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# Automatic Leaf Disease Detection using Polynomial Support Vector Machine

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***Abstract*— For the world's food security, agricultural production is essential, and the use of artificial intelligence in this field is greatly increasing output. One noteworthy use is the automated diagnosis of leaf diseases, which is difficult to do with conventional visual approaches due to the fact that symptoms might sometimes seem perfectly normal. Early disease detection is essential because problems that go unnoticed can seriously affect crop quality and output. Despite the fact that this field has seen a great deal of research, many current systems still have flaws. The suggested method makes use of a Euclidean distance measure in conjunction with a Polynomial Support Vector Machine (SVM), a potent classifier skilled in handling non-linear data, to evaluate the spatial connections between various clusters of data points. A dataset for four distinct categories—Alternaria Alternata, Bacterial Blight, Cercospora Leaf Spot, and Healthy Leaves—has been extracted from Kaggle. The accuracy of the suggested technique is 97.30%, somewhat greater than that of the KNN classifier.**

***Keywords*— Leaf Disease, Machine Learning, Convolutional Neural Network, Alternaria Alternata, Bacterial Blight, Cercospora, Leaf Spot .**

## I. INTRODUCTION

India, whose economy heavily depends on agricultural productivity, is one country where agriculture needs immediate attention. Timely detection of plant diseases is essential in this critical industry to preserve crop health and optimize production. Conventional techniques for identifying plant diseases mostly rely on expert visual evaluations, which may be a labor-intensive and constrained procedure, particularly when farms grow in size. Continuous monitoring is necessary for such dependence on professional observation, but it can be difficult in many areas where farmers do not have direct access to agricultural specialists. Furthermore, it can be prohibitively expensive and time-consuming to consult these specialists, which makes it challenging for farmers to get timely support. Under these conditions, the suggested automated disease detection techniques show promise as a useful way to keep an eye on large agricultural areas. These methods simplify and lower the cost of disease diagnosis by evaluating plant leaf photos, making the procedure more affordable for farmers. Despite being widely employed, visual examinations are generally restricted to small regions and are naturally less accurate and time-consuming. On the other hand, automatic detection greatly improves speed and accuracy. Brown and yellow spots, early and late blight, and a variety of bacterial, viral, and parasitic illnesses are examples of common plant diseases. Farmers now have access to a more dependable diagnosis tool thanks to the use of sophisticated image processing algorithms that evaluate the afflicted areas and differentiate between various disease kinds [1]. Farmers can respond to plant health problems more skillfully by putting automated systems in place, which will ultimately increase agricultural output and sustainability.

Imaging tests offer useful information that can assist forecast the existence of illnesses with a certain degree of accuracy, even if they cannot conclusively detect leaf diseases on their own. Since early-stage symptoms of plant diseases are sometimes mild, rapid identification is essential to successful management and treatment. Artificial Neural Networks (ANNs) are a popular approach for classification jobs among other techniques, especially when trained with carefully chosen features [2]. The identification of leaf diseases has advanced significantly with the use of automatic diagnosis technologies, which enable effective monitoring and prompt action.

Recent research has increasingly focused on machine learning techniques, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and ResNet architectures. However, these deep neural networks require substantial datasets for training, leading to high computational demands and longer training times. Consequently, there is a growing need for lightweight models that utilize small, intelligent filters in their hidden layers to achieve effective results without the extensive resource requirements typically associated with deep learning. Making judgments based on classifiers that can distinguish between normal and aberrant pictures is an alternate strategy.

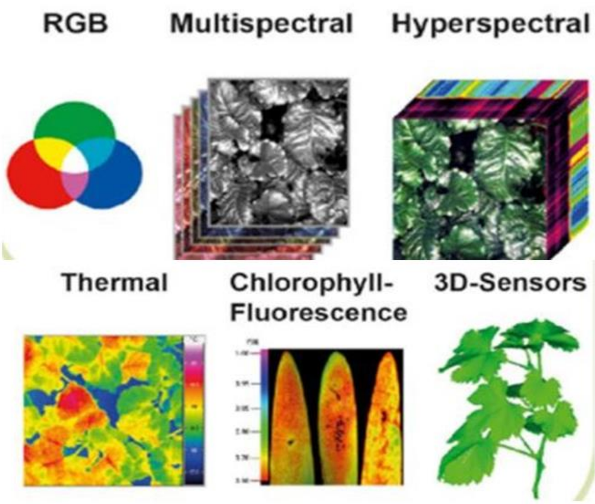



Fig. 1. Overview of Sensors [3]

