A REVIEW ON PLANT LEAF DISEASE DETECTION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT: The world's food security is threatened by plant leaf diseases, which is major source of economic losses. The pathogens, such as bacteria, fungi, and viruses causes plant diseases. It also cost agriculture Corporation a significant amount of money worldwide. For tracking plant disease, both quantity and quality is essential in crop security. The various kinds of diseases and pests impacts cardamom plant growth at different stages and crop yields. The disease detection and classification at early and accurate will have possibilities to decrease further plant damage. They are some major issues in diseases' classification and detection. The diseases are identified and classified by testing with different methods, at which researchers have previously made significant progress. However, reviews results, new developments and discussions need improvements needed. By using machine learning techniques plant leaf disease detection review is given. The identifying research gaps or limitations and analyzing of plant leaf disease detection methods are objectives of this research. By utilizing deep learning and machine learning based on artificial intelligence (AI) a thorough analysis of the different methods used in plant disease detection is presented.

KEYWORDS: Plant leaf disease, Agriculture, Crops, Artificial Intelligence, Machine Learning.

I. INTRODUCTION

In all aspects of life, plants are essential for maintaining the environment. The largest portion of any nation's economy is hold by agriculture, which is primary sector. Many nations face many difficulties in terms of financial loss because of lowest crop productivity as there depend significantly on agriculture. The crop production is decreased mainly because of plant leaf diseases, which can be caused by bacterial infections, fungi, pests, and other factors [1]. The regular growth of plant is mainly impacted by plant diseases and it also impacts entire plant, including leaves, stem flowers and fruits. The plant diseases identification is an important task. The effective management of agricultural resources, early detection and accurate identification of these diseases can allow for timely interventions minimize crop damage [2].

The other main causes are climate change and environmental conditions which are unstable. The yield of crops by hindering their average growth is reduced. The plant leaves are experiences damage of crops by specific physical properties, low soil fertility, pathogens, crop type, viruses, weeds, waterlogging, insects,and drought.

By observing various kinds of abnormalities and unique, noticeable patterns, such as lesions, cuts, or wounds on their leaves, flowers, or fruits that are frequently display disease-ridden plants. The main source of these abnormalities will initially appear on plant leaves as majority of disease symptoms [3]. The plant leaf diseases are highly significant and fully developed in early detection and prevention. This effective treatment and knowledge may result in fewer complications are considered which are crucial for growing at an excessively appropriate rate. The farmers will get help in making an appropriate decision and accurately produce more crops at the right times and places. The automated plant leaf disease detection and classification system is accurately detected but manually high yield is impossible. Additionally, farmers' profits and conserve land resources are increased [4].

The plant diseases must be identified early to reduce crop loss. The agricultural processes are affected by soil and environmental factors by its long interest and concerns. The climate and weather significantly affects disease epidemic's precise epidemiology. In laboratory settings in field the conditions are determines critical threshold of climatic factors for disease occurrence, spread, and exacerbation of limited applications. In real-world settings while micrometeorological factors are being observed for identification and monitoring simultaneously. The LS disease is occurred by primary weather factors like soil temperature (ST), ambient temperature (AT), ambient humidity (AH), leaf wetness sensor (LWS) and Soil moisture (SM) are the primary weather factors which impact the occurrence of LS disease[5].

The rice, maize and wheat are important food grains with numerous non-infected advantages. The world with food and energy are provided and produced in vast quantities. The expanding population food grains are an essential source of food for many countries. The pests and illnesses shows impact on these and prevent crop growth or reduce yield because of disease affect [6]. The various food grains are prioritized in this manuscript shows affect of disease with rice, wheat, and maize/corn plants. The common diseases that impact rice plants are sheath blight, bacterial leaf streak, Rice blast and bacterial leaf blight. The powdery mildew, snow mold, tanspot, and septoria leaf spot are some wheat plants that affect by diseases. The black bundle disease, commonrust, charcoal rot, and Downey mildew are some common diseases that affect maize plants [7].

