

Smart Tomato Disease Diagnosis: A Hybrid Approach Using Zebra Optimization Segmentation and Compact Attentional Residual Convolutional Network

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Abstract

Tomato crop diseases caused by pathogens such as fungi, bacteria, and viruses can severely impact the health and yield of tomato crops. Early detection of these diseases is crucial to prevent significant crop losses and ensure optimal growth conditions. While existing tomato leaf disease detection systems demonstrate high accuracy, they face challenges due to high computational requirements, limiting their efficiency and practical deployment in real-time applications especially in resource-constrained environments such as mobile devices or field systems. To overcome these challenges, this work proposes a hybrid model called Smart Tomato Disease Diagnosis using Zebra Optimization Segmentation and Compact Attentional Residual Convolutional Network (ZOS-CRCN). The process begins with the input of tomato leaf images, which undergo preprocessing, including resizing to 224×224 pixels and normalization using the Tanh-estimator method. This step standardizes the images and mitigates the influence of outliers for stable model training. Next, the Zebra Optimization Algorithm (ZOA) is applied for precise segmentation which isolates regions of interest (ROI) that contain diseased areas. ZOA simulates natural foraging and defense behaviors for effectively optimizing the segmentation process. For feature extraction and classification, the Compact Attentional Residual Convolutional Network (CRCN) is utilized. This lightweight network focuses on important image areas using attention mechanisms and reduces computational complexity through residual connections. The CRCN classifies the diseases into ten categories such as Healthy Tomato Leaf, Early Blight, Late Blight, Septoria Leaf Spot, Yellow Leaf Curl Virus Disease, Bacterial Spot, Target Spot, Spider Mite (Two-Spotted), Leaf Mold, and Mosaic Virus. The proposed ZOS-CRCN model achieves 99.99% accuracy, an execution time of 89ms, an AUC of 0.995, and a high F1-score of 99.99%. By this, it demonstrates its effectiveness for real-time disease detection in resource-limited environments.

Keywords: Compact Attentional Residual Convolutional Network, Zebra Optimization Segmentation, Tanh-estimator method, Tomato crop diseases, Agricultural technology.

1. INTRODUCTION

Tomato leaf diseases represent detrimental conditions induced by diverse pathogens, including fungi, bacteria, and viruses, which adversely impact the health and productivity of tomato plants [1]. These diseases present symptoms such as yellowing, spotting, curling, or wilting of the leaves [2]. In severe cases, diseases lead to a significant reduction in crop yield and quality [3]. Effective detection of these diseases at early stages is crucial to mitigate their impact and ensure optimal growth conditions for tomato plants [4]. Early diagnosis helps in implementing targeted treatments such as pesticide application or environmental control, thereby preventing further spread and damage [5]. Tomato leaf disease detection has become increasingly

important in modern agriculture due to the rise in demand for efficient farming practices [6-7]. Accurate and timely identification of plant diseases plays a critical role in enhancing crop management, improving yield, and reducing losses [8]. Automated detection systems enable farmers to detect diseases quickly and with greater precision, thus leading to informed decision-making [9]. To ensure sustainable farming practices, early detection of rapidly spreading diseases is crucial before it causes significant harm to crops. Advanced technologies offer a promising solution for timely disease identification [10]. Existing deep learning and machine learning-based tomato leaf disease detection systems face several challenges. These include the high computational

requirements, reliance on large and diverse datasets for training, and difficulty in handling various environmental conditions that affect the appearance of tomato leaves [11-13]. Moreover, many existing models require complex preprocessing and extensive training to adapt to new or unseen disease types [14-15]. These challenges make real-time, practical deployment difficult, particularly in environments with limited resources, such as portable devices or on-site applications, where both time and computational power are limited [16]. To address these limitations, the proposed method called Smart tomato disease diagnosis using Zebra optimization segmentation and a Compact Attentional Residual Convolutional Network for feature extraction and classification (ZOS-CRCN) is utilized. Zebra Optimization algorithm inspired by the adaptive behavior of zebras, that provides an efficient segmentation technique that accurately isolates regions of interest, thus enhancing the tomato disease detection process. The Compact Attentional Residual Convolutional Network ensures effective feature extraction and classification, while minimizing computational complexity. The use of the PlantVillage dataset for training guarantees the system's ability to handle various disease patterns and ensure robustness. The combined approach is designed to be lightweight and highly efficient, thus offering accurate identification of tomato leaf disease in real-time scenarios, thus paving the way for scalable and practical agricultural monitoring solutions. The main contribution of the proposed ZOS-CRCN work is given below,