There are several classifiers available, such as Support Vector Machines (SVMs), K-means clustering, and Naive Bayes. Because of their better prediction skills in categorizing the many patterns, textures, and variations present in plant imaging, support vector machines (SVMs) are frequently considered the most successful among them [4]. Researchers and practitioners may optimize the process of leaf disease identification in agricultural operations by using SVMs to reduce computing overhead and improve diagnosis accuracy. The key to achieving great accuracy with low resource demands is to create lightweight network models with clever little filters in their hidden layers. Alternatively, classifiers may be used to identify normal and abnormal pictures so that decision-making is informed. Improved classification results may be achieved by using a variety of classifiers, including Support Vector Machines (SVM), K- means clustering, and Naive Bayes. Because it is so good at predicting patterns and textures in plant pictures, SVM is frequently regarded as the most efficient of these. Through the use of SVM, practitioners are able to preserve efficiency in the identification of leaf diseases while improving diagnostic accuracy.

## II. RELATED WORKS

Many researchers have successfully retrieved lesions with excellent accuracy and some false alarm rates from leaf pictures. A research using the KNN classifier and region-based segmentation was presented by Jaskaran Singh et al. [5].They concluded that the identification of plant ailments depends on the diagnosis of those disorders. In their study, they employed k-means clustering for region-based segmentation, the GLCM approach for textural feature analysis, and the KNN classifier for sickness prediction. A research study utilizing the KNN classifier to identify illnesses based on color and textures was proposed by Eftekhar Hossain et al. [6]. Their technique used KNN to identify and classify a variety of diseases that impact plant leaves, such as Alternaria alternata, bacterial blight, leaf spot, blisters, and anthracnose. The disease segment was identified using the k-nearest neighbor classifier, and the classification was done using GLCM texture features. The quantitative performance of their proposed approach was evaluated using the DSC, MSE, and SSIM metrics. Plant disease diagnosis with the KNN classifier-based segmentation was quite accurate.

In order to acquire findings, Aamir Yousuf et al. [7] developed an ensemble classifier research that included KNN and Random Forest classifiers. However, SVM is a more sophisticated and superior classifier than the others. With its exceptional prediction accuracy, SVM is the most suitable classifier for diagnosing illnesses related to image processing, as it can handle both linear and non-linear data. Furthermore, the textural qualities of the picture are extracted using GLCM and used by classifiers to determine the condition.

Researchers Ch. Usha Kumari et al. [8] suggested using ANN and K-means clustering in their study. In this study, segmentation is done using K-means clustering, and leaf disease is detected using a neural network classifier. Many characteristics are retrieved for sicknesses of tomatoes and cotton, such as Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, and Variance. Among the diseased leaves that were taken into consideration for the study were those with bacterial leaf spot, target spot, septoria leaf spot, and leaf form disease. Features from the disease-affected clusters 1 and 3 are calculated and fed into the classifier in order to identify and categorize the illnesses. One cotton sample had the target spot categorization done erroneously, whereas nine out of the twenty samples had the bacterial leaf spot diagnostic done correctly. Abirami Devaraj et al.'s study proposal [9] used an image processing methodology. This technique includes preprocessing, photo loading, segmentation, classification, and feature extraction. By enabling farmers to identify illnesses early on, the development of an automated detection system that leverages cutting-edge technologies, such image processing, helps them control infections. They wish to continue their efforts to discover illnesses in new areas. A web-based application was created by M. Bhange et al. [10] that allows users to contribute photographs to the system in order to diagnose fruit illnesses. The program extracts features like color, morphology, and CCV (color coherence vector) from the provided fruit pictures. Fruit is classified as either infected or not using support vector machines (SVM), while clustering is done using the k- means method. The accuracy rate of this approach in identifying pomegranate diseases was 82%. In order to identify fungal infections on plant leaves, J.D. Pujari et al. [11] investigated a variety of crop kinds, including fruit crops, vegetable crops, cereal crops, and commercial crops. They used many techniques, one for each type of crop. Singh et al.'s [12] main goal was to apply genetic algorithms as an image segmentation approach to automate the identification and categorization of plant diseases. They employed a small set of images from four distinct plant species—roses, bananas, beans, and lemons—

