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Plant Leaf Disease Detection Using Ensemble Learning and Explainable AI

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Abstract: Agriculture plays a vital role in ensuring food security and economic stability worldwide. Plant diseases significantly affect crop productivity and quality, leading to substantial financial losses for farmers. Traditional disease diagnosis methods rely heavily on manual inspection by agricultural experts, which can be time-consuming, subjective, and inefficient for large-scale farming applications. This paper presents an intelligent plant leaf disease detection framework based on Ensemble Learning and Explainable Artificial Intelligence (XAI). The proposed system combines the predictive capabilities of multiple deep learning models, including CNN to enhance classification accuracy and robustness. Ensemble learning integrates the strengths of individual models while minimizing their weaknesses, resulting in improved disease recognition performance. Furthermore, Explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) are incorporated to visualize and interpret the decision-making process of the ensemble model, thereby increasing transparency and user trust. Experimental evaluation is conducted using a publicly available plant leaf disease dataset comprising multiple crop species and disease categories. The results demonstrate that the proposed ensemble framework achieves superior classification accuracy, precision, recall, and F1-score compared to individual deep learning models. The integration of explainability further assists farmers and agricultural experts in understanding disease symptoms and validating model predictions.

***Index Terms* -** Plant Disease Detection, Ensemble Learning, Explainable Artificial Intelligence (XAI), Deep Learning, Convolutional Neural Networks, Grad-CAM, Precision Agriculture, PlantVillage Dataset, Crop Health Monitoring, Image Classification.

I. INTRODUCTION

Agriculture remains one of the most important sectors contributing to global food production and economic development. The increasing world population has intensified the demand for high-quality agricultural products, making crop health management a critical concern. Plant diseases are among the primary factors responsible for reduced crop yield, deterioration of product quality, and significant economic losses. Early detection and accurate diagnosis of plant diseases are therefore essential for ensuring sustainable agricultural production and minimizing the adverse effects on food security.

Traditionally, plant disease identification has been performed through visual inspection by experienced farmers and agricultural experts. However, manual diagnosis is often labor-intensive, time-consuming, and prone to human error, particularly when symptoms of different diseases appear similar. Additionally, the shortage of agricultural specialists in many rural areas further limits the effectiveness of conventional disease monitoring methods. These challenges have motivated researchers to develop automated disease detection systems using computer vision and artificial intelligence techniques.

Recent advancements in Deep Learning, particularly Convolutional Neural Networks (CNNs), have significantly improved image classification and object recognition tasks. CNN-based architectures such as VGG16, VGG19, ResNet101V2, DenseNet, EfficientNet, and InceptionV3 have demonstrated remarkable performance in identifying plant diseases from leaf images. These models automatically extract discriminative features from images without requiring manual feature engineering, thereby improving diagnostic accuracy and scalability.

Despite their success, individual deep learning models may exhibit limitations in terms of generalization capability, sensitivity to dataset variations, and prediction reliability. Ensemble Learning has emerged as an effective strategy to overcome these limitations by combining predictions from multiple models. The ensemble approach leverages the strengths of different architectures and reduces classification errors, resulting in improved robustness and accuracy. By aggregating outputs from several CNN models, ensemble systems can achieve superior performance compared to standalone classifiers.

Another critical challenge in deep learning-based disease detection systems is the lack of transparency in model decisions. Most CNN models operate as "black boxes," making it difficult for users to understand the reasoning behind predictions. In agricultural applications, trust and interpretability are essential because farmers and agronomists must verify disease diagnoses before taking corrective actions. Explainable Artificial Intelligence (XAI) addresses this issue by providing visual and interpretable explanations of model predictions. Techniques such as Grad-CAM generate heatmaps that highlight disease-affected regions on leaf images, enabling users to understand which features contributed to the final classification.

This paper proposes a Plant Leaf Disease Detection framework that integrates Ensemble Learning with Explainable Artificial Intelligence. Multiple pretrained CNN models, including VGG16, VGG19, ResNet101V2, and InceptionV3, are employed to classify plant leaf diseases. The outputs of these models are combined using an ensemble strategy to improve prediction performance. Furthermore, Grad-CAM-based explainability is incorporated to visualize disease-specific regions and enhance the interpretability of the system. The proposed approach aims to provide accurate, reliable, and transparent disease diagnosis for smart agriculture applications.