- A novel segmentation technique called Zebra Optimization algorithm (ZOS), based on adaptive behavior for precise tomato disease area isolation.
- The Compact Attentional Residual Convolutional Network (CRCN) represents a compact and efficient framework design for feature extraction and classification.
- The hybrid model is designed to enable real-time disease detection with minimal computational requirements.
- The approach ensures high accuracy, thereby providing reliable detection across different disease types and varying environmental conditions.

- It is optimized for practical implementation in environments with limited resources, that includes handheld devices and field-based systems.
- It is capable of handling diverse datasets, including the PlantVillage dataset, thus ensuring scalability and robust performance across different conditions.

The paper is structured as follows. Section 2 discusses related work on tomato plant disease identification. Section 3 outlines the proposed integrated approach, focusing on ZO-based segmentation and CRCN-driven classification. Section 4 showcases the experimental findings along with comprehensive evaluation. Section 5 concludes by summarizing the results and proposing future research opportunities.

2. LITERATURE SURVEY

This section explores recent progress in deep learning methodologies for identifying tomato leaf diseases. In 2022, Özbilge, E., et.al [11] developed a streamlined convolutional neural network (SCNN) consisting of six layers for detecting tomato plant diseases. The model was trained on the PlantVillage tomato dataset, which contains 10 categories, including nine disease types and one healthy class. To benchmark performance, pre-trained ImageNet models were employed through transfer learning. It attains high accuracy and F-Score value. However, it exhibited high computation time. In 2022, Hammou, D.R. and Boubaker, M., [12] created an artificial neural network based on convolutional layers for identifying diseases in tomato plants. The PlantVillage database, which contained 18,162 images across nine diseased classes and one healthy class, was used for training. DenseNet169 and InceptionV3 CNN architectures were applied for tomato disease classification. Transfer learning was utilized with a batch size of 32 samples along with RMSprop and Adam optimizers, was utilized. It also showed high computation time.

In 2022, Moussafir, M., et.al [13] proposed advanced approaches for identifying tomato leaf diseases integrated genetic algorithms with deep neural networks. The process began by sourcing images from the PlantVillage dataset. Various transfer learning models, such as VGG16, ResNet50, and different EfficientNet variants (B0 to B4), were employed to optimize model performance, coupled with fine-tuning

methods using genetic algorithms. This hybrid model achieved high accuracy in identifying and classifying tomato plant diseases, but it had a low F-score value.

In 2023, Baser, P., et.al [14] proposed the TomConv model for tomato leaf disease classification. The process began with collecting images from the PlantVillage dataset. Preprocessing was performed to resize images to 150×150 pixels. The TomConv model included four CNN layers followed by a max pooling layer. It achieved high accuracy, but its computation time was high.

In 2022, Deshpande, R. and Patidar, H., [15] employed deep convolutional neural networks (DCNN) For enhanced feature extraction and correlation along with generative adversarial networks (GANs) were utilized to augment data and address class imbalance. Images of tomato leaves from the PlantVillage collection were processed and expanded using GAN. The DCNN model was subsequently trained on the augmented data to identify tomato plant diseases, resulting in high accuracy. However, it also exhibited high computation time.

In 2024, Vivek Anandh, K.M., et.al [16] utilized three lightweight mid-generation Deep learning architectures based on convolutional networks for detecting diseases in tomato leaves. It used the PlantVillage dataset, then applied geometric data augmentation to enhance the model's robustness. Transfer learning with ImageNet weights was integrated into the MobileNet architecture, using augmented images as input. The model achieved high accuracy, but it showed high computation time.

