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RESEARCH ARTICLE

Improving Plant Disease Classification With Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence

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ABSTRACT Plant diseases can have profound effects on the economy, impacting both local and global scales. These diseases can lead to substantial losses in agricultural productivity, affecting crop yields and quality. In this context, deep learning algorithms are widely acknowledged as effective solutions. However, the use of these black-box approaches raises concerns about trust in interpreting and validating the decisions generated by the models. This study proposes an explainable artificial intelligence (XAI) based plant disease classification system to classify and identify distinct ailments with improved accuracy. The system correctly identifies 38 different plant diseases with accuracy, precision, and recall as 99.69%, 98.27%, and 98.26%, respectively. These predictions are subjected to additional analysis employing the local interpretable model-agnostic explanations (LIME) framework to produce visual explanations aligning with prior beliefs and adhering to established best practices in explanations. This system will serve as a promising avenue for revolutionizing disease detection, fostering informed decision-making, and ultimately contributing to global food security.

INDEX TERMS Plant disease detection, deep learning, explainable artificial intelligence, prediction model.

I. INTRODUCTION

With the increasing global population and changing climatic conditions, the challenges faced by farmers have been intensified. One of the critical challenges worldwide is the identification and management of plant diseases [1]. These diseases, if undetected, can lead to substantial reductions in crop yield and quality, posing severe economic losses and threatening food security on a larger scale [2]. The traditional methods of disease diagnosis often involve manual inspection by experts, which is both time-consuming and subjective [1]. Moreover, by the time symptoms are visible to the naked eye, the disease might have already spread extensively, making mitigation efforts less effective.

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In recent years, agriculture has witnessed a significant transformation driven by technological advancements [3], offering solutions that can revolutionize traditional farming practices. Furthermore, as the global population continues to rise, leveraging technology in agriculture is not just an innovative approach but a necessary one to ensure a sustainable and secure food supply for the future. Image recognition using machine learning (ML), has shown promise in detecting plant diseases at early stages, providing an opportunity to curb their spread and minimize damage [4]. This early assessment also depends on the plant species and the diseases. It varies from disease to disease, some disease takes around 1 week whereas some takes 2 or more weeks.

Numerous computer-aided diagnosis (CAD) systems [5] have been created to aid farmers. These systems effectively tackle prevailing challenges and improve the accuracy, efficiency, and objectivity of the diagnostic process. In this regard, deep learning (DL) algorithms have emerged as particularly promising, demonstrating significant potential for image processing and data analysis. The integration of deep learning techniques, particularly convolutional neural networks (CNNs), holds promise for accurate and efficient disease identification in plants [5].

Nevertheless, the ambiguity surrounding the processing cycle involved in model learning and feature encoding in these CAD systems raises doubts about their reliability [6]. The DL model without a rational explanation is a barrier in accurate decision making. Hence, these models are of black-box nature which makes them not to use with 100% confidence. Therefore, there is a need to develop robust methods that can help better understand the decisions made by the black box. These methods are often known as interpretable deep learning or XAI [6]. The incorporation of XAI ensures transparency and interpretability in the decision-making process, addressing the crucial need for trust and understanding in agricultural practices.

In this study, the state-of-the-art model, namely, EfficientNetB0 [7] is applied for classifying 38 plant diseases. The explanation method employed is LIME, incorporating enhanced explanations to improve both interpretability and accuracy. The EfficientNetB0 with 237 layers is utilized for feature extraction and model training. The model loads pre-trained weights from a local file to enhance efficiency and accuracy. At first, EfficientNetB0 predicts the disease or no disease; after that LIME is applied to generate explanations for the predictions of the classifier. LIME typically provides feature importance scores, highlighting the regions or aspects of the input that influenced the model's decision. The significance of this study lies in its potential to empower farmers with a robust tool that not only identifies plant diseases but also provides insights into the underlying factors contributing to the classification decisions. The combination of deep learning and explainability enhances the system's reliability and enables farmers to make informed decisions regarding disease management strategies. In summary, we introduce a robust model that exhibits improved accuracy, achieved through the integration of XAI techniques for plant disease detection. The main contributions of this study include:

- i) **New System Design:** A novel system is designed using DL and XAI for accurate and quick diagnosis of 38 distinct plant diseases with improved accuracy. The system also provides farmers with actionable insights including treatment suggestions
- ii) **Comparative Study of State-of-the-art Algorithms:** Various cutting-edge ML algorithms are compared for the diagnosis of plant diseases.
- iii) **Mobile Application Development:** A user-friendly mobile application named as 'PlantCare' is also developed for farmers assistance.
- iv) **Data Set:** The proposed approach is tested on both real-world and benchmark data instances from Kaggle.

