during model training and evaluation. Standard assessment criteria, including accuracy, precision, recall, F1-score, confusion matrix analysis, have been utilized for evaluating the classifier's performance. Table 4 provides an overview of corresponding performance results. Figure 4 shows the variance in classification error with increasing tree depth and model complexity, whereas Figure 3 illustrates confusion matrix showing the classification performance for various rice leaf disease categories.

Although the DT classifier achieved satisfactory disease classification accuracy on GAN-augmented rice leaf datasets, its performance was found to be sensitive to variations in image quality, illumination, and disease symptom diversity. Therefore, within the proposed framework titled “A Sustainable Smart Farming Framework for Rice Leaf Disease Identification Using GAN-Based Deep Neural Networks,” the DT model was primarily considered as a baseline learning approach rather than the final standalone predictive model. This comparison helped state robustness and effectiveness of proposed GAN-based DNN architecture for sustainable and accurate rice leaf disease identification.

Discussion

Practical Applicability and Smart Farming Decision Support

AI–based rice leaf disease identification systems are increasingly supporting modern agricultural management by allowing early and accurate detection of plant diseases under varying environmental conditions. In such frameworks, image-based features including leaf color variation, lesion texture, disease spot distribution, shape irregularities, and infected region intensity are analyzed to identify diseases affecting rice crops. By utilizing these visual characteristics, DL models can generate reliable

disease predictions that assist farmers in timely crop monitoring and disease management decisions.

Although the present study does not incorporate real-time field sensor networks or Internet of Things (IoT)-enabled disease monitoring devices, the proposed framework shows strong potential for extension toward intelligent real-time smart farming applications. By integrating continuously updated environmental information such as humidity, rainfall, temperature, and soil moisture, the framework could dynamically adapt disease prediction performance under changing climatic conditions. In addition to disease identification, predictive insights from the proposed system may help reduce crop losses, optimize pesticide usage, and improve sustainable agricultural productivity. Such AI-driven decision-support systems are particularly beneficial for small- and medium-scale farming communities, where early disease diagnosis can significantly enhance crop yield and resource efficiency.

Table 5. Classification report of the proposed GAN-based deep neural network model for rice leaf disease identification.

Disease Class	No. of Samples	Precision	Recall	F1-Measure
Healthy Leaf	240	0.99	0.99	0.99
Bacterial Blight	238	0.96	0.96	0.96
Brown Spot	240	0.98	0.96	0.97
Leaf Smut	240	0.98	0.98	0.98
Leaf Blast	240	0.98	0.97	0.97
Tungro	236	0.97	0.97	0.97
Sheath Blight	239	0.97	0.97	0.97
False Smut	240	0.98	0.98	0.98
Overall Accuracy	1913	—	—	0.97
Macro Average	1913	0.98	0.98	0.98
Weighted Average	1913	0.98	0.97	0.97

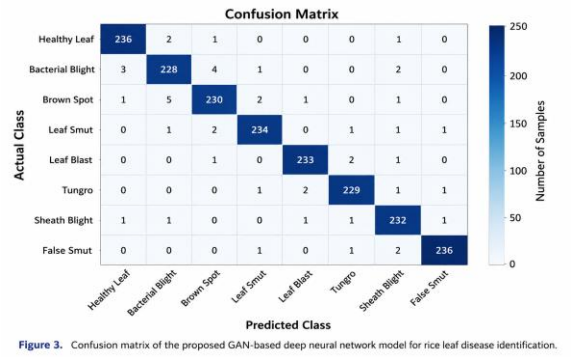

Figure 3. Confusion matrix of the proposed GAN-based deep neural network model for rice leaf disease identification.