Overall, existing tomato leaf disease detection systems face significant challenges due to high computation times, which limits their efficiency and practicality for real-time systems in resource-limited settings [11-16]. Although various models demonstrate high accuracy, the computational demands limit their practical deployment. Thus, there is a clear need for more efficient, lightweight models that can provide accurate disease detection while minimizing computation time.

3. PROPOSED METHODOLOGY

The methodology for the Smart Tomato Disease Diagnosis system is presented in this section, incorporating the Zebra Optimization Segmentation (ZOS) and Compact Attentional Residual Convolutional Network (CRCN). The proposed ZOS-CRCN framework is depicted in Figure 1. Below is a

detailed explanation of the components and processes involved in the ZOS-CRCN framework,

3.1 Dataset description

The PlantVillage dataset provides 54,305 leaf images from 14 crops, including both healthy and diseased leaves. For this study, 18,162 images of tomato plants across nine disease categories and one healthy class were used. The conditions addressed are Early Blight of Tomato, Late Blight of Tomato, Septoria Leaf Spot of Tomato, Yellow Leaf Curl Virus Disease of Tomato, Bacterial Spot of Tomato, Target Spot of Tomato, Spider Mite (Two-Spotted) of Tomato, Leaf Mold, and Mosaic Virus. The labeled images enable effective disease classification and support the development of robust diagnostic models [17-18]. The distribution of Tomato Crop Images Across Disease Categories in the PlantVillage Dataset are given in Table 1.

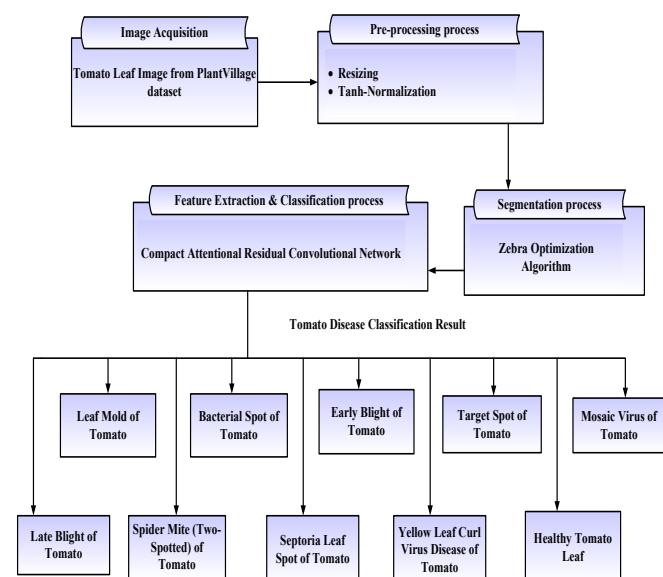


Figure 1: Block diagram of proposed ZOS-CRCN framework

Table 1: Categorical Distribution of Tomato Crop Images in the PlantVillage Dataset

Category	Disease Name	Causal Agent	Disease Type	Image Count
A	Healthy Tomato Leaf	-	-	1,592
B	Early Blight of Tomato	Alternaria solani	Fungal	1,000
C	Late Blight of Tomato	Phytophthora infestans	Mold	1,910
D	Septoria Leaf Spot of Tomato	Septoria lycopersici	Fungal	1,771
E	Yellow Leaf Curl Virus Disease of Tomato	Tomato yellow leaf curl virus (TYLCV)	Virus	5,357

F	Bacterial Spot of Tomato	Xanthomonas campestris pv. vesicatoria	Bacterial	2,127
G	Target Spot of Tomato	Corynespora cassiicola	Fungal	1,404
H	Spider Mite (Two-Spotted) of Tomato	Tetranychus urticae	Mite	1,676
I	Leaf Mold	Fulvia fulva	Fungal	952
J	Mosaic Virus	Tomato Mosaic Virus		373
Total				18,162

3.2 PRE-PROCESSING PROCESS

The preprocessing process transforms tomato leaf images into a standardized format suitable for model training. Each tomato leaf image was resized to a fixed resolution of 224×224 pixels to ensure consistent input dimensions for the deep learning model. Pixel intensity values were adjusted using the Tanh-estimator normalization method. One advantage of the Tanh-estimator normalization is its ability to effectively mitigate the influence of outliers while preserving the intrinsic characteristics of the input. This contrasts with other standard normalization methods, which are more sensitive to extreme values. The robust mapping provided by this method ensures improved stability and consistency during model training. The Tanh-estimator normalization is mathematically expressed using following equation (1)

$$TI_{Normalization} = \frac{1}{2} \left\{ \tan h \left[0.01 \left(\frac{TI - \mu_{Hampel}}{\sigma_{Hampel}} \right) \right] + 1 \right\} \quad (1)$$

