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Plant Disease Detection and Analysis using Generative Artificial Intelligence

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Abstract: ***Plant diseases are significant contributors to crop loss in the global economy, as it has been a significant problem to the food security and livelihoods of farmers. The traditional method is manual diagnosis which has been very slow, subjective and depends on the availability of experts. This paper suggests an integrated AI-based plant disease detection-diagnosis system that is able to combine CNNs with ensemble learning, generative AI, and XAI. Some pretrained CNNs like the VGG16 are used to extract the features of the preprocessed image of the leaves whilst the implementation of an ensemble learning model based on the Random Forest classifier enhances the accuracy of the prediction with improved generalization. The XAI methods such as Grad-cam, LIME and SHAP produce graphical descriptions of the affected areas of leaves and increase transparency and consequently user confidence. Lastly, the generative AI models provide context-related treatment advice based on the disease severity, environmental conditions, and past crop data. The diagnostic accuracy and scalability of smallholder and commercial farming are considerable because of experimental assessment of benchmark datasets. Therefore, the suggested framework can be said to be useful in ensuring sustainable agriculture as well as providing farmers in rural areas with smart and available plant health management tools.***

Keywords— plant disease detection, deep learning, convolutional neural networks, ensemble learning, explainable AI, generative AI, smart farming.

I. INTRODUCTION

Agriculture is the backbone of many economies and thus plays a vital role in ensuring food security. Plant diseases pose one of the main challenges in agriculture, with about a quarter of global agricultural production lost each year due to their attack. Traditional plant disease detection mainly relies on the manual inspection of leaves and stems, which is very time-consuming, subjective, and reliant on the availability of experts. In most cases, such limitations make diagnosis late and treatment ineffective, especially in rural areas where agricultural expertise is minimal.

Fig 1: Plant Leaf Showing Disease Symptoms

Plant diseases are complicated biological processes which are influenced by environmental factors such as humidity, temperature, and soils. The majority of the diseases have similar visual symptoms of spots, lesions, discoloration, and it is hard to make proper diagnosis without any special knowledge. This confusion often results in wrong diagnosis or late treatment, which incurs large loss of crops and economic harm. The absence of scalable and automated diagnostic tools is one of the greatest challenges to the contemporary agriculture.

The latest trends in AI have provided new opportunities in the automatization and improvement of the process of identification of plant diseases. Deep learning methods and specifically CNNs performed remarkably in image classification tasks, thereby making them very suitable in analyzing plant leaf images. Hierarchical features of color variations, texture patterns and shapes of lesions would be taught to CNNs in order to classify plant diseases with high precision. Nonetheless, the vast majority of single-model-based methods have challenges with cross-crop/cross-environmental generalization, which limits their practical application.

These obstacles are currently being resolved through the inclusion of AI-driven frameworks that include ensemble learning, explainable AI, and generative AI. The ensemble learning incorporates different models to offer better accuracy and strength. XAI encompasses, Grad-CAM, LIME, and SHAP which visualize the prediction process by marking the affected parts of the leaves and inspires confidence amongst the farmers. Generative AI also increases the usefulness of the system to provide context-based and disease severity-based treatments based on the environment and historical data of crops.

In the majority of rural and resource limited environments, lack of access to agricultural knowledge tends to propagate disease, decrease quality of crop and limit farmers on a financial basis. Mobile-based AI applications can be used as an alternative solution since farmers can take pictures of leaves with smartphones and immediately get feedback. This type of architecture coupled with cloud-based processing and light model deployment is effective in low-bandwidth settings and hence is best suited to mass dissemination of large scale in developing areas.

Whether to use Explainable AI or Generative AI, integrating them can transform the diagnostic process into a transparent and action-support decision-making process. Farmers do not merely get a disease label but they are also shown visuals of the areas of the disease as well as customized treatment recommendations. This interpretability breeds trust and adoption, and its generating aspect forms the foundation of sustainable farming through the advice of context-sensitive interventions. The divide between the state-of-the-art AI and the application to the agricultural field is thereby narrowed in creating the system to play its part in precision farming and align with the world trends of smart farming and food security.

