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A Fusion Method for Detection and Classification of Diseases in Tomato Plants Using Swarm-based Deep Learning

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Abstract: Precise identification and detection of ailments in tomato plants are essential for preserving crop vitality and optimizing agricultural productivity. This promotes the use of agricultural methods that can be maintained over time and decreases financial losses caused by plant diseases. Detecting and classifying diseases in tomato plants is critical for ensuring crop health and maximizing agricultural productivity. Utilizing advanced computer vision techniques for this purpose enhances precision in monitoring plant health, ultimately leading to more efficient and targeted agricultural interventions. This research work presents a novel framework for Tomato Plant Disease Detection and Classification (TPDDC) using a fusion of swarm-based methods and deep-learning techniques. Our approach leverages K-means clustering with Grasshopper Optimization (GO) for segmenting Regions of Interest (ROI) from tomato leaf images, followed by feature extraction and optimization using Maximally Stable Extremal Regions (MSER) and GO. The optimized features are then classified using a Convolutional Neural Network (CNN). The proposed TPDDC model was evaluated using the Plant Village Dataset, encompassing ten different tomato leaf diseases. Experimental results demonstrate significant improvements in detection and classification accuracy, achieving an average accuracy of 97.6% with the GO-based approach compared to 92.7% without GO. These results underscore the effectiveness of integrating swarm-based optimization with deep learning for robust and precise disease detection in tomato plants.

Introduction

There is a strong trend towards using image processing or computer vision-based plant disease detection and their classification to achieve the demand in agriculture (Noonari et al., 2015). The global population is growing daily, and the demand for food is also increasing correspondingly. It is seen that the requirement for agriculture grows rapidly in direct proportion to this population rise. With a good farming mechanism, agricultural goods fulfill many human needs, including food, clothing, and warmth (Chowdhury et al., 2021). These items are crucial for facilitating import and export activities inside a well-established nation. Agricultural income pointedly contributes to the development and expansion of the national economy. Therefore, it is crucial to ensure that the goods derived from plants are of superior quality and that the plants are safeguarded from illnesses to produce high-quality products. Several sources, including unfavorable environmental conditions, fungi, bacteria, and viruses, may cause plant diseases. The presence of diseases in plants may impair essential physiological processes, including photosynthesis, pollination, fertilization, and germination (Thangaraj et al., 2022). Thus, in order to provide effective therapy, it is crucial to promptly identify illnesses. Depending on the manual inspection by domain experts, it is feasible to use modern technological gadgets to ascertain the presence and specific kind of illness or disease in a plant at an

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early stage. As the picture capture quality of hi-tech equipment increases, processes such as object detection and their classification with the help of image processing or computer vision by integrating the concept of Artificial Intelligence (AI) algorithms provide favorable results (Sahoo et al., 2011). Machine Learning (ML) and Deep Learning (DL) mostly surpass classical optimization and prediction approaches in this field. Firstly, these approaches provide the capability to acquire knowledge automatically from vast quantities of plant data like leaf, stem etc., while conventional methods need the human extraction of features and are constrained by the scale of the data. Furthermore, ML or DL models possess the ability to effectively generalize to unfamiliar data, which sets them apart from conventional techniques. Furthermore, ML and DL models possess the ability to acquire intricate and non-linear data connections, which sets them apart from conventional approaches. Artificial Neural Network (ANN) is a fundamental technique used in AI for disease detection in several plants. Convolutional Neural Network (CNN), an enhanced version of ANN image data helping to save spatial features, has gained significant attention due to its high detection accuracy and ability to reduce manual effort (Tian et al., 2019). However, the accuracy of any model's detection is directly contingent on the quality of the input data.

tropical countries, particularly in India. It is thought to focus on detecting and classifying diseases in tomato plants using CNN as a deep learning algorithm with a novel swarm-based Grasshopper Optimization (GO). Here, firstly, segmentation of Leaf region or region of the leaf (ROL) from the tomato leaf images is performed and then the proposed model is trained with the help of CNN and the general architecture of the proposed Tomato Plant Disease Detection and Classification (TPDDC) model is shown in Figure 1.

Motivation

Agriculture serves as the predominant source of income for a large portion of the Indian population. Plant diseases, which arise naturally, substantially influence crop yield. If not effectively controlled, these diseases may have severe repercussions on crop quality, productivity, and quantity. The high incidence of illnesses in tomato plants presents a substantial risk to agricultural output and the stability of the food supply. Conventional techniques for illness detection are often characterized by lengthy time requirements, demanding physical effort, and a tendency to produce errors. Recent developments in deep learning have shown potential in automating and enhancing the precision of plant disease identification. Nevertheless, the difficulty is in maximizing the efficiency of these techniques to manage a wide range of intricate illness symptoms successfully

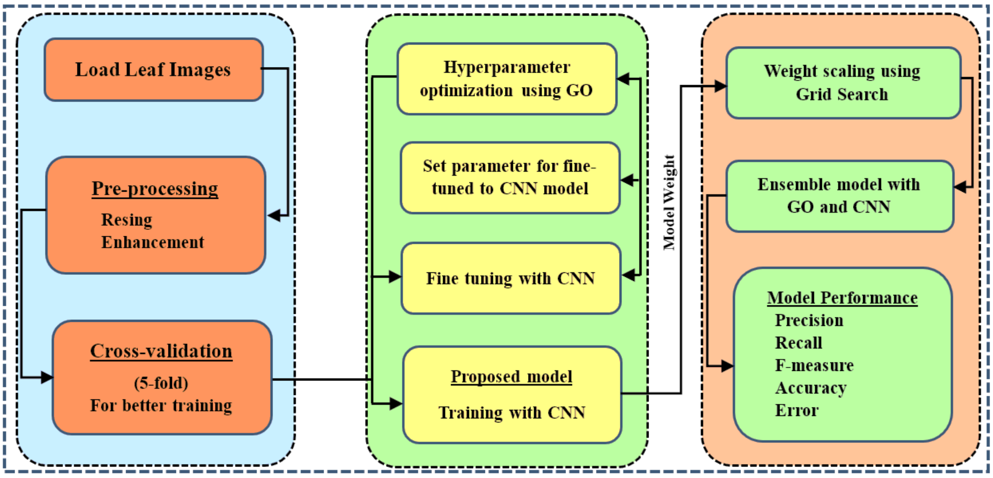

Figure 1. Working on Architecture of TPDDC Model.

The segmentation of the leaf area from the captured photos of tomatoes is of great importance. When the input to a CNN is very specific in terms of the illness or afflicted region, the CNN will be able to carry out more effective feature engineering, which will be advantageous for the model. Diagnosing plant diseases is essential because of several localized lesions on plant foliage, stems, and other components (Singh et al., 2012). The tomato is a highly farmed agricultural commodity in

(Goel et al., 2023). This research aims to use swarm-based optimization in conjunction with deep learning to develop a fusion technique that improves the precision, effectiveness, and resilience of disease identification and categorization in tomato plants. By harnessing this state-of-the-art technology, we can provide farmers and agricultural experts with a potent instrument to reduce crop losses, guarantee more robust harvests, and advocate for sustainable farming methods. The main goal is to provide a technique for recognizing tomato plant illnesses and improving production levels, with the classification process mostly relying on ROL segmentation. The default approach for plant leaf image segmentation involves thresholding and clustering. This method seeks to group objects or pixels into subsets depending on the background and foreground of the picture, as shown in Figure 2.

