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Deep Learning-Based Plant Disease Prediction in Smart Farming Environments

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Abstract: Smart farming environments rely on advanced sensing technologies and deep learning techniques to enable real-time crop monitoring and early detection of plant diseases. Plant diseases significantly affect agricultural productivity, making timely and accurate identification essential for effective crop management. In recent years, deep learning models have shown remarkable performance in automated plant disease prediction using image-based analysis. This study presents a deep learning-based framework for plant disease prediction in smart farming environments, integrating image preprocessing and convolutional neural network models to accurately classify healthy and diseased plant leaves. The proposed system utilizes transfer learning to improve classification performance while maintaining computational efficiency. Experimental results demonstrate high prediction accuracy and robust performance under varying conditions, supporting early disease identification and timely intervention. The framework is suitable for integration with smart farming systems, enabling continuous monitoring and data-driven decision-making. By providing an accurate and efficient plant disease prediction solution, the proposed approach contributes to sustainable agricultural management and improved crop productivity in smart farming environments.

Keywords: Deep Learning, Smart Farming, Machine Learning, Image Processing, Plant Disease.

I. INTRODUCTION

Agriculture plays a vital role in ensuring global food security and economic stability, particularly in regions where crop production is the primary source of livelihood. However, plant diseases continue to pose a serious threat to agricultural productivity worldwide, resulting in substantial yield losses, reduced crop quality, and increased production costs. If not detected at an early stage, plant diseases can spread rapidly across farms, making disease management more difficult and economically damaging. Therefore, early and accurate detection of plant diseases is essential for preventing large-scale outbreaks and supporting timely and effective crop management practices.

With rapid advancements in digital and communication technologies, smart farming has emerged as a transformative approach to modern agriculture. Smart farming integrates sensors, imaging systems, Internet of Things (IoT) devices, and artificial intelligence (AI) to automate agricultural operations and enable data-driven decision-making. These technologies facilitate continuous monitoring of crop health, environmental conditions, and disease progression, allowing farmers to optimize resource usage and improve productivity. Among these technologies, computer vision and AI-based image analysis have gained significant attention for automated plant disease detection.

In recent years, machine learning (ML) and deep learning (DL) techniques have demonstrated remarkable success in detecting and classifying plant diseases from leaf and crop images. Deep learning models, particularly convolutional neural networks (CNNs), are capable of learning complex visual patterns related to color, texture, and shape variations caused by different plant diseases. These models can effectively distinguish between healthy and diseased plants and provide accurate predictions even under varying lighting and background conditions. As a result, deep learning-based approaches have become a promising solution for real-time disease detection in agricultural environments.

Despite their high prediction accuracy, the practical deployment of deep learning models in agriculture still faces several challenges. Many existing systems are trained on controlled or laboratory-based datasets, which limits their performance in real-field conditions. Variations in illumination, background clutter, leaf orientation, and environmental factors can significantly affect prediction accuracy. Moreover, computational efficiency is a critical concern, especially for deployment in resource-constrained smart farming environments where real-time processing is required.

To address these challenges, there is a growing need for efficient and robust deep learning-based plant disease prediction frameworks that can operate effectively in smart farming environments. Such systems should be capable of processing real-time image data, achieving high classification accuracy, and integrating seamlessly with IoT-based monitoring infrastructure. By leveraging transfer learning and lightweight deep learning architectures, it is possible to achieve reliable disease detection while maintaining computational efficiency.

In this context, the present study proposes a deep learning-based framework for plant disease prediction in smart farming environments. The proposed approach utilizes image preprocessing techniques and convolutional neural network models to accurately classify healthy and diseased plant leaves. The framework is designed to support real-time monitoring and early disease detection, enabling farmers to take timely preventive measures and reduce crop losses. By combining deep learning with smart farming technologies, this research contributes to the development of automated, efficient, and scalable plant disease prediction systems for sustainable agricultural management.