II. RELATED WORK

Deep learning firstly was applied by Mohanty et al. [1] to detect plant diseases using images. They demonstrated that convolutional neural networks (CNNs) are significantly superior to the traditional algorithms with handcrafted features. This formed a good stepping point towards automation of plant disease identification.

The paper by Sreenivasula Reddy et al. [2] focused on finding the significant patterns of high-dimensional data with the help of an ISSA-based KMC in conjunction with a VGHHO model of clustering data. Their studies further developed data mining and clustering process applicable in the management of huge and multifaceted agricultural and biological data.

In an attempt to classify diseases in 58 plant classes, Ferantinos [3] used deep learning models on large datasets of agriculture. Although the accuracy was good, the study identified challenges associated with noise in the environment and real world implementation conditions.

Sladojevic et al. [4] developed a pipeline of deep neural networks to classify the images of plant leaves belonging to different species. Their results had a high accuracy in their classification and proved that CNNs are good tools to analyze the agriculture image.

Sreenivasula Reddy et al. [5] introduced a knowledge-optimal method of colossal pattern mining and dimensionality reduction methods in the high-dimensional biological data. This enhanced calculation speed and aptitude in pattern recognition.

Too et al. [6] have provided a comparison study of deep learning models that identify plant diseases. Their results indicated that the application of transfer learning and pre-trained models such as VGG16 and ResNet significantly enhanced the accuracy in classification.

According to Chen et al. [7], an ensemble approach was proposed where an ensemble of classifiers is included with CNN based features extraction. This enhanced the performance of the plant disease identification and also generalized across different crops datasets.

Sreenivasula Reddy et al. [8] presented a method that is premised on the idea of differential evolutionary arithmetic optimization to extract colossal patterns optimised in terms of length constraints. This offered high optimization methods that could be used in analyzing the agricultural data.

The picture below illustrates how Singh et al. [9] combined explainable AI with CNN-based models to detect plant diseases using Grad-CAM visualization. This technique enabled less ambiguous interpretation of the leaf affected regions, increasing transparency of the model.

Wang et al. [10] developed a hybrid system between CNNs and Transformers. This framework is not only able to capture local spatial characteristics but also long-range relationships of crop disease images, which makes it more robust and effective at classifying crops.

Zhou et al. [11] came up with a hybrid in which they combined the deep semantic features with edge-sensitive attention mechanisms. This enhanced the localization of the disease and the detection accuracy in complicated background environments.

Patel et al. [12] presented an artificial intelligence system based on generating diagnoses to examine plant illnesses. This system not only diagnosed diseases but also gave treatment advice linking the detection with decision support.

Roy et al. [13] applied spatial and channel squeeze-and excitation concurrently in CNN structures. This enhanced feature representation, and thus the model was capable of giving more attention to areas of interest in diseases.

Barbedo [14] examined major issues that influence the results of the deep learning in plant disease recognition. They emphasized issues such as imbalanced dataset, differences in image quality and environmental factors.

Picon et al. [15] suggested a mobile application to classify crop diseases with the help of deep CNNs. They proved to be vulnerable in real field conditions to recognize disease effectively and enhance accessibility to farmers.

Brahimi et al. [16] used deep learning to classify tomatoes disease and visualise the symptoms. They demonstrated in their work that CNNs could be successfully used to distinguish between visually related disease patterns.

Selvaraju et al. [17] proposed Grad-CAM, which is a method that offers gradient-based visualizations of CNN predictions. It is a crucial approach in explainable AI enforceable plant disease detectors.

Fuentes et al. [18] have introduced a deep learning-based system of phenotyping that utilized both global and local feature representations to identify plant anomaly and disease symptoms. Their method demonstrated high-level performance in real-field settings, which was featured by strict adherence to visual details and the extraneous information related to the setting, which resulted in an enhanced accuracy in plant disease detection.

Lu et al. [19] created an in-field and automated system of diagnosing wheat diseases using deep learning methods. He developed the system in agricultural settings where it could appear in real-time as it would react to changing lights, background, and field conditions which became feasible and affordable to the farmers.

Ribeiro et al. [20] presented the Local Interpretable Model-Agnostic Explanations (LIME) framework to explain the predictions of machine learning models in a way that is easy to understand. This contribution formed the basis of explainable artificial intelligence and has been extensively used to increase the fulfillment of transparency, trust, and interpretability in AI-based plant disease detection systems.

