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# Classification System for Plant Leaf Diseases Using a Hybrid Machine Learning Model

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Leaf disease identification is essential to farmers' decision-making since plant diseases often lower agricultural output and quality. Human visual plant examinations are difficult and time-consuming operations that are realistically limited to small regions, particularly since numerous infections have identical symptoms. Farmers may greatly benefit from a sophisticated image surveillance system for automated inspection in this way. Even if many algorithms have been developed recently for detecting leaf diseases, a straightforward approach that uses just the most essential information from images is useful in field situations. This research proposes an enhanced ResNet50 architecture-based Enhanced Hybrid Machine Learning Model (EHMLM) for Plant Leaf Disease (PLD) detection. The proposed approach extracts features using an enhanced ReNet50 framework. An Augmented Support Vector Machine (ASVM) was used for classification. The Adam optimizer fine-tunes the traditional SVM hyperparameters to provide a superior performance model. The activation from the preceding fully connected layer is effectively max-pooled to the convolution layer by the proposed ResNet-50. The current work aims to proactively address such an agricultural disaster using a Machine Learning (ML) model to categorize tomato PLD image datasets and take appropriate action. The plant-village database used in this study was gathered from a publicly accessible source. Regarding accuracy, classification efficiency, error rate, and execution time, baseline models like VGG19 and ResNet50 have been compared with the enhanced ResNet50 model with the ASVM classifier in the EHMLM technique.

**Keywords:** Machine Learning, Leaf diseases, ResNet50, SVM, Classification.

## 1. Introduction

Tomato (Lycopersicon esculentum) is a significant agricultural product, ranking second to the potato in demand. Our planet requires around 150 million tons of freshly harvested tomatoes [1][27]. The maturation time of this day-length agnostic crop is rather rapid, ranging from 3 months to 5 months, with a mean temperature need of 19-26 °C during daytime hours and 12-21°C during night. The crop is susceptible to excessive humidity and low sunlight, negatively impacting produce quality. Elevated humidity increases the susceptibility of plants to illnesses, pests, and decay. Therefore, an arid climatic situation is advantageous for cultivating high-quality tomatoes. Considering the potential risks of insect infestations and tomato wilt caused by fungus, bacteria, and viruses is crucial. Preventing illness may be achieved by implementing timely mitigating measures [2][17].

The rest of this section will describe many illnesses that impact the leaves and fruit of this crop. Early blight is an infection of the plant that specifically targets several portions of the tomato plant, including the fruit. Black spots on mature leaves and circular rings characterize it. The leaves experience early mortality, and the fruit sustains harm. This disease is often transmitted via the soil and thrives in humid weather conditions [18]. To avoid the spread of the illness, it is essential to maintain a hygienic garden and promptly remove any infected plants[21].

Gray leaf soft is a condition that only targets the mature leaves of the tomato crop. The plant develops small black spots on its upper and lower parts, gradually getting larger and turning into a grayish-brown hue [3]. The core region of these blemishes ultimately undergoes collapse, resulting in the eventual detachment of the damaged leaf. This illness, often prevalent in hot and humid climates, leads to a decline in fruit yield. The one viable method to prevent further illness dissemination on a bigger scale is to eliminate the infected plants and debris [23][29].

The late blight disease is a risky form of illness with a documented history of causing Irish starvation [25]. It rapidly spreads to neighboring plants, causing irregularly shaped gray patches on leaves that have a greasy texture. The spots sometimes develop a white periphery throughout the winter, causing the leaves to acquire a paper-like feel and eventually fall off. The fruits also exhibit the formation of such substantial oily patches, and the recommended course of action is to apply copper spray to the plants frequently. Septoria leaf spot exhibits symptoms that resemble late blight, with an initial impact on older leaves followed by gradual spread to other plant areas. In this scenario, copper spray is the most effective measure to be implemented [4][20].

