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Enhancing Leaf Disease Detection with SVM: A Reliable Approach

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Abstract: - ***Detecting leaf diseases with high accuracy is a topic of utmost significance and interest. Support Vector Machines (SVM), a powerful machine learning algorithm known for its effectiveness in classification tasks, can be employed to distinguish between healthy and diseased leaves. Leaf diseases in crops pose a major threat to global food security, leading to substantial economic losses and reduced crop yields. Timely and precise identification of these diseases is crucial for effective disease management and prevention. However, manual identification methods are prone to inaccuracies and time-consuming processes.***

In this study, we investigate the efficacy of SVM classifiers for identifying leaf diseases. Our Support Vector Machine (SVM) model achieves an impressive accuracy rate of 99.84% in accurately identifying leaf diseases. These findings have significant implications for the practical implementation of SVM classifiers, as they demonstrate the ability to accurately recognize various plant ailments and enhance crop disease control, ultimately improving crop yields.

Keywords: Accurate, Comparison, Classifiers, Hybrid Deep Learning, plant growth

I. Introduction

The agricultural segment plays a key role in providing essential resources such as food, shelter, medicine, energy, and textiles to the global population. Additionally, it serves as a significant contributor to the global energy supply. Accurate identification of plant diseases is of paramount importance owing to their capacity to negatively impact agricultural yields in terms of both quantity and quality. Traditional methods for disease identification are often associated with extended timeframes and require specialized expertise, making image processing an attractive alternative.

Various image processing methodologies can be utilized to identify and classify plant diseases. Before their application, it is imperative to subject the images to pre-processing procedures that aim to enhance their fundamental characteristics. Pre-processing involves a range of tasks, such as image normalization,

segmentation, and feature extraction, among others. Following the pre-processing of images, it is possible to utilize machine learning algorithms for the purpose of training and identifying plant diseases.
Efficient techniques for identifying and categorizing diseases in leaf imagery are crucial for enabling prompt intervention and reducing the likelihood of disease spread. The employment of computational software has the capability to augment the effectiveness and accuracy of quality assurance methodologies. The application of machine learning in the domain of disease diagnosis is of great significance, as it enables the automation of disease detection and classification, thereby reducing the probability of human error and improving effectiveness.

In recent years, there has been a significant uptick in interest regarding the application of techniques derived from machine learning to the diagnosis and classification of plant diseases. CNNs can accurately detect plant diseases in leaf images. On the other hand, it is essential to carry out a comparison analysis of the various classification models in order to identify the strategy that is the most successful in terms of disease detection and classification.
The goal of this study is to compare how well ResNet50V2, SVM, as well as hybrid classifiers based on deep learning can spot leaf diseases. This study assesses the precision and efficacy of various classifiers and ascertains the optimal methodology for detecting plant diseases. Significant implications for improving crop yield and food safety can be drawn from this study's findings regarding the practical application of algorithms based on machine learning for identifying the presence of plant diseases.

II. Literature Review

In recent years, there has been a discernible improvement in the identification of plant diseases, which can be attributed to the implementation of a variety of techniques, including artificial intelligence, deep learning, and others. Scholars have put forth diverse methodologies and algorithms with the aim of precisely categorizing different plant diseases through the utilization of image-based processing techniques.

In their study, Patokar and Gohokar [1] evaluated different optimization algorithms to determine how well they worked with deep convolutional neural networks. This investigation's goal was to find ailments that might affect tomato plants' leaves. The study by Imam et. al. [2] used transfer learning in conjunction with the Inception V3 model to achieve a 95% accuracy rate for identifying leaf diseases in Saudi Arabia. Li et al. [3] proposed the use of DCNNs for categorizing different plant ailments, while Harpale et al. [4] achieved 92% accuracy by developing an image processing-based approach using color, texture, and shape features. Gowrishankar and Prabha [5] created an integrated image-based processing approach using ANNs and

GLCM features to identify disease in groundnut plant leaves with 94.44% accuracy using the back propagation algorithm. Kaur et al. [6] employed deep learning and an object detection system to identify a disease that affects tomato leaves with a precision rate of 96.75%. Vijayalata et al. [7] utilized the EfficientNet-B0 model to detect diseases in cassava plant leaves with 97.33% accuracy, while Vishnoi et al. [8] used convolutional neural networks and the Inception-v3 model to diagnose apple leaf/plant ailments with 99.04% accuracy.

By combining image processing with the VGG-16 architecture, Sharma et al. [9] created a classification system that accurately identified disease leaves with 95.33%. Using a multilayer convolutional neural network and various image processing techniques, the researchers Tusher et al. [10] presented an innovative method for automatically identifying the presence of plant leaf diseases in their study. This method was presented as a novel approach. The ResNet-50 model demonstrated a significant level of precision, as indicated by the authors' reported accuracy rate of 99.67%. Li and Chao [14] developed a semi-supervised few-shot learning method for leaf infection detection that outperformed existing methods.. The method was evaluated on the few-shot Plant Village database. Ahmed and colleagues [15] proposed a machine learning approach that achieved a 97.87% accuracy rate in the identification and classification of leaf diseases. In their study, Lathamaheswari et al. [16] examined various techniques and strategies for classifying leaf diseases through the utilization of image-based methods. Similarly, Ali et al. [17] employed a PCA-LDA classification approach to accurately diagnose plant leaf diseases, achieving a precision rate of 99.54%.