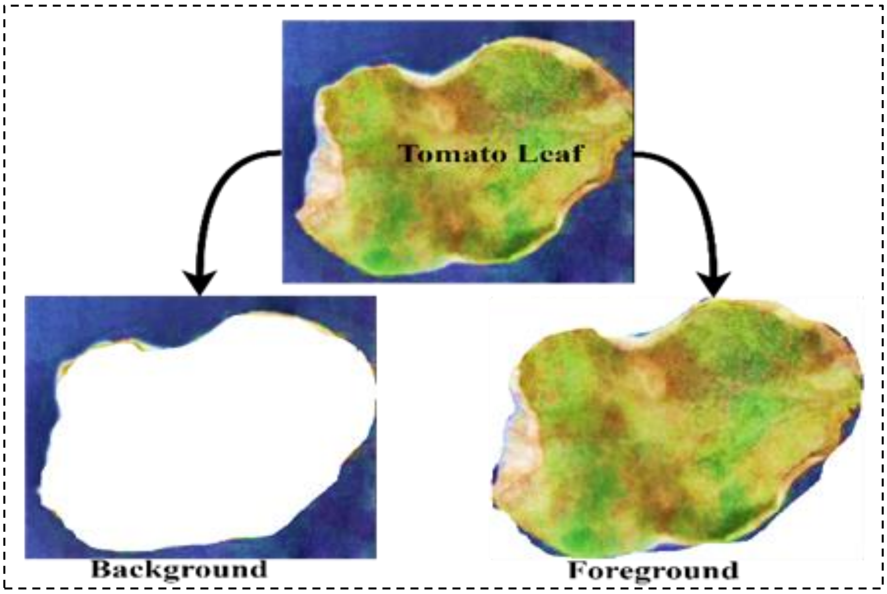

Figure 2. Detection of ROL from Tomato Leaf Image.

The objective is to generate clusters or components that are internally cohesive but exhibit significant dissimilarity from one another. Put simply, pixels within the same category should exhibit maximum similarity, whereas objects within the same category should have substantial dissimilarity from those in a different cluster. Several tough aspects were presented that provided us with the motivation:

❖ Huge number of research articles are available on this topic, but there seems to be a lack of appropriate comparisons of Traditional and SI-based segmentation to find a better and more robust approach.

❖ Plant leaf segmentation is a challenging task and still needs lots of improvements to develop a better agriculture diagnosis system, especially in the case of multiple diseases in a single leaf.

❖ Most models suffer from over-fitting problems and need to tackle such difficulty to detect the diseases early for better productivity. The overfitting problem in deep learning typically arises when an improper leaf region is passed to the CNN model (Shrivastav et al., 2024).

Contributions

Using DL with extracted ROL from tomato plant leaf images is essential for several purposes. Thus, this work introduces a framework for tomato plant leaf detection and their classification into ten different classes using fusion with swarm-based methods. The primary contributions of this research are as follows:

❖ To study the existing models for detecting and classifying diseases in tomato plants to find better ones.

❖ To develop an innovative pre-processing technique for tomato plant leaf images, such as enhancing quality and contrast, which, in turn, helps to achieve better detection as well as classification accuracy.

❖ K-means with GO are used as an optimized approach to segment ROL from tomato plant leaf images, and the same algorithm is used to select feature sets.

❖ To train the model using CNN as a DL algorithm based on the segmented ROL features by fusion with GO as a swarm technique.

❖ To validate the proposed hybrid framework, using performance evaluation parameters like Precision, Recall, F-measure and accuracy with Matthews's correlation coefficient (MCC), Dice coefficient (DC), and Jaccard coefficient (JC) are calculated.

This section of the article presents a brief introduction about the proposed TPDDC model and the rest of the article is as follows: Section 2 describes the brief survey on the related work to find out the gaps. Section 3 provides further information on the design TPDDC model using CNN along with the GO as an optimization technique and Section 4 outlines the obtained results for the proposed model with several experiments. Finally, Section 5 presents an overview of the conclusion and future possibilities.

