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Original scientific paper

Designing a New Tomato Leaf Disease Classification Framework using RAN-based Adaptive Fuzzy C-Means with Heuristic Algorithm Model

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Abstract: In tomato production, one of the most significant problems is the identification of Tomato Leaf Disease (TLD). Plant leaf disease is the primary factor that influences both the quality and quantity of crop production. India holds the second position in tomato making. However, multiple diseases contribute to the decline in the quality of tomatoes and the decrease in crop yield. Hence, it is important to accurately categorize and diagnose the tomato plant leaf infection. The productions of tomatoes are impacted by many leaf diseases. Early recognition of the diseases helps to reduce the disease infection and improve the yield of crops. Certain diseases are identified and шlassified using several methods. Therefore, the TLD classification and identification model is developed to solve the above problems. The images related to tomato leaves are aggregated in the initial phase through online sources. Then, the images are forwarded to the pre-processing phase. Further, the pre-processed image is given to the segmentation process, where the Adaptive Fuzzy C-Means (AFCM) technique is utilized. Meanwhile, the parameters of the AFCM algorithm complicate the cluster assignment in the presence of outliers or noise, thus resulting in reduced clustering performance. So, the parameters of AFCM are tuned by utilizing the new improved algorithm named Dingo Optimization Algorithm (DOA) to improve the clustering accuracy. It is done by assuming the AFCM parameters as a population of Dingoes and the maximum classification accuracy as its fitness function. Finally, the segmented images are fed to the classification process, where the Residual Attention Network (RAN) is used to attain the classified outcomes. Therefore, the investigated system shows a more efficient TLD prediction rate

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compared to traditional techniques in the experimental investigation. The results from the experiments indicate that the suggested models exhibit exceptional classification performance, achieving an accuracy rate of 95.22%. Therefore, the model suggests advancement in predictive capabilities over traditional methods.

Keywords: Tomato Leaf Disease Classification, Contrast-Limited Adaptive Histogram Equalization, Dingo Optimization, Adaptive Fuzzy C-Means-based Segmentation, Residual Attention Network.

1 Introduction

The classification of TLD presents a significant challenge in the agricultural sector. Early detection of plant infections is crucial for minimizing disease spread and reducing financial losses incurred by farmers [1]. However, conventional methods for identifying leaf diseases often lack accuracy and reliability [2]. Moreover, the absence of experts with agricultural training in remote areas further exacerbates these challenges, impacting global food security and causing substantial losses in tomato production [3]. To address these issues, automated procedures and technologies are increasingly being employed, leveraging Artificial Intelligence (AI) techniques, such as Deep Learning (DL) and Machine Learning (ML) [4, 5]. These advanced methods offer the potential for precise and efficient identification of TLDs, improving agricultural productivity and enhancing farmers' profitability [6].

Precision farming employs AI techniques, including conventional DL methods and ML approaches. These methods are utilized to automatically identify and detect TLDs [7]. Classification applications, such as identifying and categorizing human diseases, are utilized across a variety of domains, including industry, healthcare, and medical image analysis [8]. The identification of plant diseases has been addressed in several ways utilizing conventional ML techniques [9]. Although the classifiers used in standard ML approaches rely heavily on hand-crafted features, these features are manually developed by the expert [10]. These methods are time-consuming and expensive [11]. DL techniques automatically extract deep features from images. This process overcomes the time-consuming issue, thus providing higher classification accuracy than conventional ML methods [12]. Convolution Neural Network (CNN) is one of the DL methods employed extensively in classifying plant diseases [13]. The possibility of identifying diseases in tomato plants is based on changes in leaf appearance and it is performed using CNN method [14]. This detection is used to improve the treatment decisions based on the disease. It requires a lot of computational power, which raises the complexity of classification [15]. Therefore, the TLD classification is implemented to solve the above problems.

TLD presents a significant hurdle to global agriculture, affecting crop productivity, quality, and farmers' financial security. Despite TLD being a common issue for tomato plants, accurately identifying and managing TLD remains challenging in conventional methods. This research aims to create a robust TLD detection system using advanced technologies. By combining image preprocessing, Adaptive Fuzzy C-Means (AFCM) for segmentation, parameter optimization with the DOA, and Residual Attention Network (RAN) for classification, the proposed model seeks to enhance accuracy, efficiency, and predictive capabilities. The study mainly contributes to TLD management by identifying the various diseases on tomato leaves with the novel approach,which is further pointed out below:

– The leaf images are processed in this novel approach via preprocessing, segmentation, parameters optimization, and classification processes to ensure the accurate detection of TLDs.
– A promising and reliable solution for managing the TLD is provided for the agricultural practitioners using the proposed methodology.
– Through detailed testing and validation, the study intends to demonstrate the model's potential impact on crop yield, financial stability, sustainability, and food security.
– The accurate classification of different types of TLD, including Bacterial spots, black mold, gray spots, late blight, and powdery mildew makes farmers take relevant actions in the earlier stage, thereby preventing the further impact of disease on the other healthy leaves.

The objectives of the TLD classification system using DL are described below:

– To develop an effective TLD classification model for classifying the various types of diseases from leaf images at an early stage.
– To design an effective AFCM-based segmentation, the parameters are tuned using DOA optimization for increasing the efficacy of the model.
– To implement a RAN model that classifies the TLDeffectively for improving the efficacy of the system using DOA optimization.
– For evaluating the efficacy of the suggested TLD classification modelwith the conventional approaches using several effectiveness metrics.

The article's structure is organized as:

– Section 2 provides insights into existing TLD classification methods and their respective advantages and disadvantages.
– Section 3 outlines the architecture and dataset utilized in the proposed TLD classification system.

– Section 4 delves into the details of the Adaptive Fuzzy C-Means (AFCM)-based segmentation method and the suggested algorithm.
– Section 5 presents the experimental setup and outcomes, evaluating the effectiveness of the proposed TLD classification system.
– Finally, Section 6 concludes the article with a summary of key findings and future research directions.

By addressing the challenges associated with TLD classification and proposing an advanced AI-based solution, this article aims to contribute to the improvement of agricultural practices and the enhancement of crop yield and farmer profitability.

2 Literature Survey

2.1 Related works

In 2021, Hammou et al. [16] implemented an efficient classification model using a DL framework. It was effectively supported by smartphone applications. The investigated tomato plant leaf disease classification was used to overcome the issues of farmer harvesting. The model enhanced the product quality due to the disease detection on various complex leaf structures. The tomato leaf images of the Plantvillage dataset with 9 class diseases were used in this framework. This framework employed a batch size of 32. DL approaches like DenseNet169 were used to identify the tomato plant infection. The Adam and RMSprop optimizers were used in this implementation to improve the efficacy of the system.

In 2014, Zhang et al. [17] implemented plant disease detection using neural methods with multi-modal data. The ResNet34 approach was employed to increase the efficacy of solving the data dependency and overfitting issues. The initial stage was feature extraction. The features were extracted by Mask Residual-CNN. The complex backgrounds and difficult regions of backgrounds were effectively recognized. The environment database was utilized to recognize and classify the disease types in this model. This model provided greater classification precision and accuracy while predicting the six classes of TLD. The six types of TLD, namely early blight, gray mold, bacterial spot, yellow aspergillosis, late blight, and disease leaf mold were predicted. This system provided a lower error rate than other classification systems.

In 2021, Zhou et al. [18] implemented a hybrid model that combined the benefits of deep residual networks and dense networks for the identification of TLDs. This model reduced the training parameter's count to enhance the accuracy of the calculation. Also, it improved the gradients and data flow. Here, the neural network model was employed. They changed the image of hyper parameter's input and characteristics to implement the classification tasks. The Tomato AI Challenger 2018 dataset was used, and the experimental findings demonstrated high identification accuracy. This network model achieved better effectiveness and low cost compared to other models.

In 2022, Anandhakrishnan et al. [19] recommended a deep-learning method that focused on agricultural fields for identifying leaf disease in tomatoes. The TLD images from the Plantvillagedataset were employed in this proposed work. In the investigational study, this dataset used several images for training and testing. The suggested model provided a better rate of accuracy when compared to recently used plant leaf disease prediction systems.

In 2023, Attallah et al. [20] designed three neural networks for the automatic diagnosis of TLDs. From the fully connected layer of DL, the deep variables were removed via transfer learning. Then, it combined features from the three DLs to maximize the effectiveness of each deep network. It employed a selection of hybrid parameters and provided a feature group with completely smaller measurements. The identification process for TLDs used six classifiers. The findings showed that the developed system achieved the greatest accuracy.

In 2023, Shubhangi Solanki et al. [21] explained a methodology incorporating both traditional classification techniques and DL approaches. During the conventional categorization phase, this study employed six different classification methods - Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-layer Perceptron (MLP), Logistic Regression (LR), and Naïve Bayes (NB). Among these, SVM demonstrated the highest accuracy. Subsequently, a Convolutional Neural Network (CNN) was utilized, revealing a noteworthy improvement in overall performance compared to traditional classifiers.

In 2023, Shubhangi Solanki et al. [22] delivered a thorough examination of classification and segmentation techniques centered on images. The manuscript was primarily delved into contemporary deep-learning methodologies and strategies. The survey encompassed an exploration of recent literature, particularly emphasizing DL models employed for image segmentation and classification. Despite the superior performance attained by these models, there remained certain areas warranting future research focus, notably the high costs and complexity associated with model structures.