The paper is organised into 6 section. Section II overviews the background and related works. The proposed approach is in Section III followed by experimental design and results in section IV. Section V presents the limitations of this work. This study concludes in section VI with future directions.

II. LITERATURE REVIEW

A. BACKGROUND

Machine learning for plant disease detection has emerged as a transformative technology in agriculture, offering efficient and accurate solutions to identify and combat crop diseases [4]. By leveraging advanced algorithms, ML models can analyze datasets to detect subtle signs of diseases that may go unnoticed by the human eye [8]. In this context, we assess the effectiveness of cutting-edge algorithms for diagnosing plant diseases. The rationale behind choosing these algorithms is their simplicity in implementation, coupled with the fact that a majority of them are open source.

The convolutional neural networks (CNNs) [9] are a class of deep neural networks designed specifically for image recognition and processing tasks. Inspired by the visual processing in the human brain, CNNs excel in capturing hierarchical features and patterns within images. A basic CNN model consists of an input layer, multiple convolutional layers followed by pooling layers, and fully connected (dense) layers leading to the output layer. The convolutional layers apply filters to the input to extract features, while the pooling layers downsample the spatial dimensions, leading to more efficient processing. The dense layers then perform classification based on the extracted features [10]. CNNs have proven highly effective in computer vision applications, such as image classification, object detection, and facial recognition.

Residual network (ResNet) [11] is one of the most powerful deep neural networks, demonstrating outstanding performance in addressing classification problems. Built upon CNN architecture, ResNet is designed to accommodate hundreds or even thousands of convolutional layers.

EfficientNetB0 [7] is a state-of-the-art CNN architecture designed to achieve impressive performance with high efficiency in terms of both computational resources and model size. This architecture is particularly notable for its ability to outperform larger and computationally expensive models on various computer vision tasks, including image classification [7].

MobileNet [12] is a lightweight CNN architecture designed specifically for efficient and high-performance image classification on mobile and embedded devices. MobileNet focuses on achieving a balance between accuracy and computational efficiency, making it well-suited for applications with limited computational resources [12].

LIME [13] is a method used in the field of ML for explaining the predictions of complex models in a human-understandable way. The LIME is designed to provide insights into the decision-making process of black-box machine learning models by approximating their behavior locally. It focuses on local interpretability, aiming to explain individual predictions rather than the entire model [13]. This makes it particularly useful for understanding specific instances where model predictions may be unclear. The explanations are generated by perturbing input data and observing the model's response.

B. RELATED WORKS

Plant disease detection plays a crucial role in agriculture productivity with significant impact on the economy [28]. Timely identification and management of plant diseases helps in preventing crop losses, ensuring a stable food supply and supporting the livelihoods of farmers [22]. This section presents an overview of recent ML model-based approaches for plant disease detection.

Ferentinos et al. [4] presented the development of CNN models with variants (AlexNet, AlexNetOWTBn, GoogleNet, Overfeat, VGG) for plant disease detection and diagnosis using images of simple leaves from healthy and diseased plants. The models were trained on an extensive database of 87,848 images, encompassing 25 plant species in 58 unique [plant, disease] combinations. The best-performing model achieved an impressive 99.53% success rate in accurately identifying the [plant, disease] combination or healthy plants.

Mehedi et al. [14] developed a transfer learning approach with three pre-trained models (EfficientNetV2L, MobileNetV2, ResNet152V2). The study detected 38 leaf diseases across 14 different plants. The dataset was taken from Kaggle [15]. EfficientNetV2L demonstrated the highest accuracy at 99.63%. The integration of XAI through LIME enhances model interpretability.

Mohanty et al. [16] utilized a public dataset [17] containing 54,306 images of diseased and healthy plant leaves, deep CNNs (AlexNet and GoogLeNet) were trained to identify 14 crop species and 26 diseases with an impressive accuracy of 99.35% on a held-out test set.

Jasim et al. [18] explored the application of DL models in the early detection and classification of plant diseases, highlighting the potential for increased accuracy compared to traditional ML approaches. The Plant Village [17] dataset was used with 20,636 images as three plants, namely, tomato, pepper, and potato crops were chosen because of the most famous types of plants. The CNN classifier achieved 98.029% accuracy, with the potential for further improvement with a larger training dataset.

Ramesh et al. [19] employed Random Forest for classifying healthy and diseased leaves based on leaf images. The proposed methodology involved dataset creation, feature extraction using Histogram of an Oriented Gradient (HOG), classifier training, and classification. In testing with 160 papaya leaf images, the Random Forest classifier achieved approximately 70% accuracy.

