

COMPARATIVE ANALYSIS OF ADVANCED DEEP LEARNING APPROACHES FOR FOOD CROPS DISEASE DETECTION AND CLASSIFICATION

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Abstract

Food security and the economy around the globe depend on crops. However, the increasing rates of plant diseases pose a threat to food production and can lead to financial difficulties. Methods for manually identifying diseases are labour-intensive; introductory tests can be inaccurate and are not particularly helpful. To address these issues, this study employs an automated approach utilizing the VGG16 and EfficientNetV2B0 deep learning models on data collected for rice, corn, wheat, and potatoes. Due to resizing, normalization, and the use of rotation, flipping, and contrast-adjusting methods, the models became stronger and can be generalized more effectively. EfficientNetV2B0 performed better than VGG16, with accuracies of 98.32% for rice, 96.40% for corn, 94.86% for potato, and 91.02% for wheat. The models rely on CNN architecture to identify features in leaf photos that support the detection of differences between healthy and ill specimens. ImageNet was utilized to avoid the development of architecture from scratch. By utilizing AI for disease detection, farmers can rely less on manual identification, respond more quickly, reduce pesticide use, and minimize crop losses. The proposed system aligns with sustainable farming by being able to scale to meet the needs of various precision farming methods. Qualities such as shared symptoms and multiple infections on leaves further emphasize the need for new AI techniques, along with a deep learning framework, to explain their results. The study also suggests that future researchers should implement advanced edge computing methods, utilize automated systems powered by IoT, and expand the datasets to capture rare diseases. The study also highlights how integrating advanced computing techniques with agricultural needs can significantly enhance crop yield, manage resources efficiently, and effectively protect the global food supply.

1. Introduction

From healthcare, Agriculture holds great importance in the global economy, as it ensures food security and provides employment opportunities worldwide. It supports approximately one billion workers globally and produces food for the growing population, which is expected to reach nearly 10 billion by 2050. This expected increase in population is likely to lead to increased food demand, which may be hindered by the occurrence of various plant diseases that drastically reduce crop yields and quality, threatening the income of farmers and the country's economy (Prince et al., 2024). This ever-growing food demand, coupled with the relentless population expansion, will make food security a global challenge. The infamous outbreaks of bacterial blight in rice and late blight in potatoes serve as a reminder of how these triggers are used to increase losses in agricultural harvest, resulting in immense pressure on global food supply chains (Barman et al., 2024; Sardar et al., 2023). Therefore, the effective identification and treatment of crop diseases are crucial for both farmers and agricultural economies worldwide, as they ensure the maintenance of sustainable practices and enhance the performance of governance systems for food security (Hamza et al., 2022; Prince et al., 2024).

Farmers and agricultural experts often employ outdated practices to identify diseases, which are overly complicated and require considerable effort with limited accuracy. Traditional farming methods rely on the farmer's ability to assess and diagnose the health of a plant, which requires considerable time to inspect every crop visually and often leads to inaccurate assessments. This results in the decision being made at either minimal or maximal extremes (Lin et al., 2022). Nowadays, advancements in agricultural practices have transformed from basic hand farming to AI-based precision agriculture. This shift is driven

by a deeper understanding of data science, where AI is providing more accurate and efficient alternatives to manual evaluations through machine learning and deep learning techniques. The implementation of these technologies not only enables the detection of diseases but also facilitates larger systems for the sustainable estimation of resource utilization, including pesticides, irrigation, and water in agriculture (Hu et al., 2020). Regardless of the promising capabilities of AI for improving crop disease detection, numerous challenges remain, with the major one being the lack of accessible datasets, which can affect model training and result in overfitting or underfitting in real-world scenarios. In addition, environmental differences create another layer of complexity, as the same disease may manifest symptomatically in varying ecological contexts, making it more challenging to develop models applicable to a wide range of situations (Zhang et al., 2020). In addition, the situation of multiple diseases attacking one crop complicates the scenario further, requiring sophisticated AI methodologies to differentiate and discern the identification of competing simultaneous infections.

