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Classification Techniques for Plant Disease Detection

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Abstract: ***Production of crops with better quality is the necessary attribute for the economic growth of any country. The agricultural sector provides employment to many people and accounts for major portion of gross domestic product in many countries around the world. Therefore, for enhanced agricultural productivity the detection of diseases in plants at an early stage is quite significant. The traditional approaches for disease detection in plants required considerable amount of time, intense research, and constant monitoring of the farm. However, optimized solutions have been obtained over the past few years due to technological advances that have resulted in better yields for the farmers. Machine learning and image processing are used to detect the disease on the agricultural harvest. The image processing steps for plant disease identification include acquiring of images, pre-processing, segmentation and feature extraction. In this review paper, we focused mainly on the most utilized classification mechanisms in disease detection of plants such as Convolutional Neural Network, Support Vector Machine, K-Nearest Neighbor, and Artificial Neural Network. It has been observed from the analysis that Convolutional Neural Network approach provides better accuracy compared to the traditional approaches.***

Keywords: Classification mechanisms, Image Processing, Machine Learning and Plant Leaf Disease Detection.

I. INTRODUCTION

Agriculture is an important source of livelihood in India. Majority of the country's population is directly or indirectly associated with the agricultural sector. Hence, producing high-quality agricultural yield is necessary to sustain the country's economic development. In order to obtain crops with better quality and productivity the farmers decide upon the right products by monitoring and controlling the necessary temperature, light and humidity requirements [1]. Furthermore, the agricultural industry has started to look for new ways to increase food production due to population growth, weather changes, and political instability. This has attracted the researchers to look for unique, resourceful, and reliable technologies that would help to enhance the productivity of agriculture. Still, there are challenges such as early identification of diseases in plants that the farmers are struggling with. To observe the type of disease on the plant's leaf through naked eyes is not possible all the time, so an automated expert system that will help detect the disease timely would be quite useful.

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The advancement in technology, specifically the use of image processing in combination with the machine learning approach would help the farmers in terms of discovering the plant disease in the initial stages [2].The goal of this paper is to review and discuss the different classification techniques of plant disease detection. The paper has been structured into following parts. A brief introduction of the significance of plant disease detection is provided in the first section. The second section categorizes the different types of plant families. In the third section, the methodology for plant disease detection has been discussed.

The fourth section addresses the related work in the area and the classification techniques that have been used by the researchers. Finally, in last section conclusion is given which is followed by the references.

II. BASIC TYPES OF PLANT FAMILIES

The detection of plant diseases is easier if the automated system recognizes the family to which the plant belongs. Primarily, there are two plant categories that are as follows:

(A) Monocotyledonous plant family and
(B) Dicotyledonous plant family. [3]

A. Monocotyledonous plant family: These are commonly referred to as Monocots. The characteristics of the monocot family plant are as follows:
   i. The seeds have only one cotyledon.
   ii. Long narrow leaves having parallel veins.
   iii. Vascular bundles that are arranged in a complex way.

Plants such as wheat, ginger, corn, rice, banana, onion, bamboo, sugarcane, turmeric are all examples of the Monocot family plant. There are various diseases with which these plants get affected. Some of them are discussed below:

a. Leaf Blotch: These are small oval and rectangular/irregular brown spots, as displayed in Figure 1. To control this type of disease, Mancozeb pesticide can be used [4].

Figure 1: Leaf Bloch [4]

b. Leaf Spot: It is formed in gray color bounded with brown color boundary, and it appears in different sizes and shapes. After a few days, leaves get dry and die as represented in Figure 2. Zineb pesticide can be utilized to control this type of disease [4].

Figure 2: Leaf Spot [4]

B. Dicotyledonous plant family: These are commonly referred to as Dicots. The dicot plants have the following characteristics:
   i. The seeds have two cotyledons.
   ii. Broad leaves that have nested veins.
   iii. Vascular bundles arranged in rings.