Harakannanavar et al. [20] focused on addressing plant diseases in tomato crops. Employing machine learning and image processing, the study introducesd a robust algorithm for early detection of leaf diseases. The proposed model employs Support Vector Machine (SVM) [29], K-Nearest Neighbor (K-NN) [30], and CNN for classification, achieving high accuracy rates of 88%, 97%, and 99.6% respectively. Benito Fernández et al. [21] used CNN model leveraging XAI methods, specifically LIME [13], SHAP [31], and Grad-CAM [32], to enhance the interpretability of CNN outputs.

Kinger et al. [22] addressed the challenge of making deep learning models for plant disease detection more interpretable for human users. The VGG16 was employed with achieved accuracy rate of 98.15%. They used XAI method Grad-CAM, to provide human-understandable explanations for the model's decisions.

Nahiduzzaman et al. [23] introduced an XAI-based CNN model for classifying mulberry leaf diseases. They utilized a novel lightweight CNN model and achieved impressive accuracy of 95.05 ± 2.86% for three-class classifications and 96.06 ± 3.01% for binary classifications. The model outperformed well-known deep transfer learning models, offering better accuracy, fewer parameters, layers, and overall size. The interpretability of the model was ensured through SHAP explanations.

Arsenovic et al. [1] addressed the significant agricultural challenge of plant diseases by leveraging DL methods for accurate detection. They introduced a novel dataset comprising 79,265 diverse leaf images, employing both traditional augmentation and state-of-the-art generative adversarial networks for dataset expansion. Experimental evaluations demonstrate the model's effectiveness in identifying plant diseases under various conditions, achieving an accuracy of 93.67%.

Khattak et al. [24], addressed the crucial issue of less citrus fruit yield due to diseases, by proposing an integrated approach using CNN. The CNN model is designed to differentiate healthy citrus fruits and leaves from those affected with common diseases and achieved a remarkable test accuracy of 94.55%. The proposed model outperformed other classifiers, achieving a high accuracy of 95.65% in classifying citrus fruit/leaf diseases, establishing its potential as a valuable decision support tool for farmers.

Singh et al. [26] addressed the significant issue of plant disease-related crop yield loss in India by proposing a novel solution using computer vision. The authors introduced a comprehensive dataset comprising 2,598 data points across 13 plant species and up to 17 disease classes, annotated with approximately 300 human hours of effort. This study demonstrates the efficacy of the dataset by training three models for plant disease classification, revealing a notable increase of up to 31% in classification accuracy compared to existing datasets.

Besides these, some studies [2], [3], [5], [28], [33] review the application of DL models in visualizing and detecting plant diseases. Various DL architectures and visualization

TABLE 1. Research matrix of related works.

Study	Dataset(s)	Methodology	Results	XAI Method	Mobile App	Classes	Species	Instances
Ferentinos et al. [4]	Open Database	CNN and Variants	accuracy: 99.53%	No	No	58	25	87,848
Mehedi et al. [14]	Kaggle [15]	EfficientNetV2L, MobileNetV2, ResNet152V2	accuracy: 99.63%	Lime	No	38	14	54,305
Mohanty et al. [16]	PlantVillage [17]	AlexNet and GoogLeNet	accuracy: 99.35%	No	No	26	14	54,306
Jasim et al. [18]	PlantVillage [17]	CNN	accuracy: 98.029%	No	Yes	15	3	20,636
Ramesh et al. [19]	Random	Random Forest	accuracy: 70%	No	No	2	1	170
Harakannanavar et al. [20]	PlantVillage [17]	SVN, K-NN, CNN	accuracy: 99.6%	No	No	2	1	-
Fernandez et al. [21]	PlantVillage [17]	CNN	Lime is better	LIME, SHAP, Grad-CAM	No	15	-	20,639
Kinger et al. [22]	PlantVillage [17]	VGG16	98.15%	Grad-CAM	No	38	14	>70,000
Nahiduzzaman et al. [23]	Real	Proposed CNN	accuracy: 95.05 ± 2.86%	SHAP	No	3	1	6,327
Arsenovic et al. [1]	PlantVillage [17]	Proposed: PlantDiseaseNet	accuracy: 93.67%	No	No	42	12	79,265
Khattak et al. [24]	Citrus [26], PlantVillage [17]	Proposed CNN	accuracy: 94.55 %	No	No	5	1	2,293
Singh et al. [26]	Google Images + Ecosia [27]	MobileNet, Faster-RCNN	accuracy: increase by 31%	No	No	17	13	2,598