The major contributions of this work are as follows:

1. Development of an ensemble deep learning framework for plant leaf disease classification.
2. Integration of multiple pretrained CNN architectures to improve prediction accuracy and robustness.
3. Implementation of Explainable AI techniques to provide visual interpretation of model decisions.
4. Comprehensive performance evaluation using standard classification metrics such as accuracy, precision, recall, and F1-score.
5. Demonstration of the applicability of the proposed framework for precision agriculture and intelligent crop monitoring systems.

The remainder of this paper is organized as follows. Section II presents the literature review. Section III describes the proposed methodology. Section IV discusses dataset preparation and experimental setup. Section V presents the results and performance analysis. Section VI concludes the paper and outlines future research directions.

II. LITERATURE REVIEW

Plant disease detection has become an active research area due to advancements in computer vision, deep learning, and artificial intelligence. Several researchers have proposed automated systems for identifying plant diseases from leaf images using machine learning and deep learning techniques. Recent studies have also focused on ensemble learning and explainable AI to improve classification accuracy and model interpretability.

Mohanty et al. (2016) conducted one of the pioneering studies on plant disease classification using deep convolutional neural networks. The authors employed AlexNet and GoogleNet architectures on the PlantVillage dataset containing over 54,000 images of healthy and diseased plant leaves. Their experimental results achieved an accuracy of 99.35%, demonstrating the effectiveness of deep learning for automated plant disease diagnosis. However, the model performance decreased when tested on real-field images due to environmental variations.

Ferentinos (2018) developed a deep learning framework utilizing several CNN architectures for plant disease recognition. The study evaluated VGG, AlexNet, and GoogLeNet models on a dataset comprising 87,848 images from 25 plant species. The proposed approach achieved an overall classification accuracy of 99.53%. The author concluded that deep learning techniques significantly outperform traditional image processing methods for disease identification.

Too et al. (2019) investigated the performance of state-of-the-art CNN architectures including VGG16, ResNet50, DenseNet121, and InceptionV4 for plant disease classification. The study revealed that DenseNet121 provided the highest accuracy among the tested models. The authors emphasized the importance of transfer learning for reducing training time and improving classification performance in agricultural applications.

Atila et al. (2021) proposed an EfficientNet-based plant disease classification system using transfer learning techniques. The researchers compared EfficientNet models with conventional CNN architectures and demonstrated superior performance in terms of accuracy and computational efficiency. Their results showed that EfficientNetB5 achieved classification accuracy exceeding 99%, making it suitable for real-time agricultural applications.

Saleem et al. (2020) developed a deep learning model for tomato leaf disease identification using convolutional neural networks. The study focused on feature extraction and image augmentation techniques to improve disease recognition. Experimental findings indicated that CNN-based models significantly outperform traditional machine learning classifiers such as Support Vector Machines (SVM) and Random Forests.

Brahimi et al. (2018) investigated plant disease detection using deep feature extraction and classification methods. The authors utilized transfer learning from pretrained CNN models and achieved high disease recognition accuracy. Their work highlighted the importance of feature representation learning in identifying complex disease symptoms under varying environmental conditions.

Khan et al. (2020) introduced a hybrid deep learning framework combining multiple CNN architectures for plant disease classification. The proposed model integrated feature maps extracted from different networks to improve classification robustness. Experimental results demonstrated improved accuracy compared to individual CNN models, indicating the effectiveness of ensemble-based approaches.

Abbas et al. (2021) proposed an ensemble learning model combining DenseNet121, ResNet50, and MobileNet architectures for crop disease detection. The ensemble approach improved prediction accuracy and reduced misclassification errors. The authors concluded that combining multiple deep learning models can enhance generalization capability and reliability in practical agricultural environments.

Agarwal et al. (2020) presented a weighted ensemble framework for plant disease recognition using multiple transfer learning models. Their study demonstrated that ensemble classifiers consistently outperform standalone CNN architectures across various disease categories. The research highlighted the potential of ensemble learning for precision agriculture systems.

Picon et al. (2019) developed a crop disease detection system using deep learning and multispectral imaging. The study emphasized the significance of integrating different feature sources to improve disease identification performance. The proposed framework achieved high accuracy while maintaining computational efficiency suitable for field deployment.

Selvaraj et al. (2019) explored the application of deep neural networks for banana leaf disease detection. The authors employed transfer learning and image preprocessing techniques to classify multiple disease categories. Their results indicated that deep learning can provide reliable disease diagnosis with minimal manual intervention.