Where, $TI_{Normalization}$ represents the normalized pixel intensity of the tomato leaf image, μ_{Hampel} and σ_{Hampel} represent the mean and standard deviation calculated using the Hampel estimator, which reduces the influence of outliers [19]. The Hampel estimator is defined using the following formulation (2)

$$\psi(g) = \begin{cases} g; & 0 \\ u \times \sin(g); & u \leq |g| < v \\ u \times \sin(g) \left[\frac{(w-|g|)}{(w-v)} \right]; & v \leq |g| < w \\ 0; & w \leq |g| \end{cases} \quad (2)$$

In this formulation, u , v , and w are threshold values that control the influence of residuals, while g represents the deviation of pixel intensity from the mean. This robust estimator reduces the effect of outliers, that ensures the normalization is effective and stable. The result of this normalization process maps

the pixel intensities into the range $[0, 1]$, which preserves the intrinsic characteristics of the tomato leaf image while minimizing the impact of outliers. These pre-processing steps ensure that the images are optimized for effective classification.

3.3 ZEBRA OPTIMIZATION SEGMENTATION

In this section, a novel method for segmenting tomato leaf disease regions using the Zebra Optimization Algorithm (ZOA) is proposed. The ZOA is employed to identify optimal segmentation parameters by simulating the foraging and defense behaviors of zebras. Each solution in the optimization process represents a set of potential segmentation parameters, and the position of each solution in the solution space corresponds to the segmentation process. Through iterative updates, the algorithm converges to the best set of parameters, thus ensuring accurate detection of diseased regions in pre-processed tomato leaves. ZOA improves segmentation accuracy by effectively exploring the solution space through dynamic foraging and defense behaviors [20]. The advantage of ZOA lies in its ability to enhance both robustness and convergence speed compared to other methods. This results in more precise tomato leaf disease segmentation outcomes, particularly in complex datasets.

The ZOA-based segmentation process begins with an initialization step, where the initial positions of the solutions are randomly assigned within the solution space. The population matrix S is formulated using equation (3)

$$S = [S_1 \dots \dots S_j \dots \dots S_Z]_{Z \times y} \quad (3)$$

Where S is the population matrix, S_j is the position vector of the j^{th} solution, Z is the population size, y represents the segmentation parameters. The objective function evaluates the fitness of each solution, which represents the quality of the segmentation result. The function is computed using the following equation (4)

$$FF = [FF(S_1) \dots FF(S_j) \dots FF(S_Z)]_{Z \times 1} \quad (4)$$

Where FF_j represents the fitness of the j^{th} solution, $FF(S_j)$ is the fitness value corresponding to the j^{th} solution's position. The fitness function $FF(S_j)$

evaluates the quality of segmentation, such as boundary accuracy and pixel classification precision, for tomato leaf disease detection. During the foraging behavior phase, the segmentation process iteratively updates the solution positions toward the optimal solution. The update equation for the solution positions is expressed using equation (5)

$$s_{j,i}^{new,Pos_1} = s_{j,i} + R \times [best_i - A \times s_{j,i}] \quad (5)$$

Where $s_{j,i}^{new,Pos_1}$ is the new position of the j^{th} solution in the i^{th} dimension, $best_i$ is the i^{th} dimension of the best solution's position, $A = round(1 + R)$ with R being a random number in $[0,1]$. The new position is accepted if it improves the fitness using equation (6)

$$S_j = \begin{cases} S_j^{new,Pos_1}; & FF_j^{new,Pos_1} < FF_j \\ S_j; & \text{Otherwise} \end{cases} \quad (6)$$