Literature Survey

This section of the paper provides a review of the

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current models pertaining to the segmentation of tomato leaf diseases, along with their categorization. It is seen in the literature that many times, tomato leaf features, including color, shape, texture, and other parameters, are manually extracted to segment and identify illnesses that impact tomato leaves effectively. Concepcion et al. (2020) developed a model using the swarm-based Artificial Bee Colony (ABC) algorithm to analyze tomato plants' necrotic and chlorotic regions impacted by Septoria leaf spot. The authors proposed to assess tomato illness using computer vision (CV) methods and computational intelligence to assess tomato illnesses. The dataset comprises tomato leaves that exhibit both healthy and sick conditions. The authors first used the CIE-Lab color space to remove non-vegetation pixels from the pictures. They next adopted a threshold-based segmentation technique, followed by the extraction of texture information from the segmented area of the leaf. ABC was used to normalize the visible red reflectance and set ratios between red-green and red-blue reflectance to improve the quality of pixels impacted by Septoria leaf spots and minimize their impact on unaffected green pixels. The constructed model achieved an accuracy of 97.46%, exceeding the results of prior studies (Concepcion et al., 2020). Darwish et al. (2020) created a model that combines the idea of Particle Swarm Optimization (PSO) with Convolutional Neural Networks (CNN) in the same year. This model aims to diagnose plant leaf problems at an early stage, hence enhancing production. In this work, the researchers used a unique approach known as orthogonal learning PSO (OLPSO) to improve the hyperparameters of CNN. Unlike traditional approaches such as human experimentation or trial and error, OLPSO seeks to determine the ideal values for hyperparameters that impact the model's output (Deva et al., 2024). The current research utilizes an architecture called Exponentially Decaying Learning Rate (EDLR) to efficiently train Convolutional Neural Networks (CNNs) and overcome the problem of being trapped in local minimums. This work employs random minority oversampling and random majority under sampling strategies to tackle the unbalanced dataset problem and overcome sample size and diversity constraints. The authors achieved a noteworthy achievement in classifying diseases, achieving an accuracy rate of 98.2% with the aid of OLPSO (Darwish et al., 2020). Anam and Fitriah (2021) used the K-means algorithm in conjunction with a Swarm Intelligence-based algorithm to create a model for segmenting and classifying the Early Blight disease in tomato leaves. Tomato plants around the globe are often affected by a destructive fungal disease that greatly diminishes their productivity. The researchers used the K-means algorithm as an unsupervised clustering approach to separate the affected area from the image of the leaves. This was done in order to identify diseases in the first stage of the study. In addition, they introduce the concept of the PSO, which is considered a significant technique among swarm intelligence algorithms due to its capacity to manage the trade-off between exploration and exploitation successfully. The Hue is the input for the HSV color scheme. The experimental findings indicate that the segmentation approach for early blight illness, which combines the K-means algorithm with a swarm intelligence-based algorithm, has exceptional performance. The tomato leaf disease segmentation approach implemented using the K-means algorithm had an average calculation time that was 7.184 seconds longer than the recommended method. The suggested technique exhibited an average calculation time of 142.062 seconds and attained an F-measure of 41.8%. When using the K-means method in conjunction with PSO, the F-measure attains a value of around 90%, notably superior to the F-measure attained without PSO (Anam and Fitriah, 2021). Venkata Subramanian (2021) introduced the innovative idea of Chaotic Slap Swarm (CSS) swarm-based optimization for feature selection in 2021. This method aims to identify diseases in Apple and Tomato Plant Leaves. The author used the Bi-directional Long Short-Term Memory (Bi-LSTM) approach in this specific situation to categorize illnesses seen in apples and tomatoes. The researchers used the Bi-LSTM architecture to identify illnesses by using the PlantVillage dataset. The constructed model achieved a testing phase accuracy of 96%, exceeding the performance of previous efforts (Venkata Subramanian, 2021). David (2023) used a mixture of multilevel thresholding and K-means clustering together with an optimization approach. The authors use an Adaptive Extreme Learning Technique (AELT) to classify the disease in their study. Before the classification phase, the segmentation and feature extraction techniques are carried out to improve the accuracy of illness detection. The study introduces a method for dividing leaf areas into segments using a K-means clustering algorithm that incorporates multilevel thresholding. The clustering procedure is improved by integrating a butterfly optimization process directed by probability. Using entropy, plant pictures are used for attribute extraction (Sharma et al., 2021; David et al., 2023). Jamjoom et al. (2023) developed a method that employs unsupervised K-means clustering and Support Vector Machine (SVM) to distinguish the affected region of plant leaves for disease classification. This work aims to improve the K-means method's efficiency by including SVM for the segmentation-based classification of Phytophthora infesting, Fusarium gramine arum, Puccinia graminis, and tomato yellow leaf curl. The SVM algorithm is used as a classifier to categorize illnesses using several image-processing stages, such as picture acquisition, pre-processing, segmenting afflicted areas, accurate feature extraction, and subsequent classification. The damaged region of the plant leaf was identified and the illness was classified using the Grey Level Co-Occurrence Matrix (GLCM) concept in combination with Local Binary Pattern (LBP) characteristics. The model and method presented in this study outperformed the existing state-of-the-art work and achieved an accuracy of 97.2% (Jamjoom et al., 2023). Umamageswari et al. (2023) proposed a similar concept by using the Chameleon Swarm-based Fuzzy C-means (FCM) technique to detect and partition the affected region. They then used the Progressive Neural Architecture (PNA) Search to categorize the data. The authors have developed a suggested model that consists of four independent stages: pre-processing, impacted area segmentation, feature extraction, and illness classification. During pre-processing, they use noise reduction methods and tackle overfitting problems. Next, they use the Chameleon swarm-based FCM technique to divide the affected region into segments. After identifying the exact location on the leaf that was affected, they proceeded to do feature extraction using the GLCM approach. The PNA search approach was used to categorize illnesses discovered in various plants, such as apples, cherries, maize, grapes, peppers, potatoes, and tomatoes. The author provided a rationale for the effectiveness of the work by considering several metrics such as precision, recall, sensitivity, specificity, and accuracy. The values for these parameters are 0.9612, 0.9721, 0.9700 and 0.9743, respectively. These values surpass the achievements of prior state-of-the-art investigations (Umamageswari et al., 2023). Ulutaş and Aslantaş (2023) used the PSO technique to improve the hyperparameter optimization of CNN models. Four separate convolutional neural networks were introduced: MobileNetV3Small, EfficientNetV2L, InceptionV3, and MobileNetV2. Furthermore, they used the grid search process to optimize the weights of these structures. The experimental results indicate that the ensemble models described in this study have the ability to train and test quickly and achieve a classification accuracy of 99.60%. This finding will expedite the timely detection of plant difficulties by experts and assist in the avoidance of future ailments (Ulutaş and Aslantaş, 2023). The overall conclusion related to existing work is described in Table 1.

Upon conducting a thorough analysis of previous research in the area of tomato leaf segmentation for classification purposes, some constraints have been found and will now be elucidated:

- ➢ The main drawback of the present clustering-based segmentation approach is the presence of overlapping between the foreground and background parts of the tomato leaf during the segmentation (Sahu et al., 2024).
- ➢ To solve such a problem, the utilization of swarm-based methodologies would be beneficial.
- ➢ Optimization-based approaches often utilize bio-inspired algorithms, which might result in lengthier execution times for the segmentation process of the leaf region.
- ➢ This is mostly due to the presence of an unknown and potentially large number of clusters.
- ➢ The literature review emphasizes the difficulties encountered in the process of segmenting images of tomato plant leaves. These obstacles originate from issues related to image quality and the imperative to enhance the quality of these images.
- ➢ Researchers frequently encounter the issue of pixel mixing due to rapid fluctuations in the values of neighboring pixels.
- ➢ In classification phase, most models are designed for very little data as well as class (categories) and fail to extract the best feature from the ROI of images.

Based on the aforementioned investigations, it can be inferred that the division of tomato plant leaves is a complex process that involves many crucial stages, each tailored to the specific characteristics of the data involved. Leaves, composed of different configurations of pixels, may be subjected to a process called segmentation to enhance the precision of analysis. This approach divides the picture into two parts by recognizing clusters of pixels known as background and foreground. Inadequate foreground quality may result in misclassification during the classification process, a problem that can be addressed by using swarm methods. Various swarm-based optimization methods, such as PSO, GO and ABC, may be used to enhance segmentation precision. Furthermore, scientists have developed more advanced techniques to enhance the process of dividing photos of tomato plant leaves into segments. However, the existing conventional methods are less effective due to their practical incompatibility with various medical imaging techniques. Identifying the optimal combination that can efficiently address the issue

Table 1. A comparative analysis of the existing approach using a distinctive set of features.

