Journal of Advanced Zoology

ISSN: 0253-7214

Volume 44 Special Issue -02 Year 2023 Page 893:906

# LEAF DISEASE DETECTION AND IDENTIFICATION USING HYBRID MULTICLASS SVM (HM-SVM)

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**Article History**

Received: 27Aug 2023

Revised: 28Sept 2023

Accepted: 06Oct 2023

**Abstract**

The agricultural industry is critical to long-term economic growth & food security. Crop diseases, on the other hand, can pose a significant threat to achieving this expansion. Early diagnosis and categorization of plant diseases are essential for a good outcome. This opened up a slew of new options for study in this field. A lot of effort is being done now to use neural networks to better identify and categorise plant diseases. A Hybrid Multiclass SVM (HM-SVM) model strategy towards leaf disease detection is presented in this research. To distinguish healthy and sick leaves, the researchers developed an HM-SVM for automated feature extraction and classification. Experiment results indicate that the proposed technique is capable of reaching high accuracy. Disease detection as well as identification in large fields using automated techniques is beneficial since it minimises people or farmers' labour, as well as time and money spent on observation and study of illness signs. This study explains how to use Hybrid multiclass SVM to identify and detect leaf diseases. Hybrid Multiclass SVM classifier is used to classify illnesses, and thus the detection accuracy is increased by maximising the information exploitation. We are applying image processing algorithms to classify diseases in this suggested system, and diagnosis may be done fast according to the disease. Crop productivity will be increased as a result of this strategy. Acquisition, image pre-processing, segmentation, and feature extraction are some of the procedures involved

**Key Words:** Plant Disease detection, Image processing, HM-SVM Classifier, Segmentation.

## 1. INTRODUCTION

Agricultural crops have an impact on plant growth and crop yield, as well as the cultural, environmental, and economic elements of agriculture [1]. According to recent studies, roughly half of all crops are harmed by illnesses. Farmers lose a lot of money because of plant leaf diseases [2]. The importance of early illness identification cannot be overstated. The forecasts are made based on the accessible surface of the leaves of the plants. The diagnosis of a disease in its earliest stages, as soon as the first symptoms appear, is beneficial to the treatment of disease. In the past, detection was generally carried out either by human experts or by automation cultivation. It is essential to identify and categorise infections in a timely manner in order to avoid more damage to commodities and plant leaves. Over the last several years, CNN models have seen widespread use in the context of image categorization issues [3]. The Fully Convolutional model is designed and produced in order to conduct plant disease recognition and tracking utilising apple and tomato leaf images of healthy and sick plants. The model will be used to identify and classify plant diseases [4]. Crop failures detection is a tool that precision agricultural firms are eager to have, since it allows them to make early choices and save financial losses. In order to identify failed rows of crops, the recommended approach makes use of mathematical morphology operators. This method takes into consideration the many different options that are possible when digital image processing methods are used [5]. The fundamental concept is to apply several mathematical operators in a sequential manner in order to expose failures that might otherwise go unnoticed.

### 1.1 Fundamentals of Plant Diseases

Plant disease is an important element in agricultural output that contributes to a decrease in both plant quality and plant quantity. In plant diseases, the most typical strategy is to use a classification and detection model.

#### i. Diseases Caused By Bacteria

The bacterial illness is commonly referred to as "bacterial leaf spot." To begin, it appears as little, golden blemishes on young leaves, which are regularly warped and twisted. Alternatively, it appears as dark, liquid, greasy blisters on older foliage. Both forms are commonly deformed and twisted.

#### ii. Diseases Caused By Viruses

All viral illnesses result in a decrease in output, and plants that have been infected with viruses often only have a short lifespan. The leaves are the most common location for disease symptoms to appear on plants; however, symptoms may also be caused by different viruses on the fruits and roots of the plant as well as the leaves. The investigation of a disease that is caused by a virus is a very difficult task. As a consequence of the virus, the plant's development may be slowed down, and its leaves may have a wrinkled and curled appearance.

