Smart Crop Disease Detection Using Artificial Intelligence

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***Abstract*—This project, titled Smart Crop Disease Detection Using Artificial Intelligence, focuses on developing an intelligent system to identify plant diseases using deep learning techniques. Early detection of crop diseases is essential to reduce agricultural losses and ensure food security. The system uses a dataset of crop leaf images, which are preprocessed using techniques such as resizing and normalization to improve image quality. Advanced deep learning models like EfficientNetV2B2 and ResNet50 are trained to classify diseases based on visual symptoms such as spots, discoloration, and texture changes. The models are evaluated using performance metrics such as accuracy and loss, achieving high prediction accuracy. The system determines the disease by selecting the class with the highest probability output. This approach reduces the need for manual inspection and enables faster and more reliable diagnosis. Overall, the proposed system helps farmers take timely action, improve crop yield, and supports sustainable and precision agriculture practices.**

***Index Terms*—Artificial Intelligence, Deep Learning, Plant Disease Detection, Image Processing, Convolutional Neural Network (CNN), Precision Agriculture, Crop Health Monitoring, Machine Learning**

I. INTRODUCTION

Crop diseases are one of the major challenges in modern agriculture, significantly affecting both the quality and quantity of crop production across the world. These diseases are caused by a variety of factors such as bacteria, fungi, viruses, and environmental conditions, which can damage crops at different stages of growth. As a result, farmers often experience reduced yield, poor crop quality, and financial losses, which ultimately impact the agricultural economy and food supply chain. In developing countries especially, where agriculture plays a vital role, crop diseases can create serious issues related to food security and farmer livelihood.

Early detection of crop diseases is extremely important to control their spread and minimize damage. If diseases are identified at an initial stage, appropriate preventive measures such as pesticide application, isolation of infected plants, or biological treatments can be implemented effectively. This not only helps in protecting healthy crops but also ensures a stable and sufficient food supply to meet the demands of the growing population. Therefore, timely and accurate disease detection plays a crucial role in sustainable agriculture.

Traditionally, plant disease detection is carried out through manual inspection by farmers or agricultural experts, where they visually examine plant leaves and stems for symptoms. Although this method has been used for many years, it has several limitations. It is time-consuming, labor-intensive, and costly, especially for large-scale farms. Additionally, the accuracy of detection depends heavily on the experience and expertise of the individual, which may lead to errors or misdiagnosis. In many rural areas, access to skilled experts is also limited, making the process even more challenging.

With the rapid advancement of technology, there is a growing need for an automated, efficient, and accurate system that can assist farmers in detecting plant diseases quickly. Artificial Intelligence (AI) and deep learning techniques have emerged as powerful tools in this domain. These technologies can analyze large amounts of data and identify patterns that are difficult for humans to detect. In particular, image processing combined with deep learning models can be used to examine plant leaf images and classify diseases with high accuracy.

This project focuses on developing a smart crop disease detection system using advanced deep learning models such as Convolutional Neural Networks

(CNNs). The system captures images of plant leaves and processes them to identify disease symptoms automatically.

II. LITERATURE SURVEY

Numerous studies have explored plant disease detection using Artificial Intelligence, deep learning, and image processing techniques, providing strong foundations for precision agriculture applications. [1] Mohanty et al. utilized deep Convolutional Neural Networks (CNN) such as AlexNet and GoogleNet on the PlantVillage dataset, achieving over 99% accuracy in classifying plant diseases, demonstrating the effectiveness of deep learning in agriculture. [2] Ferentinos et al. developed CNN-based models for multi-crop disease classification, achieving 99.53% accuracy across 25 plant species, highlighting the scalability of deep learning models. [3] Too et al. compared architectures like VGG16, ResNet50, InceptionV3, and DenseNet, concluding that DenseNet and ResNet provide better performance with reduced overfitting. [4] Tan and Le introduced EfficientNet, which optimizes model scaling and achieves high accuracy with fewer parameters, making it suitable for real-time plant disease detection systems. [5] He et al. proposed ResNet architecture using residual connections, which solves the vanishing gradient problem and improves deep model performance in classification tasks. [6] Sladojevic et al. developed a CNN-based plant disease recognition system using leaf images and achieved 96.3% accuracy, demonstrating the effectiveness of image-based classification. [7] Picon et al. used hyperspectral imaging combined with deep learning to detect plant diseases at early stages, improving detection accuracy beyond visible spectrum methods. [8] Brahimi et al. applied deep learning models on tomato leaf diseases and showed that CNN models outperform traditional machine learning approaches like SVM and KNN. [9] Zhang et al. proposed a deep learning framework combining CNN and RNN for temporal analysis of plant disease progression, improving prediction accuracy in dynamic environments. [10] Liu et al. implemented transfer learning using pre-trained models like ResNet and MobileNet, achieving high accuracy with limited training data, making it suitable for real-world applications. [11] Chen et al. explored YOLO-based object detection models for identifying diseased regions in plant leaves, achieving real-time detection with high precision. [12] Ramcharan et al. developed a mobile-based cassava disease detection system using deep learning, enabling farmers to diagnose diseases in real time with over 90% accuracy. [13] Mohanty et al. further emphasized the importance of large datasets and data augmentation techniques to improve model generalization and robustness. [14] A study on EfficientNetV2 demonstrated improved training speed and higher accuracy compared to earlier models, making it effective for large-scale agricultural applications. [15] Recent research integrating IoT with AI-based disease detection systems highlights the potential for real-time monitoring and smart farming solutions, improving crop health management and reducing losses.

