Integration of Deep Learning with Fox Optimization Algorithm for Early Detection and Classification of Tomato Leaf and Fruit Diseases

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ABSTRACT

Tomato is a common vegetable crop extensively cultivated in the farming lands in India. The hot climate of India is perfect for its development, but particular weather conditions along with many other aspects affect the growing of tomato plants. Apart from these natural disasters and weather conditions, plant diseases consist a major issue in crop production. Precisely classifying leaf and fruit diseases in tomato plants is a vital step toward computerizing processes. Traditional disease detection models for tomato crops often fall short in predictability. To address this, Machine Learning (ML) and Deep Learning (DL) models have been developed, presenting advanced classification capabilities and the ability to manage the vast variability in agricultural data that conventional computer vision models struggle with. This work presents an Integration of DL with Fox Optimization Algorithm (FOA) for the Recognition and Classification of Tomato Leaf and Fruit Diseases (IDLFOA-DCTLFD). The major objective of the proposed IDLFOA-DCTLFD model is to enhance the detection and classification outcomes of tomato leaf and fruit diseases. At the initial stage, the Median Filter (MF) model is used for pre-processing and the Efficient Channel Attention-SqueezeNet (ECA-SqueezeNet) model is employed for feature extraction. For the hyperparameter tuning process, the proposed IDLFOA-DCTLFD technique implements the FOA. Finally, a Wasserstein Generative Adversarial Network (WGAN) is utilized for the detection of tomato leaf and fruit diseases. The IDLFOA-DCTLFD method is experimentally examined in a tomato leaf and fruit dataset. The experimental validation of the IDLFOA-DCTLFD methodology portrayed a superior accuracy value of 98.02%, surpassing the existing techniques.

Keywords-DL; FOA; tomato disease detection; feature extraction; image processing

I. INTRODUCTION

Tomato is a rich food plant, which is cultivated extensively [1]. It is the greatest nutrient-rich crop in the world, and its production and cultivation have a major influence on the farming economy [2], while its demand is rising [3]. Based on statistics, small farmers harvest more than 80% of the farming output due to pests and diseases, and nearly 50% of the initially planted cropt. In farming, plant diseases are a primary miscreant [4]. Various tomato diseases can be found on fruits, leaves, roots, and stems of the plant [5]. Frequent plant diseases are fungi, nematodes, bacteria, and viruses that are the causes of spots in stems or leaves, black or brown lesions, yellowing of lower leaves, black spots, and final death of low leaves. Each disease has various selected prevention measures [6].

The recognition and classification of tomato leaf and fruit diseases over open-eye observation with agricultural specialists is a challenging task and less precise, but it is commonly used in restricted regions [7]. It is vital to address the plant disease issues with technological solutions and several of those have been proposed [8]. The current development in computing technology gave birth to ML and AI models that help in the automated detection of tomato leaves and fruit disease utilizing computerized methods for observing tomato crops [9]. ML-based methods have advanced disease recognition, leveraging digital image processing for classifying leaf and fruit diseases. DL with Neural Networks (NN) improves accuracy through effectual feature extraction. Given the significant role of tomatoes, enhancing disease detection and classification is crucial for sustainable farming amidst the rising demand [10].

Authors in [11] used YOLOV8s as the fundamental structure. The Ultralytics Hub offers optimum settings for training YOLOV5 and YOLOV8 methods. Authors in [12] propose TomatoDet by integrating a Swin-DDETR's self-attention mechanism. Afterward, the dynamic activation function Meta-ACON in the backbone network intensifies the system's capability to illustrate relevant disease features. Authors in [13] proposed a Convolutional Neural Network (CNN) model in different regions. The integration of image processing and computer vision with DL models caused prominent progressions in these regions. Authors in [14] present a technique based on the enhanced YOLOv7. In [15], a new technique by utilizing the Yolov8 structure in DL models is proposed. Authors in [16] studied the performances of InceptionResNetV2 and Xception. Authors in [17] propose a ResNet-50-based DL classification. Authors in [18] present seven Bayesian optimized hybrid models by integrating a customized CNN with conventional ML techniques. In [19], a DL approach by utilizing CNNs, incorporating multiple feature extraction methods and Grey Wolf Optimization (GWO) is introduced for the enhanced accuracy across various plant leaves. In [20], a multi-objective hybrid fruit fly optimization model that depends on simulated annealing optimized SVM is presented. Authors in [21] present an automated technique by using a two-stream DL approach with ML classifiers. Authors in [22] utilize a DL method by integrating a range of classifiers, including Random Forest (RF), Inception V3, DenseNet, ResNet50, Xception, and MobileNet. In [23], an optimized CNN methodology is introduced.

