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Plant Leaf Disease Detection System Using Machine Learning And Deep Learning: A Survey

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Abstract
Plant diseases are becoming more common, which is a serious threat to profitability of agriculture worldwide and requires the creation of reliable and efficient disease detection technologies. This work uses machine learning (ML) and deep learning (DL) approaches to give an extensive assessment of previous research on plant leaf disease identification. We examine and evaluate the many approaches used in the last several research, emphasizing the advantages, disadvantages, and useful uses of each. The study covers both sophisticated deep learning designs, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), as well as more conventional machine learning techniques, such support vector machines (SVM) and decision trees. According to our research, plant leaf diseases can be more accurately identified and classified using deep learning techniques, especially CNNs, when applied to a variety of crop categories. The study also looks at the field's obstacles and promising directions, highlighting the use of multifaceted approaches and real-time illness monitoring systems.
Keywords: *Convolution Neural Network, Deep Learning Machine Learning, Plant Disease Detection, Support Vector Machine*

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I. INTRODUCTION

India's economy is primarily driven by agriculture. Most Indians make their living from agriculture. Agriculture productivity is a major contributor to India's economic expansion. Approximately 70–80% of India's economy is derived from agricultural production. The governments of all countries, rich or poor, give agriculture top importance because it is one of the main providers of food. Water, atmosphere, climate, and a host of other environmental factors influence the growth of fungi, bacteria, viruses, and non-biotics in agriculture. Consequently, damage to the crops may cause a large drop in productivity, which might eventually impact the financial structure [1]. The leaves of various plants are the most crucial part for early symptom appearance. Many diseases that affect plants can cause significant decreases in yield, putting daily lives at risk for humans. Global financial stability, food availability, and agricultural production are all seriously threatened by plant illnesses. Because they are so important to photosynthesis, leaves are especially susceptible to various diseases such as viruses, germs, and fungal. To efficiently handle and manage leaf diseases and reduce crop damage while increasing productivity in agriculture, early and precise detection of these diseases is crucial. Previously, skilled specialists have used eye inspection to diagnose plant diseases. Although time-consuming, costly, and prone to errors made by humans, this approach can be useful. Furthermore, even for highly qualified medical personnel, accurately diagnosing certain diseases can be difficult due to their complex and variable symptoms. As a result, the demand for automated, dependable, and scalable systems for the accurate diagnosis and early recognition of plant leaf diseases is rising.

New developments in deep learning (DL) and machine learning (ML) technology present viable ways to create these autonomous systems. These technologies utilize massive data sets and complex algorithms to uncover trends and characteristics that are often invisible to humans. It is possible to create a sophisticated plant leaf disease detection system by utilizing deep learning and machine learning methods. These sophisticated models have impressive rate of accuracy, having been trained on large datasets such as the PlantVillage dataset [2][3]. Such systems, which are essential for improving agricultural production and food safety, may efficiently recognize and identify a range of crop illnesses, particularly viruses, bacteria, and fungal illnesses, by employing CNN architectures [4]. By using innovative neural networks to accurately recognize and diagnose a variety of plant illnesses, deep learning models have completely changed the identification of plant leaf diseases systems [5].

These models AlexNet, Yolo-v5, MobileNet, and others can identify viruses, bacterial, and fungi illnesses in crops including tomato, grapes, maize, sugarcane, potatoes, and apples [6]. With the use of convolutional neural Networks (CNNs), these systems categorize diseases and alert farmers in advance so they can take the appropriate precautions to avoid financial loss.

In this study, we investigate the use of deep learning and machine learning in the identification of plant leaf diseases. We examine the existing approaches, emphasizing their advantages and disadvantages, and we contrast contemporary deep learning methods with conventional machine learning methods. A thorough review of the field is presented in this study to promote the development of effective, autonomous plant disease control systems with an overall aim of ensuring food safety and environmental sustainability.

II. RELATED WORK

R. Nalawade et al. [7] suggested a system that offers continuous tracking of field variables like temperature, relative humidity, wetness, and so on, in addition to providing identification of leaf diseases and whole field surveillance. It is possible to control the flow of water using an app even if the user is not physically at the device and monitor real-time information. The suggested method effectively displays the current state of the produced application while routinely monitoring the harvested field. The program allows users to control the water pump. Application provides details on the plant, necessary fertilizers, soil conditions, and chemicals for disease treatment. The model’s overall precision is 98.07%. A combination of machine learning and edge detection is used to identify leaf diseases at an early stage. Machine learning methods are used to train the model that assists in making an informed decision regarding diseases. It is recommended that the insecticide be applied as a treatment for contaminated ailments.