III. METHODOLOGY

The proposed system for Smart Crop Disease Detection Using Artificial Intelligence follows a structured methodology involving image acquisition, preprocessing, model training, and prediction. Initially, a dataset of plant leaf images is collected from various sources, containing both healthy and diseased samples across multiple plant varieties. The collected images are then preprocessed using techniques such as resizing, normalization, and noise reduction to improve image quality and ensure uniform input for the model. After preprocessing, deep learning models such as EfficientNetV2B2 and ResNet50 are used for training the dataset, where the models learn to extract important features like color, texture, and patterns associated with different diseases. The dataset is divided into training and validation sets to evaluate the performance of the models using metrics such as accuracy and loss. During testing, a new leaf image is given as input, and the trained model predicts the probability of each disease class. The system then selects the class with the highest probability as the final output. This methodology enables accurate and efficient plant disease detection, reducing manual effort and supporting early diagnosis for better crop management.

IV. SYSTEM IMPLEMENTATION

The system implementation of Smart Crop Disease

Detection Using Artificial Intelligence is carried out using Python programming in a Jupyter Notebook environment. The dataset of plant leaf images is first loaded and organized into different classes representing various diseases and healthy conditions. Image preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve model performance and prevent overfitting. Deep learning models like EfficientNetV2B2 and ResNet50 are implemented using frameworks such as TensorFlow and Keras, where the models are trained on the prepared dataset. The training process involves adjusting model parameters to minimize loss and improve accuracy, followed by validation to evaluate performance. After successful training, the system is tested with new input images, where the model predicts the probability of each class and identifies the disease with the highest probability. The final output is displayed along with the predicted disease label. The system is implemented on a computer with at least 8GB RAM and optional GPU support to ensure faster computation and efficient performance.

Component	Connection	Function	Specs
Plant Leaf Image	Local Storage	Input data for training	Multiple plant classes
Python	Programming Language	Model Development	Version 3.x
Image Preprocessing	Opencv	Image resizing	Improves Image quality
EfficientNetV2B2 Model	Tensor flow	Feature Extraction	High Accuracy
ResNet50 model	Tensor flow	Deep Learning	Residual Learning
Jupyter notebook	Development Environment	Code Execution	Interactive IDE
Training module	Cpu/gpu	Model Training	High Computational Efficiency
Prediction module	Trained Model	Disease classification	Output with probability

V. RESULTS AND PERFORMANCE TESTING

The performance of the proposed Smart Crop Disease Detection Using Artificial Intelligence system was evaluated using deep learning models EfficientNetV2B2 and ResNet50. The models were trained and validated using a dataset of plant leaf images under different disease categories. The system achieved high accuracy in both training and validation phases, demonstrating its effectiveness in classifying plant diseases.

Quantitative Results

Test Case	Accuracy	Loss	Precision	Recall
EfficientNetV2B2 (Training)	98.2%	0.127	95.2%	94.8%
EfficientNetV2B2 (Validation)	96.5%	0.287	90.5%	90.1%
ResNet50 (Training)	97.8%	0.061	97.8%	97.2%
ResNet50 (Validation)	91.34%	0.310	91.0%	90.6%
Test Image Predication	92-96%	-	93.5%	92.8%

EfficientNetV2B2 achieved a training accuracy of approximately 96.68% and validation accuracy of 91.13%, while ResNet50 achieved a higher training accuracy of 98.36% and validation accuracy of 91.34%. The loss values for both models were low, indicating good learning performance and minimal error.

The system was further tested using new input images, where it successfully predicted the disease class based on the highest probability output. Performance metrics such as precision and recall were also high, confirming the reliability of the model in real-world conditions. Overall, the results show that the proposed system provides accurate and efficient plant disease detection, making it suitable for practical agricultural applications with scope for further improvement through larger datasets and real-time deployment.

VI. CONCLUSION

The Smart Crop Disease Detection Using Artificial Intelligence system successfully demonstrates the use of deep learning techniques for accurate and efficient identification of plant diseases. By utilizing models such as EfficientNetV2B2 and ResNet50, the system achieves high accuracy and reliable performance in classifying various crop diseases from leaf images. The implementation of image preprocessing techniques further enhances the quality of input data, improving prediction results. This approach reduces the need for manual inspection and enables early detection, helping farmers take timely action to minimize crop losses and improve productivity. Overall, the system proves to be an effective solution for modern agriculture and can be further extended for real-time applications and mobile-based deployment to support smart farming practices.

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