A technique for the detection of leaf diseases utilizing a swarm optimization algorithm was proposed by Abdul Razzaq and Khaleel in their study [18]. An efficient method for identifying plant leaf diseases was proposed by Pratapagiri and coworkers [19] using a network of convolutional neural networks (CNN). Kurzadkar et al. (2020) utilized machine learning methodologies to differentiate various categories of leaf ailments. For the categorization of diseased cotton leaves, Rai and Pahuja [21] proposed an enhanced deep convolutional neural network (CNN) model, achieving a high precision rate of 96.70%. Ganesh Babu et al. [22] used image analysis and machine learning methods to predict and analyze agricultural plant-leaf diseases, achieving an accurate classification of 98.6% for eight different diseases. Wang et al. [23] introduced a new end-to-end object detection technique, named Dba_ssd, which achieved 97.89% accuracy when tested with the PlantVillage dataset. Finally, Mangla et al. [24] recommended a technique of fuzzy C-mean and the Gaussian smoothing to identify leaf infections with 93.9% accuracy, and Kumar et al. [25] proposed a ResNet-based method to identify and categorize diseases of plant leaves with a 97.14% accuracy rate using the PlantVillage dataset.

The studies reviewed demonstrate the effectiveness of various deep learning techniques for identifying crop leaf diseases. Multiple models such as ResNet, Inception V3, VGG-16, EfficientNet-B0, and hybrid deep learning classifiers have been used to achieve high accuracy rates ranging from 92% to 99.67%. Different optimization algorithms such as transfer learning, PCA-LDA classification, swarm optimization algorithm, and image processing techniques have also been applied. These findings have significant implications for practical implementation, as accurate identification of plant diseases is essential for effective disease control and prevention, ultimately enhancing crop productivity and global food security.

III. Methodology

a) Feature Extraction in SVM

In SVM-based image classification, the process of extracting relevant and meaningful features from raw image data is essential. These features serve as inputs to the SVM model, enabling effective classification. The following feature types are commonly extracted in SVM-based image classification:

1. Shape-based features: These features are used to differentiate objects based on their shape characteristics. Examples of shape-based features include area, perimeter, circularity, compactness, and eccentricity of objects.
2. Color-based features: These features capture the color distribution of the image and aid in distinguishing between objects based on their color properties. Examples of color-based features include color coherence vectors, color moments, and color histograms.
3. Texture-based features: These features focus on the texture properties of objects and enable differentiation based on texture characteristics.

In this study, the feature extraction process involved categorizing the extracted image features into three groups: geometric features, shape-based features, and texture-based features. This classification allows for a comprehensive representation of the image properties and facilitates accurate SVM-based classification.

b) Dataset used in the Study

In this study, we focused on developing an accurate image classification model for three plant leaf images: pepper bell, potato, and tomato, which are listed in Table 1. The dataset for our study consisted of a 21,846 images in 15 classes, 17,474 in the train set and 4,372 in the testing set. The images were labelled based on the type of plant leaf they represented, with both diseased and healthy leaves included.

Table 1 leaf Image dataset

class	Plant Name	Disease Type	Image count
0	Pepper bell Plant	Bacterial spot	1301
1	Pepper bell Plant	healthy	1478
2	Potato Plant	Early blight	1000
3	Potato Plant	healthy	608
4	Potato Plant	Late blight	1000
5	Tomato Plant	Bacterial spot	2127
6	Tomato Plant	Early blight	1000
7	Tomato Plant	healthy	1591
8	Tomato Plant	Late blight	1909
9	Tomato Plant	Leaf Mold	952
10	Tomato Plant	Mosaic virus	821
11	Tomato Plant	Septoria leaf spot	1771
12	Tomato Plant	Spider mites Two spotted spider mite	1676
13	Tomato Plant	Target Spot	1404
14	Tomato Plant	Yellow leaf Curl Virus	3208

IV. Result and discussion

The present study presents the outcomes of an investigation that sought to construct a model for classifying images of plant diseases. The dataset utilized for training the model encompassed 15 discrete categories of ailments that frequently afflict peppers, potatoes, and tomatoes. Furthermore, the dataset incorporated a classification for plants that exhibit sound health. The present study reports on the outcomes of a classification model that was developed to effectively discern and categorize plant ailments on the basis of their visual attributes.

The SVM classifier model achieved an accuracy of 99.84% in correctly classifying the plant disease images as shown in figure 1. Additionally, it demonstrated high precision, recall, and F1-score values, indicating its effectiveness in accurately identifying the presence of plant diseases.