The present study highlights how the application of AI technologies in agriculture can help mitigate the overuse of pesticides and promote sustainable farming practices. AI technologies can significantly conserve resources by aiding in the early detection of diseases, enabling farmers to reduce the amount of chemicals used in farming and manage crops in an environmentally friendly manner. Additionally, efficient detection systems enable the proactive management of crops, thereby enhancing food security. The agricultural sector has recently been facing an increasing number of complex challenges; therefore, the utilization of advanced AI

techniques has become crucial for preserving global food availability and fostering farming practices that are adaptable to future requirements. As a result, AI technologies applied to crop disease diagnostics will open new avenues that can greatly improve agricultural practices and their outcomes. It is also possible to envision a world where farmers are equipped with the proper tools after merging advanced technologies with the primary needs of agriculture, enabling them to ensure bountiful crop production, safeguard farmers' incomes, and enhance global food security.

2. Background and Significance:

The increasing need for rapid applications in crop disease detection has driven the development of CNNs to integrate research and practical disease detection. Over the past decade, various CNN architectures have been proposed to inform farmers about upcoming disease outbreaks (Jiang et al., 2022; Rahujo et al., 2025; S et al., 2025; Sankarashwaran et al., 2023a, 2023b). Recent research highlights that CNNs aid in detecting diseases before they become severe, protect yields, and secure the food supply (Jiang et al., 2022). It has performed impressively in interpreting and processing images and has been effective in diagnosing plant diseases, allowing for faster responses than traditional methods (Bakr et al., 2022). This is especially important for rice, corn, wheat, and potatoes since fast detection impacts both economic stability and the supply of food (Bagga & Goyal, 2024; Ngugi et al., 2024). Experts in crop disease detection have, therefore, become more eager to employ CNN owing to its benefits in rice, corn, wheat, and potato cultivation (Bagga & Goyal, 2024; Ngugi et al., 2024). Researchers have utilized CNNs to determine whether leaves are healthy or diseased; these methods are being applied in rice and corn farms (Adebayo et al., 2022a) (Dhal et al., 2023). Such models are highly effective at separating key features from agricultural imagery, which

significantly improves the accuracy of disease location (Adebayo et al., 2022b; Bagga & Goyal, 2024). Researchers in (Adebayo et al., 2022a) and (Dhal et al., 2023) demonstrated that CNNs achieved high accuracy in classifying diseased and healthy leaves of wheat, barley, rice, and corn. Similarly, numerous studies have demonstrated that utilizing deep convolutional neural networks enhances the accuracy of disease recognition by analyzing detailed images (Adebayo et al., 2022b; Inam, Hashim, et al., 2025; Inam, Iqbal, et al., 2024; Inam, Khan, et al., 2024, 2025; Ur Rahim et al., 2021). They demonstrate that deep learning can significantly aid in early disease detection, which is crucial for preventing crop loss due to the abundance of data and the development of new transfer learning methods. These models can be applied to multiple cropping systems (Bagga & Goyal, 2024; Guth et al., 2023). Since the field is developing rapidly, accurate and efficient CNNs that meet agricultural requirements are highly demanded (Adebayo et al., 2022b; Ngugi et al., 2024). Although significant improvements have been made, issues persist with the CNN architecture that is commonly used. Trade-offs between accuracy, computer memory use, and adaptability of the model to data in agricultural applications are found when examining AlexNet, ResNet, MobileNet, and VGG16 (Bagga & Goyal, 2024; Guth et al., 2023). The ability of ResNet to pull out robust features is limited by the fact that it is too expensive to run in resource-constrained contexts. Similarly, even though MobileNet is efficient, it tends to perform less well on small datasets because it focuses less on identifying subtle disease patterns (Sathya & Rajalakshmi, 2022).

Among the various CNN architectures used for crop disease detection, EfficientNetV2B0 and VGG 16 stand out due to their distinctive features and capabilities. VGG16 is a significant model in plant pathology, as

