# A PSO-CNN-based approach for Enhancing Precision in Plant Leaf Disease Detection and Classification

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**Keywords:** plant disease, PSO, CNN, classification

**Received:** September 22, 2023

*The Plant diseases that impact the leaves can hinder the progress of plant species, making earlier and more precise diagnoses crucial to minimize additional harm. However, the intriguing methods required additional time, expertise, and exclusivity. Utilizing leaf images for disease identification, research into deep learning (DL) holds significant promise for enhancing accuracy. The substantial progress in deep learning has opened up opportunities to enhance the precision and efficiency of plant leaf disease identification systems. This work introduces an innovative approach for plant disease detection and classification called Particle Swarm Optimization with Convolutional Neural Network (PSO-CNN). The work also explored disease categories in plant leaves using Particle Swarm Optimization (PSO), which extracts color, texture, and leaf arrangement information from images through a CNN classifier. Several effectiveness metrics were employed to evaluate and suggest that the presented approach outperforms existing techniques in terms of accuracy and performance measures, particularly during the stages of disease detection, including image acquisition, segmentation, noise reduction, and classification.*

*Povzetek: Inovativen pristop globokega učenja PSO-CNN izboljšuje točnost odkrivanja in klasifikacijo bolezni rastlin.*

## 1 Introduction

In India, agriculture serves as the cornerstone of the nation's economy, with plants representing a vital resource for human survival. Therefore, it is of paramount importance to ensure their well-being. The analysis of both healthy and diseased plants plays a pivotal role in fostering successful agricultural progress. Identifying infected plants is a crucial step in safeguarding uninfected ones [1]. Plant leaves serve as the primary indicators of leaf infections, as most disease symptoms manifest prominently on the leaves [2]. Detecting leaf diseases is a highly recommended method for identifying plant infections, as it involves recognizing various symptoms associated with different types of infections. Some common signs of leaf diseases in plants include Chlorosis, Damping off of seedlings, Stem rust, Powdery mildew, Leaf rust, white mold, Leaf spot, and Birds-eye spot on berries [3].

The CNN is a frequently employed classifier in image processing, renowned for its effectiveness in precise image filtering and categorization [04]. CNN stands out as the prominent ANN extensively utilized for image recognition tasks. In the context of leaf disease detection, image-processing techniques are applied [5]. CNN is characterized by its inclusion of fully connected layers in subsequent phases, where all adjustable parameters of the leaf image segments are fine-tuned through error reduction during training [6]. Deep learning, as a subset of machine learning methods, offers distinct advantages such as not requiring a predetermined feature arrangement, distinguishing it from other machine learning techniques. While the other plant disease detection technique has demonstrated better results, they often demand more time and lack flexibility [7].

A Partial swarm technique has been employed for the purpose of identifying plant diseases. PSO is a category of optimization techniques inspired by the behavior of particles of swarm. In this algorithm, an artificial ant navigates through the problem space in search of better solutions. To guide this process, the PSO algorithm manages the levels of pheromones on each trail, ensuring that shorter paths have lower pheromone evaporation compared to longer paths [8]. This accumulation of pheromones on shorter paths attracts more particle swarms, ultimately leading them to discover the shortest route. Consequently, this algorithm transforms the given problem into the task of finding the optimal route for complicated issues. During the initial phase of solution generation, every swarm devises a solution, and through the PSO technique, it becomes possible to detect unhealthy or infected areas in plants.

The remaining sections are structured as follows: The second section provides an overview of related research. Section 4 details the proposed PSO-CNN algorithm for detecting leaf diseases. Section 5 evaluates the efficiency and performance of the suggested method, with results presented in tables and graphs. The final section offers a summarized conclusion.

## 2 Related work

The deep learning approach is frequently employed for the computer vision-based diagnosis of plant diseases.

In the article [8] The paper introduces the Particle Swarm Optimization (PSO) algorithm, which draws inspiration from the foraging behavior of birds. PSO is regarded as an intelligent and efficient optimization algorithm, supported by numerous research studies and experiments. Within this study, traditional PSO was further enhanced to improve its global search capabilities. Experimental results demonstrate that this enhanced PSO (IPSO) outperforms traditional PSO and the Genetic Algorithm (GA) on benchmark functions, particularly when dealing with challenging functions

In the article [9] This paper conducts an analysis of existing research conducted between 2017 and 2019 in the field of technical taxonomy. The analysis encompasses various aspects, including hybridization, and enhancement of the Particle Swarm Optimization (PSO) algorithm, as well as its real-world uses. These applications are classified into sectors such as healthcare, environmental, and natural aspects. The analysis also considers characteristics like accuracy, and evaluation of natural environments, and presented case studies to assess the efficaciousness of various PSO techniques and applications. Each of the reviewed studies has its unique advantages and inherent limitations, which are discussed, leading to insights on how to address weaknesses, issues, and potential avenues for further research in the field of PSO.