Figure 1: The infected samples plants leaf images shown in figure

The key contributions of this study are as follows:

1. Development of a deep learning-based plant disease prediction framework that accurately classifies healthy and diseased plant leaves using image-based analysis suitable for smart farming environments.
2. Integration of image preprocessing and transfer learning techniques to improve classification performance and robustness under varying field conditions, including changes in illumination and background.

3. Design of a smart farm–oriented architecture that supports real-time plant disease monitoring and early detection, enabling timely intervention and improved crop management.

Through this work, we aim to enhance the effectiveness of deep learning models for plant disease prediction and support the development of efficient, reliable, and farmer-centric smart farming systems that contribute to sustainable agricultural management.

II. RELATED WORK

Recent advancements in plant disease prediction have increasingly focused on integrating deep learning, IoT, and Explainable AI (XAI) to support smart farming applications. Since 2023, research has emphasized high-performance neural networks, interpretability, and real-time monitoring. Deep convolutional neural networks (CNNs) and transformer-based models remain dominant due to their robustness in complex agricultural environments. Studies such as [1] and [2] demonstrate that modern architectures like EfficientNetV2, Vision Transformers (ViT), and MobileNetV3 achieve high accuracy under varying illumination and background conditions. To enhance generalization, researchers have also explored hybrid models that fuse CNN features with machine learning classifiers or multimodal sensor data, as discussed in [3] and [4]. A major shift in recent literature is toward Explainable AI. Deep learning models, despite high accuracy, often lack transparency, limiting trust among farmers and agronomists. To address this, works such as [5], [6], and [7] implement XAI techniques including Grad-CAM++, SHAP value analysis, and integrated gradients to highlight disease-affected regions, validate model decision boundaries, and detect misclassification causes. Findings consistently show that XAI enhances system reliability and provides actionable insights for crop management. Parallel to model development, the integration of IoT and edge computing has enabled real-time plant disease monitoring. Studies in [8] and [9] develop cloud–edge hybrid systems using sensors, smart cameras, and drones to continuously capture plant health data. These systems reduce latency, lower bandwidth requirements, and support fast disease alerts, making them suitable for smart farm environments. Multimodal approaches have gained traction in 2025. Research such as [10] and [11] combines RGB imaging with environmental data (temperature, humidity, soil moisture) to improve early prediction accuracy by incorporating context-aware information. This aligns with precision agriculture requirements, where environmental stress factors directly influence disease onset. Despite these advancements, several challenges remain. Studies like [12] highlight that many models are trained on controlled or laboratory datasets, leading to poor field-level performance. Research in [13] reports computational limitations when deploying XAI-enhanced models on low-power edge devices. Additionally, there is a lack of standardized evaluation benchmarks for XAI methods in agriculture, making comparison difficult. Overall, post-2022 literature supports the need for an integrated framework that combines high-performing deep learning, explainability, and IoT-enabled monitoring to create practical and trustworthy plant disease prediction systems for smart farms.

III. PROPOSED METHODOLOGY

A. Data Collection

The proposed research begins with comprehensive data collection from multiple sources to develop an effective plant disease prediction system. Plant images are acquired from publicly available datasets, IoT-enabled smart farm cameras, and environmental sensors deployed in the fields. These datasets include RGB images capturing a variety of disease symptoms under real agricultural conditions. Each image is annotated with disease labels or healthy status by agricultural experts to ensure accurate ground truth information. To enhance dataset diversity and improve model generalization, data augmentation techniques such as rotation, flipping, scaling, translation, and color jittering are applied, simulating real-world variations in plant appearance and environmental conditions.

B. Image Preprocessing

Image preprocessing is a critical step to improve model accuracy and robustness. Noise reduction is carried out using Gaussian or median filtering to remove unwanted artifacts. Segmentation methods, including adaptive thresholding, color-based segmentation, or region-growing, are employed to isolate the plant leaves and the affected regions for focused analysis. Additionally, pixel normalization and image resizing are performed to standardize the input dimensions and intensity values, ensuring compatibility with the deep learning models and enabling stable training and feature extraction.