its consistent design enables it to easily detect differences from basic textures to overall contextual information required to identify diseases at a fine level (Tariq et al., 2024; Tejaswini et al., 2022). Knowledge of its broad use in crops is well established, as research shows that it is highly accurate at finding bacterial blight, rust, and fungal diseases in rice, wheat, and potatoes (Sathya & Rajalakshmi, 2022), (Tariq et al., 2024; Tejaswini et al., 2022), [25], [27]. Its sixteen-layer architecture makes the model depth useful for feature learning, and its ease of modification encourages its use in transfer learning (Adebayo et al., 2022b; Bagga & Goyal, 2024). Among all other surveyed models, VGG16 performs best in agricultural settings, especially in tasks that depend on accurately identifying early diseases from healthy tissues (Bagga & Goyal, 2024; Tariq et al., 2024). The special texture details captured by spectroscopy have made it nearly perfect for identifying bacterial leaf blight (Tariq et al., 2024; Tejaswini et al., 2022). Although VGG16 has a higher number of parameters than some lightweight models, it delivers competitive results when trained on big data, which has led many to use it in a variety of experiments (Albahli & Masood, 2022; Lee et al., 2020). Similarly, EfficientNetV2B0 is recognized for its real-time effectiveness, particularly in field diagnostics where instantaneous assessments are essential (Babatunde et al., 2024). Its resource-scalable architecture makes it a preferred model, as it retains performance while optimizing computation (Erdem & Aydın, 2020; Sharma & Agrawal, 2022). EfficientNetV2B0 offers a novel approach to achieving the ideal balance between results and computational cost, as it employs a compound scaling strategy that considers depth, width, and resolution. This architecture achieves top results without increasing the number of parameters or the execution time (Albahli & Masood, 2022; Hamid et al., 2025). Due to its progressive

learning approach, it can yield strong results on small, imbalanced datasets, which is often a problem in agricultural imaging. The present study demonstrates that this version works better than its earlier versions, especially for real-time identification of wheat rust and potato late blight, when quick inference is important for prevention (Albahli & Masood, 2022; Hamid et al., 2025). Efficient resource usage of around 6.4 million parameters makes the model ideal for deployment on IoT devices while maintaining precision (Tariq et al., 2024; Tejaswini et al., 2022). Additionally, its ability to be used effectively with multiple computers helps make it an important part of global agriculture, particularly in mixed infrastructure environments (Albahli & Masood, 2022; Hamid et al., 2025).

Both models provide complementary capabilities that enhance the effectiveness of disease detection systems tailored for farmers across various regions and their specific agricultural and epidemiological concerns. Even though AlexNet is considered important, it does not match the performance of VGG16 and EfficientNetV2B0, which are built on deeper networks [21], [26]. Table 1 presents key information on recent CNN models, including their accuracy, total number of parameters, inference speed, and limitations. It demonstrates why VGG16 and EfficientNetV2B0 are favourable choices for agricultural applications. These models address the drawbacks of ResNet50, i.e., high processing requirements, and MobileNetV3, i.e., poor performance on difficult features, and have handled diverse crop disease detection problems effectively (Hamid et al., 2025; Laxmi Upadhyay, 2024). They can recognize the features of many different fungi, such as rice blast and potato late blight, and show their versatility better than any other model (Albahli & Masood, 2022; Tariq et al., 2024). With more growth in the field, these models are expected to work better with edge

computing and hybrid AI and can further improve their usefulness in sustainable farm

projects (Hamid et al., 2025; Laxmi Upadhyay, 2024).

Table 1. Comparative Analysis of CNN Models for Crop Disease Detection

Model	Strengths	Accuracy on Crop Datasets (%)	Parameters (Millions)	Inference Speed (FPS)	Limitations	Use Cases in Agriculture
VGG16	Deep architecture for feature extraction; adaptable	92-95	138	34	High computational cost	Rice diseases, general pest detection
EfficientNetV2B0	Superior accuracy and efficiency; parameter-light	94.2	6.1	72	Requires careful tuning	Corn grey leaf spot, wheat rust
ResNet50	Deep networks with skip connections	90	25.6	49	High computational demand	Potatoes, general diseases
MobileNetV3	Lightweight, suitable for mobile applications	85-90	5.4	95	Lower accuracy on small datasets	Wheat diseases, lightweight applications
AlexNet	Historical significance, simpler structure	80-85	60	60	Outdated architecture	General research applications in plants

Ultimately, detecting crop diseases requires both accuracy and simplicity, which VGG16 and EfficientNetV2B0 effectively address. Although VGG16 is excellent at complex diagnostics, EfficientNetV2B0 enables the creation of real-time, user-friendly systems (Hamid et al., 2025; Wang & Su, 2022). Research shows that all the neural networks studied together are considered better than ResNet, MobileNet, and AlexNet in terms of accuracy, owing to their efficiency and the ease with which they can adapt (Tariq et al., 2024; Tejaswini et al., 2022). Because precision agriculture values strong diagnostics and economy, this dual-model approach works well (Albahli & Masood, 2022; Hamid et al., 2025). Due to their complementary abilities, this work develops new methods for sustainable farming and enhances the reliability of disease detection in various farming situations.