In 2023, ShubhangiSolanki et al. [23] illustrated a study that entailed evaluating the efficacy of autonomously identifying brain tumors from MR and CT imaging using fundamental image processing methods coupled with various computational techniques. Six traditional classifiers were initially employed for tumor identification, followed by the integration of CNNs and Deep CNNs into the analysis. Among these, VGG16 emerged as the top-performing DL model, surpassing traditional methods notably. Particularly, a five-layered CNN with an 80:20 split ratio yielded the highest accuracy of 97.86%, showcasing substantial performance enhancement over conventional classifiers.

In 2019, Siddharth Singh Chouhanet et al. [24] conducted a survey that analyzed articles using computer vision and soft computing techniques for identifying and classifying diseases based on plant leaf images. The objective was to provide an overview of the latest advancements in digital image processing and soft computing methodologies, including their applications and associated theories.

2.2 Motivation

The challenges in detecting TLDs arise from the complex and varied nature of leaf structures and the similarity of symptoms between different diseases. Traditional classification systems faced difficulties in accurately identifying and distinguishing between various diseases due to the following reasons, such as variability in leaf shapes,complexity of diseases, interference from environmental factors, and limited feature extraction. The conventional system gave slow convergence rates while predicting the disease with a large amount of data. They faced challenges related to classification complexity and did not address the problem of gradient disappearance. Hence, several deep-learning techniques were employed to develop TLD classification. The advantages as well as disadvantages are listed in **Table 1**. DenseNet [16] provides scalable outcomes for detecting the TLD. Hence, it improves productivity and predicts the TLD effectively. Although it solves the harvesting problems, it struggled to predict the diseases due to the greenhouse effect and did not solve the problem of gradient disappearance. R-CNN [17] prevents the overfitting problems. Also, it reduces the information dependencies. Yet, the implementation needed more time, and it was hard to detect the disease because of the bad weather conditions. RDN [18] reduces the economic losses. Also, it increases the prediction efficiency while using a large amount of dataset. However, it suffers from dimensionality issues and also it does not support real-time implementations. DCNN [19] enhances the gradients and information flow and reduces the computational complexity issue. Yet, the cost is high for the implantation of TLD detection. Also, it gives slow convergence while using a large amount of data. CNN [20] reduces the error rates by providing the training of the model. It obtains robustness and better accuracy. Yet, it increases the classification complexity, and the automatic detection concept is not supported. Hence, these disadvantages suggested building an effective TLD classification framework utilizing DL.

2.3 Problem statement

The identification of TLD represents a critical challenge in tomato production, impacting the productivity and quality of tomato crops. Despite India’s prominent position in tomato production, the industry faced significant losses due to various diseases affecting tomato plants. The presence of disease in tomatoes reduces the production quality, so accurate TLD categorization and diagnosis are needed. Conventional methods for TLD identification often lacked the precision and efficiency required to effectively manage disease spread and minimize crop losses. Additionally, the absence of early disease recognition mechanisms further exacerbated the problem, hindering proactive disease management practices. Addressing these challenges necessitated the development of advanced TLD classification and identification models capable of providing timely and accurate diagnoses. Such models should leverage innovative technologies and methodologies to enhance disease detection capabilities and improve agricultural productivity. Therefore, the problem at hand involves developing a robust TLD classification and identification model that integrates cutting-edge techniques to accurately categorize and diagnose tomato plant leaf infections, ultimately enhancing crop yield and quality in agriculture.

Table 1

Features and Challenges of TLD Classification Models using Deep Learning.

Author	Methodology	Features	Challenges
Hammou et al. [1]	DenseNet	• It provides scalable outcomes for predicting the TLD. Hence, it improves the productivity. • It predicts the TLD effectively. Hence, it solves the harvesting problems.	• It struggles to detect the disease due to the greenhouse effect. • It does not solve the problem of gradient disappearance.
Zhang et al. [2]	R-CNN	• It prevents overfitting problems. • It reduces the information dependencies.	• The testing takes overtime during the implementation. • It is hard to detect the disease because of the bad weather conditions.
Zhou et al. [3]	RDN	• It reduces the economic losses. • It increases the prediction efficiency while using a large amount of dataset.	• It suffers from dimensionality issues. • It is not supported for real-time implementation.
Anandhakrishnan et al. [4]	DCNN	• It enhances the gradients and information flow. • It reduces the computational complexity issue.	• The cost is high for the implantation of TLD detection. • It gives slow convergence while using a large amount of information.
Attallah et al. [5]	CNN	• It decreases the error rates by providing the training of the model. • It obtains robustness and better accuracy.	• It increases the classification complexity. • The automatic detection concept is not supported.

3 Heuristic-Aided Fuzzy Model for Tomato Leaf Disease Classification with Elucidation of Dataset and Image Preprocessing

3.1 Architectural explanation

The traditional TLD classification framework provides high complexity to the computation. Most of the traditional classification system gives high error rates. The simple architecture of the existing classification model is implemented in the agricultural sector at a low cost with limited resources. But, the implementation of the cost is huge. It is complex to predict and recognize plant leaf disease because of the complex pattern variation present in the model. It is hard to overcome the disease due to the complex location, infection status, surrounding things, and various diseases in the image. In the conventional models, accurate identification of affected areas on leaves is very difficult due to the color similarity between infected and healthy areas in the tomato leaves. The correct disease class is not identified at an early stage. The low-quality input samples do not classify the disease effectively, and they provide a low recall rate for the prediction. The small texture, same color, and small size of the diseased area on leaves make the system struggle to identify and classify the disease. The traditional methods decreased the system's prediction performance. The diagrammatic design of the DL-based TLD classification structure is shown in Fig. 1.

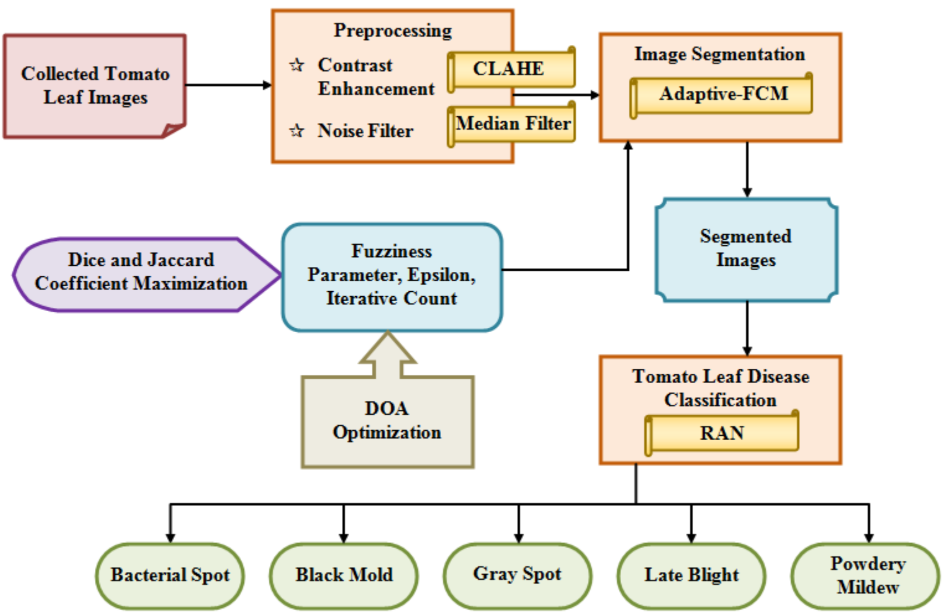


Fig. 1 – *Diagrammatic depiction of deep learning-based TLD classification structure.*

The recently developed TLD classification system is utilized to accurately identify various categories of TLD, such as Powdery mildew, Late blight, Bacterial spot, Gray spot, and Black mold, in their early stages. The tomato leaf images are collected and stored on the internet. The input image is incorporated into the preprocessing phase.

The contrast enhancement in the image is performed by the CLAHE method andthe technique of median filtering is utilized to eliminate undesired noise from the image and the pre-processed images are fed into the AFCM-based segmentation. The DOA optimization is utilized to optimize the values like fuzziness parameter, epsilon, and iteration count to improve the dice coefficient and Jaccard coefficient. The fuzziness parameter can also be associated with the level of intersection between sets or the extent to which an element belongs to a specific set. Jaccard's Index measures the degree of overlap between bounding boxes or masks, and the Dice Coefficient quantifies the similarity between two masks. The images of segmented features are inserted into the RAN-based classifier by which various types of leaf diseases are effectively identified and classified. The effectiveness of the proposed model is evaluated in comparison to various traditional methods.

