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AI TECHNIQUES FOR PLANT DISEASE DETECTION

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ABSTRACT

Plant diseases affect agricultural production, food security, and economic stability, making them a major concern for global agriculture. To reduce losses and guarantee sustainable farming methods, these diseases must be identified early and managed effectively. Manual inspections, which are labour-intensive, unreliable, and unscalable for large-scale agricultural applications, are frequently the basis of traditional disease monitoring techniques. Innovative approaches to plant disease tracking have been made possible by the quick development of artificial intelligence (AI), which offers improved scalability, accuracy, and efficiency. This study provides a comprehensive assessment of AI-based plant disease tracking systems, concentrating on techniques that integrate machine learning, deep learning, computer vision, and datadriven models. Key uses include integrating satellite imagery and IoT-enabled devices for real-time monitoring, predicting disease outbreaks using environmental data, and detecting diseases using picture processing. Additionally examined is the function of mobile applications in providing farmers with easily accessible diagnostic tools. The study also discusses important issues like model generalisation, data scarcity, computational constraints, and socioeconomic obstacles to AI adoption in agriculture. This review highlights the revolutionary potential of AI in building resilient agricultural systems, ultimately promoting global food security and sustainable development, by combining recent developments and pointing out research needs.

Keywords: Plant diseases

I. INTRODUCTION

Plant diseases pose a significant threat to food security and economic growth as they are one of the main variables influencing worldwide crop yields and agricultural sustainability. Plant disease detection, monitoring, and management are becoming more challenging for farmers and other agricultural stakeholders, especially as globalisation and climate change fuel the spread and evolution of pathogens. Large-scale agricultural systems cannot benefit from the labourintensive, time-consuming, and specialist knowledge-required nature of traditional disease detection techniques like visual inspection and laboratory testing. This emphasises how urgently novel, effective, and scalable methods of disease management and monitoring are needed. Data-driven, automated solutions in agriculture have been made possible by the quick development of artificial intelligence (AI), especially machine learning (ML).

Convolutional Neural Networks (CNNs) have been a ground-breaking tool in this field for tackling problems with plant disease identification. CNNs are perfect for jobs like recognising illness symptoms from photos of plant leaves, stems, and fruits since they are a subset of deep learning algorithms built to analyse and interpret visual input. Even in complicated and varied environmental settings, CNNs can reliably classify diseases and differentiate between healthy and sick plants by learning patterns from large datasets. Data-driven, automated solutions in agriculture have been made possible by the quick development of artificial intelligence (AI), especially machine learning (ML). Convolutional Neural Networks (CNNs) have been a ground-breaking tool in this field for tackling problems with plant disease identification.

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This paper seeks to emphasise the revolutionary potential of CNNs and machine learning technologies in developing resilient agricultural systems by combining recent developments and pointing out potential future directions. Their implementation could transform disease control, lower crop losses, and promote sustainable farming methods globally.