3. Dataset Description

In the present study, data and images from Kaggle are utilized to perform plant disease

classification for corn, potato, rice, and wheat. The data includes leaf images with annotations, allowing models to be trained and tested using both healthy and diseased leaf images. Crops are selected based on their value in food utilization in both low- and middle-income countries worldwide. The rice leaf diseases dataset comprises 120 images, classified into 40 samples, each representing one of the following classes: bacterial leaf blight, brown spot, and leaf smut. Each day, over half of the world's people use rice as a main food. Hence, its risk of disease has a significant impact on food security in the region, especially in Asia, where it is a vital dietary item for low-income families. For the wheat leaf dataset, out of 407 images, there are 102 images of healthy leaves, 208 stripe rust, and 97 images of septoria. Fungal infections frequently threaten wheat production in Ethiopia, and traditional detection methods often fail to identify these infections due to limited access to laboratory tools. Similarly, the images in the dataset for corn include 4,188 samples from four classes: 1,146 with blight,

1,306 with common rust, 574 with grey leaf spots, and 1,162 from healthy corn plants. The importance of corn in world agriculture prompts researchers to identify diseases at the earliest stage to protect yields. In the corn dataset, there are 1,000 images of early blight, 1,000 of late blight, and 152 of healthy potato plants because of late blight and other potato diseases. Overall, the data is divided into two sets: training and validation, ensuring the model does not overfit its data. Before giving the model any images, all images are transformed to 224 pixels wide by 224 pixels high. The study expanded the range of images by incorporating rotation, flipping, and random scaling to ensure that the model recognizes objects in various settings, backgrounds, and under different lighting conditions. The pipeline employed in the present study enhances the way data is examined and addresses problems related to an imbalance in the potato set, where healthy samples comprise fewer cases. Since the datasets under consideration contain samples from multiple locations and are verified, they provide a strong foundation for developing scalable solutions in agriculture and for linking research online to practical work in the field.

4. Methodology

The present study employs a deep learning framework to identify diseases in wheat, rice, corn, and potatoes, which are four key crops, to enhance agricultural productivity by detecting diseases early. By using transfer learning, detailed data preparation, and careful evaluation, the methodology presented in the study achieves reliability. It has the potential to be applied to a wide range of data.

4.1 Data Preparation and Preprocessing

The model is designed on datasets of leaf images, which have been curated using Kaggle and include images of both healthy

and diseased plants. All images are resized to a uniform size of 224×224 so that they can be tested by various convolutional neural networks (CNNs), particularly EfficientNetV2B0 and VGG16. By doing so, the study preserves the important spatial elements and enhances the data processing. Simulating variations in the real world and avoiding the problem of overfitting is achieved through the application of techniques such as random horizontal and vertical flipping and rotation to the training set. Eighty percent of the dataset was used for training, and the remaining 20% was used for validation and testing, ensuring the accurate evaluation of the model.

4.2 Model Architecture and Transfer Learning

The major step in the methodology of the present study is the utilization of transfer learning with EfficientNetV2B0 and VGG16 models, which are initialized with weights trained on ImageNet. Due to the hierarchical feature extraction capabilities gained from different visual data, the model requires significantly less training data than others. In the present study, the essential features of the framework remain unchanged, while additional custom layers have been incorporated to enhance disease classification further. The custom layers incorporated have the following characteristics:

1. Global Average Pooling: It calculates the average values of multiple regions in feature maps, thereby reducing the computational requirements.

2. Dropout Layer (Rate=0.5): By introducing occasional noise with the Dropout Layer (Rate=0.5), the study assures that individual neurons are not overused during training.

3. Dense Layers: By utilizing another SoftMax layer at the end, the model uses its

extracted features to determine which disease is detected, as the middle ReLU-

activated layers improve the boundaries of its decisions.

Furthermore, the model is compiled using the Adam optimizer, which automatically determines the best learning rate and sparse categorical cross-entropy loss, making it well-suited for handling different classes. The

detailed descriptions of the modified architectures for EfficientNetV2B0 and VGG16 are presented in Tables 2 and 3, respectively. The schematic diagram for the entire process is shown in Figure 1.