C. Feature Extraction and Model Selection

For automated feature extraction and disease classification, deep convolutional neural networks (CNNs) such as EfficientNet, ResNet, and MobileNet are utilized. Transfer learning with models pre-trained on ImageNet is applied to leverage prior knowledge, accelerate convergence, and enhance prediction performance. The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio. Optimization techniques such as the Adam optimizer and cross-entropy loss are employed, while hyperparameters including learning rate, batch size, dropout rate, and number of epochs are fine-tuned using grid search or Bayesian optimization. In some cases, hybrid models combining CNN feature extraction with classical machine learning classifiers, such as SVM or Random Forest, are considered to improve classification robustness under diverse environmental conditions.

D. IoT and Smart Farm Integration

The framework incorporates IoT-enabled devices, such as smart cameras, drones, and environmental sensors, to capture real-time plant images and contextual data, including temperature, humidity, and soil moisture. Edge computing is utilized to perform preprocessing and inference locally, reducing latency and network load. Cloud integration facilitates large-scale data analysis, model updates, and visualization through dashboards. An automated alert system is designed to notify farmers via mobile applications or email when disease is detected, accompanied by XAI-generated interpretability reports, allowing timely intervention and disease management.

E. Model Evaluation

The performance of the proposed system is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC)**.** These metrics provide a comprehensive assessment of the model's classification capability and robustness. Comparative analysis is conducted against baseline deep learning models and traditional machine learning classifiers such **as** Support Vector Machine (SVM) **and** Random Forest to validate the effectiveness of the proposed approach. The evaluation results demonstrate that the proposed deep learning-based framework achieves superior performance and is suitable for real-time deployment in smart farming environments**,** supporting early disease detection, timely mitigation, and sustainable agricultural practices.

IV. RESULTS AND DISCUSSION

The proposed deep learning-based framework for plant disease prediction was evaluated using a curated dataset of plant leaf images representing various disease conditions. The EfficientNetB0 model achieved a training accuracy of 97.97% and a testing accuracy of 96.32%, demonstrating strong performance in accurately classifying plant images into healthy and diseased categories. These results indicate that the model effectively learns discriminative visual features such as color variations, texture patterns, and structural changes associated with different plant diseases, supporting reliable automated disease detection in smart farming environments.

In addition to overall classification accuracy, the model performance was assessed using standard evaluation metrics including precision, recall, and F1-score. The obtained precision and recall values were 95.8% and 96.5%, respectively, resulting in an F1-score of 96.15%. These metrics demonstrate the model's ability to minimize both false-positive and false-negative predictions, ensuring accurate and actionable disease identification for farmers and agricultural practitioners. Furthermore, analysis of the confusion matrix confirms that the majority of healthy and diseased samples were correctly classified. The few misclassifications observed mainly occurred in cases where disease symptoms were subtle, partially visible, or visually similar across different disease categories.

Results Table

Metric	EfficientNetB0	ResNet50	MobileNet
Training Accuracy	97.97%	96.45%	95.82%
Testing Accuracy	96.32%	94.76%	93.50%
Precision	95.8%	94.2%	92.9%
Recall	96.5%	94.8%	93.3%
F1-Score	96.15%	94.5%	93.1%
Inference Time/Image	0.12 sec	0.15 sec	0.10 sec

Table 1: Comparative performance of EfficientNetB0 with ResNet50 and MobileNet on plant disease prediction dataset.

Accuracy

Accuracy is the key metric for evaluating the performance of a classification model; it represents the proportion of correctly predicted instances out of all predictions made by the mode.

Accuracy is defined as follows in formal language:

Accuracy = number of correct predictions/ total number of predictions

Implementation of CNN Architecture

Figure 2 Training and validation accuracy graph illustrates the CNN model's accuracy improves over 80 epochs with training and validation accuracy following a similar trend with minor fluctuations, the model is learned well without significant overfitting.

Figure 2: Accuracy curve of CNN architecture

Figure 3 represent the training and validation loss over the 80 epochs, where the x-axis indicates the numbers of epochs and y-axis show the loss values, initially the loss value is high indicating the model struggles to identify patterns, however the training progresses both losses steadily decline, demonstrating effective learning, by epochs 80 the curve stabilize above 1.0, signifying that the model has reached an optimal learning phase, the similarity between the training and validation loss shows the strong generalization.