Year	Authors	Used Algorithms/Models	Motivation/Objective	Dataset	Key Findings	Evaluation Benchmark
2020	Concepcion et al.	• ABC, • CIE-Lab color space, thresholding	Analysing necrotic and chlorotic zones in tomatoes	Healthy and diseased tomato leaves	Achieved high accuracy by standardizing visible red reflectance and establishing red-green/blue reflectance ratios	97.46%
2020	Darwish et al.	• OLPSO, • CNN, EDLR	Early-stage plant leaf disease diagnosis	Not specified	Enhanced productivity by optimizing CNN hyperparameters and using oversampling/under sampling techniques	98.20%
2021	Anam and Fitriah	• K-means, Swarm Intelligence PSO	Segmenting and classifying Early Blight in tomatoes	Not specified	Improved segmentation performance and F-measure using K-means and PSO	90% (F-measure)
2021	Venkata Subramanian	• CSS, Bi-LSTM	Feature selection and disease detection in apples and tomatoes	PlantVillage dataset	Achieved high accuracy in disease classification with Bi-LSTM architecture	96%
2023	David et al.	• Multilevel Thresholding, • AELT, • K-means, Butterfly optimization	Enhancing precision in disease detection	Plant images	Effective segmentation and classification using K-means with multilevel thresholding and Butterfly optimization	Not specified
2023	Jamjoom et al.	• K-means, • SVM, • GLCM, LBP	Segmentation-based classification of various plant diseases	Not specified	Achieved high accuracy in disease classification with improved K-means and SVM	97.20%
2023	Umamageswari et al.	• Chameleon Swarm-based FCM, • PNA, GLCM	Identifying and segmenting affected areas in various plants	Various plant images	High efficiency and accuracy in disease classification using Chameleon Swarm-based FCM and PNA search	Precision: 0.9612, Recall: 0.9721

2023	Ulutaş and Aslantaş	• PSO, • CNN • MobileNetV3Small, • EfficientNetV2L, • InceptionV3, MobileNetV2	Hyperparameter optimization of CNN models	Not specified	Rapid training and testing with high classification accuracy using ensemble CNN models	99.60%

of the clustering-based segmentation approach, thereby improving the efficacy of the agricultural diagnostic system.

Material and Methods

This section of the paper provides a concise overview of the developed Tomato Plant Disease Detection and Classification (TPDDC) model. Figure 10 illustrates the structure of the proposed TPDDC model using the concept of CNN with GO. The TPDDC employs an external feature extraction approach with GO known as feature fusion, effectively decreasing the classification time while maintaining optimal accuracy. The concept of MSER (Maximally Stable Extremal Regions) with GO as a feature optimization or selection is used as a feature fusion technique. Figure 3 outlines the sample image, which is further used in the process of detecting and classifying diseases in tomato plant leaves using a combination of image processing techniques, optimization algorithms, and a CNN. The process is divided into two stages named as Section 1 for Segmentation and Section 2 for classification.

Section 1:

Input Leaf Data:

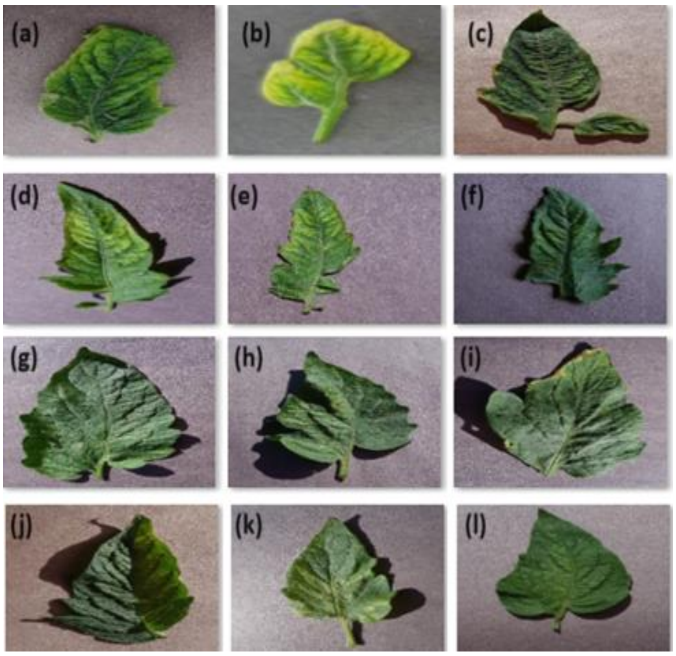

Figure 3. Sample leaf images of tomato plants from the dataset.

The TPDDC model methodology begins with uploading acquired tomato leaf images. These images include both healthy and diseased leaves. This section outlines the algorithms used for detecting illnesses from photographs of tomato plant leaves. In order to identify and categorize plant illnesses known as "Tomato Leaf Diseases," data was originally gathered from a dataset known as the famous open source "Plant Village Dataset Master".

The dataset includes 10 illnesses affecting tomato leaves named as (a) Bacterial_spot, (b) Early_blight, (c) Late_blight, (d) Leaf_Mold, (e) Septoria_leaf_spot, (f) Spider_mites (g) Two-spotted_spider_mite, (h) Target_Spot, (i) Yellow_Leaf_Curl _Virus, (j)-(k) mosaic_virus and (l) Tomato___healthy. Figure 3 displays the many kinds of illnesses found in the "Plant Village Dataset Master" sample. To upload the image for further processing, the following algorithm is used:

Algorithm 1: Tomato Leaf Uploading from Dataset

I/P: N → No. of images
P-name→ Path name of image
F-name → File name of image
O/P: T-image→Tomato Image
Start
Define the leaf image browsing option from the dataset
Pathname = Browse (Image format, Title of uploading panel)
For I = 1 → N
F-path = concatenation (P-name, F-name)
T-mage (I) = Read (F-path)
End – For
Return: T-image as a tomato plant leaf image
End – Algorithm 1

Algorithm 1 is used to read the image and extract the pixel from the uploaded tomato leaf images, as shown in Figure 4.

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Figure 4. Uploaded Tomato Leaf Image (Bacterial_spot).

Pre-processing on Input Tomato Leaf: the necessary pre-processing steps are followed as under:

1. Enhancement of Input Tomato Leaf

This phase entails enhancing the quality and contrast of the tomato leaf to permit more important analysis during the detection mechanism because detection totally depends on the image quality. This is a method of adjusting the intensity of an image by mapping its intensity values to a new range without any information loss.

This approach improves the quality of the image by using the notion of limited contrast. For 8-bit grey-level leaf graphics, the pixel values range from 0 to 255. We have established the bottom and upper boundaries by the implementation of a contrast enhancement technique, denoted as 'L' and 'H' accordingly. The most basic kind of pixel normalization involves scanning the picture to identify the lowest and highest pixel values that are presently present in the leaf image. This process is necessary in order to improve the image and provide a higher-quality result. The term used to refer to these pixels is L_n and H_n. Next, the enhancement of each pixel (P) in the tomato leaf is achieved using the following equation:

$$\boldsymbol{P_E = \left(P_{Image} - L_N\right)\left(\frac{H-L}{H_N-L_N}\right) + L} \qquad \text{... (1)}$$

As equation (1) shows, P_E is the enhanced pixels, and P_{image} is the original uploaded leaf image. H_N and L_N denote the maximum and minimum values of pixels. To illustrate, below mentioned figure 5 shows the effect of the image enhancement approach in terms of enhanced tomato leaf image and the algorithm is given as:

Algorithm 2: Quality Enhancement Algorithm

I/P: T-image→ Tomato Image

O/P: ET-image→Enhanced Tomato Image

Start
Compute R, C, D = size (T-image)
If D==3
  I_Red=Red Part of T-image
  I_Green= Green Part of T-image
  I_Blue= Blue Part of T-image
  Using equation (1)
  $P_{CL} = P_{Clip} - P_{average}$ (2)
P_{CL}, or the pixels clip limit, is a parameter that is used to establish the limit on contrast during the quality enhancement of a tomato leaf.
For Clip Limit = 1 → D
  E-Red = Quality (I_Red, P_{CL})
  E-Green = Quality (I_Green, P_{CL})
  E-Blue = Quality (I_Blue, P_{CL})
End – For
 ET-image=cat (3, E-Red, E-Green, E-Blue)
Else
  For Clip Limit = 1 to all
    ET-image= Quality (T-image, P_{CL})
  End – For
End – If
Return: ET-image as an Enhanced Tomato Image
End – Algorithm 2

Figure 5. Enhanced Tomato Leaf Image using Algorithm 2.

