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Research Article

Detection of Plant Diseases using Advanced Deep Learning Methods

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ABSTRACT

Plant diseases are a major global danger to crop productivity. The labor-intensive and time-consuming nature of traditional disease detection technologies causes delays in diagnosis and treatment. The progression of automated methods for identifying and diagnosis plant diseases has gained popularity with the growth of deep learning techniques, especially vision for computers and machine learning. This study examines the application Region based Convolutional Neural Networks (R-CNN) and Visual Geometry Group (VGG) to detect plant disease with highest accuracy of 0.9827 . With particular emphasis on the creation of a reliable and effective system for quick recognition and medical treatment. Used Village dataset and it is compared with existing models and achieved higher accuracy. The results of the experiments show the suggested model works to precisely detect different plant diseases Modern deep learning techniques have made a significant contribution to the diagnosis of plant diseases, providing prospective means of reducing crop losses, raising agricultural output, and securing the world's food supply.

Keywords- Plant Disease Identification, Computational Intelligence, Deep Learning, R-CNN, **VGG.**

I. INTRODUCTION

Plant infections have historically a substantial worry for the productivity of agriculture and food security worldwide. These illnesses may result in significant yield losses, threatening the livelihoods of farmers and impacting global food supply chains. Traditional methods of disease detection, primarily reliant on visual inspection by human experts or manual analysis of plant samples in laboratories, are frequently insufficient for prompt and accurate diagnosis. These methods are labor-intensive, time-consuming, and subject to human error, leading to delays in intervention and ineffective disease management strategies.
Recently, there has been a growing interest in leveraging AI techniques, particularly machine learning and computer vision, to develop automated systems for plant diseases identification and diagnosis. AI-based approaches offer the capacity to get beyond the constraints of traditional methods by enabling real-time, accurate, and scalable disease detection solutions. By analyzing large datasets of plant images, AI algorithms can learn to identify subtle visual indicators connected to a variety of diseases, facilitating identifying early and targeted intervention.
The aim of this research paper is to investigate of the use of AI in identifying illness in plants and diagnosis, with a focus on developing an efficient and accurate early illness detection system in crops. The suggested approach leverages algorithms for deep learning trained on annotated datasets of plant images to enable

automatic identification of illness. By integrating AI techniques with image processing algorithms, the system aims to provide real-time diagnosis, thereby enabling timely intervention and mitigation strategies to minimize yield losses and ensure food security. Here Figure 1 implements the architecture diagram for the purpose of plant categorization and disease identification.

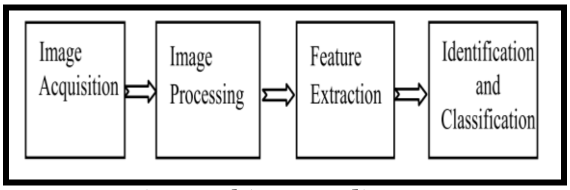

Fig1: Architecture diagram

In the face of new obstacles brought on by pests, diseases, and climate change, we aim to improve global food security and advance sustainable agricultural practices by utilizing AI for plant disease identification.

II. LITERATURE REVIEW

Vijai Singh et al. [1] provides insights into the utilization of imaging techniques, machine learning, and advanced methods for identifying plant diseases in agriculture. It discusses various methods for identifying plant diseases hyperspectral imaging, magnetic resonance imaging, and photoacoustic imaging for recognizing and categorizing diseases of plants. Researchers have developed algorithms and models utilizing deep learning and ANN(artificial neural networks) to differentiate between wholesome and unwholesome plants with high accuracy rates. Additionally, the document highlights the significance of early illness identification in plants to enhance crop quality and reduce disease occurrence

M. Nagaraju et al. [2] provides a thorough ananlys of deep learning techniques for identifying plant diseases, focusing on the automated disease detection through hyperspectral photos for ecological agriculture. The document discusses the significance of in-depth education models in addressing the primary challenge of ailments detection in crops. It highlights the use of convolutional neural networks (CNNs) for processing imaging data to recoginize and categorize plant illness efficiently. Additionally, the document emphasizes the importance of hyperspectral data analysis in improving the precision of agricultural disease detection system.