The tomato is the most widely grown crop worldwide, and it can be seen in every kitchen, regardless of the type of food prepared. It's the most widely grown crop in the world, right behind sweet potatoes and potatoes. In terms of cultivation of tomatoes, India came in second. However, a variety of illnesses lower both the quantity and the grade of the tomato harvest. Thus, the study discusses a deep learning-based method for illness detection. A method based on convolution neural networks is used for disease diagnosis and categorization was built by M. Agarwal et al. [8]. Two completely linked layers are positioned after three convolution and three max pooling layers in this model. Authors used the PlantVillage dataset to obtain the tomato leaf data for the experiment. There are nine disease categories and a single category with healthy images in the collection. Since the images presented in the class are unbalanced, methods for data enhancement have been utilized to fix the image imbalance. The suggested model average success rate for the nine diseases and one healthy class is 91.2%. The accuracy of VGG16 model was 77.2%, Mobilenet recognition accuracy was 63.75%, and finally Inception algorithm accuracy was 63.4%. The experimental findings demonstrate the suggested model superiority over pre-trained models, such as VGG16, MobileNet, and InceptionV3. The advantages of not employing a pre-trained model are further shown by this study, which discovers that the suggested model used significantly less storage space just 1.5 MB than the pre-trained models, which required 100 MB.

The A. A. Yatoo et al. propose an approach for identifying and detecting illnesses of apple leaves using an improved model. They provide an improved model that was retrained utilizing the Plant Pathology data set and exhibited a low learning rate. In general, fine-tuning means making minor adjustments to a process to get the desired outcome or effectiveness [9]. A model must usually be unfrozen entirely or in part and retrained with a low learning rate on the new data to be fine-tuned. The performance of the model was increased by relieving some more layers from freezing and by adjusting the layer weights during training. Following several examinations, the model's first 12 layers are frozen and the remainder of them are unfrozen, resulting in a significant improvement in performance. Since the model was previously trained, the weights have not changed all that much. Consequently, a very sluggish learning rate optimizer is used. The model additionally employs the advantages of transfer learning and blocks VGG16 CNN model layers to increase efficiency. The results of the investigation show how effectively the improved model classified apple leaves into three categories: cedar apple rust, scabbed, and healthy. After a series of tests, the model effectively achieved an 85% accuracy rate in classifying the images of leaves into three separate groups.

A CNN algorithm was proposed by S. Pawar et al. [10] that identifies diseases from leaf pictures and provides pesticide recommendations based on findings associated with the disease. This study aims to identify the probable class of appearance on a plant leaf. An uncontrolled method called Neural Network is employed for this kind of estimation. Convolution neural networks (CNNs) are used in this research to identify plant illnesses. CNN has fifteen layers in the suggested strategy. In addition to providing the identity of the pesticide provider for each location, the proposed system will additionally give further details regarding the plant disease affecting the leaves in the affected area, including the illness's name, full accuracy, timing, and weather prediction details. Ten plant species are included in the dataset: rice, corn, apple, sugarcane, cucumber, soyabean, tomato, potato, and pepper. The system employs Gaussian dimensions, restriction, and selection to pre-scan the picture and segregate the leaf area. The suggested system with filtering technique is useful to identify the type of leaf disease with up to 93%

efficiency. The Convolution Neural Network offers exceptional accuracy in disease diagnosis when all the contributing components are included. The suggested system gives farmers access to weather prediction data, Which can assist them in daily decision-making such as determining which fertilizer is best for a certain weather situation.

Farmer's monetary status is significantly impacted by the plant disease. Thus, prior to the plant disease causing serious harm, it needs to be stopped or managed. A remedy to this issue has been proposed by using machine learning techniques that analyze the underlying causes of the illness and suggest suitable pesticides for treating the plant [11]. Even though several methods have been discovered to detect crop disease, the ways used today have not yielded consistent results. While numerous existing systems struggled to capture agricultural data using dataset and image processing tools, the proposed CNN method made use of these features by creating web-based applications that let customers to identify several plant illnesses that had occurred. The proposed CNN has been implemented to classify and compare the visual appearance of the diseased or pathogenic plant. The two primary modules of the recommended approach image categorization and disease detection have been evaluated and implemented. Apart from precisely recognizing the crop disease and evaluating the overall quality of the affected images, the technique also suggests the most effective pesticides to apply on the affected plant. Although it can more accurately recognize plant illnesses and prescribe the appropriate pesticides, the trained model is excellent. The outcome has confirmed that the recommended task was completed incredibly well.