If plant has disease then production will be less and quality of the yields is not given proper consideration. Based on rapid detection and accurate leaf disease classification, crop yield will be improved with high quality and quantity [8]. In image processing, different detection methods shows benefits from recent advances and trends. To predict and increase image analysis technologies, agricultural yield, and digital image processing for plant diseases have recently achieves importance [9].

In image processing, basic terms are pre-processing, segmentation, feature extraction, and classification. The segmentation and classification accuracy levels are impacted by errors and irregularities in the input images. A proper quality assessment is necessary in result [10]. The plant diseases identified and classified by using human intervention in current process. To observe plant diseases with the naked eye is observed continuously by experts and monitors plants over an extended period of time. The diseases are identified frequently by current methods as it difficult and time-consuming.Therefore, some automatic methods are used to observe plant disease at an early stage [11].

The image-based, sensor-based, and lab-based techniques are used by researchers to predict plant diseases. But, these Lab-based techniques are selective and accurate. The sensor-based approaches made early disease prediction, but it faces problems with sensors, so results are inaccurate. The early predictions are not possible with Image-based techniques which are produce less false alarms [12]. The plant disease detection and identification, traditional methods are replaced by artificial intelligence techniques with significantly enhancing accuracy [13].

Numerous computer-aided diagnosis (CAD) systems have been created to aid farmers. These systems effectively tackle prevailing challenges and improve accuracy, efficiency, and objectivity of diagnostic process. The introduction of computer vision and Artificial Intelligence (AI) transforms precision farming methods. For outstanding results, a number of Deep Learning (DL) and Machine Learning (ML) models have demonstrate disease detection systems in plant [14].

An advanced technology that enables machines to learn without direct programming is depended on Machine Learning (ML) for precision agriculture. The Internet of Things (IoT) which enables for farm equipment is combined with ML. For the future of agriculture, ML holds great potential. To identify or categorize plant diseases by ML techniques have been used or proposed in a number of studies [15]. The plant or leaf image is used as input to determine whether a disease is presented by these programs. By using a multi-class classification (targeting different diseases) or a binary classification (healthy or diseased plant/leaf) works on problem as a classification problem. The Random Forest (RF) and Deep Learning (DL) are used for traditional machine learning techniques [16].

The improper detection of plant diseases at early stages of infection can lead to inappropriate disease control measures. So, identification and diagnosis of plant diseases automatically recommended. In plant disease diagnosis, main challenge is lack of huge amounts of data that are unprocessed to large extent.
The laboratory images are PlantVillage, iBean, citrus, rice, cassava, and AI Challenger 2018 with most popular plant disease datasets. The datasets are trained extensively for classifiers to detect and categorize plant diseases. During training, to attain high classification accuracy these datasets uses neural networks. If it is tested in actual field environments these systems' performance drastically declined [17]. The other leaves, stems, fruits, soil, and mulch have complex background features for field images and laboratory images. By removing background disease recognition accuracy is enhanced when contribute drop in performance. Therefore, this study significantly demonstrates complex backgrounds in field images [18].

II. LITERATURE SURVEY

Chouhan.S.S, Kaul.A, Singh.U.P, and Jain.S et. al., [19] introduces the Plant Pathology for Automatic Approach: Plant Leaf Disease Identification and Classification for Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN). Based on BRBFNN, plant leaf diseases can be automatically identified and classified using a technique called bacterial foraging optimization. The BRBFNN optimal weight is assigned by bacterial foraging optimization, in identifying and classifying the plant leaf regions affected by various diseases will further improve network's speed and accuracy. In the feature extraction process grouping seed points with similar characteristics for region growing algorithm improves the network's efficiency. This model evaluates fungal diseases such as common rust, leaf spot, cedar apple rust, leaf curl, late blight and early blight.
Jiang.S, Liu.X, Wang.L Mei.S, and Min.W, et. al., [20] describes Recognition of Plant Disease: A Loss Reweighting and Visual Region Method and a Large-Scale Benchmark Dataset. The

plant diseases with brand-new, extensive dataset is developed, which includes 271 categories and 220,592 photos. The plant diseases are recognized using this dataset by reweighting both loss to recognize diseased parts and visual regions. The each patch's discriminative level is determined by first weights of all categorized patches. It also calculates each image by using cluster distribution of these patches. The weight to every loss was determined for every patch-label pair during weakly-supervised training with help of discriminative disease part learning. The network trained with loss reweighting by LSTM network was then used to encode weighed patch feature sequence into comprehensive feature representation after patch features that were finally extracted. The extensive evaluations on both sample data and publicly available dataset by suggested approach is advantageous effect. However, clustering process before training provides this method's drawback which makes it a little slow.

