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MONITORING PLANT DISEASES USING A DEEP LEARNING – BASED APPROACH

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Abstract: During the conventional agricultural era, farmers are not keen on increasing production due to thelack of effective approaches for diagnosing diseases in different crops. Early identification of crop diseases is vital as it significantly influences the growth of plant species. While a variety of Machine Learning (ML) models have been employed to organize and identify agricultural diseases, recent advancements in DeepLearning (DL) provide substantial promise for enhancing precision in this domain. The suggested approach accurately and efficiently detects crop disease symptoms by using a neural network based on convolution (CNN). Model performance is evaluated using a variety of efficiency signs, which show how effective it is in early disease identification. The report fills research gaps for reliable disease detection approaches and offers a thorough investigation of deep learning frameworks for crop disease visualization. The suggested convolutional neural network approach seeks to transform the plant leaf diseases identification, including those that do not yet exhibit symptoms. Expanding on prior work emphasizing the significance of plant disease identification, this research introduces an advanced solution. With the support of an automated system and the deep learning algorithm Convolutional Neural Network (CNN), people can identify illnesses with cell phones. Furthermore, a stunning 99.81% classification accuracy is achieved by integrating DenseNet-121 into the framework, demonstrating its superiority over other models. This method has the potential to transform crop disease detection and boost food security and agricultural output.

Keywords: Convolutional Neural network, DenseNet- 121, Alternaria solani, Phytophthora infestans, Machine Learning, early bright, late blight.

I. INTRODUCTION

Agriculture is an important source of food and contributes significantly to the global economy. In India, 18% of the country's income depends on agriculture. Crop diseases are an important risk to agricultural crops and the loss of agricultural crops directly affects a nation's economic stability [7]. The quantity and quality of agricultural goods reduce as a result of these diseases, in addition to lowering productivity and causing financial losses.[1][6] Farmers encounter challenges when transitioning from one disease control strategy to another. The conventional method of agriculture relying on the naked eye observations of expertise which is not only time-consuming and costly but also prone to inaccuracies. By improving early plant disease identification, producing more accurate results, and enablingtimely plant treatments, this technology provides a solution. In India, farmers often have to travel long distances, covering hundreds of miles, to seek advice from experts, which is both time-consuming and expensive.

With the advancement of computer vision technology, numerous solutions have been developed to address the detection challenges associated with plant infections, as these infections often manifest as distinctive patterns or spots on leaves. Several techniques have been developed by researchers to accurately diagnose and categorize various plant diseases. Customized segmentation and feature extraction techniques are integrated with standard image processing techniques in certain methods [1]. The K-means clustering method was used to separate the affected leaf portions, and a multi-class support vector machine (SVM) was subsequently used to finish the classification.

To enhance result accuracy and decrease processing time, advancements in the algorithm have been pursued. Unlike other systems that have been developed before, this model has an advanced deep learning algorithm is known as Neural based on Convolutional that is specifically made for processing images. [9] This technological innovation provides a non-intrusive, real-time, and cost-effective solution, empowering farmers to promptly implementnecessary actions for safeguarding their crops. The utilization Of CNN in image processing represents a substantial leap forward, signifying a pivotal enhancementin the system's capability to deliver precise and timely information to farmers. This cutting-edge approach not onlyensures heightened accuracy but also facilitates quicker decision-making, thereby optimizing the overall efficiency of crop protection measures.

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Deep learning models that are frequently employed in image-based research include Convolutional Neural Networks (CNNs), in specific, due to their abilities in removing complex, low-level information from images. Deep learning CNN layers, however, can require a lot of processing power to train. Researchers have developed transfer learning models as a response to this problem, which provides a way around the difficulty of training deep layers. Prominent transfer learning models that have been pre-trained on the ImageNet dataset, which covers a wide range of classes, are VGG-16, ResNet, DenseNet, and Inception [8]. By utilizing the insights gleaned from ImageNet to perform exceptionally well when trained on alternative datasets, transfer learning models exhibit their versatility. This flexibility results from the common characteristics—like edges and contours—found in manydatasets. As a result, transfer learning has become a favored and reliable method for picture classification tasks. More significantly, it works well even with smaller datasets. Figure 2 illustrates the fundamental idea of transfer learning and highlights how well it can be used to improve learning on a target job by utilizing previously acquired knowledge from a source task (in this case, ImageNet). This leads to better performance and efficiency in picture categorization. After an experimental analysis of various transfer learning methods and exploring different hyper parameters, it has been observed that DenseNet-121 stands out as the most successful model. Specifically, DenseNet-121 achieved an impressive training accuracy of 99.81%, showcasing its capability to effectively learn and generalize patterns from the training dataset. Moreover, the model demonstrated a maximum validation accuracy of 0.0154, underscoring its robustness and high performance on previously unseen data[8]. These results emphasize the effectiveness of DenseNet-121 in the context of the experimental setup, suggesting its suitability for the given task.