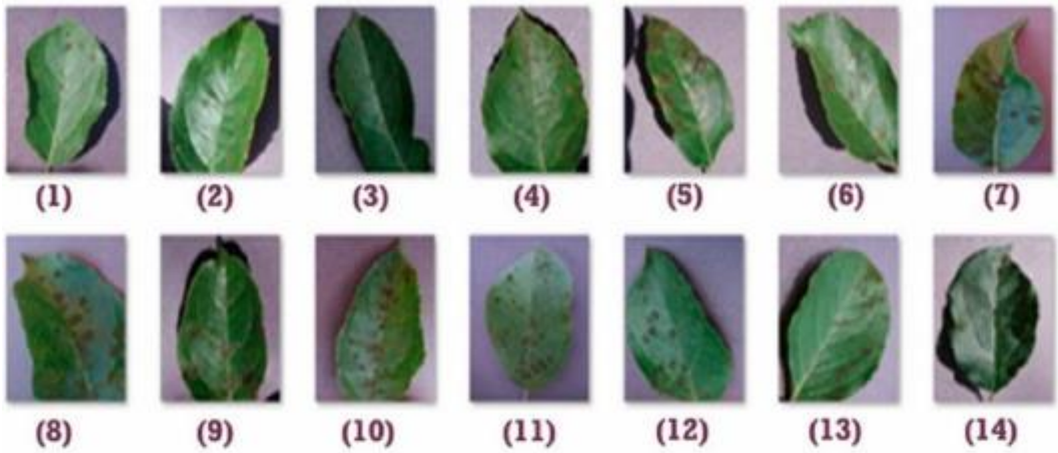
II. PLANT DISEASE DETECTION USING MACHINE LEARNING TECHNIQUES

The world's population depends heavily on the agricultural industry, however it is extremely susceptible to plant diseases, which can result in significant losses in crop production and economic productivity. To reduce these losses, plant diseases must be identified accurately and promptly. Conventional techniques, such laboratory testing and manual observation, are frequently costly, time-consuming, and unscalable for large-scale operations. These difficulties have prompted the creation of cutting-edge technology to improve the effectiveness and accuracy of plant disease identification. In this field, machine learning (ML) has become a potent instrument, offering automated, data-driven methods for accurately identifying plant diseases. ML approaches are perfect for agricultural applications because they can handle vast datasets, identify intricate patterns, and adjust to a variety of settings. Among the different machine learning algorithms, supervised learning techniques including k-Nearest Neighbours (k-NN), Random Forests, and Support Vector Machines (SVM) have been widely employed for illness classification. In order to train models that can diagnose certain diseases, these techniques rely on labelled datasets, from which characteristics like leaf colour, texture, and shape are collected. By enabling end-to-end feature learning from raw picture data, deep learning—a subset of machine learning—has improved the diagnosis of plant diseases. Specifically, Convolutional Neural Networks (CNNs) have demonstrated remarkable efficacy in identifying illness symptoms in plant photos. CNNs eliminate the need for human feature engineering by automatically extracting pertinent features from images. They have been effectively used to categorise a variety of illnesses, identify symptoms in their early stages, and accurately distinguish between relatedproblems.

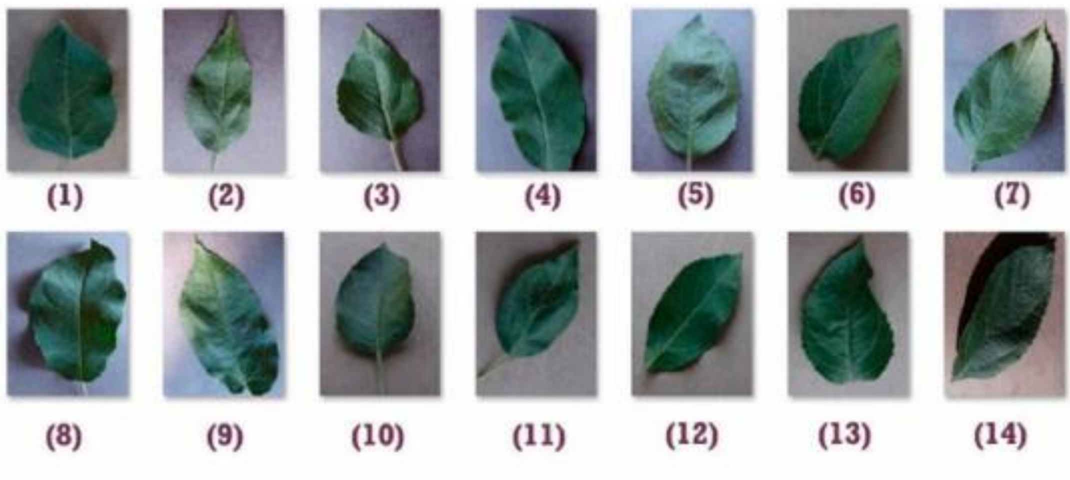
Real-time disease monitoring and prediction have been made possible by the combination of machine learning with other technologies, including cloud computing and the Internet of Things (IoT). Temperature, humidity, and other environmental data can be gathered by IoT sensors, and ML models can use this information in conjunction with visual inputs to forecast disease outbreaks.