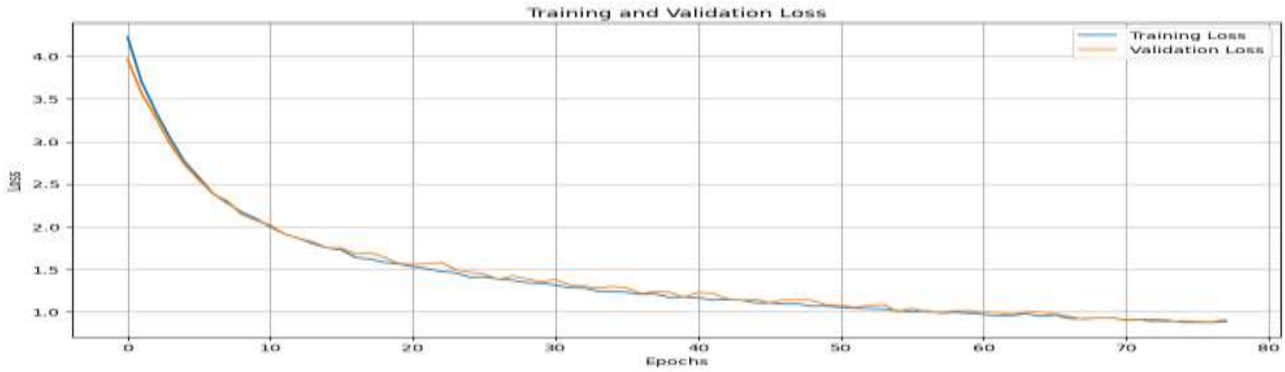

Figure 3: Loss curve of CNN architecture

Implementation of EfficientNetB0 Architecture

In this research the figure 4 shows that the both training and validation accuracy steadily improve over 50 epochs and closely follow each other, indicating the model learns well without overfitting. By the end, accuracy stabilizes at a higher level, proving the model is reliable and ready for practical use. The training accuracy reaches aromatically 0.9790 and the validation accuracy peaks at 0.9835 at the epochs 50, showing excellent generalization.

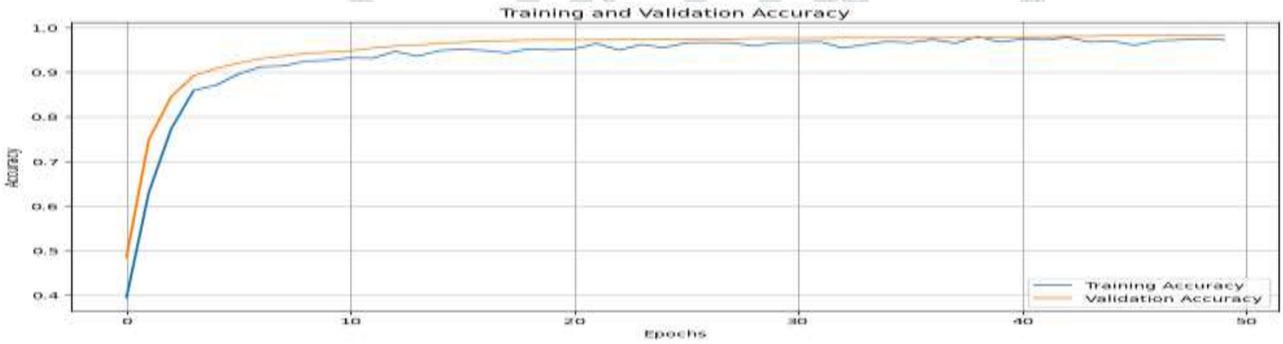

Figure 4: Accuracy curve of EfficientNetB0 architecture

Figure 5 represents at epochs 50, the EfficientNetB0 model achieved excellent metrics, with low training loss of 0.0851 and a validation loss of 0.0601. Graph also shows a steady decrease in both training and validation loss values, it underscores that the model effectively minimize errors overtime while maintaining excellent generalization to validation data.