Punam Bedi et al. [3] discusses a innovative hybrid model for employing convolutional neural networks(CNN) to diagnose plant diseases and Convolutional Autoencoder (CAE) . The suggested framework model aims to lower the quantity of training parameters while maintaining high classification accuracy. By leveraging CAE for prior to using CNN for classification, dimensionality reduction, the model achieves impressive testing accuracy and performance metrics. The study compares the proposed approach with existing state-of-the-art systems, highlighting its efficiency in terms of training time, prediction time, and parameter usage.

Houda Orchi et al. [4] presents a detailed examination of the application of Internet of Things (IoT) and Artificial Intilligence in crop sickness detection within the agricultural sector. The document explores various methodologies, algorithms, and models utilized for the recognizing and categorizing crop diseases, including deep learning, transfer learning, machine learning, and computer vision. It discusses the challenges faced in crop disease detection, proposes solutions and outlines evaluation metrics for assessing the performance of disease detection models.

Jun Liu et al. [5] discusses the use of deep learning technology in plant diseases and pest detection, emphasizing its superiority over traditional methods because of its capacity to achieve better detection results in challenging conditions. It compares single-stage and two-stage detection networks, highlighting the faster inference speed of single-stage networks like SSD and YOLO. The study addresses the need to reduce complexity and improve model efficiency for deployment on mobile platforms, emphasizing the importance of selecting appropriate hyperparameters.

M. Oussalah et al. [6] discusses the challenges in identifying crop disease by use of high-resolution satellite images, emphasizing the result of clouds and rapid changes in agricultural land cover. It emphasizes the significance of multimodal data fusion, combining information from numerous sensors like temperature, humidity, and light intensity, to enhance disease detection accuracy. Studies mentioned in the document showcase using deep learning models like the BBI model and ELR for predicting rice yield and phenotyping from sensor data.

Muhammad E. H. Chowdhury et al. [7] presents a comprehensive study on detecting leaf damage automatically and reliably with deep learning methods in AgriEngineering. The methodology involves utilizing info on tomato leaves from the Plant Village collection for binary and multi-class classification tasks, exploring different variants of U-net segmentation models, and employing EfficientNet networks for classification. The study outperforms existing state-of-the-art works in this domain, offering a promising solution for accurate and efficient detection of leaf disease in agriculture.

Sreya John et al. [8] discusses the importance of agriculture in developing nations like India and the challenges faced in manually observing and identifying plant diseases, emphasizing the necessity of automated categorization and detection methods. It compares and suggests novel techniques for recognizing various

infections affecting agricultural plants, highlighting the function of machine learning in efficiently analyzing and diagnosing plant diseases.
André S. Abade et al. [9] provides a through examination of the current state of investigation in this area. The evaluation highlights the efficiency of CNNs in precisely recognizing and categorizing plant illnesses from images, showcasing their potential as a robust tool for the purpose of detecting illness in agriculture. Key findings include the use of various CNN architectures and frameworks, the value of thorough approach descriptions for replication and result verification, and the clear reporting of main findings and study limitations.
Shima Ramesh et al. [10] discusses the significance of promptly identifying crop diseases for food security and presents accurate techniques for leaf-based machine learning for the categorized data of the images technology. Traditional methods face challenges in detecting plant diseases efficiently, leading to decreased food production and insecurity. By employing modern technologies such utilizing machine learning approaches like Random Forest, scientists seek to improve the accuracy and recognition rate of disease detection in crops.
SK MAHMUDUL HASSAN et al. [11] explains the construction of a revolutionary convolutional neural network for plant disease identification, utilizing depth wise separable convolution, Inception, and Residual connections to reduce parameters significantly while maintaining high performance. The model outperforms existing deep learning frameworks, achieving accuracy on three different plant disease datasets: The rice plant dataset, the cassava plant dataset, and the Plant Village dataset. The proposed model's efficiency in parameter usage and accuracy can benefit farmers and agricultural professionals by enabling timely disease identification and effective crop protection measures.
Ahmed Elaraby et al. [12] explores the optimization of deep learning algorithms to identify plant disease utilizing using Particle Swarm Optimizer (PSO). By leveraging neural network-based transfer learning like AlexNet, the study aims to improve the precision of identifying plant diseases. Using PSO, the research optimizes hyperparameters of the neural network model to improve performance. The evaluation metrics include sensitivity, specificity, and accuracy, showcasing the effectiveness of the using deep learning to precisely classify plant diseases.
K.Renugambal et al. [13] investigates image processing methods for automated sugarcane leaf disease detection and categorization. It supports Vector Machines and talks about using fuzzy feature selection techniques(SVM) for pattern recognition. It presents accuracy results of classifiers, with Non-Linear SVM achieving the highest accuracy rate. The document underscores the importance of machine vision systems in early disease identification, emphasizing texture measurements and SVM machine learning for effective disease recognition. Additionally, it mentions other research studies on cotton categorization of leaf spot disease employing several techniques for image processing.
Apostolos Xenakis et al. [14] discusses using advanced technology like Convolutional Neural Networks (CNNs) in an IoT Robotic System to help farmers detect plant diseases early. By uploading leaf images to a mobile app, the system can identify diseases and send results back to the user. The system includes a robotic construction for precision sowing and plant health monitoring. Through real-time monitoring and control, farmers can improve crop quality and quantity. Overall, this technology aims to enhance agricultural productivity and profitability by leveraging AI and IoT solutions.
Zafar Salman et al. [15] discusses the developments in deep learning to identify plant diseases, emphasizing the significance of automated diagnosis in agriculture. Researchers have utilized customized datasets and lightweight ViT models to classify diseases effectively, showcasing comparable performance to traditional CNN models. The requirement for methodical technical knowledge in order to identify intricate patterns in real-time scenarios is emphasized, with future directions focusing on imporving models for lightweight object dection and improving accuracy in crop disease detection.