L. Tian *et al*. [21] describes VMF-SSD: Identification of Apple Leaf Disease with novel VMF-SSD (V-space-based Multi-scale Feature-fusion SSD). The apple leaf disease is detected by this technique to enhance detection performance by extracting reliable multi-scale feature representations for a number of diseased spot sizes. The identification of disease is enhanced by using multi-scale feature extraction with multi-scale feature representation, particularly for small spots. By using V-space, texture feature improved with help in the further identification of disease spot location and location branch. The diseased spots are identified by varying sizes is automatically learned through the use of attention mechanisms for feature channels at various scales. The apple leaf disease detection task and meet needs of agricultural production applications by suggested VMF-SSD approach can perform effectively. The experimental results show that this system shows detection speed (27.53 FPS) and mAP (83.19%) on testing.

Rad.A.M, Aghighi.H, Mobasheri.M.R Matkan.A.A, and Ashourloo.D, et. al., [22] discusses about leaf rust disease detection by using machine learning regression methods for hyperspectral measurement. This study examined 1) the detection of wheat leaf rust disease by using GPR (Gaussian process regression), v-SVR (v support vector regression) and PLSR (partial least square regression) methods. 2) training sample size is effected by outcomes, 3) disease symptoms is impacted by predictions made by the methods mentioned above, and 4) comparisons between machine learning techniques and SVI. In electromagnetic region range from 350 and 2500 nm, spectra of infected(unhealthy) and non-infected(healthy) leaves in various disease symptoms were detected by using non-imaging spectroradiometer. The disease severity and disease symptom fractions are created ground truth dataset is calculated by using digital camera images. By using collected datasets, each method was trained with various sample sizes. The machine learning methods are reliable and insensitive to various disease symptoms when compared with SVIs. Therefore, other existing methods are compared with GPR, then shows better results in terms of accuracy when using a smaller training dataset. Therefore, there will be slight changes in reflectance because of machine learning regression techniques that reduce difficulties plant disease detection at earlier.

E. Elfatimi, R. Eryigit and L. Elfatimi et. al., [23] introduces classification of bean leaf diseases mobile net models are used in this study. For effective network architecture technique is developed to identify and characterize(hyperparameters and optimization techniques) as well as to categorize bean leaf disease. Therefore, each architecture is independently implemented and compared to determine most effective configuration for bean leaf disease classification. To meet classification requirements, MobileNetV2 architecture is used to train model under certain controlled conditions. The public dataset like two unhealthy classes (angular leaf spot disease and bean rust disease) and one healthy class with 1296 images of bean leaves is taken for evaluation. Then implement MobileNet architecture to that datasets, then results show training (faster times), accuracy (higher), and retraining (easier).

Saini.R, Palaparthy.V.S, Kumar.A, Surya.S.G and Patle.K.S et. al., [24] multi-input multi-output neural network based attention on is used to predict plant diseases to known use a multisensor system is explained. The temperature, humidity, and LWSs are three sensor nodes used to provide data that is needed to train model. To train each ensemble model with different submodels separately by using data from distinct sensor nodes makes up designed network. The networks are trained separately combining the results to obtain final output. To produce better results, network's design uses attention mechanism to strengthens the impact of the most crucial feature for knowing of prediction.

Yu .H *et al*., [25] describes deep Learning and K-Means Clustering is used to Diagnosis of Corn Leaf Diseases. The different enhance deep learning models like (Inception v3, VGG-16, VGG-19 and ResNet18). The k values like 2, 4, 8, 16, 32, and 64 affect the diagnosis of corn disease. The experiment's findings are observed by most significant method's identification effect on (32-means) samples. The accuracy for average diagnostics (84.42% and 83.75%) and VGG-16 and ResNet18 also produce better diagnostics output on (32-means) samples. Therefore, VGG-19 shows (82.63%) and Inception v3 shows (83.05%) better performance on (64-means) samples.