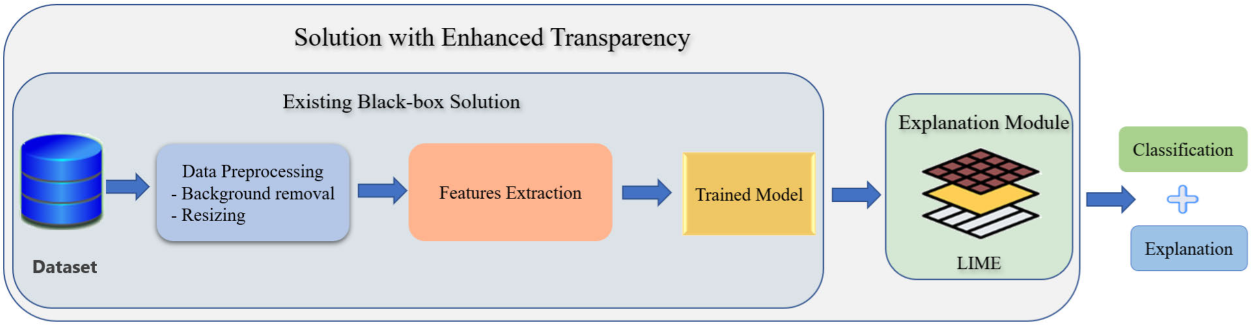


FIGURE 1. The proposed methodology workflow.

techniques were discussed; however, the review identifies research gaps, including the limited diversity in datasets used for evaluation, emphasizing the need for more realistic environmental considerations.

Table 1 provides a summary of these studies. It is evident that a significant number of researchers have not integrated XAI methods. This observation motivates our research, which seeks to develop a robust XAI-based model, with the goal of improving transparency, traceability, and the overall efficacy of plant disease classification in AI models.

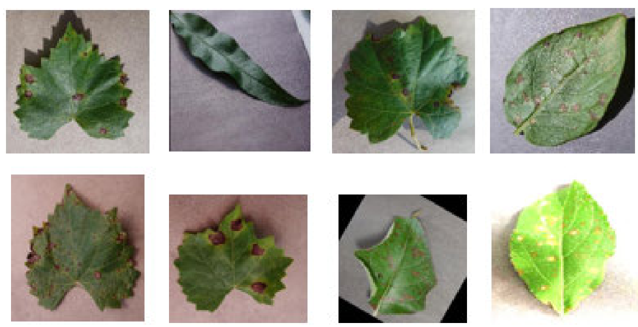


FIGURE 2. Randomly selected plant images before preprocessing.

III. PROPOSED METHODOLOGY

This section describes the proposed methodology in detail as shown in Fig. 1.

A. DATA PRE-PROCESSING

In this step, background is removed from the images to separate the region of interest (ROI). The background can introduce noise into the data, leading to potential misdiagnoses. For instance, a leaf's shadow or the surrounding environment might be mistaken for a disease symptom, skewing the results. The images are also separated into distinct classes based on different crops to enhance model training efficiency. This step overall enhances the optimal accuracy and reliability of the trained classifier in disease detection, while decreasing the corresponding computation time. Some results before and after pre-processing are shown in Fig. 2 and 3 respectively.

B. FEATURES EXTRACTION

This step involves selecting a subset of the most important features from the existing data for developing a ML model. It is a crucial step in the ML workflow, given that the performance of a model can be significantly influenced by the quality and quantity of features. The default feature extraction technique is transfer learning with the EfficientNetB0 model, where the base model's layers are frozen to prevent training. The model is then extended with global average pooling and a dense layer for multi class classification. It is employed to generate multiple features, enhancing the capabilities of disease detection.

C. MODEL TRAINING AND VALIDATION

To ensure the robustness of our model, the dataset is split into an 80:20 ratio, with 80% of the images being used for training and the remaining 20% for validation.

TABLE 2. Dataset description.

Plant	Disease	No of Samples	Plant	Disease	No of Samples
Apple	Apple Scab	2520	Potato	Early Blight	2424
Apple	Black Rot	2484	Potato	Late Blight	2424
Apple	Cedar Apple Rust	2200	Potato	Healthy	2280
Apple	Healthy	2510	Raspberry	Healthy	2226
Blueberry	Healthy	2270	Soybean	Healthy	2527
Cherry	Powdery Mildew	2104	Squash	Powdery Mildew	2170
Cherry	Healthy	2282	Strawberry	Leaf Scorch	2218
Corn (Maize)	Cercospora Leaf Spot / Gray Leaf Spot	2052	Strawberry	Healthy	2280
Corn (Maize)	Common Rust	2384	Tomato	Bacterial Spot	2127
Corn (Maize)	Northern Leaf Blight	2385	Tomato	Early Blight	2400
Corn (Maize)	Healthy	2324	Tomato	Late Blight	2314
Grape	Black Rot	2360	Tomato	Leaf Mold	2352
Grape	Esca (Black Measles)	2400	Tomato	Septoria Leaf Spot	2181
Grape	Leaf Blight (Isariopsis Leaf Spot)	2152	Tomato	Spider Mites / Two-Spotted Spider Mite	2176
Grape	Healthy	2115	Tomato	Target Spot	2284
Orange	Haunglongbing (Citrus Greening)	2513	Tomato	Yellow Leaf Curl Virus	2451
Peach	Bacterial Spot	2297	Tomato	Mosaic Virus	2238
Peach	Healthy	2160	Tomato	Healthy	2407
Pepper, Bell	Bacterial Spot	2391			
Pepper, Bell	Healthy	2485			

FIGURE 3. Randomly selected plant images after preprocessing.

