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Crop Disease Detection and Prevention Using Leaf Images Through an Ensemble of VGG16 and ResNet50

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Abstract

Agriculture plays a vital role in ensuring food security and economic stability. However, crop diseases significantly affect agricultural productivity and lead to substantial losses for farmers. Traditional disease identification methods rely on manual inspection by experts, which can be time-consuming, expensive, and prone to human error. This research proposes an intelligent crop disease detection and prevention system using leaf images and deep learning techniques.

The proposed system employs an ensemble model combining VGG16 and ResNet50 architectures to improve disease classification accuracy. Images from the PlantVillage dataset are utilized for model training and evaluation. Image preprocessing techniques such as resizing, normalization, and augmentation are applied to improve model performance.

The ensemble model effectively identifies various crop diseases and provides preventive measures along with pesticide recommendations. Experimental results demonstrate that the proposed approach achieves high classification accuracy and can serve as a reliable tool for early disease diagnosis in precision agriculture.

Keywords

Crop Disease Detection, Deep Learning, Ensemble Learning, VGG16, ResNet50, PlantVillage Dataset, Image Processing, Precision Agriculture.

I. INTRODUCTION

1.1 Background

Agriculture remains one of the most important sectors contributing to the global economy and food supply. The health of crops directly influences agricultural productivity and farmer income. Various plant diseases caused by fungi, bacteria, viruses, and environmental conditions can severely affect crop growth and yield.[1]

Traditional disease detection methods mainly depend on visual inspection by agricultural experts. Although effective, these methods require significant expertise and are not always accessible to farmers in remote areas. Delayed disease identification may lead to rapid disease spread and increased crop damage.[3]

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have enabled automated disease detection using leaf images. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks due to their ability to learn complex visual features.[4]

This research presents a crop disease detection and prevention system based on an ensemble of VGG16 and ResNet50 deep learning models. The system analyzes leaf images to identify diseases accurately and provides preventive actions and pesticide recommendations to assist farmers in disease management.[6]

1.2 Problem Statement

Agriculture is a primary source of livelihood for a significant portion of the global population, and crop health plays a crucial role in maintaining agricultural productivity. However, plant diseases caused by fungi, bacteria, viruses, and environmental stress factors continue to be a major challenge for farmers. These diseases reduce crop quality, decrease yield, and result in substantial economic losses. Early identification of diseases is essential because delayed diagnosis often leads to rapid disease spread and increased expenditure on disease control measures.[1][7]

Traditionally, disease detection is performed through manual field inspection by agricultural experts. Such methods are time-consuming, labor-intensive, expensive, and highly dependent on expert knowledge. Moreover, visual inspection becomes difficult when disease symptoms closely resemble healthy plant tissues or when symptoms appear in varying shapes, colors, and sizes. Environmental factors such as noise, illumination changes, image blur, background complexity, and leaf orientation further complicate accurate disease identification [4][6].

Deep learning techniques have significantly improved disease classification performance. However, many existing systems rely on a single convolutional neural network architecture, making them susceptible to limitations such as overfitting, computational complexity, reduced robustness, and poor generalization under diverse field conditions.[2][6]

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1.3 Motivation

A major motivation behind this work is the limitation of traditional disease diagnosis methods. Farmers often depend on personal experience or expert consultation to identify diseases. In many rural regions, access to agricultural specialists is limited, causing delays in disease diagnosis and treatment. Such delays can lead to severe crop damage and increased pesticide usage. Automated disease detection systems can assist farmers by providing fast and reliable diagnosis without requiring specialized knowledge. [3][9]

AI-assisted analysis is particularly important because modern financial decision-making increasingly depends on the ability to synthesize structured and unstructured information. Research on sentiment-augmented forecasting, mixture-of-expert financial language models, and agentic AI in finance shows that combining multiple information sources can improve both prediction quality and user support capabilities. This creates a strong foundation for integrating predictive analytics and conversational financial assistance into an educational trading platform [1][4][8].

