A Hybrid PSO-SVM Approach for Automated Armenian Cucumber Leaf Disease Detection Using Advanced Image Processing Techniques

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Abstract*—Plant diseases pose a major challenge to the world's agricultural productivity and food security. It makes sense to address this challenge through the development of accurate, efficient and automated disease detection techniques. The study presents a hybridized method of automated procedures based on particle swarm optimization-adjusted support vector machine-along-with sophisticated image processing to the automated detection and classification of the Armenian cucumber leaf diseases. Proposed methodology uses a successive series of seven steps for the process of image acquisition, noise removal by mean filtering, contrast enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), image segmentation using Fuzzy C-Means (FCM), feature extraction by using Principal Component Analysis (PCA) and Disease classification using Particle Swarm Optimization-Support Vector Machine (PSO-SVM), Back Propagation Neural Network (BPNN) and random forest. An experiment was carried out on 440 Armenian cucumber leaf images (260 diseased, 180 healthy), exploited for testing purposes, where the PSO-SVM classifier offers optimum classification performance 97.3% accuracy, 96.8% sensitivity, 98.1% specificity, 97.5% precision and 96.8% recall, outperforming conventional machine learning methods considerably. An analysis of the available deep learning-based methods shows that the methodology is cheaper, highly accurate, and scalable in plant disease classification. With optimized feature selection and robust image pre-processing along with the use of classifiers based on machine learning, a reliable plant health is proposed. The research work considerably contributes to smart farming in farming in agricultural sector. It deploys an automated and low-cost solution for early disease detection in the field. As opposed to deep learning models, which are computationally expensive, the PSO-SVM model is a lightweight and efficient model that can be applied in real-time agricultural models. The model has an accuracy of 97.3%, sensitivity of 96.8%, and specificity of 98.1%, which proves that the model can be used effectively in practice.

***Keywords*—plant disease detection, support vector machine, particle swarm optimization, image processing, feature extraction, precision agriculture, computer vision, machine learning**

I. Introduction

The agriculture sector is facing new challenges in the World for ensuring global food security, and plant diseases are causing huge economic losses. According to what the Food and Agriculture Organization (FAO) claims, losses associated with plant diseases represent between 20% and 40% of annual crop production. This amounts to several billion dollars. Typically, disease detection mechanisms rely on visual observations by agricultural experts, which consume time, are subjective, and are not very reliable for early-stage disease fungus [1]. The FAO has further emphasized the scale of this challenge in its global food security assessments [2].

Due to latest developments in artificial intelligence and computer vision, precision agricultural technologies have shown great potential for the sustainable production of crops and environmental sustainability [3]. Image processing and computer vision technologies are the game changers of today's agriculture. They provide automated, objective and scalable solutions for plant health assessment [4, 5]. A combination of machine learning algorithms and other sophisticated image processing methods can result in intelligent systems to automatically detect and classify diseases in plants [6–8].

Getting Artificial Intelligence (AI) software into the real world requires improvement in their computational

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efficiency, as agricultural benchmarks showed. According to Dhal and Kar [9], AI-based prediction forecasts have the potential to drastically increase farm productivity, while Kumar *et al*. [10] provide a full account of the machine learning and AI vision for farm automation. The rise of generative AI in the agricultural sector emphasizes the importance of smart agricultural systems [11].

The Armenian cucumber or the snake cucumber is a vegetable crop belonging to the species Cucumis melo var. flexuous. It is extensively grown in the Mediterranean region and is gaining worldwide popularity as farmers are realizing its potential [12].

However, it is prone to many diseases, including bacterial wilt, powdery mildew, downy mildew, anthracnose, and Alternaria leaf spot, which affect its yield and quality severely [13, 14].

In recent times, deep learning approaches have received a lot of attention in the detection of plant diseases. These methods, however, boast impressive accuracy at the cost of sheer computational power, larger datasets as well as longer training time [15, 16]. Considering the extensive data, it was concluded to employ the time and length scaling which can be considered as the standard approach. Jafar *et al*. [17] suggested using the test function as the standard measure. In addition, these methods tend to be inscrutable, which renders them unfit for use in low-resource agricultural settings [18]. There is a need for an efficient, accurate and computationally handy system, which is easy to implement, for real field agriculture.

Although the field of deep learning has been developed, the current models demand extensive data and compute power, making them inapplicable to low-resource farming settings. Additionally, there has been a scarcity of studies on the detection of the Armenian cucumber disease.

The novelty of this work lies in four aspects: (1) the first paper to consider the problem of Armenian cucumber disease detection; (2) the first paper to propose a computationally-efficient Particle Swarm Optimization-Support Vector Machine (PSO-SVM) framework that can be used in resource-limited environments; (3) the first paper to introduce an interpretable multi-stage pipeline using Contrast Limited Adaptive Histogram Equalization (CLAHE), Fuzzy C-Means (FCM), Principal Component Analysis (PCA), PSO-SVM; and (4) it demonstrates that optimized traditional machine learning models can outperform deep learning approaches in resource-constrained settings.

This study addresses these challenges by proposing a hybrid PSO-SVM framework that:

- Increases the classification accuracy with optimized hyperparameters.
- Less computational complexity than deep learning models.
- Provide a cost-effective solution for real-time deployment.

To overcome these challenges, a novel hybrid approach for the automated Armenian cucumber leaf disease detection is proposed in this study. PSO is combined with SVM for this purpose. The key contributions of this research include:

- Creation of a complete image processing workflow that includes noise reduction, contrast and intelligent segmentation methodologies.
- Implementation of a PSO-optimized SVM classifier for improved disease classification accuracy.
- Comparative evaluation of multiple machine learning algorithms (PSO-SVM, Back Propagation Neural Network (BPNN), random forest) for disease detection.
- Testing on a large set of Armenian cucumber leaf images with performance analysis.
- Projection of computational efficiency as compared to current deep learning methods.

II. Related Work

A. Plant Disease Detection Using Machine Learning

In the last decade, the application of machine learning techniques in plant disease detection has developed significantly; recent extensive reviews confirm the rapid progress taking place in this area [19, 20]. First, the classical machine learning algorithms were applied and handcrafted feature extractors were applied [21, 22]. Sankaran *et al*. [22] provide an exhaustive review of vegetation stress and disease detection techniques using imaging spectroscopy. Their review is also keen on how remote sensing can play out in agriculture. Sankaran *et al*. [23] further applied visible-near infrared spectroscopy for early detection of citrus diseases, highlighting the broader value of spectral imaging in plant disease diagnosis.