III. EXISTING METHOD

Plant Disease Detection Using CNN and Ensemble Fusion:

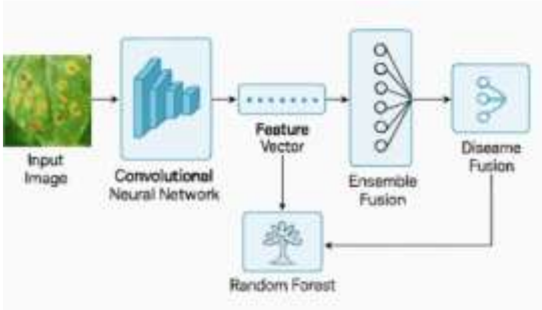

Fig 2: Plant Disease Detection Using CNN and Ensemble Fusion

The strategy taps into the database Plant Village which is a massive database of labelled leaf sample images of numerous crop species and disease classes. Preprocessing of images is done to be consistent: they are resized, normalized and multiplied by rotations, flips, and zooms to make the models more resistant. Based on this base, the environmental context of soil type, humidity, or temperature is not considered but guarantees that these leaf images can be used in deep learning classification.

The CNN is situated at the center of the field, and it is aimed at extracting the meaningful features of the leaves. The image passes through sequential convolutional layers where in between the layers are batch normalization and ReLU activations are sprinkled. These learn hierarchical patterns like textures, color changes and lesion pattern. After the features are extracted, the features are flattened and sent to fully connected layers which give out predictions of the disease.

We use two strategies together, CNN outputs and a Random Forest classifier in order to increase the predictive homogeneity being emitted. This combination allows this model to have the capabilities to learn complex representations via CNNs and to have the benefit of shallow decision boundaries based on classical statistics. Lastly, a softmax layer is used to give predictions on the type of disease in the plants. The model exploits common visual representations known in agricultural photos in differentiating between two plant diseases that seem the same. This is more of sure result but lacking in the unavailability of environmental data in the model.

Pseudo Code:

1: Preprocessing
2: Acquire leaf image from dataset or user input
3: Resize image to standard dimensions
4: Normalize pixel values
5: Apply data augmentation (e.g., rotation, flipping, zooming)
6: Feature Extraction
7: Input image into pretrained CNN (e.g., VGG16)
8: Extract hierarchical features from convolutional layers
9: Flatten feature map to form feature vector
10: Ensemble Classification
11: Input feature vector into Random Forest classifier
12: Combine CNN softmax output with Random Forest prediction
13: Apply ensemble fusion to obtain final disease class
14: Output
15: Display predicted disease class
16: return Disease class

IV. PROPOSED METHODOLOGY

Plant Disease Detection Using CNN, Ensemble Learning, XAI, Generative AI:

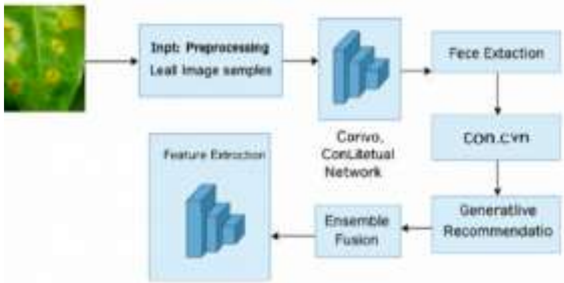

Fig 3: Plant Disease Detection Using CNN, Ensemble Learning, XAI, and Generative AI

The suggested solution will contain a hybrid AI framework of plants diseases detection and diagnosis by utilizing leaf pictures, incorporating CNNs, ensembles, Explainable AI, and Generative AI. The solution only aims at detecting the disease but does not treatment. These images are obtained on the dataset of the Plant Village and subject them to multiple operations such as image resizing, intensity normalization, and natural augmentation (rotation, flipping and zooming) to make sure that not only the consistent samples are present in the dataset, but also generalized ones.

An encoder such as VGG16 is employed as a visual pathway. This network removes the low-level spatial data such as the borders of the lesions, color boundaries and textures and expresses them in the form of the flat feature vector.The latter feature is applied to the training of the ensemble classifier. Conversely, the other boundaries in decision surface are identified using a Random Forest model which is mainly based on the knowledge of the statistical patterns.