Another important motivation arises from the success of deep learning in image classification tasks. Modern convolutional neural networks can automatically learn complex disease-related patterns from leaf images without requiring manual feature extraction. Models such as VGG16 excel at capturing fine-grained texture and color information, while ResNet50 effectively learns deep hierarchical features through residual learning. Combining these complementary strengths through ensemble learning can improve classification accuracy, robustness, and generalization capability [2][7][10].

1.4 Proposed Solution

The proposed system aims to provide an intelligent and automated solution for crop disease detection and prevention using leaf images. The system is designed to assist farmers in identifying plant diseases at an early stage and obtaining suitable preventive recommendations without requiring expert intervention. The solution combines deep learning techniques with image processing methods to achieve accurate disease classification and practical disease management support.4][10].

The workflow begins when a farmer uploads an image of a crop leaf through the web application developed using Flask. The uploaded image is first subjected to preprocessing operations to improve image quality and ensure consistency in the input data. These operations include image resizing, normalization, and enhancement techniques that help reduce noise and improve feature visibility. The processed image is then compared with the disease-related patterns learned from the PlantVillage dataset during model training.[7][11].

To perform disease identification, an ensemble learning approach is adopted by integrating two powerful deep learning architectures, namely VGG16 and ResNet50. Both models independently analyze the uploaded leaf image and extract relevant visual characteristics such as color variations, texture patterns, lesion structures, discoloration regions, and other disease-specific symptoms. VGG16 is effective in capturing detailed local features from the leaf surface, while ResNet50 utilizes residual learning to extract deeper and more complex feature representations. The combination of these complementary models enables the system to capture a wider range of disease-related information and improve classification reliability. [6][9].

1.5 Contributions

After feature extraction, predictions generated by both models are combined using an ensemble strategy to determine the final disease class. By aggregating the outputs of VGG16 and ResNet50, the system minimizes the limitations of individual models and improves overall prediction accuracy. This approach enhances robustness, reduces overfitting, and provides more consistent performance across different disease categories. [3][7].

Once the disease is identified, the system retrieves corresponding disease information from the database and presents the results to the farmer through a user-friendly interface. In addition to displaying the detected disease, the system provides detailed preventive measures that can help limit disease spread and minimize crop damage. These recommendations may include proper irrigation practices, removal of infected plant parts, crop rotation techniques, field sanitation guidelines, and environmental management suggestions. [6][13].

Furthermore, the system includes a pesticide recommendation module that suggests suitable pesticides or treatment options for the detected disease. These recommendations are generated based on disease-specific information stored in the database and are intended to support farmers in taking timely corrective actions. By combining disease detection with prevention and treatment guidance, the proposed solution extends beyond simple classification and serves as a comprehensive decision-support tool for precision agriculture [8][11].

II. LITERATURE REVIEW

2.1 Machine Learning for Crop Disease Detection

Machine Learning is a subset of Artificial Intelligence that enables computer systems to learn patterns from data without being explicitly programmed for every task. Instead of following predefined rules, machine learning algorithms analyze large datasets, identify relationships among features, and generate predictive models capable of making future decisions.[2][8]

In the context of crop disease detection, machine learning techniques are trained using images of healthy and diseased leaves. During training, the algorithms learn the distinguishing characteristics associated with different diseases. Once trained, these models can classify newly uploaded leaf images based on the patterns learned from the dataset.[6]

The advancement of deep learning has significantly enhanced machine learning capabilities by allowing models to automatically learn features directly from raw images. This eliminates the need for manual feature engineering and improves classification accuracy. Modern machine learning systems are capable of handling complex datasets, adapting to different crop species, and identifying subtle disease symptoms that may be difficult for humans to recognize. As a result, machine learning has become an essential technology for intelligent agricultural applications.[5][9]

2.2 Artificial Intelligence in crop prevention

Artificial Intelligence (AI) is a branch of computer science that focuses on developing systems capable of performing tasks that typically require human intelligence. These tasks include learning from experience, recognizing patterns, making decisions, solving problems, and understanding visual or textual information. In agriculture, AI has emerged as a powerful technology for addressing challenges related to crop monitoring, disease diagnosis, yield prediction, and resource management. [4][5]