K. Shivaprasad et al. [12] developed a deep learning-based system to detect plant leaf disease. The goal of the research was to contrast three deep learning models (CNN, VGG16, and VGG19) for the purpose of detecting plant diseases. A straightforward forward-propagating neural network, the CNN architecture is frequently used for image categorization tasks. On the other hand, VGG16 and VGG19 are deep convolutional neural networks that have demonstrated remarkable performance across a range of computer vision applications. A dataset with 9,127 images of plants labeled with illness labels was utilized to train and assess the models employing recall, precision, F1 score, and accuracy as evaluation criteria. CNN emerged as the top performer overall in the classification challenge, achieving an F1 score of 0.95 and an accuracy of 0.97. It is clear from the results that all three deep learning models can do exceptionally well on the specified classification work.

The diagnosis of plant diseases is essential for maintaining healthy crop production and preventing major crop damage due to these diseases. On the other hand, Traditional methods might be difficult and time-consuming to diagnose. Recently, deep learning techniques such as ResNet 34 have been identified as a possible approach for automating the diagnosis of plant leaves [13]. ResNet 34 is capable of accurately classifying plant leaf pictures based on trend and attribute information. Using a large dataset of annotated plant leaf pictures, a ResNet 34 model can be trained to accurately detect various leaf ailments. The reason for this is its ability to handle vanishing gradients effectively and create hierarchical visualizations of input data. ResNet-34 can be trained to consistently recognize and categorize several illnesses of plant leaves with minimal data by using large-scale datasets and transfer learning techniques.

Y. H. Bhosale et al. [14] identified several types of plant diseases, underlying climate variation, and habitat migration. The study presents the automated recognition and categorization of illnesses of plant leaves utilizing an imaging segmentation method. Furthermore, it summarizes how various illness classification techniques can be used to identify diseases of plants. This research study offers an overview of several plant illnesses and several deep machine learning categorizing methods used to identify abnormalities in a variety of plant leaves. CNN is well known for its capability to continuously retrieve attributes based on the initial photos. Neural network and machine learning techniques are widely used because of their ability to provide accurate depictions. As a result, a stacked sequencing of CNN maximizes the benefits of acquiring comprehensive knowledge for optimal simulation outcomes. In machine learning, features are a key component that affects the classifier in a major way. The study focuses on methods for classifying plant leaf diseases that rely on image processing. The morphological characteristics of the spot attributes are extracted using the length and proportion of the principal axes, the center of gravity, the position, the corresponding diameter, the deviation, the solidity, the area, the hydrodynamic radius, the degree of difficulty, and the coefficient of Euler number.

A. Mezenner et al. [15] provide a novel descriptor for producing features from plant leaves that depend on local directional patterns. The SVM classifier is linked to this descriptor to create the complete identification system. Three crop species diseases of the bell pepper, potato, and tomato are examined in the experiments. The suggested LDP characteristics are compared to the histogram of oriented gradients and features from convolutional neural networks. By using Kirsch detector on images, textural and data on edges are combined to create a powerful descriptor known as LDP. This combination draws attention to the texture details in several ways. Samples from three agricultural varieties that were taken from the PlantVillage dataset were used in the experiments. The authors employed CNN and HOG characteristics as a point of evaluation. In comparison to other attributes, HOG performs in a medium manner, according to the outcomes that were produced. SVM and CNN combine to provide results that are significantly more accurate than HOG findings. However, when the appropriate K value is applied, the link between SVM and LDP features operates better than any other method, allowing for optimum precision. These results suggest that LDP may serve as a general descriptor of plant disease. The outcomes demonstrate the efficacy of the suggested system, which achieves a 3% total accuracy gain over the LeNet-5 convolutional neural network.

Identifying plant diseases is an important task in agriculture. Early diagnosis of plant diseases is crucial because it can prevent further damage to the plants. Early recognition and treatment of plant diseases that can have a substantial influence on crop well-being and yield is made possible by the early recognition of leaf-related illnesses. Some of the state-of-the-art techniques for identifying plant leaf diseases include visual examination, spectrum analysis, DNA-based, IOT-based, and computerized image analytics. This study emphasizes using CNN and VGGNet19 [16] among other methods of deep learning to identify illnesses in leaves. The suggested methodology includes gathering datasets, preparing them, identifying plant diseases, and utilizing Tkinter to create the user interface. The responsibility of identifying plant illnesses and providing treatments for them is carried out by the suggested work. It was discovered that the model's accuracy was 83% and 85.4%, accordingly. The suggested project finds treatments for plant diseases by identifying them in the leaves of the plants.
Table 1 represents Summary of research papers on plant leaf disease detection.