D. PREDICTION EXPLANIBILITY

During this phase, the LIME framework is utilized. LIME is a method employed to explain individual predictions by using a local interpretable model to approximate any black box ML-based model.The process involves perturbing the original data points, inputting them into a black box model, and observing the resulting outcomes. Following this, the method allocates weights to the supplementary data points depending on their proximity to the initial location. Subsequently, these sample weights are employed to train a surrogate model on the dataset, such as linear regression. The resultant explanation model, once trained, can then be applied to each of the original data points.

IV. EXPERIMENTAL ANALYSIS

A. EXPERIMENTAL SETUP

1) DATASET

In this paper, the dataset named as ‘New Plant Diseases’ is taken from Kaggle as described in Table 2. This dataset is a rich collection of 87,000 images, providing a diverse range of plant diseases 38 distinct classes across 14 plant species. Determining the economic relevance of diseases per plant depends on various factors such as the crop’s economic importance, the severity and prevalence of the disease, the cost of control measures, and the potential yield losses. However, some insights are provided for diseases which are most economically relevant, per plant as shown in ‘red’ color in Table 2 and healthy instances are shown in ‘green’ color. Moreover, this dataset is imbalanced. It means that number of images in each class are not equal.

2) PERFORMANCE MEASURES

This section presents the quantitative metrics employed to assess classifier performance. The classifier is attempting to identify what kind of disease it is given plant species. It can also identify the leaf as healthy leaf which is the case in Blueberry, Raspberry, and Soyabean. In classification problems where results are categorized into positive or negative classes, the evaluation involves four potential states, often referred to as the confusion matrix [34].

i) True positive (TP): Correctly identifying instances of the positive class
ii) True negative (TN): Correctly identifying instances of the negative class
iii) False positive (FP): Incorrectly classifying instances as belonging to the positive class
iv) False negative (FN): Incorrectly classifying instances as belonging to the negative class

The performance of the results is assessed through accuracy, precision, and recall, computed as follows:

$$Accuracy = \frac{TP + TN}{FP + TN + TP + FN} \tag{1}$$

TABLE 3. Hyperparameters for classifiers.

Parameters	Values
Input Size	224*224
Batch Size	32
Error Function	Categorical Cross Entropy
Activation	ReLU
Optimizer	ADAM
Learning Rate	0.0001
Dropout	0.5
Train/Validation	80% / 20%

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall/Sensivity = \frac{TP}{TP + FN} \tag{3}$$

B. PARAMETER SETTINGS

The hyperparameter settings employed for the classification of plant diseases are outlined in Table 3.

1) EXPERIMENTAL ENVIRONMENT

The experiments are performed on GPU-enabled TensorFlow [35] with TF Lite [36] for converting the trained TensorFlow model into a format suitable for mobile applications; using Python programming language running on a personal computer with Apple M1 Chip, and 8 GB RAM.

C. RESULTS AND DISCUSSION

1) COMPARISON OF STATE-OF-THE-ART METHODS

The proposed methodology uses four distinct state-of-the-art models namely, CNN, MobileNetV2, EfficientNetB0, and ResNet-50 to detect the plant diseases. The results presented in Table 4 show that EfficientNetB0 outperforms four other models in terms of accuracy, precision, and recall. After EfficientNetB0, MobileNetV2 is performing well with the highest classification performance as 96.89%. ResNet-50 is performing least as compared to its peers with accuracy rate of 79.83%. These results demonstrate the effectiveness of the EfficientNetB0 model, achieving the highest accuracy among other models. The confusion matrix is shown in Fig. 4. The graphical representation of model accuracy is presented in Fig. 5. It is clear that there is variation in training and validation accuracy's values as the epochs count increases.

We have utilized XAI techniques, specifically leveraging the Lime framework, to enhance the interpretability of our machine learning models. This framework enabled us to explain the predictions of our model, providing valuable insights into how the model arrived at its decisions as shown in Fig. 6, which indicates LIME explanations for predicted black-box model. These are Pepper,Bell with Bacterial Spot disease images with LIME explanations. Moreover, 100% confidence means model predicted the disease with high probability. A user-friendly mobile application is also developed to assist the farmers as shown in Fig. 7.

