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A comprehensive impression on identifying plant diseases using machine learning and deep learning methodologies

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ABSTRACT

Maintaining healthy plants is essential for long-term agricultural production because agriculture is the backbone of many economies. Agricultural productivity is greatly endangered by plant diseases, which result in huge economic losses. Identifying plant diseases using traditional approaches can be quite laborious, time-consuming, and knowledge-intensive. Automated, precise, and quick diagnosis of plant diseases has been made possible by recent developments in artificial intelligence, mainly in deep learning, and machine learning. This study gives a thorough analysis of how machine learning and deep learning are currently being used to detect plant diseases. Methodologies, datasets, evaluation measures, and the inherent difficulties of the area are all examined. In order to better understand these technologies in practical agricultural contexts, this review will try to shed light on their advantages and disadvantages.

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1. INTRODUCTION

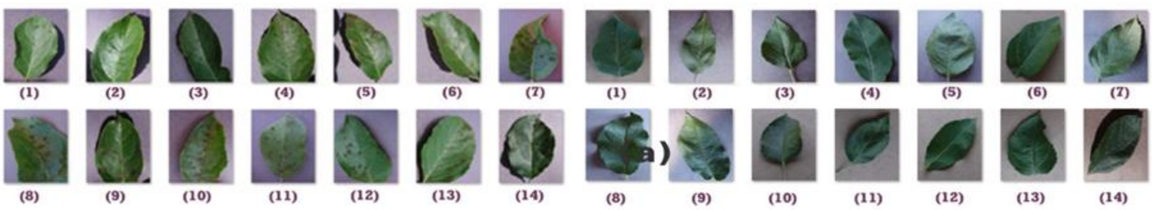
With an expected 9.7 billion people on Earth by 2050, increasing agricultural output is essential to guaranteeing food security in the face of this rapidly expanding population. Insects and other plant diseases cause substantial economic harm and yield losses on a global scale, making them a formidable obstacle to this objective. Manual inspection and laboratory analysis are the mainstays of traditional plant disease identification methods; nevertheless, these approaches regularly fail owing to their high prices, specialist knowledge requirements, and labor-intensive nature. More effective, accurate, and scalable approaches to early disease detection and management are required due to the current constraints [1], [2]. A rise in agricultural production is required to keep up with the world's rapidly expanding population. Plant diseases are a major problem because they reduce agricultural output, which in turn causes huge economic losses and puts food security at risk. Conventional approaches of plant disease diagnosis, which rely heavily on subjective expert opinion and laboratory testing, are cumbersome and not applicable in most cases. So, there are potential ways to effectively, accurately, and instantly identify plant diseases with the use of sophisticated technologies, especially machine learning and deep learning [3], [4]. There are now more ways than ever before to tackle these problems, thanks to recent technological developments, especially in the fields of artificial intelligence and machine learning. In machine learning, algorithms are taught to find patterns in data and to make judgments or predictions on their own, without human intervention or explicit programming. Deep learning is a subfield of machine learning that excels at complex tasks like image identification [5]. It uses multi-layered neural networks to extract insights from big datasets. As subfields of artificial intelligence, machine learning, and deep learning have facilitated the creation of automated systems and predictive models, which have had a profound impact on a number of industries. These technologies greatly improve the ability to detect and diagnose plant diseases quickly in agriculture. This is essential for developing and implementing management strategies that are both effective and implemented on time. This paper assesses the state of plant disease detection using deep learning and machine learning, comparing and contrasting different strategies and their relative efficacy [6].

Utilizing these technologies, automated methods for diagnosing plant diseases can be created in the agricultural sector. To help with timely intervention and minimize losses, machine learning and deep learning models can analyze properties derived from images or sensor data to accurately diagnose and categorize various plant diseases. The purpose of this research is to survey the existing literature on plant disease detection using machine learning and deep learning algorithms, focusing on important approaches, their uses, and relative efficacy [7], [8]. Following this, we will examine recent developments in artificial intelligence and deep learning methodologies, including convolutional neural networks (CNNs), and dive into several machine learning methods, with an emphasis on logistic regression (LR). The relative merits of various approaches will be laid bare by an examination of them. The paper will wrap up by discussing future prospects and how these technologies could be integrated into practical farming practices [9], [10].