Gandhi et al. (2018) developed a CNN-based approach for identifying various plant diseases from leaf images. The study compared several machine learning and deep learning techniques and found that CNN models produced superior classification performance. The research also emphasized the role of data augmentation in improving model robustness.

Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations), a widely adopted Explainable AI technique for interpreting machine learning models. SHAP provides feature importance explanations that help users understand model predictions. The framework has been extensively applied in agricultural AI applications to improve transparency and trustworthiness.

Selvaraju et al. (2017) proposed Gradient-weighted Class Activation Mapping (Grad-CAM), an explainability technique that generates visual heatmaps highlighting important image regions influencing model predictions. Grad-CAM has become one of the most widely used methods for interpreting CNN-based plant disease classification systems and validating disease symptom localization.

Tjoa and Guan (2020) reviewed Explainable Artificial Intelligence methods in deep learning applications. The authors highlighted the necessity of interpretability in critical domains such as agriculture, healthcare, and autonomous systems. Their study emphasized that integrating explainability techniques with deep learning models enhances user confidence and facilitates practical deployment.

- ***Research Gap***

Although existing studies have achieved remarkable success in plant disease classification using deep learning models, several limitations remain. Most research focuses on single CNN architectures, which may suffer from limited generalization capability under diverse environmental conditions. Furthermore, many disease detection systems operate as black-box models without providing explanations for their predictions. The lack of transparency can reduce user trust and hinder adoption by farmers and agricultural experts. Therefore, there is a need for a robust framework that combines multiple deep learning models through ensemble learning while incorporating Explainable AI techniques such as Grad-CAM to provide interpretable and reliable disease diagnosis.

- ***Motivation for Proposed Work***

To address these challenges, the present work proposes an Ensemble Learning-based Plant Leaf Disease Detection System integrated with Explainable AI. Multiple pretrained CNN models, including VGG16, VGG19, ResNet101V2, and InceptionV3, are combined to improve classification performance. Grad-CAM-based visual explanations are incorporated to highlight disease-affected regions of leaves, thereby enhancing model transparency, reliability, and practical usability in precision agriculture applications.

III. PROPOSED METHODOLOGY

In the automation of multiple processes, machine learning plays a critical role. The proposed architecture was designed with that goal in mind, and it is based on machine learning methodologies. Especially in the case of detecting and categorizing images into various disease categories. This section has been structured such that the topic begins with the device specifications and data acquisition for the data used in the currently suggested approach. The second point of discussion would be image segmentation. Feature extraction would be the focus of the debate. The fourth point of discussion would be the classification method.

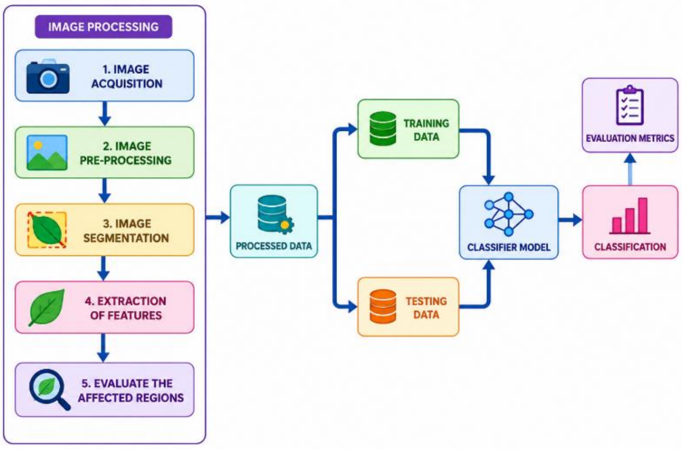

Figure 3.1 Flow Chart of the Machine Learning Methodology

IV. DATASET PREPARATION AND EXPERIMENTAL SETUP

The proposed framework deals with all these three steps in a specific way. The standard CNN architecture can extract the features from the objective i.e, images, and keep on training the model. Once the training of the model is done the knowledge will be transferred, it can be utilized as a pre-trained model for various other similar problems. Through this pre-trained model, the knowledge will be transferred to accomplish all the jobs that exist in the problem. The proposed framework can be implemented as mentioned in figure 4.