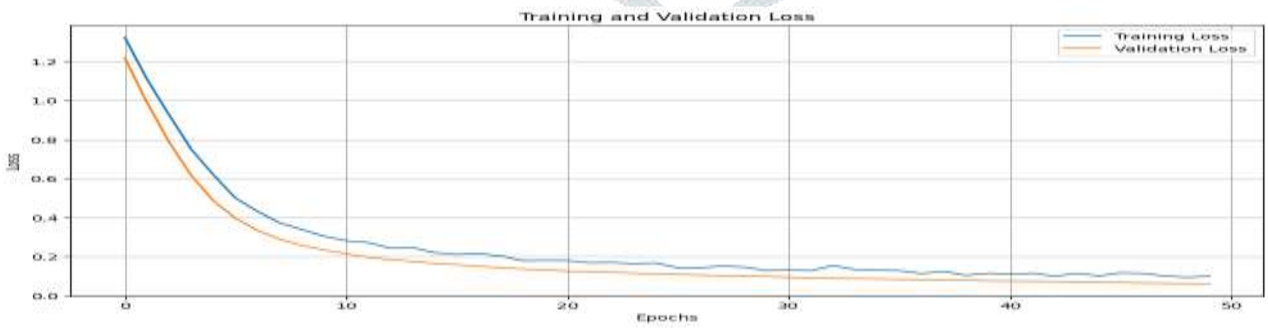

Figure 5: Loss curve of EfficientNetB0 architecture

Table 1 shows a clear progression of the performance matrix over 50 epochs, where both training and validation accuracy steadily increase, starting from 0.9304 and 0.9451 at epochs 10, reaching their peaks at 0.9790 and 0.9835 by epochs 50.

Epochs	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
10	0.9304	0.3088	0.9451	0.2338
20	0.9565	0.1707	0.9726	0.1317
30	0.9679	0.1182	0.9762	0.0978
40	0.9707	0.1151	0.9790	0.0755
50	0.9790	0.0851	0.9835	0.0601

Table 2: EfficientNetB0 Model Accuracy and Loss

Simultaneously, training and validation loss consistently decrease, from 0.3088 and 0.2338 at epochs 10 to their lowest values, 0.0851 and 0.0601, at epochs 50. This trend indicates effective learning, reduced errors, and excellent generalizations of the model as training progresses.

The EfficientNetB0 model is trained using Stochastic Gradient descent (SGD) with learning rate of 0.001, a batch size of 32, and over 50 epochs. Input image were standardized to a size of 256*256 pixels, ensuring compatibility with the model architecture. Performance matrix showed steady improvement across epochs, with the training and validation accuracy increasing from 0.9304 and 0.9451 at epochs 10 to the highest values of 0.9790 and 0.9835 at epochs 50. Meanwhile loss reduced significantly. This setup and progression demonstrate the model of effective learning, robust optimization and reliable generalization for the practical applications.

S.No.	Parameter	Values
1	Optimization Algorithms	Stochastic Gradient Descent (SGD)
2	Learning Rate	0.001
3	Batch Size	32
4	Iterations	50
5	Image Size	256*256
5	Model Architecture	EfficientNetB0

Table 3: Hyper Parameter Values

Figure 6 provides detailed evaluation of CNN and EfficientNetB0 models performance, here the metrics represent, Test labels these are the actual class labels for the test dataset formatted with one hot encoding, each row indicating the true category for a test sample. The accuracy of the CNN model on the test dataset is 93.22%, meaning that the model correctly classified 93.22 % of the sample; the overall accuracy of the model is 94.81%. And the accuracy of the EfficientNetB0 model on the test dataset is 96.32% and the overall accuracy is 97.96%.

