ELITE STOCHASTIC OPTIMIZED DISTRIBUTED LEARNING BASED ENSEMBLE MODEL FOR TOMATO LEAF DISEASE DETECTION AND CLASSIFICATION

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Abstract

Tomato leaf disease is a primary factor impacting the quality and quantity of crop yield. The rapid spread of diseases and inefficient production have driven diverse models for classifying diseases. Nevertheless, existing traditional models are constrained by poor robustness, limited generalization, and inconsistent performance. This paper proposes an Elite Stochastic Optimized Distributed Learning-Based Ensemble Deep Neural Network Long Short-Term Memory (ESD2TM) model for effective disease detection and classification. The ESD2TM framework utilized a distributed mirrored strategy featuring a replica model which engaged in parallel training to boost the training speed and reduce significant computational requirements. In addition, the Hybrid Mutual Augmented Structural Features (HMAS) technique effectively gathers the context-aware characteristics and spatial relationships within the leaves to determine the irregularities based on the disease symptoms. In addition, the Elite Stochastic Optimization Algorithm (ElSTO) refines the hyper parameters and exhibits balanced diversity to find the optimal solution. The incorporation of these mechanisms enables the ESD2TM approach to achieve an accuracy, specificity, precision and sensitivity of 98.42%, 98.46%, 97.69%, and 98.39%, respectively.

1. Introduction

Agriculture is fundamental to human existence, providing sustenance, clothing, and economic opportunities worldwide, as it is the primary source of food production in every country.Accounting for roughly 16% of the total market, tomatoes occupy an important place among crops [1] [2]. Given the tomato's abundance of nutrients, high edible value, and recognized medicinal properties, it has become an integral part of agriculture and is farmed globally [3][4].In general, an increase in tomato demand and production is apparent from the ongoing success of the international tomato market [5]. While culturally and economically significant, the tomato industry faces a major challenge from diseases that are a primary cause of reduced production and substantial economic loss [6] [7]. Moreover, the tomato leaves are vulnerable to many diseases, which affect the overall growth through substantial damage, leading to symptoms of necrosis, wilting, and shrinking leaves [2,8]. The cumulative stress from ongoing disease infestations not only compromises plant vigour but also suppresses fruit development, leading to a reduction in total yield [9][4].The traditional techniques such as visual inspection, pathological leaves analysis, and pathogen identification using biological reagents heavily depend on manual processes and are highly prone to errors, which were inefficient for addressing agricultural challenges. Hence, the trained agronomists, as well as the plant pathologists, struggled to detect the tomato leaf diseases accurately [10][7]. Henceforth, automated tomato leaf disease detection is necessary to enhance agricultural productivity, reduce losses, and ensure food security through early detection [6,11].The automatic disease detection process gathers input data from diverse sources and extracts more significant features for effective detection. Generally, images are captured through satellite platforms or drones, which could be of varying quality. Therefore, preprocessing techniques are used to enhance the quality of raw images. However, the process is complicated by diagnostic challenges arising from subtle visual differences in symptoms on tomato leaves, such as black and brown spots, patches, and holes [12].Concerning these limitations, various DL and ML approaches have been developed to improve disease detection in tomato leaves. ML approaches such as Naive Bayes, local binary pattern histogram (LBPH), Support Vector Machine (SVM), and Gray Level Co-occurrence Matrix (GLCM) have offered advancements, including better robustness, especially in high-dimensional features [13]. Yet, their effectiveness is limited due to a narrow focus on texture features and the absence of valuable shape and colour information [2].DL approaches such as You Only Look Once (YOLO) [14], Faster R-CNN [15], and EfficientNet [16] have been utilized for disease detection. Furthermore, deep neural networks (DNNs) extract more pertinent features of leaves and reveal great classification accuracy. However, these methods face computational challenges and relatively high resource demands [4,17].To address these limitations, this research introduces the ESD2TM framework for detecting diseases in tomato leaves. The incorporation of adaptive thresholding-based region of interest (ROI) extraction retrieves the disease-affected area. Focusing on these areas reduces computational requirements.The HMAS extraction technique captures optimal features required for effective detection and classification. The ElSTO algorithm improves convergence and avoids local optima. The ESD2TM model follows a distributed mirrored strategy among replica models to aggregate gradients for efficient and synchronous training.

The primary contributions of the ESD2TM are:

- **Hybrid Mutual Augmented Structural Features (HMAS):** Captures high-dimensional spatial and textural features, including spots and discoloration, to effectively identify disease patterns.
- **Elite Stochastic Optimization Algorithm (ElSTO):** Tunes hyperparameters and mitigates premature convergence while improving optimization.
- **Distributed Learning-based Ensemble LSTM Model:** Uses parallel training to reduce computational cost and improve efficiency while capturing temporal disease patterns.

2. Literature Review

The significance and shortcomings of the existing tomato leaf disease detection approaches are discussed in the section.Assaduzzaman, M., et al.