Not withstanding its potential, there are a number of obstacles to overcome before machine learning (ML) can be used to identify plant diseases. These include the requirement for sizable, varied, and high-quality datasets; the capacity to generalise models across various crops and geographical areas; and the necessity for computational efficiency in contexts with limited resources. Researchers, agricultural specialists, and technology developers must work together to address these issues.

Precision agriculture has advanced significantly with the use of machine learning algorithms for plant disease diagnosis. These technologies can support sustainable farming methods and help guarantee global food security by making disease management.



(a)



(b)

Figure 1. (a) Diseased leaf image samples and (b) healthy leaf image samples.

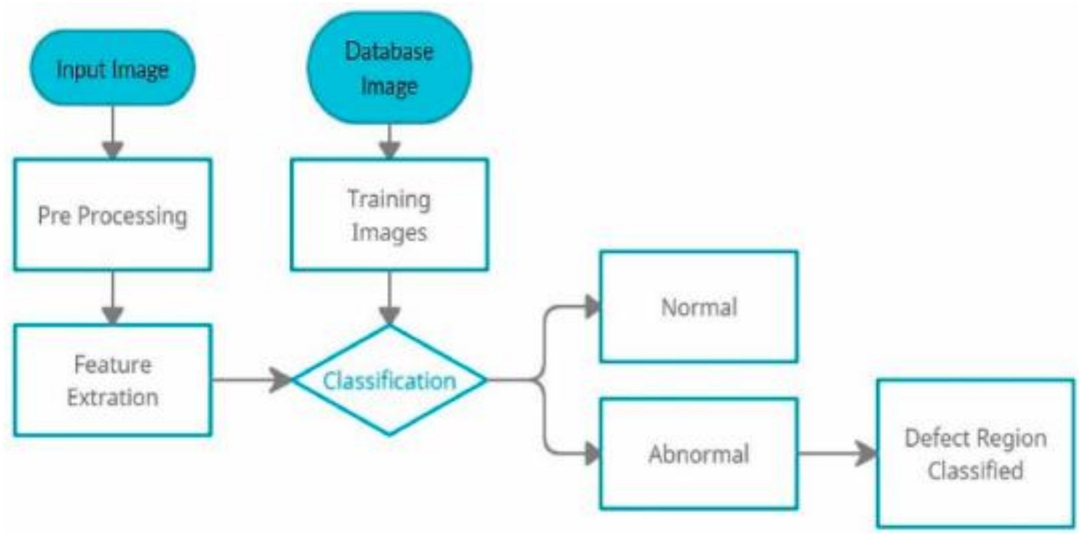


Figure 2. General steps for Crop detection.

The general procedures for crop disease identification using machine learning techniques are shown in the image. This is a thorough explanation of the procedure:

1. Input Image:

A picture of the crop, which can be acquired via gadgets like cameras, drones, or smartphones, is the first step in the procedure.

Pre-Processing:

To enhance quality and eliminate noise, the input image is pre-processed. To make sure the image is appropriate for analysis, common methods include image scaling, normalisation, and noise reduction.

Feature Extraction

The pre-processed image's colour, texture, edges, and shape are taken out. These features let the machine learning algorithm distinguish between healthy and unhealthy plants.

Database photographs (Training Data):

The machine learning model is trained using a collection of training photographs that include both healthy and damaged crops. The program uses this dataset as a reference to identify trends and characteristics linked to plant diseases.

Classification:

A classification model, such as a Convolutional Neural Network (CNN), Support Vector Machine (SVM), or Decision Tree, is fed the extracted features. The classifier determines if the picture of the plant is Normal and abnormal Defect Region Classified: In order to enable focused disease detection and treatment, the model locates and emphasises the precise defect regions (such as infected leaves or spots) if the plant is deemed abnormal.