3.2 Dataset collection

The tomato leaf images are used in the developed TLD classification system, and the explanations are given below:

Dataset-1 (Dataset of Tomato Leaves):

Utilizing the Plantvillage dataset for TLD identification and classification is a widely recognized strategy within the field. This dataset contains a substantial array of images of tomato plant leaves, each annotated with labels indicating the presence or absence of specific diseases. Leveraging this dataset to train a RAN model that is tailored for detecting TLDs offers a valuable opportunity to showcase the model's effectiveness in discerning various disease types. Additionally, it serves as a fundamental benchmark for evaluating alternative approaches in the realm of TLD detection and classification.This research utilizes a dataset comprisedof tomato plant leaf images sourced from the Plantvillage dataset, which is available at "https://data.mendeley.com/datasets/ngdgg79rzb/1" (accessed on 7th September 2023) [25]. It contains two dataset images. Totally, 14,531 images of tomato leaves are presented in the first dataset. It contains the images of the Plantvillagedataset. The image size is set to 227×227. In the first dataset, the diseases are categorized and named as Two-spotted spider mites, Healthy, Late Blight, Early Blight, Tomato Mosaic Virus, Target Spot, Bacterial Spot, Leaf Mold, Septoria Leaf Spot, and Yellow Leaf Curl Virus. It contains 4976 images. The image size is set to 227×227. The diseases are divided into six categories, such as Powdery Mildew, Black Leaf Mold, Healthy, Bacterial Spot, Late Blight, and Gray Leaf Spot. This dataset contains complex background images and single leaf and single background images. Hence, the term T_I^L is the input of tomato leaf images, where $i = 1, 2, \ldots, I$.

The collected tomato leaf images for the disease classification are displayed in Fig. 2.

Desc.	Image 1	Image 2	Image 3	Image 4	Image 5
Disease name	"Bacterial Spot"	"Black Mold"	"Gray Spot"	"Late Blight"	"Powdery Mildew"
Sample images					

Fig. 2 – *Sample tomato leaf images for the classification framework.*

3.3 Image preprocessing

The plant images T_I^L are given as input to the preprocessing phase. The dataset contains poor quality or poor lighting images. These images are used for detecting the disease in real-world applications. It impacts the classification outcome. Hence, solving the lighting issue is needed.

CLAHE:

The CLAHE method is a contrast enhancement technique that is used to improve the details and reduce the illumination issue. Histogram-based methods are generally used for preprocessing applications, and it is popularly used in the world. The leaf area's intensity distribution is highlighted from the background using CLAHE. This process is performed in the whole input tomato plant leaf image. Therefore, the CLAHE method is employed to decrease the illumination issue.

Median filter:

Images with noise are cleaned by using median filters. Nonlinear and linear filters are the two categories of the preprocessing filter methods. Fine visual details, lines, and sharp edges are performed by linear filters. It also struggled in the presence of signal-dependent noise. An example of a non-linear filter is the median filter, which is one of the most widely used nonlinear filters for eliminating Salt and Pepper noise. The preprocessed images are noted by F_g^P . The outcomes of the preprocessed phase are shown in Fig. 3.

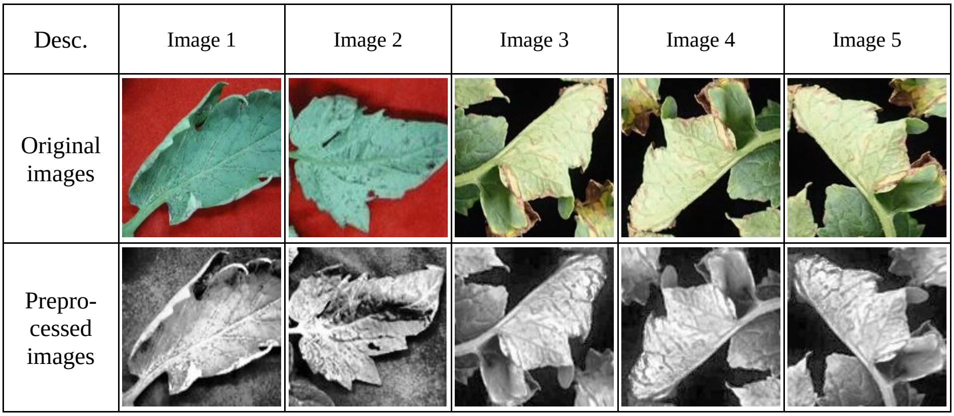


Fig. 3 – *Outcomes of the preprocessed images.*

3.4 Model validation procedures

These are essential to accurately assess the performance and generalization ability of a TLD classification model. Here are some commonly used validation procedures used in this research:

1. **Train-Validation-Test Split:**
   - **Description**: Split the dataset into three subsets: training, validation, and test sets.
   - **Process:**
     - The training set is used to train the model.
     - The validation set is used to tune hyperparameters and assess model performance during training.
     - The test set is kept separate and used only once after model training to evaluate its performance on unseen data.
   - **Advantages:**
     - Provides a fair assessment of the model's performance on unseen data.
     - Helps prevent overfitting by allowing tuning on a separate validation set.
2. **Cross-Validation:**
   - **Description:** Divide the dataset into multiple subsets (folds), iteratively train the model on a subset of folds, and evaluate its performance on the remaining fold.
   - **Process:**
     - Perform multiple iterations each time by using different folds as the validation set and the remaining folds as the training set.

- Average the performance metrics across all iterations to obtain a more robust estimate of model performance.
- **Advantages**:
  - Maximizes the use of available data for both training and validation.
  - Provides a more reliable estimate of model performance, especially with limited data.

By employing these model validation procedures, it should be ensured that the TLD classification model performs well on unseen data. It is also robust to variations and can generalize effectively to new instances, thus enhancing its reliability and applicability in real-world agricultural settings.

4 Leaf Image Segmentation Using Adaptive Fuzzy and Classification using Deep Networks for Identifying Tomato Leaf Diseases

For the segmentation of leaf images, the AFCM clustering algorithm is utilized. At the same time, the parameters of AFCM are required to be tuned for reliable segmentation. So, the parameters of AFCM are optimized using the DOA, which is inspired by their superior hunting behavior. The process of DOA for tuning AFCM parameters is described as follows,

4.1 DOA

The dingo animal behavior is used to build up the DOA [26] optimization. The dingo's prey behaviors like encircling, hunting, and searching are considered to implement the dingo algorithm. In the encircling phase, the prey's location is identified. The existing model's major aim is to identify the present location of the prey.

Encircling: Dingoes possess the capability to locate the position of their prey effectively. Once the alpha has located the prey, the pack will follow suit and encircle it. In order to represent the social structure of dingoes, it is presumed that the current best-agent approach is directed towards pursuing the prey as a goal. This is akin to an optimal strategy, considering that the specific hunting area is not known in advance. Meanwhile, other quest agencies are currently endeavoring to revitalize their strategies for the forthcoming approach.

Step 1: Primarily, the parameters of AFCM are initialized as h and are considered as the population of Dingoes. For example, the Dingoes present in the search space are assumed as the initiated parameters of AFCM in the search space.

Step 2: Then, the initial population of AFCM parameters is modeled based on the distance between the dingo and the prey. For instance, the AFCM parameters that are placed in the dingo population are properly aligned depending on the distance between dingoes and their corresponding prey. It is specified by the following mathematical equations (1) to (5).

$$\boldsymbol{E_e} = \left|\boldsymbol{BQ_q}(\boldsymbol{y}) - \boldsymbol{Q}(\boldsymbol{j})\right|. \tag{1}$$

Here, the variable $\boldsymbol{E_e}$ indicates the distance between the prey and the dingo. The present position of the prey is denoted by $\boldsymbol{Q_q}(\boldsymbol{y})$. Further, the present position of the dingo is denoted by $\boldsymbol{Q}(\boldsymbol{j})$.

$$\boldsymbol{Q}(\boldsymbol{j}+\boldsymbol{1}) = \boldsymbol{Q_q}(\boldsymbol{j}) - \boldsymbol{CE}(\boldsymbol{e}). \tag{2}$$

The terms $\boldsymbol{C}$ and $\boldsymbol{B}$ are the coefficient vectors. The term $\boldsymbol{B}$ is calculated using (3).

$$\boldsymbol{B} = 2\boldsymbol{b_1}, \tag{3}$$

$$\boldsymbol{C} = 2\boldsymbol{cb_2} - \boldsymbol{c}. \tag{4}$$

Here, the terms $\boldsymbol{b}_1$ and $\boldsymbol{b_2}$ are the random vector and it is taken in the range of $[0,1]$.

Step 3: Afterwards, the fitness function is calculated to obtain the optimal solution of tuning parameters. Here, the maximum classification accuracy $(A_{\max})$ is considered as the fitness for tuning the AFCM parameters.

Step 4: Next, based on the position of the prey, the dingo location is updated in the DO. The dingo is divided into two categories related to their hunting behaviors, namely beta and alpha dingoes. The first type of alpha dingo always gives commands during the hunting process. The dingo's position during the hunting process is given in (5).

$$\boldsymbol{c} = 3 \cdot \mathbf{1} - \boldsymbol{J}\left(\frac{3}{J_{max}}\right). \tag{5}$$

Here, $\boldsymbol{J}$ represents dingo position vectors and the variable $J_{\max}$ is the maximum iteration. **1** is the vector of ones. Similarly, the position or significance of the AFCM parameters is modified as per the updated position of the dingo location.