[18], initiated an XSE-TomatoNet framework, which incorporated Squeeze-and-Excitation (SE) blocks and multi-scale feature fusion, that showed better generalizability in unseen data. However, the widespread adoption of advanced farming technologies was limited due to the persistent inequalities in cost and access experienced by small-scale farmers. Khan, R., et al. [2], presented an ensemble model, incorporating GLCM local binary pattern histogram (LBPH), coupled with an SVM. The model extracts valuable features from images to effectively classify various disease types. Nonetheless, the key limitation was its narrow focus on texture features, which neglected valuable shape and colour information, thereby compromising its classification capabilities.According to Sun, H., et al. [8], an efficient Tomato Disease Detection Network (E-TomatoDet) framework was developed to achieve effective tomato leaf disease detection outcomes. While large-kernel convolutions enhanced the results of the E-TomatoDet model, the resulting inference speed presented a notable drawback for real-world deployment, which required further research into lightweight methods. Wang, Y., et al. [19], presented an improved YOLOv6 approach, which achieved superior performance under natural environmental conditions, compared to existing standard models. Nevertheless, because of the imbalanced disease spots that presented similar symptoms, and had generalizability issues as well. Rashid, R., et al. [7], presented a modified mobile-based CNN (MobileNetv3) for tomato leaf disease detection. The model integrated an Efficient Channel Attention (ECA) module and inverted residual blocks (IRBs) to improve accuracy. While the model deployed in the real-time field faced several challenges in efficiency, and was not well generalized. Yao, J., et al. [4], deployed a Wavelet Transform ADown DySample (WTAD-YOLO) model, which reduced substantial computational resource consumption and exhibited the least performance degradation in disease detection. On the contrary, the deployed model was still limited by dataset coverage, and misclassified healthy leaves due to the minimal distinctive visual features. Sharma, R., et al. [20], used a modified AlexNet model, which dynamically extracted significant features for effective tomato leaves. However, the validation accuracy of the modified AlexNet showed poor performance while compared to other traditional techniques. Shehu, H.A., et al. [21], have integrated transfer learning approaches, including ViT-ImageNet, ViT-Small, and ViT-Base to detect tomato leaf disease, which significantly highlighted the effectiveness, generalization ability, and reduced error rates during computation. However, the model was still limited in robustness and was prone to overfitting due to inconsistent information.

2.1 Challenges

The shortcomings faced by traditional models are discussed in the section. In [2], the key limitation was its narrow focus on texture features, which left out valuable shape and colour information that is highly required for effective classification.The large kernels available in the E-TomatoDet model exhibited a notable drawback in inference speed, prompting further investigation into lightweight methods [8].The possible limitations of the MobileNetv3 coupled with channel attention mechanisms and inverted residual were ineffectiveness and not well generalized due to a limited dataset [7].Owing to the lack of effective sophisticated techniques, the modified AlexNet had attained minimum accuracy results and poor robustness on tomato leaf disease detection [20].

2.2 Problem Statement

Tomatoes are considered one of the major cultivated food crops all around the world because of their high nutritional value and versatile consumption. The rapid decrease in the quality of tomato crops is commonly caused because of various viral, fungal, and bacterial diseases. The traditional tomato leaf disease detection relies on expensive monitoring methods and consumes an enormous amount of time for identifying the types of diseases. The conventional techniques are inefficient for precision agriculture as they include manual inspections for detection. Nevertheless, the traditional techniques involve drawbacks including minimal accuracy, lack of robustness [20], failed to extract the colour and shape of the leaves [2], and poor generalization [7].To overcome all these shortcomings, the ESD2TM framework is introduced for detecting the disease and classifying its types. In the ESD2TM model, the input leaf image is collected from dataset Q, including Tomato leaves dataset [22], Tomato leaf disease dataset [23], and Tomato village dataset [24].The HMAS extraction mechanism retrieves the colour and textural features of the leaves to identify the pattern related to disease symptoms. The ESD2TM model follows a distributed learning, which exhibits data parallelism and enables synchronous training. The ESD2TM model used categorical cross-entropy as a loss function to minimize the error between the actual and predicted outcomes.

3. Methodology of Elite Stochastic optimized distributed learning-based ensemble model for tomato leaf disease detection and classification

The main goal of the research is to design an ESD2TM model for detecting the leaf disease and classifying its types. In the initial stage, the ESD2TM gathers inputimages from the Tomato Leaf Disease Dataset [23], Tomato Leaves Dataset [22], and the Tomato-Village dataset [24]. The collected images undergo adaptive thresholding-based region of interest (ROI) extraction, which isolates specific areas by calculating a separate threshold value for smaller regions and improves the learning capability of ESD2TM. Moreover, the ROI extracted image is given to the HMAS extraction, which retrieves the crucial features for efficient training. These pertinent features emphasize the ability of model training, therefore, its accuracy in identifying diseases
can be increased. In line with this, the refined features are passed to the ESD2TM classifier to provide the final detection outcome. Meanwhile, the ability and fectiveness of the model are enhanced using the ElSTO algorithm, which tunes the hyper parameters and significantly enhances the convergence speed. The schematic representation of the ESD2TM framework is given in Figure 1.