Zhang.D, Chen.J, Zeb.A, Yang.S and Chen.W, discusses Identification and Detection of Rice Plant Disease using Lightweight Inception Networks. To detect and identify crop diseases, MobInc-Net, which is authentic lightweight network architecture. The high-quality image characterstics are extracted by using pre-trained MobileNet, Modified Inception (M-Inception) module was selected as backbone extractor. Then, by replacing depth-wise and point-wise convolutions for the original convolutions Inception module was improved. The SSD block was added separately with fully connected Softmax layer with actual number of classifications for crop disease classification and detection foundation network. To create an effective model, two-stage transfer learning was used in model training process. The suggested approach can achieve the desired outcome with good recognition accuracy is demonstrated.

Qi H, Yang.M, Chen.R, and Liang.Y et. al., [27] to identify plant leaf diseases, deep learning model is used in channel pruning and channel attention is explained. This paper suggests a model called CACPNET, to identify diseases in common species that combines channel attention and channel pruning. The channel attention mechanism is integrated into ResNet-18-based model that combines global max pooling and global average pooling by using local cross-channel approach without dimensionality reduction to enhance the plant leaf disease features extraction capability. To minimize model's parameters and complexity, model's ideal feature extraction condition is removes irrelevant channels by using L1-norm channel weight and local

III. PLANT DISEASE DETECTION

Nithya.M, Saranya.G, Meenakshi.K Geetha.G, and Samundeswari.S et. al., [28] presents Classification and Detection System using Machine Learning for Plant Leaf Disease. In Figure 1, system's execution flow is observed. The size, color, and quality of the images that make up our dataset is matched to process test image in preprocessing step. The image passes through different stages, and these steps include image resizing, noise filtering, and smoothing. The dimensionality is reduced in feature extraction technique that helps in condensing the interesting portions of an image into a feature vector. To extract features GLCM (Gray Scale Co-occurrence Matrix) and HOG (Histogram of Oriented Gradients) techniques are used. In last step of image processing phase, dataset is trained and compared images with trained model. In this classification model, KNN algorithm is used, as is used to rectify both classification as well as regression problems. It can be referred to as a supervised machine learning algorithm. The three most prevalent diseases are identified with the affect tomato leaves: curl, bacterial spot, and early blight. The image processing techniques are used for under upbringing technology, or machine learning to identify disease. The type of disease a given plant is experiencing can be determined by farmers accurately with the help of the plant's image.

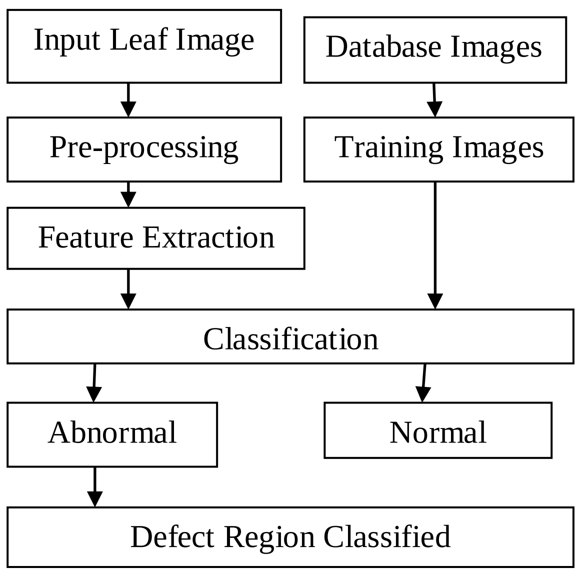

Figure 1: Execution Flow

Praneeth, Nikith.B.V, Dr. Amrita T, Keerthan.N.K.S, et. al., [29] describes Disease Detection and Classification of Leaf. In this paper, KNN (K-Nearest Neighbor), CNN (convolution neural network) and SVM (support vector machine) models are compared. The three distinct models are analyzed to identify eight distinct leaf diseases which are capable. In Figure 2, implementation diagram is observed. The leaf disease type is determined by SVM, KNN, and CNN algorithms developed in Python. By using various kinds of machine learning algorithms are first imported for the soyabean dataset. The dataset is imported, when all images undergo data analysis at which crops the images and uses image segmentation to extract leaf pixels. By using clustering colors present in channels individually because images are in RGB color format.