The examples of plants in dicot family are cotton, apple, roses, coffee, tomatoes, beans, potatoes, and many more. Many diseases are also there that damage the harvest of dicots. Some of the common diseases are as follows:

a. Alternaria Leaf Spot

This is one of the most prevalent disease affecting cotton plants. It affects the leaves of cotton plant on which small brown circular or irregular shaped spots appear, that can range in diameter from 0.5 to 10 mm. Sometimes cankers can also develop on the stems. When the leaves become dry, they fall off on the ground. High infection severity causes severe cotton defoliation and rapid decrease in yield [5].

Figure 3: Alternaria Leaf Spot [5]

b. Bacterial Blight

This is a potentially destructive disease that occurs on different parts of cotton plant that can appear in both planting and the adult stages. The disease initially appears on the leaves as water-soaked spots that later spread to the veins. In some cotton plants, the water-soaked region becomes red spots with a diameter of about 1 mm. Massive losses of yield are reported due to this disease [5].

Figure 4: Bacterial Blight [5]

III. METHODOLOGY

Many agricultural applications, such as plant disease identification and detection, use images of plant leaves on which image processing methods and machine learning are applied for extracting the data required for analysis [6]. The general structure of detection of diseases in plant leaves using image processing has been illustrated in Figure 5.

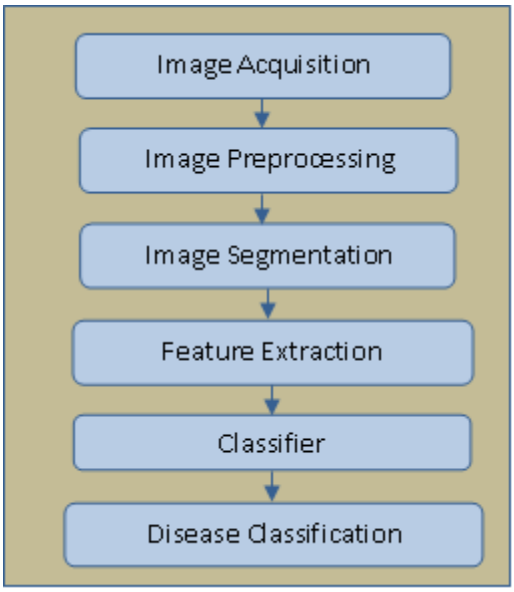

Figure 5: Classification process of Plant Leaf Disease [7]

a) **Image Acquisition:** This is the process of acquiring the images through a camera by going to the site or from other available sources such as image databases or online repositories. The captured images are in three colors, that is, Red, Green, and Blue (RGB), for which a color transformation structure is created, and a device-independent color space transformation is applied on it [8].

b) **Image Pre-processing:** To remove noise in an image, different pre-processing techniques are used. Clipping of leaf image is applied to extract the region of the image in which we are interested. The extracted plant leaf image is transferred to a digital system to remove the unnecessary areas. Some essential steps of pre-processing are: Resizing the image, Noise removal from the image, enhancement and smoothing of the image [8].

c) **Image Segmentation:** This method of image processing is used to partition an image into significant components according to similar characteristics. Various methods are available for image segmentation such as boundary and spot detection algorithm, region and edge-based methods, Otsu's method, thresholding techniques and k-means clustering, etc. [8].

d) **Feature Extraction:** It is a type of dimension reduction technique that effectively represent the useful part of the image. Various features such as texture, color, edges and morphology can be extracted for the detection of plant disease. Color co-occurrence method is used for feature extraction [8].

e) **Classifiers:** Classifiers are used to identify and categorize the different diseases that occur on plant leaves based on obtained features. Several classifiers that have been used in earlier work to detect diseases in plants are K-nearest neighbors (K-NN), Support Vector Machines (SVM), Convolutional Neural Network (CNN) and Artificial Neural Network (ANN), etc.

IV. RELATED WORK

In the past, several researchers have focused their work to enhance the accuracy of an automatic detection system for plant leaf diseases. This section discusses different techniques used for the classification of plant disease using various classifiers such as Convolution Neural Network, Support Vector Machine, K-Nearest Neighbors and Artificial Neural Network.

A. Convolutional Neural Network (CNN)

Convolution Neural Networks are a class of deep feed forward neural networks that have the ability of processing multidimensional data. The purpose of CNN is to reduce images into an easier-to-process form, without compromising the features that are essential for getting a good prediction.