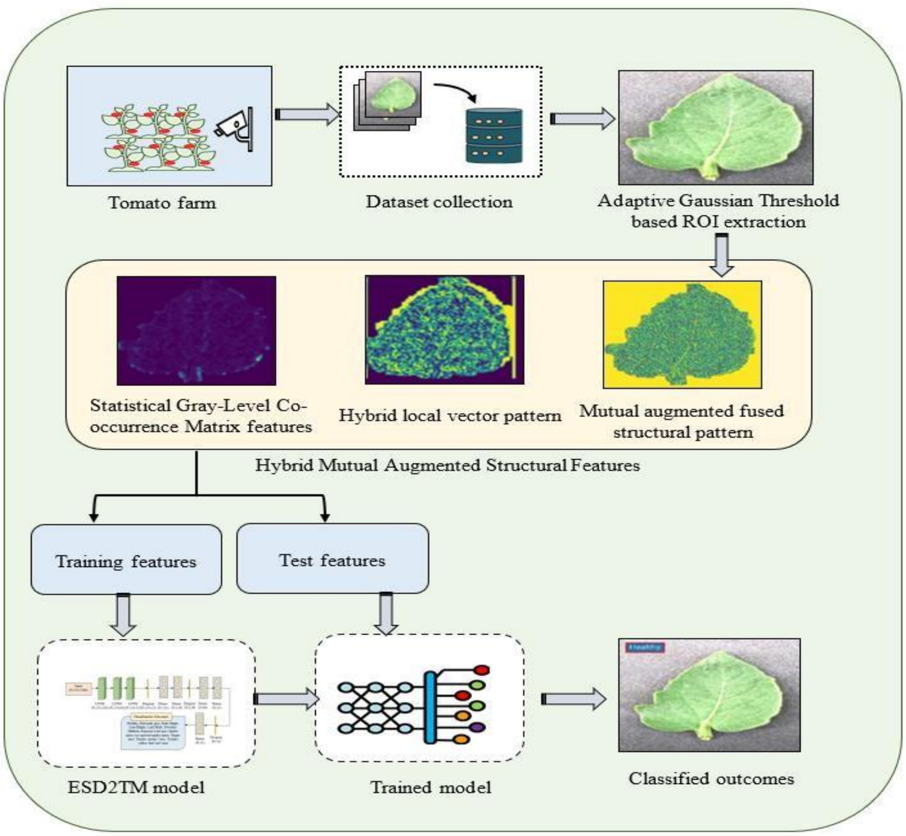

Figure 1: Diagrammatic representation of the ESD2TM approach

3.1 Input Tomato leaf images

The input tomato leaves images are aggregated from three datasets, namely, the Tomato Leaf Disease Dataset [23], Tomato Leaves Dataset [22], and Tomato-Village dataset [24].Moreover, the input image Ui of size $N,256,256,3$, which is given to the further ROI extraction process.

3.2 Adaptive Gaussian Threshold-based ROI extraction

The ROI extraction technique is used to isolate the specific area of disease spotted leaves, which enhances the accuracy through focusing on the relevant areas of the leaf images. The adaptive Gaussian thresholding mechanism is utilized in the research to isolate the foreground region from the background region of Ui . Initially, the Ui is divided into small regions and a threshold is computed for each region based on the tuned constant C and Gaussian weighted sum of neighbouring pixels.

3.3 Feature Extraction using Hybrid Mutual Augmented Structural Features

The research utilizes hybrid mutual augmented structural features, which incorporate statistical GLCM, hybrid local vector pattern, and mutual augmented fused structural pattern to extract optimal features from the disease-affected leaves of the tomato plants. The elaborated discussion of these features is presented in the subsequent section.The GLCM computes the dependencies of the gray level present in the tomato leaf images, which correlates with the number of columns and rows in the GLCM matrix [27]. Moreover, the GLCM matrices are produced to extract various texture features, including dissimilarity, contrast, energy, homogeneity, and entropy, which are explained in Table 1.

Table 1: *GLCM features and their formulae*

Features	Formula	Description
Contrast (Con)	$Con = \sum_{a,b=0}^{G_n-1} E_{a,b}(a-b)^2$	Compute the local variations in the gray-level within the neighbouring pixels.
Dissimilarity (Dis)	$Dis = \sum_{a,b=0}^{G_n-1} E_{a,b}\lvert a-b\rvert$	Calculate the average intensity difference between the nearby pixels.
Homogeneity (Hom)	$Hom = \sum_{a,b=0}^{G_n-1} \frac{E_{a,b}}{1+(a-b)^2}$	Measures the closeness of the GLCM elements corresponding to the diagonal.
Energy (Eng)	$Eng = \sum_{a=1}^{G_n}\sum_{b=1}^{G_n} E(a,b)^2$	Energy is a texture feature that computes the uniformity of the image, also specified as the angular second moment.
Entropy (Ent)	$Ent = -\sum_{a,b=0}^{G_n-1} E_{ab}\ln E_{ab}$	Compute the complexity or randomness by analyzing the spatial relationship between the pixels.

3.4 Elite Stochastic optimized distributed learning-based ensemble model for tomato leaf disease detection and classification

The elaborated working mechanism of the ESD2TM approach is provided in the subsequent context. However, the conventional techniques include drawbacks such as inaccurate detection, poor robustness [20], minimum generalization capability [7], and difficulties in extracting the textural pattern of leaves [2]. The research introduced the ESD2TM framework for detecting and classifying the types of disease. The input Fx is split up into two replica models, which comprise three Long Short-Term Memory (LSTM) with tanh activation function, three dropout, and five dense layers. The ESD2TM model performed a mirrored strategy, which is suitable for synchronous distributed training on a single machine and updates the results using the all-reduce technique. In addition, replica models ensure data parallelism, where each replica model processes a subset of Fx and utilizes the all-reduce technique to gather the gradient across the ESD2TM model through enabling synchronous training. In the ESD2TM model, the allreduce mechanism combined and distributed the outcome of each replica iteratively, and averaged the gradients across multiple modes during training. Moreover, the all-reduce consists of two phases, namely the broadcast and the reduction phase. The reduction phase combined the data from the replica models, whereas the broadcast phase sent the result back to the models. The equal splitting of features in distributed learning enables effective parallel computation to minimize the computational complexities of the ESD2TM model. Additionally, the ESD2TM exhibit collaborative training, which minimized the computational overhead especially while handling more features. The Fx is given to the LSTM layer with a tanh activation function, comprises three gates including output gate, forget gate, and input gate. The output gates learn to access the control of the memory cell, and the input gate controls the signal of the cell state. Additionally, the forget gates learns to reset the internal memory state when the information present in the memory state is no longer needed.

