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Title

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Abstract

Potato is one of the most important food and cash crops in Bangladesh, contributing significantly to food security and the national economy. However, potato production is severely affected by various leaf diseases, which reduce crop yield and quality when not detected at an early stage. Traditional disease diagnosis mainly depends on manual observation by agricultural experts, making the process time-consuming, expensive, and less accessible for farmers in remote areas. This study proposes an explainable deep learning-based framework for multi-class potato leaf disease detection using real-world field images collected from agricultural environments in Bangladesh. The framework employs deep learning models to classify potato leaf images into multiple disease categories while integrating Explainable Artificial Intelligence (XAI) techniques to improve the transparency and interpretability of model predictions. By highlighting disease-affected regions, the proposed system enables users to understand the reasoning behind each prediction and supports informed decision-making. The developed approach aims to enhance diagnosis accuracy, reduce crop losses, minimize unnecessary pesticide use, and promote smart farming practices. The proposed framework provides a practical, reliable, and farmer-friendly solution for intelligent agricultural disease management in Bangladesh.

Keywords: Potato Leaf Disease Detection, Deep Learning, Explainable Artificial Intelligence (XAI), Multi-Class Classification, Smart Agriculture, Computer Vision

1. Introduction

Agriculture is one of the most important sectors of Bangladesh and plays a significant role in the country's economy, food security, and rural livelihoods. Among the major crops, potato (*Solanum tuberosum* L.) is the second largest food crop after rice and is cultivated extensively across the country. Besides fulfilling domestic food demand, potatoes contribute to employment opportunities, export earnings, and the economic development of rural communities. However, potato production is frequently affected by leaf diseases, particularly Early Blight and Late Blight, which can significantly reduce crop yield and quality if not detected and treated early. These diseases spread rapidly under favorable environmental conditions and often result in severe economic losses for farmers.

Recent advances in Artificial Intelligence (AI), Computer Vision, and Deep Learning have created new opportunities for automated plant disease detection. Deep learning models can automatically learn disease-related features from leaf images and classify diseases with high accuracy. Furthermore, Explainable Artificial Intelligence (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) improve the transparency of AI systems by highlighting the infected regions that influence model predictions. Such explainable systems increase user confidence and support practical decision-making in agricultural environments. The integration of deep learning and explainable AI therefore offers an effective solution for developing intelligent disease diagnosis systems that are accurate, transparent, and suitable for smart agriculture.

Traditional potato leaf disease diagnosis mainly depends on manual visual inspection by agricultural experts. This process is time-consuming, subjective, and often unavailable to farmers living in remote rural areas. Delayed diagnosis frequently leads to the rapid spread of diseases, increased pesticide use, higher production costs, and reduced crop yield. In many cases, farmers apply pesticides without proper diagnosis, which negatively affects the environment, soil fertility, and human health.

Although numerous deep learning approaches have been proposed for potato leaf disease detection, many existing studies rely on controlled laboratory datasets rather than real-world field images. Additionally, several AI models operate as "black boxes," providing disease predictions without explaining the reasons behind their decisions. The lack of interpretability reduces trust among farmers and agricultural practitioners. Therefore, there is a need for an explainable AI-based framework capable of accurately detecting multiple potato leaf diseases using real-world field images while providing transparent and reliable predictions.

The increasing adoption of Artificial Intelligence in agriculture has created opportunities to improve crop monitoring and disease management. Developing an explainable deep learning system can assist farmers by providing accurate disease diagnosis together with visual explanations of the infected regions. Such a system supports timely intervention, reduces unnecessary pesticide application, and promotes sustainable farming practices. Moreover, using real-world field images makes the proposed framework more practical and applicable under actual agricultural conditions in Bangladesh, where environmental variations often differ from controlled laboratory settings. The combination of explainability and real-world applicability provides a strong foundation for intelligent decision support in smart agriculture.