Literature survey shows that still there is gap in technology that may be applied to get higher accuracy. This is achieved by utilizing cutting-edge deep learning methods Visual Geometry Group(VGG) and Region based Convolutional Neural Network (RCNN) and work is carried out.

III. METHODOLOGY

The suggested approach to plant illness detection is founded upon the incorporation of cutting-edge artificial intelligence (AI) techniques, particularly deep learning algorithms, with image processing methodologies. This amalgamation aims to build a strong and automated system capable of swiftly and precisely determining various diseases affecting plants. The suggested architecture of the proposed system is delineated as follows:

A. Feature Extraction

The R-CNNs are frequently utilized in image-based activities for feature extraction because of their ability to naturally learn hierarchical features. Features can be extracted using R-CNN models that have already been trained, such VGG. These models can capture general properties applicable to plant detection tasks because they have been trained on big datasets such as ImageNet. In order to tailor the acquired features to the particular objective of plant detection, transfer learning entails fine-tuning these pre-trained R-CNNs on a smaller dataset of plant images.

B. R-CNN Model
One kind of deep learning architecture used for object detection in computer vision tasks is the R-CNN One of the first models to combine the features of region-based techniques and convolutional neural networks to improve object detection was the RCNN. These models are appropriate for real-world settings with a variety of objects and complicated backgrounds because they can handle objects with varying sizes, orientations, and scales. Although CNNs were previously widely used for image classification, object detection needed a more sophisticated approach. At this point, the R-CNN algorithm became relevant and provided a fresh solution to this challenging issue.

C. VGG Model
Visual Geometry Group, or VGG for short, is a multi-layered, conventional deep Convolutional Neural Network (CNN) architecture. With VGG-16 or VGG-19, which are composed of 16 and 19 convolutional layers, the term "deep" refers to the quantity of layers. Innovative object identification models are built on top of the VGG architecture. The VGGNet, designed as a deep neural network, outperforms baselines on a wide range of tasks and datasets, going beyond ImageNet. Furthermore, it remains one of the most widely used image recognition architectures to this day.

IV. EXPERIMENTAL SET-UP

The making of the dataset, the process of training of the model, and the evaluation are among the crucial processes in the experimental phase of the study. Below are thorough explanations of every step, parameter configurations, and any additional tables or diagrams:

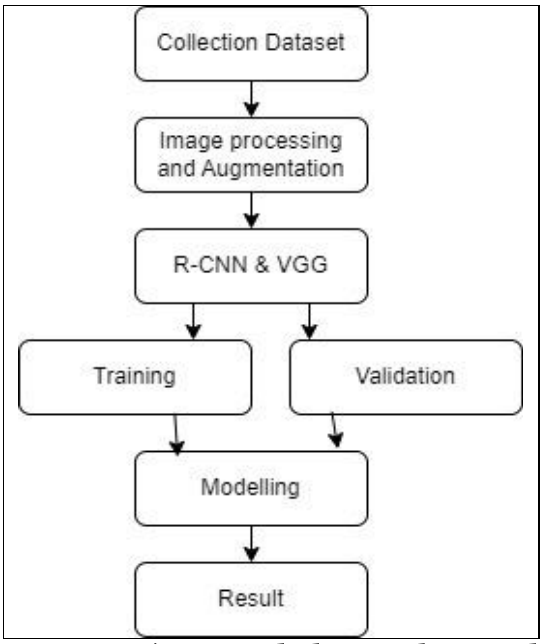

Fig 2: Workflow of Deep Learning-Based Plant Pathogen Identification System.