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2. Segmentation of Tomato Leaf

The enhanced images are then segmented to separate the background from the foreground (the leaf itself). This step involves distinguishing between the image's leaf (foreground) and background. After that, the concept GO algorithm for better selection of ROI (Region of Interest using Morphological Operations has been followed Morphological operations are used to identify and select the ROI on the tomato leaf, which is areas potentially affected by the disease in the proposed TPDDC model.

Figure 6. Segmentation of Enhanced Image (a) BG Image (b) FG Image.

In TPDDC model, an improved segmentation mechanism is used to achieve the above-mentioned segmentation result as shown in Figure 6 and the algorithm is written as:

Algorithm 3: Improved GO-based K-means algorithm

I/P: ET-imasge→ Enhanced Tomato Image

O/P: S-TROI→ Segmented ROI of Tomato Leaf Image

1 Start
2 Compute R, C, D = size (ET-image)
3 For m = 1 → R
4 For n = 1 → C
5 If ET-image (m, n) == Background
6 BG-image = Background (m, n)
7 Else
8 FG-image = Foreground (m, n)
9 End – If
10 End – For (Inner)
11 End – For (Outer)
12 S-ROI = minimum-area (BG-image, FG-image)
13 If min (S-ROI) = True
14 S-ROI = BG-image & ~ FG-image
15 Else
16 S-ROI = FG-image & ~ BG-image
17 End – If
18 Threshold = Morphology (S-ROI)
19 Compute [R, C, D] = size (S-ROI)
20 For x= 1→R
21 For y = 1→C
22 If ((S-ROI (x, y)> Threshold)
23 Mask-Img (x, y) = 1
24 Else
25 Mask-Img (x, y) = 0
26 End – If
27 End – For (Inner)
28 End – For (Outer)
29 M-image = Morphological Operation (Mask-Img)
30 Boundaries = boundaries (M-image)
31 Segmented Region = Boundaries
32 For I = 1→D
33 S-TROI = S-ROI × Segmented Region
34 End – For
35 We optimized the S-TROI by utilizing the GO algorithm and initializing it with the following parameters:
36 – Define the number of grasshoppers (swarm size)
37 – Set the maximum number of iterations (Max_iter)
38 – Define the search space for the threshold (e.g., minimum and maximum intensity values)
39 – Initialize a swarm of swarm_size grasshoppers.
40 For each grasshopper:
41 $fs = \mathrm{S} - \mathrm{TROI}\ (l)$
42 $ft = \frac{\sum_{i=1}^{Pixels} ROL(l)}{Length\ of\ ROL\ Pixels}$ … (3)

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$T_v = GO(P, T, LB, UB, N, fit(fun))$ … (4)

End – For

Define optimization iterations, O-Rep = N

While Pixel(T) = True

$\boldsymbol{Thr} = T_v$

Mask = Binary (ROL, Thr)

ROL Boundaries = Boundary (Mask)

Identify the grasshopper with the highest fitness score (best_grasshopper)

For k = 1→ D

S-TROI = S-TROI × ROL Boundaries

End – For

End – While

Returns: S-TROI as Segmented ROI of Tomato Leaf

End – Algorithm 3

Using the algorithm mentioned above, ROI was extracted from a tomato leaf image using algorithm 3, as shown in Figure 7.

Figure 7. Segmentate ROI using Algorithm 3.

MSER Feature Extraction from the ROI is a technique used to extract features from the selected ROI. These features are critical for identifying diseased areas from the segmented ROI. The concept of features is optimized with MSER and using GO technique for the selection mechanism. The extracted features are optimized or selected using the mentioned GO algorithm to ensure that the most relevant features are used for classification.

Algorithm 5: Feature Selection using GO Algorithm

I/P: KF→ MSER Key Feature

O/P: OKF→ Optimized Key Features

1 **Start**

2 Initialize GOA parameters

– Iterations (T)

– Number of Population (P)

– Lower Bound (LB)

– Upper Bound (UB)

– Fitness function

– Number of Selection (N)

3 Compute T = Size (KF)

4 Define **the** fitness function of GO:

Fitness-function: $\mathbf{f(fit)} = \begin{cases} \mathbf{1}, & \mathbf{fs < ft} \\ \mathbf{0}, & \mathbf{fs \geq ft} \end{cases}$ … (5)

For i = 1→ T

$\mathbf{fs} = \sum_{\mathbf{i=1}}^{\mathbf{Pop}} \mathbf{f(i)}$ … (6)

$\mathbf{ft} = \frac{\sum_{\mathbf{i=1}}^{\mathbf{Pop}} \mathbf{f(i)}}{\mathbf{Length\ of\ feature}}$ … (7)

$\mathbf{f(fit)}$ = fitness function using equation (5)

No. of variables = 1

Index = GO (P, Iterations, LB, UB, N, f(fit))

End – For

While T ~= Maximum

OKF = KF(Index)

End – While

Return: Optimized data as a set of optimized feature points

End – Algorithm 4

Using the above-mentioned feature extraction and selection algorithm, we extract and select optimal features only to pass CNN, and the selected feature is shown in Figure 8.

Figure 8. The Selected feature using MSER with GO.

TPDDC Model Training using CNN

The optimized features are then fed into a CNN for model training as well as classification. The CNN is trained using the optimized features, and its structure is saved once the training is complete. The trained CNN is then used to classify new tomato leaf images. If the classification matches the expected outcome, performance parameters are calculated. If not, the process is repeated, and the features are optimized further if necessary. This loop ensures that the features are continually optimized to improve the accuracy of the CNN. The Architecture of the proposed CNN for TPDDC model is shown in Figure 9. There are a lot of benefits of this concept that are mentioned as:

1. The iterative process of feature optimization ensures that the CNN continually improves its classification accuracy. By refining the features fed into the model, CNN can better distinguish between different classes, leading to more precise predictions.
2. The process of optimizing features before feeding them into CNN helps capture the most relevant and informative aspects of the data. This results in a more robust and effective feature set, which in turn improves the model's performance.
3. The loop that checks the classification results and further optimizes features, if necessary, makes the system adaptive. It allows the model to learn and adjust based on performance metrics, ensuring that the CNN evolves to handle variations in new tomato leaf images effectively.
4. By using optimized features, the CNN can be trained more efficiently. The training process becomes faster and more effective because the model works with refined and tailored features to improve learning outcomes.
5. Continuous optimization of features leads to a more robust classification model. The CNN becomes better at generalizing from the training data to new, unseen data, reducing the likelihood of misclassifications and improving overall reliability.
6. As the model and feature optimization process is automated, the system can scale to handle larger datasets and more complex classification tasks without significant manual adjustments, making it suitable for large-scale agricultural applications.
7. Optimizing features before training the CNN means using computational resources more effectively. The model can achieve high performance without unnecessary complexity, ensuring that both time and computational power are utilized efficiently.