In contrast, Southern Blight manifests as a white fungus infection, like mold, that develops toward the base of the stem, close to the soil boundary. The discoloration of both the inside and the outside of the uncommon end of the stems hampers the passage of nutrients within the plant framework, ultimately resulting in a deadly conclusion. Research has shown that using calcium, ammonia-based nutrients, and rotation of crops may be an effective preventative strategy for this disease [5].

Verticillium wilt is a plant disease caused by a fungus in the soil. This fungal infection harms crop production, particularly tomato farms. The fungus is resistant to eradication and remains in the soil for an extended time. Implementing rotating crop cultivation might be an effective strategy to prevent the illness from developing. The leaves exhibit wilting during daylight due to high temperatures but recover throughout the night. The signs and symptoms first impact the older leaves and gradually extend to the younger ones, ultimately depleting the nutrients and causing the complete demise of the plant. Extraction of the afflicted plants is the only treatment for this illness.

Anthracnose and Bacterial Speck are both fungal diseases that cause the decay of tomatoes. The illness first manifests as little circular lesions on the fruits, which gradually enlarge over time. This disease is transmitted via the environment, and every excessively ripe tomato that comes into touch with the soil becomes susceptible to it. Utilizing copper sprinkling remains the only method to avoid this illness, as is customary. Calcium shortage often results in the development of Blossom End Rot when fruits are exposed to excessive nitrogen-based chemical fertilizers and insufficient hydration [6][12][22].

The aforementioned diverse range of crop illnesses provides significant risks to growing food for the nourishment and existence of the world's main species. Architecture and algorithmic execution are necessary for identifying and preventing certain illnesses. ML [7] is widely used for early identification of PLD. Most conventional classifiers are often used in smaller databases and rely on manually designed visual characteristics for data categorization. Nevertheless, using Convolutional Neural Networks (CNN) straight on images from extensive datasets has effectively resolved issues associated with manually designed features. The incorporation of visualization strategies to comprehend symptoms and pinpoint the location of disease has shown to be notably more effective and precise in predicting plant illnesses [8].

## 2. State-of-the-art techniques in classifying tomato PLD

Research has shown that the occurrence and intensity of illnesses play a crucial role in accurately predicting PLD. Smartphone-based applications have been used to categorize the degree of damage of photographs of damaged plants [9][24]. Several extraction techniques have led to the generation of diverse outputs from the classifiers due to the collection of different characteristics. The farmers use a smartphone app to submit photographs of plant leaves afflicted with illnesses. This application aids in the identification and prediction of diseases in plant gardens.

Diseased and faulty tomatoes may be readily diagnosed and separated based on symptoms related to markings, scars, and patches. The conventional sorting method has always relied on difficult manual processes. Manual categorization is a labor-intensive process with prejudices and lacks accuracy and precision, making it susceptible to human mistakes [10]. Computer vision systems are more prevalent in classifying products in the food and agricultural industries.

In recent decades, attention has shifted toward a sophisticated Deep Learning (DL) method known as CNN. By detecting the recently arrived photographs and extracting their important features, the need for human interaction is minimized.

The authors of [11] propose a Multi-Scale Fusion (MSF) technique. CNN may identify plants based on photos of their leaves by reducing the image data into many low-level images and then inputting each one sequentially into the proposed approach. The characteristics collected at various levels are merged to offer all the information required to classify the plant species. The researchers in [28] have developed a robust and reliable deep CNN with nine levels to detect PLD accurately. To increase the sample size and facilitate the CNN learning process, the obtained data was first strengthened. The model's accuracy was evaluated by comparing it to many classifiers, resulting in a score of 95.7%.