Table 1. Summary of research papers on plant leaf disease detection

Ref. No.	Authors	Title	Year	Methodology	Key Findings
[7]	R. Nalawade et al.	Agriculture field monitoring and plant leaf disease detection	2020	Image processing and ML algorithms	The model's overall precision is 98.07%.
[8]	M. Agarwal et al.	ToLeD: Tomato leaf disease detection using convolution neural network	2020	Convolutional Neural Network (CNN)	Model average success rate for the nine diseases and one healthy class is 91.2%.
[9]	A. A. Yatoo et al.	A novel model for automatic crop disease detection	2021	Novel ML model	Model effectively achieved an 85% accuracy rate
[10]	S. Pawar et al.	Leaf disease detection of multiple plants using deep learning	2022	Deep learning	Effective for multiple plant leaf disease detection. Accuracy is 93%.
[11]	M. Kathiravan et al.	ML algorithm-based detection of leaf diseases	2022	Machine Learning algorithms	Accurate leaf disease detection using ML.
[12]	K. Shivaprasad et al.	Deep learning-based plant leaf disease detection	2023	Deep Learning	Achieving an F1 score of 0.95 & an accuracy of 0.97.
[13]	K. Harshavardhan et al.	Detection of various plant leaf diseases using deep learning techniques	2023	Deep learning techniques	Handle vanishing gradients effectively and create hierarchical visualizations of input data.
[14]	Y. H. Bhosale et al.	Multi-plant and multi-crop leaf disease detection and classification using deep neural networks, machine learning, image processing with precision agriculture - A review	2023	Deep Neural Networks, ML, Image Processing	Thorough analysis of methods for detecting diseases in several plants and crops.
[15]	A. Mezenner et al.	Local directional patterns for plant leaf disease detection	2023	Local directional patterns	Hybrid CNN and SVM model performs better than other models.
[16]	D. Tandekar et al.	Identification of various diseases in plant leaves using image processing and CNN approach	2023	Image processing, CNN	Model's accuracy was 83% and 85.4%

III. DATASETS

PlantVilage Dataset

One extensive and frequently used resource in the context of plant leaf disease identification is the PlantVillage dataset. The greatest dataset on plant diseases is found in PlantVillage [17]. 54,309 photos from 14 crop species apple, blueberry, raspberry, bell pepper, cherry, grape, peach, squash, soybean, strawberry, potato, orange, corn, and tomato were included in the preliminary reports for 2016. Some plants, though, lack disease classifications. Using an openly accessible dataset allowed us to assess system and compare it to other approaches that are currently in use. PlantVillage, a web-based resource that is now in use, made these carefully selected photos of both healthy and diseased crop leaves accessible. There are 17 fungal diseases, 2 viral diseases, 2 mold diseases,4 bacterial illnesses, and 1 mite disease that harms these plants. The datasets include 1 class of backdrop images, and one category of background image class. It is appropriate

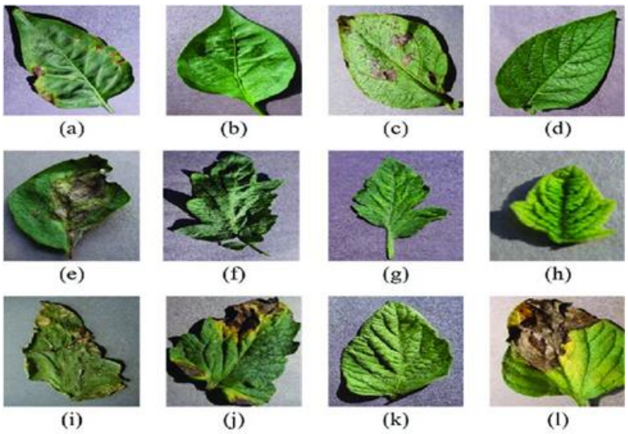

FIGURE 1. Some sample images from PlantVillage dataset. (a) Pepper bell bacterial spot, (b) Pepper bell healthy, (c)Potato Early blight,(d) Potato healthy, (e) Potato late blight, (f) Tomato – target spot, (g) Tomato – tomato mosaic virus, (h) Tomato – tomato yellow leaf curl virus, (i) Tomato bacterial spot, (j) Tomato – early blight, (k) Tomato healthy, (l) Tomato late blight.

For creating reliable disease detection systems since it covers a broad spectrum of illnesses and crop types. The performance of image processing and model training is improved by the excellent quality of the images in the dataset. Figure 1 represents the sample image from the dataset [18].