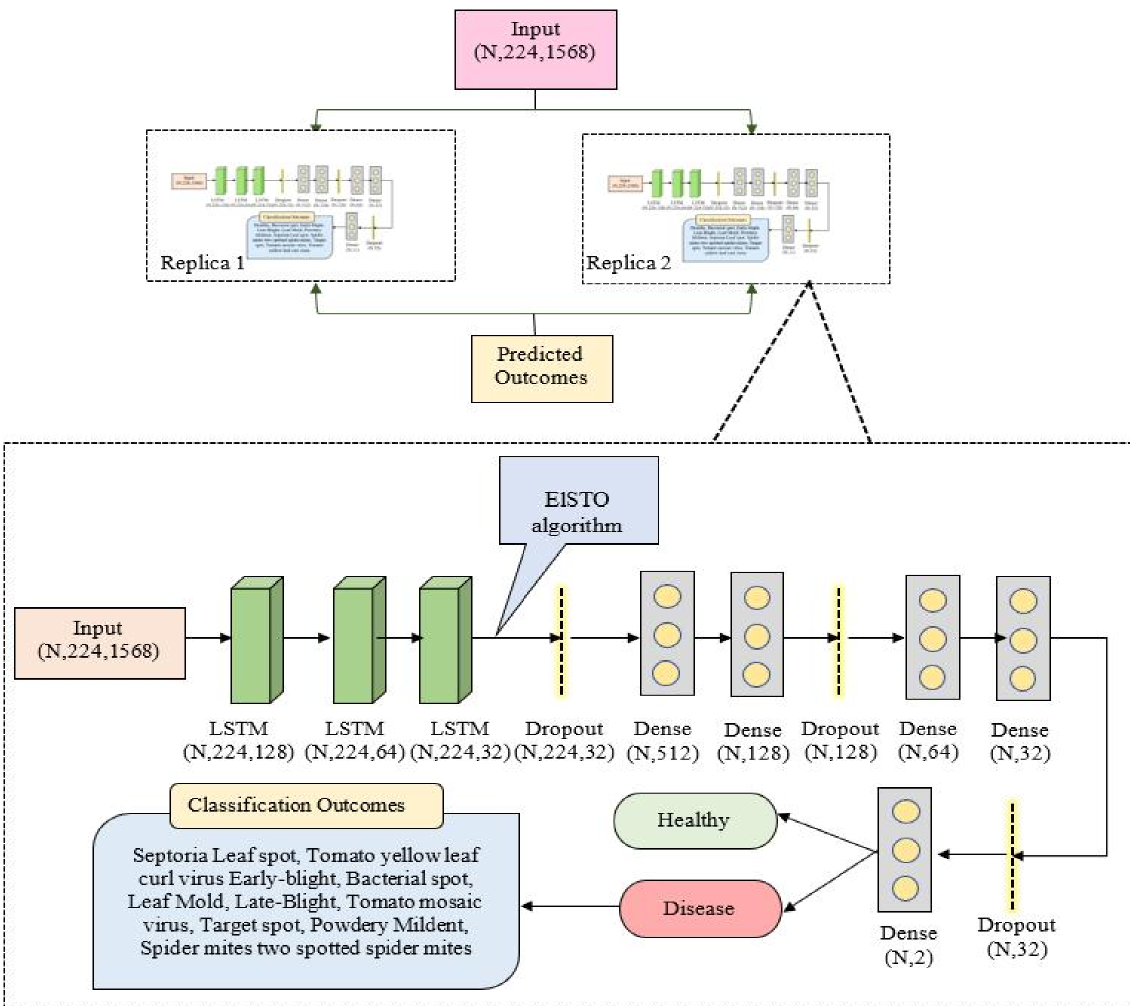

Figure 2: Architecture of ESD2TM framework

3.5 Elite Stochastic Optimization Algorithm

The research introduced the ElSTO algorithm through hybridizing two algorithms, namely, the sparrow searches algorithm (SSA) and the walrus optimization algorithm (WaOA) .Nevertheless, the traditional algorithms include the limitations of premature convergence, minimal population, and diversity local optima trapping. Henceforth, the scouting behaviour and alarm safety threshold characteristics of the sparrow in hybridized in the ElSTO. In addition, the exploratory learning strategy and elite guided exploitation phases find the optimal solution in the search space based on priority. The ElSTO algorithm follows wider exploration, which prevents premature convergence and reveals a smoother transition between exploitation and exploration.