Step 5: Then, the hunting plan for the dingoes is mathematically formulated. It is assumed that all members of the pack, including the alpha, beta, and other individuals, possess a high level of knowledge regarding the potential locations of their prey. The alpha dingo always commands the hunting. Nevertheless, sometimes beta and other dingoes might also participate in hunting. Therefore, the first 2 best values attained so far are deemed. According to the best search agent's location, other dingoes also need to update their position. As per the discussion, (6) to (14) are modeled in this concern. The positions of all the members, including alpha, beta, and other individuals are updated with respect to the best search agent. The distance between the alpha, bêta, and other individuals from the prey is mathematically derived as,

$$\boldsymbol{E}_{\boldsymbol{\alpha}} = \left|\boldsymbol{B}_1 \boldsymbol{Q}_{\boldsymbol{\alpha}} - \boldsymbol{Q}\right|, \tag{6}$$

$$\boldsymbol{E}_{\boldsymbol{\beta}} = \left|\boldsymbol{B}_2 \boldsymbol{Q}_{\boldsymbol{\beta}} - \boldsymbol{Q}\right|, \tag{7}$$

$$\boldsymbol{E}_{\boldsymbol{p}} = \left|\boldsymbol{B}_3 \boldsymbol{Q}_{\boldsymbol{p}} - \boldsymbol{Q}\right|, \tag{8}$$

where $\boldsymbol{E}_{\boldsymbol{\alpha}}$, $\boldsymbol{E}_{\boldsymbol{\beta}}$ and $\boldsymbol{E}_{\boldsymbol{p}}$ denotes the distances of the prey from alpha, beta, and other dingoes, respectively, $\boldsymbol{B}_1$, $\boldsymbol{B}_2$ and $\boldsymbol{B}_3$ represent the position vectors of alpha, beta, and other dingoes, accordingly, $\boldsymbol{Q}$ symbolizes the prey position, and $\boldsymbol{Q}_{\boldsymbol{a}}$, $\boldsymbol{Q}_{\boldsymbol{b}}$ and $\boldsymbol{Q}_{\boldsymbol{c}}$ indicate the current prey position of alpha, beta and other dingoes, correspondingly.

Simultaneously, the position of the dingoes is updated based on their prey position and is expressed as,

$$\boldsymbol{Q}_1 = \left|\boldsymbol{Q}_{\boldsymbol{\alpha}} - \boldsymbol{B}\boldsymbol{E}_{\boldsymbol{\alpha}}\right|, \tag{9}$$

$$\boldsymbol{Q}_2 = \left|\boldsymbol{Q}_{\boldsymbol{\beta}} - \boldsymbol{B}\boldsymbol{E}_{\boldsymbol{\beta}}\right|, \tag{10}$$

$$\boldsymbol{Q}_3 = \left|\boldsymbol{Q}_{\boldsymbol{p}} - \boldsymbol{B}\boldsymbol{E}_{\boldsymbol{p}}\right|, \tag{11}$$

where $\boldsymbol{Q}_1$, $\boldsymbol{Q}_2$ and $\boldsymbol{Q}_3$ indicate the updated position of alpha, beta, and other dingoes, respectively. The AFCM parameters are subjected to the hunting phase of DOA. Here, some parameters of AFCM are assumed as supreme ones, which are closely related to the optimal parameters. So, such supreme parameters are compared here with the alpha and beta dingoes. While hunting for the optimal solution (prey), the distance between the AFCM parameters and the optimal solution is analyzed. Further, the updated position of the supreme parameters and other parameters are calculated as of the above expressions.

Step 6: Further the dingo's intensity and fitness are validated to attain the optimal solution. The dingo's intensity is validated using (12) as

$$\boldsymbol{J}_{\alpha} = \log\left(\frac{1}{G_{\alpha} - (1F - 100)}\mathbf{1} + \mathbf{1}\right). \tag{12}$$

Here, the parameter $\boldsymbol{J}_{\alpha}$ is the α dingo's fitness solution. $\mathbf{1}$ is one dimensional vector of ones. Further, the fitness solution of β and p dingoes is determined as per the (13) and (14) and is given as,

$$J_{\beta} = \log\left(\frac{1}{G_{\beta} - (1F - 100)}\mathbf{1} + \mathbf{1}\right). \quad (13)$$

Here, the parameter J_{β} is the β dingo's fitness solution.

$$J_{p} = \log\left(\frac{1}{G_{p} - (1F - 100)}\mathbf{1} + \mathbf{1}\right). \quad (14)$$

Here, the parameter J_{p} is the *p* dingo's fitness solution. Locations of the dingo are used to determine the prey's position. As per this process, the fitness of all the parameters in the updated position is evaluated. The AFCM parameters are checked whether they fulfill the condition of 'maximum classification accuracy'. If the fitness solution of α, β and *p* dingo's fulfilled the fitness condition A_{max}, the optimal solution is achieved. Likewise, the significance of AFCM parameters is checked with the maximum accuracy, which is defined as the fitness function. If the parameters satisfy the fitness condition, then such parameters of AFCM are selected as the optimal parameters and are finely tuned.

Step 7: Finally, the fitness function of beta and alpha dingo is effectively determined based on the repeated progression. The process is iterated until reaching J_{max} or the optimal solution. Similarly, the parameters are made to explore in the search space of DOA until they attain the best fitness.

Hence, the parameters of AFCM are tuned using the DOA regarding the attained optimal solution.

The DOA pseudocodeis given in Algorithm 1.

Algorithm 1: Offered DOA
Set the population size
Determine the dingo's search agents
Initialize the AFCM parameters
For (d = 1 to max IR)
Find the fitness solution of dingo
For (h = 1 to Npop)
Update the recorded values
While (d < max IR)
Find the fitness function of alpha dingo using (12)
Find the fitness function of beta dingo using (13)
Find the fitness function of other dingo using (14)
Calculate the intensity and fitness of selected dingo

				End
			End For	
		End For		
		Return the dingo best solution		
		Return the optimal parameters		
End				

4.2 AFCM-based image segmentation

The preprocessed tomato leaf images F_g^P are fed into the AFCM-based segmentation. The AFCM [27] technique is generally used for image segmentation. The AFCM-based technique is used to accurately segment the TLD. The major advantage of the AFCM-based technique is that it segments the leaf disease automatically and provides higher efficacy than other k-means clustering strategies. The conventional ML models used raw images as input. Hence, it gives poor performance. But, the AFCM-based segmentation used histogram images to enhance the efficacy of the framework.

The process of AFCM for image segmentation is explained as follows,

Step 1: Initially, the number of clusters is selected among the pixels of F_g^P and is mentioned as ς.

Step 2: Then, the cluster centers are randomly chosen from ς and are indicated as κ. Here, the AFCM is measured by analyzing the histogram of F_g^P, pixel value k, and fuzziness parameter. It is defined by using the following (15).

$$L = \sum_{\kappa=0}^{255} \sum_{\sigma=1}^{\Delta} j_\kappa h_{ks} f\left(k, \kappa_s\right), \tag{15}$$

where the term j_k indicates the histogram images and the center is indicated by κ. The parameter k denotes the pixel value. The participants of fuzzy are denoted by h.

Step 3: Subsequently, the distance between the pixel values and the cluster center is noted as $f\left(k, \kappa_s\right)$, which is calculated using the Euclidean operation. It is validated using (16) as

$$L = \sum_{\kappa=0}^{255} \sum_{\sigma=1}^{\Delta} j_\kappa \eta_{\kappa\sigma} \varphi\left(\kappa, \kappa_\sigma\right) \gamma\left(\kappa, \sigma\right), \tag{16}$$

$$h\left(l,t\right) = E\left\{a_l, P_t\right\}. \tag{17}$$

Here, the centroid is notated by E , where $s = 1, 2, 3, ..., E$. The centroid's mean parameter is indicated by P_t . The segmented leaf images are notated by O_f^G .

Step 4: Then, the membership function is computed regarding the objective function. Here, increasing the dice coefficient and Jaccard coefficient serves as the objective function as both the dice coefficient and the Jaccard coefficient determine the similarity between the segmented image and the ground truth image. When the segmentation is done based on the increased dice coefficient and Jaccard coefficient values, accurate image segmentation is obtained. The objective function of increasing the dice coefficient and Jaccard coefficient is calculated in (18) as,

$$Ob_F = \underset{\left\{AT_f^{FCM}, DL_e^{FCM}, DL_i^{FCM}\right\}}{\arg\min} \left(\frac{1}{\mathrm{DI}} + \frac{1}{\mathrm{JA}} \right), \tag{18}$$

where the term AT_f^{FCM} indicates the optimized fuzziness value in the interval of $[2, 20]$. The term DL_e^{FCM} denotes the optimized epsilon in the range of $[1,10]$. The optimized number of iterations in the interval of $[10,100]$ is denoted by DL_i^{FCM} . Here, the dice coefficient to analyze the image's similarity is calculated using (19) as,

$$DI = \frac{2\sum_{j=1}^{\mathrm{O}} \theta_j \rho_j}{\sum_{j=1}^{\mathrm{O}} \left(\theta_j^2 + \rho_j^2\right)} \tag{19}$$

Here, the term $\left(\theta_j^2 + \rho_j^2\right)$ is the total pixel count. The parameter $\theta_j \rho_j$ is the area of pixels overlap. The dice coefficient is notated by DI. At the same time, theJaccard coefficient that calculates the image's similarity is calculated in (20) as

$$JA = \frac{\sum_{j=1}^{\mathrm{O}} \theta_j \rho_j}{\sum_{j=1}^{\mathrm{O}} \left(\theta_j^2 + \rho_j^2 - \theta_j \rho_j\right)} . \tag{20}$$

Here, the term JA is the index of the Jaccard coefficient.