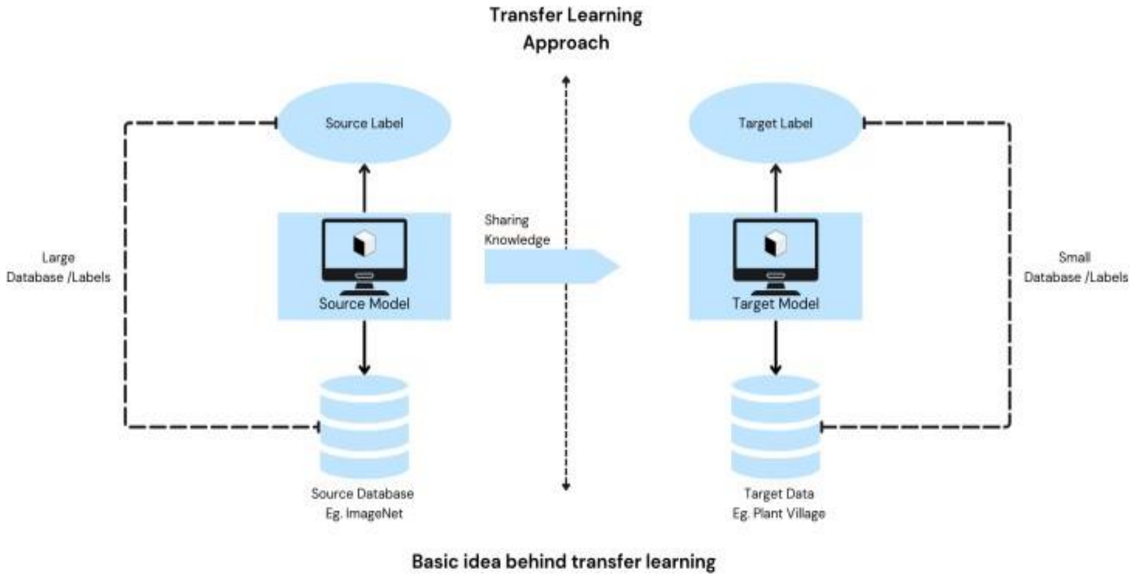

Fig. 1 Transfer learning Approach

DenseNet-121: DenseNet-121 is one of the convolutional neural models with four dense blocks which is used to overcome vanishing gradient problem. Using 1 × 1 and 3 × 3 filter sizes, convolution is applied in the initial dense block, which is repeated six times. Likewise, the seconddense block repeats convolution 12 times using 3 × 3 and 1 x 1 filter sizes. While the fourth dense block repeats thesame procedures 16 times, the third dense block conducts convolution operations 24 times using the same filter sizes. The network's overall efficacy is increased by the carefully positioned transition blocks that incorporate the convolutionand pooling layers in between the dense blocks.

TABLE I. ANALYSIS OF THE RELATIVE PERFORMANCES OF DIFFERENT TRANSFER LEARNING MODELS.

Model of Transfer learning	Training Accuracy(%)	Training Loss (%)	Test Accuracy (%)	Test loss (%)
InceptionV4	99.78	0.01	97.59	0.0586
VGG -16	84.27	0.52	82.75	0.64
ResNet-50	99.82	6.12	98.73	0.027
DenseNet - 121	99.87	0.016	99.81	0.0154

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Some are the widely used convolutional neural network (CNN) architectures employed in deep learning for image classification: Inception V4, VGG-16, ResNet-50, andDenseNet-121. These models are recognized for their effectiveness across diverse computer vision tasks. The provided training accuracies signify the models' performance on the training dataset during their trainingphase, with DenseNet-121 notably achieving an impressive accuracy of 99.87%.

Transfer learning entails utilizing pre-trained models on extensive datasets and refining them for specific tasks. Notably, DenseNet-121 distinguishes itself through itsdistinctive architecture that encourages feature reuse via dense connectivity. In this architecture, each layer receives direct input from all preceding layers, fostering efficient information flow and mitigating the vanishing gradient problem. This attribute renders DenseNet-121 particularly adept at capturing intricate patterns and dependencies withinimages, a crucial aspect in tasks like image classification. Moreover, the remarkable training accuracy of 99.87% indicates the model's proficiency in learning complex representations from the training data, making it a compelling option for transfer learning applications where robust feature extraction is pivotal. Consequently, the adoption of DenseNet-121 is substantiated in scenarios prioritizing high accuracy and intricate feature capture, establishing it as a preferred choice in various computer vision applications.