The application of AI in plant disease detection has gained significant attention because it enables automated analysis of crop images and reduces dependency on manual inspection. Traditional disease diagnosis methods rely heavily on agricultural experts, making the process time-consuming and costly. AI-based systems can process large volumes of image data, identify disease symptoms, and generate accurate predictions within a short period. This capability is particularly useful for farmers who may not have immediate access to expert consultation. [5][4]

International Journal of Engineering Research & Technology (IJERT)
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2.3 Visual Geometry Group(VGG16)

VGG16 is one of the most widely used deep convolutional neural network architectures for image classification tasks. Developed by the Visual Geometry Group (VGG), the model consists of sixteen trainable layers that use small 3×3 convolution filters arranged in a deep architecture. The simplicity and effectiveness of VGG16 make it highly suitable for transfer learning applications in agricultural image analysis.[3][7]

The studies analyzed indicate that VGG16 performs particularly well in identifying fine-grained visual characteristics that differentiate healthy leaves from diseased ones. The model's deep structure enables it to learn hierarchical representations, where initial layers capture basic image patterns while deeper layers learn disease-specific features. Through transfer learning, pretrained VGG16 weights can be utilized to reduce training time and improve prediction accuracy even when agricultural datasets are relatively limited. [7][8]

Another significant advantage of VGG16 is its ability to generalize across different crop categories. It has been successfully applied to classify diseases affecting tomatoes, potatoes, maize, grapes, and several other crops. However, despite its strong feature extraction capability, VGG16 may require higher computational resources and can occasionally struggle with learning extremely deep feature relationships. These limitations motivate its integration with complementary architectures such as ResNet50.[3][7][8]

2.4 Resnet50 model in Crop Prevention

ResNet50 is a deep residual neural network architecture consisting of fifty layers. It was introduced to overcome the degradation and vanishing gradient problems commonly encountered in very deep neural networks. The key innovation of ResNet50 is the use of residual or skip connections, which allow information to flow directly between layers without being lost during training.[10]

In plant disease detection applications, ResNet50 is highly effective at learning complex and abstract image representations. While shallow networks primarily focus on surface-level visual characteristics, ResNet50 can capture deeper relationships among disease symptoms, leaf structures, and texture variations. This capability improves classification accuracy, especially when dealing with multiple disease categories that exhibit similar visual appearances.[11]

Another important contribution of ResNet50 is its strong generalization ability. The model maintains stable performance across diverse datasets and varying image conditions such as illumination changes, background variations, and leaf orientation differences. These characteristics make it highly suitable for real-world agricultural environments where image quality may not always be ideal.[9]

2.5 Research Gap

The literature review reveals that significant progress has been made in the field of crop disease detection through the application of Artificial Intelligence and Deep Learning techniques. Several researchers have employed convolutional neural networks, transfer learning models, and image processing approaches to identify plant diseases from leaf images with promising accuracy. Although these studies demonstrate the effectiveness of deep learning in agricultural applications, several limitations and research gaps still exist that require further investigation.[4][3][1]

One of the major observations from the reviewed studies is that most existing systems rely on a single deep learning architecture for disease classification. Models such as VGG16, ResNet50.

Dense Net, Inception Net, and Mobile Net have individually achieved good performance; however, each architecture has its own strengths and weaknesses. Single-model approaches may fail to capture all disease-specific features present in leaf images, resulting in reduced classification reliability under complex conditions.[7][5]

To address these identified gaps, the proposed work introduces an ensemble-based crop disease detection and prevention system that combines VGG16 and ResNet50 for enhanced disease classification. The system not only detects diseases from leaf images but also provides preventive measures and pesticide recommendations through a Flask-based web application. This integrated approach aims to improve prediction accuracy, practical usability, and decision-making support for farmers while overcoming the limitations observed in existing research.[3][8][7]