NB classifier

Based on Bayes' Theorem, the Naive Bayes (NB) classifier is a probabilistic machine learning algorithm. Text classification, spam detection, and disease identification are among the classification tasks where it is very helpful. The word "naive" describes the simplified calculation that assumes all features are independent of one another.

Bayes' Theorem

The Naive Bayes classifier is built on the principle of Bayes' theorem: $P(C|X)= P(X|C)\cdot P(C)/P(X)$ Where:

$P(C|X)P(C|X)P(C|X)$: Posterior probability of class CCC given feature XXX.

$P(X|C)P(X|C)P(X|C)$: Likelihood of feature XXX given class CCC.

$P(C)P(C)P(C)$: Prior probability of class CCC.

$P(X)P(X)P(X)$: Probability of the feature XXX occurring.

KNN classifier

A straightforward, instance-based, non-parametric machine learning algorithm for classification and regression applications is the K-Nearest Neighbours (KNN) classifier. Because it can effectively handle multi-class issues without assuming any prior distribution of the data, it is especially helpful for plant disease identification.

DT classifier

One popular supervised machine learning method for classification and regression problems is the Decision Tree (DT) classifier. Its capacity to manage intricate decision-making processes in an understandable way makes it especially appropriate for plant disease detection.

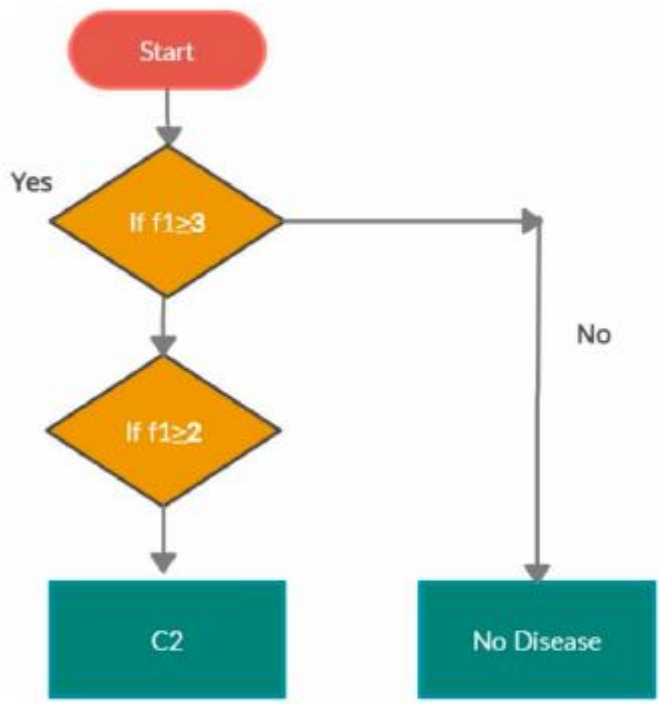


Figure 3. Decision Tree Flow chart.

SVM classifier

The Support Vector Machine (SVM) is a powerful and widely used supervised machine learning algorithm primarily employed for classification tasks, including plant disease detection. SVM is particularly effective in handling highdimensional data and distinguishing between classes with a clear margin.

RF classifier

Multiple decision trees are used by the Random Forest (RF) classifier, an ensemble learning technique, to increase classification robustness and accuracy. Because it can effectively handle big datasets and intricate patterns, it is frequently used in machine learning applications, such as plant disease identification.

MLP classifier

Regression is the foundation of an MLP paradigm. With this approach, non-linear-based learners are converted, changing the input dataset. The characteristic that is linearly distinct is the modifications from the input data. The layer of incoming data that transforms into a hidden layer. The MLP Classifier only uses one hidden layer; otherwise, it functions similarly to an artificial neural network. Even the use of numerous hidden layers is advantageous for classification.