Step 5: Subsequently, the cluster centers are updated regarding the objective function and the adaptability of the fuzziness parameters is then verified accordingly. These processes are repeated until the objective function is attained.

Hence, the leaf images are accurately segmented using the proposed method for effective TLD identification and are specified as O_f^G . The image segmentation using AFCM is illustrated below in Fig. 4.

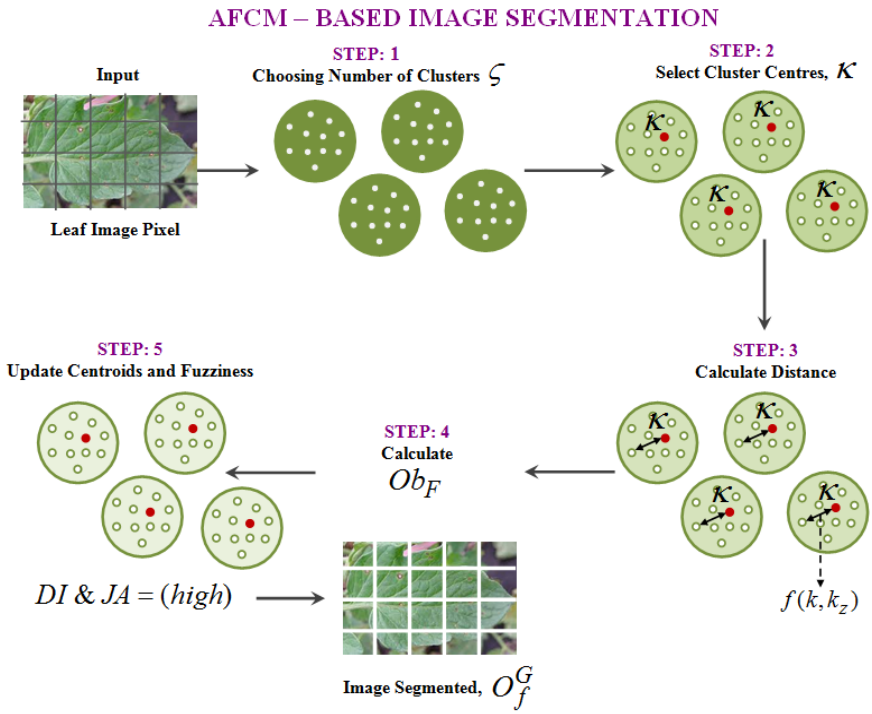


Fig. 4 – *AFCM-based Tomato leaf image segmentation.*

4.3 RAN-based image classification

The segmented images O_f^G are included in the RAN-based image classification.

The RAN [28] method is mainly used for image classification. It effectively classifies the TLD. Conventional ML techniques obtain less flexible and scalable outcomes. Thus, the RAN-based image segmentation is used to reduce the system cost and maintenance. It enhances the privacy and security of the model. It effectively decreases the loss of information issue.The RAN is developed by layering several attention components. The two components, namely pixel and channel components are included in the RAN framework, which is utilized to effectively predict the disease from complex background filter noise and fundus images. Further, most of the DL models suffer from vanishing gradients or gradient explosion problems because of poor weight initialization and backward propagation through multiple layers. These issues influence effective data learning and converge with sub-optimum classification results. But, the RAN model has to skip connections within layers, which facilitates the gradient flow among the layers. Also, the attention mechanism of RAN dynamically adjusts the neuron weights and highly focuses on the significant features of data. So, the gradient disappearance and gradient explosion issues are reduced using the RAN method, thus improving the TLD classification performance. Additionally, gradient disappearance and gradient explosion issues are reduced using the RAN method during the classification.

The RAN's channel component is measured in (21) as

$$J = \frac{1}{I \times X} \sum_{j=1}^{I} \sum_{\kappa=1}^{\Xi} \psi_{\delta}\left(j.\kappa\right). \tag{21}$$

Here, the term $\left(j.\kappa\right)$ is the location of the channel component. The channel component of RAN indicates the Convolutional layers, residual blocks, pooling layer, attention modules, feature maps, Batch normalization, and fully connected layer. The pooling operation is notated by H. The feature map size is indicated by 1×1. The RAN's pixel component is calculated in (22) as

$$G' = y \otimes QB. \tag{22}$$

Here, the term $G^{`}$ is the RAN's output. The module of pixel component is indicated by QB. The parameter y is the position of the pixel component.The diagrammatical design of RAN-based TLD classification is displayed in Fig. 5.

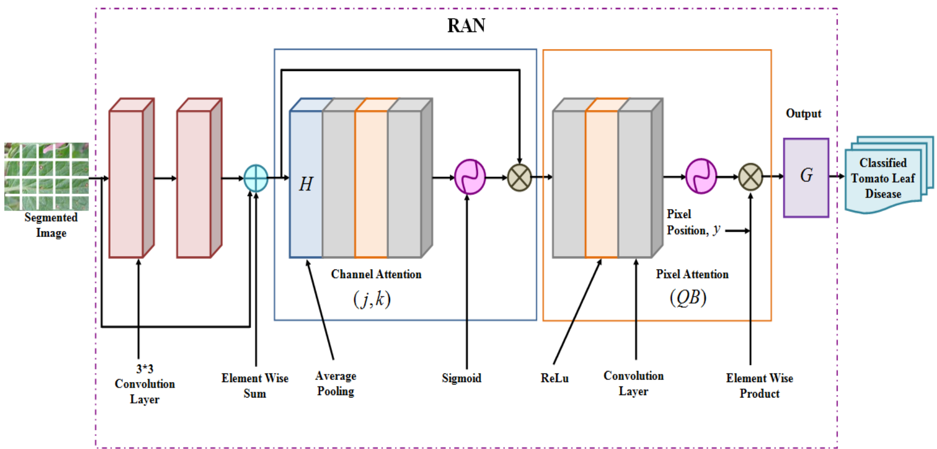


Fig. 5 – *Diagrammatical design of RAN-based TLD classification.*

The outcomes of the AFCM-based segmentation phase are displayed in Fig. 6.

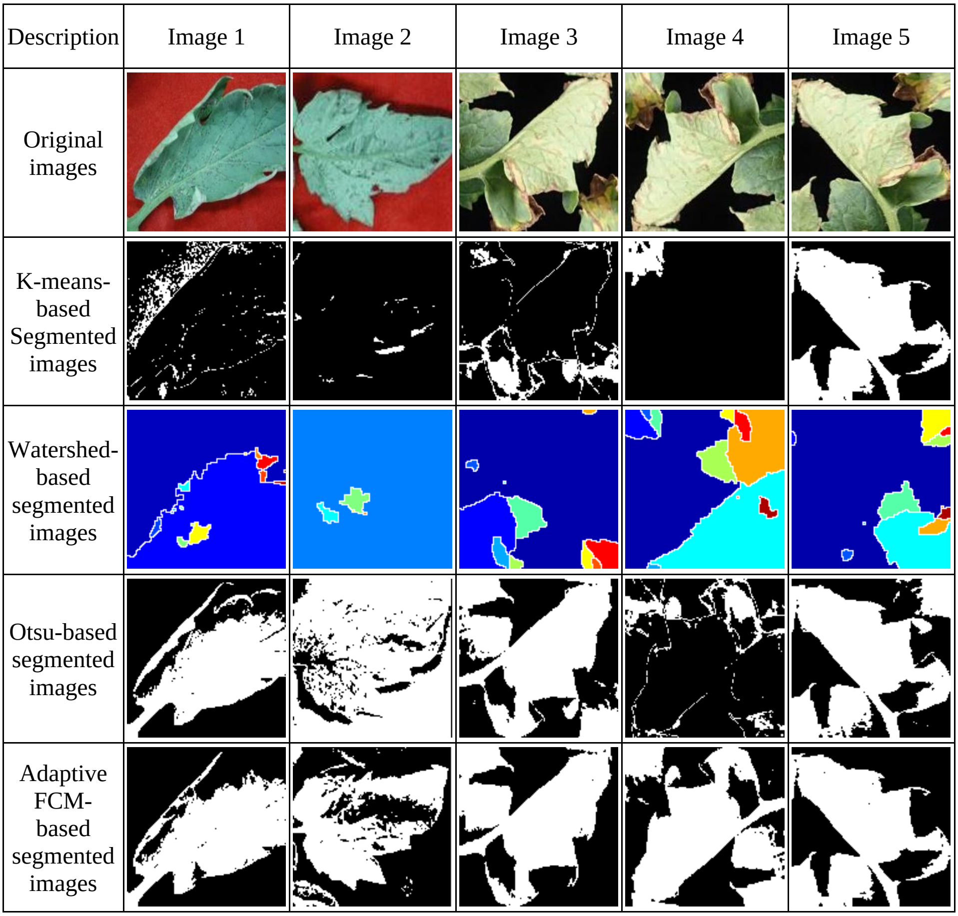


Fig. 6 – *Results of the AFCM-based segmented images.*

5 Results and Discussions

5.1 Experimental setup

The suggested RAN-related TLD categorization system is developed using MATLAB software. The experimental analysis uses a population rate fixed at 10, the chromosome length at 3, and an iteration fixed at 50. The efficacy of the implemented TLD classification system is compared with several traditional approaches like VGG16 [29], Mobile Net [30], CNN [20], Resnet [31], and RAN [25].