#### iii. Diseases Caused By Fungus

Fungal infection may influence infected seeds, ground, output, weeds, and the spread of wind and water. It appears as water-soaked, gray-green patches on lower with more seasoned clears in the initial stage. After that, the spots go away, and white fungal growth spreads across the undersides. Yellow to white stripes appear on the top of the board of more weathered clears in wool build-ups. It spreads outward over the leaf surface, turning the leaf yellow.

**iv. Detection of Failure**

Aerial images, together with digital image processing techniques, have been widely utilised in precision agricultural applications. These photographs may now be readily transformed into a variety of deliverables, including ortho shots, water stress maps, plant disease infestation indices, and more. Crop failures detection is a tool that precision agricultural firms are eager to have, since it allows them to make early choices and save financial losses. The fundamental concept is to apply several mathematical operators in a sequential manner in order to expose failures that might otherwise go unnoticed.

## 2. LITERATURE REVIEW

The model is created with four layers of convolutional layers, each of which is followed by a pooling layer. The presence or absence of illness may be determined by using two thick layers that are completely coupled to one another as well as the sigmoid function. Image dataset of apple and tomato leaves with a total of 3663 photos that are utilised for training purposes and have an accuracy of 87 percent [6]. A hybrid model that combines CNN as well as Deconvolutional Networks to retrieve contextual information from leaf characteristics [7]. Various pre-trained CNN techniques were constructed on a large dataset of open leaves. According to their findings, CNN is a great technique for automatically identifying plant illnesses. It effectively recognised diseases on plant leaf using Alex Net and Squeeze, which was when CNN architectures on such a large dataset [8].

The recognition and classification of green foliage of plant in her research "Detection of diseased section of plant leaves utilizing Image Processing & Genetic Algorithm" [9]. The best approach for class estimation, which is the k-nearest-neighbor strategy. Scheme is described as employing a KNN classifier towards plant disease prevention and analysis, with the devised method working for five different kinds of maize illnesses [10]. In this study, the author employed a number of temporal parameters to build a set of features that comprised tint intensity (through using hue moment technique), contour, and spatial-based data [11].

Scale Invariant Feature Transform (SIFT) is utilised to extract features for disease diagnosis and detection, according to the authors of Paddy Plant Leaf Images [12]. This function uses HM-SVM to recognise an image, which is more beneficial for image clustering and classification. Image acquisition, RGB to greyscale image conversion, and grayscale to binary image conversion with noise were all covered in full [13]. To reduce the noise, they employed a morphological approach [14]. The image of both the plant leaf were acquired from the system by the user in this module. A technique for recognising plant diseases that involves measuring the average of the two variables to be partitioned: the diseased patch and the leaf surface [15].

This study [16] focuses on several techniques for categorization and recognition of foliage of plants. The KNN strategy is the best method for class estimation. As an example, the created method can identify and detect plant illnesses using a Classifier algorithm, as well as function for five different types of maize diseases. In this research [17], they used several temporal factors to generate a feature set that included tint level (using the colour moment approach), outline, and spatial based features.

Based on the authors of Paddy Plant Leaves Images [18], the Scale Invariant Feature Transform (SIFT) is utilised to obtain features for disease diagnosis and detection. This characteristic is used to detect images using SVM and KNN, which is more useful for data classification and clustering [19]. In this study [20], the authors reported their work on image capture, converting RGB to grayscale images, and converting grayscale to image pixels with noise. To reduce the noise, they employed a morphological approach. The suggested technique for identifying plant illnesses involves computing overall ratio of two parameters to be divided: the disease area as well as leaf area [21].

## 3. PROPOSED METHODOLOGY

The user as well as the system server are two parties in the system model. The image of both the plant leaf were acquired from the system by the user in this module. After image capture, the server system seeks and uses Extraction, classification, and treatment of the image in the first phase, which includes Pre-processing, Image Segmentation, and Feature efficient communication. The user submits an image, which is subsequently analysed and processed by Image Processing.