III. LOGISTIC REGRESSION (LR)

A machine learning approach for supervised prediction is called logistic regression. There are two types of linear regression: basic and multiple linear. Equations (2) and (3) demonstrate that simple linear regression has both individual and multiple linear regressions and multiple independent variables.

$$Y = bo + b1*x \rightarrow (2)$$

$$Y = b0+b1*x1+b2*x2+ \ldots +bn*xn \rightarrow (3)$$

In this instance, the dependent variable is Y, and the independent variable is X. Finding the appropriate line for the given data is the aim of linear regression, as illustrated in Figure 3. The line that best fits the observations in the data set. We can use logistic regression to categorise probabilities between 0 and 1. The likelihood is referred to as larger than 0.5 because yes and less than 0.5 since no, since we are only concerned with the prediction and not the likelihood.

IV. ARTIFICIAL INTELLIGENCE AND DEEP LEARNING BASED PLANT DISEASE DETECTION

Deep learning methods for plant disease detection have grown in importance in agriculture, particularly for identifying illnesses that might cause crop loss and have a detrimental effect on agricultural output. Artificial intelligence (AI) and deep learning techniques have been used in a number of studies in recent years to improve the precision and effectiveness of plant disease identification.

Deep Learning Methods for Disease Detection:

Convolutional Neural Networks (CNNs), in particular, are a number of deep learning models that have been effectively used to identify plant diseases, including those that impact crop leaves. Deep learning models' adaptability and precision have made it possible to automate the detection of plant diseases, which helps with early disease identification, lowers crop loss, and boosts output. These developments have produced more accurate tools, which are dependable for use in agriculture.

In 2020, Monu Bhagat and Support Vector Classification (SVC) proposed:

Monu Bhagat et al. (2020) made a noteworthy addition by discussing the use of traditional Support Vector Classification (SVC) approaches for plant leaf disease identification. The writers emphasised that India's agriculture is a key economic engine that has greatly fuelled the nation's development. The study discusses the difficulties in detecting agricultural leaf diseases and suggests using SVC to improve disease detection models' performance. With an overall accuracy of 89.6%, the study produced encouraging results that highlighted the potential of SVC in agricultural applications.

Optimised Sub-Set Function Approach:

To improve the precision of plant disease diagnosis, an optimised sub-set function based on vector machine classification was implemented in a distinct method. This model increased plant disease classification performance by monitoring different cultivation forms.

Fuzzy Set-based Methods:

To deal with ambiguity in plant disease images, fuzzy logic techniques have been used. The segmentation and clustering of crop disease symptoms are improved by the introduction of fuzzy sets, which make it easier to handle pixel changes in images. This approach facilitates more precise crop disease categorisation and detection, particularly in intricate and ambiguous photos.

V. CONVOLUTION NEURAL NETWORK (CNN)

This methodology's primary goal is to classify images with the specified perspective, which sets it apart from other neural network methods. CNNs typically employ minimal pre-processing compared to calculations of other image arrangements, meaning that the classification learns the channel that is typically hand-built. The convolutional layer is the CNN's centre square structure, and the parameters layer consists of a collection of learnable channels (or pieces) with a small open field.

Inception–V4

The 48-layered deep CNN network, or Inception V4, is an expansion of the Image Net concept. The model is made up of both symmetric and asymmetric blocks that cover convolution for creating a feature map when a filter is applied to an image, average feature map computation for every pixel, maximum pooling layer, average pooling (8 × 8), and maximum pixel, which helps to lower the computation cost parameters for learning. The fully-connected layer is in charge of connecting neurones to each layer, and inputs of the same size—typically dropouts—are pooled after pooling, which helps to reduce overfit and increase accuracy. The batch norm used for loss computation and softmax are used to create the activation norm.

VGG–16

Oxford University created the "visual geometry group," or VGG, as a deep CNN model for the 2014 "Image Net Large scale recognition of visual challenge" (ILSVRC). When compared to other deep neural networks, this structure has the best function available today. This structure solely concentrates on the padding convolution layer, fully connected layer, and max pool with the softmax layer's result, even if there are many different types of parameters.

VGG –19

This is comparable to VGG-16 and other VGG variations that have an additional feature of three convolution layers that effectively aid in image recognition. The fundamental concept is to create deep neural networks with continual convolution and modest size.