5.2 Evaluation measures

When evaluating the classification of TLD, the used effectiveness metrics play a crucial role in accurately assessing the model's performance. In the below-mentioned performance measures, DVu indicates True Positive, DVo indicates True Negative, UWo indicates False Positive, and UWu indicates False Negative.

A detailed explanation of each metric and its relevance to TLD classification is given as follows:

(a) False Negative Rate (FNR): $\frac{UWu}{UWu + DVu}$.

FNR indicates the proportion of actual diseased tomato leaves that are incorrectly classified as healthy. In TLD classification, a low FNR indicates the model's ability to correctly identify diseased leaves, minimizing the risk of missing actual cases of disease.

(b) Sensitivity: $SEN = \frac{DVu}{DVu + UWu}$.

SEN indicates the proportion of actual diseased tomato leaves that are correctly classified as diseased. It measures the model's ability to detect diseased leaves accurately, providing insights into its sensitivity to disease presence.

(c) Negative Predictive Value (NPV): $N3 = \frac{DVo}{UWu + DVo}$.

NPV indicates the proportion of correctly classified healthy tomato leaves among all leaves predicted to be healthy. NPV helps to assess the reliability of the model in correctly identifying healthy leaves, which is crucial for distinguishing between diseased and healthy plants.

(d) False Positive Rate (FPR): $FPR = \frac{UWo}{UWo + DVo}$.

FPV indicates the proportion of healthy tomato leaves that are incorrectly classified as diseased. It measures the model's tendency to misclassify healthy leaves as diseased, indicating the occurrence of false alarms.

(e) Specificity: $Sf = \frac{DVo}{DVo + UWo}$.

Specificity measures the proportion of actual healthy tomato leaves that are correctly classified as healthy. Specificity complements sensitivity by focusing on the model's ability to accurately identify healthy leaves, thus providing a comprehensive assessment of its discriminatory power.

(f) F1-score: $\mathrm{F1} = \frac{2 \times DVu}{2DVu + UWo + UVu}$.

It is the harmonic mean of precision and recall, providing a balanced measure of model performance. It takes both false positives and false negatives into account, making it suitable for evaluating the overall accuracy of TLD classification.

(g) Precision: $pe = \dfrac{DVu}{DVu + UWo}$.

It indicates the proportion of correctly classified diseased tomato leaves among all leaves predicted to be diseased. Precision assesses the accuracy of positive predictions, indicating the model's ability to avoid misclassifying healthy leaves as diseased.

(h) Mathew Correlation Coefficient (MMC):

$$MCC = \frac{DV_u \times DV_o - UW_o \times UW_u}{\sqrt{(DV_u + UW_o)(DV_u + UW_u)(DV_o + UW_o)}(DV_o + UW_u)}.$$

MCC is the correlation coefficient between actual and predicted classifications with considering all four elements of the confusion matrix. MCC provides a comprehensive measure of classification performance by considering both false positives and false negatives.

(i) False Discovery Rate (FDR): $FDR = \dfrac{UWo}{UWo + DVu}$.

FDR indicates the proportion of incorrectly classified diseased tomato leaves among all leaves predicted to be diseased. FDR complements precision by focusing on the proportion of false positives among positive predictions.

(j) Accuracy: $\dfrac{UWu}{UWu + DVu}$.

Accuracy indicates the proportion of correctly classified tomato leaves (both diseased and healthy) over the total number of leaves. Accuracy provides a general measure of the model's overall correctness in classifying tomato leaves, considering both true positives and true negatives.

In tomato disease identification and classification, accuracy serves as a measure of the overall correctness of predictions, offering insight into the classifier's proficiency in distinguishing between diseased and healthy tomato leaves. Sensitivity assesses the classifier's ability to accurately identify diseased tomato leaves among all instances known to be diseased, ensuring minimal missed detections. Similarly, specificity gauges the classifier's capability to accurately recognize healthy tomato leaves among all instances known to be healthy, reducing the occurrence of false alarms or misclassifications. Precision evaluates the proportion of correctly identified diseased tomato leaves among all instances predicted as diseased, ensuring accurate disease identification. FPR measures the rate of misclassification of healthy tomato leaves as diseased, providing insights into misclassification tendencies. FNR quantifies the rate of missed disease detections essential for evaluating disease detection efficacy.

NPV assesses the proportion of correctly identified healthy tomato leaves among all instances predicted as healthy, ensuring accurate identification of healthy leaves. FDR indicates the rate of incorrect disease identifications, aiding in the understanding of misclassification rates. F1-Score, the harmonic mean of precision and sensitivity, offers a balanced evaluation of false positives and false negatives, facilitating a comprehensive assessment of disease identification performance. Similarly, MCC, considering true and false positives and negatives, provides a balanced measure of disease classification quality, accounting for class imbalances and offering insight into overall classifier performance.

5.3 Performance analysis over previously used methods

The efficacy of the suggested RAN-based TLD categorization system is compared over conventionaltechniques, which is shown in Fig. 7.

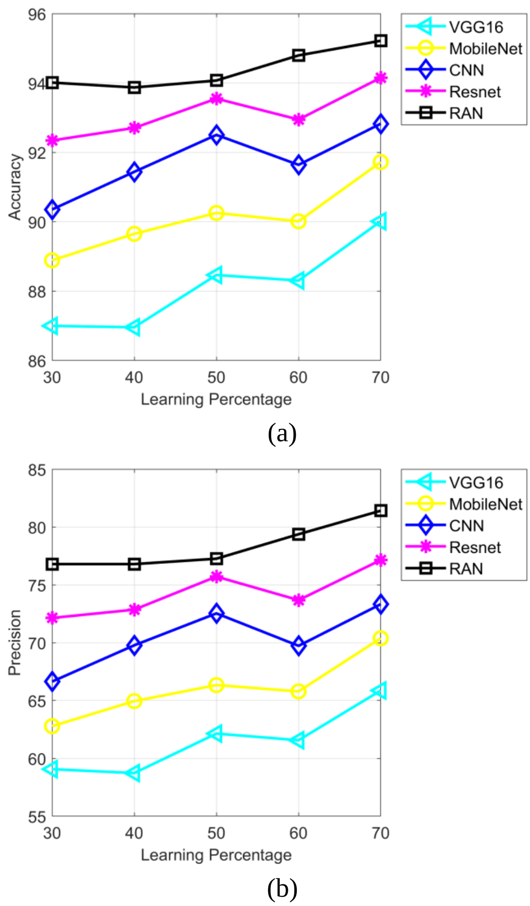
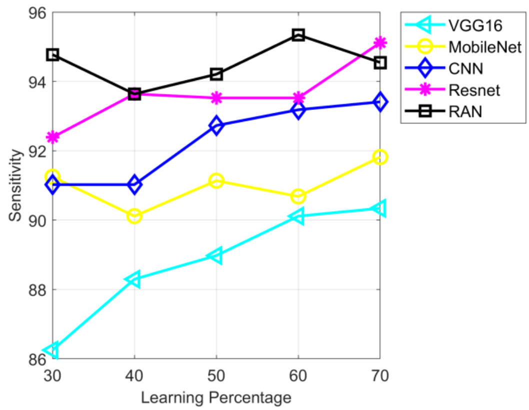
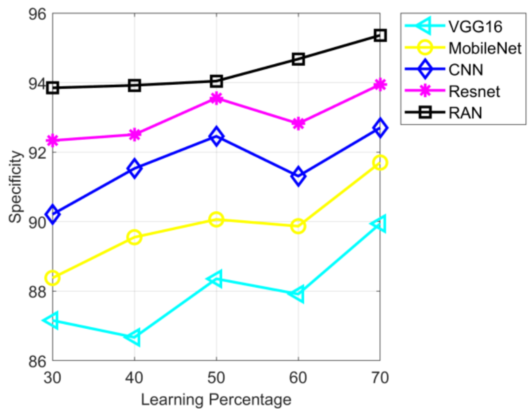


Fig. 7 – *Effectiveness evaluation on implemented TLD categorization system using deep learning over various techniques in regards to:* (a) *Accuracy;* (b) *Precision.*



(c)



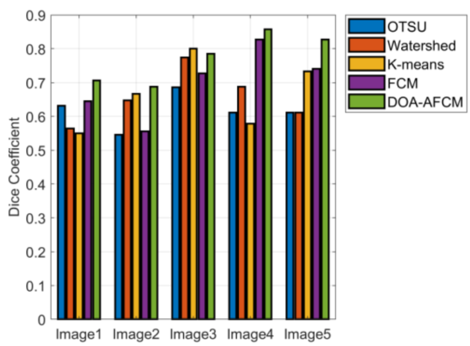
(d)

Fig. 7 – *Effectiveness evaluation on implemented TLD categorization system using deep learning over various techniques in regards to:* (c) *Sensitivity;* (d) *Specificity.*

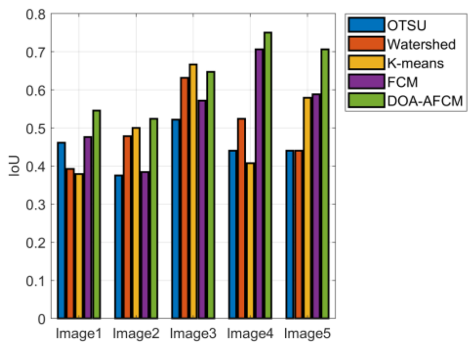
The suggested RAN-based TLD classification system providesa higher accuracy of 4.05% than VGG16, 6.15% than MobileNet, 9.12% than CNN, and 8.08% than Resnet at the learning percentage of 50.This improved performance is due to the suppression of overfitting or vanishing gradients problem by the skip connections within the layers and the attention mechanism involved in the proposed model. Also, accurate image segmentation is done based on a higher Dice coefficient and Jaccard coefficient prior to the classification process. It further aids RAN in better data learning by focusing on the important image features. Meanwhile, the existing methods suffered from the overfitting issue, which degraded the learning capability of the model. As this issue was not focused on disease classification, the lower classification accuracy is obtained by the existing methods. Hence, the improved performance is achieved using the RAN model compared to the prevailing methods.