Where FF_j^{new,Pos_1} is the fitness value after the position update. The defense behavior phase of the algorithm reacts to disturbances by adjusting the positions according to two strategies. Tactic 1 (escape behavior) adjusts the position in a zigzag pattern using the equation (7)

$$s_{j,i}^{new,Pos_2} = s_{j,i} + \beta(2R - 1) \left(1 - \frac{\text{Current Iteration}}{\text{Max Iteration}}\right) \times s_{j,i} \quad (7)$$

Where $\beta = 0.01$ is a constant, $Max Iteration$ is the maximum number of iterations, R is a random number in the interval $[0,1]$. Tactic 2 (gathering behavior) adjusts the position based on neighboring solutions using the equation (8)

$$s_{j,i}^{new,Pos_2} = s_{j,i} + R \times (Nearby_i - A \times s_{j,i}) \quad (8)$$

Where $Nearby_i$ is the position of a neighboring solution, and A is a binary indicator based on the strategy. The new position is accepted if it improves the fitness using equation (9)

$$S_j = \begin{cases} S_j^{new,Pos_2}; & FF_j^{new,Pos_2} < FF_j \\ S_j; & \text{Otherwise} \end{cases} \quad (9)$$

Through these iterative updates, the algorithm identifies the best solution, which provides the optimal parameters for the segmentation process. As the segmentation progresses, the quality of the results improves, thus leading to more accurate detection of

diseased regions in the tomato leaves. By this, the Zebra Optimization Algorithm (ZOA) offers an effective approach for optimizing the segmentation of tomato leaf diseases by simulating natural foraging and defense behaviors. By exploring the solution space dynamically and ensuring convergence to the optimal segmentation parameters, ZOA achieves precise and robust disease detection in tomato leaves.

3.4 Compact Attentional Residual Convolutional Network for Feature Extraction and Classification in Tomato Leaf Disease Detection

In this section, Compact Attentional Residual Convolutional Network (CRCN) is designed to handle both feature extraction and classification tasks for tomato leaf disease detection. It processes segmented Regions of Interest (ROI) from tomato leaf disease images, where it efficiently identifies disease patterns. The CRCN leverages efficient feature extraction with reduced computational complexity, while enhancing the accuracy of disease detection in tomato leaves. The advantage of using attention mechanisms is that the network focus on important areas of the image, leading to more precise identification. Additionally, the integration of residual connections provides the advantage of faster convergence and better generalization compared to other neural networks. The network architecture is composed of two main parts such as the feature extraction section and the classification section. During the feature extraction phase, fine-grained features from the tomato leaf images are captured, which are subsequently used in the classification phase to detect specific diseases.

Feature Extraction Section

The feature extraction section integrates Lightweight Spatially Adaptive Convolution Layers (LSAC-Layers), Adaptive Attention Enhancement Blocks (AAE-Blocks), and Enhanced Gradient Propagation Blocks (EGP-Blocks) [21]. LSAC-Layers reduce computational complexity and model size by separating the convolution process into Spatially Focused Convolution and pointwise convolution. In Spatially Focused Convolution, a separate convolution filter is applied to each input channel, and pointwise convolution integrates the results using a 1×1 filter. This approach is advantageous for applications involving low-resource devices. The mathematical formulations for Spatially Focused Convolution and

pointwise convolution are expressed in the following equations (10-11)

$$SF_{Conv}(k, f)_{p,q,r} = \sum_{h,w} k_{h,w} \times f_{p+h,q+w,r} \quad (10)$$

$$Point_{Conv}(k, f)_{p,q} = \sum_r k_r \times f_{p,q,r} \quad (11)$$

In this formulation, k and f represent the convolution kernel and feature map, respectively, and h, w correspond to spatial dimensions and depth. The AAE-Block enhances feature extraction by focusing on the relationships between local features within the segmented ROI of the tomato leaf image. These components apply a combination of average and max pooling operations to capture spatial details, which are then fused. The pooled outputs are passed through a convolutional layer with a sigmoid activation to create an attention map. This map is then element-wise multiplied with the input features to refine the features extracted, as outlined in the equation (12-15)

$$f_{avg\ pooling} = \text{Avg pooling}(f) \quad (12)$$

$$f_{Max\ pooling} = \text{Max pooling}(f) \quad (13)$$

$$SC(f) = \varphi [f_{3 \times 3}(f_{avg\ pooling} \oplus f_{Max\ pooling})] \quad (14)$$

$$\tilde{f} = f \times SC(f) \quad (15)$$

In this formulation, $f_{3 \times 3}$ is a 3×3 convolution kernel. This process allows the model to better capture spatial dependencies within the segmented ROI of the tomato leaf image, which is crucial for identifying various diseases.