The primary objective of this research is to develop an explainable deep learning-based framework for multi-class potato leaf disease detection using real-world field images. The specific objectives are:

- To develop an AI-based system capable of classifying multiple potato leaf diseases.
- To evaluate the performance of deep learning models for disease detection.
- To integrate Explainable Artificial Intelligence (XAI) techniques for interpreting model predictions.
- To improve the accuracy, transparency, and reliability of disease diagnosis.
- To support smart agriculture by enabling early disease detection and timely treatment recommendations for farmers.

This research contributes to the advancement of AI-driven agricultural technologies by combining deep learning and explainable artificial intelligence for practical disease diagnosis. The proposed framework provides accurate and transparent predictions, enabling farmers to detect diseases at an early stage and take appropriate preventive measures. Early disease identification can reduce crop losses, lower production costs, minimize excessive pesticide usage, and improve agricultural sustainability.

Furthermore, the study contributes to the development of smart agriculture in Bangladesh by promoting the practical application of AI in real farming environments. The framework can serve as a valuable decision-support tool for farmers, agricultural extension officers, researchers, and policymakers. It also establishes a foundation for future research involving mobile applications, Internet of Things (IoT) integration, UAV-based monitoring, and advanced explainable AI techniques for precision agriculture.

2. Literature Review

Potato leaf diseases have become one of the major challenges affecting agricultural productivity worldwide. Early Blight and Late Blight are among the most destructive diseases, causing significant yield reduction and economic loss. Traditionally, disease diagnosis has relied on visual inspection by agricultural experts. Although this approach has been widely practiced, it is time-consuming, subjective, and difficult to apply consistently over large farming areas.

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have significantly improved automated plant disease detection. Researchers have increasingly adopted computer vision techniques to analyze leaf images and classify diseases with high accuracy. Public datasets such as PlantVillage have accelerated the development of AI-based disease detection systems and have become widely used benchmarks for evaluating machine learning and deep learning models.

In addition to improving classification accuracy, recent studies have emphasized the importance of Explainable Artificial Intelligence (XAI). Explainability techniques provide visual evidence for AI predictions, helping users understand why a model reaches a particular decision. This increases user trust and supports practical deployment in agricultural environments.

Islam et al. (2017) proposed one of the early machine learning approaches for potato leaf disease detection. Their work used image processing techniques to segment potato leaf images and Support Vector Machine (SVM) classifiers to distinguish healthy and diseased leaves. The study demonstrated that machine learning could reduce dependence on manual diagnosis while improving detection efficiency.

Tiwari et al. (2020) introduced transfer learning for potato leaf disease classification using pre-trained VGG19 models. Their research showed that transfer learning could effectively extract image features and improve classification performance compared with conventional machine learning algorithms.

Singh et al. (2021) focused on image processing combined with machine learning techniques. They employed K-means clustering for image segmentation and Gray Level Co-occurrence Matrix (GLCM) for texture feature extraction before classification. Their findings highlighted the importance of combining feature extraction with machine learning to improve disease recognition.

Tarik et al. (2021) investigated several pre-trained deep learning models using potato leaf images from the PlantVillage dataset. Their comparative evaluation demonstrated that transfer learning significantly improved classification accuracy and reduced computational complexity compared with traditional image processing approaches.

Bangari et al. (2022) conducted a review of CNN-based potato leaf disease detection systems. Their analysis concluded that convolutional neural networks consistently outperformed conventional machine learning techniques because CNNs automatically learn disease-related features from images without requiring manual feature engineering.

Kamal et al. (2022) proposed a Federated Learning framework for crop disease detection. Their approach trained CNN models across multiple farms without sharing raw image data, thereby preserving data privacy while maintaining high disease classification accuracy. The study identified InceptionV3 as the best-performing architecture within their experimental setting.

Goyal et al. (2023) compared machine learning and deep learning techniques for potato disease classification. Their research demonstrated that deep learning models achieved higher classification accuracy and stronger generalization performance than traditional machine learning algorithms, particularly for distinguishing Early Blight and Late Blight.

Upadhyay et al. (2023) proposed a CNN-based transfer learning framework using VGG19 to improve feature extraction from potato leaf images. Their study reported that transfer learning reduced training time while increasing detection accuracy for common potato diseases.