III. PROPOSED SYSTEM

3.1 System Overview

The proposed **Crop Disease Detection and Prevention System Using Leaf Images** is an intelligent web-based application developed to assist farmers in identifying crop diseases accurately and at an early stage. The system utilizes advanced Deep Learning techniques, image processing methods, and transfer learning models to analyze leaf images and provide disease diagnosis along with preventive recommendations. The primary objective of the system is to reduce crop losses by enabling timely disease detection and supporting farmers in making informed agricultural decisions.The design is based on the principle that financial understanding improves when execution, analysis, and explanation are combined.[2]

A farmer interacts with the system through a user-friendly Flask-based web application where a leaf image of the affected crop is uploaded. The uploaded image serves as the input for the disease detection process. Since raw images may contain noise, varying lighting conditions, background disturbances, and size inconsistencies, the image first undergoes preprocessing operations. These preprocessing techniques include image resizing, normalization, enhancement, and data preparation to ensure that the input image is suitable for deep learning analysis.[5]

After preprocessing, the image is passed to the disease classification module. The proposed system employs an ensemble learning approach by combining two state-of-the-art deep learning architectures, namely VGG16 and ResNet50. Both models are pretrained using transfer learning techniques and further trained on the PlantVillage dataset to recognize various crop diseases. The use of transfer learning enables the models to utilize previously learned visual features, thereby reducing training time and improving classification performance.[3]

The ensemble module combines the predictions obtained from VGG16 and ResNet50 to determine the final disease classification result. This integration enhances prediction reliability by utilizing the strengths of both models. Ensemble learning helps reduce individual model errors, improve classification accuracy, minimize overfitting, and increase the robustness of the system. The final output generated by the ensemble model represents the most probable disease affecting the crop leaf.[8]

International Journal of Engineering Research & Technology (IJERT)
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3.2 System Architecture

The proposed Crop Disease Detection and Prevention System follows a structured workflow that enables accurate disease identification and provides preventive recommendations to farmers. The system begins with the **Farmer User Interface (UI)**, where the farmer uploads an image of a crop leaf suspected to be affected by a disease. The user interface acts as the interaction layer between the farmer and the application, allowing users to submit leaf images and receive disease prediction results along with preventive measures.[7]

Once the image is uploaded, it is transferred to the **Data Management Module**. In this module, the uploaded image is stored temporarily in the image storage repository. The storage component maintains image records and facilitates efficient data handling during the prediction process. After storage, the image is forwarded to the preprocessing unit. Image preprocessing is an important stage because raw images may contain variations in size, brightness, background noise, and orientation. Therefore, preprocessing techniques such as image resizing, normalization, noise reduction, and enhancement are applied to improve image quality and prepare the data for deep learning analysis.[3]

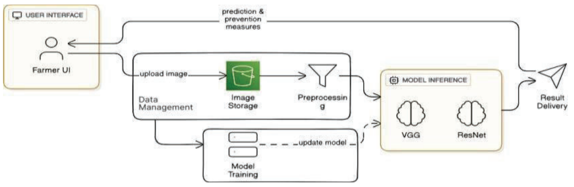

Figure 3.1 System Architecture Diagram

The preprocessed image is then sent to the **Model Inference Module**, which represents the core component of the proposed system. This module consists of two deep learning models: **VGG16** and **ResNet50**. Both models independently analyze the input image and extract disease-related visual features. VGG16 focuses on capturing detailed local characteristics such as color changes, texture patterns, spots, and lesions present on the leaf surface. Simultaneously, ResNet50 utilizes residual learning to identify deeper and more complex disease patterns, improving feature representation and classification capability. The predictions generated by both models are combined using an ensemble approach to obtain a more accurate and reliable disease classification result.

After disease classification is completed, the prediction results are transferred to the **Result Delivery Module**. This module retrieves disease-specific information from the database and generates meaningful outputs for the farmer. The final result includes the detected disease name, confidence score, preventive measures, and recommended pesticides or treatment methods. These recommendations assist farmers in taking timely corrective actions to prevent disease spread and minimize crop damage.