Enhanced Gradient Propagation Blocks (EGP-Blocks) are incorporated to improve gradient propagation throughout the training phase. These modules facilitate the network in learning deeper architectures without suffering from gradient vanishing issues. Each EGP-Block contains two convolutional layers, batch normalization, and a LeakyReLU activation. The output from the convolutional layers is combined with the original input, forming a residual connection as expressed in equation (16-17)

$$f^* = f \oplus F(f) \quad (16)$$

$$\text{Leaky ReLU}[f^*] = \begin{cases} 1; & \text{if } f^* > 0 \\ \chi; & \text{Otherwise} \end{cases} \quad (17)$$

where χ is the leakage factor, and $F(f)$ represents the result from the convolutional layer. This block helps to maintain the flow of information throughout the network, which is essential for accurately detecting disease features in tomato leaves.

Classification Section

The classification section of the CRCN uses global average pooling, dropout, dense layers, and SoftMax to categorize the extracted features into different disease classes such as Healthy Tomato Leaf, Early Blight of Tomato, Late Blight of Tomato, Septoria Leaf Spot of Tomato, Yellow Leaf Curl Virus Disease of Tomato, Bacterial Spot of Tomato, Target Spot of Tomato, Spider Mite (Two-Spotted) of Tomato, Leaf Mold, and Mosaic Virus. This technique lowers the parameter quantity in contrast to standard CNN-based approaches, resulting in faster training and testing times. The model is particularly ideal for implementation in resource-constrained settings, such as real-time tomato disease detection systems. It ensures both accuracy and efficiency without excessive computational demands.

4. RESULTS AND DISCUSSION

This section outlines the performance evaluation of the proposed ZOS-CRCN model that integrates Zebra Optimization Segmentation (ZOS) with a Compact Attentional Residual Convolutional Network (CRCN) for tomato disease detection. The PlantVillage image collection was split into training, validation, and testing sets with a 3:1:1 ratio for evaluating the model. The setup included an Intel Core i7 CPU (2.50 GHz), 8 GB of RAM, and the Windows 10 OS and a Python programming environment. This section presents a comprehensive evaluation and comparison of the ZOS-CRCN framework against conventional approaches, including CCNN [11], DenseNet169-InceptionV3 [12], and DNN-GA [13] respectively. The output result of proposed ZOS-CRCN method is given in Figure 2.

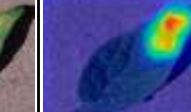
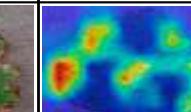
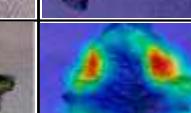
Input Image	Pre-processing Output	Segmentation Output	Classification Output
			Leaf Mold
			Bacterial Spot of Tomato
			Late Blight of Tomato
			Early Blight of Tomato

Figure 2: Output result of proposed ZOS-CRCN Method

4.1 Performance Metrics

This section details the measures employed to evaluate the system's performance,

Accuracy: It is represented as the fraction of correct predictions relative to the overall number of predictions. The calculation is done using the equation (18)

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (18)$$

Where True Positive (TP) indicates the count of diseased tomatoes accurately identified as diseased, True Negative (TN) represents the count of healthy tomatoes correctly recognized as healthy, False Positive (FP) refers to healthy tomatoes mistakenly identified as diseased, and False Negative (FN) denotes diseased tomatoes incorrectly categorized as healthy.

F1 Score: It represents the harmonic mean of precision and recall, calculated by equation (19),

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (19)$$

Where precision and recall is measured using following equation (20-21)

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (20)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (21)$$

Execution Time: It refers to the amount of time the model takes to process data and generate predictions. It is typically measured in milliseconds.