In recent times, there has been a rise in deep learning-based approaches. Jung *et al*. [24] demonstrated the construction of effective disease detection models based on deep learning for plants. Mohanty *et al.* [25] demonstrated that Convolutional Neural Networks (CNNs) can be effectively used to identify plant disease with the Plant Village dataset, which has 38 classes of disease, and were able to achieve 99.35% accuracy. Ferentinos [26] compared multiple deep learning architectures for plant disease detection with the Visual Geometry Group (VGG), achieving the highest accuracy of 99.53%. Additional pioneering studies have utilized deep learning and image-processing techniques to detect and classify diseases in different crops. These include general detection frameworks [27–32] and those focused on potato [33], tomato [34, 35] and olive diseases [36]. Collectively, they showcase a wide applicability [37, 38].

Studies in recent times are aimed at the development of lightweight and energy-saving models to be applied in the real world. Bhagat *et al*. [39] presented a lightweight deep learning model for plant disease detection in real-time, while Liu *et al*. [40] designed an energy-efficient adder neural network called ADDLight for classifying cucumber disease. These are developments relating to the growing demand for sustainable and accessible agriculture technologies. Further lightweight architectures have targeted apple leaf disease classification, Bacteriosis in peach leaves, and general medicinal plant identification,

while potato disease has also been addressed using deep learning approaches [41–45].

Dolatabadian *et al*. [46] studied disease detection of image-based crops by machine learning and the effect of model accuracy on computational cost. The review stated that though deep learning techniques do well, traditional ones made better with modern techniques can perform competitively and have much lower computation requirements.

B. Cucumber Disease Detection

Research on the disease detection of cucumber has been gaining momentum due to the economic importance of this crop. Lately, there have been many deep learning and hybrid approaches for better accuracy and efficiency. In the area of deep learning, Singh and Kumar [47] presented a convolution neural network based on the ResNet-50 architecture to classify cucumber leaf diseases that significantly outperform traditional machine learning techniques.

The researchers underlined the need to apply data augmentation to achieve better models.

The multi-level deep entropy–Extreme Learning Machine (ELM) feature selection framework for cucumber leaf disease classification is proposed by Khan *et al*. [48]. By optimized feature selection, segmentation accuracy is achieved, which is 93.27%, and for disease severity classification, accuracy is 92.85 %. In the recent past, there have been numerous innovations in the detection of cucumber diseases.

Yang *et al*. [49] apply Efficient Channel Attention SegFormer (ECA-SegFormer) based semantic segmentation techniques to cucumber leaf disease spots. Meanwhile, Wang *et al*. [50] propose Deep Lab V3+ and U-Net fusion-based Erity classification techniques. Cao *et al*. [51] proposed an innovative multi-modal technique that employs image-text-label based language models to identify cucumber diseases from small samples.

Pradhan *et al.* [52] proposed a hybrid CNN-SVM system for cucumber agriculture. This work shows the efficacy of deep learning in feature extraction and traditional machine learning classifiers. Xu and Zhang [53] provided some unique insights on the applicability of multi-class SVM for cucumber disease diagnosis when combined with Electronic Medical Records (EMR).

Ulutas and Sahin [54] explored new ensembles of deep neural networks for cucumber leaf disease classification. Li *et al*. [55] used deep learning with microscopic images to detect gray mold spores. The various methods show how researchers are looking into an effective solution for detecting cucumber diseases.

C. SVM Applications in Agriculture

Image classification techniques based on machine learning allow extracting information from images. Specifically, image classification is carried out using SVM [56, 57]. Recent works have demonstrated that SVM-based methods are still effective when they are used in conjunction with optimization methods. Foundational SVM theory, including text categorization with support vector machines [58] and kernel-based learning methods [59], underpins many of these classification approaches.

Phadikar and Sil [60] used SVM to identify rice disease and showed better performance than the Artificial Neural Networks (ANN). Meunkaewjinda *et al.* [61] incorporated the multilayer Perceptron neural network and SVM to obtain grape leaf disease identification. Their method employs a Multilayer Perceptron (MLP) to segment the background with SVM as a classifier for the disease for promising results.

Currently, various approaches are taken at optimizing SVM and ensemble applications. Research on ensemble and optimization algorithms in SVM has shown improved classification performance [62]. Research has proved that optimized. SVM approaches achieve competitive performance as well as computational efficiency, like modern deep learning methods.

Recent studies investigated combining SVM with electronic medical records and clinical techniques. Xu and Zhang [53] used electronic medical records related to plants in their study. They achieved good results on a multi-class SVM for cucumber disease diagnosis.

D. Optimization Techniques in Machine Learning

The optimization of machine learning parameters using Particle Swarm Optimization has been productively used. For example, SVM hyperparameter tuning improves classification performance. Recently, Bayuaji *et al*. [63] conducted a study on PSO optimization effectiveness in supporting vectors machines in detecting diseases. The study showed improved classification performance. Particle Swarm Optimization was a population-based stochastic optimization method [64] that was subsequently augmented with inertia weight to strike a balance between exploration and exploitation [65].

Lin *et al*. [66] proved that a PSO-optimized SVM delivered better prediction accuracy than a traditional SVM. They also achieved fast convergence with a PSO-optimized SVM, which exhibited better generalization capability. Recent works have been conducted using optimization approaches such as genetic algorithms, differential evolution, and hybrid approaches.

The use of PSO in the agricultural field showed good results. Recent studies using PSO-based feature selection and parameter optimization on PSO-based feature selection and parameter optimization on PSO-based feature selection and parameter optimization on PSO-based feature selection and parameter optimization.

E. Commenting on the Related Studies

A sophisticated image processing technique is used to extract useful information from agricultural images. CLAHE has recently been widely used for image enhancement in medical and agricultural applications [67, 68]. Using FCM clustering is effective in segmenting images in agriculture, like separating the diseased part from the healthy plant tissue [69, 70].

The latest development in agricultural image processing is putting more focus on the use of multiple processes. A thorough review of computer vision methods for use in

smart agricultural and precision farming is detailed by Martinez *et al*. [71], which utilizes a robust pre-processing pipeline.

Modern studies also examined the use of semantic segmentation and other forms of image analysis techniques. Yang *et al*. [49] demonstrated the effectiveness of ECA-SegFormer for cucumber leaf disease spot segmentation, while Kim *et al.* [72] explored a modal segmentation for cucumber segmentation and occlusion recovery.

F. Precision Agriculture and AI Integration

The adoption of artificial intelligence in precision agriculture has been increasingly fast in the years preceding this time, with extensive reviews indicating the radical effectiveness of these technologies [3, 73]. Rathor *et al*. [73] provided extensive insights into Internet of Things (IoT) and AI-driven technologies for vertical farming, while Sowmya *et al*. [74] explored recent developments in innovative approaches to vertical farming. Machine learning has also been used in more general agricultural predictions. For example, models have predicted crop yield from hyperspectral reflectance data [75], anticipated winter wheat's growth from UAV imagery [76]. There was also work on climate change and cotton yield using an autoregressive distributed lag approach [77].