2. PLANT DISEASE DETECTION USING MACHINE LEARNING TECHNIQUES

By simplifying the process of analyzing large datasets in search of patterns indicative of different plant health situations, machine learning has substantially enhanced the identification of plant diseases. In order to forecast the spread of diseases and categorize them according to features retrieved from pictures, sensor data, or other sources, these methods use algorithms that have been trained on annotated data. This section offers a synopsis of the main machine learning approaches used for plant disease diagnosis, together with an examination of their respective applications [11], [12]. Agricultural soil fertility was examined using machine learning protocols. Research on agriculture has always been the focus. Based on a number of limitations, this method of soil data analysis seeks to systematically classify and improve each representation. The study of agriculture has been greatly enhanced by innovations such as data mining and robotics. Data mining has many potential uses, and there is commercial software available to address specific needs in different fields.

Nevertheless, as seen in Figure 1, agricultural soil and plant health databases represent an expanding area of study. Figure 1(a) shows diseased leaf samples with visible infection symptoms such as spots and discoloration, while Figure 1(b) illustrates healthy leaves with uniform texture and color. Together, they form a balanced dataset useful for distinguishing between normal and diseased conditions in agricultural research.



(a) (b)

Figure 1. Sample images of leaves: (a) diseased and (b) healthy

The method offered a comprehensive breakdown of the machine learning strategy employed to classify plant disease symptoms. However, the elements impacting disease detection were not adequately captured by the technique. There needs to be thorough evaluation and application of the massive volumes of data collected in relation to crops. The approach used to pre-process the input image is shown in Figure 2.

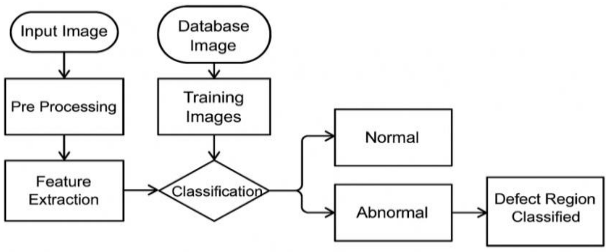


Figure 2. Typical procedures for identifying crops

Because of their effectiveness in classification tasks, support vector machines (SVM) are frequently used to identify plant diseases. To differentiate between different classes in the feature space, SVM choose the best hyperplane. Although these approaches are best used for binary classification, they can be modified to handle situations with more than one class utilizing strategies like one-versus-one or one-versus-all [13]. In the field of plant disease identification, SVM are an effective tool for distinguishing between healthy and sick plants. They look at the shape, texture, and color of the leaves in the photos. Crops like tomatoes, cucumbers, and grapes have been successfully diseased using SVM, which have achieved high rates of accuracy. SVMs efficacy is highly dependent on the kernel function optimization and parameter choice [14], [15]. An advanced method in ensemble learning, random forest (RF) combine many decision trees to improve classification performance. The final forecast is obtained by adding together the results from all the trees in the forest, typically by majority voting, and each tree in the forest is built using a randomly selected portion of the data. Due to its robustness and ability to efficiently handle high-dimensional data, RF finds extensive usage in the detection of plant diseases. They can be useful for identifying subtle signs of illness since they may include complex interactions between attributes. Disease diagnosis in wheat, maize, and rice crops is a common area of research where RFs excel, often outperforming individual decision tree models [16]. One effective and fundamental technique is k-nearest neighbors (KNN), which sorts data points in the feature space by the most common class of their KNN. The instance-based and non-parametric nature of KNN makes it easy to implement and understand. In order to detect plant diseases, KNN compares new samples to a database of labelled occurrences and uses that information to classify ailments. By analyzing features obtained from pictures, KNN has been used to detect illnesses in citrus fruits and apples. Although KNN is capable of achieving high levels of accuracy, its efficiency is affected by the quality of the feature space and the choice of k [17]. One common statistical method for binary classification tasks is LR. By analyzing input data and classifying disease presence or absence, LR is a useful method for plant disease identification. Although LR is simple, it shows great success in some situations since it is easy to understand and use. Datasets covering several plant health measures, such as leaf shape, texture, and color, have been subjected to linear regression models. By correlating these markers with the probability of illness occurrence, LR provides a simple and effective tool for preliminary disease screening. But the linear decision boundary may limit its efficacy, making it unfit for complex nonlinear problems [18], [19].