Finally, the generated results are displayed back to the farmer through the user interface. The farmer receives a comprehensive report containing disease diagnosis and prevention guidelines, enabling informed decision-making regarding crop health management. By integrating image storage, preprocessing, deep learning-based disease detection, model training, and result delivery into a single framework, the proposed system provides an efficient, accurate, and user-friendly solution for modern precision agriculture.

Functional Modules

3.2.1 User Interface (Farmer UI)

The User Interface serves as the entry point of the system. It allows farmers to upload crop leaf images and view disease detection results. The interface is designed to be simple and user-friendly so that individuals with limited technical knowledge can easily use the application..

3.2.2 Data Management Module

The Data Management module handles image storage and preprocessing operations. It ensures that uploaded images are properly stored, organized, and transformed into a suitable format before being processed by the deep learning models.

3.2.3 Preprocessing Module

The preprocessing module enhances image quality through resizing, normalization, and noise removal techniques. This step improves feature visibility and ensures consistent input dimensions for the deep learning models.

3.2.4 Model Training

The Model Training component trains the VGG16 and ResNet50 models using the PlantVillage dataset. It enables the system to learn disease-specific patterns and continuously improve prediction accuracy through model updates.

3.2.5 Model Inference

The Model Inference module performs real-time disease classification. VGG16 and ResNet50 independently analyze the uploaded image, and their outputs are combined using ensemble learning to generate the final prediction.

3.2.6 Result Delivery

The Result Delivery module communicates the prediction outcome to the farmer. Along with disease identification, it provides preventive measures and pesticide recommendations that help farmers effectively manage crop diseases and reduce yield losses.

IV. METHODOLOGY

4.1 Data Collection

The The first step in the crop disease detection system was the collection of leaf images from different crop plants. A diverse dataset was gathered containing images of both healthy and diseased leaves. The dataset included multiple disease categories so that the models could learn to distinguish between various plant health conditions accurately.The leaf images were obtained from publicly available agricultural datasets and online repositories that provide labeled plant disease images. Each image in the dataset was associated with a specific class label indicating either a healthy leaf or a particular disease affecting the plant.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

4.2 Image Preprocessing

The Image preprocessing was performed to improve the quality and consistency of the leaf images before they were used for training the deep learning models. Since the collected images came from different sources and varied in size, resolution, lighting conditions, and orientation, preprocessing was necessary to prepare the data in a suitable format for VGG16 and ResNet50. First, all images were resized to a fixed dimension required by the models. This ensured that every image had the same size and could be processed efficiently during training and testing. Resizing also helped reduce computational complexity and training time.

4.3 Data Augumentation

Data augmentation was applied to increase the size and diversity of the training dataset without collecting additional images. In crop disease detection, the number of available leaf images for certain disease classes may be limited. Training a deep learning model on a small dataset can lead to overfitting, where the model performs well on training data but poorly on new and unseen images. Data augmentation helps overcome this problem by generating multiple variations of existing images.Several augmentation techniques were used to create modified versions of the original leaf images while preserving their disease characteristics. These techniques included rotation, horizontal flipping, vertical flipping, zooming, shifting, and slight brightness adjustments. Such transformations simulate real-world conditions where leaf images may be captured from different angles, distances, and lighting environments.

4.4 Dataset Splitting

The After completing the data collection and preprocessing stages, the dataset was divided into separate subsets for training, validation, and testing. Dataset splitting is an important step because it allows the performance of the deep learning models to be evaluated on unseen data, ensuring that the models can generalize well to real-world images.The dataset was divided into three parts: the training set, validation set, and testing set. The training set contained the majority of the images and was used to train the VGG16 and ResNet50 models. During training, the models learned to identify disease-related patterns such as spots, discoloration, lesions, and texture changes present on the leaf images.

4.5 Feature Extraction

The In this research, **VGG16** and **ResNet50** were used as feature extraction models. Both models were pre-trained on the ImageNet dataset and then adapted for crop disease detection using transfer learning. The pre-trained models already possessed the ability to recognize general image patterns, which helped them learn disease-specific features more efficiently.During feature extraction, the convolutional layers of the models analyzed the leaf images and identified important visual patterns. The initial layers detected basic features such as edges, lines, colors, and textures. As the image passed through deeper layers, the models extracted more complex features, including disease spots, lesions, discoloration, vein abnormalities, and texture changes associated with different plant diseases.