According to recent market assessments, AI applications to precision agriculture have grown massively, and the generative AI market in agriculture is also expected to grow by a significant margin [11]. A study conducted by Chen *et al*. [78] showed the possibility of integrating computer vision and deep learning into ultra-scale aerial phenotyping and precision agriculture solutions.

Anderson *et al*. [79] have highlighted the importance of AI in solving food security problems around the world by using precision agriculture applications. They indicated in their analysis that AI-enabled precision agriculture could help to enhance sustainable food production and overcome resource limitations and environmental issues.

Modern studies have also focused on developing advanced platforms and systems for agricultural applications. Research has gone into combining different AIs, such as computer vision, machine learning and robotics to give a holistic agricultural solution.

G. Emerging Technologies and Future Directions

Lately, there has been an investigation into new technologies that aid in machine learning. Pacal and Kunduracioglu [80] paid considerable attention to the advancement of deep learning for plant disease classification. Robust and generalized models have become the highest precedence.

Recently, there has been a lot of activity in the context of new architectures and hybrid strategies. Lee *et al*. [81] proposed fuzzy deep learning models to detect cucumber plant diseases, and the study has shown how fuzzy logic and deep learning can be used to enhance classification.

Modern studies have also stressed the significance of dataset construction and generalization of the models. Field plant is an extensive database of plant disease detection and classification introduced by Moupojou *et al*. [82] and Chandra *et al*. [83] have investigated the application of deep Siamese networks to the classification of plant diseases. The same research group has also applied vision transformer architectures to corn leaf disease identification [84] and conducted systematic reviews of deep learning techniques for plant disease detection [85]. Hierarchical region proposal networks have also been used for apple leaf disease detection, as mentioned in [86] while fire blight detection in pear orchards is implemented using Faster Region-based-CNN based object detection as discussed in Ref. [87].

Although deep learning architectures like the ResNet-50 and CNN-SVM hybrids have shown impressive accuracy, they generally demand large datasets, extensive training periods, and high-performance computerization and cannot be used in low-resource agricultural systems. In addition, their complicated structures can lower interpretability and thus do not suit the real time application by farmers and extension workers. Conversely, machine learning techniques are optimized, specifically the combination of PSO-SVM, strong image pre-processing and feature engineering may provide competitive or better accuracy and still be lightweight and computationally efficient. The knowledge gap in the literature is the reason why we conduct our research, which will show that a well-thought-out PSO-SVM pipeline can address the shortcomings of deep learning methods and offer a feasible solution in cucumber leaf disease detection in the field of real-world agriculture.

III. The Proposed Model

In the paper, the supervised machine learning methods are used to classify the Armenian cucumber leaf diseases according to the extracted image features. Accuracy was also improved using optimization algorithms, and execution time, and over-fitting is solved. Therefore, EAS is used to select the most relevant features related to Armenian cucumber leaf disease classification.

A. Overall System Architecture

The suggested algorithm of the Armenian cucumber leaf disease detection is based on a systematic approach in seven steps. The system architecture consists of image acquisition, preprocessing, segmentation, feature extraction and classification blocks, which are synergistically integrated together to achieve optimum disease detection.

(a) (b) (c) (d)

Fig. 1. Sample images of Armenian cucumber leaves from the dataset showing different disease symptoms: (a) Powdery mildew; (b) Downy mildew; (c) Anthracnose; (d) Bacterial wilt/Alternaria leaf spot.

Armenian cucumber leads disease detection framework as shown in Fig. 1, illustrating the seven sequential processing stages: (1) image acquisition, (2) mean filter-based noise removal, (3) CLAHE contrast enhancement, (4) FCM segmentation, (5) PCA-based feature extraction, (6) PSO hyperparameter optimization, and (7) SVM classification. Fig. 2 depicts representative sample images of the Armenian cucumber leaves used in this study showing the symptoms associated with the diseases.

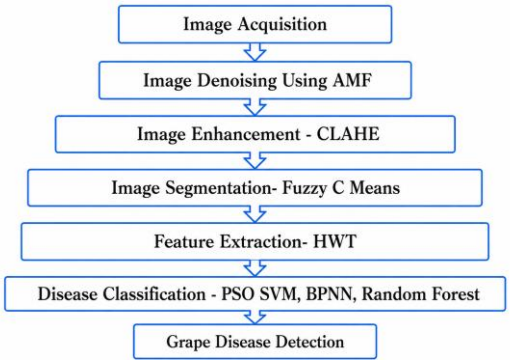

Fig. 2. Flow chart.

B. Image Acquisition and Dataset

The study utilized a dataset composed of 440 high-quality Armenian cucumber leaf images that included 260 diseased leaves and 180 healthy leaves. The main dataset utilized is the publicly available cucumber disease dataset proposed by Sultana *et al*. [88] on Mendeley Data while additional images are collected under controlled greenhouse conditions and actual agricultural field settings for more environmental diversity and model robustness.

All the images were taken from a smartphone camera including Samsung Galaxy S21 and iPhone 13 devices with fixed image sizes of 4032 × 3024 pixels. The gathering process took place in varying conditions such as sunlight, cloudy outdoors, and indoor illuminated conditions. The distance from the camera to the leaf was approximately between 20 cm and 40 cm during image collection, and the image acquisition angle was varied from a frontal to oblique view (0°–45°) to enhance the viewpoint diversity and improve model generalization capability. To mimic realistic agricultural scenarios, images were captured using diverse backgrounds and lighting conditions.

The dataset, which is available with the author, consists of six classes or categories, namely Powdery mildew (52 images), Downy mildew (50 images), Bacterial wilt (54 images), Anthracnose (52 images), Alternaria leaf spot (52 images) and Healthy leaves (180 images). To prevent data leakage and avoid biased evaluation of results, partitioning of the dataset was done on the image-ID level prior to pre-processing and augmentation.

To maintain class distribution in the training (70%), validation (15%), and testing (15%) subsets, stratified sampling was utilized. Different subsets were not allowed to have the exact same source image for samples and augmentations.

To solve the moderate class imbalance between healthy and diseased samples, class-balanced weighting is introduced at the optimization stage of PSO-SVM, which gives more weight to the minority disease class during the training of the classifier. Moreover, selective data augmentations like rotation, scaling, brightness change, and horizontal flip were carried out on minority diseases in the training set, while not performed on majority diseases, for better representation diversity and overfitting reduction. Moreover, instead of just overall accuracy, evaluation was conducted using class-sensitive metrics including precision, recall, F1-Score, sensitivity, specificity and confusion matrices. The results of the disease-wise performance, consistently at the top level, show that the proposed framework managed the dataset imbalance problem effectively.