In the referenced paper [10], the study includes an examination of the training and testing data visualization. A dataset containing 35,000 images of both healthy and unhealthy plants is utilized. While this technique achieves an impressive accuracy rate of 96.50 percent, the presented approach has achieved a perfect 100% accuracy rate, encompassing a wide range of plant leaf diseases for detection. This method successfully identifies 31 distinct plant diseases utilizing a CNN. It's worth noting that this approach demands a substantial number of data for precise recognition. The deep learning technique is used to detect plant diseases by analyzing images across various stages and categorizing them into predefined classes.

The paper [11] presents a documentation method for identifying Tomato Plant leaf infections using image processing techniques, incorporating clustering, an open algorithm, as well as image segmentation. In this approach, the CNN algorithm is employed to extract hierarchical features, which involves mapping pixel intensities from input images and comparing them with a training set of images. Additionally, the method explores the potential use of fuzzy logic, hybrid techniques, and ANN. The GLCM is applied to classify and segment leaf images based on various characteristics. The primary focus is on real-time disease identification, although it's important to note that this method may require more time during the training process.

In the paper [12], it is discussed how leaves can be categorized into multiple levels to enhance prediction accuracy by narrowing down possibilities at each level. To achieve this, YOLOv3 goal identification is employed to extract plant leaves from source images. Leveraging more precise deep learning systems proves essential in effectively identifying diseases, as these systems can discern details beyond the capabilities of the human eye [13]. Furthermore, the study utilizes ant colony optimization to investigate the feature analysis space for finding the most effective discriminative structure to distinguish between different classes. The process of feature analysis involves extracting various characteristics from leaf images, including shape, morphology, color, and texture.

The paper [14] presents a comprehensive approach to plant leaf disease identification, encompassing various stages like image segmentation, image acquisition, classification, and feature extraction. In this approach, several techniques such as SVM algorithm, BPNN, Stochastic Gradient Descent, Otsu's algorithm, and K-means clustering, are applied for leaf disease detection. It's important to note that this method requires extra time for disease detection. This process introduces multiple challenges, including automating the identification for complex images captured under varying lighting conditions and challenging environmental aspects.

In the article [15], various classification techniques are explored, and their selection depends on the characteristics of the input data. Specifically, the paper employs k-means clustering and SVM as classification methods. Choosing the appropriate method is often challenging, as the quality of results can vary depending on the specific input data. Disease detection relies on accurate segmentation of affected parts, tailored to the plant family's type. For instance, in the case of coffee leaf diseases, Convolutional Neural Network (CNN) is employed for detection, as discussed in the paper [16]. CNN has demonstrated its capability and accuracy in the classification of image and pattern recognition tasks. The primary objective of this neural network method is to achieve highly accurate coffee leaf disease detection, even though it may require extra time compared to alternative approaches.

## 3 Problem of statement

The current approaches for identifying plant diseases have failed to deliver accurate results, resulting in prolonged processing times, limited flexibility, susceptibility to environmental conditions, and issues with proper image detection. To address these shortcomings, we propose a solution that combines Particle Swarm Optimization with CNN. Our proposed method successfully mitigates these challenges and consistently delivers reliable results for the identification of plant leaf disease.

# 4 Proposed methodology

The process of detecting plant leaf diseases encompasses several steps, including dataset collection, pre-processing, feature extraction, segmentation, as well as classification. The latter three steps are improved through the utilization of the PCO-CNN method. A visual representation of the proposed PCO-CNN disease detection process is illustrated in Figure 2.

## 4.1 Data collection

The dataset used in this study comprises both healthy and unhealthy leaves, featuring distinct sets including black spots, melanosis, and canker [17]. The presented model's primary objective is to differentiate between infected and healthy leaves. Our proposed method combines Particle Swarm Optimization with CNN for this purpose. The classification model consists of two key components: the training and testing phase.