There are different available architecture's for CNN such as AlexNet, GoogLeNet, VGGNet etc. Its growth has generated a lot of interest among researchers in various fields of computer science [9]. In agriculture, it has been used for the classification of diseases in plants.

As shown in figure 6, the CNN model comprises of an input layer, convolution layer, pooling layer, a fully connected layer and an output layer. To classify the disease in plants in a precise manner the images are provided as input. The convolution layer is used for extracting the features from the images. The pooling layer computes the feature values from the extracted features. Depending on complexity of images, the convolution and pooling layer can be further increased to obtain more details. Fully connected layer uses the output of previous layers and transforms them into a single vector that can be used as an input for next layer. The output layer finally classifies the plant disease.

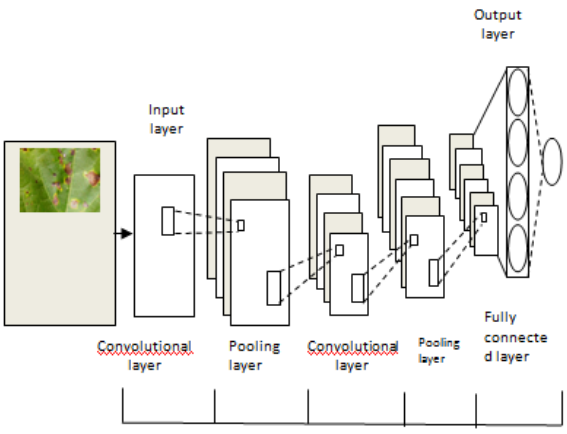

Figure 6: Plant disease classification through CNN [9]

The following work has been done in plant leaf detection using the CNN approach:

Mohanty et al. in 2016 [10] have focused mainly on two CNN architectures i.e. AlexNet and GoogLeNet and the training mechanisms that have been used are transfer learning and training from scratch. The images used are from PlantVillage dataset and about 54,306 images of different plants with 38 classes of diseases were taken. All the images in the dataset were downscaled into 256 × 256 pixels, and model optimization and predictions were performed on the resized images.

Lu et al. in 2017 [11] have proposed a model for disease detection of rice using deep convolution neural network. They have used 500 images captured with a camera from a field and 10 common diseases in rice plants have been detected. The results have been compared for different pooling (mean, max and stochastic pooling), different convolution filter sizes (5X5, 9X9, 16X16, 32X32) and for different algorithms (CNN, BP, SVM, PSO).

Gandhi et al. in 2018 [12] proposed a system based on two different CNN architectures i.e. Inception v3 and MobileNets. They have used 56,000 images with 38 classes of crops from the PlantVillage dataset. A deep convolutional generative adversarial network (DCGAN) has been used for the augmentation of limited images in the dataset.

Ferentinos, K. P. in 2018 [13] have used different architectures of CNN, such as AlexNetOWTBn, Overfeat, AlexNet, VGG, and GoogLeNet that were trained using various parameters. The training and testing of these models were implemented using Torch7, which is a computational framework for machine learning. Around 87,848 images of PlantVillage dataset having 25 plant species in 58 distinct classes of disease were used in this work. VGG and AlexNetOWTBn architectures had the highest success rates as compared to others.

Khamparia et al. 2019 [14] have integrated convolutional neural networks (CNN) with autoencoders for detection of diseases in crops. The authors have utilized a dataset with 900 images of three crops with five different types of diseases such as early blight and late blight for potato, leaf mould and yellow leaf curl for tomato and rust disease for maize crop. The convolution filters of size 2 X 2 and 3 X 3 have been used and analyzed accuracy varies for different convolution filters for different number of epochs. For loss reduction and improved accuracy while training, Adam optimizer has been used.

Kamal et al. in 2019 [15] proposed two models namely Modified MobileNet and Reduced MobileNet by using the depthwise separable convolution architecture and their results were compared with MobileNet, AlexNet and VGG. Various optimizers like SGD, Adam and Nadam were also used. Nadam performed better and with a faster convergence rate than the other two optimizers. In this work 82,161 images having 55 distinct classes of healthy and diseased plants were used from publicly available PlantVillage dataset for the training and testing of the model.