4.6 Disease Detection

The **VGG16 model** uses a deep architecture consisting of multiple convolutional layers followed by pooling layers. The **ResNet50 model** uses residual learning and skip connections, which allow information to flow directly between layers. After training, both models were tested using unseen leaf images from the test dataset. When a new leaf image was provided, the trained model analyzed the image, extracted relevant features, and predicted the most probable disease class.

The output included the detected disease along with a confidence score indicating the model's certainty in its prediction. The performance of VGG16 and ResNet50 was compared using evaluation metrics such as accuracy, precision, recall, and F1-score. This comparison helped determine which model was more effective for crop disease detection. By utilizing these advanced deep learning architectures, the proposed system was able to accurately identify plant diseases at an early stage, supporting timely preventive measures and improved crop management.

4.7 Disease Classification

Disease classification is the process of assigning a leaf image to its corresponding disease category based on the features extracted by the deep learning models. After the feature extraction stage, the VGG16 and ResNet50 models analyzed the learned patterns and determined whether the leaf was healthy or affected by a specific disease.The classification process began when a preprocessed leaf image was provided as input to the trained model. The image passed through multiple layers of the network, where important visual characteristics such as color changes, spots, lesions, wilting patterns, and texture variations were analyzed. Based on these characteristics, the model calculated the probability of the image

4.8 Performance Evaluation

Performance evaluation was conducted to measure the effectiveness and reliability of the proposed crop disease detection system. After training the VGG16 and ResNet50 models, their performance was assessed using the test dataset, which contained leaf images that were not used during the training process. This evaluation helped determine how accurately the models could identify and classify crop diseases in unseen data.Several evaluation metrics were used to analyze the performance of the models. The primary metric was **accuracy**, which measures the percentage of correctly classified images out of the total number of images tested. A higher accuracy value indicates better model performance in disease detection and classification.

4.9 Disease Prevention Recommendation System

The Disease Prevention Recommendation System was developed to provide useful guidance to users after the successful detection and classification of crop diseases. The main objective of this system is not only to identify the disease but also to suggest appropriate preventive and management measures that can help reduce the spread of the disease and minimize crop losses. Once a leaf image is uploaded, the trained VGG16 or ResNet50 model analyzes the image and predicts the disease affecting the crop. Based on the predicted disease, the recommendation system retrieves relevant prevention and control information from a predefined database containing disease-specific recommendations. These recommendations are designed to assist farmers in taking timely action to protect their crops.

V. RESULTS

5.1 Dataset Performance Evaluation

Dataset performance evaluation was carried out to assess the quality of the dataset and its impact on the performance of the crop disease detection models. A well-structured and balanced dataset is essential for training deep learning models effectively, as it directly influences the accuracy and reliability of disease prediction. The collected dataset was analyzed to ensure that it contained sufficient images for each disease category as well as healthy leaf samples. The distribution of images across different classes was examined to identify any imbalance that could affect the learning process. Maintaining a balanced dataset helped the VGG16 and ResNet50 models learn disease patterns more accurately and prevented bias toward any specific class.

International Journal of Engineering Research & Technology (IJERT)
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Vol. 15 Issue 06 , June - 2026

5.2 Performance of VGG16 model

The performance of the VGG16 model was evaluated to determine its effectiveness in detecting and classifying crop diseases from leaf images. VGG16 is a deep convolutional neural network consisting of multiple convolutional and pooling layers that enable it to learn important visual features from images. Its structured architecture makes it suitable for identifying disease symptoms such as spots, discoloration, lesions, and texture variations present on crop leaves.The model was trained using the preprocessed and augmented dataset through a transfer learning approach. During training, VGG16 learned to recognize disease-specific patterns by analyzing a large number of leaf images belonging to different disease categories. The training process continued until the model achieved stable performance on both the training and validation datasets.