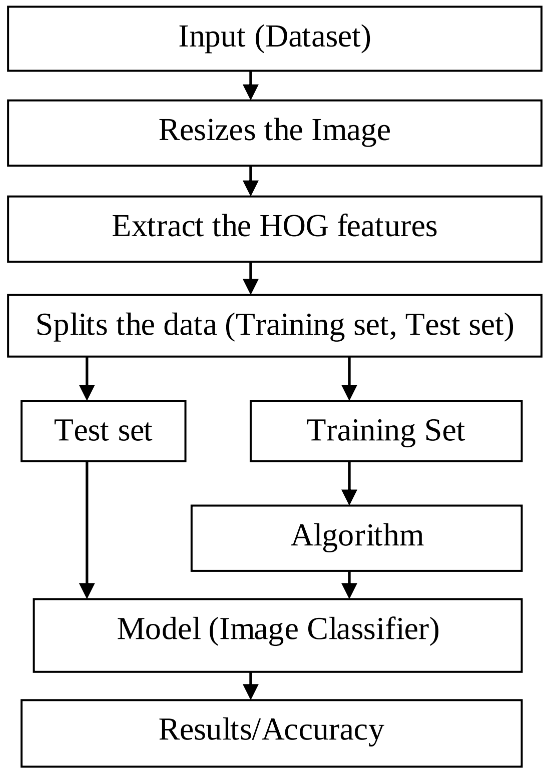

Figure 2: Block Diagram of Leaf Disease Detection and Classification

After performing K means clustering on b channel, leaf component is found in K means clustering for perfect b channel. To build model CNN algorithm is used with component identification and dataset is split as training and testing for accuracy prediction. The CNN model achieved 96 percent accuracy by trained model outperforming SVM and KNN algorithms, which shows accuracy of 76% and 64% respectively for soy leaf disease dataset's images.

Haroon.Z, Zafar.N, Aqib.M, Khan.F, Waheed.H and Tahir.MN et. al., [30] presents identification and categorization of leaf diseases in maize plants by using deep learning-based mobile system. In Figure 1, block diagram is described. The dataset is collected from (PMAS-AAUR) University Research Farm Koont of three maize crop diseases Leaf Spot, Blight and Sugarcane Mosaic virus, observed various growth stages at under varying climatic condition. To resizing, data collection is followed by image preprocessing. The flipping, rotating, scaling, and cropping were used in data augmentation techniques. Based on the expertise images were labeled or annotated in data annotation by experts. By using deep learning model the annotated data is trained. The maize crop diseases are identified, categorized, segmentation, and monitored in real-time environment in this study.