During the training phase, the set of data is subjected to deep learning techniques to generate precise results. Subsequently, the testing phase evaluates the model performance utilising various performance measures. The emphasis in the testing phase is mainly on the speed at which accurate results are obtained.

## 4.2 Data pre-processing

Upon selecting the image, the starting phase of leaf disease detection involves pre-processing. To reduce noise and eliminate extraneous objects, we employ the median filter, a highly effective non-linear digital filtering approach commonly utilized to increase the quality of images. The equation for the median filter is as follows:

$$g(x.y) = median_{(a.b\in T_{(xy)})}\{f(a.b)\} \tag{1}$$

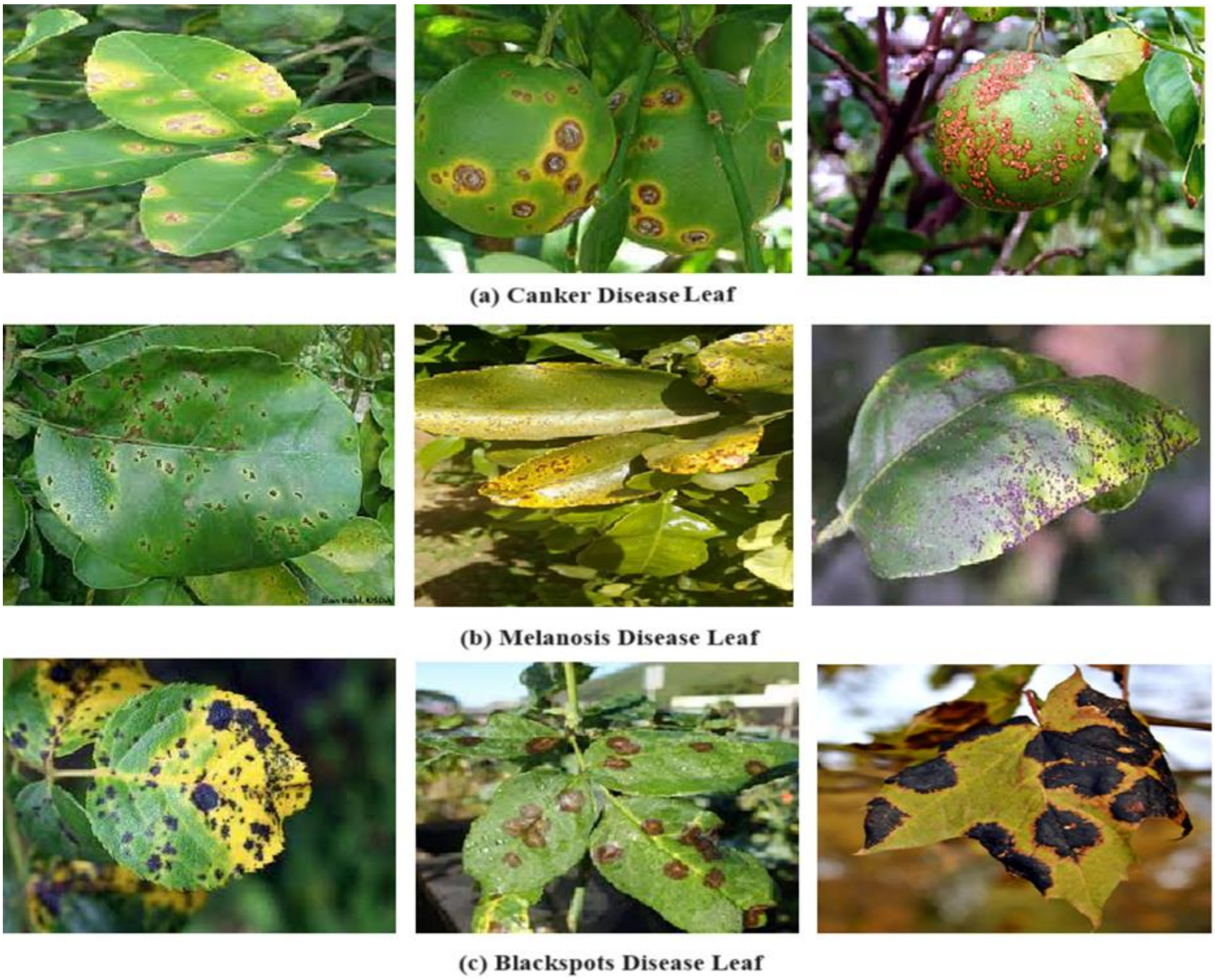

Figure 1: Shows the different plant disease

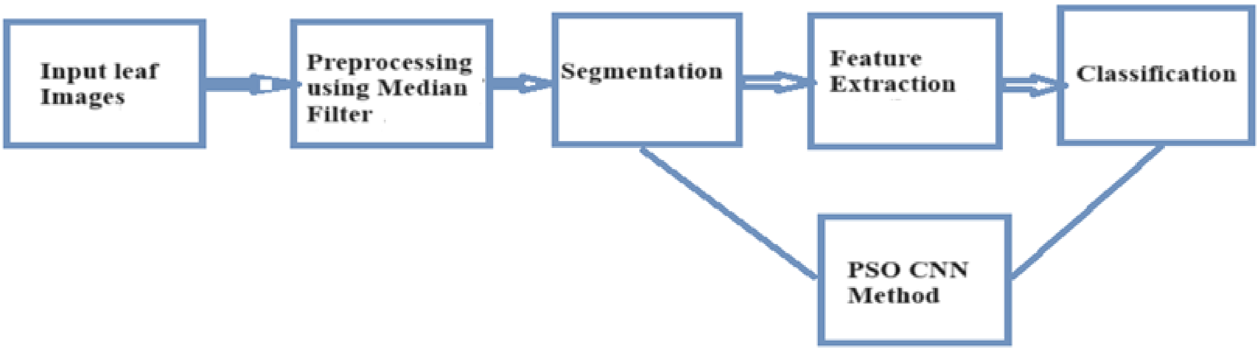


Figure 2: Phases of identification and classification plant diseases

## 4.3 Segmentation

Segmentation involves the classification of plant leaf images into smaller, characteristic-related sections on the surface. The proposed method is employed to separate the leaf's edge as well as divide it into distinct regions. This segmentation process utilizes two key properties: pixel concentration similarity and variation, with color-based thresholding employed to assess the similarities. An equation has been provided to facilitate the segmentation process [18].

## 4.4 Feature extraction and classification using PSO-CNN

Utilizing a combination of PCO for feature extraction and CNN for classification, this method plays a crucial role in identifying infected regions by mimicking ant communication behavior and classifying infected plant leaves, ultimately aiding in future prevention efforts.

$$|S(r.p)| = \begin{bmatrix} 0.\,g(r.p) < \;r \\ 1.\,g(r.p) \geq r \end{bmatrix} \quad (2)$$