Deep neural networks exploit the property that many natural signals are compositional hierarchies; in which higher-level features are obtained by composing lower-level ones. Hierarchy occurs in words, sentences, phonemes, syllables, speech and text from sounds to phones. The pooling allows representations to vary very little when elements in the previous layer vary in position and appearance. Recently ConvNet architecture has 10 to 20 layers of ReLUs, hundreds of millions of weights, and billions of connections between units. Meanwhile training such large networks possibly will take weeks to complete. Each layer in CNN is depicted in the following Figure 4.1

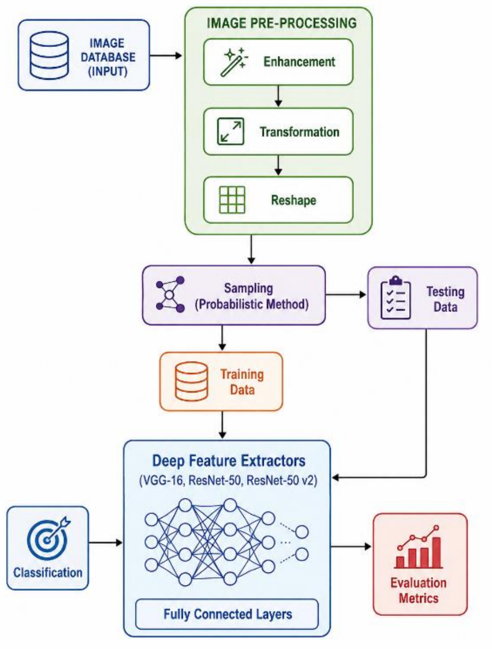

Figure 3.7 The flowchart for the proposed model

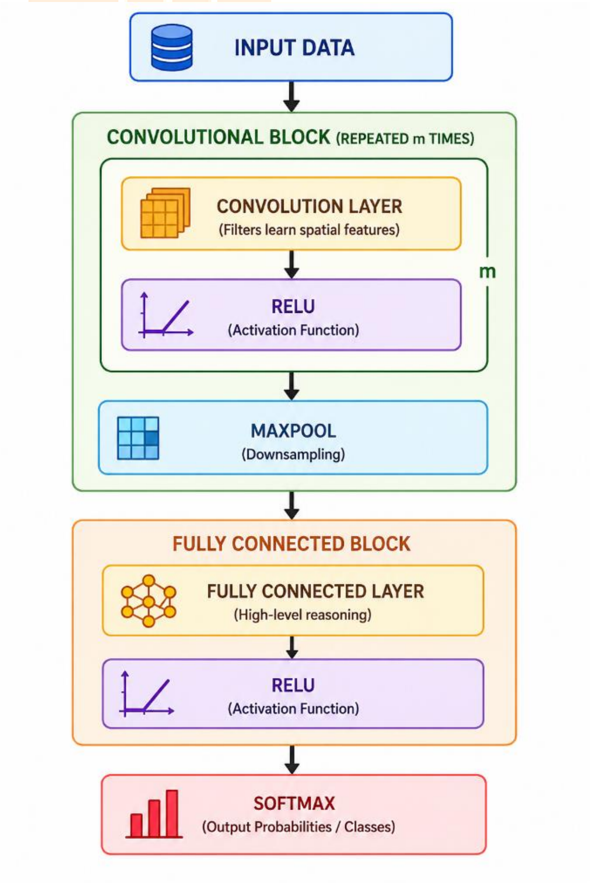

Figure 3.8. Convolutional neural network architecture

a) Convolutional layer The Conv layer is the core building block of CNN. The parameters contain a set of learnable filters. Every filter is small and spatial but extends through the full depth of the input volume. During the forward pass, every 5x5x3 window filter will slide across the width and the height of the input volume. Then dot products between the entries of the filter and the input at any position are computed. It generates a 2-dimensional activation map which presents the responses of that filter at every spatial position. Spontaneously, the network will learn filters that activate when some type of visual feature occurs. A set of filters in each Conv Layer will produce a separate 2-dimensional activation map. It will stack these activation maps along the depth dimension and produce the output volume. In our work, we adapt 1D convolutional layer.