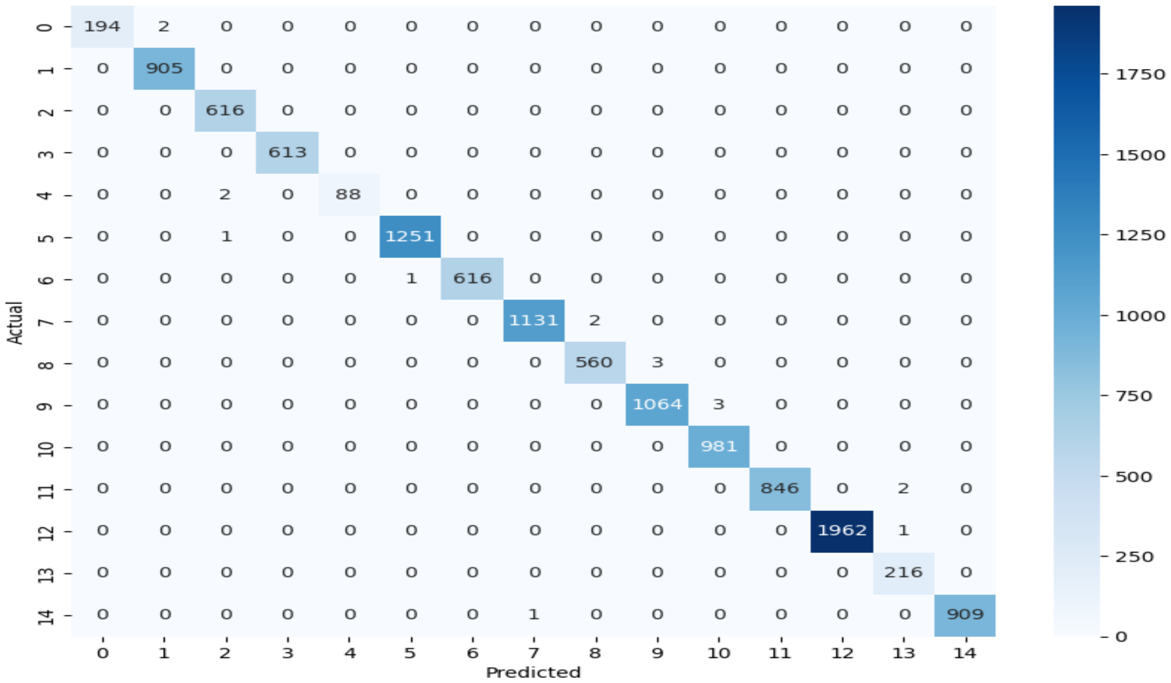

Figure 1 Confusion Matrix SVM

The SVM model also demonstrated high accuracy, with a 100% confidence level in predicting potato early blight.

Classification Report:				
class	precision	recall	f1-score	support
0	1.0	0.99	0.99	196
1	1.0	1.0	1.0	905
2	1.0	1.0	1.0	616
3	1.0	1.0	1.0	613
4	1.0	0.98	0.99	90
5	1.0	1.0	1.0	1252
6	1.0	1.0	1.0	617
7	1.0	1.0	1.0	1133
8	1.0	0.99	1.0	563
9	1.0	1.0	1.0	1067
10	1.0	1.0	1.0	981
11	1.0	1.0	1.0	848
12	1.0	1.0	1.0	1963
13	0.99	1.0	0.99	216
14	1.0	1.0	1.0	910
accuracy			1.0	11970
macro avg	1.0	1.0	1.0	11970
weighted avg	1.0	1.0	1.0	11970

Figure 2 Classification Summery SVM

The figure 2 is a report on classification, which displays the efficacy of a model in addressing a multiclass classification task. The document is structured based on class and presents various metrics, including precision, recall, and F1-score, for each class. The support column denotes the count of instances belonging to each class.

As an illustration, in the case of class 0 (Pepper_bell_Bacterial_spot), the precision metric attains a value of 1.0, indicating that all instances classified as class 0 were accurately predicted. The model's recall score is 0.99, indicating that it accurately classified 99% of the samples as belonging to class 0. The F1-score, a metric commonly used in classification tasks, is calculated as the harmonic mean of precision and recall, and in this particular case, it has been determined to be 0.99. The dataset contains 196 samples that are classified as belonging to class 0, as indicated by the support value of class 0.

The metrics of macro average and weighted average are included in the evaluation, which offer a comprehensive assessment of the model's efficacy across all categories. The column denoted as "accuracy" reflects the comprehensive precision of the model across the complete dataset. The present model exhibits a precision of 100%, indicating that it accurately categorized all instances within the dataset.

V. Conclusion

This study has demonstrated the remarkable accuracy rate of 99.84% in identifying leaf diseases by utilizing SVM classifiers. The results emphasize the significant potential of SVM in recognizing various plant ailments and enhancing crop disease control. By implementing SVM-based leaf disease detection, the timely and precise identification of diseases can be achieved, leading to early disease management and proactive measures. The models developed in this study have shown high accuracy and effectiveness in distinguishing between healthy and diseased plants, making them reliable tools for farmers and agricultural researchers. The use of SVM for disease classification has resulted in the best classification performance, which could potentially improve the management of crop diseases and ultimately increase crop yields.

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