Geetharamani, G., & Pandian, A. in 2019 [16] presented a plant leaf disease identification approach by using a deep convolutional neural network (Deep CNN). The Deep CNN framework is trained and tested on an open access data that the authors have downloaded from PlantVillage dataset. About 54,448 images of 13 different plant leaves have been used in this work.

Augmented image dataset and a non- augmented image dataset have been used to train the model. The augmented images have been created using techniques such as gamma correction, colour augmentation, noise injection, rotation, principal component analysis (PCA), and image flipping that increase the size of augmented dataset to 61,486 images.

Karthik et al. in 2020 [17] utilized two distinct deep learning mechanisms for the first time to detect the diseases such as late blight, early blight, and leaf mold on tomato leaves. The authors in the first architecture have used residual learning on CNN. In the second approach they have integrated residual learning with attention mechanism on CNN for the efficient learning of features. This task has been done on Plant Village Dataset and about 95,999 images have been used for training their model. The Summary of work done for plant disease detection using the CNN technique is presented in Table 1.

Table 1: Summary of work done using CNN technique

Title	Technique(s)	Plants Used (Dicots or Monocots)	Outcome/ Accuracy
Using Deep Learning for Image-Based Plant Disease Detection [10]	CNN	Apple, Blueberry, Cherry, Corn, Grapes, Orange, Peach, Potato, Strawberry, Tomato (Dicots)	The overall accuracy is obtained in the range of 85.53% to 99.34%. It has been observed that GoogLeNet performed better than AlexNet with an accuracy of 98.21%.
Identification of rice diseases using deep convolutional neural networks [11]	Deep-CNN	Rice (Monocot)	Maximum accuracy was achieved using stochastic pooling and a 16x16 filter size which was 95.48% and 93.29% respectively.
Plant Disease Detection Using CNNs and GANs as an Augmentative Approach [12]	CNN with GANs	Multiple Plants	In this the inception v3 model achieves an accuracy of 88.6% and MobileNets achieved an accuracy of 92%.
Deep learning models for plant disease detection and diagnosis [13]	CNN with different architecture	Apple, Blueberry, Corn, Cabbage, Cassava, Cherry, Peach, Strawberry, Tomato (Dicots)	The proposed model has an accuracy that varies from 97.26%- 99.47%. The highest accuracy was achieved by, Visual Geometry Group (VGG) convolutional neural network.
Seasonal crops disease prediction and classification using deep convolutional encoder network [14]	CNN and autoencoders	Potato, tomato (Dicots) maize (monocots)	This work attained 97.50% accuracy in $\mathbf{2 \times 2}$ filter size of convolution in 100 epochs, whereas 100% accuracy corresponds to $\mathbf{3 \times 3}$ filter size.
Depthwise separable convolution architectures for plant disease classification [15]	CNN	Distinct plants including Tomato	The accuracy achieved by Modified MobileNet, Reduced MobileNet and MobileNet were 97.65, 98.34 and 98.65% respectively.
Identification of plant leaf diseases using a nine-layer deep convolutional neural network [16]	Deep convolutional neural network (Deep-CNN).	Apple, grape, tomato, potato, soybean, cherry, peach, and blueberry (Dicots)	The method obtained an accuracy of 96.46% which is better as compared to other models like SVM, Decision tree, Logistic Regression and KNN.
Attention embedded residual CNN for disease detection in tomato leaves [17]	CNN	Tomato (Dicot)	The result of the experiments of proposed work has been able to detect the disease with an accuracy of 98%.

B. Support Vector Machine (SVM)

Support vector machine (SVM) is a type of learning algorithm that is based on structural risk minimization and is also used for classification and regression problems. It is designed in such a way as to maximize the classification boundaries so that two classes are separated as widely as possible.

As shown in figure 7, to get the appropriate data point, SVM has been applied to this region and it is termed as hyperplane. The adjacent points of hyperplane are recognized from both sides of the plane i.e., support vectors. To make a separation between these vectors a fixed margin that must be maximum is used, through which the SVM can be trained in an effective way.