This present scheme, which is a leaf disease detection framework, is separated into 2 phases: in the first, users establish the depth of knowledge by introducing a set of training images into a series of processing steps that include pre-processing image techniques such as crop rotation, resizing, and fuzzy chromaticity equalisation, and then extracting a collection of colour and texture features and that use them to create the knowledge base that can be used as the testing phase for HM-SVM. The HM-SVM classifier, which was trained using knowledge base, is used in the second part of the research to detect and diagnose plant leaf diseases. We split the sample photos into 80 percent training and 20 percent testing to generate the knowledge base. We have employed three illnesses in each yield, in part to the right state of the each crop of leaf, to ensure that disease identification is accurate and efficient. The system server then checks if the image uploaded by the user is illness-oriented or not, and classifies it using HM-SVM, which displays the disease name, afflicted region on the leaf, and the reliability result in percentage.

### 3.1 Morphological Operations

The mathematics underpinning morphological operations on a image is built just on algebra of non-linear operators working on object forms. The keypoint, the neighbourhood in the source image that the structuring element covers, and the kind of operation all have a role in determining the pixel values in the output image. In this study, binary images are subjected to a number of different morphological procedures. A binary image is a two-dimensional arrangement of dots, often known as pixels, each of which is either "on" or "off" (1 or 0). The following are many definitions of binary images. The number 1 denotes the whole output image, X denotes the collection of pixels in the image that have the value 1, and B denotes the structuring element.

### 3.2 Obtaining Images

Image acquisition is the initial stage in every vision system. Several portable sensors with varying resolutions are used to acquire sample images of the leaves, which are subsequently used to prepare the network during processing. These samples are kept in a standardised manner. The examples are all in RGB mode. Images gathered may include either diseased or healthy foliage, including such fungal pathogens, rust, black, and dark spots, among other things. To fulfil the many diverse vision tasks that are necessary, several processing techniques can be implemented to the image as shown in fig 1.

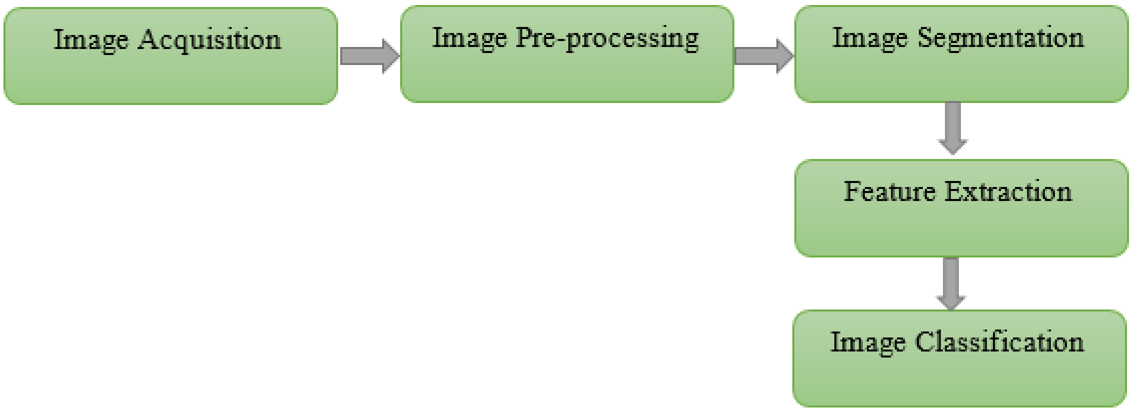


Figure 1. Steps for Image Processing

### 3.2.1 Pre-processing

There is some undesired noise and also redundancy in an input image. As a result, noise reduction, contrast enhancement, and illumination equalisation are all techniques used in pre-processing. This is featured in it to reduce ambient noise and to also prevent unwanted distortion. These sorts of variances can arise for a variety of causes, including camera settings, light fluctuations, and so on. To address such difficulties, the RGB image is converted to a gray-scale pixel intensity. It also converts RGB data to greyscale by calculating a weighted sum of such R, G, as well as B elements.

### 3.2.2 Segmentation

The primary goal of segmentation seems to be to extract pertinent and useful data from a image based on a specific attribute. In this work, a histogram-based technique and thresholding are used to divide an image into groups. MATLAB software was used to pre-process and analyse the recorded images. The methods used in image segmentation is represented pictorially in Fig 2.