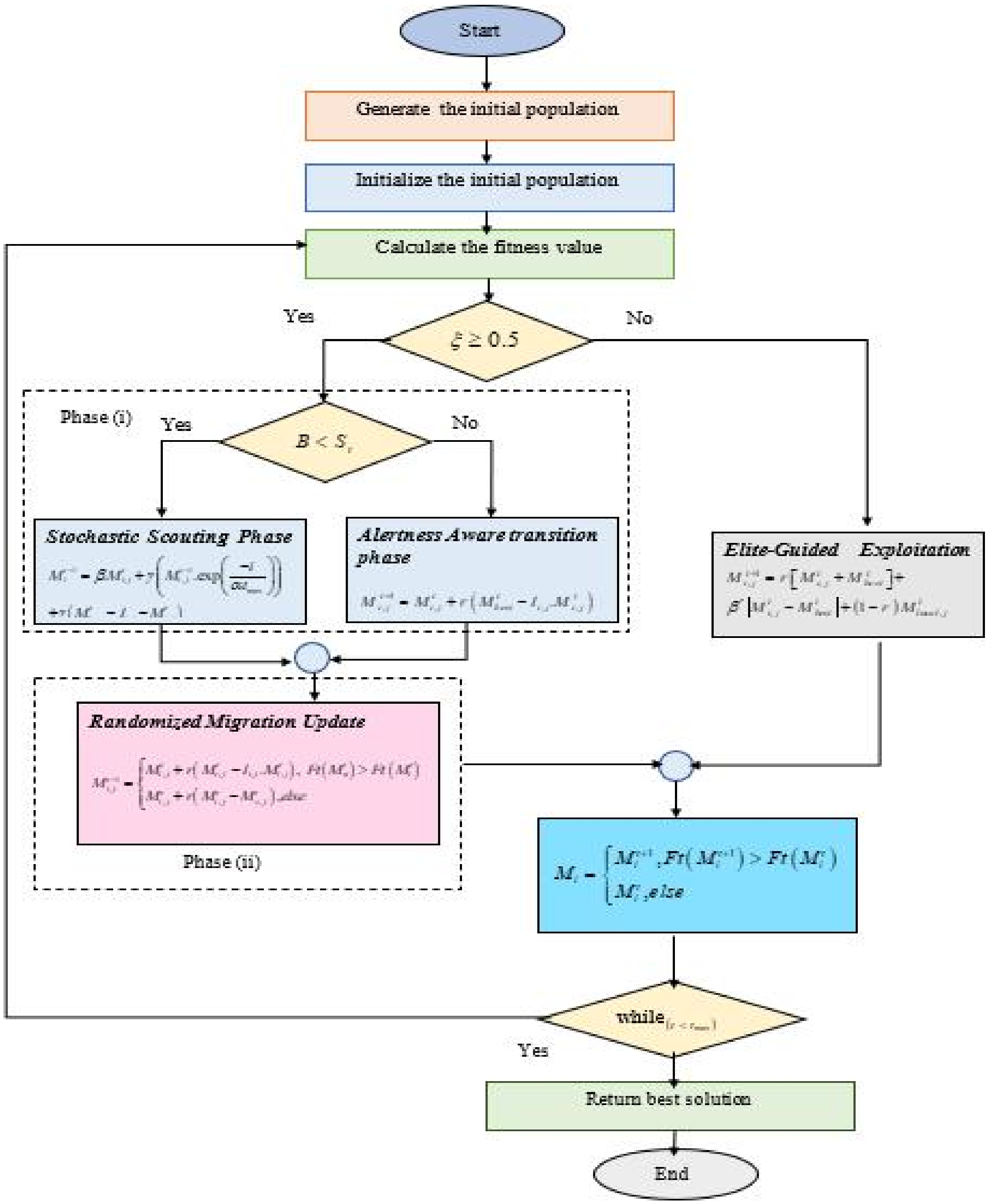

Figure 3: Flow diagram of the ElSTO algorithm

4. Results and Discussion

The section demonstrates the outcomes of the ESD2TM approach in detecting the disease and classify its types. Furthermore, the experimental setup, performance evaluation, time complexity analysis, convergence analysis, and comparison with traditional models are elaborated in this section.

4.1 Experimental Setup

The ESD2TM approach is implemented in Windows 11 with the storage tendency of 16GB RAM, more than 100GB ROM with 1.7GHz processing speed. The ESD2TM research is carried out in Python software for optimized training efficiency. The hypermeter's details of the ESD2TM are provided in Table 2.

Table 2: *Hyper parameters and their specification*

Hyperparameters	Range/Types
Epochs	500
Optimizer	Adam
Dropout	0.25
Batch Size	32
Learning rate	1e-3
Dense layer	128, 512, 64, 32
LSTM	128, 64, 32
Activation	ReLU
Optimization	Layer – 17, fitness - Accuracy
epochs	500
Loss	CCE

4.2 Dataset Description

The input sample images are aggregated from the three datasets, such as, Tomato Leaf Disease Dataset [23], Tomato Leaves Dataset [22], and Tomato-Village Dataset [24]. The description of all these datasets is given in the context below.

Tomato Leaves Dataset [22]: The Tomato Leaves dataset consists of 20,000 samples with 1 healthy class and 10 disease classes, such as healthy, Septoria leafspot, TomatoYellow LeafCurl Virus, Bacterial spot, Powdery Mildew Target Spot, Late blight, Leaf Mold, Spidermites Two-spotted spider mite, Tomatom osaicvirus, and Early blight.

Tomato Leaf Disease Dataset [23]: In the dataset, various diseases are sorted in different folders based on the disease types. Additionally, the folders comprise eight classes such as Tomato healthy, Early blight, Tomato mosaic virus, Late blight, Leaf Mold, Bacterial spot, Spider mites Two-spotted spider mite, Tomato Yellow Leaf Curl Virus, Target Spot, and Septoria leaf spot.

Tomato-Village Dataset [25]: The dataset consists of three variants such as multi-label tomato disease classification, tomato-based detection, object detection-based, and multiclass tomato disease classification. Spotted wilt virus, Leaf Miner, and Nutrition deficiency diseases are the major diseases spotted in the tomato leaves, which are included in this dataset for effective detection.

4.3 Experimental Analysis

The remarkable outcomes of the ESD2TM framework at each stage, such as Input, ROI extraction, Hybrid Mutual Augmented Structural Features, and the detected outcomes, are visualized in Figure 4.

<table>
<tr><td>Techniques</td><td>Tomato Leaves Dataset</td><td>Tomato Leaf Disease Dataset</td><td>Tomato-Village Dataset</td></tr>
<tr><td>Input</td><td></td><td></td><td></td></tr>
<tr><td>ROI extraction</td><td></td><td></td><td></td></tr>
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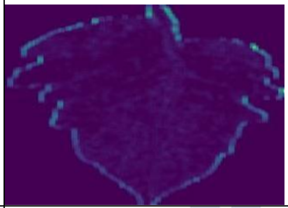
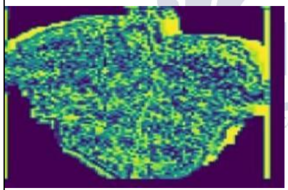
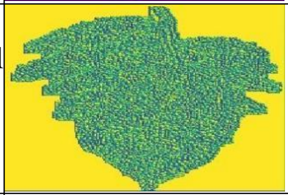
<table>
<tr><td rowspan="3">Hybrid Mutual Augmented Structural Features</td><td>GLCM</td><td></td><td></td><td></td></tr>
<tr><td>LVP</td><td></td><td></td><td></td></tr>
<tr><td>Structural pattern</td><td></td><td></td><td></td></tr>
<tr><td colspan="2">Output</td><td></td><td></td><td></td></tr>
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Figure 4: Experimental Analysis of ESD2TM approach