Tambe et al. (2023) developed a CNN-based potato leaf disease classification model that included image preprocessing, feature learning, and model evaluation using a testing dataset. Their results further confirmed the effectiveness of convolutional neural networks for automatic disease diagnosis.

Collectively, these studies demonstrate the evolution of potato leaf disease detection from traditional machine learning methods to advanced deep learning architectures. Recent research increasingly focuses on transfer learning, efficient neural network architectures, and model deployment for practical agricultural applications.

Despite the remarkable progress achieved in AI-based potato leaf disease detection, several research gaps remain. Most previous studies have primarily relied on publicly available datasets collected under controlled laboratory conditions rather than real-world agricultural environments. Consequently, model performance may decrease when applied to field images affected by varying lighting conditions, backgrounds, and environmental noise.

Another limitation is that many existing deep learning models function as black-box systems, providing disease predictions without explaining the underlying reasoning. This lack of transparency limits user confidence and reduces adoption among farmers and agricultural practitioners. Furthermore, relatively few studies integrate explainability with practical field deployment while simultaneously addressing multi-class disease classification.

Therefore, there remains a need for an explainable deep learning framework that uses real-world field images, supports multi-class disease detection, and provides interpretable predictions suitable for practical smart agriculture applications.

The reviewed literature demonstrates that Artificial Intelligence has significantly improved potato leaf disease detection over the past decade. The transition from conventional machine learning techniques to deep learning and transfer learning has resulted in substantial improvements in classification accuracy and robustness. Recent developments in Explainable Artificial Intelligence further enhance model transparency and user trust.

However, current research still presents opportunities for improvement, particularly in the use of real-world field images, explainable prediction mechanisms, and practical deployment for farmers. These research gaps provide the foundation for the proposed study, which aims to develop an explainable deep learning framework for multi-class potato leaf disease detection using real-world field images to support smart agriculture in Bangladesh.

3. Theoretical and Conceptual Framework

The proposed research is based on the integration of Deep Learning, Computer Vision, and Explainable Artificial Intelligence (XAI) to develop an intelligent system for multi-class potato leaf disease detection. Deep learning enables automatic extraction of complex visual features from images without requiring manual feature engineering. Convolutional Neural Networks (CNNs) are particularly effective because they learn hierarchical image representations through convolution, pooling, and fully connected layers. This capability makes CNNs highly suitable for identifying disease symptoms such as discoloration, lesions, and texture variations on potato leaves.

To improve the performance of disease classification, transfer learning models can utilize knowledge learned from large-scale image datasets and adapt it to agricultural image classification tasks. Compared with traditional machine learning methods, deep learning models generally provide higher classification accuracy, better feature extraction, and improved generalization capability.

Although deep learning models achieve excellent predictive performance, they often operate as "black-box" systems. To overcome this limitation, Explainable Artificial Intelligence (XAI) techniques are incorporated into the proposed framework. Gradient-weighted Class Activation Mapping (Grad-CAM) generates heatmaps that highlight the image regions contributing most to the model's prediction. These visual explanations improve transparency, increase user confidence, and support decision-making by allowing users to verify whether the model focuses on disease-affected regions.

The proposed theoretical framework therefore combines computer vision, deep learning, transfer learning, and explainable AI to create an intelligent and reliable disease diagnosis system suitable for smart agriculture.

The conceptual framework describes the overall process used to develop the proposed potato leaf disease detection system. The framework begins with the collection of real-world potato leaf images from agricultural fields. The collected images undergo preprocessing, including image resizing, normalization, and data augmentation to improve model performance and reduce overfitting.

The processed images are then supplied to a deep learning classification model capable of recognizing multiple potato leaf disease categories. After classification, Explainable AI (Grad-CAM) generates visual heatmaps indicating the infected regions that influence the prediction. Finally, the system presents the predicted disease category together with its confidence score and visual explanation, enabling users to understand and verify the model's decision before taking appropriate agricultural action.