PlantDoc Dataset

Another publicly accessible resource with comparable classes and illnesses to PlantVillage is the PlantDoc dataset [19]. Nevertheless, with a total of 2598 photos, the PlantDoc collection is far smaller. The images included in the PlantDoc dataset are of corn diseases that were collected under field circumstances. Thirteen plant species and eighteen disease classifications are depicted in these photos. This dataset can be downloaded by the public and used as an open dataset for benchmarking. The overall range of image sizes ranges from 0.01 mp to 24.00 mp, with an average of 0.53 mp. 800 x 675 is the median picture ratio [20]. To train algorithms to identify crop illnesses from field condition photographs, PlantDoc comprises field plant disease images that have been downloaded from the web and labeled. Most of the photos in the collection were of low quality since they were downloaded from the web, and a few of them had leaves that were not actually captured on plants and instead looked more like photos from a lab. Figure 2 represents the sample image from the PlantDoc dataset [21].

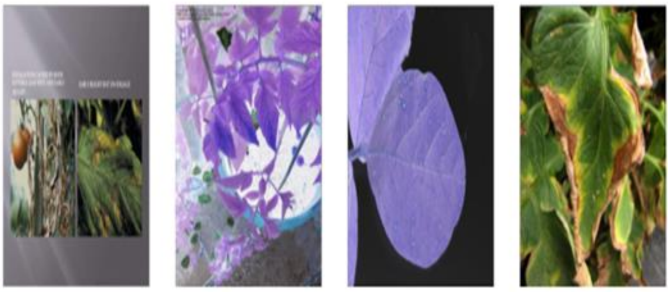

FIGURE 2. Some sample images from PlantDoc dataset

IV. MACHINE LEARNING AND DEEP LEARNING METHODS

Support Vector Machine (SVM)

One of the supervised learning methods that is most used to solve the classification problem is the SVM [22]. According to the input data, the SVM's iterative learning process will ultimately generate perfect hyperplanes in a high-dimensional feature space with the largest margin between each category. Maximum-margin hyperplanes will therefore function as judgment borders for categorizing various data chunks. Consequently, the effectiveness of classification improves as the difference between collective data and hyperplanes rises. Consequently, SVM separation obtains the most comprehensive selection limit rather than just a boundary. The maximum margin classifier, known as the high margin hyper planes, is the name given to this SVM restriction. A hyperplane's points in close proximity extend the intervals between decision boundaries known as support vectors [23]. A system that acquires statistical aspects of input signals is called a support vector machine (SVM).

Decision Tree (DT)

A decision tree is a model that resembles a tree, with branches standing in for possible results and nodes for features [24].

A non-parametric supervised learning approach for regression and classification applications is the decision tree. There are internal nodes, leaf nodes, branches, and a root node that form the hierarchical tree layout. Decision trees are used to perform regression and classification operations, which yields models that are easy to understand. Using random occurrences, resource costs, and utility, a decision tree is a hierarchical framework used in decision support to show potential outcomes. The term itself implies that it displays the forecasts that arise from a sequence of feature-based divisions using a flowchart comparable to a tree structure. A decision reached by the leaves marks the end of it, which begins with a root node [25].

Random Forest (RF)

The Random Forest machine learning algorithm uses supervised learning techniques. It can be used for issues involving both regression and classification. Its foundation is ensemble learning, which combines several classifiers to tackle a challenging problem and improve the efficiency of the model. A Random Forest algorithm uses many decision trees on different dataset segments, averaging them to improve the dataset's estimated accuracy. The random forest predicts the ultimate outcome based on the majority votes of projections, gathering results from multiple decision trees rather than depending on just one. RF is essentially a refined form of bagging in which the trees are built using a randomization technique. In this case, the training procedure is determined by choosing the arbitrary characteristics. The two standards that form the basis of the randomness principle are that training samples are randomly sampled during tree creation, and random attribute groups are selected during node splitting.

The goal of the non-pruning method is to reduce bias and variance. To improve estimation and prevent over-fitting, the concept of merging several trees is used [26].