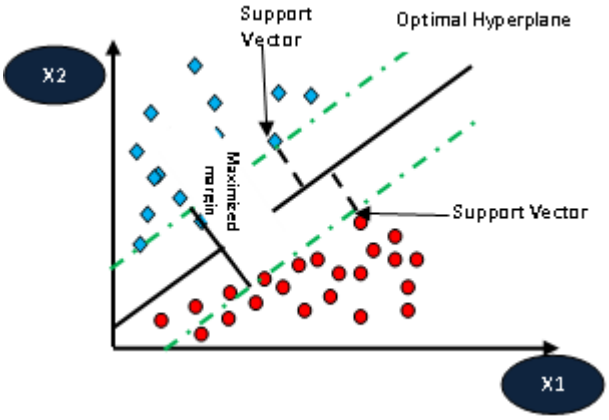

Figure 7: Classification using SVM

The work done using SVM for the classification of diseases in plants is discussed below:

Badol et al. in 2016 [18] have used a Linear Support Vector Machine for the classification of two types of diseases i.e. Downey and Powderly Mildew in grape leaves. The researchers used 137 images of grapes that they captured using a camera. Images are preprocessed to remove the noise using gaussian filter and thresholding is done to remove unwanted components. Then, segmentation of images is done using k-means and later features are extracted and the images are then fed to the SVM classifier.

Singh et al. in 2017 [19] have identified and classified pea rust disease that is caused by a fungus known as Uromyces fabae (Pers.) de Bary. About 500 images of pea plants were used that have been collected from Hill Agricultural Research and Extension Centre in Himachal Pradesh, India. Various steps of image processing were used and at the classification phase, SVM was utilized for disease detection.

Bhimte et al. in 2018 [20] presented a model which detected Bacterial blight and Magnesium Deficiency in cotton plants. The dataset consisted of 130 images that were captured with a camera. Quality of images are improved using preprocessing techniques and then k- means clustering is used for segmentation. The images are then classified using SVM classifier after the features have been extracted using Gray Level Co-occurrence Matrix (GLCM).

Kumar et al. in 2018 [21] introduced a new exponential spider monkey optimization (ESMO) technique of feature selection for identification of disease in plant leaves. For feature extraction subtractive pixel adjacency model (SPAM) technique is used. In this work 1000 images from PlantVillage dataset have been used for detection of disease. To make classification among healthy and diseased leaves KNN, SVM, ZeroR, and LDA classifiers were used. After analysis, SVM classifier performed better than the other classifiers.

Hossain et al. in 2018 [22] proposed a system to identify two classes of diseases namely brown blight and algal in the tea plant. About 300 images of healthy and diseased tea plant were captured using a camera from Bangladesh Tea Research Institute. After preprocessing and feature extraction the data was fed to the SVM classifier for the accurate prediction of the disease.

Aruraj et al. in 2019 [23] have developed a method to classify the diseases in banana plant. They have used 123 images of banana plant which included both the diseased and healthy images from the PlantVillage dataset. For texture analysis the technique of local binary pattern has been used and the features that have been extracted are fed to the SVM classifier through a 7-fold cross validation. In Table 2, we discussed the work that makes use of the SVM technique to detect plant disease.

Table 2: Summary of work done using SVM technique

Title	Technique(s)	Plants Used (Dicots or Monocots)	Outcome/ Accuracy
SVM Classifier Based Grape Leaf Disease Detection [18]	SVM	Grape (Dicot)	The system provided an average accuracy of 88.89 per cent for both Downey and Powderly grape leaf disease.
Support vector machine classifier based detection of fungal rust disease in Pea Plant (Pisam sativam) [19]	SVM	Pea (Dicot)	Proposed method can successfully diagnose and analyze disease with 89.60% accuracy.
Diseases Detection of Cotton Leaf Spot using Image Processing and SVM Classifier [20]	SVM	Cotton (Dicot)	The proposed system detected the disease in cotton plant with 98.46% accuracy.
Plant leaf disease identification using exponential spider monkey optimization [21]	SVM	Potato and Apple (Dicot)	An accuracy of 92.12% has been obtained using this method.