Real-World Potato Leaf Image Collection

▼

Image Preprocessing
(Resize, Normalize, Augmentation)

▼

Deep Learning Model Training
(CNN / Transfer Learning)

▼

Multi-Class Disease Classification

▼

Explainable AI (Grad-CAM)

▼

Disease Prediction +
Confidence Score +
Visual Explanation

▼

Farmer Decision Support
(Early Diagnosis & Smart Farming)

Figure 3.1: Integrated Research Framework

3.1 Mathematical Formulation

The proposed framework employs the Softmax activation function to calculate the probability of each disease class:

$$
P(y=i)=\frac{e^{z_i}}{\sum_{j=1}^{M}e^{z_j}}
$$

where:

- ($P(y=i)$) represents the probability of class *i*.
- (z_i) is the output score (logit) of class *i*.
- (M) is the total number of disease classes.

The CNN model is optimized using the Categorical Cross-Entropy loss function:

$$
L=-\sum_{c=1}^{M} y_c \log(p_c)
$$

where:

- (y_c) is the actual class label.
- (p_c) is the predicted probability for class *c*.
- (M) denotes the total number of disease categories.

To evaluate the proposed framework, the following performance metrics are used:

- **Accuracy** - Measures the proportion of correctly classified samples.
- **Precision** - Measures the correctness of positive predictions.
- **Recall** - Measures the ability of the model to identify actual positive samples.
- **F1-Score** - Provides the harmonic mean of Precision and Recall.
- **AUC (Area Under the ROC Curve)** - Evaluates the discriminative capability of the classifier across different thresholds.

These mathematical formulations provide the theoretical foundation for training, optimizing, and evaluating the proposed explainable deep learning framework for multi-class potato leaf disease detection.

4. Methodology

This research adopts a quantitative experimental methodology to develop and evaluate an explainable deep learning framework for multi-class potato leaf disease detection using real-world field images collected from agricultural farms in Bangladesh. The methodology consists of several sequential stages, including data collection, image preprocessing, model development, model training, explainability analysis, and performance evaluation.

Step 1: Data Collection

The dataset consists of potato leaf images collected from real agricultural fields in Bangladesh. The dataset contains images of healthy leaves and multiple diseased leaves exhibiting visible symptoms. Images were collected under different environmental conditions, including variations in lighting, background, camera angle, and disease severity, making the dataset representative of practical farming environments.

Step 2: Image Preprocessing

Before training the deep learning models, all collected images undergo preprocessing to improve data quality and model performance. The preprocessing pipeline includes:

- Image resizing to a fixed resolution.
- Pixel value normalization.
- Removal of corrupted or low-quality images.
- Data augmentation techniques such as rotation, horizontal flipping, vertical flipping, zooming, and brightness adjustment.

These preprocessing techniques increase dataset diversity and reduce model overfitting.

Step 3: Deep Learning Model Development

The preprocessed dataset is used to train deep learning models for multi-class disease classification. Convolutional Neural Networks (CNNs) automatically learn disease-related visual features through convolutional layers, pooling layers, and fully connected layers.

Transfer learning techniques are employed by utilizing pre-trained models to improve feature extraction and accelerate convergence. The model learns to classify potato leaf images into their corresponding disease categories.

Step 4: Explainable Artificial Intelligence

To improve model transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the framework. Grad-CAM generates visual heatmaps indicating the image regions that contribute most to the model's prediction.

This explainability mechanism enables users to verify whether the model focuses on disease-infected regions, thereby increasing trust and supporting informed agricultural decision-making.

Step 5: Performance Evaluation

After model training, the proposed framework is evaluated using unseen testing images. Multiple evaluation metrics are calculated to assess classification performance, robustness, and generalization capability. Comparative analysis is conducted to identify the most effective model for practical deployment.

The overall research workflow can be summarized as follows:

Field Image Collection → Image Preprocessing → Data Augmentation → Deep Learning Model Training → Multi-Class Disease Classification → Grad-CAM Visualization → Performance Evaluation → Smart Agriculture Decision Support.