for training and testing. In order to extract features, texture and color information were combined using the color co-occurrence technique. The Minimum Distance Criterion was used to the SVM classifier and k-means clustering in order to categorize illnesses; the results showed accuracy rates of 86.54% and 95.71%, respectively. Using a fuzzy decision maker, Kiani et al. [13] sought to identify disease-infected leaves in an outdoor strawberry field. With a 1.2-second processing time, they were able to detect and segregate plant illnesses with an overall accuracy of 97%. With an overall accuracy of 99.9%, H. Ali et al. [14] used color histograms and textural cues for illness classification in addition to applying the ΔE color difference method to identify disease-affected regions. They employed a range of classifiers, such as cubic SVM, fine KNN, bagged trees, and boosted trees classifiers. An automated system for plant disease detection was suggested by G. Saradhambal et al. [15]. Their research focused on forecasting the impacted leaf area using Otsu's classifier and the k-means clustering technique. The process involved extracting the textural qualities and form of the leaves. Shape-oriented features included things like area, color axis length, eccentricity, solidity, perimeter, and homogeneity, whereas texture-oriented features included things like contrast, correlation, energy, homogeneity, and mean. In this work, categorization was carried out using a classifier built on neural networks.

## III. IMPLEMENTATION DETAILS

The proposed system utilizes a Polynomial Support Vector Machine (SVM) in conjunction with an Euclidean Distance Metric to automatically diagnose leaf diseases and classify them into distinct categories. Leaf images often contain various types of noise, necessitating techniques to mask or erode background information to accurately identify lesion areas.

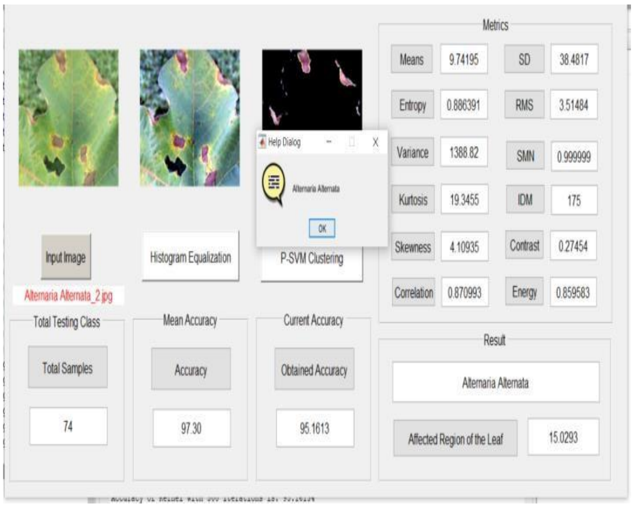



Fig. 2. Graphical User Interface

Image preprocessing plays a critical role in enhancing the quality of the images, allowing for clearer differentiation of affected regions. SVM is particularly effective in grouping similar cells into clusters based on identifiable patterns, and the use of a Polynomial SVM allows for the classification of non-linear data. Given the complex structures often present in leaf images, employing a non-linear classifier significantly improves precision in diagnosis. This combination of advanced techniques ensures a robust and accurate system for identifying and categorizing leaf diseases, paving the way for more effective agricultural management. The proposed system's graphical user interface, which incorporates procedures like clustering and histogram equalization, is seen in Figure 2. The first step in the suggested technique is to apply histogram equalization after obtaining the original picture from the dataset. Histogram equalization improves the image's brightness and contrast, making lesions more visible. This procedure helps categorize the background, which might have noise in it that can be eliminated using edge detection.