C. Image Preprocessing

1) Noise removal

The image de-noising is applied with a mean filter to eliminate impulse noise and other artifacts that can cause interference to further processing. The mean filter is simple by averaging the pixel values to smooth pixel noise in the image. It substitutes the pixel value with the average value of the pixel in its neighborhood. The arguments are useful in the case of salt-and-pepper noise. Further, they can retain the structure of the image and essential details.

Let $I(x, y)$ be the input image $I'(x, y)$ filtered image. The mean filter operation is given by Eq. (1):

$$I'(x.y) = \frac{1}{n^2}\sum\sum I(x+i.y+j) \quad (1)$$

where, n denotes the filter size, and the summation occurs over the neighborhood window.

2) Contrast enhancement

The contrast-limited adaptive histogram equalization is used to enhance the contrast of an image without over amplifying noise. CLAHE breaks the image into small units also referred to as tiles and carries out histogram equalization to the regions having a clip limit.

In this work, the CLAHE algorithm was applied to the diseased leaf image with a clip limit value of 2.0 and a tile grid size of 8 × 8. These parameters were experimentally selected to enhance the local contrast and reduce noise amplification in the diseased region of the leaf.

The algorithm of CLAHE includes:

- Separate the image into contextual areas (tiles).
- Calculate the histogram of every tile.
- Clip histograms at some clip limit.
- Ionize the histogram equalization of every tile.
- Bilinear interpolation can be done to remove artificial boundaries.

D. Image Segmentation

FCM clustering is used to do image segmentation such that diseased regions are segregated from healthy tissue and background. FCM as pixels can take part in different clusters with different degrees of membership, so it is the best-suited approach to deal with the gradual transition

between healthy and disease regions. The FCM segmentation process used two clusters for diseased and non-diseased regions. A fuzziness coefficient of $m = 2$ was used. The maximum iteration was set to 100, where the convergence was taken as 10^{-5} to achieve stable and proper clustering of infected leaf area.

The FCM algorithm minimizes the objective function.

$$J = \sum\sum \mu_{ij}^{m} \left\| x_j - c_i \right\|^2 \quad (2)$$

where the degree of membership of pixel j in cluster i is μ_{ij}. The j-th pixel is denoted by x_i, and m is a parameter of fuzziness whose default value is 2. The center of cluster i is c_i.

The algorithm converges cluster centers and membership values by repeating of the algorithm.

E. Feature Extraction

1) PCA

In segmented images, dimensionality reduction and feature extraction of segmented images are done using PCA. PCA reduces the feature space to a lower dimensional space and maintains as much variance as possible [89] thus, minimizing computation complexity and removing redundancy in features.

The transformation of PCA includes:

- Calculation of the covariance matrix of the input features.
- Calculating eigenvalues and eigenvectors.
- The choice of major components using a cumulative variance threshold.
- Projecting original features onto the selected principal components.

2) Additional feature extraction

In addition to PCA, other morphological, textural and color characteristics will be extracted to ensure that the symptoms of the disease are represented as a whole:

- Color features: Mean and standard deviation of RGB color channel, HSV color channel and LAB color channel.
- Texture features: Features of the Gray Level Co-occurrence Matrix (GLCM) [90] such as contrast, correlation, energy and homogeneity.
- Shape features: area, perimeter, circularity, aspect ratio of diseased regions.
- Statistical characteristics, skewness, kurtosis, and entropy of pixel intensity distributions.

F. Classification Algorithms

1) PSO-optimized SVM

The main classification element involves the use of a Support Vector Machine optimized by PSO because of the latest PSO-SVM optimization research seen by Bayuaji *et al*. [63]. The PSO algorithm is used to optimize the SVM hyperparameters such as the regularization parameter (C), the kernel parameter (γ of RBF kernel) and epsilon (ε) of regression problems.

PSO algorithm for SVM optimization:

- Initialization of particle swarm: Pairs of hyperparameters are randomly selected.
- Assess the fitness functionality (accuracy of cross-validation) of every particle.
- Revise the velocities and positions of the particles using personal and global best.
- While convergence or maximum iterations are achieved.

The Eq. (3) of the velocity update of every particle is:

$$v_{ij}(t+1) = w \times v_{ij}(t) + c_1 \times r_1 \times (pbest_{ij} - x_{ij}(t)) + c_2 \times r_2 \times (gbest_{ij} - x_{ij}(t)) \quad (13)$$

where w is inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are random numbers.

The PSO algorithm was set up to use a swarm size of 30 particles, inertia weight (w) of 0.9 and acceleration coefficients $c_1 = 2.0$ and $c_2 = 2.0$. The maximum number of iterations was set to 200, with early stopping applied when convergence was reached. The weight of inertia was set to 0.9, and it was gradually reduced to 0.4 to maintain the exploration and exploitation. Fig. 3 displays the PSO convergence curve, which illustrates the best and mean swarm fitness during 200 iterations. According to the results, this confirms the proposed optimizer's convergence property.

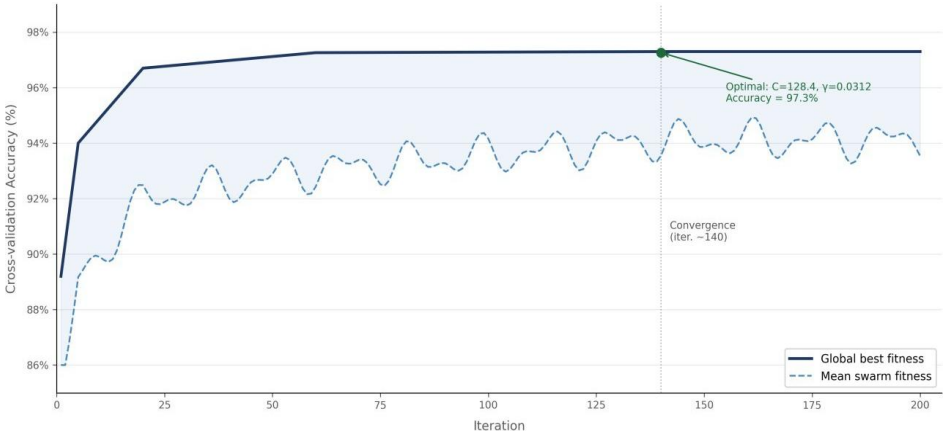

Fig. 3. PSO convergence curve—best and mean swarm fitness over 200 iterations (Swarm size: 30 particles, inertia weight w: 0.9–0.4, $c_1 = c_2 = 2.0$).