5.3 Comparative Analysis of VGG16 and ResNet50

A comparative analysis was conducted between the **VGG16** and **ResNet50** models to evaluate their effectiveness in crop disease detection and classification using leaf images. Both models are widely used deep learning architectures for image recognition tasks, but they differ in their network design, learning mechanisms, and overall performance characteristics. Both models were trained and tested using the same preprocessed and augmented dataset to ensure a fair comparison. The evaluation was performed using standard performance metrics such as **accuracy, precision, recall, F1-score, training time, and classification efficiency**. These metrics provided a comprehensive understanding of each model's strengths and limitations.

5.4 Disease Classification Results

The disease classification results demonstrate the ability of the proposed crop disease detection system to accurately identify and categorize plant diseases from leaf images. After training the VGG16 and ResNet50 models using the prepared dataset, both models were tested on unseen leaf images to evaluate their classification performance. When a leaf image was provided as input, the trained models analyzed the visual characteristics of the leaf, including color changes, spots, lesions, texture variations, and other disease symptoms. Based on the extracted features, the models predicted the most likely disease category and generated a confidence score indicating the certainty of the prediction.

5.5 Prevention Recommendation Outcomes

The Prevention Recommendation Outcomes represent the final stage of the proposed crop disease detection and prevention system. After a disease was successfully identified by the VGG16 or ResNet50 model, the system generated appropriate prevention and management recommendations based on the detected disease. This feature enhanced the practical usefulness of the system by helping users take timely actions to reduce disease spread and protect crop health. The recommendation system successfully provided disease-specific guidance for each predicted crop disease. Once the classification process was completed, the detected disease was matched with a predefined knowledge base containing information about disease symptoms, causes, prevention methods, and control measures. The relevant recommendations were then displayed to the user in a simple and understandable format.

5.6 Impact Of Transfer Learning

Transfer learning played a significant role in improving the performance of the crop disease detection system. Instead of training deep learning models from scratch, the pre-trained **VGG16** and **ResNet50** models were utilized. These models were originally trained on the large-scale ImageNet dataset, which contains millions of images from various categories. By using the knowledge already learned from ImageNet, the models were able to recognize important visual patterns and adapt them to the task of crop disease classification. The use of transfer learning significantly reduced the amount of training data required for the project. Since agricultural datasets are often smaller than general image datasets, training a deep neural network from scratch may lead to poor performance and overfitting. Transfer learning helped overcome this limitation by allowing the models to start with pre-learned image features rather than learning everything from the beginning.

5.7 Overall System Performance

The overall performance of the proposed crop disease detection and prevention system was evaluated by analyzing the combined effectiveness of all its components, including data preprocessing, data augmentation, feature extraction, disease detection, disease classification, and the prevention recommendation module. The system was designed to accurately identify crop diseases from leaf images and provide suitable preventive measures to support effective crop management. The implementation of deep learning models, namely **VGG16** and **ResNet50**, enabled the system to learn important disease-related features directly from leaf images. Through transfer learning, both models achieved strong classification performance while reducing training time and computational requirements. The models successfully identified disease symptoms such as spots, discoloration, lesions, and texture changes, allowing accurate classification of healthy and diseased leaves.