A. Preparing the Dataset
A variety of plant images, featuring both healthy and unhealthy plants, compose the dataset that was utilized to instruct and assess the AI models.The dataset is partitioned into training, validation, and testing sets, with a usual ratio of 70:15:15 to provide sufficient generalization and representation.To improve model robustness and reduce overfitting, methods for augmenting data, like random rotations, flips, and shifts, utilised to enrich the dataset.

B. Training of the AI Model
The training dataset is employed to access the trained models' performance in disease identification. Evaluation metrics are calculated to measure the efficiency of the models in differentiating between plants that are healthy and those are not, like recall, accuracy, and precision, and F1-score.The evaluation of model robustness and trade-offs between frequencies of false positives and real positives can be achieved by using Area Under the Curve(AUC) scores and Reciever Operating Characteristics(ROC) curves

C. Configuring Parameters
To balance model complexity, computational resources, and performance, parameter values for model training and evaluation are carefully selected. Learning rate: Usually set using adaptive scheduling algorithms, in the interval [0.001, 0.01].Batch size: Usually between 16 and 128; determined by available memory limits and CPU resources. Number of epochs: Training epoch counts are normally between 50 and 100, and are modified based on convergence behavior. Using momentum in stochastic gradient descent (SGD) or the Adam optimizer with default parameters are two popular optimization algorithms.

D. Pre-processing

Following data acquisition, the obtained images go through a number of pre-processing techniques aimed at enhancing their quality and facilitating subsequent feature xtraction. Pre-processing steps may include image resizing to ensure uniform dimensions, normalization to standardize pixel intensities, and noise reduction techniques to lessen the effects of artifacts or distortions within the images.

Table 1: Configuring Parameters for Model Training

Parameter	Setting
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Optimization	Adam Optimizer
Architecture	ResNet-50
Loss Function	Binary Cross-Entropy

V. RESULT

The Results/Outputs and Discussion section provides an in-depth examination of the experimental findings, including the outputs developed by the AI-based method for detecting plant diseases and their implications for agricultural practices. This section is structured to present the outcomes in a clear and informative manner, followed by a comprehensive discussion of their significance.

A. Experimental Analysis

The AI-based plant disease detection system demonstrates promising performance in accurately identifying and diagnosing various plant diseases across different crop species. Quantitative measures like precision and accuracy, recall, and F1-score are reported to assess the system's effectiveness in identification and categorization of diseases. Representative output screenshots depicting the system's predictions for sample images are presented to provide visual insights into its performance.

B. Comparing the Current System

To contrast the AI-based system's performance to other methodologies or current methods, a comparative analysis can be performed. The potential of the suggested methodology to transform disease management tactics in agriculture is highlighted, along with its advantages and limitations when compared to conventional disease detection methods.

C. Illustrations and Comprehensibility:

It may be possible to provide qualitative evaluations of the model outputs, such as saliency maps or class activation maps, to improve interpretability and clarify the AI models' decision-making process. In addition to offering insights into the regions of interest within the plant photos that aid in disease diagnosis, these visualizations support the system's predictions.