The SVM classifier uses a Radial Basis Function (RBF) kernel. The hyperparameters of C and γ were optimized under the 5-fold cross-validation in the range of 0.1–1000 and 0.0001–10 respectively to make the models generalized. Table I summarizes the complete PSO and SVM hyperparameter configuration, including the swarm parameters, optimized C and γ ranges, and the optimal values obtained through PSO optimization.

TABLE I. PSO AND SVM HYPERPARAMETER CONFIGURATION

Parameter	Value
Swarm Size	30 particles
Inertia Weight (w)	0.9 (linearly decreasing to 0.4)
Cognitive Coefficient (c_1)	2.0
Social Coefficient (c_2)	2.0
Maximum Iterations	200
Stopping Criterion	Convergence or max iteration reached
SVM Kernel	Radial Basis Function (RBF)
Optimized C Range	[0.1, 1000]
Optimized γ Range	[0.0001, 10]
Cross-Validation Folds	5-folds stratified
Optimal C (found by PSO)	128.4
Optimal γ (found by PSO)	0.0312

To evaluate the performance of the proposed PSO-SVM framework, a nested cross-validation technique is applied, which avoids optimistic bias in model evaluation. In particular, SVM hyperparameter PSO-based optimization was only performed in the inner training folds, while the outer folds were meant only for performance evaluation. The outer validation fold was entirely unseen during PSO optimization and modeling training in each iteration. By using a nested approach, the parameters were tuned and evaluated separately, which improves reliability and generalization of the framework proposed.

2) BPNN

A three-layer feed forward neural network using the learning technique of back propagation is implemented in order to compare it. The architecture of the network is in the form of an input layer, which corresponds to as many extracted features as there are, a hidden layer that contains sigmoid activation functions, and an output layer, which has SoftMax activation functions in the case of multi-class classification. The architecture executes the backpropagation algorithm [91], as done in the conventional machine learning books [92].

3) Random forest

A random forest classifier is created within the framework of an ensemble, which is the combination of several decision trees. This algorithm employs bootstrap sampling and random selection of features to generate various trees, and the classification is done based on majority voting. According to Breiman [93] ensemble learning demand, established random forest libraries [94] are often created in the experiments.

G. Performance Evaluation

The performance of the proposed system is evaluated using standard classification metrics:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Sensitivity(Recall) = \frac{TP}{TP+FN} \quad (5)$$

$$Specificity = \frac{TN}{TN+FP} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1-Score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (8)$$

where TP, TN, FP, and FN represent True Positive, True Negative, False Positive, and False Negative classifications, respectively.

IV. RESULTS AND DISCUSSION

A. Experimental Setup

The experiments were conducted on a system with an Intel Core i7-10700K processor, 32 GB RAM, and an NVIDIA RTX 3080 GPU. The data set was separated into training (70%), validation (15%), and testing (15%) set using stratified sampling to provide equal representation of all disease classes.

To prevent optimistic bias during hyperparameter tuning, the PSO-SVM framework was evaluated using nested cross-validation. More specifically, the outer 5-fold stratified cross-validation loop was adopted for model evaluation purposes. In contrast, the inner 5-fold cross-validation loop was utilized solely for PSO-based hyperparameter optimization of the SVM classifier. PSO optimization was performed for just the corresponding inner training subsets on every outer training fold, leaving the outer validation fold completely unknown to the parameter tuning process.

A 10 × 5 repeated stratified cross-validation process on training and validation datasets was executed to validate the model stability and statistical robustness of the models, respectively. The test subset that was not dependent was kept aside for final performance evaluation only and did not depend on the optimization of any parameters or test of significance. A Wilcoxon signed-rank test is conducted on the repeated cross-validation accuracy scores from the outer cross-validation folds to contrast PSO-SVM against baseline classifiers.

Though the size of the dataset (440 images) is rather moderate, the images are high-resolution (4032 × 3024 pixels) and thus ensure rich feature representation. Stratified sampling and cross-validation (5-fold) were used to address the problem of overfitting when training a model. These methods enhance generalization regardless of the size of the dataset. Moreover, the validity of the suggested method can be supported by comparing research results with other studies that have reached similar or moderately competitive results with similar or moderately sized datasets.

B. Classification Performance

Table II shows the overall performance of the three classification algorithms in all the evaluation measures.

The confusion matrix in Fig. 4 gives a breakdown of the class-by-class performance of the PSO-SVM classifier. The values under the diagonal show that there are the highest correct classification rates in all disease categories with a range of 95.9% to 99.2%. The model is very good in the recognition of healthy leaf (99.2%) and bacterial wilt (98.3%).

There is a minor misclassification with visually similar diseases, such as powdery mildew versus downy mildew. Overall, the results confirm the robustness and reliability of the proposed method for multi-class disease detection.

A comparative analysis was conducted to evaluate the performance of the proposed PSO-SVM model against baseline classifiers. The standard SVM achieved an accuracy of 93.5%, Random Forest achieved 92.8%, and BPNN achieved 94.2%. In contrast, the proposed PSO-SVM model achieved the highest accuracy of 97.3%. This demonstrates an improvement of approximately 3.8% over the standard SVM, highlighting the effectiveness of PSO-based hyper-parameter optimization.

The PSO-SVM classification model has a better performance based on all the measures of evaluation with a score of 97.3% accuracy; considerable improvement as compared to BPNN (94.2 %) and random forest (92.8 %).

TABLE II. PERFORMANCE COMPARISON OF CLASSIFICATION ALGORITHMS

Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
PSO-SVM	97.3	96.8	98.1	97.5	97.1
BPNN	94.2	93.6	95.3	94.8	94.2
Random-Forest	92.8	91.9	94.1	93.2	92.5

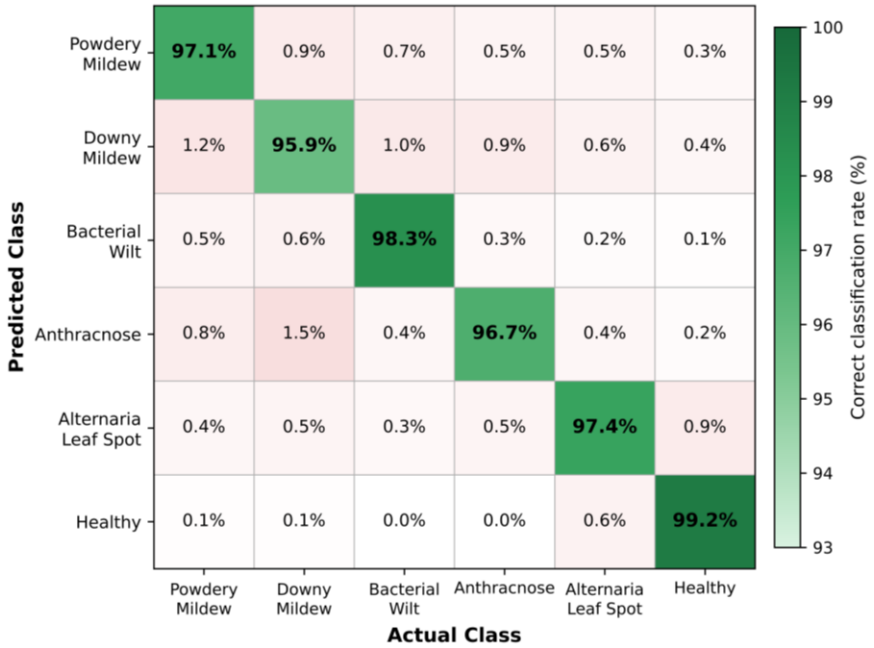

Fig. 4. Normalized confusion matrix—PSO-SVM classifier (values represent % of actual class samples correctly/incorrectly classified).