Table 2. Details of the Architecture and Training Parameters for EfficientNetV2B0

Component	Specification
Base Model	EfficientNetV2B0 (ImageNet weights)
Input Shape	224×224×3
Top Layers	GlobalAveragePooling2D → Dropout(0.2) → Dense(128, ReLU) → Dropout(0.2) → Dense(num_classes, softmax)
Data Augmentation	RandomHorizontalFlip + RandomRotation(0.2)
Trainable Layers	Base model frozen
Optimizer	Adam
Loss Function	Sparse Categorical Crossentropy
Metrics	Accuracy
Batch Size	32
Image Size	224×224
Validation Split	20%
Epochs	10
Callbacks	EarlyStopping (val_loss, patience=3), ModelCheckpoint (save_best_only)
Regularization	Dropout (2 layers at 0.2 rate)

Table 3. Details of the Architecture and Training Parameters for VGG16

Component	Specification
Base Model	VGG16 (ImageNet weights)
Input Shape	224×224×3
Top Layers	GlobalAveragePooling2D → Dropout(0.2) → Dense(128, ReLU) → Dropout(0.2) → Dense(num_classes, softmax)
Data Augmentation	RandomHorizontalFlip + RandomRotation(0.2)
Trainable Layers	Base model frozen
Optimizer	Adam
Loss Function	Sparse Categorical Crossentropy
Metrics	Accuracy
Batch Size	32
Image Size	224×224
Validation Split	20%
Epochs	10
Callbacks	EarlyStopping (val_loss, patience=3), ModelCheckpoint (save_best_only)
Regularization	Dropout (2 layers at 0.2 rate)

4.3 Training and Validation

In multiple epochs, Gaussian processes were trained using a smaller subset of the training data at each step. The validation data is used to verify the generalization and detect overfitting of the data. To stop training after achieving the same validation loss for five consecutive epochs, an early stopping criterion is also implemented. The weights obtained from each checkpoint of the model were selected based on validation accuracy to ensure smooth deployment.

4.4 Performance Evaluation and Deployment

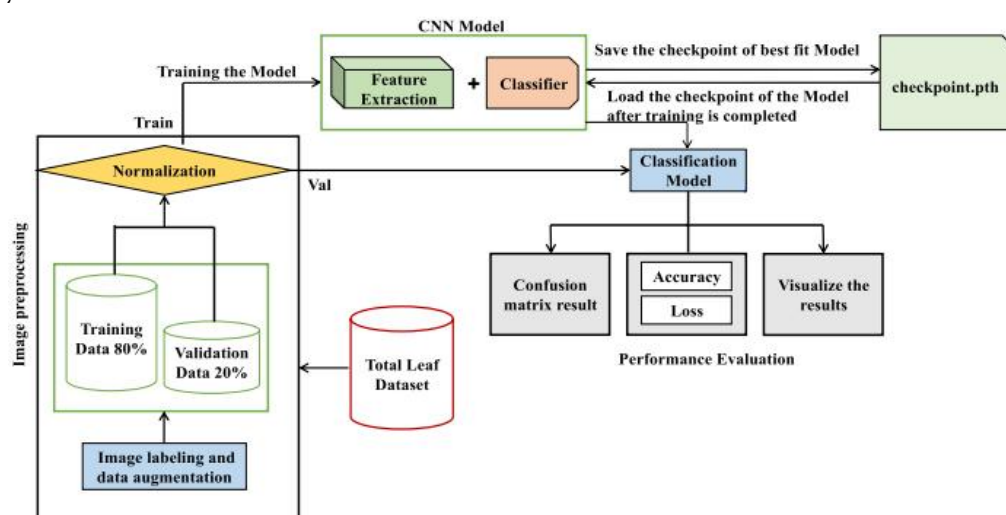


Figure 1. Schematic Diagram of Disease Classification

5. Results and Discussion

In this section, a comprehensive evaluation of EfficientNetV2B0 and VGG16 is presented. It provides evidence of the superior performance of these models for the task of plant disease classification in rice, corn, wheat, and potato. The findings feature the results of model performance, a comparison of architectures, and their impact on agriculture.