4.4 Performance Metrics

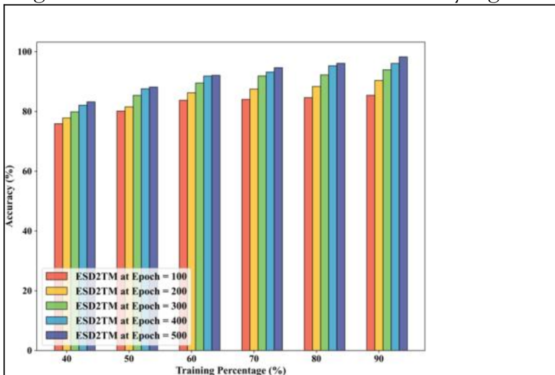
The research used precision, specificity, sensitivity, and accuracy as the metrics for the ESD2TM approach. Accuracy measures the overall percentage of correctly classified leaves to the total leaves. The precision specifies the proportion of positive predictions among the total positive instances. Further, the tendency of the model to find the actual positive cases from the total positive cases is measured by sensitivity. The actual negative cases correctly identified by the ESD2TM is computed using the specificity metric. The formulation of the metrics is given in Table 3 below.

Table 3: *Metrics and their formulas*

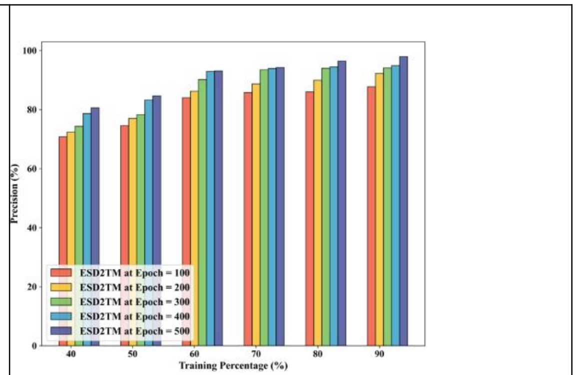
Metrics		Formula
Accuracy	Ac	$Ac = \dfrac{Tr_p + Tr_n}{Tr_p + Tr_n + fl_p + fl_n}$
Precision	Pr	$\mathrm{Pr} = \dfrac{Tr_p}{Tr_p + fl_p}$
Sensitivity	Sen	$Sen = \dfrac{Tr_p}{Tr_p + fl_n}$
Specificity	Spe	$Spe = \dfrac{Tr_n}{Tr_n + fl_p}$

4.4.1 Performance Analysis using Training Percentage

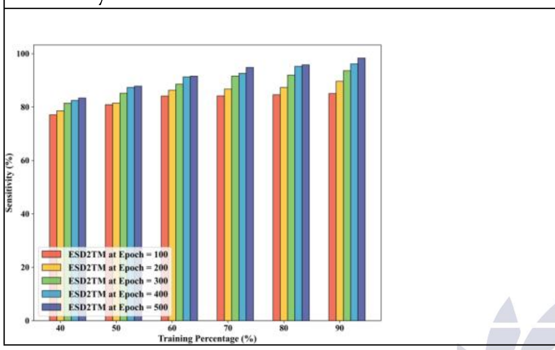
The significant outcome of the ESD2TM model using three available datasets, namely, Tomato-Village Dataset, Tomato Leaves Dataset, and Tomato Leaf Disease Dataset with a training percentage 90% and epochs ranging from 100 to 500, is given in the below context. Figure 5 reveals the remarkable results of the ESD2TM model with Tomato Leaves Dataset of 90% training. The ESD2TM exhibits better performance with an accuracy of 85.40%, 90.36%, 93.91%, 96.07%, and 98.25% when the epochs increase from 100 to 500. These values highlight the strength and dependability of the ESD2TM across various evaluations. The attained precision values of 87.81%, 92.27%, 94.12%, 94.93%, and 98% at different epochs offers a thorough insight into the classification of the ESD2TM. The ESD2TM attained the sensitivity of 85.05%, 93.61%, and 98.35% at epochs 100, 300, and 500, which represents the enhanced capability of the ESD2TM to find all the positive instances correctly. The ESD2TM model obtained the specificity of 86.10%, 91.78%, 94.49%, 95.88%, and 98.05% across various epochs, which exhibits the tendency of the ESD2TM to find the negative instances correctly. The results of the ESD2TM using the Tomato Leaf Disease Dataset are shown in Figure 6. The ESD2TM framework attained 90.47%, 92.65%, 93.30%, 95.98%, and 98.42% accuracies with a training percentage 90%. While, the maximum precision attained by the ESD2TM model is 89.20%, 90.75%, 96.28%, 97.01%, and 97.69% as epochs rise from 100 to 500. The percentage of sensitivity increased to 90.40%, 92.76%, 93.18%, 95.20%, and 98.39% at 90% of training. Furthermore, the specificity of the ESD2TM model, when the epochs increase from 40% to 90% is 90.60%, 92.44%, 93.55%, 97.56%, and 98.46%, which indicates the model is good at identifying the healthy leaves and minimizing the false positives. Figure 7 depicts the results of the ESD2TM framework in terms of the Tomato-Village Dataset. The ESD2TM attained the accuracy of 88.99%, 94.35%, 95.66%, 96.24%, and 98.28% in 90% training and diverse epochs. The ESD2TM framework obtained the precision value of 86.93%, 93.29%, 96.61%, 96.65%, and 98.43% from epochs 100 to 500. The sensitivity of the ESD2TM framework is 90.46%, 95.28%, and 98.23%, while the specificity attained by the ESD2TM model is 86.05%, 96.42%, and 98.37% at epochs 100, 300, and 500. The incorporation of a grid-based structural pattern captures the intricate pattern from the leaves and reducesthe intensity variation for better classification. Both the quantitative and qualitative outcomes reveal that the ESD2TM model exhibits good robustness for detecting the tomato leaf disease and classifying its types.