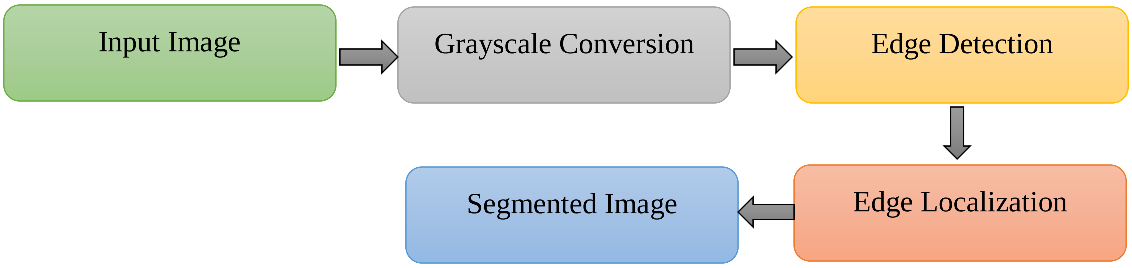


Figure 2. Image Segmentation Process

At this stage, a histogram is constructed from all of the pixels in a image, while colour or intensity may be employed as a measure. The graph may also be used on a sensor basis to determine the most frequent colour for a specific pixel location, with the resultant data being used. Thresholding may be used to produce binary images from a grey scale image in this manner.

For the purpose of calculating the quadratic distance between two pixels, the Euclidean distances formula (dist(x)) is used in eq 1. The *dist(n)* between the (*ni* ) and (*nj*) in the image is computed using

$$dist\ (n) = \sqrt{\sum_{i,j}\left(n_i - n_j\right)^2} \qquad (1)$$

After computing the distances of intra-cluster for each of the clusters, the biggest of those distances is selected for inclusion in $dist_{max}$, which is specified in the following eq 2.

$$dist_{max} = \max_{n=1}\{\sum dist\ (p, B_{ij})/\ |C_{ij}|\ \} \qquad (2)$$

Where clusters is denoted as *Ci*, *Bij* represents the centroid values, *p* is the partition matrix.

After computing the distances of inter-cluster for each and every cluster, the $dist_{min}$value that corresponds to the cluster with the smallest distance is given in eq 3.

$$dist_{min} = \min_n\{dist(B_1, B_2)\} \qquad (3)$$

**3.2.3 Feature Extraction**

The technique of obtaining useful data from such an input image is known as feature extraction. The process of converting original data into a collection of features is known as feature extraction. Color, texture, form, and borders are just a few of the features that may be found in leaf photos. To obtain a decent result and accuracy, leaves in context colour and texture characteristics are extracted. GLCM Features in Action Contrast, correlation, and homogeneity of the image are extracted using image analysis techniques.

Frequencies in GLCM, $\left(\boldsymbol{P}\ (x, y; dist, \theta)\right)$ of concurrent occurrences of pixel $(x1, y1)$ and pixel $(x2, y2)$. Distance between pixel $(dist1, dist2)$ and pixel to the $\theta$ direction as shown in eq 4 and correlation is given in eq 5.

$$\left(\boldsymbol{P}\ (x, y; dist, \theta)\right) = \begin{Bmatrix} (x1, y1)(x2, y2)\mid c(dist1, dist2) = n\mid \\ (dist1, dist2) - P(x2, y2)\ = dist\ =\ \theta \end{Bmatrix} \qquad (4)$$

$$Correlation = \sum_{x=1}^{n}\sum_{y=1}^{n}\frac{(x - \mu_x)(y - \mu_y)}{\sqrt{(\sigma_x)(\sigma_y)}} \qquad (5)$$

P(x, y) is the standardised grey value at locations x and y of a matrices with a sum of 1.

**3.2.4 Classification**

The classification approach is employed throughout the testing and training processes. This is the extremely last step of the procedure. A comparison is made between the features that are gained from testing leaves and those that are derived from training leaves. After that, the photographs are classified into several categories according to the characteristics that have been matched. As a consequence of this, a method known as support vector machine is used in order to classify leaf disease. A hyperplane is used in the binary classification method known as HM-SVM. This hyperplane is a vector that splits a surface into two pieces, one for each class. The objective training vector is labelled "+1" in one class, whereas the training vector is labelled "-1" in the other. HM-SVM uses this training examples vector to find a hyperplane that minimizes the distance between the two classes.