$$P_n = \frac{number\ of\ Pixel\ Intensity\ n}{Total\ number\ of\ pixels} \quad n = 0,1 \ldots . L-1$$

Where $P_n$ is the affected pixel value after histogram equalization. The histogram equalized image γ will be defined as

$$\gamma_{i,j} = floor\left((L-1)\sum_{n=0}^{f_{i,j}} P_n\right),$$

Where floor() can be considered as the nearest integer. It is equivalent to pixel intensity k;

$$k = floor\left((L-1)\sum_{n=0}^{f_{i,j}} P_n\right)$$

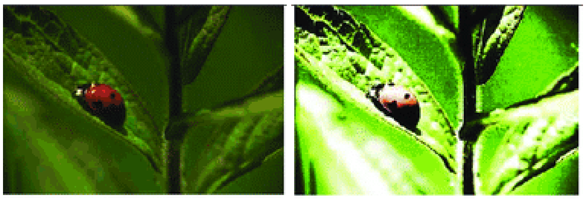


Fig. 3. Original Image & HE Affected Image

Figure 3 shows the picture following histogram equalization, showing improved visibility of the original leaf image. This improvement is essential to raising the system's detection accuracy for leaf diseases. Polynomial Support Vector Machine has been used to classify the impairments which is consider as the best classifier till now. Because it can handle non-linear data, Polynomial Support Vector Machine (SVM) is a sophisticated classification technology that is especially well-suited for identifying leaf diseases. Complex patterns seen in leaf pictures may be effectively separated using this approach, which maps input characteristics into higher- dimensional spaces using polynomial kernel functions. The Polynomial SVM is particularly good at spotting minute differences in color, texture, and structure that can point to the existence of a leaf disease. The algorithm effectively classifies the status of the leaves by grouping related data points according to these characteristics, differentiating between healthy and sick specimens. This capacity helps to improve crop management and productivity by improving the accuracy of disease diagnosis and facilitating prompt responses.

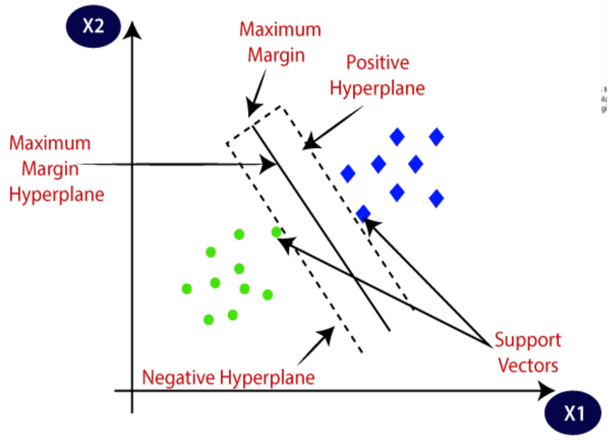



Fig. 4. SVM for Two Sample Classes [9]