5.4 Performance analysis of the suggested system over previously used methods for segmentation

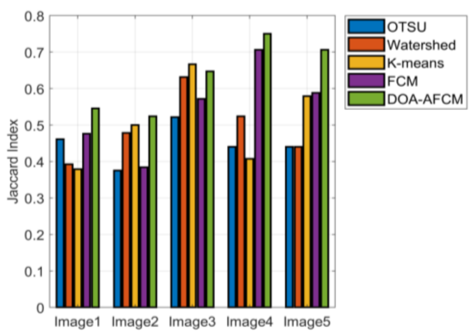
The efficacy of the suggested DOA-AFCM-based segmentation for the TLDcategorization systemis compared over conventionaltechniques as shown in Fig. 8. The suggested DOA-AFCM-based segmentation for the TLD system provided a higher dice coefficient of 5.05% than OTSU, 7.85% than Watershed, 10.22% than K-means, and 9.28% than FCM using Image 2. The proposed segmentation approach utilizes DOA for tuning the parameters of AFCM. The proper tuning of AFCM improves the cluster quality, adapts to image features, and rapidly converges with better clustering results. So, the dice coefficient and Jaccard coefficient of the segmented image are also increased, indicating the enhanced clustering of image pixels. However, the existing methods did not focus on the parameters tuning, which caused complexity and lowered the segmentation efficiency. Therefore, it is clear that the leaf image gets accurately segmented using the proposed approach. For the experimental testing, the DOA-AFCM-based segmentationfor the TLD categorization system gives a high dice coefficient compared to previously used segmentation methods.



(a)



(b)



(c)

Fig. 8 – *Effectiveness evaluation on implemented TLD categorization system using deep learning over various techniques in regards to:* (a) *Dice coefficient;* (b) *IoU;* (c) *Jaccar Index.*

5.5 Efficacy testing of the offered system

As displayed in **Table 2**, the implemented RAN-based TLD classification system's efficacy is compared with existing approaches. The suggested RAN-based TLD classification system showedimproved performance with a high specificity of 3.35% than VGG16, 4.25% than MobileNet, 6.22% than CNN, and 8.88% than ResNet. These prevailing techniques offered limited data learning due to the vanishing gradients or gradients explosion problem. So, the gradient flow was not regulated among the neuron layers. Thus, the complex relationships among the image features were not properly learned by these models, which also trapped with the local optimum classification results. The RAN-based TLD classification system achieves significantly higher specificity compared to VGG16, MobileNet, CNN, and ResNet. Specificity measures the proportion of true negatives correctly identified by the classifier, indicating its ability to accurately classify non-diseased tomato leaf images. The observed improvements in specificity suggest that the RAN-based system can effectively discriminate between healthy and diseased tomato plants, reducing false positive rates.The offered classification model outperforms other systems and gives high accuracy.The overall accuracy of the RAN-based TLD classification system is superior to other systems. Accuracy represents the proportion of correctly classified instances across all classes, reflecting the overall performance of the classifier. The higher accuracy achieved by the RAN-based system indicates its ability to accurately classify tomato leaf images across different disease categories, contributing to more reliable disease diagnosis and management.

The Residual Attention Network (RAN) architecture is designed to leverage attention mechanisms to focus on salient features while suppressing irrelevant information in the input images. This attention mechanism likely contributes to the system's improved performance by enhancing feature representation and discriminative power.Additionally, the residual connections in RAN facilitate the training of deeper networks by mitigating the vanishing gradient problem, enabling more effective learning of complex patterns and relationships within the data.The observed improvements in specificity and accuracy highlight the significance of the RAN-based TLD classification system in enhancing disease diagnosis and management in tomato plants. Accurate and reliable classification of diseased leaf images is essential for timely intervention and targeted treatment, ultimately leading to improved crop yield and quality.Further validation and testing of the RAN-based TLD classification system under diverse environmental conditions, disease severities, and tomato varieties are essential to assess its robustness and generalizability. In future work, the RAN-based system will be integrated into user-friendly platforms or mobile applications. So, the system becomes well adopted by farmers and agricultural extension workers, enabling real-time disease monitoring and decision support in the field.

Table 2
Performance testing of the developed TLD categorization model with several techniques.

Measures	VGG16 [22]	MobileNet [23]	CNN [5]	ResNet [24]	RAN
Accuracy	90.012	91.72	92.826	94.152	95.217
Sensitivity	90.341	91.818	93.409	95.114	94.545
Specificity	89.941	91.699	92.7	93.945	95.361
Precision	65.866	70.383	73.327	77.143	81.409
FPR	10.059	8.3008	7.2998	6.0547	4.6387
FNR	9.6591	8.1818	6.5909	4.8864	5.4545
NPV	89.941	91.699	92.7	93.945	95.361
FDR	34.134	29.617	26.673	22.857	18.591
F1-Score	76.186	79.684	82.159	85.191	87.487
MCC	71.462	75.638	78.642	82.291	84.912

5.6 Efficacy testing on the offered system among previously used methods for segmentation

The evaluation metrics used to compare the segmentation models include Intersection over Union (IoU), Dice Coefficient, and Jaccard Index. These metrics are commonly employed in image segmentation tasks to assess the overlap and similarity between the predicted and ground truth segmentation masks.The results demonstrate that the DOA-AFCM-based segmentation method outperforms existing approaches, such as Otsu's method, Watershed, K-means, and Fuzzy C-means in terms of the Jaccard index. This improvement indicates that the proposed method is more effective in accurately segmenting regions of interest in tomato leaf images, which is crucial for disease detection. As displayed in **Table 3**, the system's efficacy is improved by using DOA-AFCM-based segmentation for the TLD categorization and is compared with existing approaches. The suggested DOA-AFCM-based segmentation for the TLD categorization system shows improved performance with a higher Jaccard index of 29.41% than OSTU, 34.75% than Watershed, 9.09% than K-means, and 5.88% than FCM. The offered segmentation model outperforms other systems and gives a high Jaccard index.As the parameters of these existing methods are not properly tuned, the cluster quality is lowered, resulting in decreased Dice coefficient and Jaccard coefficient. Hence, the results suggest that the DOA-AFCM-based segmentation model consistently outperforms or matches the performance of existing techniques across all evaluated metrics. This overall superiority indicates the effectiveness of the proposed approach in accurately segmenting TLD regions, as reflected by higher IoU, Dice Coefficient, and Jaccard Index values. The improved segmentation accuracy offered by the DOA-

AFCM-based model has significant implications for TLD detection systems. Accurate segmentation is crucial for identifying and quantifying disease-affected areas on tomato leaves, facilitating early detection and intervention measures to prevent crop yield loss.While the results demonstrate promising performance, it is essential to consider potential limitations, such as computational complexity, robustness to variations in imaging conditions, and generalizability to diverse datasets and disease types. Addressing these limitations is crucial for the practical deployment of the proposed segmentation model in real-world TLD detection scenarios.

Table 3
Performance testing of the developed DOA-AFCM-based segmentation model with several techniques.

Measures	OTSU[28]	Watershed [29]	K-means [30]	FCM [31]	DOA-AFCM
IoU	0.54545	0.52381	0.64706	0.75	0.70588
Dice Coefficient	0.70588	0.6875	0.78571	0.85714	0.82759
Jaccar Index	0.54545	0.52381	0.64706	0.75	0.70588

6 Conclusion and Future Work

Conclusively, the challenges associated with identifying and categorizing TLD in agriculture are substantial, particularly given the repercussions on both crop quality and yield. The impact of TLD on agriculture is especially noteworthy due to its adverse effects on crop quality and yield. With India holding the second position in tomato production, the presence of numerous diseases compounds the problem, resulting in diminished crop output.Timely identification of these ailments is essential for reducing contagion and improving crop productivity.To tackle these obstacles, a model for classifying and identifying TLD was created, employing a multi-step methodology.The model began by aggregating tomato leaf images from online sources, followed by preprocessing to enhance image quality. Subsequently, the Adaptive Fuzzy C-Means (AFCM) technique was employed for segmentation, enabling effective delineation of diseased regions. Notably, parameter tuning within the segmentation process was facilitated by the innovative DOA, enhancing the accuracy of disease localization.Finally, the classified images underwent a rigorous classification process using the Residual Attention Network (RAN), culminating in highly efficient TLD prediction rates. This suggested a significant advancement in predictive capabilities compared to conventional methods. The integration of innovative algorithms and DL frameworks not only improved the accuracy of disease identification but also paved the way for more effective disease management strategies in agriculture. Therefore, the developed model showed the potential to tackle the obstacles linked to TLD detection and control. It could ultimately lead to improved crop health and productivity in tomato farming.