### 3.2.5 Hybrid Multiclass SVM

Within the realm of machine learning, the supervised learning strategy known as HM-SVM, together with its associated learning algorithms, may be used to the process of evaluating data for the purposes of clustering, classification, and regression analysis. When supplied with a training data set, which are labelled as methods are divided into two categories, the HM-SVM training technique generates a model that utilises that modelling to allocate subsequent sequence data to one of two main categories, based on a non-binomial. The training data are labelled as belonging to one of two categories.

The following equation (6) and (7) describes the HM-SVM process:

$$\text{HM-SVM}=\frac{1}{2}\omega^T\omega + C\ \textstyle\sum_1^N K \qquad (6)$$

$$= y_i(\omega^T\emptyset(x_i) + b)\ \geq 1 - K, and\ K \geq 0, i = 1 \ldots n \qquad (7)$$

The HM-SVM model provides an example of examples as spatial points structured in such a way that the examples of the separate classes are divided through as many gaps as possible. As illustrated in fig 3, new occurrences are moved into the same region and allocated to categories depending on which side of the gap they reside in a certain section or segment.

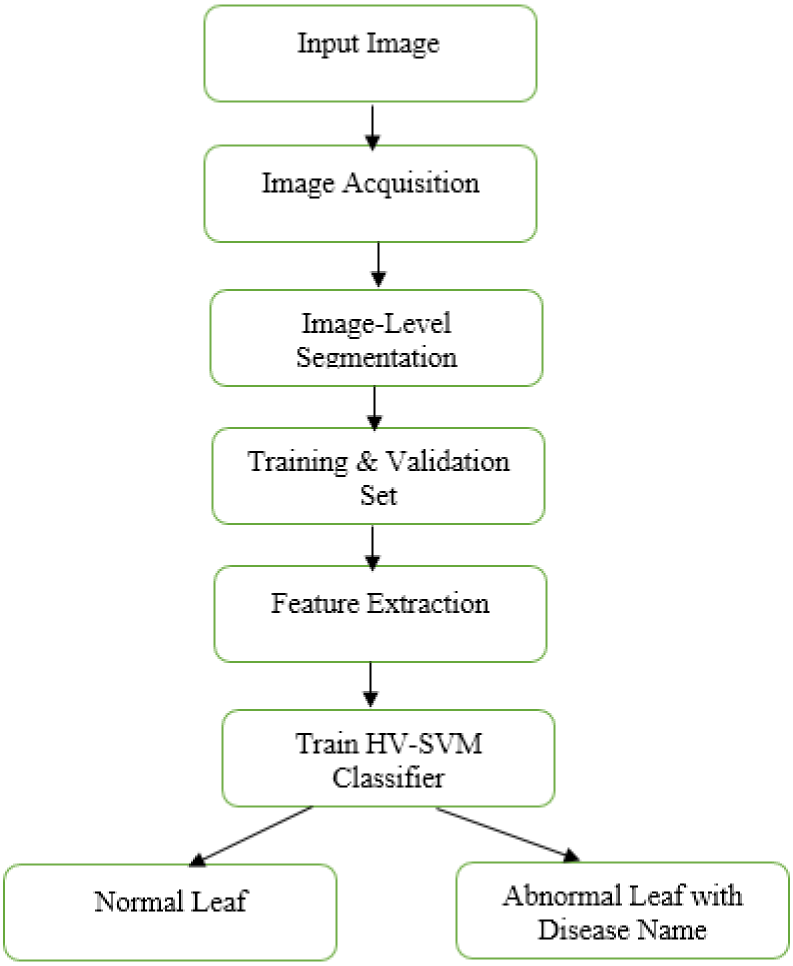


Figure 3. System Overview

In regression classification, a support vector machine is a sort of model that is used to evaluate data and uncover patterns of analysis. HM-SVM is utilised when your data contains precisely two classifications. HM-SVM classifies data by determining the optimal separating hyperplane in pieces of data that divides all pieces of data of one category from all pieces of data of the other. The better the model, the greater the difference between the two groups of data points. HM-SVM works effectively with data sets with a lot of characteristics.