VI. COMPARATIVE REVIEW ON MACHINE AND DEEP LEARNING TECHNIQUES

To get discriminating information, the input photos are subjected to feature extraction. A variety of characteristics, including colour, texture, and shape, may be helpful in identifying particular plant diseases. The classifier receives the set of features as input, classifies the plant as either healthy or unhealthy, and/or detects the disease. The classification accuracy has a significant impact on the efficacy and applicability of such systems. The ability to automatically learn characteristics is the primary function of feature extraction in plant disease detection. The characteristics of plant leaf photos, such as their shape, texture, and colour, are mostly used to identify plant diseases. An image feature is a piece of information about an object or piece of material that makes it easier to identify it. Although convolutional neural networks were developed to address issues with picture data, they can also function when provided with sequential inputs. The convolution process compares the estimated threshold level of the defined algorithm models with the colour variation range of the brown (affected portion).

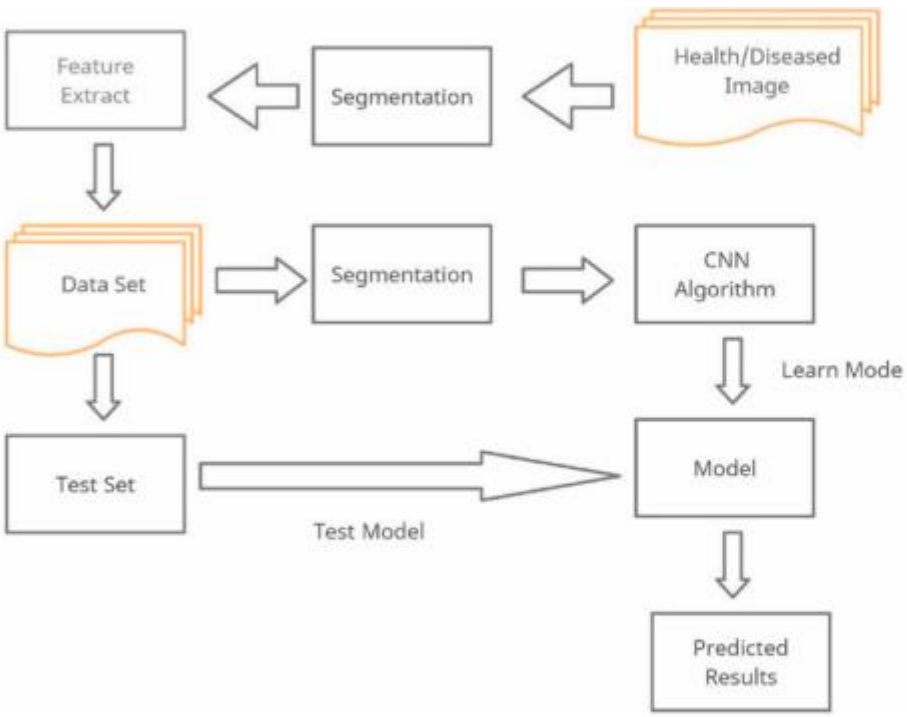


Figure 4. System architecture for plant leaf disease detection.

If the variation level is greater than 200, the image will be labelled as unhealthy (diseased); if it is less than 200, the image will be regarded as a healthy leaf (see Figure 5).