K-Nearest Neighbors (KNN)

A popular machine learning method for regression and classification is K-Nearest Neighbors (KNN). It is predicated on the notion that comparable data points typically have comparable labels or weights. The KNN method is based on the complete training dataset and uses it as an indicator throughout the training process. To estimate the distance between the training instance and the input data item, Euclidean distance is selected as a distance measurement. Depending on their distances, the method then determines the K closest neighbors of the input data item. When it comes to classification, the method predicts the attribute for the input data point based on the most prevalent class name among the K neighbors [27]. To forecast the probable value for the input data point in regression, the mean or weighted average of the desired values of the K neighbors is computed. K's choice and the associated isolation metric fundamentally determine how a *KNN classifier is implemented. Because the overall coverage* of the surrounding area is determined by the distance between the Kth nearest neighbor to the query and varied K produces distinct restriction category probabilities, the gauge is impacted by the affectability of the region determine K determination. When K is little, the local gauge will typically be quite bad because of the noisy, ambiguous, or incorrectly identified areas and the poor quality of the available data [28].

Adaboost

The boosting idea is used by the AdaBoost method to create an effective classifier from weaker learners. By combining ineffective classifiers and obtaining the estimated value, AdaBoost can improve the outcome of machine learning classifiers. This superior classifier is referred to as an ensemble classifier. The AdaBoost classifier helps to achieve improved outcomes by reducing overfitting-related issues. It chooses the optimal values by taking into account each classifier's optimal values [26]. Optimizing algorithms involves creating a first model on the dataset, then fixing errors in the first model using a second model.

Convolution Neural Network (CNN)

Sequential layers make up the class of machine learning techniques known as deep learning. Deep learning has the benefit of automatically extracting information from photos. During training, the neural network trains how to gather features. The outcome of the layer before it is used as the input for each layer. There are three types of learning processes: semi-supervised, supervised, and unsupervised. CNN is the recommended deep learning technique. CNN is successful in evaluating visual pictures and can readily separate the necessary attributes with its multi-layered structure. CNN can effectively recognize and categorize objects with little pre-processing. [29] Convolutional, pooling, activation function, and completely connected layers make up its four primary layers. CNN, a feed-forward neural network with several layers, is a widely used algorithm in deep learning. Data such as epoch, batch size, depth, optimizer, activation function, learning rate, and width are crucial in determining the hyperparameter for training [30].

Transfer learning for identifying plant leaf diseases has recently attracted much interest. Various pre-trained deep learning models are taken into consideration, including ResNet, VGG16, and Inception. The size of the model, computational capabilities, and unique qualities of the plant leaf dataset all influence the model design selection. It is usual practice to fine-tune a model that has been previously trained on an enormous dataset such as ImageNet [31]. Transfer Learning is a machine learning technique that trains a new model using a pre-trained model, such as VGG16, VGG19, GoogleNet, or AlexNet. It takes longer to train a neural network from beginning with fewer inputs, and it can lead to an over-fitting problem that makes the model prone to failure [32]. To get around this, data from pretrained models is transferred to the created classifier for effective learning using the concept of transfer learning.

V. EVALUTION METRICS

True Positive (TP): A situation in which the scenario satisfied the model's positive prediction.
True Negative (TN): The point in time at which the scenario was negative notwithstanding the model's prediction that it would be negative.
False Positive (FP): When the scenario is negative, yet the model expected a positive outcome.
False Negative (FN): The instance turned out to be positive even though the model had projected it to be negative.

The following four accuracy factors were considered when comparing the various models:
Precision

The ratio of "True Positive" to the total of "True Positive" and "False Positive" is known as precision. Stated alternatively, it refers to the precision of the favorable assessment.
Precision=TP / (TP + FP) (1)

Recall

This is the proportion of positives that were correctly determined, calculated as the ratio of "True Positives" to the total of "True Positive" and "False Negative".
Recall=TP / (TP + FN) (2)

F1-Score

This is the precision and recall weighted mean score. The question "What percentage of positive expectations were right"? would be answered with this score.
F1-Score=2*(Recall*Precision) / (Recall + Precision) (3)

Accuracy
A classifier's accuracy is calculated by dividing the total number of right estimates by the total number of cases.
Accuracy=(TP+TN) / (TP +TN+ FP+FN) (4)

VI. CONCLUSION

This research study has thoroughly reviewed the state-of-the-art approaches for detecting plant leaf disease utilizing machine learning (ML) and deep learning (DL) models. While ML techniques such as support vector machines, decision trees, random forest ,adaboost, and k-nearest neighbors have displayed substantial effectiveness across different situations, in particular when utilized in conjunction with efficient feature extraction approaches, the field has been transformed by the arrival of DL models, especially convolutional neural networks (CNNs), which offer more accurate effectiveness for image classification and diagnosing diseases. Therefore, the rapid improvements in these technologies represent immense potential in improving the preciseness and efficacy of disease identification, thus offering exciting opportunities for accurate farming. Even with these developments, there are still issues with model comprehension, processing power, and the requirement for huge databases with annotations. The creation of hybrid models that combine the best features of machine learning and deep learning could help address these problems in a way that leads to more reliable and flexible solutions.