**Algorithm for proposed model**

Input: Training data X, Training labels Y, Number of classes K
Output: Trained hybrid multiclass SVM model
Step 1: Generate ECOC codebook
1.1. Create an empty codebook matrix C of size K x L, where L is the number of binary SVM classifiers required for ECOC
1.2. Generate L unique binary codes, each of length K
1.3. Assign each code to a row in the codebook matrix C
Step 2: Train binary SVM classifiers
2.1. For each binary SVM classifier i from 1 to L:
2.1.1. Initialize the training labels for the binary classifier as follows:
For each sample j from 1 to N (N is the number of training samples):
If Y[j] == i-th codebook element:
Set the label for sample j as +1
Else:
Set the label for sample j as -1
2.1.2. Train a binary SVM classifier using training data X and corresponding binary labels
Step 3: Classify test samples
3.1. For each test sample:
3.1.1. Initialize an empty score vector of size K
3.1.2. For each binary SVM classifier i from 1 to L:
3.1.2.1. Classify the test sample using the i-th binary SVM classifier
3.1.2.2. If the prediction is +1, increment the score of the corresponding class in the score vector
3.1.2.3. If the prediction is -1, decrement the score of the corresponding class in the score vector
3.1.3. Assign the class with the highest score as the predicted class for the test sample
Step 4: Return the trained hybrid multiclass SVM model

HM-SVM divides data points in two groups based on their common characteristics, such as colour, size, and shape. We used HM-SVM to segment the leaf image in our produced system to determine the impacted and non-affected regions of the leaf.

## 4. EXPERIMENTAL RESULTS

As seen in Fig. 5 and 6, image pre-processing is used to improve image data including undesired abnormalities or to enhance certain image attributes.


Figure 5. Input Image

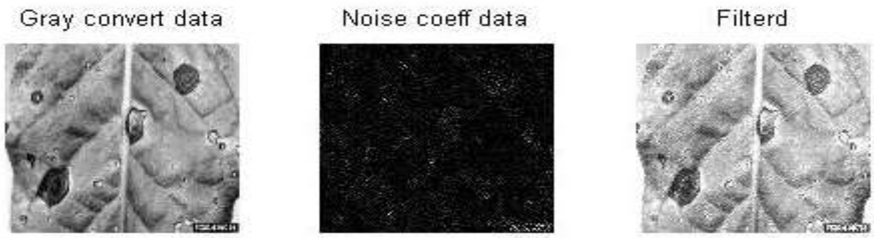


Figure 6. Pre-processing

Figure 7 depicts segmentation of a leaf image with three clusters created by the clustering approach.


Figure 7. Clustering an image

Image segmentation, as seen in Fig. 8, is the process of dividing an image information into too many segments and putting an image into a form that facilitates study.


Figure 8. Segmented Image

The crucial issue, the area of the source image encompassed either by center pixel, or the kind of operations determine the pixel values of the output image. As seen in Figure 9 and 10, this study employs a number of morphological approaches on binary images as well as feature extracted parameters.