Proposed model is simulated using various sample images. To assess its effectiveness, the proposed model, which has a feature fusion-based CNN with GO algorithm, is compared with a model. The next section is derived from the generated scenarios.

Result and discussion

In order to determine a more effective method compared to the proposed TPDDC model, a novel pre-processing method has been designed with the goal of boosting the quality and contrast of the tomato leaf image that is mentioned in algorithm 2, then applying improved K-means with GO and morphological operations for ROI segmentation. This is important for increasing the accuracy of detecting and classifying these images. GO technique is used to improve a K-means clustering approach for segmenting ROI in tomato leaf images. A derived optimal technique was used for the selection of feature sets to help the CNN for model training with maximum accuracy. During the next stage, the segmented ROI features to train a CNN, using the GO algorithm as a swarm optimization approach. In order to assess the efficacy of the suggested TPDDC model, many performance assessment metrics, such as Precision, Recall, F-measure, Accuracy, MCC, DC, and JC, are calculated. These measurements thoroughly evaluate the model's performance and potential for practical use in agriculture. Table 2 describes the Precision, Recall and F-measure obtained for the proposed TPDDC model

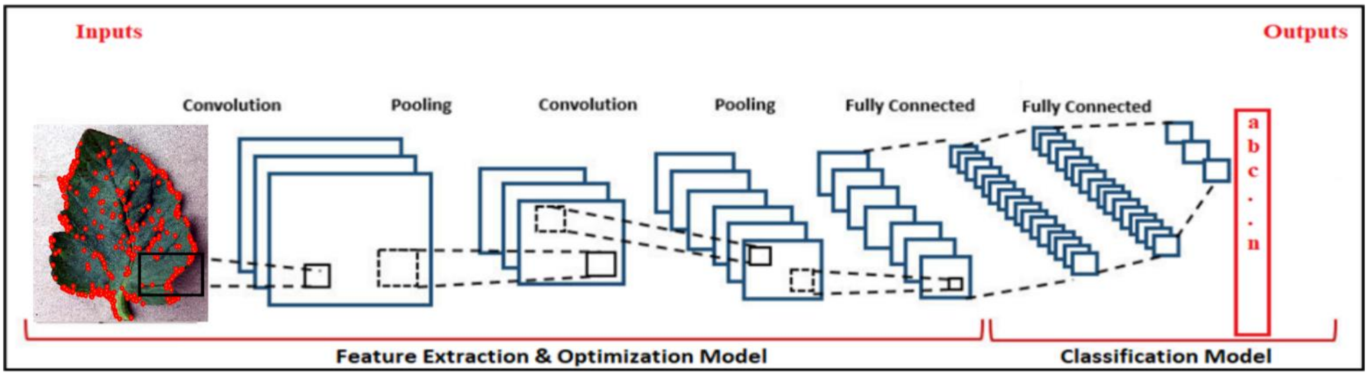

Figure 9. Proposed CNN with Feature Selection.

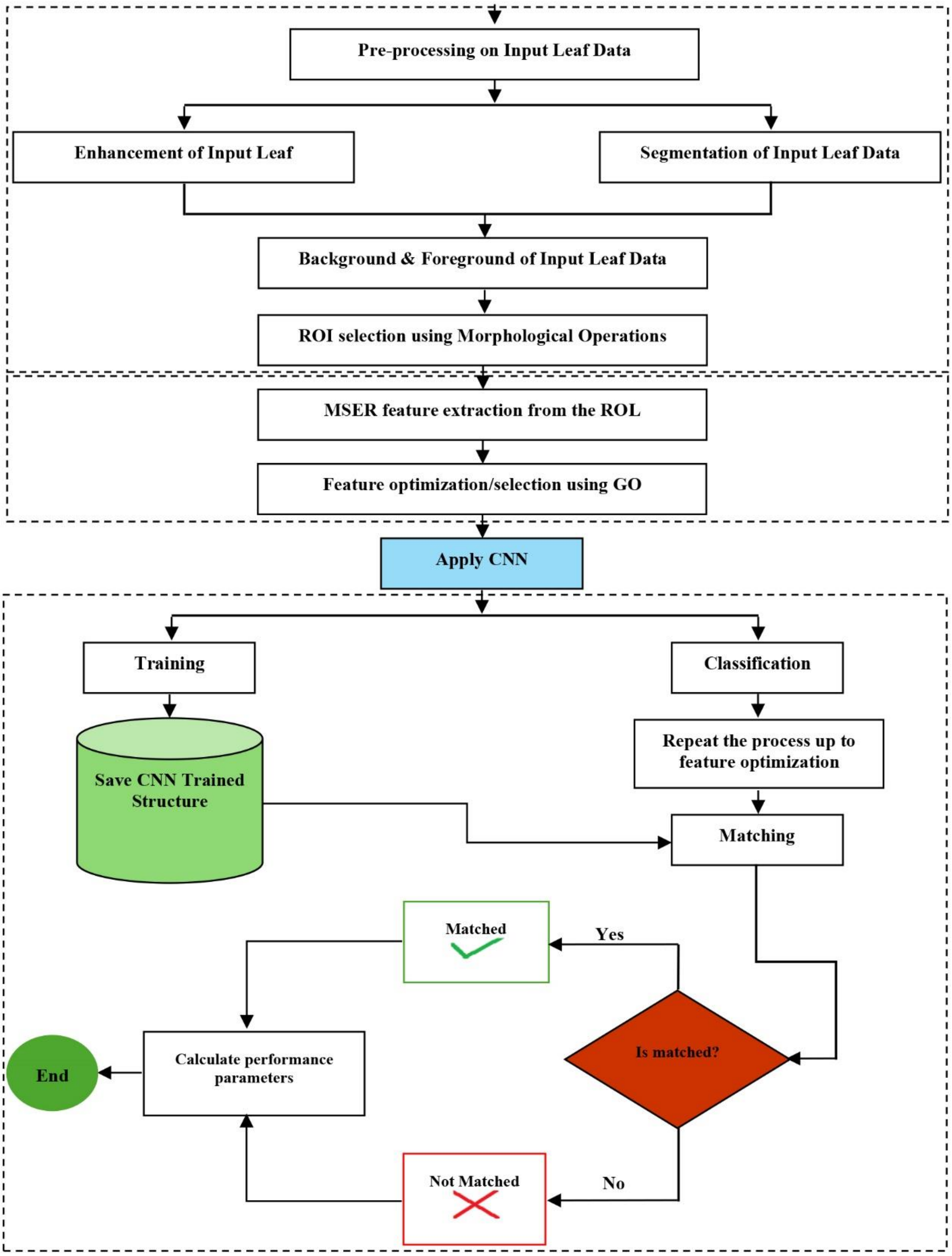

Figure 10. Proposed Feature Fusion-based TPDDC Model.