4.2 Performance Analysis for PlantVillage image dataset

Figures 3-6 present a comparative analysis of the ZOS-CRCN model and existing methods, including CCNN [11], DenseNet169-InceptionV3 [12], and DNN-GA [13] on the PlantVillage image dataset.

Figure 3 illustrates the performance evaluation of classification accuracy on the PlantVillage image dataset. The proposed ZOS-CRCN model demonstrates a high accuracy of 0.55%, 7.78%, and 1.30% for Healthy Tomato Leaf images. For Early Blight of Tomato leaf image, the model achieves 0.65%, 3.69%, and 2.44% accuracy. In the case of Late Blight of Tomato leaf image, the accuracy is 0.09%, 5.33%, and 3.68%. For Septoria Leaf Spot of Tomato leaf image, the model reports 0.55%, 4.89%, and 3.82% accuracy. With respect to Yellow Leaf Curl Virus Disease of Tomato leaf image, the model performs with 1.90%, 5.60%, and 2.52% accuracy. The accuracy for Bacterial Spot of Tomato leaf image is 1.02%, 0.24%, and 1.29%. For Target Spot of Tomato leaf image, the model achieves 0.34%, 1.36%, and 1.47% accuracy. In detecting Spider Mite (Two-Spotted) of Tomato leaf image, the accuracy is 2.98%, 0.29%, and 2.87%. For Leaf Mold of tomato leaf image, the model attains 1.01%, 2.99%, and 1.32% accuracy. Finally, for Mosaic Virus of tomato leaf image, the model reports 1.37%, 0.76%, and 4.11% accuracy. These results are compared to existing methods such as CCNN, DenseNet169-InceptionV3, and DNN-GA, respectively. Thus, it highlights the effectiveness of the proposed ZOS-CRCN model in improving classification accuracy.

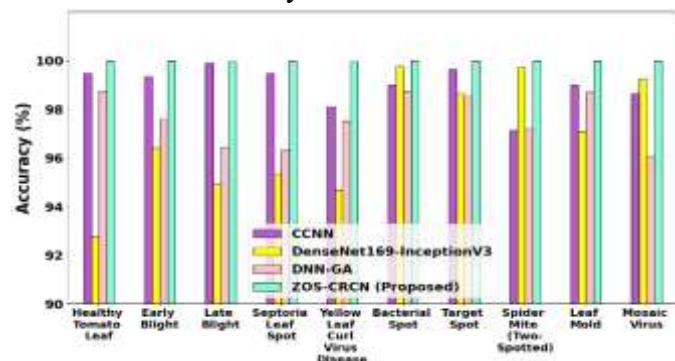


Figure 3: Performance evaluation of classification accuracy on the PlantVillage image dataset

Figure 4 presents the performance evaluation of the F1-Score on the PlantVillage image dataset. When compared to existing methods such as CCNN, DenseNet169-InceptionV3, and DNN-GA, the proposed ZOS-CRCN model achieves notable improvements of 2.03%, 9.96%, and 4.79%, respectively. These results suggest that the ZOS-CRCN model is more capable of accurately identifying plant diseases, thereby demonstrating an enhanced ability to minimize both false positives and false negatives. The improvement in F1-Score further indicates that the model is more effective in handling class imbalances, thus making it a robust solution for real-world applications in tomato plant disease detection.

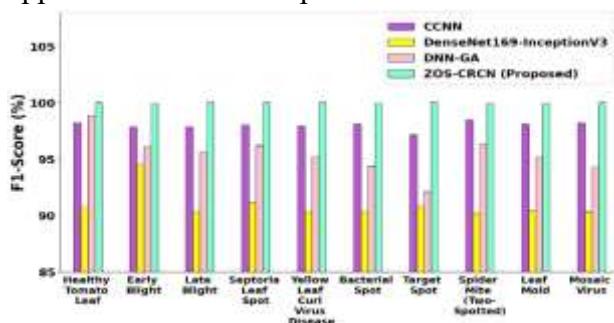


Figure 4: F1-score analysis for classification performance on the PlantVillage image dataset