TABLE 4. Performance metrics of CNN models.

Model	Accuracy (%)	Precision (%)	Recall (%)
CNN	96.44	94.22	94.22
MobileNetV2	96.89	96.12	96.14
EfficientNetB0	**99.69**	**98.27**	**98.26**
ResNet-50	79.83	75.21	75.21

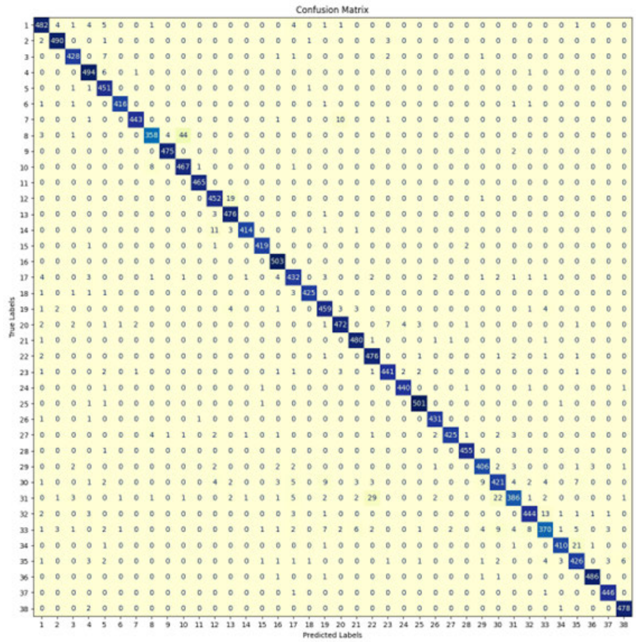


FIGURE 4. Confusion matrix of proposed model.

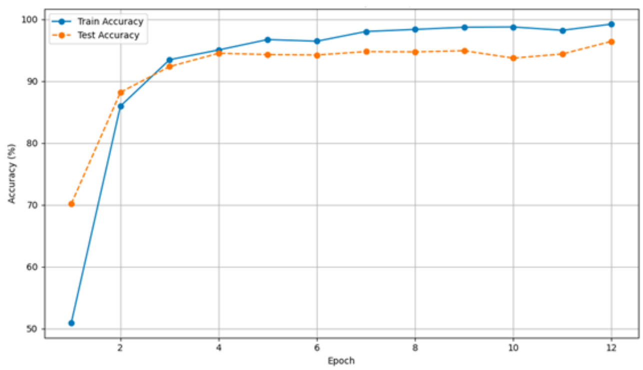
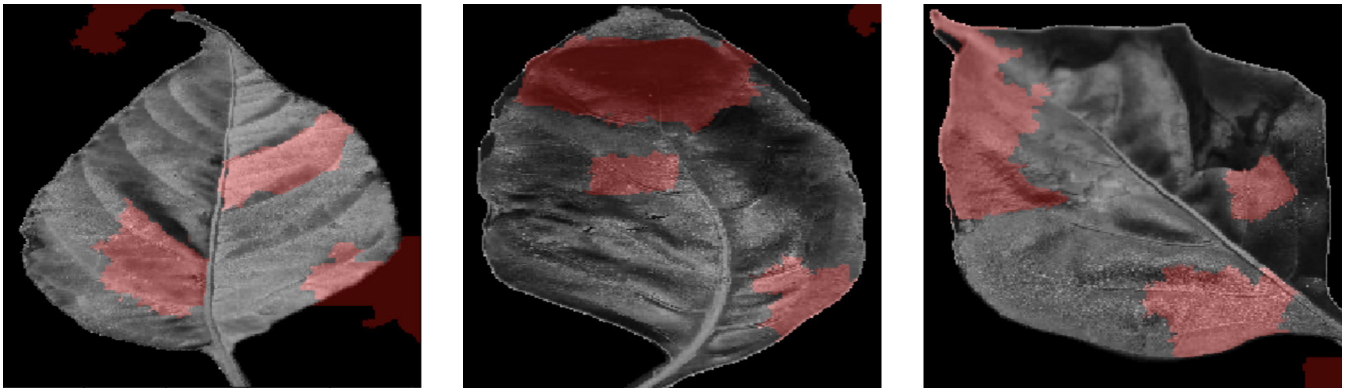


FIGURE 5. Accuracy Curve for plant disease detection.