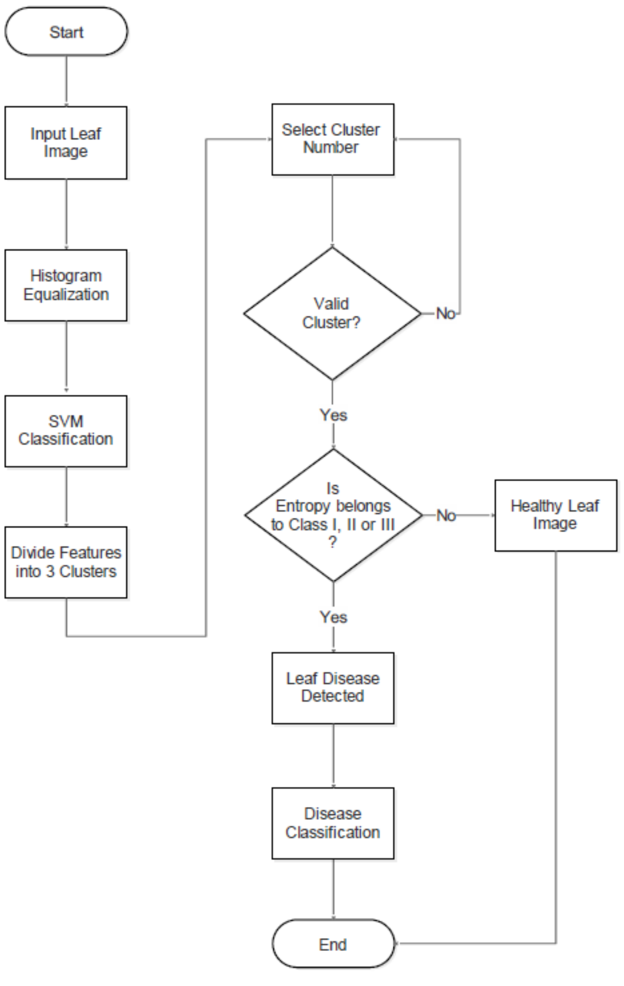



Fig. 5. Flowchart of Proposed System

$$min_w \|w\|^2 + \sum_{i=1}^{n}(1 - y_i\langle x_i, w\rangle)$$

The proposed system's flowchart, which loads the dataset picture as input data initially, is seen in Figure 6. The pre-processing module has then been started in order to improve the photos' visibility. One of these is the histogram, which is in charge of maintaining the system's equilibrium between brightness and contrast. When visibility increases, features are retrieved, and after features are chosen, SVM classification may be used to categorize the data points. The cluster that the system has built must be chosen by the user. The retrieved lesion's entropy is then computed by the system. It determines the lesion's density, which is then compared to the threshold value. The system has four switch scenarios, thus comparisons may be done in accordance with those. Entropy will be regarded as the corresponding illness, such as Alternaria alternata, Bacterial Blight, or Cercospora Leaf Spot, if it meets the requirements of cases 1, 2, and 3. However, entropy would be regarded as a healthy leaf picture if it satisfied case 4. Thus, the technique additionally categorizes the impacted area based on the lesion's density. Make it more concrete by providing the suggested algorithm and the algorithm's stages.

Table I Proposed Algorithm

**Polynomial SVM Algorithm**

Initialization
Input: Set of Image I=(i1, i2, i3,……… in)
Output: Entropy
**Step 1:** Input image
**Step 2:** Apply histogram equalization

$$P_n = \frac{number\ of\ Pixel\ Intensity\ n}{Total\ number\ of\ pixels} \quad n = 0,1 \ldots .L - 1$$

Where $Pn$ is the affected pixel value after histogram equalization.
**Step 3:** Collect data points as vectors $w_i$.

$$y = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 \ldots\ldots\ldots$$

$$= w_0 + \sum_{i=1}^{m} w_i x_i$$

$$w_i = w_0, w_1, w_2 \ldots\ldots\ldots\ldots . w_m$$

Where $w_i$ is the vector, b is the bias and x is the variable
**Step 4:** Calculate the margin

$$w * x + b = 1$$
$$w * x + b = 0$$
$$w * x + b = -1$$
$$h(x_i) = \begin{cases} +1\ if\ w.x + b \geq 0 \\ -1\ if\ w.x + b < 0 \end{cases}$$

**Step 5:** Compute loss function

$$min_w \|w\|^2 + \sum_{i=1}^{n}(1 - y_i\langle x_i, w\rangle)$$

**Step 6:** Calculate Entropy of the cluster

$$E = -\sum_{i=0}^{n-1} p_i log_b p_i$$

Where n is the number of gray-levels, p is the probability of pixel having gray-levels i and b is the base of function.
**Step 7:** if E is True for Class I, II & III then
Leaf disease detected;
Classify disease;
else
Healthy Leaf Image Detected;
end else
end if
**Step 8:** End