The existing studies have limited adaptability to diverse datasets, and complicate computations, while existing models struggle with small object detection and generalization, underscoring the requirement for more robust models to enhance classification accuracy.

This work presents the Integration of DL with Fox Optimization Algorithm for Recognition and Classification of Tomato Leaf and Fruit Diseases (IDLFOA-DCTLFD) model. The major objective of the IDLFOA-DCTLFD method is to enhance the detection and classification outcomes of tomato leaf and fruit diseases. The major contributions of the IDLFOA-DCTLFD method are:

- The MF model is used for efficient noise reduction in input images, resulting in enhanced data quality that improves the accuracy of subsequent analyses and enhances the reliability of the overall diagnostic process.
- The ECA-SqueezeNet method is utilized for extracting features from images, improving the sensitivity of the model to crucial patterns.
- The FOA is implemented for fine-tuning model parameters, contributing to optimal performance and significantly enhancing classification accuracy.
- The WGAN is used for the precise detection of tomato leaf and fruit diseases, contributing to a reliable diagnostic tool that enhances the accuracy and efficiency of disease detection.
- The IDLFOA-DCTLFD model integrates state-of-the-art techniques in a cohesive framework, incorporating preprocessing, feature extraction, optimization, and classification, which improves the overall effectualness in detecting diseases.

II. THE PROPOSED METHODOLOGY

In this article, the IDLFOA-DCTLFD methodology is proposed. The main objective of the IDLFOA-DCTLFD methodology is to enhance the detection outcomes of tomato leaf and fruit diseases. To accomplish this, the IDLFOA-DCTLFD model involves image preprocessing, feature extraction, FOA-based parameter tuning, and the WGAN-based classification process. Figure 1 represents the workflow of the IDLFOA-DCTLFD method.

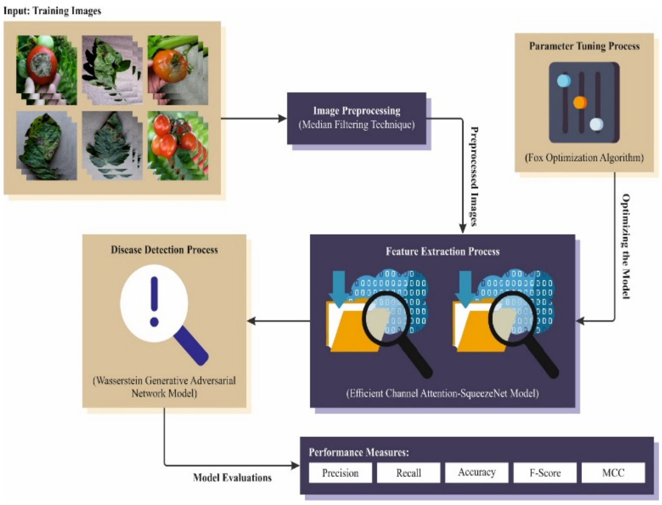

Fig. 1. Workflow of the IDLFOA-DCTLFD technique.

A. *MF-based Preprocessing*

At first, the proposed IDLFOA-DCTLFD model utilizes MF for pre-processing [24, 25]. This model is chosen due to its efficiency in removing noise while conserving edges, making it superior to methods like mean filtering, which can blur significant details in images. The MF substitutes every pixel's rate within the image through the median grayscale rate from the adjacent pixels.

$$\hat{F}(h, Q) = median_{zW \in z_r Q}\{G(z, W)\} \quad (1)$$

Let $z_{h,Q}$ signify a coordinating set controlled by rectangular sub-image positioned at a particular point (h, Q). The median of images is calculated by using a new rate of pixels. MFs are exceptional at eliminating particular kinds of noise, mainly random noise while presenting low blurring combined into linear filters of related dimensions. They are important and valued for their noise-reducing abilities.