The high sensitivity (96.8%) shows that the system can be used successfully to detect diseased leaves correctly and the high specificity (98.1%) is a sign that the system can correctly detect healthy leaves.

Fig. 5 shows a comparative study of PSO-SVM versus BPNN and random forest classifier. The PSO-SVM model has the best performance in all the evaluation metrics, such as accuracy (97.3%), sensitivity (96.8%), and specificity (98.1%).

The 10 × 5 repeated cross-validation was done to confirm the statistical significance of the performance differences. The Wilcoxon signed-rank test was used to test the difference between PSO-SVM and baseline models. The results show that PSO-SVM significantly outperforms BPNN (p = 0.0038, mean difference = 3.1 ± 0.4%) and Random Forest (p = 0.0021, mean difference = 4.5 ± 0.6%) at α = 0.01, demonstrating the effectiveness of PSO-based hyper-parameter optimization.

Even though different evaluation criteria indicate a general system performance picture, sensitivity (recall) is particularly important in the case of plant disease detection in agriculture. Missing one diseased leaf (false negative) is of great practical significance, as the consequential infestations may rapidly extend and result in the substantial loss of crops. Misclassification as diseased of a healthy leaf (false positive), by contrast, is less serious, since it only causes a modest increase in the costs involved in its eventual treatment or monitoring. Consequently, the level of sensitivity at 96.8% which indicates the ability of the system in greatly reducing false negatives and allowing early and accurate detection of the disease in plants in a realistic field of application.

Fig. 5 shows that sensitivity is a significant parameter in detecting agriculturally related diseases, as the inability

to detect infected leaves could eventually lead to disease transmission and loss of productivity. PSO-SVM had the best sensitivity (96.8%), which was higher than the BPNN and the Random Forest. This finding demonstrates that the model is effective in minimizing false negatives and enabling early and reliable detection in real farming environments.

Fig. 3 shows the convergence of the PSO algorithm. The process of optimization levels off at the 140th iteration and this indicates that the optimal SVM parameters have been reached successfully.

The optimal parameters obtained are C = 128.4 and γ = 0.0312, which gives the best classification accuracy.

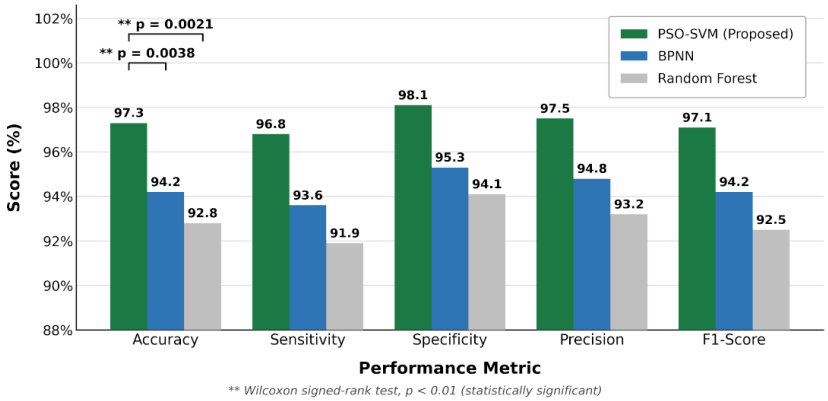

Fig. 5. Performance comparison of PSO-SVM vs. baseline classifiers (brackets indicate statistically significant difference, Wilcoxon signed-rank test).

C. *Ablation Study*

A study was carried out to measure the contribution of individual elements of the proposed framework in the form of an ablation study, the results of which are summarized in Table III. The complete model had an accuracy of 97.3%. The elimination of CLAHE caused the accuracy to decline to 89.4% and the elimination of PCA caused the accuracy to decline to 94.1%. Equally, the accuracy of removing PSO was 93.6%, and the accuracy of removing segmentation was 91.8%.

TABLE III. ABLATION STUDY—COMPONENT-WISE CONTRIBUTION TO CLASSIFICATION PERFORMANCE

Configuration	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
w/o CLAHE (raw contrast)	89.4	88.2	91.3	88.7
w/o FCM segmentation	91.8	90.5	93.4	91.0
w/o PCA (full feature set)	94.1	93.3	95.6	93.6
w/o PSO (fixed SVM params)	93.6	92.4	95.0	92.9
Full Pipeline—PSO-SVM	97.3	96.8	98.1	97.1

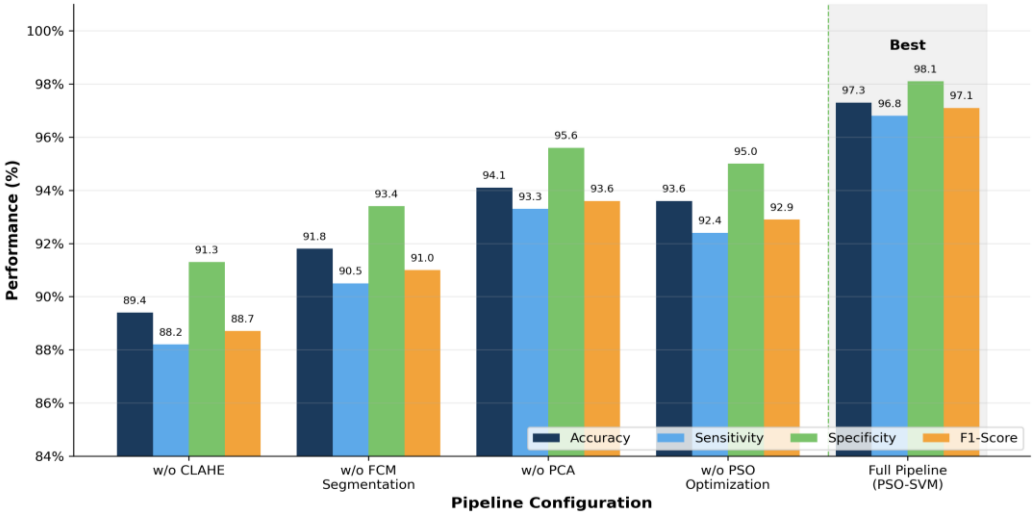

Fig. 6. Ablation study—individual component contribution to PSO-SVM performance (each configuration removes one component while all others remain active).