Table 2: Experimental Results of AI-Based Plant Disease Detection

Disease Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Powdery Mildew	95.2	94.8	96.5	95.6
Leaf Rust	91.6	92.3	90.8	91.5
Bacterial Blight	88.9	89.7	87.4	88.5
Fusarium Wilt	92.3	91.5	93.8	92.6

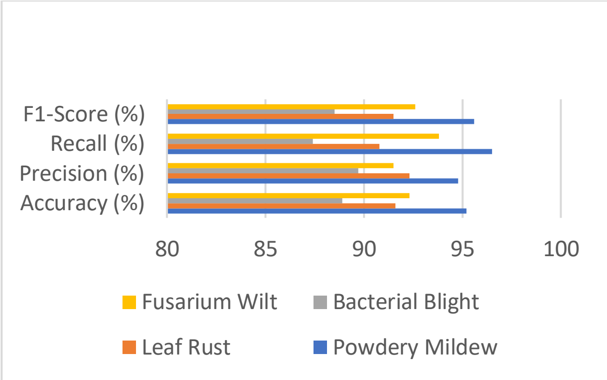

Fig 3: Bar Graph Of Deep Learning Plant Disease Detection

Table 3: Experimental Results Form Different Models before applying optimization

Model Name	Epochs	Accuracy	Loss
R-CNN	10	0.9571	0.871
VGG	10	0.973	0.02

D. Optimization

Momentum: For the purpose of detecting plant diseases, momentum optimization can be utilized in the training of neural networks or other machine learning models. By gradually building up gradients and smoothing out updates, momentum optimization speeds up the training process when models are trained on plant picture datasets. This can be very helpful when working with intricate model structures or large-scale information.

Ada Grand: In the domain of plant disease diagnosis, AdaGrad can also be helpful, particularly when working with sparse or noisy data. Image datasets used for plant disease identification can differ greatly in terms of the distribution and features of samples of healthy and sick plants. Through the use of previous gradients to inform model parameter learning rates, AdaGrad's adaptive learning rate mechanism facilitates effective optimization across various dataset segments.

Table 4: Experimental Results Form Different Models after applying optimization

Model Name	Epochs	Accuracy	Loss
R-CNN	10	0.9827	0.732
VGG	10	0.9897	0.013

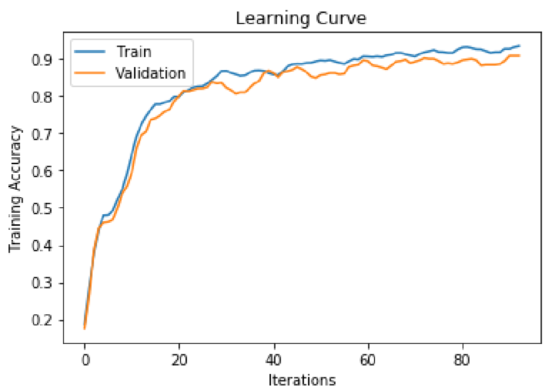

Fig 4: Model Accuracy Over Iterations

E. Discussion

The experimental findings are examined in light of current research on detection of plant diseases as well as creative techniques that highlight the advantages and drawbacks of the suggested methodology. To shed light on possible areas for development, factors impacting the system's performance—such as parameter settings, model design, and dataset quality—are thoroughly explored. The study's implications for precision farming, sustainable crop management, early disease detection, and other agricultural techniques are examined. The difficulties and potential avenues for further study in AI-based plant disease detection are noted, opening the door for more breakthroughs and innovation in the area.

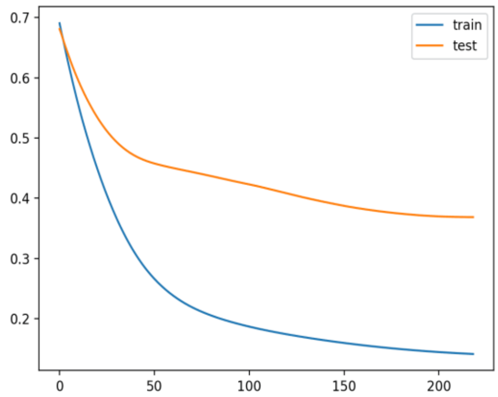

Fig 5: Model Loss Over Iterations

VI. CONCLUSION

In conclusion, the research on AI-based identification of plant diseases represents a pivotal advancement in agricultural technology, showcasing the system's effectiveness in precisely recoginzing various diseases across different crop species. With high accuracy metrics and promising performance in distinguishing between plants that are healthy and those that are not, the proposed methodology holds immense potential to revolutionize disease management strategies, promoting early detection, targeted intervention, and sustainable agricultural practices. The incorporation of AI techniques into agricultural workflows not only enhances crop yield and food security but also contributes to the economic stability and livelihoods of farmers worldwide. Research activities must continue in order to further refine and optimize these systems, fostering innovation and resilience in the face of evolving agricultural challenges.

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