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Table 2. Evaluation Parameters Precision, Recall and F-measure for the proposed TPDDC Model.

No. of Sample	Precision		Recall		F-measure	
	Without GO	With GO	Without GO	With GO	Without GO	With GO
100	0.918	0.926	0.903	0.91	0.910	0.917
200	0.922	0.951	0.908	0.912	0.914	0.931
300	0.927	0.955	0.909	0.917	0.917	0.935
400	0.933	0.959	0.913	0.925	0.922	0.941
500	0.934	0.968	0.926	0.932	0.929	0.949
600	0.941	0.974	0.927	0.932	0.933	0.952
700	0.941	0.983	0.929	0.934	0.934	0.957
800	0.943	0.983	0.931	0.953	0.936	0.967
900	0.944	0.985	0.939	0.979	0.941	0.981
1000	0.954	0.987	0.959	0.988	0.956	0.987
Average	**0.936**	**0.967**	**0.924**	**0.938**	**0.929**	**0.952**

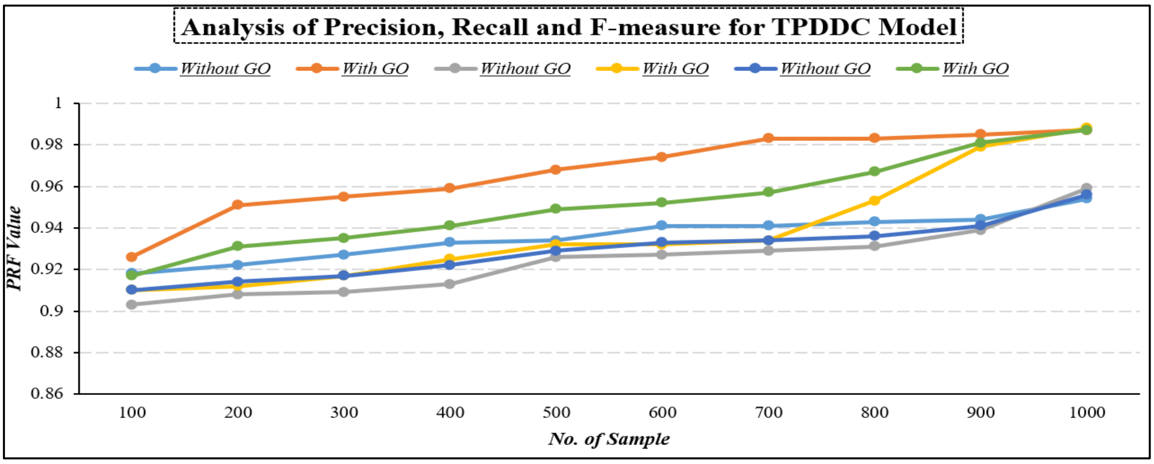

Figure 12. Analysis of Precision, Recall and F-measure for TPDDC Model.

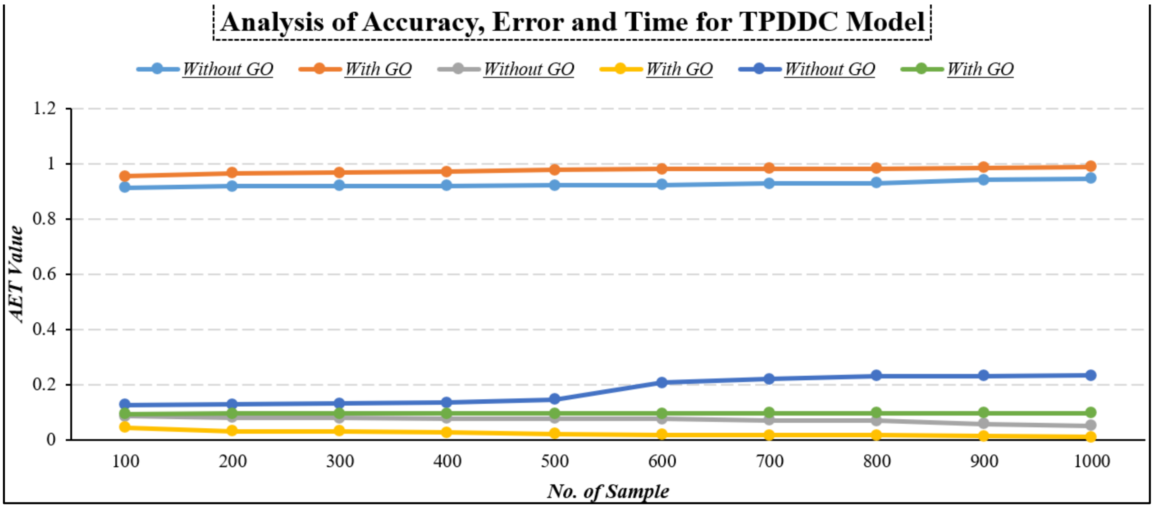

Figure 11. Analysis of Accuracy, Error and Execution Time for TPDDC Model.

Figure 11 presents the Precision, Recall, and F-measure (PRF) analysis for the TPDDC model, comparing results with and without the GO algorithm across different sample sizes. Y-Axis (PRF Value) represents the PRF performance metrics values, ranging from 0.86 to 1.00, whereas X-Axis (No. of Samples) represents the number of samples used in the evaluation, ranging from 100 to 1000. The orange and green lines show consistently higher PRF values across all sample sizes compared to the lines without GO. As the number of samples increases, the models utilizing GO (orange and green lines) show a notable upward trend, reaching close to 0.98-0.99 PRF value when the sample size is 1000. The blue, grey, and yellow lines generally exhibit

Table 3. Evaluation parameters accuracy and error rate for the proposed TPDDC model.

No. of Sample	Accuracy		Error Rate		Time	
	Without GO	With GO	Without GO	With GO	Without GO	With GO
100	0.914	0.955	0.086	0.045	0.127	0.0954
200	0.918	0.967	0.082	0.033	0.129	0.0957
300	0.92	0.968	0.08	0.032	0.133	0.0961
400	0.921	0.972	0.079	0.028	0.136	0.0962
500	0.922	0.978	0.078	0.022	0.147	0.0967
600	0.923	0.981	0.077	0.019	0.208	0.0969
700	0.928	0.982	0.072	0.018	0.221	0.098
800	0.93	0.983	0.07	0.017	0.232	0.0986
900	0.942	0.986	0.058	0.014	0.233	0.0987
1000	0.947	0.989	0.053	0.011	0.234	0.0987
Average	**0.927**	**0.976**	**0.074**	**0.024**	**0.18**	**0.0971**

Table 4. Comparison with Existing Work.