2.1. Logistic regression

LR serves as a foundational statistical technique commonly applied in binary classification challenges, such as the identification of plant diseases. Even though it is less complex than advanced machine learning and deep learning methods, LR continues to be an important tool because of its clarity, efficiency, and effectiveness in specific applications. LR estimates the likelihood that a specific input is associated with a certain class. In contrast to linear regression, which forecasts continuous values, LR estimates the likelihood of a binary outcome. The model employs the logistic function, commonly referred to as the sigmoid function, to convert predicted values into probabilities ranging from 0 to 1. The logistic function is characterized as (1) and (2).

$$\sigma(z) = 1 + e - z1 \tag{1}$$

where z is a linear combination of the input features:

$$z = \beta 0 + \beta 1 \times 1 + \beta 2 \times 2 + \cdots + \beta n \times nz = \beta 0 + \beta 1 \times 1 + \beta 2 \times 2 + \cdots + \beta n \times n \tag{2}$$

here, $\beta 0$ is the intercept, βi are the coefficients for the input features xi, and n is the number of features.

The LR model calculates the coefficients βi in order to optimize the likelihood of the observed data. LR is applicable in the realm of plant disease detection through the utilization of features derived from plant images or sensor data. The characteristics may encompass color, texture, shape, and spectral data that signify the existence of a disease [20], [21]. The procedure typically encompasses these stages: i) gathering and preparing data: gather a collection of plant images or sensor data, and carry out preprocessing to identify and extract pertinent features. This could involve methods like image segmentation, feature extraction, and normalization; ii) feature selection: determine and choose the most pertinent features that aid in the classification of diseases. Feature selection may rely on expertise in the field or utilize automated techniques like recursive feature elimination; iii) training the model: divide the dataset into training and testing subsets. Utilize the training set to develop the LR model, incorporating the extracted features as input variables and the disease labels as the target outputs; and iv) model evaluation: assess the model's performance using the testing set. Typical evaluation metrics for binary classification encompass accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). LR continues to be an important method for detecting plant diseases, especially when factors like simplicity, interpretability, and efficiency are crucial. The use of this approach, in conjunction with more sophisticated techniques, can greatly enhance sustainable agriculture through the facilitation of early and precise disease identification and management [22], [23].

2.2. Artificial intelligence and deep learning-based plant disease detection

Recent developments in artificial intelligence and deep learning have greatly improved the precision and effectiveness of tools used to detect plant diseases. When it comes to identifying and classifying plant diseases from photos and other data sources, these technologies especially deep learning models like CNNs are indispensable. In this section, we will take a look at how deep learning and artificial intelligence are helping with plant disease identification. We will highlight some of the most important methods, applications, and recent developments in this field both [24], [25]. Multiple computational approaches to pattern recognition, decision-making, and data-driven learning make up artificial intelligence. Artificial intelligence's deep learning subfield uses multi-layered neural networks to discover new features and learn on its own from raw data. Image identification and classification are two examples of difficult jobs that deep learning excels at. Using CNN architectures, deep learning models have shown exceptional accuracy in disease identification in plants. Because of its ability to learn spatial hierarchies of information from input visuals in an autonomous and flexible manner, CNNs are very good at recognizing illnesses through photographs. When it comes to deep learning models, image processing is where the CNN class really shines. Convolutional, pooling, and fully connected layers make up the architecture. Each successive layer refines the incoming data by highlighting key characteristics and patterns. The input image's edges, textures, and forms are detected by convolutional layers with the use of filters. A feature map is created for each filter that helps to find patterns in the image. Pooling layers use downsampling to decrease the spatial dimensions of feature maps, keeping important properties while reducing computational complexity. The last predictions are made by fully connected layers using the data from the convolutional and pooling layers. Standardly used for grouping. To improve their performance as plant disease detectors, CNNs may train on their own and extract relevant features from photos, doing away with the necessity for human feature engineering.

2.3. Convolution neural network

One class of sophisticated learning models developed specifically for the examination of structured grid data, such as pictures, are CNNs. The system's several layers can learn to recognize hierarchical elements in photos on their own. The ability of CNNs to detect subtle changes in disease symptoms has led to their impressive performance in plant disease identification. An example of a CNN design for plant disease detection might have convolutional layers for feature extraction, pooling layers for down-sampling, and fully connected layers for classification. Models for plant disease detection have been immensely enhanced by the use of transfer learning, which entails refining a pre-trained CNN on a particular dataset. Impressive accuracy in detecting diseases such as powdery mildew, rust, and bacterial blight has been achieved by CNNs, which have shown efficiency across several plant species. For the purpose of developing efficient systems for detecting plant diseases, CNNs are the ideal choice because to their scalability and versatility.