Prospects for the advancement of precision agriculture research and development involve combining various data streams, such as satellite imagery and ground sensors. Progress will also involve the refinement of autonomous agricultural systems that can operate with limited human involvement. The focus of the research will include predictive analytics and decision-making tools customized for agriculture, promoting sustainable farming techniques using precision technologies, and improving digital agricultural infrastructure to facilitate data-driven decision-making. Furthermore, investigating blockchain and traceability solutions, fostering collaboration among stakeholders, and advocating for favorable policy frameworks will be essential for promoting sustainable and fair agricultural practices. While the focus is on TLD in this manuscript, there is a potential for extending the developed model to identify and classify other crop diseases. Future research should explore the applicability of the model to a broader range of plant diseases, thereby offering a more comprehensive solution for disease management in agriculture.While this study focuses on TLD categorization in tomato plants, it is believed that this framework can be extended to other crops, areas, and agricultural settings with appropriate modifications and customization.

7 References

[1] A. R. Al-Shamasneh, R. W. Ibrahim: Classification of Tomato Leaf Images for Detection of Plant Disease Using Conformable Polynomials Image Features, MethodsX, Vol. 13, December 2024, p. 102844.

[2] G. Yang, G. Chen, Y. He, Z. Yan, Y. Guo, J. Ding: Self-Supervised Collaborative Multi-Network for Fine-Grained Visual Categorization of Tomato Diseases, IEEE Access, Vol. 8, November 2020, pp. 211912 – 211923.

[3] D. K. Pandey, R. Mishra: Towards Sustainable Agriculture: Harnessing AI for Global Food Security, Artificial Intelligence in Agriculture, Vol. 12, June 2024, pp. 72 – 84.

[4] M. S. Alzahrani, F. W. Alsaade: Transform and Deep Learning Algorithms for the Early Detection and Recognition of Tomato Leaf Disease, Agronomy, Vol. 13, No. 5, May 2023, p. 1184.

[5] M. Javaid, A. Haleem, I. H. Khan, R. Suman: Understanding the Potential Applications of Artificial Intelligence in Agriculture Sector, Advanced Agrochem, Vol. 2, No. 1, March 2023, pp. 15 – 30.

[6] N. Schor, A. Bechar, T. Ignat, A. Dombrovsky, Y. Elad, S. Berman: Robotic Disease Detection in Greenhouses: Combined Detection of Powdery Mildew and Tomato Spotted Wilt Virus, IEEE Robotics and Automation Letters, Vol. 1, No. 1, January 2016, pp. 354 – 360.

[7] Y. Zhang, C. Song, D. Zhang: DeepLearning-Based Object Detection Improvement for Tomato Disease, IEEE Access, Vol. 8, March 2020, pp. 56607 – 56614.

[8] K. Roy, S. S. Chaudhuri, J. Frnda, S. Bandopadhyay, I. J. Ray, S. Banerjee: Detection of Tomato Leaf Diseases for Agro-Based Industries Using Novel PCA DeepNet, IEEE Access, Vol. 11, February 2023, pp. 14983 – 15001.

[9] K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou, G. A. Papakostas: Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern, IEEE Access, Vol. 11, June 2023, pp. 62307 – 62317.

[10] L. Zhang, G. Zhou, C. Lu, A.Chen, Y.Wang, L. Li, W.Cai: MMDGAN: A Fusion Data Augmentation Method for Tomato-Leaf Disease Identification, Applied Soft Computing, Vol. 123, July 2022, p.108969.

[11] C. Zhou, S. Zhou, J. Xing, J. Song: Tomato Leaf Diseases Identification by Restructured Deep Residual Dense Network, IEEE Access, Vol. 9, February 2021, pp. 28822 – 28831.

[12] Q. Wu, Y. Chen, J. Meng: DCGAN-Based Data Augmentation for Tomato Leaf Diseases Identification, IEEE Access, Vol. 8, May 2020, pp. 98716 – 98728.

[13] Y. Wu, X. Feng, G. Chen: Plant Leaf Diseases Fine-Grained Categorization Using Convolutional Neural Networks, IEEE Access, Vol. 10, April 2022, pp. 41087 – 41096.

[14] V. Sharma, A. K. Tripathi, H. Mittal: DLMC-Net: Deeper Lightweight Multi-Class Classification Model for Plant Leaf Disease Detection, Ecological Informatics, Vol. 75, July 2023, p. 102025.

[15] P. Baser, J. R. Saini, K. Kotecha: TomConv: An Improved CNN Model for Diagnosis of Diseases in Tomato Plant Leaves, Procedia Computer Science, Vol. 218, January 2023, pp. 1825-1833.

[16] D. R. Hammou, M. Boubaker: Tomato Plant Disease Detection and Classification Using Convolutional Neural Network Architectures Technologies, Proceedings of the 4th International Conference on Networking, Intelligent Systems and Security, Kenitra, Maroco, April 2021, pp. 33 – 44.

[17] N. Zhang, H. Wu, H. Zhu, Y. Deng, X. Han: Tomato Disease Classification and Identification Method Based on Multimodal Fusion Deep Learning, Agriculture, Vol. 12, No. 12, December 2022, p. 2014.

[18] C. Zhou, S. Zhou, J. Xing, J. Song: Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network, IEEE Access, Vol. 9, February 2021, pp. 28822 – 28831.

[19] T. Anandhakrishnan, S. M. Jaisakthi: Deep Convolutional Neural Networks for Image Based Tomato Leaf Disease Detection, Sustainable Chemistry and Pharmacy, Vol. 30, December 2022, p. 100793.

[20] O. Attallah: Tomato Leaf Disease Classification via Compact Convolutional Neural Networks with Transfer Learning and Feature Selection, Horticulturae, Vol. 9, No. 2, February 2023, p. 149.

[21] S. Solanki, U. P. Singh, S. S. Chouhan, S. Jain: Brain Tumour Detection and Classification by using Deep Learning Classifier, International Journal of Intelligent Systems and Applications in Engineering, Vol. 11, No. 2s, February 2023, pp. 279 – 292.

[22] S. Solanki, U. P. Singh, S. S. Chouhan, S. Jain: A Systematic Analysis of Magnetic Resonance Images and Deep Learning Methods Used for Diagnosis of Brain Tumor, Multimedia Tools and Applications, Vol. 83, No. 8, March 2024, pp. 23929 – 23966.

[23] S. Solanki, U. P. Singh, S. S. Chouhan: Brain Tumor Classification Using ML and DL Approaches, Proceedings of the IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), Hamburg, Germany, October 2023, pp. 204 – 208.

[24] S. S. Chouhan, U. P. Singh, S. Jain: Applications of Computer Vision in Plant Pathology: A Survey, Archives of Computational Methods in Engineering, Vol. 27, No. 2, April 2020, pp. 611 – 632.

[25] M.- L. Huang, Y.- H. Chang: Dataset of Tomato Leaves, Mendeley Data, May 2020, Ver. 1, Available at: https://data.mendeley.com/datasets/ngdgg79rzb/1

[26] A. K. Bairwa, S. Joshi, D. Singh: Dingo Optimizer: A Nature-Inspired Metaheuristic Approach for Engineering Problems, Mathematical Problems in Engineering, Vol. 2021, June 2021, p. 2571863.

[27] D. L. Pham, J. L. Prince: An Adaptive Fuzzy C-Means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities, Pattern Recognition Letters, Vol. 20, No. 1, January 1999, pp. 57 – 68.

[28] C. K. Sunil, C. D. Jaidhar, N. Patil: Tomato Plant Disease Classification Using Multilevel Feature Fusion with Adaptive Channel Spatial and Pixel Attention Mechanism, Expert Systems with Applications, Vol. 228, October 2023, p. 120381.

[29] Z. Qu, J. Mei, L. Liu, D.- Y. Zhou: Crack Detection of Concrete Pavement with Cross-Entropy Loss Function and Improved VGG16 Network Model, IEEE Access, Vol. 8, March 2020, pp. 54564 – 54573.

[30] S. Ashwinkumar, S. Rajagopal, V. Manimaran, B. Jegajothi: Automated Plant Leaf Disease Detection and Classification Using Optimal MobileNet Based Convolutional Neural Networks, Materials Today: Proceedings, Vol. 51, No. 1, January 2022, pp. 480 – 487.

[31] S. R. G. Reddy, G. P. S. Varma, R. L. Davuluri: Resnet-Based Modified Red Deer Optimization with DLCNN Classifier for Plant Disease Identification and Classification, Computers and Electrical Engineering, Vol. 105, January 2023, p. 108492.