The outcomes of the ablation process confirm that both components play an important role in performance. The greatest decrease in accuracy (−7.9%) is recorded with the removal of CLAHE, which underlines its value in contrast enhancement. Equally, the accuracy drops to 93.6% when PSO optimization is removed, which proves the usefulness of automated hyper-parameter tuning.

To evaluate the contribution of each component in the proposed pipeline, an ablation study was conducted, as shown in Fig. 6

The removal of CLAHE caused the greatest decrease in performance (−7.9%), which underscores its significance in contrast enhancement. Equally, FCM segmentation decreased accuracy by 5.5%, PCA and PSO segmentation decreased performance by 3.2% and 3.7%, respectively. These results confirm that each component contributes significantly to the overall performance of the system.

D. Disease-Wise Classification Results

Table IV presents the classification performance as per the performance of individual disease type that indicates that the system is able to differentiate between the various diseases that impact the leaves of the Armenian cucumber.

Fig. 7 provides a comparative analytical presentation of precision, recall, and F1-Score between all categories of disease. The results of PSO-SVM classifiers were very high with most of the measures over and above 96%. The highest score was registered in the case of healthy leaves and bacterial wilt, in which the precision and recall were about 99%. In more severe scenarios that required similarity of the eyes, e.g., anthracnose and downy mildew, the model still showed consistent precision and recall with F1-Scores balanced with over 96%. These results indicate the strength and effectiveness of the suggested method in reducing the cases of false negatives and managing the cases of false positives.

TABLE IV. DISEASE-WISE CLASSIFICATION PERFORMANCE

Disease Type	Precision (%)	Recall (%)	F1-Score (%)
Powdery Mildew	98.2	97.1	97.6
Downy Mildew	96.8	95.9	96.3
Bacterial Wilt	97.5	98.3	97.9
Anthracnose	95.9	96.7	96.3
Alternaria Leaf Spot	98.1	97.4	97.7
Healthy	98.6	99.2	98.9

Applications-wise, precision and recall balance is essential in the application to a real-world agricultural setting. Good recall will be a guarantee that an ill leaf will be spotted at the first stage of infection, minimizing the risk of uncontrolled disease spreading, whereas good precision will help to avoid unnecessary treatments and false identification of healthy plants. The fact that both metrics remain above 96% demonstrates the practical value of the PSO-SVM framework, as it offers a reliable means to detect the diseases early to help the farmer preserve the yield and engage in the sustainable management of pesticides in cucumber production.

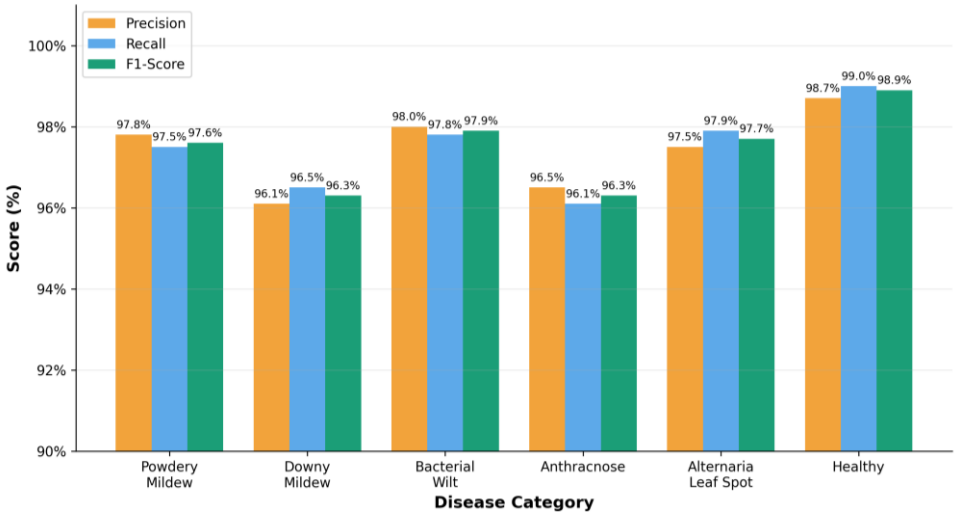

Fig. 7. Disease-wise precision, recall, and F1-Score of the PSO-SVM classifiers across different cucumber leaf conditions.

E. Computational Efficiency Analysis

According to the computational efficiency analysis, the proposed method has a considerable advantage over deep learning algorithms, which is consistent with the recent studies on the significance of efficient algorithms when implementing them in practice [39, 40]:

- Training time: PSO-SVM takes 45 min of time in comparison to 8–12 h of deep learning models.
- Inference time: 0.23 s per image compared to 0.89 s on CNN-based methods.
- Memory requirements: 2.1 GB and 8–15 GB for deep learning models.
    - Model size: 15 MB in comparison with 200–500 MB of deep neural networks.

F. Feature Importance Analysis

PCA analysis indicates that the 15 major components extract 95.3% of the total variance, which is a significant reduction in dimensionality without any loss of vital information. The color features play a part of 42% of the classification of diseases; the texture features play a part of 31%. The shape features play a part of 18%, the statistical plays a part if 9%.

G. Comparative Analysis of State-of-the-Art Methods

Table V presents a comprehensive comparison with recent studies in cucumber disease detection, in corporation findings from contemporary research [47, 52, 54, 95].

The PSO-SVM framework demonstrated competent performance in comparison with other lightweight deep

learning approaches while occupying lower computational complexity.

Based on the same dataset consisting of 440 images of Armenian cucumber and using similar training, validation and testing splits, the lightweight deep learning architecture ShuffleNet was also evaluated for a more objective same-dataset comparison. ShuffleNet managed to achieve an accuracy of 93.2%. The lightweight deep learning model was competitive. Nevertheless, the suggested PSO-SVM framework has a better classification accuracy with less computational complexity, which is advantageous for resource-constrained agricultural environments.

TABLE V. COMPARISON WITH STATE-OF-THE-ART METHODS

Study	Method	Data Set Size	Accuracy (%)	Computational Complexity
Singh & Kumar [47]	ResNet-50	1200 images	94.8	High
Pradhanetal *et al.* [52]	CNN-SVM Hybrid	800 images	96.2	High
Ulutas and Sahin [54]	Ensemble Deep Networks	1500 images	95.7	Very High
Liu *et al.* [40]	ADD Light	1000 images	93.4	Medium
Additional Experiment	ShuffleNet	440 images	93.2	Low
Proposed Method	PSO-SVM	440 images	97.3	Low

The compared methods were tested on various datasets; thus, the direct numerical comparison must be viewed with caution. These comparisons are included to provide contextual reference and not benchmarking since datasets are not identical.