Accuracy



Precision



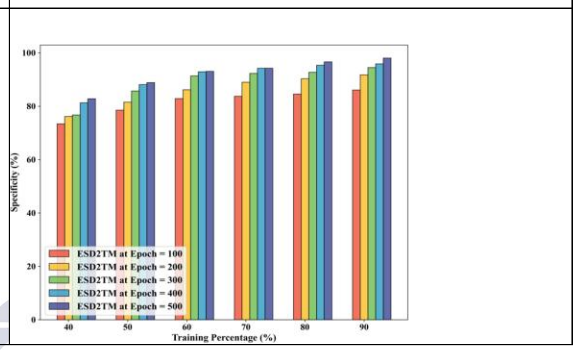
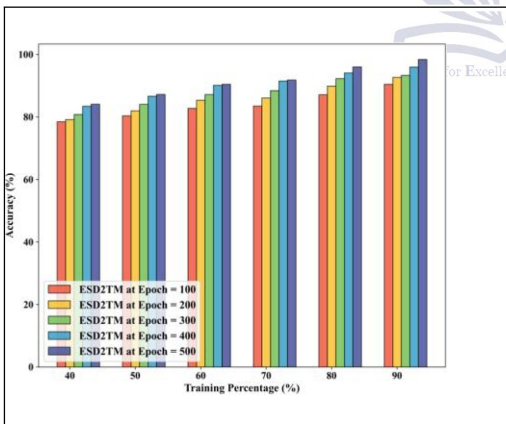
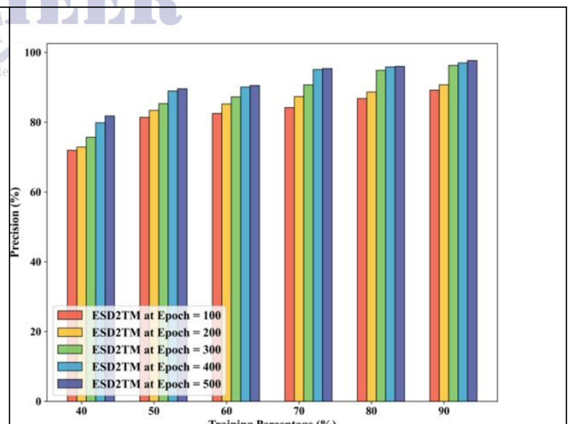