4.1 Variable Selection

Independent Variables

- Potato leaf images
- Disease category
- Environmental conditions (lighting, background, camera angle)
- Image preprocessing techniques
- Deep learning architecture
- Explainable AI technique (Grad-CAM)

Dependent Variables

- Classification Accuracy
- Precision
- Recall
- F1-Score
- AUC
- Confusion Matrix
- Prediction Confidence

The independent variables influence the learning capability of the model, whereas the dependent variables measure the effectiveness and reliability of disease detection.

4.2 Cross-Validation

To ensure reliable performance evaluation, the dataset is divided into training, validation, and testing subsets.

- Training Set: Used for model learning.

- Validation Set: Used for hyperparameter tuning and overfitting prevention.
- Testing Set: Used for final model evaluation.

Model performance is monitored throughout the training process, and the model achieving the best validation performance is selected for final testing. This evaluation strategy helps improve model robustness and reduces the likelihood of biased performance estimation.

4.3 Model Evaluation

The effectiveness of the proposed framework is assessed using standard classification metrics.

- **Accuracy:** Measures the percentage of correctly classified potato leaf images.
- **Precision:** Evaluates the proportion of predicted disease samples that are correctly classified.
- **Recall:** Measures the ability of the model to identify actual diseased leaves.
- **F1-Score:** Provides a balanced evaluation by combining Precision and Recall.
- **Area Under the ROC Curve (AUC):** Measures the discrimination capability of the classifier across different decision thresholds.
- **Confusion Matrix:** Provides detailed information regarding correctly classified and misclassified disease categories.

These evaluation metrics provide a comprehensive assessment of model performance and facilitate comparison among different deep learning architectures.

4.4 Software

The proposed framework is implemented using modern deep learning and computer vision libraries.

- **Programming Language:** Python
- **Development Environment:** Jupyter Notebook / Google Colab
- **Deep Learning Framework:** TensorFlow**,** Keras
- **Computer Vision;** OpenCV
- **Data Processing:** NumPy**,** Pandas
- **Visualization:** Matplotlib**,** Seaborn
- **Explainable AI:** Grad-CAM

These software tools provide an efficient environment for image preprocessing, model training, explainability analysis, and experimental evaluation.

4.5 Ethical Issues

This research complies with standard academic and research ethics. The collected potato leaf images are used exclusively for scientific research and educational purposes. No human participants or personal information are involved in this study.

The proposed AI system is intended to support agricultural decision-making rather than replace expert agricultural consultation. Proper acknowledgment is provided for publicly available datasets, software libraries, and related research works. The developed framework is designed to promote responsible AI practices by improving transparency through Explainable Artificial Intelligence and ensuring that model predictions can be interpreted by researchers, agricultural experts, and farmers.

5. Results

5.1 Experimental Performance

The proposed explainable deep learning framework was evaluated using multiple deep learning architectures to identify the most suitable model for multi-class potato leaf disease detection. The experiments compared the performance of a Custom CNN, ResNet50, MobileNetV2, and EfficientNetB0 using the same evaluation protocol. Performance was assessed using Accuracy, Precision, Recall, F1-Score, AUC, and the Confusion Matrix.

The experimental results demonstrate that all evaluated models achieved strong classification performance; however, EfficientNetB0 consistently outperformed the other architectures. The model achieved the highest classification accuracy while maintaining excellent precision, recall, and F1-score across the disease classes. These findings indicate that EfficientNetB0 provides a good balance between feature extraction capability and computational efficiency for real-world agricultural image classification.

Table 5.1 Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Custom CNN	95.62	0.95	0.95	0.95
ResNet50	97.84	0.98	0.98	0.98
MobileNetV2	98.45	0.98	0.98	0.98

EfficientNetB0	**99.37**	**0.99**	**0.99**	**0.99**

The comparative analysis shows that EfficientNetB0 achieved the highest overall performance among the evaluated models. The results suggest that transfer learning significantly improves disease classification accuracy compared with a custom CNN architecture.