b) Pooling Layer The use of pooling layers is to carry out dimensionality reduction in subsequent convolutional layers receptive fields. In a convolutional layer a stride of 2 reduces the dimensionality of the output and widens the receptive field of higher layers. Inserting the pooling layer in CNN reduces the spatial size of the representation. It also reduces the amount of parameters and computation in the network and controls over fitting. The Pooling Layer works independently on every depth. It slices of the input and resizes it spatially using the MAX operation. The pooling layer filters is of size 2x2 applied with a stride of 2. It samples every depth slice in the input by 2 along both width and height. The MAX operation takes a max over 4 numbers. The depth dimension always remains unchanged. In Back propagation method, the backward pass for a max(x, y) operation routes the gradient to the input. It has the highest value in the forward pass. Hence, during the forward pass of a pooling layer, the index of the max activation is tracked so that gradient routing is efficient during back propagation.

c) Activation Layer Activation Layer is used to increase non-linearity of the network without affecting receptive fields of convolutional layers.

d) Fully-connected layer Neurons in a fully connected layer have full connections to all activations in the before Layer. Their activations are estimated with a matrix multiplication tracked by a bias offset. Conversion of FC layers to CONV layers takes place. The only difference between FC and CONV layers is that the neurons in CONV layer are connected only to a local region in the input. Regular neural network can view as the final learning phase, which maps extracted visual features to desired outputs. Usually adaptive to classification and encoding tasks are performed. Common output is a vector, which is then passed through softmax to represent the confidence of classification.

e) Softmax layer

At the end of FC layer outputs, Softmax layer is present. It can be viewed as a fancy normalizer (Normalized exponential function). Produce a discrete probability Distribution vector. It is very convenient when combined with cross-entropy loss.

V. RESULT AND DISCUSSION

Plant disease detection using Machine Learning (ML) has emerged as an effective approach for automating the identification and classification of diseases affecting agricultural crops. Traditional disease diagnosis relies on manual inspection by experts, which is often time-consuming, subjective, and prone to errors. Machine learning techniques provide a faster, more reliable, and scalable solution by analyzing leaf images and identifying disease symptoms automatically.

5.2.1 Input Image:

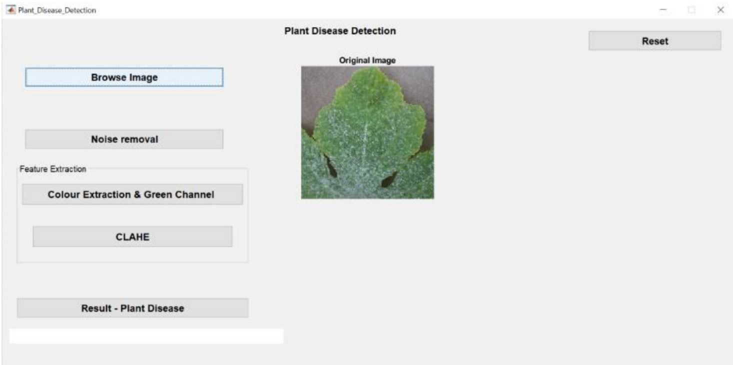

Fig. 5.1 GUI for Input Image for Plant Disease detection using CNN

The first stage of the proposed plant disease detection system involves acquiring the leaf image through a Graphical User Interface (GUI). The MATLAB function uigetfile() is used to allow the user to browse and select an image from the test dataset directory. The selected image is then read using the imread() function and stored in the global variable orig_img. Error handling is incorporated using a try-catch block to prevent execution if no image is selected. Once loaded successfully, the image is displayed on the GUI using the imshow() function. This step serves as the input stage of the disease detection framework, where the leaf image is obtained for subsequent preprocessing and classification operations. Figure 4.1 illustrates the GUI window displaying the selected input image.