Both CNN and the Random Forest model give predictions and the last task is the ensemble fusion which enhances the strength of the model and eliminates overfitting.

To achieve increased understanding of the system, the model uses approaches of XAI. In Grad-CAM, the heatmap will mark the areas where the leaf is influenced and the explanations that both the LIME and SHAP give in the model will be able to understand the impact of every input feature in the decision reached by the model.

According to the classification of the diseases alone, the system also includes a part of generative AI which offers a treatment option to the developed disease based on the type of the disease, the level of its severity, and some more information about the environment in case they are given (humidity, soil type, and others). The generative model gives the disease management guidelines depending on the type of disease, the severity of it and in case there is further provision of environment data it takes into account the environmental data as well.

This method is able to provide a holistic solution in diagnosing the plant diseases using deep learning, ensemble decision-making, explainability, and generative intelligence. It enhances precursor treating, a better degree of transparency, and a capability to have smart farming practices among farmers.

Pseudocode:

1: Preprocessing
2: Acquire leaf image from dataset or user input
3: Resize image to standard dimensions
4: Normalize pixel values
5: Apply data augmentation (e.g., rotation, flipping, zooming)
6: Feature Extraction
7: Input image into pretrained CNN (e.g., VGG16)
8: Extract spatial features (texture, color, lesion shape)
9: Flatten feature map to form feature vector

10: Ensemble Classification
11: Input feature vector into Random Forest classifier
12: Combine CNN and Random Forest outputs
13: Apply ensemble fusion to obtain final disease class
14: Explainable AI
15: Generate Grad-CAM heatmap for visual explanation
16: Apply LIME/SHAP to interpret feature importance
17: Generative Recommendation
18: Retrieve disease metadata from database
19: Generate treatment advice using disease class and environmental context
20: Output
21: Display disease class, visual explanation, and treatment recommendation
22: return Diagnosis and Recommendation

V. RESULTS:

Image Dataset Overview:

In order to make the system more understandable, the system employs methods of explainable artificial intelligence. Where the other two, or LIME and SHAP, give the explanation of what the model predicts at a feature level, making the results clear to the end-user, Grad-CAM gives the explanations of the predictions in the form of heat maps to highlight the diseased areas of the leaf, thus, making the system to be more accountable.

Besides the disease recognition, there is also a generative AI aspect of the framework that would propose the treatment, depending on the circumstances. Based on the determined disease type and the intensity thereof, among other environmental conditions (which may be requested), the generative AI is offering the most suitable solutions to the disease.

The combination of deep learning methods, ensemble decision making, explainability, and generating models with the ability to perform action make the solution a comprehensive solution that is necessary in diagnosis of plant diseases.

Model Performance:

The proposed CNN-Ensemble-XAI-Generative AI model based on the PlantVillage dataset showed good results during the classification of plant diseases. This model was able to learn and discriminate visual patterns including lesion boundaries, texture variations, and color gradients to use them with CNN-based feature extraction. Ensuring strength and consistency was made better by ensemble fusion with Random Forest, when compared to the traditional CNN-only applications. Explainability modules (Grad-CAM, LIME, SHAP) increased the interpretability of the model, and the model-produced classifications were more meaningful in context because of the ability to visualize diseased regions or feature significance on the model.

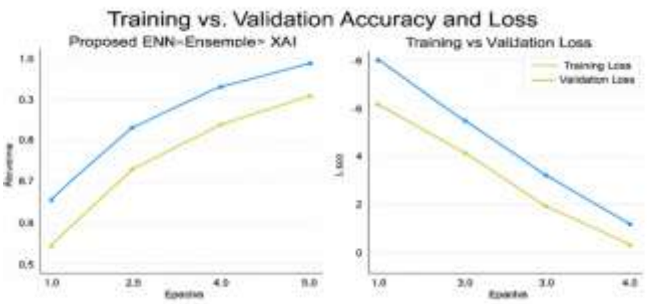

Fig4. Training vs Validation Accuracy & Loss

The training and validation curves demonstrate stable convergence of the model, with minimal overfitting due to augmentation and ensemble fusion