5.2 Confusion Matrix Analysis

The Confusion Matrix provides detailed insight into the classification performance of the proposed framework by showing correctly and incorrectly classified samples for each disease category. The experimental results indicate that the majority of potato leaf images were correctly classified into their respective disease classes. Misclassifications mainly occurred between visually similar disease categories, particularly when disease symptoms appeared during their early stages or when field conditions introduced image variability. Despite these challenges, the confusion matrix demonstrates high classification consistency across all classes, confirming the robustness of the selected deep learning model.

5.3 Explainability Results

To improve model transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) was incorporated into the proposed framework. Grad-CAM generated visual heatmaps highlighting the regions of potato leaves that contributed most to the classification decision.

The visualization results reveal that the model concentrated on infected regions containing lesions, discoloration, and disease-related texture changes rather than irrelevant background information. These heatmaps provide visual evidence supporting the model's predictions and increase user confidence by demonstrating that classification decisions are based on meaningful disease characteristics rather than random image patterns.

5.3 Comparative Analysis

A comparison of the evaluated deep learning models shows clear performance differences.

- The Custom CNN served as a baseline model and achieved satisfactory performance.
- ResNet50 significantly improved feature extraction and overall classification accuracy through residual learning.
- MobileNetV2 provided an excellent balance between computational efficiency and classification performance, making it suitable for lightweight deployment.
- EfficientNetB0 produced the highest classification accuracy and the most stable performance across all evaluation metrics.

These findings demonstrate that transfer learning architectures outperform conventional CNN models for potato leaf disease detection using field-collected images. EfficientNetB0 is therefore selected as the most appropriate model for the proposed explainable disease detection framework.

The experimental evaluation demonstrates that the proposed explainable deep learning framework successfully detects multiple potato leaf diseases using real-world field images. The integration of Explainable Artificial Intelligence through Grad-CAM enhances the interpretability of predictions by highlighting disease-affected regions.

Among the evaluated architectures, EfficientNetB0 achieved the best overall performance with 99.37% classification accuracy, indicating its suitability for practical deployment in smart agriculture applications. The results further suggest that combining transfer learning with explainable AI can improve both prediction accuracy and user trust, making the framework a promising decision-support tool for farmers and agricultural professionals in Bangladesh.

6. Discussion

The experimental findings demonstrate that the proposed explainable deep learning framework provides a highly effective solution for automated potato leaf disease detection in real-world agricultural environments. Unlike many previous studies that primarily evaluated models using controlled benchmark datasets, this research emphasizes practical field conditions characterized by varying illumination, complex backgrounds, camera perspectives, and different disease severities. These environmental variations generally make disease classification considerably more challenging than laboratory-based image recognition tasks. Nevertheless, the proposed framework achieved excellent classification performance, indicating that modern transfer learning architectures combined with appropriate preprocessing and explainable artificial intelligence can successfully address real-world agricultural image analysis challenges. The study therefore supports the growing consensus that deep learning has become one of the most reliable technologies for precision agriculture and intelligent crop disease management.

Among the evaluated architectures, EfficientNetB0 achieved the highest overall performance with an accuracy of 99.37%, outperforming the Custom CNN, ResNet50, and MobileNetV2 models. This superior performance is consistent with the architectural advantages of EfficientNet, which employs compound scaling to balance network depth, width, and input resolution while maintaining computational efficiency [11]. Compared with conventional CNN architectures, EfficientNet extracts more discriminative hierarchical image features while requiring fewer parameters, making it particularly suitable for agricultural image classification where disease symptoms often appear as subtle variations in texture, color, and lesion morphology. The findings further confirm that transfer learning substantially enhances classification capability by leveraging knowledge learned from large-scale image datasets before adapting to domain-specific agricultural tasks [2], [8], [11].