II. LITERATURE SURVEY

The suggested expert method, according to Kalita, Hemanta, Shikhar Kr Sarma, and Ridip Dev Choudhury [2], is intended to help in the diagnosis of common illnesses that affect rice fields. Users engage with the system by selecting "YES" or "NO" in response to questions about different disease symptoms. Typically, a farmer with a crop disease issue inputs their problem through the user interface. The system then compares these responses to its knowledge base, which is represented as a set of rules, to identify the likely disease affecting the crop.

Himanshu V. Taiwade, Ketan D. Bodhe, Virendra P. Yadav, Nikesh V. Aote [5] the research project focuses on detecting and diagnosing diseases affecting cotton leaves. It includes using template matching techniques to create a prototype Android mobile application. The Vidharbharegion's various cotton farms provide the photographs required for this application. Farmers may easily detect diseases in cotton fields by using smartphones with internet access. The suggested approach can help accomplish early disease pattern recognition so that timely intervention can beimplemented.

Mr. Ramachandra Hebbar, Shima Ramesh, P. V. Vinod,Neveditha M, Pooja R, Prasad Bhat N, and Shashank N etc.[4] The Random Forest approach is utilized in this research to differentiate between healthy and unhealthy leaves. The implementation process involves multiple stages, such as dataset creation, feature extraction, classifier training, and image classification. A Random Forest classifier is trained using the datasets that include both healthy and diseased leaf images. The trained classifier is then utilized to distinguish between the two types of images.The Histogram of Oriented Gradients (HOG) approach is used to extract image features.

S. Ponni Alias Sathya a, S. Ramakrishnan a, M.I. Shafreena, R. Harshini a, P. Malini [5] the proposed system is designed to identify plant leaf diseases by processing leaf images. The process involves image acquisition, followed by pre-processing steps like quality assessment, smoothing, and shape analysis to pinpoint the affected areas. Genetic algorithms are employed for component segmentation, whilethe Support Vector Machine (SVM) Classifier is used for image classification. The system can accurately detect and display the cause of the plant disease, along with identifying healthy areas on the leaf and providing an accuracy assessment using a Fuzzy system.

Sk Mahmudul Hassan, Khwairakpam Amitab, etc. [11] This proposed system provides a comprehensive overview of research efforts in plant disease detection, covering bothtraditional handcrafted-feature and modern deep-learning-based techniques. It highlights challenges encountered in handcrafted-feature approaches and the advantages of deep learning. While deep learning models like GoogleNet and InceptionV3 exhibit superior feature extraction capabilities, they may face performance issues when applied to real-world or diverse datasets. The review also identifies ongoingchallenges in achieving effective plant disease identification.

Kaushika , Ishita Sharmad , Isha Jindale , Vaishali Deshwalf [9] The paper aims to detect plant diseases and reduce financial losses using deep learning for image recognition. Itexplores three neural network architectures: Faster R-CNN, R-CNN (SSD), and single-shot multi-box detector. The proposed technique efficiently handles diverse scenarios and achieves a promising 94.6% accuracy in validation, indicating the potential of convolutional neural networks for complex problem-solving with AI-based deep learning.

J., A.; Eunice, J.; Popescu, D.E.; Chowdary, M.K.; Hemanth, This paper explores the use of pre-trained convolutional neural network (CNN) models, including DenseNet-121, ResNet-50, VGG-16, and Inception V4, for efficient and accurate plant disease recognization. Among which DenseNet-121, has achieved maximum trainingaccuracy of 99.87%.

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M. A. Khan, T. Akram, M. Sharif, M. Awais, K. Javed, H. Ali, and T. Saba, [8] In particular, this study usesarchitectures such as AlexNet and VGG16 to offer a revolutionary visualization method that blends correlation coefficients with deep learning models. To identify grape diseases, Kerkech et al. used the LeNet model in conjunction with vegetation indices in color space.

In a different article, several methods for interpreting deep learning models were looked at, such as gradient time input, boot back-propagation, depth Taylor decomposition, integration gradient layered related transmission, and significant figure. Several biological and non-biological soybean stressors were used to train DenseNet121 to identify them. He study discovered that interpretability techniques were useful in emphasizing infected leaf regions as critical characteristics in accurately categorized photos.

III. POTATO LEAF DISEASES

In general, each disease has distinct symptoms that may be recognized by looking at the plant's leaf and stem. The diseases that follow have been chosen to create aprototype model for.