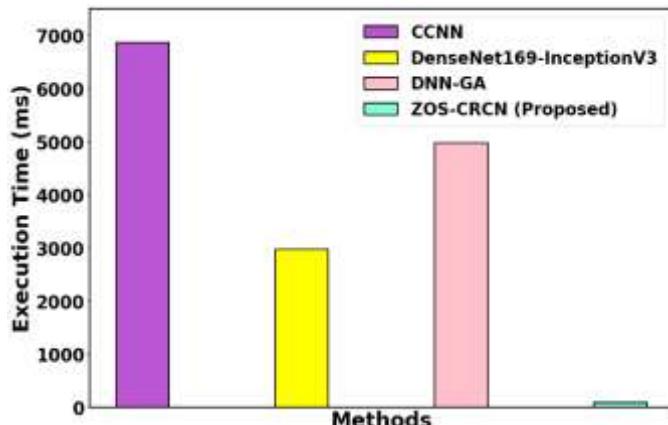


Figure 5: Execution time comparison of various models on the PlantVillage image dataset

Figure 5 illustrates the performance evaluation of execution time on the PlantVillage image dataset. The ZOS-CRCN model demonstrates 98.71%, 97.01%, and 98.22% lower execution time in comparison to the existing methods, including CCNN, DenseNet169-InceptionV3, and DNN-GA, respectively. These results highlight the efficiency of the ZOS-CRCN model, thus showing its capability to perform tomato plant disease classification tasks with significantly reduced computational time. The reduction in execution time

emphasizes the model's potential for handling large-scale datasets with improved speed and efficiency.

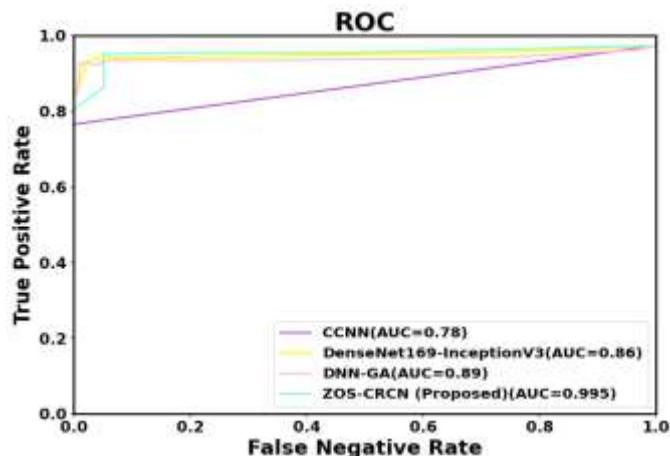


Figure 6: ROC curve

Figure 6 presents the ROC curve. The proposed ZOS-CRCN model achieves 27.56%, 15.70%, and 11.80% higher AUC in comparison to the existing methods, including CCNN, DenseNet169-InceptionV3, and DNN-GA, respectively. These improvements highlight the ability of the ZOS-CRCN model to discriminate between different tomato plant disease classes more effectively. The enhanced AUC values further indicate that the model excels in both sensitivity and specificity.

5. Conclusion

The proposed Smart Tomato Disease Diagnosis system using Zebra Optimization Segmentation and Compact Attentional Residual Convolutional Network (ZOS-CRCN) offers an effective solution for real-time tomato leaf disease detection. By combining the Zebra Optimization Algorithm (ZOA) for precise segmentation with the CRCN for efficient feature extraction and classification, the system ensures high accuracy while minimizing computational complexity. The ZOS-CRCN model outperforms existing methods achieving 98.71%, 97.01%, and 98.22% lower execution time, 27.56%, 15.70%, and 11.80% higher AUC, 2.03%, 9.96%, and 4.79% higher F-score, and 1.04%, 3.29%, and 2.48% higher accuracy when compared to CCNN, DenseNet169-InceptionV3, and DNN-GA, respectively. The approach is optimized for deployment in resource-constrained environments to ensure practicality for mobile devices and in-field systems. Future studies could focus on incorporating Explainable Artificial Intelligence (XAI) approaches to improve the clarity and interpretability of the model's decision-making process. This integration would

increase the value of the system in agricultural decision support by providing clarity on the rationale behind disease predictions that are crucial for effective crop management and decision-making.

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