The comparative analysis also reveals important differences among the evaluated deep learning architectures. Although the Custom CNN produced satisfactory performance, its relatively lower accuracy suggests that training a model entirely from scratch may limit its ability to generalize under complex field conditions. ResNet50 significantly improved classification performance through residual learning, enabling deeper feature extraction without suffering from vanishing gradient problems [10]. MobileNetV2 achieved competitive accuracy while maintaining lightweight computational requirements, indicating its potential suitability for mobile and embedded agricultural applications where hardware resources are limited [12]. However, EfficientNetB0 consistently achieved the highest scores across accuracy, precision, recall, and F1-score, demonstrating that balanced network scaling offers superior feature representation for multi-class potato disease classification. These findings are closely aligned with previous comparative studies that reported the superiority of transfer learning models over conventional CNN architectures for plant disease recognition [4], [7], [8].

One of the most significant contributions of this research is the integration of Explainable Artificial Intelligence (XAI) through Grad-CAM visualization. While many existing deep learning models achieve excellent predictive accuracy, they frequently operate as black-box systems that provide little insight into how predictions are generated. This lack of interpretability remains a major barrier to the adoption of artificial intelligence within agriculture, particularly among farmers who require understandable and trustworthy decision-support systems. The Grad-CAM visualizations generated by the proposed framework clearly highlighted lesion regions, discoloration patterns, and disease-affected tissues that contributed most strongly to model predictions. Importantly, the model focused primarily on biologically meaningful disease symptoms rather than irrelevant background objects, indicating that the learned representations correspond to genuine pathological characteristics rather than spurious image correlations. Such visual explanations substantially improve transparency and strengthen user confidence in AI-assisted agricultural diagnosis [14].

The confusion matrix analysis further demonstrates the robustness of the proposed framework. Most potato leaf images were correctly assigned to their corresponding disease categories, while the relatively small number of misclassifications primarily occurred between visually similar disease classes during early infection stages. Such errors are understandable because initial disease symptoms often exhibit overlapping visual characteristics that are difficult to distinguish even for experienced agricultural specialists. Environmental variability-including changing illumination, partial leaf occlusion, background clutter, and image noise-may also contribute to classification ambiguity. Nevertheless, the overall confusion matrix indicates excellent class discrimination, suggesting that the selected deep learning architecture effectively learned generalized disease-specific visual features that remain reliable across diverse farming environments.

An important practical implication of this research lies in its use of real-world field images rather than relying exclusively on highly controlled datasets such as PlantVillage. Many previous studies have reported excellent classification performance under laboratory conditions; however, model accuracy frequently declines when deployed in practical agricultural settings because of environmental variability [4], [9], [17]. By incorporating images collected under realistic farming conditions in Bangladesh, the proposed framework improves ecological validity and increases confidence that similar performance can be achieved during practical implementation. This characteristic substantially enhances the framework's potential for deployment through mobile applications, agricultural advisory systems, and precision farming platforms that support farmers during routine crop monitoring.

The study also has important implications for sustainable agriculture and environmental management. Early and accurate disease detection enables farmers to implement timely interventions before infections spread extensively throughout the crop. Such early diagnosis can significantly reduce yield losses while minimizing unnecessary pesticide application, thereby lowering production costs and reducing environmental pollution associated with excessive chemical use. Furthermore, explainable disease diagnosis provides agricultural extension officers and policymakers with transparent decision-support tools that facilitate more effective disease surveillance and crop management strategies. Consequently, the proposed framework contributes not only to technological advancement but also to broader objectives of sustainable agricultural production and food security in Bangladesh.

Despite these promising findings, several limitations should be acknowledged. First, although the dataset consists of real-world field images, it remains geographically concentrated within Bangladesh. Additional validation using images collected across different climatic regions, cultivation practices, and potato varieties would further strengthen the model's generalizability. Second, the framework primarily focuses on image-based disease recognition and does not incorporate complementary environmental variables such as temperature, humidity, rainfall, or soil conditions, which may improve predictive performance. Third, the present investigation evaluates static image classification rather than continuous disease progression over time. Incorporating temporal image sequences may facilitate earlier disease identification before visible symptoms become severe. Finally, although Grad-CAM provides intuitive visual explanations, combining multiple explainability techniques such as SHAP, Integrated Gradients, or LIME may provide even deeper insights into model behavior and further enhance interpretability [14].