## IV. EXPERIMENTAL RESULT

True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are the four metrics that are commonly used to assess experimental outcomes. When a picture falls into a disease category and the algorithm accurately classifies it as positive, it is indicated as a True Positive. When a picture does not fit into any disease category and the system accurately classifies it as negative (healthy), it is indicated as True Negative. When an image does not fit into any illness category but the algorithm mistakenly flags it as positive, this is known as a false positive. When a picture falls into a disease category but the system misclassifies it as negative (normal), this is known as a False Negative. True positive means if an image belongs to either class 1, 2 or 3 and system diagnosed it positively, True Negative means if an image does not belong to either Class 1, 2 or 3 and system diagnosed it as healthy. False Positive means if an image class 4 and system diagnosed it as Class 1, 2 or 3, False Negative means if an image belongs to the Class 1, 2 or 3 but system diagnosed it as normal. There are total 74 testing images where 34 images belong to class 1 (Alternaria Alternata), 18 images from class 2 (Bacterial Blight), 7 images belong from class 3 (Cercospora Leaf Spot) and 15 images from normal class in Kaggle benchmark.

Table II Experimental Results

| Terms | Proposed |
|---|---|
| Total Testing Class | 74 |
| True Positive | 57 |
| True Negative | 15 |
| False Positive | 2 |
| False Negative | 0 |
| Specificity in % | 88.24 |
| Precision in % | 96.61 |
| Accuracy in % | 97.30 |
| F1 Score in % | 98.28 |
| Sensitivity in % | 100 |
| Negative Prediction Rate in % | 100 |
| False Positive Rate in % | 11.16 |
| False Negative Rate in % | 0 |
| Recall | 100 |

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100\ \%$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP} + \text{TN}} * 100\ \%$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100\ \%$$

$$\text{Negative Prediction Rate} = \frac{\text{TN}}{\text{FN} + \text{TN}} * 100\ \%$$

$$\text{False Positive Rate} = \frac{\text{FP}}{\text{FP} + \text{TN}} * 100\ \%$$

$$\text{False Negative Rate} = \frac{\text{FN}}{\text{FN} + \text{TP}} * 100\ \%$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} * 100\ \%$$

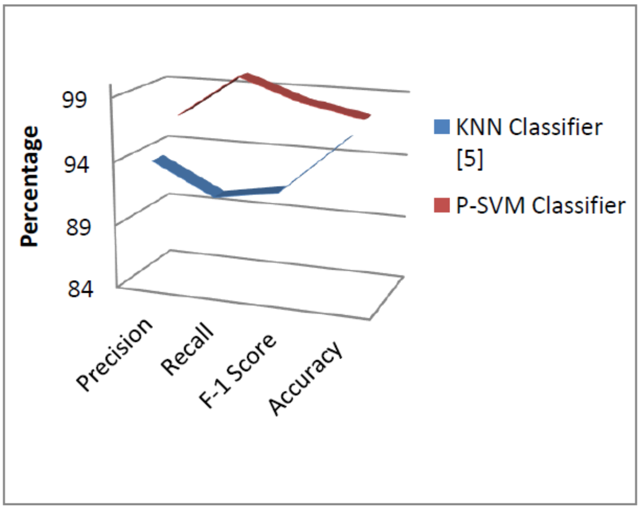
$$\text{F1} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} * 100\ \%$$

$$\text{Recall} = \frac{\text{TP}}{\text{FN} + \text{TP}} * 100\ \%$$

Table III Result Comparison

| Methods | KNN Classifier [5] | **P-SVM Classifier** |
|---|---|---|
| Precision in % | 94.00 | **96.61** |
| Recall in % | 91.56 | **100** |
| *F*1-Score in % | 92.39 | **98.28** |
| Accuracy in % | 96.76 | **97.30** |

Graph I Result Comparison




## V. CONCLUSION & FUTURE SCOPE

The proposed approach efficiently distinguishes between normal and aberrant cells using a Polynomial Support Vector Machine (SVM), allowing precise decision-making based on this categorization. The approach surpasses the K-Nearest Neighbors (KNN) classifier in terms of accuracy and shows considerable efficiency across a range of parameters. This strong classification method finds the right category for every image in addition to differentiating between healthy and unhealthy cells. The system outperformed earlier models when it was evaluated against the Kaggle benchmark. In the future, more tests using different benchmarks that include large image datasets might improve the system's efficiency. Furthermore, using sophisticated preprocessing methods might boost accuracy even more, increasing the system's capacity to identify leaf illnesses.

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