Figure 9. Morphological Operations

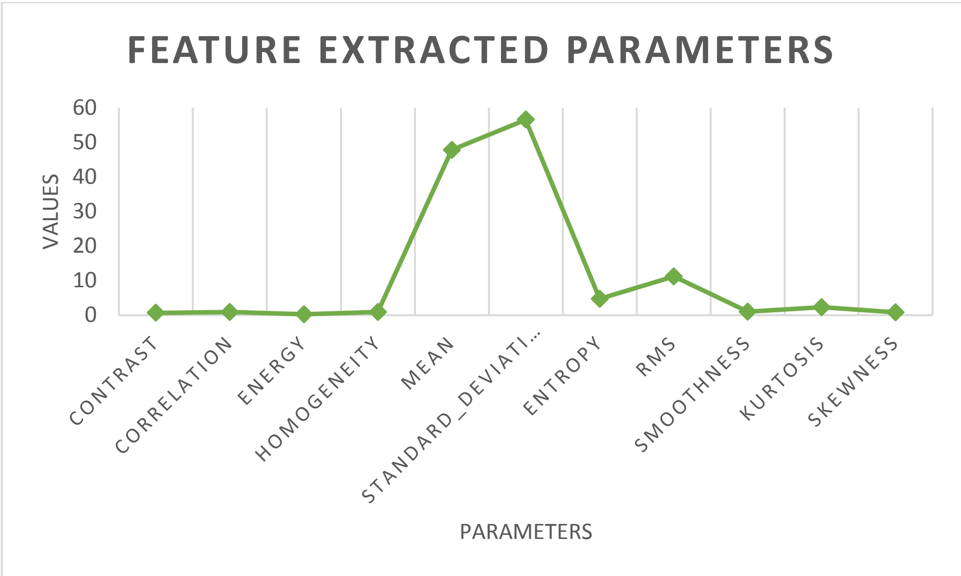


Figure 10. Feature Extracted Parameters

After that Segment image shows the image which is black and white, the black area is healthy and white dots shows the damage part of the leaf by diseases with its name as shown in fig 11.

Figure 11. Output Image with disease name

Mean square error (MSE) was derived by taking the average of the squares of error. The mean square error measurement unit is the same as the quantity being assessed. The MSE is determined as follows in eq 8:

$$MSE\ (x,y) = \frac{1}{xy}\sum_{i=1}^{m}\sum_{j=1}^{n}(x_{mn} - y_{mn})^2 \qquad (8)$$

where 'x' is indeed the initial image and 'y' is indeed the segment image of similar size, and 'm' and 'n' are the columns and rows. The MSE is lower for fewer distorted images and higher for more distorted ones as shown in fig 12.

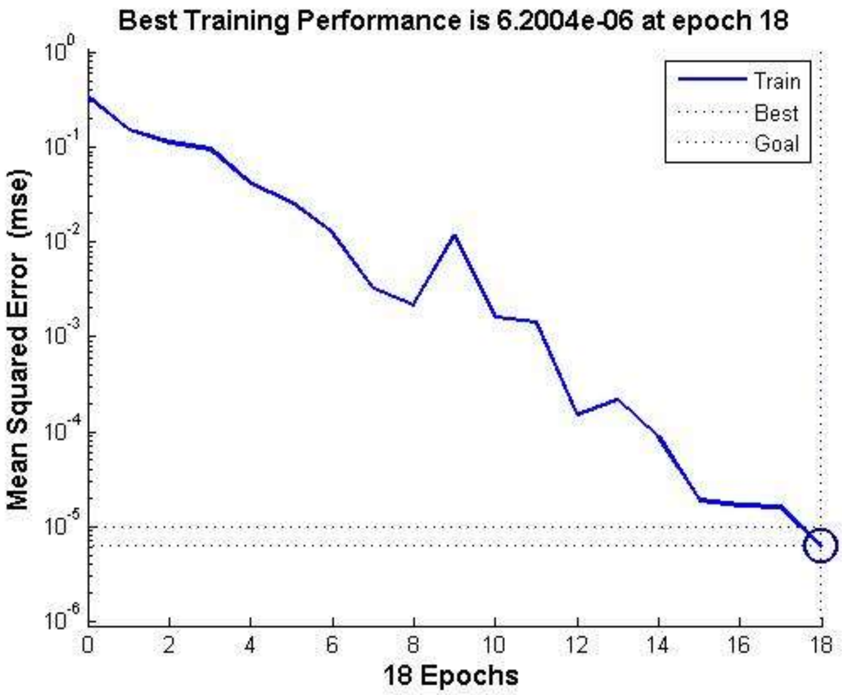


Figure 12. MSE Value

Throughout this research, the plant illness was recognised through image processing, with the coloured coordination removed in the pre-processing step, as well as dividing and extracting operations done inside the classification approaches segmentation process as demonstrates in Table 1.