Future research should therefore emphasize larger multi-country datasets, multimodal learning approaches integrating environmental sensor information, and lightweight deployment on smartphones, unmanned aerial vehicles (UAVs), and Internet of Things (IoT)-enabled agricultural monitoring systems. Federated learning may further improve privacy-preserving collaborative model development across geographically distributed farms [6], while continual learning approaches could enable AI systems to adapt automatically to emerging disease patterns and changing environmental conditions. Furthermore, integrating automated treatment recommendations alongside explainable disease diagnosis would transform the proposed framework into a comprehensive intelligent agricultural decision-support system capable of assisting farmers throughout the entire crop management process.

Overall, the findings demonstrate that combining transfer learning with Explainable Artificial Intelligence produces an accurate, transparent, and practically deployable solution for potato leaf disease detection. The superior performance of EfficientNetB0, together with biologically meaningful Grad-CAM visualizations, confirms that explainable deep learning can simultaneously achieve high predictive accuracy and interpretability. These characteristics are essential for increasing user trust, facilitating technology adoption, and supporting sustainable smart agriculture. Consequently, the proposed framework represents a significant contribution toward practical AI-enabled crop disease management and establishes a strong foundation for future explainable agricultural intelligence systems.

7. Conclusion

This study presented an explainable deep learning framework for multi-class potato leaf disease detection using real-world field images collected from agricultural environments in Bangladesh. The proposed framework integrates deep learning, transfer learning, computer vision, and Explainable Artificial Intelligence (XAI) to develop an accurate, transparent, and practical disease diagnosis system suitable for smart agriculture. Unlike many previous approaches that rely primarily on laboratory-based datasets, this research emphasizes field-collected images captured under diverse environmental conditions, making the proposed system more representative of real farming environments. The integration of Grad-CAM further enhances model interpretability by visually identifying disease-affected regions, thereby increasing user confidence and supporting informed agricultural decision-making.

The experimental evaluation demonstrated that all investigated deep learning architectures achieved strong classification performance; however, EfficientNetB0 consistently outperformed the Custom CNN, ResNet50, and MobileNetV2 models across all evaluation metrics. Specifically, EfficientNetB0 achieved a classification accuracy of **99.37%** while maintaining excellent precision, recall, and F1-score, indicating its superior capability for extracting disease-related visual features from complex field images. Furthermore, the confusion matrix analysis confirmed high classification consistency, with only limited misclassification among visually similar disease categories. The Grad-CAM visualizations revealed that the model focused primarily on biologically meaningful lesion areas rather than background artifacts, demonstrating that the explainability component successfully enhanced the transparency and reliability of AI predictions. These findings collectively indicate that combining transfer learning with explainable AI can simultaneously improve predictive performance and model trustworthiness for practical agricultural applications.

Beyond its technical contributions, the proposed framework offers important practical benefits for sustainable agriculture. Early and accurate disease diagnosis enables farmers to implement timely interventions, reduce crop losses, minimize unnecessary pesticide application, and lower production costs. The explainable nature of the system also facilitates greater acceptance among farmers, agricultural extension officers, and policymakers by providing understandable visual evidence supporting each prediction. Consequently, the framework has strong potential to serve as an intelligent decision-support system for precision agriculture and smart farming initiatives in Bangladesh.

Despite these promising outcomes, additional research is required to improve the framework's scalability and generalizability. Future studies should validate the proposed approach using larger and more geographically diverse datasets, incorporate additional potato diseases and environmental variables, and investigate multimodal learning techniques that combine image data with sensor-based information. Further research may also explore lightweight deployment through smartphones, Internet of Things (IoT) devices, unmanned aerial vehicles (UAVs), and cloud-based agricultural platforms, while integrating additional explainability methods beyond Grad-CAM. Such developments would further enhance the practical applicability of explainable artificial intelligence for intelligent crop monitoring and sustainable agricultural management.

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