Recognition and Detection of Tea Leaf's Diseases Using Support Vector Machine [22]	SVM	Tea (Dicot)	The system achieved an overall accuracy of 93.33%.
Detection and Classification of Diseases of Banana Plant Using Local Binary Pattern and Support Vector Machine [23]	SVM	Banana (Monocot)	The maximum accuracy that the proposed work attained was 89.1% and 90.9%.

C. K-Nearest Neighbor (K-NN)

This classification scheme is statistical along with non-parametric and the weight is given corresponding to neighbors. Here, the classification is done based on the computed Euclidean distance metric.

It is also known as a lazy learner because it simply stores all the training tuples given to it as inputs in its learning phase without performing any calculations and thus prevents it from being used in areas where dynamic classification is needed for large databases.

In figure 8, a blue star represents the test data point. This test point is bounded through the red circles, and green squares that serve two classes. As shown in figure, there are six points, so six distances need to be calculated.

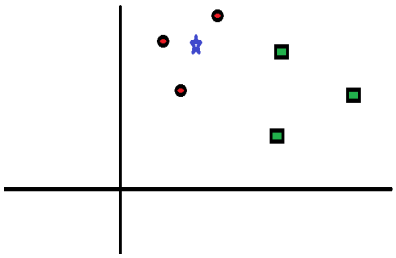

Figure 8: K-NN classifier

For K-NN classification the three essential aspects are as follows:

- Easy resultant output interpretation
- Short computational time
- High prediction rate

This technique is used widely in areas such as text mining, pattern recognition, forecasting the trends in stock market and in agriculture for classifying various diseases in plants. The following work has been done using the K-NN approach for detecting plant diseases.

Parikh et al. in 2016 [24] proposed a system that uses cascades of KNN classifiers and multiple training sets to successfully detect Grey Mildew, a fungal disease in cotton plants from unconstrained images. The authors have collected 130 images from Sardarkrushinagar Dantiwada Agriculture University. The images are segmented, and the features extracted and KNN classifier is then used.

Ramcharan et al. in 2017 [25] utilized transfer learning mechanism on the basis of SVM and KNN, by utilizing the convolutional layers of existing trained Inception v3 model. The classification of the disease has been done in three specific ways; SVM, KNN and original softmax layer of inception v3 model.

Suresha et al. in 2017 [26] presented a system for detecting diseases such as Blast and Brown Spot in paddy plant. About 300 images taken from a camera in paddy fields of Shivamogga district in Karnataka state have been used in this paper. For segmentation Otsu technique have been used along with global threshold. Connected component has been used for feature extraction and classification is done using the KNN technique.

Hossain et al. in 2019 [27] have considered plant diseases such as alternaria alternata, anthracnose, bacterial blight, leaf spot, and canker of plants and used K-NN to classify them. The dataset comprises of 237 leaf images acquired from the Arkansas plant disease database. The features of plants have been extracted using the GLCM technique. To prevent overfitting, the 5-fold cross validation was applied on the training dataset.

Abdulridha et al. in 2019 [28] developed an automatic early identification of diseases such as laurel wilt, phytophthora root rot (Prr), and deficiency of iron and nitrogen in avocado plants. The images were acquired using cameras and Multilayer perceptron (MLP) and K-nearest neighbor (K-NN) classification techniques were used. The table 3 given below, summarizes the work that uses KNN technique for various plant disease detection.

Table 3: Summary of work done using KNN technique

Title	Technique(s)	Plants Used (Dicots or Monocots)	Outcome/ Accuracy
Disease Detection and Severity Estimation in Cotton Plant from Unconstrained Images [24]	KNN	Cotton (Dicot)	Accuracy of 82.5% was achieved using this system.
Deep learning for image-based cassava disease detection [25]	KNN and SVM	Cassava (Dicot)	The obtained accuracy is 73% by applying KNN, and by using SVM 91% accuracy was achieved.
Recognition of Diseases in Paddy Leaves Using kNN Classifier [26]	KNN	Paddy (Moncot)	With this method the authors achieved an overall accuracy of 76.59%.
A Color and Texture Based Approach for the Detection and Classification of Plant Leaf Disease Using KNN Classifier [27]	KNN	Various Plant leaves	The classification performance of KNN on plant leaf disease provides 96.76% accuracy. This approach provides better results compared to some existing methods.
A remote sensing technique for detecting laurel wilt disease in avocado in presence of other biotic and abiotic stresses [28]	KNN and MLP	Avocado (Dicot)	In all cases, the MLP approach obtained higher classification values than the KNN and sometimes reached up to 98%.