In the LeafSnap database, the scientists developed a 50-level recurrent neural network that attained an accuracy of 98.7% with an error rate of 0.0514%. Transfer learning (TL) is a highly dynamic component of ML. The idea of TL has been explicitly defined in reference [14]. ResNet50, Inception V3, VGG-16, and VGG-19 are the most often used models in computer vision applications. These contemporary buildings are open-source. Many scholars may use the attributes and principles they have gained via their education to tackle problems in their respective disciplines. In a previous study [15][26], a CNN model called D-Leaf was proposed to extract data from the input photographs. The method's efficacy was compared to the improved Alexnet and the edge detection technique from Alexnet. Subsequently, several classifiers were provided with these qualities as input. The ANN achieved the greatest level of accuracy, reaching 95.1% [19].

This research proposes an enhanced ResNet50 architecture-based Enhanced Hybrid Machine Learning Model (EHMLM) for Plant Leaf Disease (PLD) detection. The proposed approach extracts features using an enhanced ReNet50 framework. An augmented support vector machine (ASVM) was used for classification.

## 3. Hybrid Machine Learning Model (EHMLM) for Plant Leaf Disease (PLD) detection

The suggested study consists of four phases: image pre-processing, segmentation, extraction of attributes, and categorization. The first stage involves capturing digital images of the plant leaf samples. The segmentation and pre-processing stages receive the leaf images of the tomato plant for further extraction of characteristics and categorization. The enhanced ResNet50 architecture is used to extract the properties of the leaf, hence obtaining valuable data. Ultimately, the characteristics are classified using ASVM algorithms.

a. Database used

The experiments used the tomato PLD database obtained from the plant–village database repository. The database includes images depicting both sick and healthy tomato leaves. The technological methodologies used in the article facilitated the differentiation of damaged leaves from healthy ones. The research used features obtained from the plant-village dataset repository [16]. The images representing all diseases are shown in Fig. 1.

b. Pre-processing

This stage eliminates the background to mitigate potential bias in the retrieved attributes and the learned architecture. Color cast reduction is achieved by independently normalizing the grayscale values of the three color channels. To enhance its usefulness, the background removal job should be executed automatically without human intervention. There are two methods to do it: pixel grouping and edge detection. This work used a hybrid approach, using gray-level thresholding for pixel grouping and the Canny technique for edge identification.