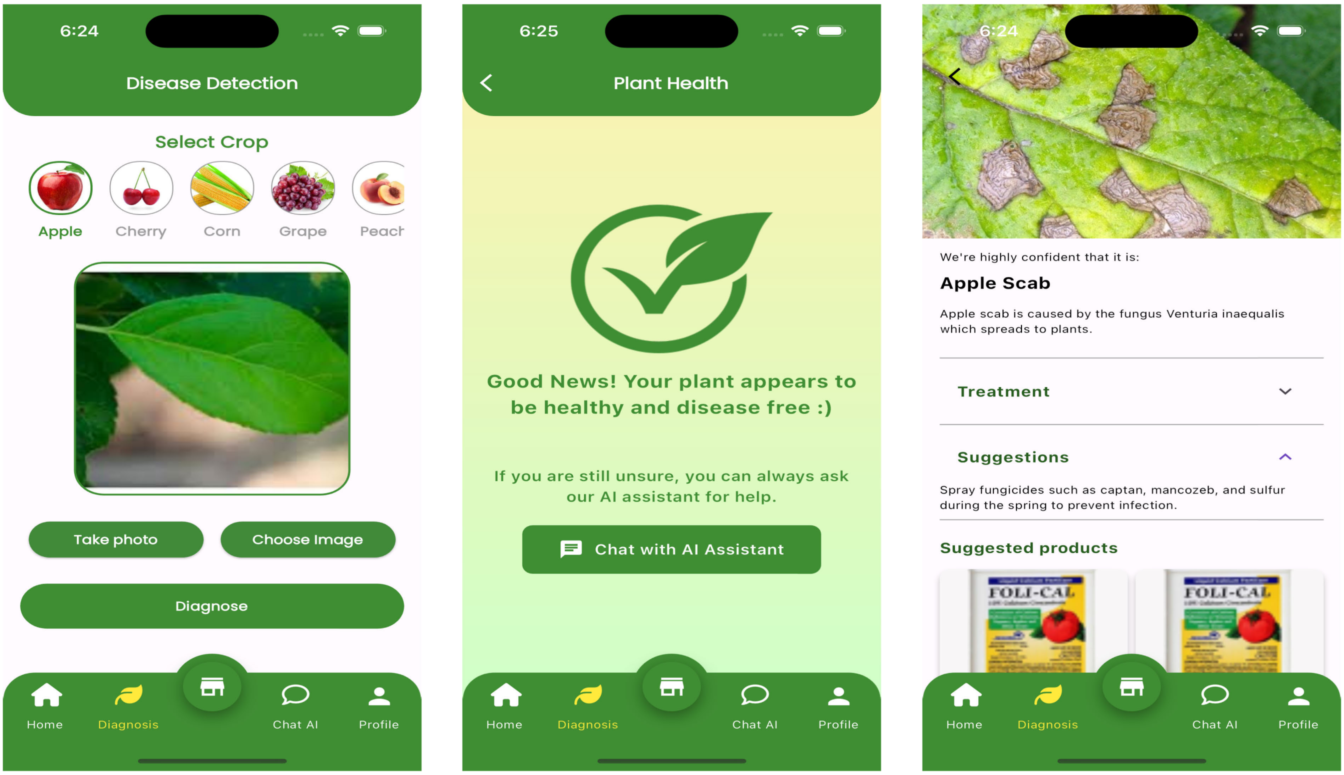
2) STATISTICAL ANALYSIS

In this section, an analysis of variance (ANOVA) test [37] is conducted to evaluate the statistical significance of the machine learning models. ANOVA serves as a statistical method employed to analyse variations among group means within a sample. It assesses whether the variations between the means are statistically significant or if they could occur by chance. ANOVA is particularly useful when comparing the means of three or more groups, providing insights into whether there are significant differences among them. The



(a) (b) (c)

FIGURE 6. Infected images detection by our developed model with 100% confidence.



(a) Main Interface (b) Plant Health Diagnosis (c) Suggestions and Recommendations

FIGURE 7. Plant disease detection - mobile application.

TABLE 5. ANOVA test results for model accuracy.

Statistical Measure	Value
F-statistic	20.8237
p-value	0.0002

F-statistic and p-value obtained from the ANOVA test are presented in Table 5.

Since the p-value is less than the chosen significance level ($\alpha = 0.05$), therefore, we reject the null hypothesis. These results suggest that the variations in disease detection accuracy across different models are statistically significant based on our model's performance.