### 4.4.1 Particle swarm optimization (PSO)

Particle Swarm Optimization is increasingly employed for approximate optimization in recent times, driven by its ability to mimic swarm-seeking behavior. The key inspiration for Particle Swarm Optimization (PSO) lies in the individual characteristic of ants: indirect communication, enabling them to find the shortest path to their food source. In the context of PSO, this unique ant behavior is harnessed to distinguish infected plant leaves from healthy ones.

One critical parameter to adjust initially in this process is the pheromone rate. The pheromone information for feature assessment is stored in a matrix (h) with dimensions G*G, where G represents both rows & columns, representing the entire set of novel feature vectors. Particle Swarn Optimization parameters are fine-tuned, and primary computation, such as the experimental function F, is computed to identify the optimal subset as well as assets for subsequent iterations.

To apply the PSO algorithm effectively, the first crucial step effort initializes its factors, including numerous candidate particles. The PSO technique exhibits robustness and features an isolated computational mechanism, making it readily combinable with other methods. PSO excels in tackling complex optimization problems, functioning by updating pheromone levels and guiding swarm movements in the search space through mathematical formulas. Its operation is grounded in both local and global search strategies.

**Transition probability of region (n)** Equation determining the transition probability of a region employed to identify the diseased area of the plant leaf.

$$Q_n(z) = \frac{z_n(z)}{\sum_{i=1}^{d} z_i z} \quad (3)$$

In this context, z_n(z) denotes the cumulative pheromone level in region m, while d represents the count of global particle swarm members.

The equation for pheromone update. The eq. governing the update of pheromones, utilized for communication within the swarm.

$$m_j(m+1) = (1-z)m_j m \quad (4)$$

In this context, 'z' represents the rate of pheromone evaporation.