III-A. Early Blight Diseases

Fig. 2 Early blight diseases infected potato leaf

Introduction:
Early blight of potato is caused by the fungus, Alternaria solani, which can cause disease in potato, tomato, other members of the potato family, and some mustard. Thisdisease, also known as target spot, rarely affects young, vigorously growing plants. It is found on older leaves first. Early blight is favored by warm temperatures and high humidity. Images of late blight leaf disease shown in fig. 1.Here is an in-depth exploration of early blight in potatoes:

Symptoms:
The symptoms of early blight manifest primarily on the leaves, stems, and, occasionally, tubers of potato plants. They include dark, concentric rings with a target-like appearance, brown to black spots with yellow halos, and lesions that compromise the plant's overall health.

Environmental Conditions:
Early blight thrives in warm and humid conditions. The pathogen overwinters in infected plant debris, contributing to its persistence and recurrence in subsequent growing seasons.

Disease Cycle:
The disease spreads through spores carried by wind, rain, or irrigation. Plant debris and contaminated soil serve as sources of infection, emphasizing the importance of proper sanitation practices and crop rotation to break the disease cycle.

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Impact on Plants:
Severe infections can lead to a substantial reduction in potato yields. The quality of tubers may also be compromised as lesions on the skin affect marketability.

III-B. Late blight Disease

Fig. 3 Late blight disease infected potato leaf

Introduction:
Late blight, scientifically known as Phytophthora infestans, is a notorious pathogen responsible for one of the most destructive diseases affecting potato plants (Solanum tuberosum). The impact of late blight on potato crops extends beyond economic losses, as it played a historic role in the Irish Potato Famine during the 19th century. T

he disease is characterized by its rapid spread and the ability to cause devastating epidemics under favorable environmental conditions. Figure 2 displays images of the late blight leaf disease.

Pathogen and Disease Cycle:
Phytophthora infestans is an oomycete pathogen that thrives in cool, wet conditions. The disease cycle typically begins with spores (sporangia) produced on infected plant tissues orvolunteer potatoes. These spores are dispersed by wind or rain, facilitating their spread to healthy plants. Upon reaching a susceptible host, the spores germinate, and the mycelium penetrates plant tissues, leading to infection.

Symptoms:
Late blight symptoms manifest on various parts of the potato plant. Initial signs include dark lesions on leaves, resembling water-soaked spots. As the disease progresses, these lesions enlarge, often exhibiting a characteristic white mold on the undersides of leaves. Infected tubers develop dark, firm lesions that can lead to rotting, rendering them inedible and causing substantial economic losses for farmers.

Environmental Conditions:
Late blight thrives in cool and humid conditions, with optimal growth occurring between 10 to 24 degrees Celsius. Regions with frequent rainfall or high humidity levels are particularly conducive to disease development. Climate variability and changes can influence the prevalence and severity of late blight outbreaks.

Impact on Agriculture:
Late blight poses a significant threat to global potato production. The rapid spread of the disease can result in complete crop failure if not adequately managed. The economic impact includes yield losses, increased productioncosts due to fungicide applications, and potential food shortages.

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TABLE II. SURVEY ON VARIOUS MACHINE LEARNING ALGORITHM

Algorithm	Use	Accuracy	Speed
SVM (Support Vector Machine)	SVMs can be used in combination with handcrafted image features, like color histograms, texture feature to classify plant disease images.	89.4%	40%
KNN (K-Nearest Neighbors)	K-NN can be used for image classification by comparing test images to a database of labeled plant disease images and selecting the k-nearest neighbors for classification.	98.56%	20%
CNN (Convolutional Neural Network)	CNNs are widely used for image classification and recognition tasks. They are effective in learning features from plant disease images and have been the basis for many successful plant disease detection models.	96.88%	70%

IV. CONCLUSION

In this study, we examined leaf image data to do a thorough assessment of the different machine learning methods used in plant disease detection. Convolutional neural networks (CNNs) have been shown through a thorough assessment to be the best option, outperforming other techniques in terms of accuracy and speed. CNNs' strong performance makes them a viable option for improving the accuracy and efficiency of plant disease detection systems, opening the door for significant applications in crop management and agriculture. This research has important ramifications for theagriculture industry since CNN integration has the potential to transform crop management by giving farmers a powerfultool for fast and precise disease detection. The groundwork laid by this research opens avenues for impactful applications, fostering advancements that can positively impact agricultural practices and crop productivity.

In future research, addressing the computational challenges associated with deep convolutional neural network (CNN) layers remains paramount for enhancing the efficiency of plant disease detection models. The current study recognizes the computational expense involved in training deep CNN layers and identifies a promising avenue for resolution through the application of transfer learning-based models. Specifically, future work will focus on leveraging pre- trained models such as denseNet-121 to overcome the intricacies of training deep layers. The implementation of denseNet-121 in this project as a prospective solution aimsto determine the optimal model for accurately classifying diverse plant diseases. This approach is anticipated to streamline the training process and enhance the overall performance of the plant disease detection system, providinga more robust and computationally efficient solution for agricultural applications.

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