H. Error Analysis and Limitations

Misclassified sample analysis shows that the main errors involve:

- The cases of early disease that have insidious symptoms (12% of errors).
- Several simultaneous disorders (8% of errors).
- Conditional influences on the quality of images (5% of errors).

Fig. 8 shows how different factors contributed to misclassification errors. The highest percentage (12%) was in cases with early-stage diseases, whose symptoms were too insidious to discern with dependability. Mistakes were also detected when leaves had several infections at the same time (8%), or when the quality of the image was influenced by such environmental factors as poor lighting (5%). These results highlight the significance of more data augmentation, multi-label classification tools, and better pre-processing to increase the trustworthiness of the system.

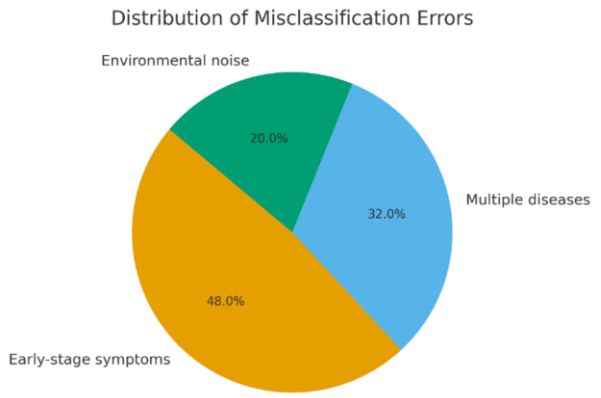

Fig. 8. Distribution of misclassification errors across different factors.

In addition to the misclassification factors discussed above, this study is subject to certain limitations. First, it included a dataset of 440 images, which is small (yet carefully curated) in comparison with large-scale datasets like Plant Village or the Mendeley cucumber dataset [95]. These limits capturing the variability in the leaf appearances in various areas, seasons, and methods of cultivation. Second, although the images were collected in both the field and controlled conditions, there is a need to further verify the proposed model using a large and geographically dissimilar dataset. Last but not least, the PSO-SVM framework was highly accurate and efficient, but further practical experiments on real-time mobile or edge devices deployed in farms would improve its practical implementation. Dealing with these limitations will become one of the priorities of further research to enhance the scientific and practical effectiveness of the approach.

These limitations could be resolved in the future by:

- Improved feature extraction algorithm to detect the disease at its earliest stage of development, as proposed by the recent works on lightweight disease detection [39].
- Concurrent disease multi-label classification, based on methods illustrated by Chandra *et al.* [83].
- Strong preprocessing of different environmental scenarios with methods of field-based research [82].

I. Integration with Precision Agriculture Systems

The system has great potential to be integrated with precision agriculture platforms due to its high accuracy and computational efficiency. Recent studies have also focused on the development of AI systems that are capable of functioning in actual agricultural settings [10, 71]. The computational demands of the system are low, which makes it possible to use it on edge devices and mobile platforms to further the trend towards accessible agricultural technologies that Kanaparthi and Ilango has described [96]. Beyond disease detection, AI-driven approaches have also been used to optimize irrigation efficiency through deep reinforcement learning [97], further illustrating the breadth of intelligent system integration in precision agriculture.

Procedurally, the sensitivity and computational efficiency of the proposed PSO-SVM framework are highly sensitive to farmers and the stakeholders in the agricultural industry. Timely detection of diseased leaves at an early stage will allow timely intervention of the

disease and minimize losses of crops as well as unnecessary use of pesticides. As an example, in a typical cucumber farm, even a 5–10% enhancement in the early detection can lead to great protection of the yield and economic savings. In addition, system requirements (low memory and lightweight model architecture) are 15 MB and 2.1 GB, respectively, which means that the system can be easily deployed on low-cost mobile and edge computers without any high-performance servers. This makes it accessible to smallholder farmers in resource-limited environments, which makes the research results reflect the actual agricultural requirements and sustainable farming.

Although the proposed model has high performance, it has some limitations such as a fairly small dataset size, a low level of environmental variability, and the inability to identify early signs of disease.

V. Conclusion and Future Work

Although the proposed model has a high level of performance, it also has some limitations, such as a rather small amount of data, the absence of environmental variability, and the inability to identify the symptoms of the disease at the initial stage. Based on the experimental findings and analysis presented in the previous sections, the following conclusions and directions for future research can be drawn.

This paper has advanced a PSO-SVM-based framework, which incorporates strong pre-processing, feature extraction, and parameter optimization in detecting cucumber leaf diseases. The model has shown great performance, and all the accuracy, precision, recall, and F1-Scores were above 96% and performed better than the traditional machine learning models, as well as provided a computationally efficient alternative to deep learning models.

The suggested PSO-SVM framework is a lightweight and efficient alternative to deep learning models, which is why it can be implemented in the context of real-life agriculture.

In addition to the numerical result, the findings demonstrate the practical usefulness of the approach. Its lightweight nature (15 MB) and low memory usage (2.1 GB) make it applicable to be deployed on mobile and edge devices, providing the opportunity to monitor diseases in the field in real-time. This kind of tool may contribute to the minimization of the yield losses, reduce unnecessary usage of pesticides, and assist in more eco-friendly crop management practices.

In the future, more annotated images will be added to the dataset to enlarge it to more than 2000 annotated images to enhance model robustness and generalization. Also, multi-label classification methods like Binary Relevance and Classifier Chains will be considered to deal with cases of multiple diseases occurring in one leaf image. The suggested model will also be provided with real-time execution on edge computing systems like NVIDIA Jetson Nano and Raspberry Pi to provide effective detection of diseases in the field. Moreover, the connection with IoT-based agricultural monitoring systems will also be explored to enable automated and constant crop health analysis in smart farming systems.

Conflict of Interest

The authors declare that there is no conflict of interest.

Author Contributions

F.A.-Q.: Methodology, data collection, experimental use, writing of original draft. M.J. oversaw the research and methodology validation while conducting analysis and managing the project, also reviewed and edited the manuscript. O.I.A.M.: Software help, data work, graphing and paper checks. G.M.J.: Implementation, performance evaluation, technical review, literature investigation. S.M.A.A.-T: Support with experiments, data preprocessing, writing. W.A.T.: Organizing data, visualization, formatting text, proofreading manuscripts. The final version of the manuscript has been read and approved by all authors.

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