D. Artificial Neural Network (ANN)

ANN is an information-processing model inspired by the way information is processed by a biological system i.e. the brain. It consists of artificial neurons or processing elements (PEs) that are connected with coefficients, which forms the neural structure. They gather the knowledge by detecting data patterns and relationships and they learn through experience and not by programming. Artificial Neural Networks can be used for pattern extraction due to their capability of deriving meaning from complex data.

The two types of ANN are the feed forward ANNs in which the behavior of any layer will not affect that same layer and the feedback ANNs in which signals propagate in both directions by requiring network loops [29].

As shown in figure 9, an artificial neuron comprises of several inputs that can take any value between 0 and 1, but only a single output. For each input the neuron has weight and an overall bias [29].

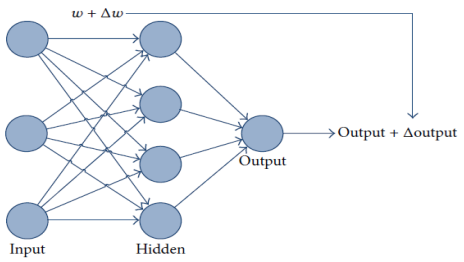

Figure 9: Classification using ANN [29]

The work done on the classification of diseases in plants using SVM is discussed below:

Pawar et al. in 2016 [30] developed a system for detecting two classes of diseases in cucumber along with the treatment for the detected disease. Images have been acquired from an experimental field using a camera. Features have been extracted using first order statistical moments and GLCM.

Kho et al. in 2017 [31] presented an efficient system using a pattern recognition approach for identification of Ficus plant based on the leaf images. They have used 60 images of three different species of Ficus plants i.e., F. benjamina, F. sumatrana and F. pellucidopunctata.

Gupta et al. in 2019 [32] have identified diseases in citrus plants and used ANN to classify them. They have used a dataset of 60 images and applied the image processing steps for extracting and classification of the diseases.

Kumari et al. in 2019 [33] proposed an automated system for detection of four classes of diseases in cotton and tomato plants. A sample of 20 images from PlantVillage dataset is used. Images are segmented using K means clustering and features are extracted through GLCM, that are given as input to the ANN. The related work that uses ANN technique to classify different plant diseases is listed in Table 4

Table 4: Summary of work done using ANN technique

Title	Technique(s)	Plants Used (Dicots or Monocots)	Outcome/ Accuracy
Cucumber Disease Detection using Artificial Neural Network [30]	ANN	Cucumber (Dicot)	The system's accuracy by applying KNN is 80.45 percent.
Automated plant identification using artificial neural network and support vector machine [31]	SVM and ANN	Ficus (Dicot)	In this SVM and ANN were used, where both produced an accuracy of 83.3%. However, accuracy of system was better by using ANN with an AUC curve.
Disease Detection in Plant using Artificial Neural Network [32]	ANN	Citrus plant leaves	The classification performance on plant leaf disease gives 96% accuracy.
Leaf Disease Detection: Feature Extraction with K-means clustering and Classification with ANN [33]	ANN	Cotton and Tomato (Dicots)	The overall accuracy in classification is 92.5 % using ANN.

V. CONCLUSION

Severe diseases in plants leads to the annual losses of the agricultural yield. Therefore, detecting the diseases at an early stage in plants is very crucial for the prevention of such drastic losses in the future. In this paper, we have discussed the Monocotyledonous and Dicotyledonous plant families along with the related methodology encompassing of the image processing steps. Classification techniques that are most widely used for the identification and detection of diseases on plant leaves have been reviewed. The most recent work has been analyzed and it is depicted in the form of tables. It can be concluded that amongst the techniques that have been used in the existing work done, highest accuracy has been achieved with the deep learning concepts that is through the CNN approach.

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