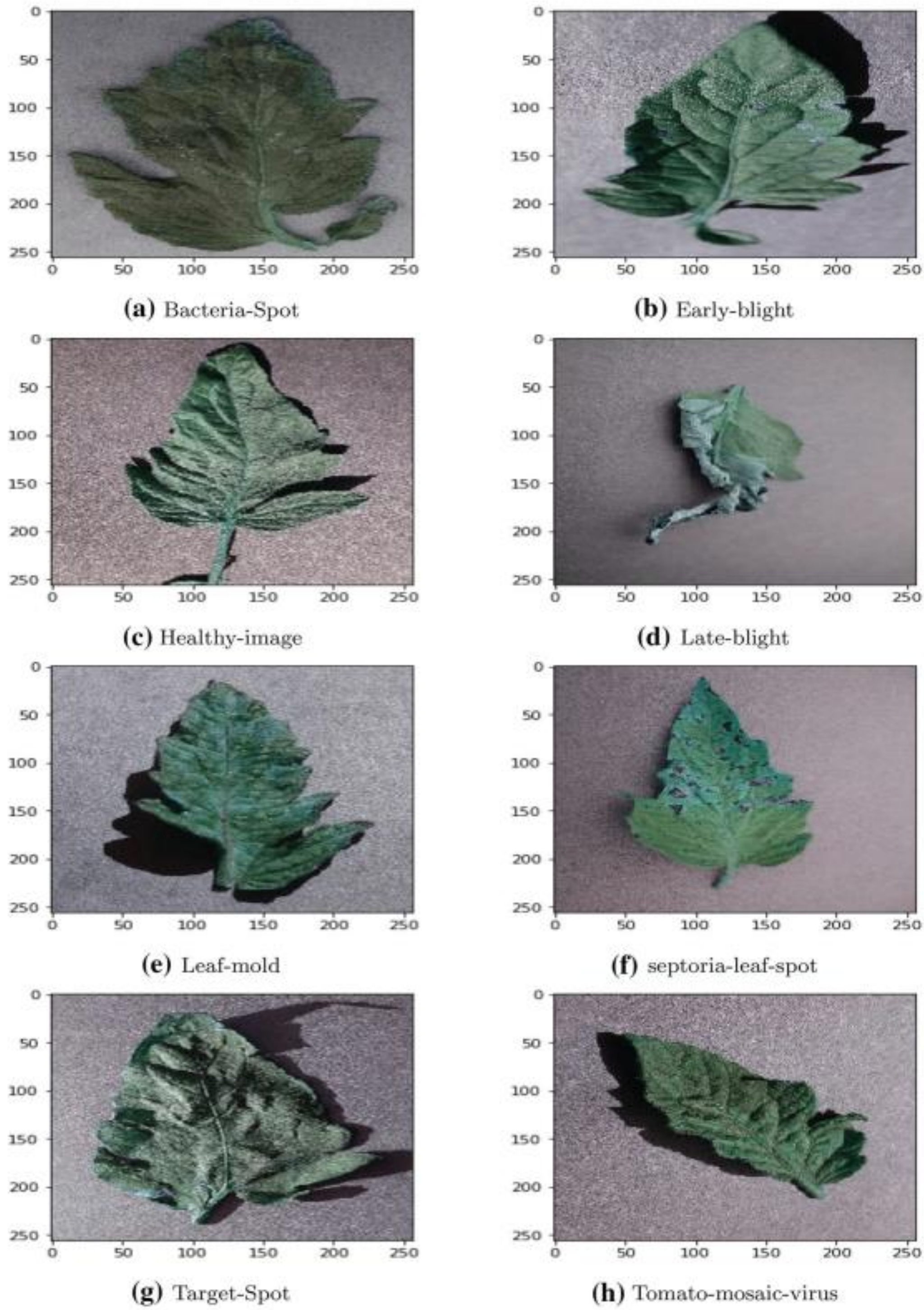


Fig. 1 Various PLD for tomato crop

c. Segmentation

To differentiate between the main subject and the surrounding area, the picture of a tomato plant's leaf, whether captured by a camera or scanned, is adjusted to a resolution of 1200x1200 pixels. The original black background of the source file is substituted with a white background utilizing several techniques from the OpenCV library. Before using the grab-cut technique, an approximated contour, foreground, and backdrop masking were created to identify the specific background and foreground of the picture. Noise reduction has been achieved by filtering to eliminate salt and pepper noises. The foreground and background of the tomato plant leaf have been separated using Python modules.

d. Enhanced Hybrid Machine Learning Model (EHMLM) for Plant Leaf Disease (PLD) detection