### 4.4.2 Convolutional neural networks

(CNNs) serve as classifiers to detect various leaf diseases efficiently. They analyze graphical images and extract essential features using their multi-layered architecture. The CNN classifier comprises several layers, including image input, convolutional, max-pooling, fully connected, & output layers. The dataset contains an area of pixel intensity values for leaf images before training the CNN model. CNN proves to be a swift model in the training stage, provided that the input images are of uniform size, and a formula for image normalization is applied to each image in the training set.

$$p(x.y) = \frac{o(x.y) - \mu}{\sigma} \quad (5)$$

**(i) convolutional layer**

The convolutional layer takes a set of input images and assesses the intricacies within each image through its individual layers. This layer specifically focuses on identifying the features we seek within the provided images

$$f_j^n = x(\Sigma_{i\varepsilon M_j} f_i^{n-1} {}_* p_{ij}^m + a_j^n \quad (6)$$

Ni - It signifies an input selection. An additive bias 'b' is provided as an outcome. The kernel is applicable to map 'j' such that it sums over both map 'i' and map 'k'[24].

**(ii) Max pooling layer**

The Pooling layer is employed to reduce overfitting as well as downsize neuron dimensions, which is particularly useful in the down sampling phase. This layer effectively decreases the number of parameters, computation requirements, feature map dimensions, and training duration, and helps mitigate overfitting, which is typically defined as a 50% reduction in performance on test data compared to 100% on the training dataset.

$$a_{nxy} = max_{z.t\in} f_{nzt} \quad (7)$$

In the context of this statement, Map, f_nzt refers to the element located at (z, t) within the pooling area denoted as p_xywhich signifies a local neighborhood centered across the position (x, y)

**(iii) Fully connected layer**

In the realm of image classification, the Fully Connected (FC)Layer plays a crucial role. These Fully Connected layers are typically positioned after the Convolution layers in network architecture. Their primary purpose is to establish a mapping between the input & output. FC layers are typically positioned as the final layers in the network, and the input for these layers is derived from the output of the max pooling layer[25].

**(iv)The SoftMax layer**

The Scores are transformed into a normalised probability distribution by the SoftMax layer, and the classifier uses these outputs as inputs..

The SoftMax classifier is commonly employed for classifying leaf diseases and is implemented within the SoftMax layer

$$\sigma(\underset{A}{\rightarrow})_m = \frac{e^{a_m}}{\sum_{j=1}^{n} e^{a_j}} \quad (8)$$

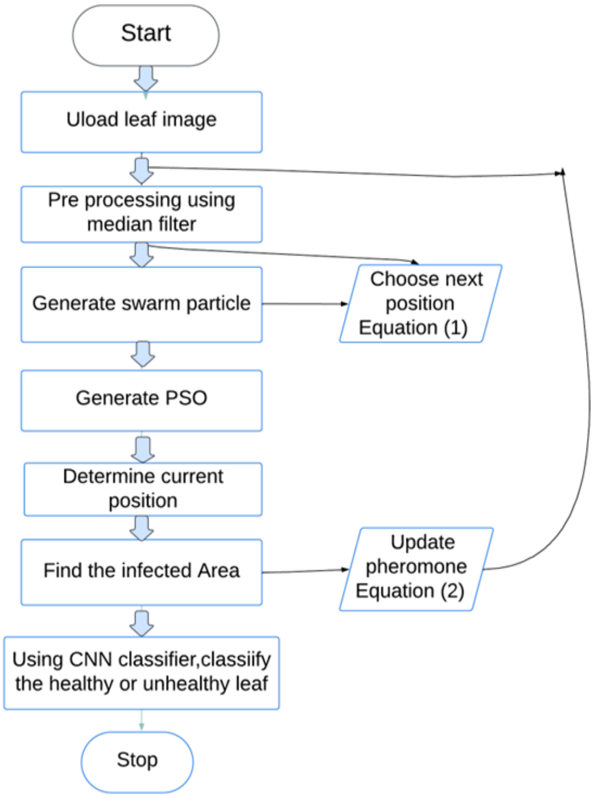


Figure 3: Flow chart of presented approach

The entire workflow is depicted in Figure 3, commencing with the importation of images. Subsequently, pre-processing is executed through the application of a median filter. Features of the component are extracted as well as the classification is carried out employing PSO-CNN to distinguish between infected and healthy leaves, as illustrated in Figure 4.