Table 1 Classification performance of diseased and normal leaf images

| **Leaf types** | **Normal** | **Bacterial blight** | **Blast** | **Brown spot** | **Sheath rot** |
|---|---|---|---|---|---|
| **Accuracy** | 92.3 | 97.4 | 99.2 | 93.1 | 92.4 |
| **F1 score** | 81.5 | 86.5 | 97.8 | 84.1 | 91.2 |
| **Precision** | 72.5 | 82.1 | 92.1 | 83.5 | 72.3 |
| **FDR** | 15.1 | 21.2 | 9 | 25.5 | 23.6 |
| **FPR** | 5.9 | 5.2 | 1.2 | 5.3 | 6.1 |
| **FNR** | 9 | 16 | 6.1 | 8 | 9 |
| **TPR** | 69.2 | 92.2 | 92.3 | 88.2 | 73.3 |
| **TNR** | 88.1 | 92.2 | 97.5 | 95.7 | 96.8 |
| **NPV** | 90.6 | 93.2 | 96.2 | 92.4 | 95.9 |

Where, FDR-false discovery rate, FPR- False Positive rate, FNR-False Negative rate, TPR-True Positive rate, TNR- True Negative rate, NPV- Net Present Value

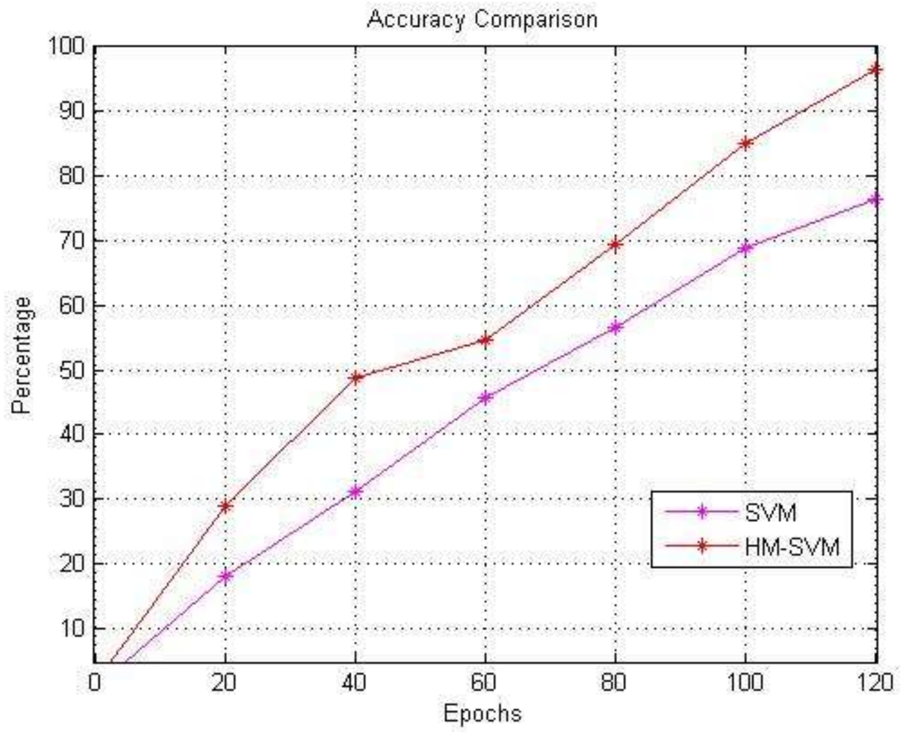


Figure 13. Accuracy Comparison

The comparison of existing algorithm with proposed method for accuracy as shown in fig 13. As it clearly states that proposed method gives more efficient than an existing technique.

**5. CONCLUSIONS**

The major goal of this method is to use HM-SVM to detect and diagnose illnesses in leaves. Detection and Recognition of Leaves Diseases Utilizing HM-SVM is a critical part of agriculture's problem-solving process. Using the disease's description and features, this technique automatically diagnoses leaf illnesses. This methodology has been used effectively to treat a variety of diseases of plant leaves such as bacterial leaves blight, brown patch, green blistering, and leaf blast. The HM-SVM is used to categorise diseases, increasing detection accuracy by 91%. HM-SVM has been demonstrated to be an emphasises for the distinction as well as classification of plant diseases with normal preciseness with affected region of the leaf that had more accuracy in result shows in proportions by combining HM-SVM to technique for image processing to maximise the function as diseases of a leaves.

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