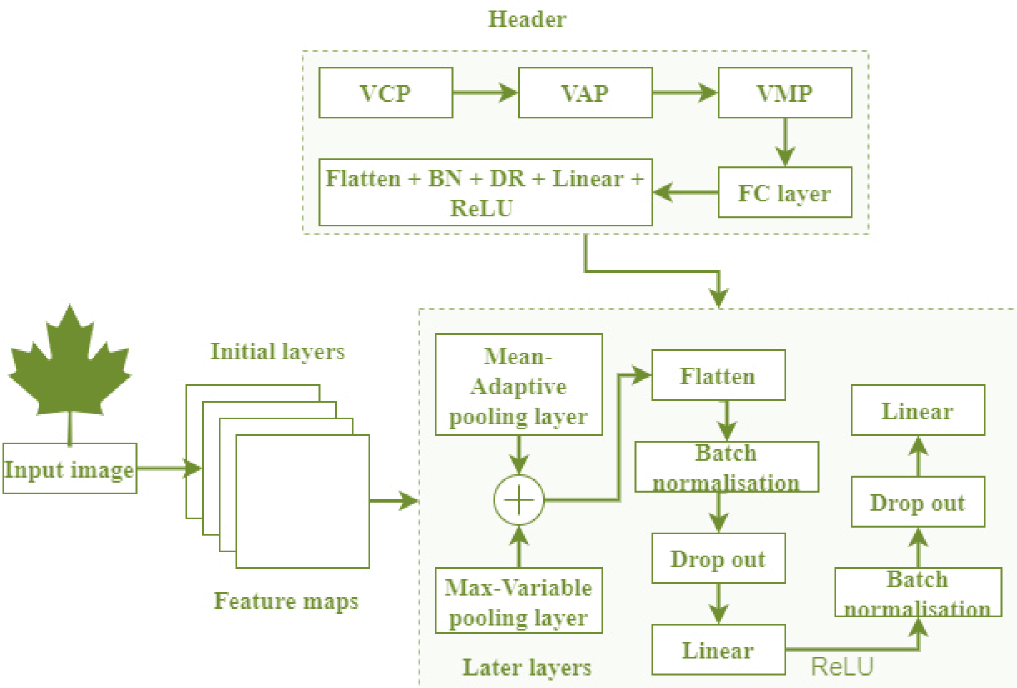


Fig. 2 EHMLM for Plant Leaf Disease (PLD) detection using enhanced ResNet50 architecture

Fig. 2 illustrates the revised ResNet50 architecture, which consists of six tiers, including input and output layers. The original ResNet-50 design has six levels: Input, level-1, level-2, level-3, level-4, and output. It also includes Fully Connected (FC) levels. The proposed technique restructures the traditional FC layers by including a "Header" layer composed of Variable Average Pool (VAP) and Variable Max Pool (VMP) layers, which are combined using Variable Concat Pool (VCP). The system employs a mean Max-pooling operation, followed by a layer of 500 FC neurons. To tackle the problem of vanishing gradients, a deep residual structure is used, whereby a constraint design is utilized to minimize the communication overhead that arises when more layers are included in the network architecture. The identity unit in Fig. 2 has 11 additional convolution levels at the beginning and end of each unit. It helps decrease the number of variables without compromising or hindering system performance.

The system has three main components: the body, header, and layer. Preserving both maximum and mean activations in the final CL allows the neural network to identify the most effective approach without the need for individual trial and error. The outcome of the last layer's feature mapping surpasses the average results; conversely, the average results are inferior. The revised design integrates the VAP and VMP layers with the VCP level. ResNet50 applies a basic max-pooling operation on the activation output from the previous CL and passes it to the subsequent FC layer. Three distinct pooling levels connect the CL with the FC layers during the transition phase. The model retains the highest and average activations from the previous convolution, allowing it to gain insights and improve efficiency.

e. Categorization of PLD using ASVM

The SVM is a conventional method of supervised learning that is particularly effective in dealing with high-dimensional environments and imbalanced attribute values. SVM aims to preserve the greatest difference in attribute values between the groups to be classified. This marginal closeness refers to the maximum distance from the limit of choices. The proximity of the attribute values to the differentiating hyperplane determines its location. This paper presents two approaches utilizing an SVM classifier. The first approach does not employ the Adam optimizer. In contrast, the second approach incorporates the ASVM to improve the precision and execution speed of the SVM model parameters (kernel and P values) based on the provided information. The S parameter, often known as the " cost parameter," controls the balance between accurately categorizing training data points and the constraint on the number of choices.
The error function used to predict the category in the SoftMax layer is cross-entropy loss. Enhancing techniques such as illumination, affine transformations, rotations, warping, and brightness adjustments are used during the learning phase. An improved version of the Adam optimization algorithm has been used for optimization. The arduous process of training a system with a fixed speed is further improved using a one-cycle technique, where cyclic training speeds are used instead of constant values. It significantly improved classification accuracy by circularly altering the training speed within tolerable limits instead of gradually reducing it.