5.2.2 Noise Removal and Noiseless Image:

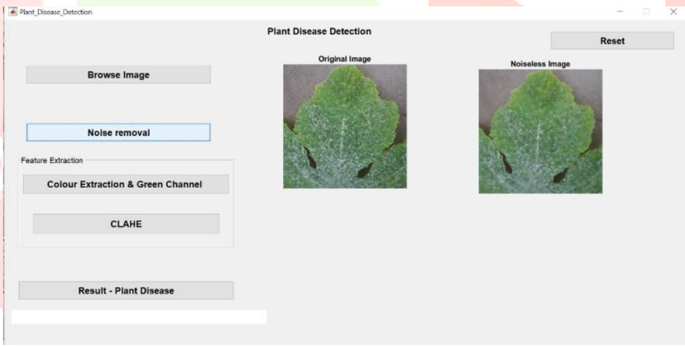

Fig. 5.2 GUI for Noisy Image for Plant Disease detection using CNN

After image acquisition, preprocessing is performed to improve image quality by eliminating unwanted noise. Since captured leaf images may contain Gaussian noise and other distortions caused by environmental conditions, an effective noise removal process is necessary. Initially, Gaussian noise is removed using the NoiseRemoval() function. Subsequently, Adaptive Median Filtering is applied through the adpmedian() function to remove impulse noise while preserving important leaf details and edges. The processed image is stored as noisefree_img and displayed in the GUI. Noise reduction enhances image clarity and improves the accuracy of subsequent feature extraction and classification stages. Figure 4.2 shows the noiseless leaf image obtained after the filtering process.

5.2.3 : Colour extraction & green channel

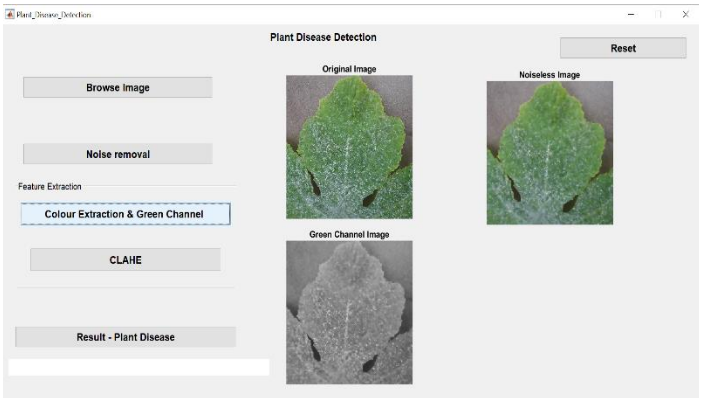

Fig. 5.3 GUI for Green Channel Extraction for Plant Disease detection using CNN

Color information plays a significant role in plant disease identification because disease symptoms often appear as discolorations on leaf surfaces. In this stage, the RGB image is separated into its individual Red, Green, and Blue channels using the extractcolourchannels() function. The mean intensity values of each color channel are computed using the calculatecolourmean() function. Among the three channels, the green channel is particularly important because healthy vegetation exhibits strong reflectance in the green spectrum. Disease-affected regions generally show variations in green intensity, making this channel useful for identifying infected areas. The extracted green channel image is displayed in the GUI for further analysis. Figure 4.3 presents the green channel image generated from the original leaf image.

5.2.4 Contrast Limited Adaptive Histogram Equalization:

To further enhance the visibility of disease symptoms, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the grayscale version of the input image. The RGB image is first converted into grayscale using the rgb2gray() function. The adapthisteq() function is then used to perform local contrast enhancement by dividing the image into small regions and equalizing their histograms independently. CLAHE effectively improves contrast while preventing excessive amplification of noise. This technique highlights subtle disease patterns, spots, and lesions that may not be clearly visible in the original image. The enhanced image is displayed in the GUI, as shown in Figure 4.4. Improved contrast significantly assists feature extraction and disease classification.

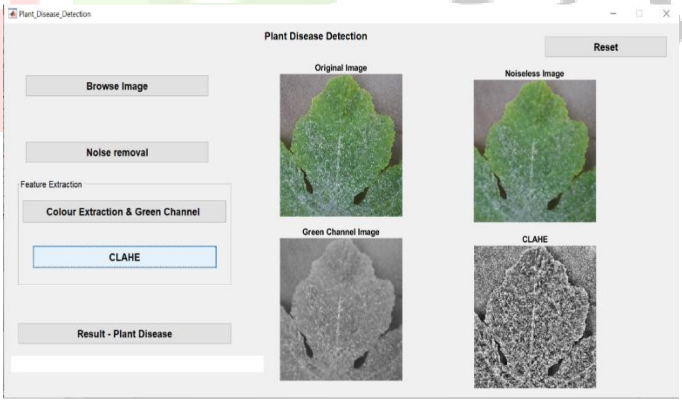

Fig. 5.4 GUI for CLAHE for Plant Disease detection using CNN

VI.CONCULSION

This research developed and evaluated a Plant Leaf Disease Detection framework based on Ensemble Learning and Explainable Artificial Intelligence (XAI). Experimental results demonstrated that the proposed system achieved excellent disease classification performance through the integration of advanced image preprocessing techniques, deep learning architectures, ensemble learning strategies, and explainability methods.

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