3. RESULTS AND DISCUSSION

It is clear that there are advantages and disadvantages to both machine learning and deep learning approaches when it comes to diagnosing plant diseases. RF, LR, and SVM are some of the more intuitive and easier methods to learn and use. Despite their great performance with smaller datasets and well-structured features, they could struggle with high-dimensional picture data. On the other hand, deep learning techniques, and CNNs in particular, are very good at processing huge datasets and unstructured input, such as pictures. They can detect critical traits on their own, which eliminates the need for human feature engineers. Deep learning models necessitate large training datasets and powerful computing resources to function at their best. Figure 3 shows the final picture masking process, which involves using convolutional logic from the produced model to combine the lower and top green and brown masking images.

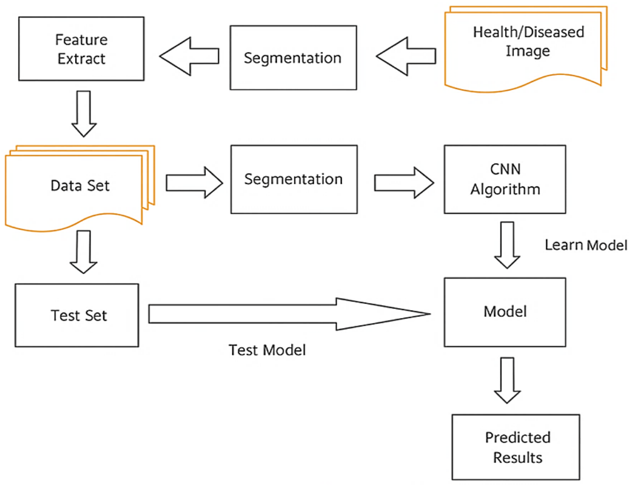


Figure 3. Plant leaf disease detection system architecture

The input photos are subjected to feature extraction in order to retrieve comprehensive information. It may be possible to identify certain plant diseases by analyzing different traits like color, texture, and shape. If the subject is "healthy," "not healthy," or sick, the classifier will process the feature set and output a status accordingly. How useful and efficient these systems are is heavily dependent on how accurate their classifications are. In order to automatically learn the relevant properties for identifying plant diseases, feature extraction is a highly successful approach. The typical criteria for evaluating images of diseased plant leaves are their color, shape, and texture. Image features are bits of information about objects or content that help with their unique identification. CNNs can efficiently handle sequential inputs as well as the picture data that inspired their development. Figure 4 shows the convolution process in action, comparing the brown's (affected region) color variation range to the estimated threshold level set by the given algorithm models. The image is categorized as unhealthy (diseased) if the variance level is more than 200, and as healthy if it is less than 200.

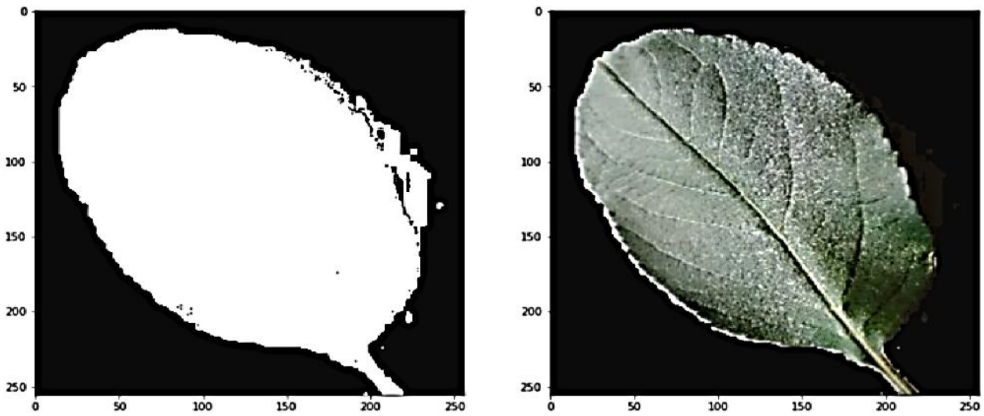


Figure 4. Analyses of the classification results

Figure 5 depicts the estimation of processing time for different machine learning algorithms, such as LR, RF, and CNN, in the context of deep machine learning. The processing time is approximated and can be represented graphically. Figure 6 represents the estimation of accuracy for the Inception v4 model's performance. The training and testing accuracy are estimated and the results are displayed in graphical form. Likewise, it depicts the accuracy performance of visual geometry group-16 (VGG16) refer to Figure 7. The choice between machine learning and deep learning approaches depends on various factors, such as the nature of the dataset, the complexity of the disease symptoms, and the available computational resources. A combined approach that merges machine learning with deep learning techniques can leverage the strengths of both, resulting in more robust and flexible systems for detecting plant diseases.