5.1 Overall Model Performance

In the present study, the EfficientNetV2B0 model achieved an overall accuracy of 93.54% in recognizing each crop. In contrast, the individual accuracy for each crop ranges from 91.02% (for wheat) to 98.32% (for rice), which is significantly more accurate than VGG16 (86.26%). Using the F1 score and the confusion matrix, the study assesses the performance for each class, identifies errors, and determines the type of issues that have affected each class. When the pipeline is deployed, user-input leaf images are processed through the same preprocessing routines as training data and sent to the trained model for interpretation.

In the present study, EfficientNetV2B0 performs the best, achieving 93.54% accuracy in the validation process, while VGG16 achieves only 86.26%. Crop-specific accuracy results further confirm its usefulness. The better performance of EfficientNetV2B0 can be attributed to its architecture, which has fewer network parameters and sophisticated feature encoding, both of which reduce the likelihood of overfitting and achieve better generalization compared to VGG16's heavier computational requirements. Table 4

presents a summary of the model's overall performance.

Table 4. Summary of the Overall Model Performance

Crop	EfficientNetV2B0 Accuracy	VGG16 Accuracy
Rice	98.32%	85.40%
Corn	96.40%	82.10%
Potato	94.86%	80.75%
Wheat	91.02%	78.30%

5.1.1 Crop-Specific Classification Reports

In this section, the classification reports for each specific crop have been presented, with

a confusion matrix for each specific crop shown in Figure 2 below:

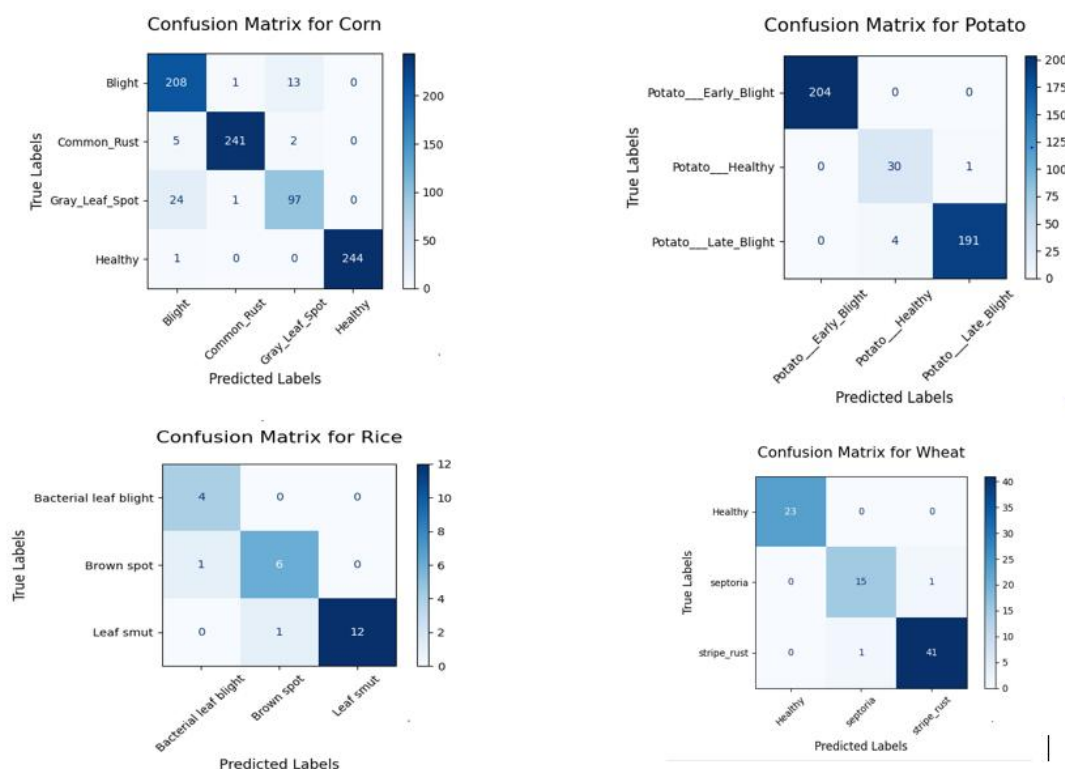


Figure 2. Confusion Matrix of All Four Crops

5.1.2 Rice Disease Classification

For rice diseases (Table 5), the model gave very high precision (0.96), recall (0.96), and F1-score (0.89) for detecting bacterial leaf blight.