## 4. Experimental Results

In order to conduct the experiment, Google Colab, a GPU framework offered by Google, is equipped with a 50 GB hard drive and 25 GB of GPU-based RAM. The study performed experiments on the customized database by creating source and target models. The CNN architectures, including VGG-16, VGG-19, ResNet50, and improved ResNet50, have been used to extract features from the database. The classification process used a three-tier machine learning classification technique on the database, namely SVM and ASVM.

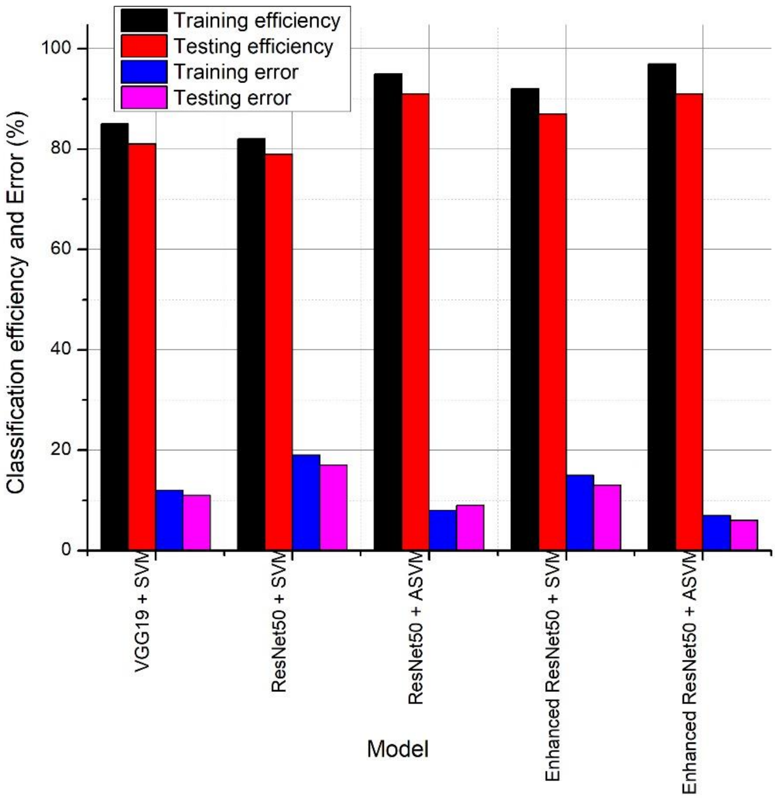


Fig. 3 Classification efficiency analysis (%) and error analysis (%) of various hybrid ML models

Fig. 3 depicts the classification efficiency analysis (%) and error analysis (%) of various hybrid ML models.

(i) The VGG19 + SVM model demonstrated a training accuracy of 85% and a testing classification accuracy of 81%. The error rates for training and testing were 12% and 11%, respectively.

(ii) The ResNet50 + SVM model exhibited a marginally reduced classification efficacy, achieving 82% accuracy during training and 79% during testing. The error rates for training and testing were 19% and 17%, respectively.

(iii) The fusion of ResNet50 and ASVM resulted in a notable improvement in classification efficiency, with a training accuracy of 95% and a testing accuracy of 91%. The error rates for training and testing decreased to 8% and 9%, respectively.

(iv) The Enhanced ResNet50 + SVM model obtained a training classification efficiency of 92% a testing classification efficiency of 87%. The error rates for training and testing were 15% and 13%, respectively.

(v) The Enhanced ResNet50 + ASVM model demonstrated superior performance, with a training classification efficiency of 97% and a testing classification efficiency of 91%. The error rates achieved the lowest values, with 7% for training and 6% for testing.

The Enhanced ResNet50 + ASVM model generally exhibited exceptional performance, achieving the maximum classification efficiency and lowest error rates throughout the training and testing stages.