References	Models	Accuracy (%)
[18]	**H Ulutaş & V Aslantaş (PSO with CNN model)**	95.74
[13]	**S Anam & Z Fitriah (K-means + SI model)**	90.05
[17]	**A Umamageswari et al. (FCM-CSA model)**	97.43
Proposed with GO-based CNN	**TPDDC Model without GO**	92.7
Proposed with GO-based CNN	**TPDDC Model with GO**	97.6

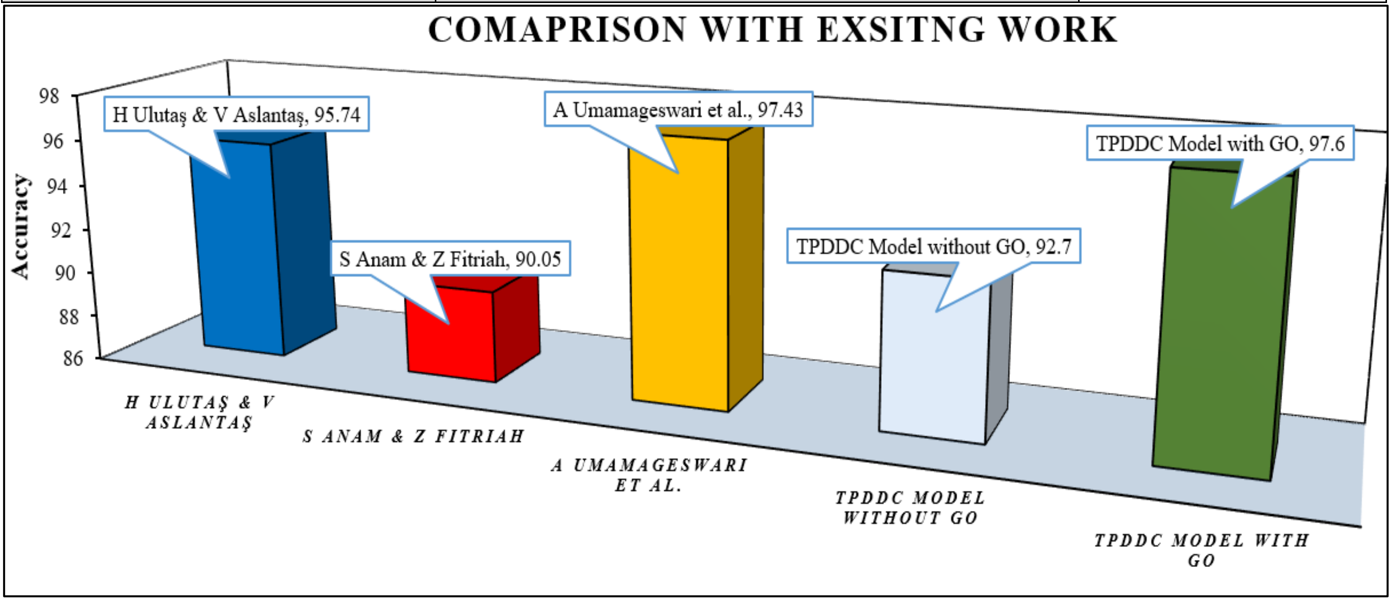

Figure 13. Comparison with Existing Work.

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lower PRF values compared to their GO-enhanced counterparts. There is a gradual improvement in PRF values as the number of samples increases, but the improvement is less pronounced compared to the models with GO. Initially, with 100 samples, the gap between the models with and without GO is smaller, but it widens significantly as the number of samples increases. This suggests that the GO algorithm enhances the model's ability to learn effectively from larger datasets, resulting in better performance metrics. For better analysis, we also analyse and compare the model accuracy and error rate with the execution time that is given in Table 3.

Figure 12 presents the Accuracy, Error rate, and Time (AET) analysis for the TPDDC model, comparing results with and without the GO algorithm across different sample sizes of 1000 test images. The orange line (Accuracy with GO) remains consistently high, close to 1, across all sample sizes, indicating high accuracy when using GO. The blue line (Accuracy without GO) also shows high accuracy but is slightly lower than the orange line, especially as the sample size increases. The grey and yellow lines represent the error rates without and with GO, respectively. Both lines remain consistently low across all sample sizes. The yellow line (Error with GO) shows slightly lower error rates than the grey line (Error without GO), indicating that GO reduces the error rate. The green line represents the time taken with GO, which remains consistently low and stable across all sample sizes. This suggests that the integration of GO does not significantly increase the time required for the model to process the data.

Figure 13 illustrates a comparative analysis of the TPDDC model's accuracy against existing works. The Y-axis represents the accuracy and X-axis displays different models being compared. Observed key comparisons are highlighted as

Ulutaş and Aslantaş (2023):

→ Accuracy: 95.74% and represented by a blue bar. This existing work demonstrates a high accuracy but is outperformed by the TPDDC model with GO.

Anam and Fitriiah (2021):

→ Accuracy: 90.05%, represented by a red bar; this model has the lowest accuracy among the compared works.

Umamageswari et al. (2023):

→ Accuracy: 97.43% and represented by a yellow bar, this research shows a slightly lower accuracy compared to the TPDDC model with GO.

TPDDC Model without GO:

Accuracy: 92.7% and represented by a light grey bar, this version of the TPDDC model, without the Gravitational Optimization (GO) algorithm, shows a significant improvement over Anam and Fitriiah's (2021) work but is less accurate than the model with GO.

TPDDC Model with GO:

Accuracy: 97.6% and represented by a green bar, this model demonstrates the highest accuracy among all compared models, indicating the significant enhancement provided by the GO algorithm.

Based on the above result analysis and discussion, we can say that the efficiency of the proposed TPDDC model is far better than other existing work in terms of accuracy due to the use of GO with CNN as a feature selection mechanism with novel fitness criteria and the final conclusion is discussed in next section of the article.

Conclusion and Future Work

The proposed model known as a Tomato Plant Disease Detection and Classification (TPDDC) model showcases notable progress in identifying and categorizing illnesses in tomato plants via swarm-based deep learning methods. The model demonstrates enhanced precision, recall, F-measure, accuracy, and error rate performance compared to previous techniques by combining the GO algorithm with CNN. The main advancements consist of a unique pre-processing methodology that enhances image quality, an enhanced method for selecting features using MSER and GO, and a robust segmentation procedure that utilizes an improved K-means clustering algorithm. By iteratively optimizing the features before inputting them into the CNN, the model consistently improves its ability to accurately classify tomato leaf images, effectively addressing variances in fresh images. The comparative research demonstrates that the TPDDC model, including GO, surpasses previous models with an accuracy rate of 97.6%. This indicates a noteworthy improvement over the conventional method. The adaptability and scalability of this model make it well-suited for large-scale agricultural applications, providing a more efficient and dependable approach for detecting diseases at an early stage. Subsequent efforts will prioritize the fine-tuning of the optimization algorithms to minimize the time required for execution. Additionally, there will be an investigation into the potential application of this model to other crops, aiming to improve its adaptability and effectiveness in precision agriculture.

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Conflict of interest

None

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