**Algorithm: PSO-CNN Methods**

**Input**: *Images of leaf*
**Output**: *Classification of Categories, Healthy and Unhealthy Plant Leaves*
*Upload the input Images data)*
*I=I1,I2,I3.I4….* *//Data Acquisition*
*Data preprocessing of leaf images*
*IP=I-n* *//Median Filter*
*Feature extraction of images* *//Particle Swarm Optimization*
*Established the starting point for the infected leaf*
*if it reaches the next position*
*Collect the subset*
*Determine the infected area of the leaf using Equation (1)*
*Else*
*Determine the next component of the leaf using Equation (2)*
*Continue iterating until the stopping criterion is satisfied*
*End if*
*Return*
*Classification of Categories, Healthy and Unhealthy Leaves* *//CNN Classifier*

Integration of PSO with CNN:
The primary motivation behind integrating PSO with CNN is to harness the optimization power of PSO to improve the weights and hyperparameters of the CNN. Here's how the integration typically works:

• Initialization: Instead of initializing CNN weights randomly, a swarm of particles (each representing a possible set of weights for the CNN) is initialized.

• Fitness Function: The accuracy of the CNN (or any other chosen metric) when using a particle's weights represents that particle's fitness. In essence, the better a set of weights, the better the fitness of the associated particle.

• Optimization: PSO optimizes the particles' positions (i.e., the CNN weights) based on individual and group experiences. This means that if a particular particle (set of weights) achieves better accuracy, other particles will be influenced by it and will adjust their weights accordingly.

• Update: The weights of the CNN are updated based on the best position found by the PSO.

Validation Process:
Data Splitting: The dataset is divided into training, validation, and test sets. The training set is primarily used for the learning process, the validation set helps in tuning and making decisions to prevent overfitting, and the test set offers an unbiased evaluation of the final model's performance.

# 5 Performance metrics

Accuracy yields meaningful results based on the available leaf images and is mathematically expressed in equation (9)

$$Accracy = \frac{T^{-}+T^{+}}{F^{-}+F^{+}+T^{+}+T^{-}} \quad (9)$$

Precision offers a detailed evaluation of a classifier's performance. When plant leaves have few positives, precision tends to be high, whereas when plant leaves have many positives, precision tends to be low. This concept is mathematically represented in equation (10)

$$Precision = \frac{T^{+}}{F^{+}+T^{+}} \quad (10)$$

Recall assesses the comprehensiveness of the classifier, with a higher recall indicating that large positive image samples are successfully detected. A formula for calculating recall is presented in equation (11).

$$Recall = \frac{T^{+}}{F^{-}+T^{+}} \quad (11)$$

The F1-score serves as a measure that combines both recall and precision. It is computed based on these two metrics and is mathematically represented in equation (12).

$$F - Score = \frac{2\times(Precision\times Recall)}{(Precision+Recall)} \quad (12)$$

Where:
$T^{-}$ represents True Negative, $F^{-}$ represents False Negative, $T^{+}$ represents True Positive, and $F^{+}$ reprsent False Positive.

## 6 Results

In this study, we have examined the effectiveness of our proposed method using a dataset of collected plant leaf images. Our approach utilizes Particle Swarm Optimization in conjunction with Convolutional Neural Network (PCO-CNN) to differentiate between infected and uninfected leaves. To assess the performance of our method, we have employed four standard evaluation measures: classification Recall, Precision, Accuracy, as well as F1-score, in the comparison of SGD, CNN, and GAN, their accuracy rates are 85.00, 99.97, and 99.6 percent respectively. However, in the PSO-CNN approach, the accuracy significantly improves to 99.98%. Moreover, the precision, recall, as well as F1-Score also demonstrate superior performance in the PSO-CNN method when compared to the other approaches. Notably, the F1-score achieves the higher rate among all the approaches, as depicted in Figure 4. Figure 6 illustrates the ROC curve, which assesses the performance of our plant disease detection model

Accuracy: It's the most straightforward metric, indicating the ratio of correctly predicted instances to the total instances. For the PSO-CNN, the accuracy is remarkably high at 99.98%.

Precision: Precision gives insight into the correctness of positive predictions. At 99.41% for PSO-CNN, it indicates that out of all positive predictions made by the model, 99.41% were indeed correct.

Recall (or Sensitivity): Recall measures the proportion of actual positives that were correctly classified. With a value of 99.46% for PSO-CNN, it means that the model caught 99.46% of all positive cases.

F-Score: The F-Score is the harmonic mean of precision and recall and provides a singular metric that balances the two. A score of 99.98% for PSO-CNN suggests near-perfect harmony between precision and recall.