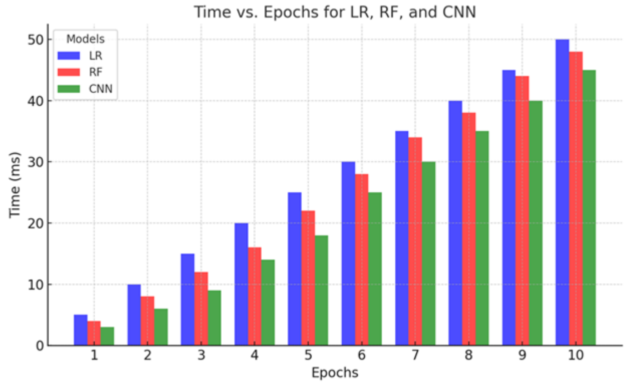


Figure 5. Estimates of deep machine learning processing times (LR, RF, and CNN)

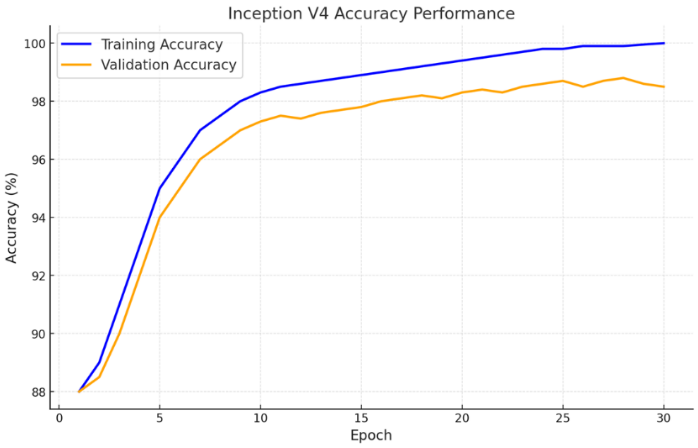


Figure 6. The accuracy estimation of Inception v4 performance

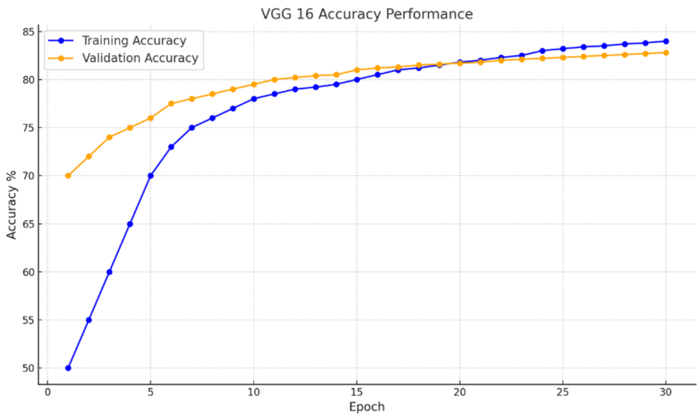


Figure 7. Illustrates the accuracy estimation of VGG16 performance

4. CONCLUSION

In order to detect and categorize plant illnesses, a battery of machine learning and deep learning experiments were run. Consequently, more machine learning classification methods might be employed for plant disease detection. It would be immensely helpful for farmers if different agricultural illnesses could be detected automatically. The purpose of this study is to investigate several deep learning methods for illness diagnosis in plants. In addition, numerous methods and examples for identifying symptoms of disease were provided. We will go over the most recent developments in deep learning algorithms that can identify and categorize diseases affecting plant leaves. This discovery is going to be a priceless asset for those working on plant disease detection. We examine both deep learning and machine learning approaches side by side. We still need to fill up a few research gaps before we can successfully apply methods for diagnosing plant diseases, even though we've come a long way in the past few years.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest regarding the publication of this paper.

ETHICAL APPROVAL

This article does not contain any studies involving human participants or animals performed by any of the authors.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available from the corresponding author, [JTMD], on reasonable request.

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