B. ECA-SqueezeNet based Feature Extraction

At this stage, the ECA-SqueezeNet model extracts the features [26]. This method is chosen for its lightweight design and effectual channel attention, optimizing feature extraction with minimal computational load. The SqueezeNet network can detect images with high precision, but its classification accuracy is low. This network processes insulator defect detection in two phases: detection and localization, ensuring accurate identification while reducing classification issues. The ECA attention mechanism enhances accuracy by redistributing attention on significant features without altering dimensionality, enhancing localization while keeping low complexity. The ECA attention mechanism is a lightweight, plug-and-play module that compresses input feature maps into channel descriptors using global average pooling. It uses 1D convolution to assess channel correlation, utilizing the sigmoid function to recalibrate important channels while addressing dimensionality reduction drawbacks. The ECA attention mechanism utilizes the band matrix. W_k for learning channel attention:

$$W_k = \begin{bmatrix} w^{1,1} & \dots & w^{1,k} & 0 & 0 & \dots & \dots & 0 \\ 0 & w^{2,2} & \dots & w^{2,k+1} & 0 & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & 0 & \dots & w^{C,C-k+1} & \dots & w^{C,C} \end{bmatrix} \quad (2)$$

The parameter count concerned in the band matrix W_k is $k * C$. It is significant for avoiding complete individuality between several groups. In (2), the weight w_i of y_i is calculated only by considering the interaction between k neighboring objects,

$$w_i = \sigma\left(\sum_{j=1}^{k} w_i^j \, y_i^j\right), y_i^j \in \Omega_i^k \quad (3)$$

where σ signifies the sigmoid function. Ω_i^k characterizes the set of k neighboring channels of y_i^j. To compute the weight w_i, it is more efficient to allow every channel to share similar learning parameters. Hence, the optimization of (3) is:

$$w_i = \sigma\left(\sum_{j=1}^{k} w^j \, y_i^j\right), y_i^j \in \Omega_i^k \quad (4)$$

Such an approach is easily and conveniently applied over 1D convolution using a kernel dimension of k:

$$w = \sigma\left(C1D_k(y)\right) \quad (5)$$

C. FOA-based Hyperparameter Tuning

FOA is employed for the hyperparameter tuning process [27]. This model is chosen due to its effective exploration of the search space and capability to converge quickly, outperforming traditional models in optimization efficiency. This approach replicates the hunting strategies of foxes in snowy conditions, integrating stages like aimless wandering, prey detection through ultrasonic waves, and precise navigation based on sound wave time differences to effectually reach the optimal position. In the FOX optimizer, the population matrix X computes the fitness of optimal positions, with a random variable balancing exploration and exploitation. If a random number exceeds 0.18, the fox seeks a new position based on prey distance and jump height.

$$Dist_{S\_T_{it}} = Sp_{\_S} \cdot Time_{s\_T_{it}} \quad (6)$$

where $Dist_{S\_T_{it}}$ denotes the sound propagation distance, while it depicts the current iteration, $Sp_{\_S}$ represents sound speed, and $Time_{s\_T_{it}}$ comprises of random values in $[0, 1]$ showing the propagation time. The $Sp_{\_S}$ value is determined based on these parameters as shown in (7):

$$Sp_{\_S} = \frac{BestPosition_{it}}{Time_{s\_T_{it}}} \quad (7)$$

where $BestPosition_{it}$ characterizes the current finest fox location. $Time_{s\_T_{it}}$ denotes the sound propagation time amongst prey and foxes. The distance $Dist_{\_Pox\_Prey_{it}}$ among the fox and its victim is half the sound propagation distance.

$$Dist_{\_Pox\_Prey_{it}} = 0.5 Dist_{\_S\_T_{it}} \quad (8)$$

The fox will inspect for an original location to pounce and jump to catch its prey afterwards measuring the distance concerning it and the prey. The subsequent equation defines the jumping procedure, which is a parabolic motion:

$$Iump_{it} = \frac{1}{2} g t^2 \quad (9)$$

In the equation, $Iump_{it}$ symbolizes the leaping height of the fox. This parameter t refers to the average time needed for the propagation of sound. The following equations are utilized to upgrade the fox's location:

$$X_{(it+1)} = Dist_{\_Fox\_Prey_{it}} \cdot Iump_{it} \cdot c_1 \quad (10)$$

$$X_{(it+1)} = Dist_{\_Fox\_Prey_{it}} \cdot Iump_{it} \cdot c_2 \quad (11)$$

where c_1 and c_2 are the updated position parameters based on the success of the fox's leaps, with $c_1 \in [0, 0.18]$, and $c_2 \in [0.18, 1]$. A random variable p in $[0, 1]$ dictates position updates: if $p > 0.18$, the fox's position is updated using (10), else it is computed with (11). During the random walking phase, the fox is guided toward previously discovered optimal positions through a short-time controlled walk:

$$tt = \frac{sum(Time_{\_s\_T_{it}}(i,:))}{D}, MinT = \min(tt) \quad (12)$$

$$a = 2\left(\frac{it-1}{\mathrm{Max}_{it}}\right) \quad (13)$$

where tt depicts the time-averaged value for every row, *MinT* is the shortest average time, and D indicates the problem size. The dynamic variable relates to iterations, with Max_{it} portraying the maximum iterations. To enhance the FOX model's global search capability, both $MinT$ and this variable are used to update the optimal fox location.