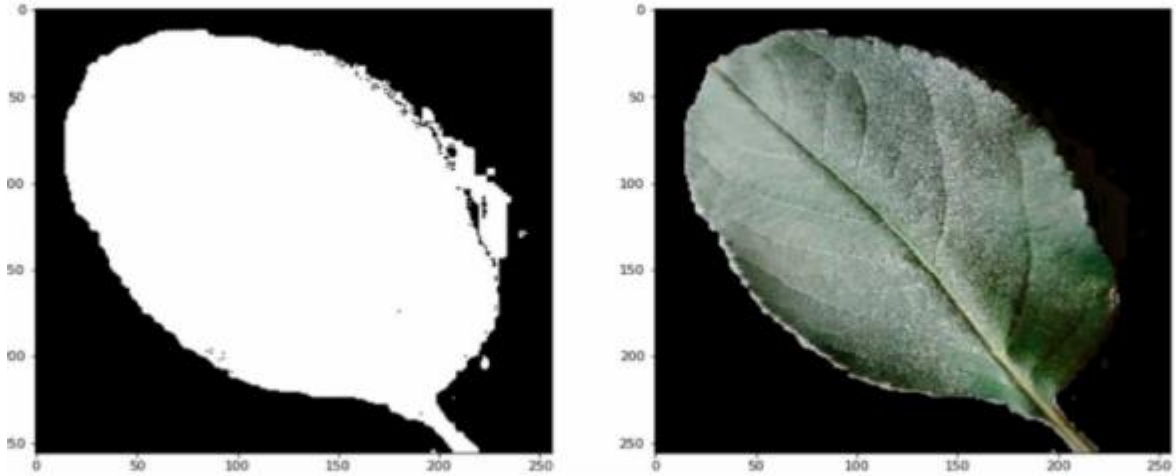


Figure 5. Classification result analyses.

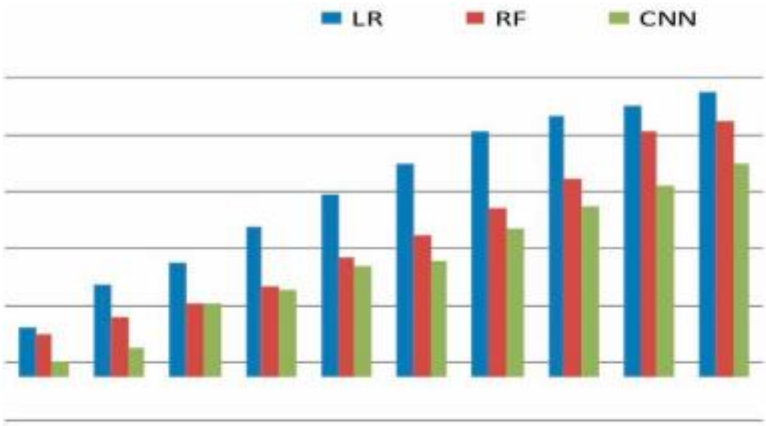


Figure 6. Processing time estimations of deep machine learning approaches (LR, RF and CNN).

VII. CONCLUSION

Numerous studies on machine learning (ML) and deep learning (DL) methods for classifying and identifying plant diseases have shown how these technologies have the potential to completely transform agricultural operations. Plant disease detection has become increasingly important over time, particularly in order to ensure crop productivity and health. Automated plant disease detection systems have become vital tools for farmers to increase output and decrease losses due to the growing problems faced by pests, diseases, and climate change. This study examined many machine learning and deep learning-based classification methods, emphasising their functions in the identification and categorisation of plant diseases. Earlier phases of plant disease identification have made extensive use of machine learning methods like Support Vector Machines (SVM), k-Nearest Neighbours (KNN), Decision Trees (DT), and Random Forests (RF). Although these methods have demonstrated encouraging outcomes, their effectiveness may be constrained by elements like their dependence on well-labeled datasets and the requirement for human feature extraction. It is becoming more and more clear as the agriculture sector develops that more sophisticated methods, including deep learning (DL), are required to manage complicated datasets and more precisely detect diseases. In recent years, one of the most promising methods for detecting plant diseases has been deep learning, especially using Convolutional Neural Networks (CNNs). CNNs improve accuracy by automatically learning and extracting features from images, doing away with the requirement for human feature engineering. Deep learning has become a vital tool for agricultural scientists due to its capacity to process vast amounts of picture data and identify patterns. Plant disease detection has been greatly enhanced by recent advances in deep learning technology, with systems now able to recognise a variety of illnesses in real-time under a range of field settings. These autonomous technologies can minimise crop loss by giving farmers early warnings and empowering them to take timely corrective action before the illness spreads.

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