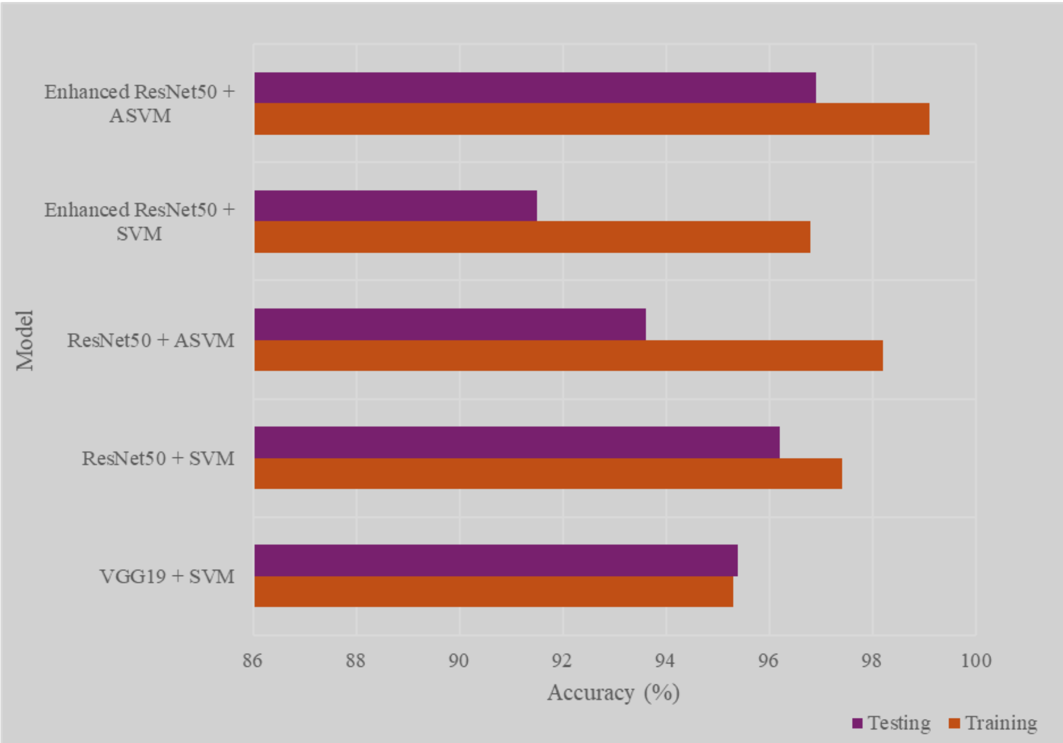


Fig. 4 Accuracy (%) of various hybrid ML models to detect PLD

Fig. 4 displays the accuracy of various ML models in both the training and testing stages. The VGG19 + SVM model has a training accuracy of 95.3% and a testing accuracy of 95.4%, demonstrating a consistent level of performance. The ResNet50 + SVM model demonstrates enhanced accuracy, achieving 97.4% during training and 96.2% during testing. Nevertheless, the ResNet50 + ASVM model has a training accuracy of 98.2% but experiences a decline to 93.6% during testing, indicating potential overfitting. The Enhanced ResNet50 + SVM model has a well-balanced performance, with a training accuracy of 96.8% and a testing accuracy of 91.5%. The Enhanced ResNet50 + ASVM model demonstrates the highest level of performance, with 99.1% accuracy in training and 96.9% in testing. This indicates its strong and dependable capacity to identify PLD.