Table 1: Comparisons of various other approaches

| Approach | Accuracy in % | Precision in % | Recall in % | F-Score in % |
|---|---|---|---|---|
| SGD | 85.00 | 86.00 | 85.00 | 86.00 |
| C-GAN | 99.60 | 97.00 | 97.00 | 97.00 |
| CNN | 99.97 | 99.30 | 99.40 | 99.90 |
| PSO-CNN | 99.98 | 99.41 | 99.46 | 99.98 |

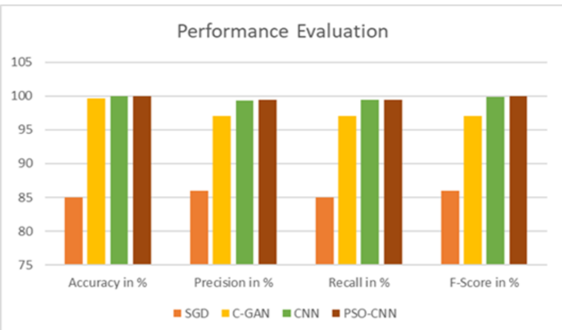


Figure 4: Comparison chart between various other approaches

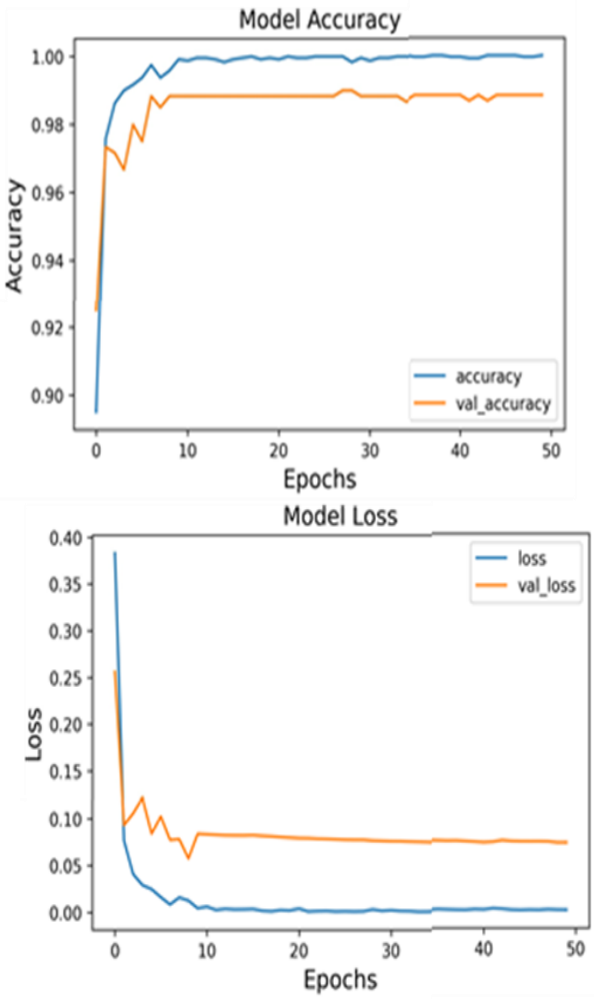


Figure 5: Training & validation accuracy and loss curve

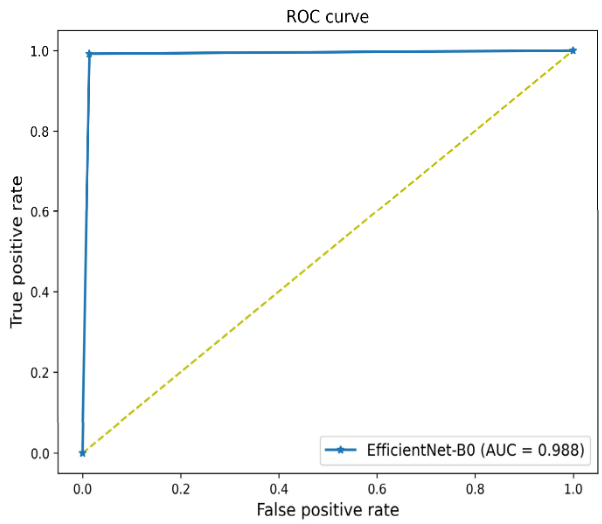


Figure 6: ROC graph for proposed PSO-CNN model

Table 2 Comparison of proposed work with other state-of-the-art approaches

| Reference/Year | Methodology | Merits | Demerits |
|---|---|---|---|
| [18] 2016 | Employed a Genetic Algorithm in conjunction with a Support Vector Machine (SVM) and utilized HSI design | Obtained a classification accuracy ranging from 88.72% to 92.59% for the GA-SVM model | Classified only six specific types of illnesses |
| [19] 2019 | The discussion centered around a hybrid technique designed for the detection of crop diseases. | The approach involved a combination of computer vision and machine learning techniques for the detection of crop diseases. | The discussion did not include a comparison with other methods. |
| [20] 2019 | Employed ANN and SVM approach for the analysis of tomato and corn leaves | The method employed for feature extraction was HOG | The SVM achieved a precision rate ranging from 55% to 65% for corn crop classification |
| [21] 2022 | A lightweight network architecture was suggested for the recognition and detection of crop diseases | It was custom-designed for the specific purpose of recognizing and detecting crop diseases | The discussion solely focused on the proposed architecture without any comparisons to other methods |
| [22] 2022 | A method was suggested based on ResNet101 with modified variables | The proposed model achieved a remarkable 98.14% reduction in model parameters, significantly enhancing its efficiency. | There were limitations in terms of the dataset used and the generalizability of the findings. |
| Proposed Model | This work presented Particle Swarm Optimization with Convolutional Neural Network | The proposed model achieved a remarkable 99.98% | There was a challenge in distinguishing between other diseases. |

# 7 Discussion

The study encompassed a wide variety of plant leaves, each exhibiting distinct leaf shapes, clustering behavior, and sizes. It is essential to acknowledge that the performance of the proposed method may vary across these diverse attributes. Nonetheless, the method outperforms traditional approaches in terms of classification accuracy, effectively determining whether leaves are healthy or unhealthy. This empowers farmers to get timely and informed actions in addressing specific diseases during their early stages.

The selection of optimal features crucial for decision-making employed Particle Swarm Optimization, which played a pivotal role in enhancing the overall effectiveness of the approach. The integration of (PSO-CNN) represents a promising and intriguing research direction, particularly when dealing with large and complex problem instances. This approach holds substantial potential for addressing challenging real-world problems.