3) VISUALIZATION

We also performed an analysis using Power BI to gain insights from our dataset, presenting them in various types of charts and graphs. In Fig. 8, number of samples per plant are shown, whereas Fig. 9 represents accuracy achieved by each plant. These values may also depends on the quality of the

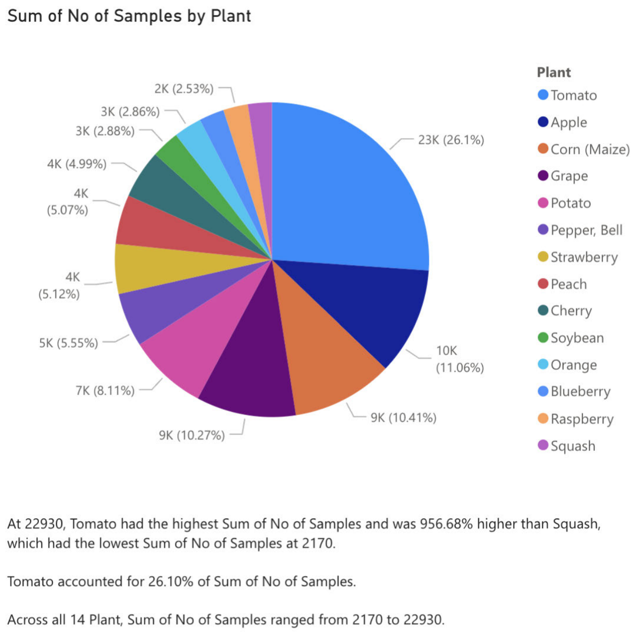


FIGURE 8. Number of samples per plant.

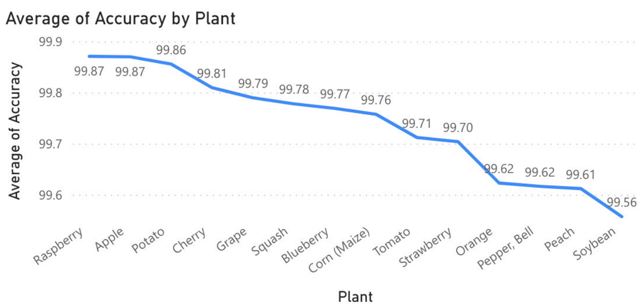


FIGURE 9. Achieved average accuracy for each plant.

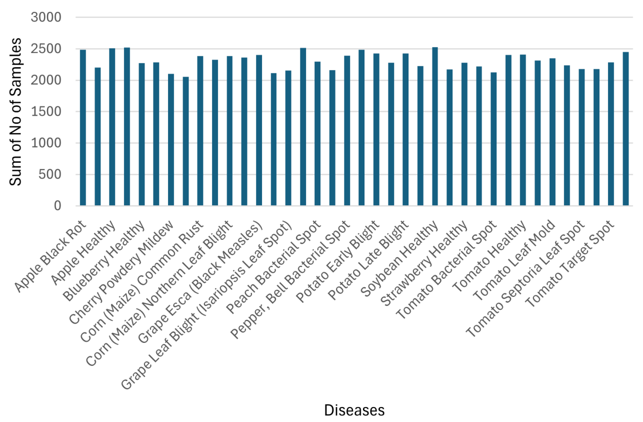


FIGURE 10. Number of samples by disease.

images in data. The number of samples by disease are shown in Fig. 10.

V. THREATS TO VALIDITY

The primary objective of this study is to assist farmers in the early assessment of plant diseases. Nonetheless, this study has certain constraints. Initially, we did not account for extensive or diverse datasets. Secondly, our approach relied on four pre-trained models for comparsion. Extending the model to integrate more advanced pre-trained models may enhance classification performance. Lastly, employing a larger set of training data could potentially yield superior results.

VI. CONCLUSION

Plant diseases pose a significant threat to our economy, causing substantial losses in agricultural productivity and impacting the livelihoods of farmers. Addressing plant diseases is not just a matter of agricultural concern but also a strategic move for economic prosperity. In this regard, this research presents the effectiveness of a deep learning-based plant disease detection system employing explainable artificial intelligence (XAI). The integration of advanced deep learning models not only enhances the accuracy of disease identification but also provides interpretability through the incorporation of XAI techniques.

This paper employs EfficientNetB0 to develop the ML model, utilizing a dataset consisting of 87,000 images. The developed model demonstrates proficiency in accurately categorizing 38 distinct types of diseases, achieving accuracy, precision, and recall rates of 99.69%, 98.27%, and 98.26%, respectively. Further, the LIME framework is employed to provide meaningful explanations that supports informed decision-making. The visual explanations not only showcase the model's effective generalization but also reveal biases acquired from outlier images. These insights empower researchers and field experts to gain a deeper understanding of the rationale behind the classification of plant diseases, shedding light on the inner workings of the black-box model. Additionally statistical analyses, notably ANOVA, showcases significant models' performance.

In future, there is potential for the creation of a more resilient model that takes into account diseases affecting various plant species. Moreover, the compilation of written reports documenting disease observations in both technical and non-technical languages stands as an additional task that contributes to the model's adoption. Furthermore, the integration of Internet of Things (IoT) devices will contribute to the fully automated disease detection systems on farms.

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