Figure 5: Performance evaluation using Tomato Leaves Dataset



Accuracy



Precision

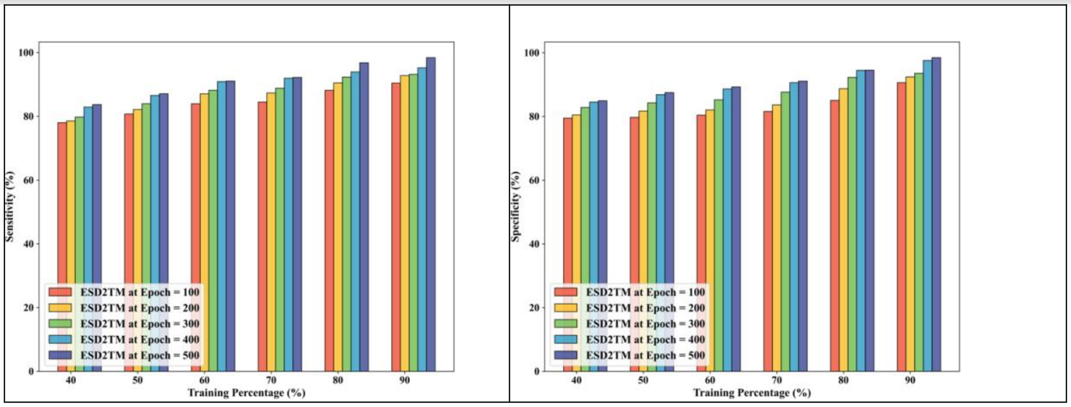


Figure 6: Performance evaluation using Tomato Leaf Disease Dataset

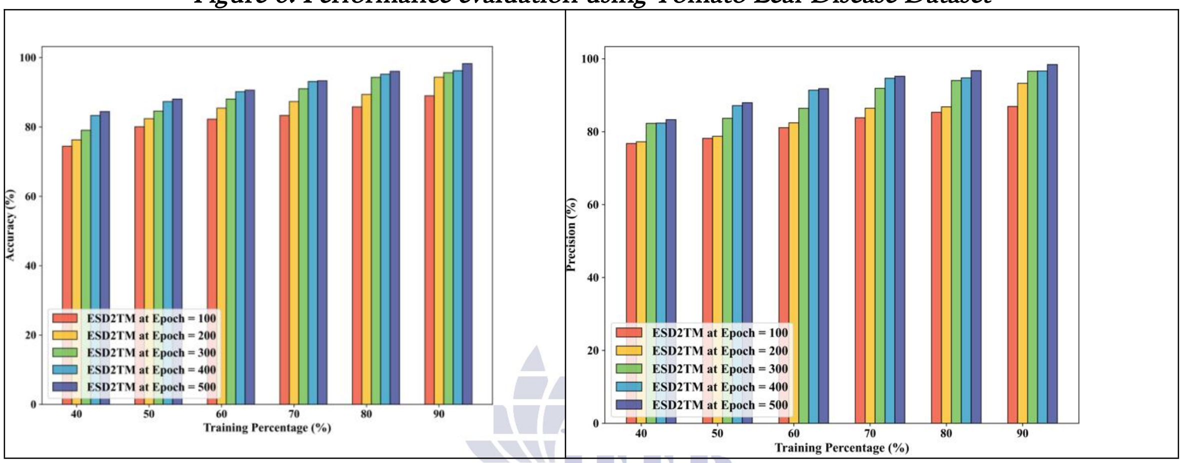


Figure 7: Performance evaluation using Tomato-Village Dataset

4.5 Convergence Analysis

The convergence analysis of the ElSTO algorithm is compared with different algorithms, including SSA and WaOA to evaluate the loss of the model, is shown in Figure 8. At epoch 3, the ElSTO attained the minimum loss of 2.35, whereas the remaining two techniques obtained 2.54, and 2.47, respectively. The loss of ElSTO algorithm at epoch 50 is 0.25, whereas the traditional techniques, such as SSA, obtain 0.43, and WaOA attain 0.36 losses. Similarly, at epoch 100, the ElSTO has 0.24 loss, on the other hand, the SSA and WaOA obtain 0.43, and 0.35, respectively. These significant minimal losses are attained due to the incorporation of the scouting and alarming behaviour, which boost the convergence towards the best solution and refine the hyperparameters of the ESD2TM framework.

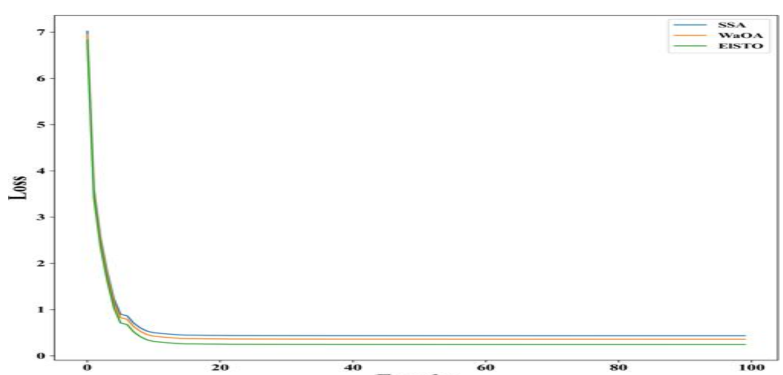


Figure 8: Convergence analysis

4.6 Comparative Discussion

Table 4 shows the comparative performance of the ESD2TM approach using three available datasets. The traditional tomato leaf detection model includes limitations such as poor generalization ability [7] a lack of robustness and inaccurate classification results, and a struggle to retrieve the textural pattern of the leaves.Thus, the ESD2TM uses three specific datasets, which include more samples for training, thereby enhancing the generalization capability of the ESD2TM. The ESD2TM followed a distributed mirrored strategy to enable parallelism and speed up the training process, which captures a wider range of disease variation, leading to a potentially robust model with accurate classification.The incorporation of HMAS features captures the local spatial and textural relationship which reduces computational resources and leads to efficient model training. Additionally, the ElSTO algorithm performs hyper parameter tuning and mitigates premature convergence for identifying the optimal solutions. Henceforth, the ESD2TM model attains accuracy, specificity, precision and sensitivity of 98.42%, 98.46%, 97.69%, and 98.39%, respectively.

Table 4: *Discussion on the ESD2TM using Training Percentage 90%*

Methods metrics	Vs.XSE-TomatoN [18]	E-etTomatoD [8]	MobileNet et[7]	v3AlexN [20]	etDNN - LST [36]	SSA-MDNN - LST [34]	WaO LSTM M	A-DNN- [35]	ESD2TM
Tomato Leaves Dataset									
Accuracy (%)	94.54	92.80	93.61	95.37	96.66	97.65	97.96		98.25
Precision (%)	88.41	87.15	93.21	94.77	97.03	97.33	97.72		98.00
Sensitivity (%)	95.63	91.14	94.03	96.35	96.50	97.78	98.16		98.35
Specificity (%)	92.35	96.13	92.77	93.39	96.97	97.39	97.56		98.05
Tomato Leaf Disease Dataset									
Accuracy (%)	91.97	92.90	91.33	88.78	94.97	96.22	97.60		98.42
Precision (%)	87.34	95.34	93.88	93.45	96.23	96.23	96.81		97.69
Sensitivity (%)	90.77	92.35	90.57	87.23	94.80	95.58	97.32		98.39
Specificity (%)	94.36	93.99	92.84	91.89	95.32	97.50	98.14		98.46
Tomato-Village Dataset									
Accuracy (%)	96.77	93.03	94.27	96.31	97.30	97.63	97.97		98.28
Precision (%)	93.34	85.08	90.09	88.74	93.75	96.92	97.31		98.43
Sensitivity (%)	97.15	97.15	97.15	97.15	97.15	97.15	97.15		97.15
Specificity (%)	96.00	94.29	94.92	94.91	96.56	97.22	97.81		98.37

5. Conclusion

The research initiated the ESD2TM framework for detecting disease-affected tomato leaves and classifying their types. Moreover, the ESD2TM incorporated a distributed mirrored strategy, in which the replica model exhibits parallel training to speed up the training and minimize the excessive computational demands. In addition, the ElSTO algorithm exhibits better hyperparameter tuning and convergence speed towards the optimal solution, which boosts the reliability and robustness of the model. The HMAS features capture the spatial relationship to learn intricate patterns and context-aware features of the leaves. Additionally, the extraction of local textural features helps to analyze the irregularities in the leaves caused due to the disease symptoms. The integration of adaptive thresholding ROI extraction focuses on the relevant disease-affected region, which minimizes the excessive computation time required for detection. Therefore, the inclusion of these techniques overcomes the limitations of poor robustness, lack of generalization, inaccurate results, and ensure the ESD2TM model to achieve accuracy, specificity, precision, and sensitivity 98.42%, 98.46%, 97.69%, and 98.39%, respectively. Future research would focus on integrating a hybrid attention module and ensemble models to further enhance the performance results of the model.

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