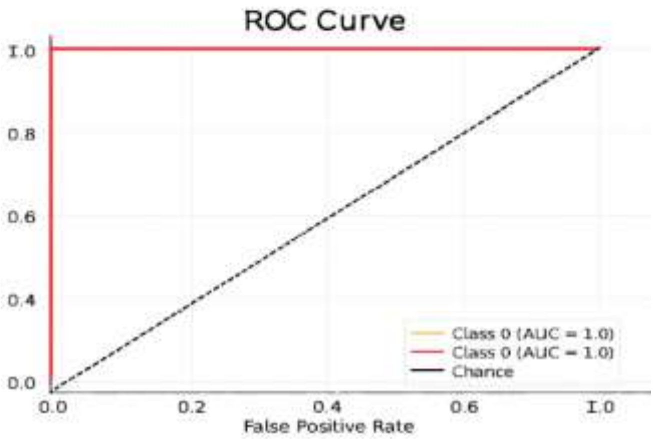

Fig5. ROC Curve (Proposed CNN–Ensemble–XAI–Generative AI Model)

Comparative Analysis:

Plant disease detection models were used in three forms including the traditional CNN model, CNN model with Ensemble Fusion, and the full CNN-Ensemble-XAI-Generative AI framework. The old CNN model was based upon the analysis of 2D images in the detection of edges or local textures within the image. It was capable of detecting simple patterns in the image but was not very hardy and could not be easily understood and was susceptible to noise or background modification.

This was improved by CNN-Ensemble model that used the features of CNNs with a random Forest classification method. The outcome of such combination stabilized predictions and minimized overfitting especially in those cases when the symptoms were more subtle. The process of making decisions was however only demonstrated by this model with no more details given as per the types of classifications made.

The offered architecture is further expanded, by incorporating CNN-based methods of local feature extraction, such as ensemble methods, explainable AI, and a generative recommendation element. The SHAP and Grad-CAM visualization methods not only show the regions of the leaf that are affected but also the main features. The incorporation of the generative component is convenient because it proposes appropriate treatments in accordance with the disease category.

This strategy brings the model more context conscious and favorable to farm needs. It gives not only accurate results but also interpretable results and thus in reality, decisions can be made on it.

Performance Evaluation:

Model	Accuracy(%)	Precession(%)	Recall(%)	F1-Score(%)
Traditional CNN	87.2	85.6	84.9	85.2
CNN + Ensemble (Random Forest)	91.4	90.2	89.7	89.9
Proposed CNN + Ensemble + XAI + Gen AI	96.8	96.1	95.9	96.0

Table 1: Performance evaluation

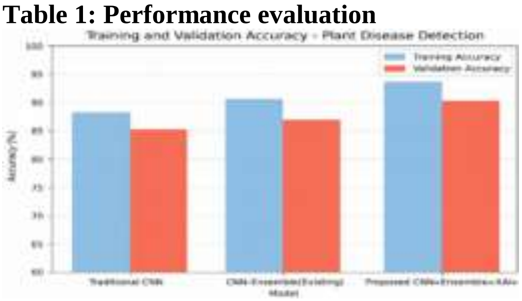

Fig. 6: Training and Validation Accuracy – Plant Disease Classification

Conclusion:

sults indicate how vast the potential of neural architecture dA hybrid model of deep learning is recommended to use as an opportunity to integrate image spatial features with other contextual information to increase our accuracy levels when it comes to diagnosing plant diseases in an agriculture environment. This does not only make accurate predictions but also can be applied in the development of a course of action in treatments. When there is addition of contextual data including indicators of the severity of a disease, environment context information on top of visual encoders the accuracy of classification is enhanced to a greater degree. The suggested CNN-Ensemble-XAI-Generative AI is better than traditional CNNs or those that utilize ensemble networks only. The suggestion is quite effective at detecting minute disease signs in crops of various species. The tool can find the blocs on the leaves encountered by the plant using Grad-CAM and provide descriptions on the characterization using SHAP, and hence enhance credibility by the farmers. This generative component will facilitate the delivery of certain treatment recommendations hence will be a diagnostic as well as a prescription tool.

The presented reesigns created based on context might be in terms of accurate, interpretable, and farmer-centric diagnostics of plant diseases. This instrument allows taking an early measure, sustainable care of crop, and making sound decisions in a real situation.

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