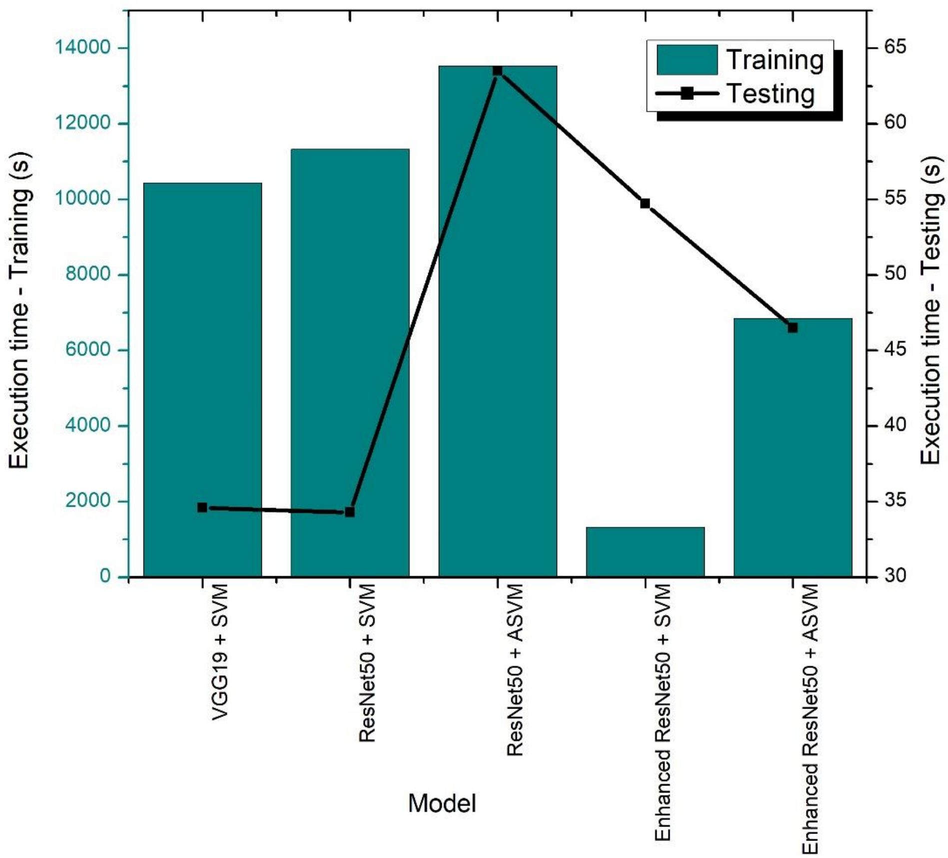


Fig. 5 Execution time (s) of various hybrid ML models to detect PLD

Fig. 5 shows the Execution time (s) of various hybrid ML models to detect PLD. The training time for the Enhanced ResNet50 + SVM model is 1324 seconds, which is the smallest, while the ResNet50 + ASVM model has the longest training time at 13,532 seconds. Regarding the duration of testing, the VGG19 + SVM model exhibits the shortest performance time, taking just 34.6 seconds, while the ResNet50 + ASVM model is the most time-consuming, requiring 63.5 seconds. In general, the Enhanced ResNet50 + SVM model is effective for training but requires 54.7 seconds for testing. On the other hand, the Enhanced ResNet50 + ASVM model balances reduced training and testing periods, with durations of 6,853 and 46.5 seconds, respectively.

## 5. Conclusion

This study presents an improved ResNet50 architecture-based EHMLM for the identification of PLD. The suggested method utilizes an improved ReNet50 framework to extract features. A classification task was performed using an ASVM. The Adam optimizer refines the conventional SVM hyperparameters to provide a more advanced performance model. The

ResNet-50 architecture successfully transfers the activation from the previous FC layer to the convolution layer via a process called max-pooling. This study aims to tackle agricultural disasters proactively by using an ML model to classify datasets of tomato leaf disease images and implement suitable measures. The plant-village database used in this investigation was obtained from a publicly available source. The Enhanced ResNet50 + ASVM model exhibited exceptional performance, with a training classification accuracy of 97% and a testing classification accuracy of 91%. The error rates reached their minimum levels, with 7% for training and 6% for testing. The Enhanced ResNet50 + ASVM model accomplishes a trade-off between shorter training and testing times, with 6,853 and 46.5 seconds, respectively.

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