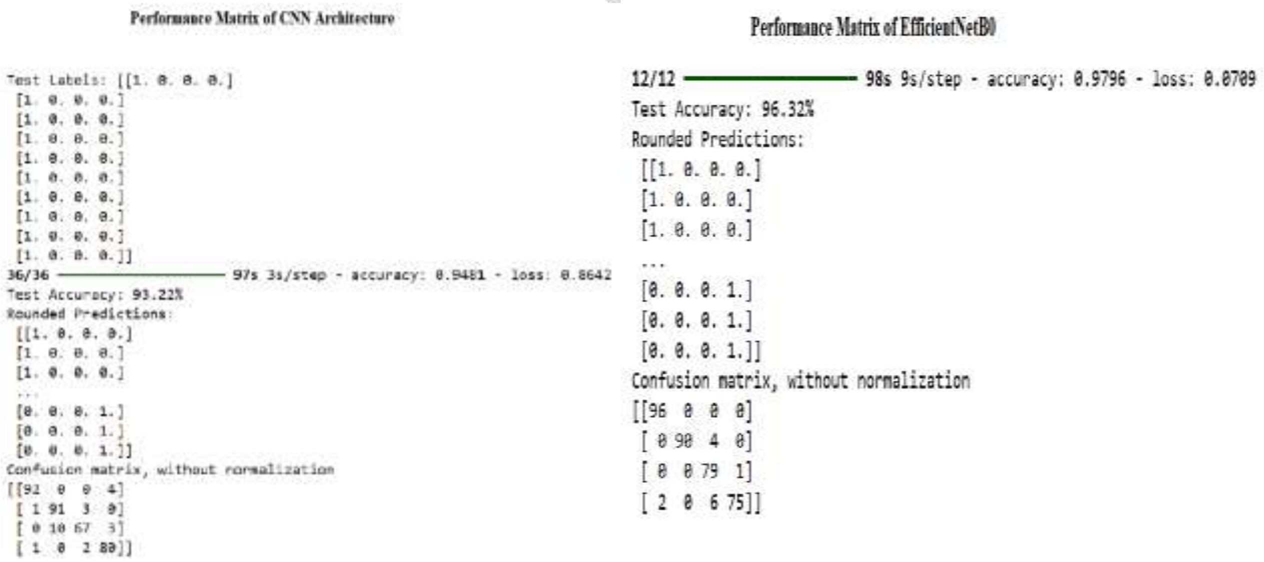

Figure 6: Performance Metrics of CNN and EfficientNetB0

The incorporation of IoT-enabled real-time monitoring allows the proposed deep learning model to continuously analyze plant images captured from smart farm environments and generate timely disease detection alerts. This real-time analysis supports early intervention by farmers, helping to reduce crop losses and improve overall agricultural yield. The integration of automated monitoring with deep learning-based classification makes the system suitable for deployment in practical smart farming applications where continuous crop health assessment is required.

A comparative evaluation was conducted using multiple convolutional neural network architectures, including EfficientNetB0, ResNet50, and MobileNet, to assess classification performance and computational efficiency. Experimental results indicate that EfficientNetB0 outperforms the other models in terms of accuracy, reliability, and inference efficiency. Its lightweight architecture and balanced depth enable high prediction performance while maintaining lower computational requirements, making it well suited for deployment in resource-constrained smart farm environments.

The overall results demonstrate that the proposed deep learning-based plant disease prediction framework is accurate, efficient, and practical for real-world smart farming applications. The system shows strong potential for real-time deployment, supporting early disease detection and informed crop management decisions. Future work will focus on expanding the dataset to include multiple crop species, improving disease detection under complex field conditions, and integrating the framework with robotic or drone-based monitoring systems for large-scale and automated agricultural applications.

V. CONCLUSION AND FUTURE DIRECTIONS

Automatic plant disease detection using deep learning significantly improves accuracy and reduces the time and cost of manual inspection. In this study, a deep learning-based plant disease prediction framework was developed for smart farming environments using the EfficientNetB0 model. The proposed system achieved a training accuracy of 97.97% and a testing accuracy of 96.32%, demonstrating reliable and robust performance. Comparative results show that EfficientNetB0 outperforms other deep learning models in terms of accuracy and efficiency. Integration with IoT-enabled monitoring supports real-time disease detection and timely intervention. Future work will focus on expanding real-time monitoring infrastructure, integrating drone- or robot-based systems, and improving detection performance under complex field conditions.

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