References

[1] P. Chaitanya Reddy, R. M. S. Chandra, P. Vadiraj, M. Ayyappa Reddy, T. R. Mahesh, And G. Sindhu Madhuri, "Detection Of Plant Leaf-Based Diseases Using Machine Learning Approach," In 2021 Ieee International Conference On Computation System And Information Technology For Sustainable Solutions (Csitss), 2021.
[2] D. Mishra, A. Pandey, Deepanshu, And V. Sharma, "Plant Image Disease Detection Using Deep Learning," In 2023 4th International Conference On Smart Electronics And Communication (Icosec), 2023.
[3] M. Belmir, W. Difallah, And A. Ghazli, "Plant Leaf Disease Prediction And Classification Using Deep Learning," In 2023 International Conference On Decision Aid Sciences And Applications (Dasa), 2023.
[4] Shruti Et Al., "Plant Leaf Disease Detection Using Machine Learning," In 2023 1st International Conference On Circuits, Power And Intelligent Systems (Ccpis), 2023.

[5] V. Binnar, S. Sharma, R. Doriya, B. Soni, A. Shukla, And X. Z. Gao, "Plant Leaf Diseases Detection Using Deep Learning Algorithms," In Machine Learning, Image Processing, Vol. 946, Singapore: Springer, 2023.

[6] D. H. Chau Et Al., "Plant Leaf Diseases Detection And Identification Using Deep Learning Model," In The 8th International Conference On Advanced Machine Learning And Technologies And Applications (Amlta2022), Cham: Springer International Publishing, 2022, Pp. 3–10.

[7] R. Nalawade, A. Nagap, L. Jindam, And M. Ugale, "Agriculture Field Monitoring And Plant Leaf Disease Detection," In 2020 3rd International Conference On Communication System, Computing And It Applications (Cscita), 2020.

[8] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, And S. Gupta, "Toled: Tomato Leaf Disease Detection Using Convolution Neural Network," Procedia Comput. Sci., Vol. 167, Pp. 293–301, 2020.

[9] A. A. Yatoo And A. Sharma, "A Novel Model For Automatic Crop Disease Detection," In 2021 Sixth International Conference On Image Information Processing (Iciip), 2021.

[10] S. Pawar, S. Shedge, N. Panigrahi, A. P. Jyoti, P. Thorave, And S. Sayyad, "Leaf Disease Detection Of Multiple Plants Using Deep Learning," In 2022 International Conference On Machine Learning, Big Data, Cloud And Parallel Computing (Com-It-Con), 2022.

[11] M. Kathiravan, K. H. Priya, S. Sreesubha, A. Irumporai, V. S. Kumar, And V. V. Reddy, "Ml Algorithm-Based Detection Of Leaf Diseases," In 2022 4th International Conference On Smart Systems And Inventive Technology (Icssit), 2022.

[12] K. Shivaprasad And A. Wadhawan, "Deep Learning-Based Plant Leaf Disease Detection," In 2023 7th International Conference On Intelligent Computing And Control Systems (Iciccs), 2023.

[13] K. Harshavardhan, P. J. V. A. Krishna, And A. Geetha, "Detection Of Various Plant Leaf Diseases Using Deep Learning Techniques," In 2023 International Conference On Advances In Computing, Communication And Applied Informatics (Accai), 2023, Pp. 1–6.

[14] Y. H. Bhosale, S. R. Zanwar, S. S. Ali, N. S. Vaidya, R. A. Auti, And D. H. Patil, "Multi-Plant And Multi-Crop Leaf Disease Detection And Classification Using Deep Neural Networks, Machine Learning, Image Processing With Precision Agriculture-A Review," In 2023 International Conference On Computer Communication And Informatics(Iccci), 2023, Pp.1–7.

[15] A. Mezenner, H. Nemmour, Y. Chibani, And A. Hafiane, "Local Directional Patterns For Plant Leaf Disease Detection," In 2023 International Conference On Advances In Electronics, Control And Communication Systems (Icaeccs), 2023, Pp. 1–5.

[16] D. Tandekar And S. Dongre, "Identification Of Various Diseases In Plant Leaves Using Image Processing And Cnn Approach," In 2023 14th International Conference On Computing Communication And Networking Technologies (Icccnt), 2023, Pp. 1–6.

[17] E. Moupojou Et Al., "Fieldplant: A Dataset Of Field Plant Images For Plant Disease Detection And Classification With Deep Learning," Ieee Access, Vol. 11, Pp. 35398–35410, 2023.