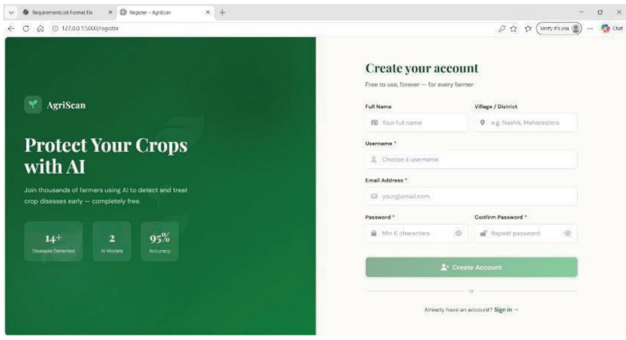

Figure 5.1 User Registration

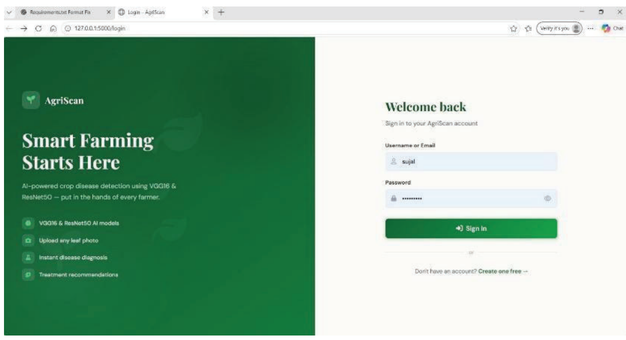

Figure 5.2 User Login

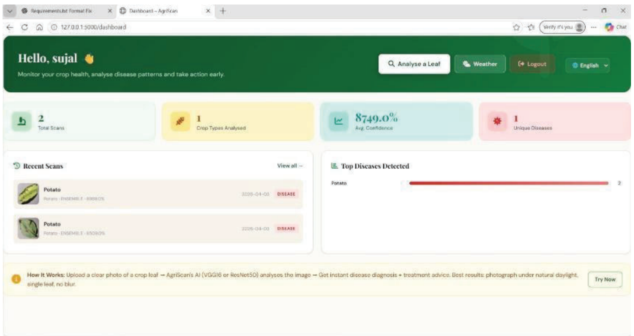

Figure 5.3 User Dashboard

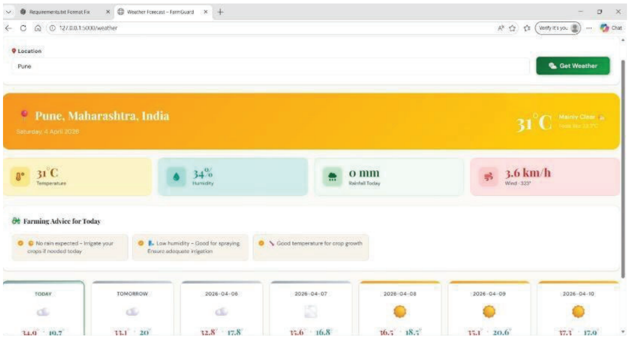

Figure 5.4 Weather Forecast

VI. CONCLUSION

This research presented an effective crop disease detection and prevention system using leaf images and deep learning techniques. The primary objective of the study was to develop a system capable of accurately identifying crop diseases at an early stage and providing suitable prevention recommendations to support farmers in disease management.The proposed methodology involved data collection, image preprocessing, data augmentation, dataset splitting, feature extraction, disease detection, and disease classification using two pre-trained deep learning models, **VGG16** and **ResNet50**. Transfer learning was applied to improve model performance and reduce training time by utilizing knowledge learned from large-scale image datasets. The models were trained to recognize disease-related features such as leaf spots, discoloration, lesions, and texture abnormalities

The experimental results demonstrated that both VGG16 and ResNet50 were effective in classifying healthy and diseased crop leaves. Performance evaluation using metrics such as accuracy, precision, recall, and F1-score confirmed the reliability of the proposed system. A comparative analysis showed that while both models achieved strong classification results, **ResNet50 generally outperformed VGG16** due to its deeper architecture and residual learning capability, enabling it to capture more complex disease patterns.
In addition to disease detection, the system incorporated a prevention recommendation module that provided disease-specific guidance and management practices. This feature increased the practical usefulness of the system by helping users take timely preventive actions to reduce disease spread and minimize crop losses. Overall, the developed system successfully combined advanced deep learning techniques with agricultural knowledge to create a reliable decision-support tool for crop disease diagnosis and prevention. The results indicate that the proposed approach can assist farmers in monitoring crop health, improving disease management practices, enhancing agricultural productivity, and reducing economic losses caused by plant diseases. The study demonstrates the potential of artificial intelligence and deep learning in modern agriculture and highlights the importance of early disease detection for sustainable farming and food security. Future improvements may include the use of larger and more diverse datasets, real-time mobile applications, and the integration of additional deep learning models to further enhance system performance and usability.

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