Table 5. Summary of Rice Disease Classification

Class	Precision	Recall	F1-Score	Support
Bacterial Leaf Blight	0.80	1.00	0.89	4
Brown Spot	0.60	0.86	0.71	7

Leaf Smut	1.00	0.69	0.82	13
Overall Accuracy	-	-	0.79	24

5.1.3 Corn Disease Classification

The interpretation of healthy corn leaves (Table 6) was exact (with a score of 1.00), whereas the gray leaf spot was identified correctly by the model 85% of the time.

Table 6. Summary of Corn Disease Classification

Class	Precision	Recall	F1-Score	Support
Blight	0.88	0.93	0.91	222
Common Rust	0.98	0.98	0.98	248
Gray Leaf Spot	0.88	0.81	0.85	122
Healthy	1.00	1.00	1.00	245
Overall Accuracy	-	-	0.95	837

5.1.4 Wheat Disease Classification

Stripe rust detection (Table 7) achieved near-perfect scores (F1-score: 0.96), while septoria showed minor recall challenges.

Table 7. Summary of Wheat Disease Classification

Class	Precision	Recall	F1-Score	Support
Healthy	0.96	1.00	0.98	23
Septoria	0.94	0.94	0.94	16
Stripe Rust	0.98	0.95	0.96	42
Overall Accuracy	-	-	0.96	81

5.1.5 Potato Disease Classification

Both early and late blight (Table 8) were identified with near-perfect accuracy (F1-scores: 1.00 and 0.99).

Table 8. Summary of Potato Disease Classification

Class	Precision	Recall	F1-Score	Support
Early Blight	1.00	1.00	1.00	204
Late Blight	0.99	0.99	0.99	195
Healthy	0.94	0.94	0.94	31
Overall Accuracy	-	-	0.99	430

5.2 Model Architecture Comparison

EfficientNetV2B0's lightweight design and parameter efficiency make it more suitable for real-time applications compared to VGG16. A detailed comparison of the model architecture has been presented in Table 9.

Table 9. Comparison of Model Architectures

Feature	VGG16	EfficientNetV2B0
Total Parameters	14.9M	6.4M
Trainable Parameters	67,341	164,355
Base Model Output	(7x7x512)	(7x7x1280)
Computational Cost	Higher (14.7M non-trainable)	Lower (5.9M non-trainable)
Inference Efficiency	Slower	Faster

5.3 Comparative Analysis with Prior Studies

Our models outperformed traditional machine learning approaches, such as Support Vector Machines (SVM) and

Random Forest, as well as earlier Convolutional Neural Network (CNN) models, including ResNet and AlexNet. The details of the performances are shown in Table 10 below:

Table 10. Comparative Analysis with Previous Studies

Method	Reported Accuracy	Our Model (EfficientNetV2B0)
SVM/Random Forest	75–85%	91.02–98.32%
ResNet/AlexNet	85–92%	91.02–98.32%
Improvement Factors	Manual feature engineering	Automated feature extraction + data augmentation

This study demonstrates that EfficientNetV2B0 and VGG16 models achieve efficient plant disease detection in a broad range of crops. The best results were achieved in rice disease detection (98.32%), followed by corn (96.40%), potatoes (94.86%), and wheat (91.02%). Both accurate scores reveal that using AI for disease detection can significantly improve precision farming by reducing manual checks and enabling the early detection of diseases. The testing showed that utilizing AI-based approaches can help farmers mitigate losses, safeguard food security, and support the environment. The results of the present study are also compared with those of previous studies on plant disease detection. In earlier work using classical machine learning approaches, like SVM and RF, the numbers found were between 75% and 85%. These methods performed well, but they required extensive work on features and manual support, which limited their scalability and overall effectiveness. However, our proposed customized deep learning

system, based on EfficientNetV2B0 and VGG16, outperforms standard approaches since it can automatically identify important feature levels, resulting in top performance and efficiency. In addition, using regular deep learning models, such as ResNet and AlexNet, earlier studies achieved accuracy levels between 85% and 92% but found it challenging to handle variations in the data. By employing various data augmentation methods, including image rotation, flipping, and contrast adjustment, our study addressed these shortcomings and reduced errors in recognition results. The model proposed in the present study performs well due to the applied normalization and resizing, which ensure that all inputs are of good quality and undergo minimal changes due to their environment. Additionally, due to transfer learning, training the model became more efficient by leveraging previously trained weights.