[18] M. Ahmad, M. Abdullah, H. Moon, And D. Han, "Plant Disease Detection In Imbalanced Datasets Using Efficient Convolutional Neural Networks With Stepwise Transfer Learning," Ieee Access, Vol. 9, Pp. 140565–140580, 2021.

[19] A. Ahmad, A. E. Gamal, And D. Saraswat, "Toward Generalization Of Deep Learning-Based Plant Disease Identification Under Controlled And Field Conditions," Ieee Access, Vol. 11, Pp. 9042–9057, 2023.

[20] V. Balafas, E. Karantoumanis, M. Louta, And N. Ploskas, "Machine Learning And Deep Learning For Plant Disease Classification And Detection," Ieee Access, Vol. 11, Pp. 114352–114377, 2023.

[21] Y. Liu Et Al., "A High-Precision Plant Disease Detection Method Based On A Dynamic Pruning Gate Friendly To Low-Computing Platforms," Plants, Vol. 12, No. 11, P. 2073, 2023.

[22] R. Thyagaraj., T. Y. Satheesha, And S. Bhairannawar, "Plant Leaf Disease Classification Using Modified Svm With Post Processing Techniques," In 2023 International Conference On Applied Intelligence And Sustainable Computing (Icaisc), 2023, Pp. 1–4.

[23] A. Wahal, S. S. S. Choudhary, And N. Singh, "Leaf Disease Detection And Crop Prediction Using Machine Learning," In 2021 3rd International Conference On Advances In Computing, Communication Control And Networking (Icac3n), 2021.

[24] Shiffa, Suchithra, And A. Vijayakumar, "Potato Leaf Diseases Detection Using Machine Learning And Deep Learning," In 2023 Intelligent Computing And Control For Engineering And Business Systems (Iccebs), 2023, Pp. 1–6.

[25] B. Rajesh, M. V. Sai Vardhan, And L. Sujihelen, "Leaf Disease Detection And Classification By Decision Tree," In 2020 4th International Conference On Trends In Electronics And Informatics (Icoei)(48184), 2020, Pp. 705–708.

[26] G. S. Yogananda, A. Babu., Ramya, M. Maheswari, And S. M. Sundaram, "Plant Leaf Disease Detection Using Novel Machine Learning Approach," In 2023 International Conference On Evolutionary Algorithms And Soft Computing Techniques (Easct), 2023, Pp. 1–5.

[27] Gurunathan, S. Priya, Dhanasekar, I. Niranjana, And S. Suganya, "Plant Leaf Diseases Detection Using Knn Classifier," In 2023 9th International Conference On Advanced Computing And Communication Systems (Icaccs), 2023, Vol. 1, Pp. 2157–2162.

[28] M. P. Vaishnnave, K. S. Devi, P. Srinivasan, And G. A. P. Jothi, "Detection And Classification Of Groundnut Leaf Diseases Using Knn Classifier," In 2019 Ieee International Conference On System, Computation, Automation And Networking (Icscan), 2019, Pp. 1–5.

[29] M. Sardogan, A. Tuncer, And Y. Ozen, "Plant Leaf Disease Detection And Classification Based On Cnn With Lvq Algorithm," In 2018 3rd International Conference On Computer Science And Engineering (Ubmk), 2018, Pp. 382–385.

[30] R. Shanker, D. Sharma, And M. Bhattacharya, "Development Of Plant-Leaf Disease Classification Model Using Convolutional Neural Network," In 2022 Ieee 4th International Conference On Cybernetics, Cognition And Machine Learning Applications (Icccmla), 2022.

[31] D. Yaswanth, S. Sai Manoj, M. Srikanth Yadav, And E. Deepak Chowdary, "Plant Leaf Disease Detection Using Transfer Learning Approach," In 2024 Ieee International Students' Conference On Electrical, Electronics And Computer Science (Sceecs), 2024, Pp. 1–6.

[32] Vinaykumar, A. Babu, P. Bhargavi, S. Aluvala, And L. H. Alzubaidi, "An Inception Architecture With Transfer Learning For Apple Plant Leaf Disease Detection," In 2023 International Conference On Ambient Intelligence, Knowledge Informatics And Industrial Electronics (Aikiie), 2023, Pp. 1–5.

[33] R. Garg, A. K. Sandhu, And B. Kaur, "A Systematic Analysis Of Various Techniques For Mango Leaf Disease Detection," In 2023 International Conference On Disruptive Technologies (Icdt), 2023, Pp. 349–354.