Real- word Implication:

Early Disease Detection: With a high-performance model like PSO-CNN, practitioners can detect plant diseases at a very early stage. Early detection allows for timely interventions, reducing the spread and impact of the disease, thus potentially saving large portions of crops that would otherwise be lost.

Precision Agriculture: Your findings can be integrated into precision agriculture systems. By incorporating the model into drones or IoT devices, farmers can get real-time insights into the health of their crops and take localized actions. This targeted approach reduces the wastage of resources like water, fertilizers, and pesticides.

Resource Optimization: Instead of applying preventive treatments across an entire farm, treatments can be applied only where needed, saving costs and reducing the environmental impact.

Digital Farming: Incorporating such advanced models into mobile applications can empower even small-scale farmers. They could simply take a picture of a plant, and the app would notify them if there's a potential disease, long with advice on managing it.

# 8 Conclusion

The biggest challenge in organic farming is crop protection, requiring in-depth skill about pathogens, potential pests, and the specific crops under cultivation. Early detection of plant leaf diseases is of paramount importance to the agricultural sector. In this context, we introduced the fundamental concepts of identifying plant leaf infections and recognizing symptoms of such infections.

To test the identification of leaf diseases in real-time images, traditional methods have historically been utilized. However, our proposed method offers a novel approach that empowers farmers with the capability to detect and identify plant leaf diseases effectively. We introduced the PSO-CNN optimization approach, where

PSO was leveraged for feature extraction and CNN classifier was employed for classification as well as organization. The outcome of this method is the successful identification of infected leaves from healthy ones, providing valuable support for agricultural practices.

In future endeavors, enhancing the PSO-CNN model's robustness through techniques like augmented training and utilizing semi-supervised learning methods can be pivotal. Additionally, there's potential in optimizing the model for real-time applications by implementing quantization and pruning. An intriguing extension could be integrating environmental data for a comprehensive plant health monitoring system. There's also the potential to expand this approach to other domains, such as livestock health monitoring, medical imaging, and industrial quality control.

**Acknowledgment**
The researchers wish to extend their sincere gratitude to the Deanship of Scientific Research at the Islamic University of Madinah for the support provided to the Post-Publishing Program 3.

**Conflict of Interest**
The authors declare that there are no conflicts of interest.

**Data Availability**
Data is available on request.

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