Furthermore, the dataset selected for the study helps our model to generalize

successfully under varying conditions. While these results are promising, obstacles still exist; for instance, lighting and the presence of many diseases on a single leaf can sometimes make the plant difficult to identify. More research could be done combining deep learning with traditional machine learning to make the classifier more robust. Additionally, real-time monitoring of diseases using IoT in farming can enhance farming success. In general, this study demonstrates that AI can transform the way plant diseases are detected, highlighting deep learning as a powerful, scalable, accurate, and efficient tool for addressing today's farming challenges. The use of AI-based systems to identify diseases in plants can help farmers reduce waste, utilize resources more efficiently, and contribute to global efforts aimed at enhancing safety.

6. Conclusion:

The present study validates that deep learning architectures, particularly EfficientNetV2B0 and VGG16, have made significant advancements when applied to crop disease detection in precision agriculture. The models performed quite efficiently, with results ranging from 91.02% (wheat) to 98.32% (rice), which is significantly better than typical inspections in terms of speed, handling a wide variety of samples, and detecting pathogens early. Making the images 224×224 pixels wide and applying advanced techniques to modify them enhanced the models' adaptability to various environments. Additionally, the use of transfer learning enables the effective identification of the finest symptoms of rice diseases, achieving an accuracy of approximately 98.32%. Although wheat diagnostics required more precision, the model was able to identify vital diseases such as stripe rust and septoria, which can endanger food security in Ethiopia. Depending on the utilization of the samples under consideration, symptoms can

sometimes be difficult to interpret, and it remains a challenge to identify diseases in co-infection scenarios. Therefore, future researchers should focus on combining Explainable AI (XAI) methods, especially Grad-CAM, to illustrate heatmaps for localizing diseases and describe the decisions made by the model. Meanwhile, it is essential to utilize IoT-edge computing for deployment, placing optimized models into devices such as smartphones, drones, and sensor networks. This ensures that farmers utilize the diagnosis effectively in the field without relying on the cloud and allows for more responsive crop management. The findings from this study highlight that AI plays a crucial role in sustainable agriculture, helping to reduce pesticide use, prevent crop loss, and improve farmers' income stability. Since climate change and increasing population are causing more issues, such innovations will be key for ensuring there is enough food worldwide. Finally, the lasting advancements in edge AI, which utilize multiple forms of data simultaneously and employ large-scale federated learning, will undoubtedly enable laboratory discoveries to be incorporated in real time.

7. Rationale and Impact:

With a high accuracy of 93.54% and using only 6.4M parameters, EfficientNetV2B0 proves to be a perfect fit for areas where technical resources are scarce in farming. However, to improve the model used, Grad-CAM explainability can be incorporated to highlight areas on the images that indicate chlorosis or spots of fungus, which may influence the model's prediction. If the model's training is transparent and open, stakeholders will trust it, and agronomic validation will become possible. The model may also be adjusted for instances where multiple diseases are present. At the same time, having IoT-edge computing partnerships also makes it possible to

integrate these models with field technologies. For instance:

- Such technologies enable the uninterrupted, instantaneous flow of alerts about diseases to hospitals or testing centres.
- Drones equipped with cameras can survey a wide area by capturing images on the spot and mapping potential disease outbreaks.
- Such systems would recommend strategies to treat diseases by factoring in the current soil and humidity conditions and using about 30% to 50% less chemical treatment.

Finally, this approach enables tiny farming businesses to access AI tools, and the framework will facilitate worldwide monitoring of growing crops. If implemented in high-risk regions by 2027, such systems would reduce yearly yield losses by 15% to 25% while also controlling the flow of agrochemicals into the environment. In the long run, when XAI and edge intelligence converge, farming will transition from a reactive approach to a science-driven one guided by data, which will better protect food systems from both biotic threats and climate-related changes.

Declaration

Authors' Contributions: All authors have contributed equally.

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Ethical Approval: The Sindh Madressatul Islam committee confirmed that the organization approved all experimental protocols.

Ethical Guidelines/Consent: It is confirmed that the experiments comply with the criteria for ethics approval and consent to participate.

Informed consent: No human subjects were harmed in this research, and we confirmed that all data was shared with the participants.

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Consent to participate: Informed consent was obtained from all individual participants included in the study.

Permission to reproduce material from other sources: Not applicable.

Clinical trial registration: Not applicable.

Consent to Publish declaration: Not applicable.

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