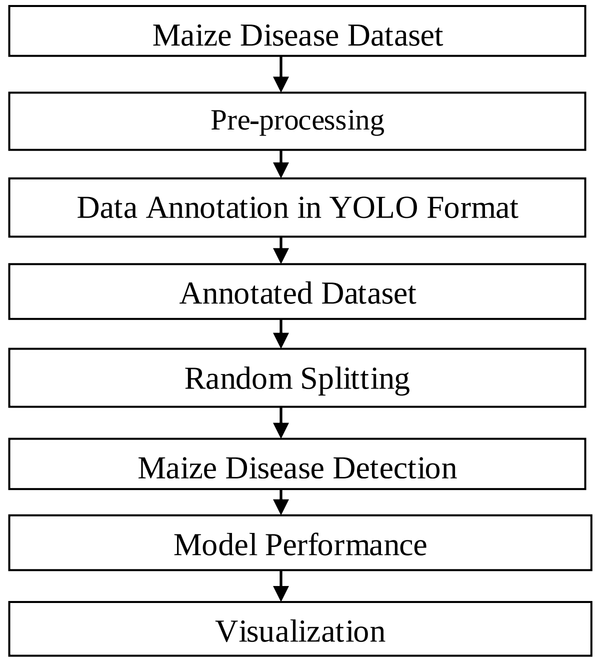

Figure 3: Pipeline of Maize disease detection by YOLO detectors

Kaur K, Bansal K et. al., [31] describes by using Advanced Deep Learning Models Detection of Plant Disease is Enhanced. The Figure 3 describes the framework of this model. The dataset included in the article was sourced from New Plant Diseases dataset, which encompasses collection of leaf images from 38 distinct plant categories. This study focuses on four categories of plant diseases: Maize (Corn), Black Measles (Grape Esca), Common Rust (Corn), Northern Leaf Blight), and Grape Black Rot. In the pre-processing phase, color image from the RGB color space to grayscale image

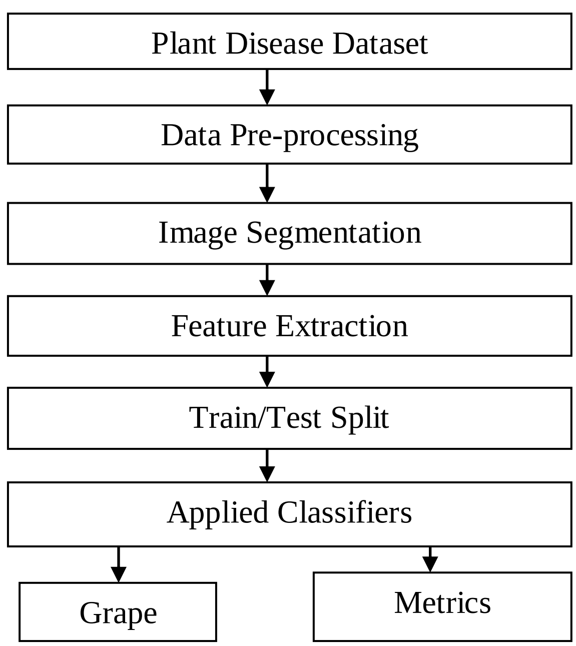

Figure 4: Framework of Plant Disease Detection

The study used advanced deep learning models such as ResNet50V2, Xception, MobileNetV2, InceptionV3, and DenseNet169. To categorize various plant diseases 7623 training and 1906 validation images are used. The noise removal, Otsu thresholding, watershed techniques, distance transform, and then few techniques are applied to improve their quality for RGB images are first converted to grayscale. The extracting contour features by computing morphological values obtain required region will correspond with plant images of effected area. This novel approach not only improved efficiency of disease identification and also provided valuable insights as potential of AI-based systems in revolutionizing plant disease management efforts. However, certain challenges and limitations like risk of over-fitting as well as use of small data.

The Table 1 presents the brief description of various Plant leaf disease detection techniques.

Table 1: Various Plant Leaf Detection and Classification Techniques

Author and Citation	**Title**	**Proposed Technique**	**Results**
Alshehri MS, Ullah N, Khan JA, Almakdi S, El-Rashidy N, El-Sappagh S, Al Qathrady M, and Ali F et. al., [32]	An effective approach for plant leaf diseases classification based on a novel DeepPlantNet deep learning model	A DeepPlantNet framework was made available for effective plant disease detection and classification. The plant disease images are categorized into many classifications by proposed DeepPlantNet model.	The proposed framework is than current methods shows better average accuracy. The variety and variability of plant diseases represents model that only uses a small number of photos, which is insufficient.

Eray Önler et. al., [33]	Feature fusion based artificial neural network model for disease detection of bean leaves	By combining descriptive vectors extracted from bean leaves with HOG feature extraction and transfer learning feature extraction techniques by using artificial neural network model to detect bean leaf disease.	The feature fusion model outperforms models that use HOG and Transfer Learning feature extraction for training, validation, and test datasets. In this study, bean leaf dataset has been analyzed.
Siti Nurul Aqmariah Mohd Kanafiah, Mohd Hafiz Fazalul Rahiman, Syafiqah Ishak, Hashim Saad, et. al., [34]	Leaf Disease Classification Using Artificial Neural Network	The two types of neural networks are multiple layers Multi-layer perceptrons with feed forward and radial basis functions. The leaves are categorized by network's RBF structures are either healthy or unhealthy.	MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function) are compared with two in terms of accuracy percentage.
Margala.M Natarajan.S, Chakrabarti.P, et. al., [35]	Robust diagnosis and meta visualizations of plant diseases through deep neural architecture with explainable AI	To classify deep features that are extracted from a down sampled feature map of a fine-tuned neural network is used by customized K-Nearest Neighbors Algorithm.	The specificity, sensitivity, accuracy, and AUC are suggested system's performance is evaluated.