$$X_{(it+1)} = BestX_{it} \cdot rand(1, D) \cdot MinT \cdot a \quad (14)$$

The fitness selection is a major feature manipulating the performance of the FOA. This hyperparameter process of selection includes the solution encoder method to estimate the effectiveness of the candidate performances. During this section, the FOA considers precision as the key principle for designing the fitness function that is expressed below:

$$Fitness = \max(P)$$

$$P = \frac{TP}{TP+FP}$$

where TP and FP signify the true and false positive values.

D. WGAN-based Classification

The WGAN method is utilized for the detection of tomato plant diseases [28]. WGAN is chosen for its stability and ability to generate high-quality outputs, improving classification accuracy in complex image datasets. WGAN uses KL or JS divergence for optimizer networks, but KL can cause imbalanced training due to infinite divergence, while JS divergence provides consistent results.

$$H(p) - H(p,q) = -\int p(x)\log p(x)dx - \left(-\int p(x)\log q(x)dx\right) \quad (15)$$

where q and p represent the predicted and real label distributions, with $H(p)$ being the entropy and $H(p,q)$ the cross-entropy. JS divergence measures the variance between the two distributions, addressing the asymmetrical issues of KL divergence. The JS divergence description is calculated by:

$$JSD(p||q) = \frac{1}{2}D(p||m) + \frac{1}{2}D(q||m), m = \frac{1}{2}(p+q) \quad (16)$$

KL and JS divergences inadequately compare real and synthetic data in GANs. Wasserstein distance enhances training stability by accurately measuring distribution distances, even when they don't overlap:

$$W(P_1, P_2) = \gamma \sim \prod^{\infty}(p_1{}'p_2)^{E(x,y)\sim\gamma[||x-y||]} \quad (17)$$

where $\gamma \sim \Pi^{inf}(p_1, p_2)$ represents a collection of the joint probability γ of each potential edge distribution joined with the distributions of P_1 and P_2 and $W(P_1, P_2)$ stands for the low limits of the predictable value of the sample $E_{(x,y)\sim\gamma}[||x-y||]$. The loss functions of the generator and discriminator are:

$$J(G) = E_{Z\sim P_Z}\left[f_W\left(G(z)\right)\right] - E_{x\sim P_r}[f_W(x)] \quad (18)$$

$$J(D) = -E_{Z\sim P_Z}\left[f_W\left(G(z)\right)\right] \quad (19)$$

To guarantee that the data made in the generator are dispersed in the discriminator gradient direction, the 1-Lipschitz state is presented to stop the gradient from vanishing throughout training:

$$\left||f(x_t) - f(y_t)|\right| \le K\left||x_t - y_t|\right| \quad (20)$$

where x_t and y_t are dual points in the function field, and K represents constant and refers to 1-Lipschitz limitation if $K = 1$.

$$W(P_1, P_2)_{\min} = ||D||_L^{sup} \le 1\left(E_{x\sim p(x)}[D(x)] - E_{z\sim p(z)}\left[D\left(G(x)\right)\right]\right) \quad (21)$$

where $||D||_L^{sup} \le 1$ signifies the limitation condition and limits the discriminator loss function. In order to enhance the discriminator, a regularization term is added to the loss value of the discriminator to gain the gradient fine computation:

$$\Omega_{\bar{X}} = 1 - \lambda E_{\bar{X}\sim p(\bar{X})}||\nabla_x D(\bar{X})||^2 \quad (22)$$

where λ is the regularization coefficient, $||\varepsilon||$ denotes the norm, and $\overline{\chi}$ characterizes the randomly generated data between dual points.

III. EXPERIMENTAL ANALYSIS

The data were collected from various resources from Google Images and manually collected in formers gardens [29]. The tomato leaf and fruit dataset contains 10125 images under nine class labels as shown in Table I. The experimental test was performed in Python 3.6.5 tool on a PC i5-8600k, with 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings are: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

TABLE I. DATASET DESCRIPTION

Diseases Type	Class Labels	No. of Images
Bacterial cancer	C1	1125
Fusarium wilt	C2	1125
Septoria leaf spot	C3	1125
Early blight	C4	1125
Late blight	C5	1125
Powdery mildew	C6	1125
Scab	C7	1125
Anthracnose	C8	1125
Viral diseases	C9	1125
Total No. of Images		**10125**

Table II and Figure 2 show the performance comparison of tomato leaf disease classification of IDLFOA-DCTLFD with existing techniques [30-33]. The outcomes state that IDLFOA-DCTLFD outperforms Resnet50, Vgg16, Mobilenet, Googlenet, Xception, ResNet-101, and VGG-19.