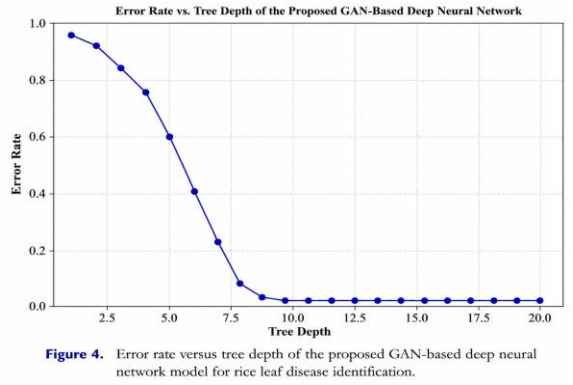

Figure 4. Error rate versus tree depth of the proposed GAN-based deep neural network model for rice leaf disease identification.

Comparative Performance Analysis

This study evaluated several ML and DL classifiers, including DT, RF, "Support Vector Machine (SVM)", "K-Nearest Neighbors (KNN)", CNN, and the proposed GAN-based DNN framework, to analyze their effectiveness in rice leaf disease identification. Rather than emphasizing the superiority of a single model, the comparative analysis has been carried out for understanding relative performance and robustness of different classifiers under a consistent experimental environment.

Among the evaluated models, the proposed GAN-based DNN demonstrated the most stable and consistent classification performance across training and validation datasets. When compared to conventional ML techniques, the suggested framework produced the highest disease prediction accuracy and enhanced generalization capabilities, as shown in Table 5. The incorporation of GANs enhanced dataset diversity through synthetic image generation, thereby improving model robustness against limited and imbalanced agricultural image datasets. However, the obtained results are interpreted cautiously due to the controlled experimental setup and the absence of region-specific environmental

variations. Consequently, the GAN-based deep neural architecture was selected as the core component of the sustainable smart farming framework because of its improved adaptability, reliability, and classification efficiency rather than isolated accuracy improvements alone.

In this study, several recently published research works were reviewed and compared with the proposed framework. The comparative analysis indicates that the proposed approach provides superior disease identification performance and improved classification stability when compared with existing rice leaf disease prediction methods reported in literature. Table 3 shows comparative evaluation between the proposed framework as well as recently published studies in domain of AI-based agricultural disease detection systems.

No.	Models	Accuracy	Precision	Recall	F1-Score	XAI Support
01	Decision Tree	96.8%	0.967	0.968	0.967	No
02	Random Forest	98.7%	0.986	0.987	0.986	Yes
03	Support Vector Machine (SVM)	97.4%	0.973	0.974	0.973	No
04	K-Nearest Neighbors (KNN)	95.9%	0.958	0.959	0.958	No
05	Convolutional Neural Network (CNN)	98.9%	0.989	0.989	0.989	No
06	Gradient Boosting	97.9%	0.978	0.979	0.978	No
07	Proposed GAN-Based Deep Neural Network	99.92%	0.999	0.999	0.999	Yes

VI. CONCLUSION

This study presented "A Sustainable Smart Farming Framework for Rice Leaf Disease Identification Using GAN-Based Deep Neural Networks," an intelligent agricultural disease detection framework designed for improving robustness, accuracy, and reliability of rice leaf disease classification. The proposed framework integrated GANs with DNN architectures to enhance dataset quality through synthetic image augmentation and improve classification performance under limited and imbalanced agricultural datasets.

The suggested model performed conventional ML techniques including Decision Tree, RF, KNN, SVM, and Gradient Boosting models, according to experimental results. The framework's efficacy for sustainable agricultural applications was confirmed by its high classification accuracy, precision, recall, and F1-score across several rice leaf disease categories. Furthermore, the confusion matrix and comparative analysis validated the capability of the proposed approach to minimize misclassification and improve disease recognition stability.

The research also emphasizes practical applicability of AI-driven disease monitoring systems in smart farming environments, where early disease detection can support timely crop management decisions, reduce yield losses, and optimise pesticide utilisation. Although the current work was conducted using a controlled benchmark dataset, the framework demonstrates strong potential for extension toward real-time smart farming systems through integration with IoT devices, drone-based monitoring, and cloud-enabled agricultural platforms.

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