C. P. Diana Cyril, S. Amritraj, and N. Hans et. al., [36]	An Automated and Fine- Tuned Image Detection and Classification System for Plant Leaf Diseases	The pant leaf diseases by bacteria, viruses, fungi, and pests are identified by eight distinct classes of dataset by using modern YOLO algorithm with computer vision method.	This system accurately predicted the diseases and produced positive outcomes by using bounding boxes and class probabilities.
E. Deepak Chowdary, M. Srikanth Yadav, D. Yaswanth, and S. Sai Manoj, et. al., [37]	Plant Leaf Disease Detection Using Transfer Learning Approach	The proposed method leverages pre-trained deep learning models to extract relevant features from plant leaf images, thereby enhancing the detection accuracy and reducing need for extensive labelled data.	The results demonstrated that transfer learning significantly enhanced the models' ability to differentiate between diseased and leaves healthy, with good accuracy and minimize false positives.
A. S. Tulshan and N. Raul et. al., [38]	Plant Leaf Disease Detection using Machine Learning,	The current classification methods for plant leaf disease detection to enhance by using machine learning is major objective.	The performance of this system is evaluated in terms of accuracy. Further work need to be done for performance improvement.

Francis.J, Anoop.B.K, and Anto Sahaya Dhas.D et. al., [39]	Identification of leaf diseases in pepper plants using soft computing techniques	The pepper plant leaves are taken as set of leaves in detecting leaf diseases.	The algorithm produces better results and healthy and unhealthy plants can be differentiated with help of this method. In future images taken in varying lighting condition is taken for further modification of method.
Jindam.L, Ugale.M Nagap.A, and Nalawade.R, et. al., [40]	Agriculture Field Monitoring and Plant Leaf Disease Detection	By using real-time field factor values like temperature, humidity, moisture, etc is surveillance that full fills the suggested system for detecting leaf disease.	For users, disease detection app shows the field report as output will be visible. In real-time interaction with agricultural experts via video call or chat, etc, could be added to the suggested method to make it even more extensive. Additional features like a list of pesticides and fertilizers, the location of stores that are currently available.

Aote.N.V, Taiwade H. V,Bodhe.K.D, and Yadav.V.P et. al., [41]	Implementation of Prototype for Detection & Diagnosis of Cotton Leaf Diseases using Rule Based System for Farmers	To identify this disease, 4 images are (filtered images that cover all disease conditions) of cotton leaves are used. So, in this system, users have to answer questions regarding symptoms and risk factors with yes/no. To determine the degree of impact of cotton leaf disease score accumulation method is used. .	To make detection simple and easier this Knowledge Base Expert System's is used.

V. CONCLUSION

In this analysis, A Review on plant leaf disease detection using Machine Learning Techniques is presented. The physical examination is not accurately predict by plant diseases as it is time-consuming and produced low accuracy results. An automated classification system is developed to handle these problems. The crop disease inspection is manual for limited problems with accuracy and a shortage of personnel. The review presents various well-known approaches such as acquisition, preprocessing, segmentation, feature extraction, and classification. The plant disease detection system performance mainly depends on the feature extraction and classification technique used. Most of authors only focused on single plant leaf disease only. Very few authors were focused on multiple plant leaf diseases. In addition considering less data, lack of accuracy are the major drawbacks of previous models. By using large datasets with significant variation as well as additional techniques improves accuracy in plant disease detection and classification. Hence from the review, it can be concluded that Accurate multiple plant leaf disease detection and classification with huge amount of data is essential for effective crop growth as well as for improving crop yields.

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