TABLE II. COMPARATIVE RESULT ANALYSIS

Method	$Accu_y$	F_{score}	$Reca_l$	$Prec_n$	MCC
Resnet50	89.65	81.00	79.00	80.00	79.99
Vgg16	81.75	80.00	79.00	77.00	82.80
Mobilenet	79.20	77.00	79.00	80.00	83.35
Googlenet	82.81	82.00	83.00	82.00	80.34
Xception	88.16	83.19	82.14	83.25	76.64
ResNet-101	90.13	80.04	80.13	81.95	77.98
VGG-19	90.42	82.43	80.47	80.39	82.28
IDLFOA-DCTLFD	**98.02**	**90.98**	**91.16**	**90.96**	**89.92**

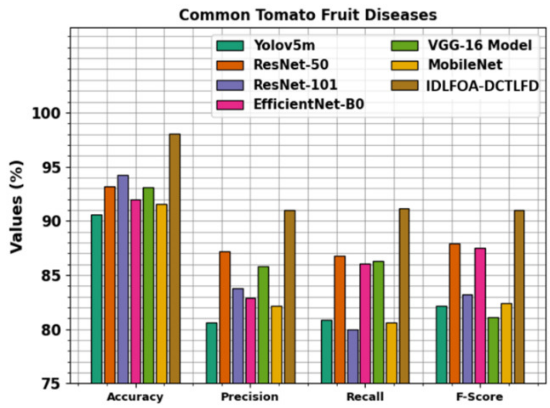

Fig. 2. Tomato fruit diseases classification result comparison.

IV. CONCLUSION

The IDLFOA-DCTLFD method is proposed in this paper. The main objective of the IDLFOA-DCTLFD method is to enhance the tomato leaf and fruit diseases detection and classification outcome. At the initial stage, an MF is used for image preprocessing to enhance the image quality and reduce noise. Further, the ECA-SqueezeNet method is employed for the feature extraction process to capture intricate patterns from the pre-processed images. FOA is applied to the hyperparameter tuning method. Eventually, the detection of tomato leaf and fruit diseases takes place using the WGAN model. The experimental outcome of the IDLFOA-DCTLFD method is examined under a constructed tomato leaf and fruit dataset. The experimental validation of the IDLFOA-DCTLFD methodology portrayed a superior accuracy value of 98.02%, outperforming the existing techniques.

Limitations of the current study comprise potential overfitting on specific datasets and issues in real-time implementation under varying lighting and background conditions. Future work may concentrate on improving model robustness and adaptability to diverse environmental conditions for improved disease detection.

REFERENCES

[1] A. Chug, A. Bhatia, A. P. Singh, and D. Singh, "A novel framework for image-based plant disease detection using hybrid deep learning approach," *Soft Computing*, vol. 27, no. 18, pp. 13613–13638, Sep. 2023, https://doi.org/10.1007/s00500-022-07177-7.

[2] H. M. Zayani *et al.*, "Deep Learning for Tomato Disease Detection with YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13584–13591, Apr. 2024, https://doi.org/10.48084/etasr.7064.

[3] M. S. Alzahrani and 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, Art. no. 1184, https://doi.org/10.3390/agronomy13051184.

[4] A. Wang *et al.*, "NVW-YOLOv8s: An improved YOLOv8s network for real-time detection and segmentation of tomato fruits at different ripeness stages," *Computers and Electronics in Agriculture*, vol. 219, Apr. 2024, Art. no. 108833, https://doi.org/10.1016/j.compag.2024.108833.

[5] M. M. Elsharkawy *et al.*, "Systemic resistance induction of tomato plants against tomato mosaic virus by microalgae," *Egyptian Journal of Biological Pest Control*, vol. 32, no. 1, Apr. 2022, Art. no. 37, https://doi.org/10.1186/s41938-022-00538-2.

[6] N. Aishwarya, N. G. Praveena, S. Priyanka, and J. Pramod, "Smart farming for detection and identification of tomato plant diseases using light weight deep neural network," *Multimedia Tools and Applications*, vol. 82, no. 12, pp. 18799–18810, May 2023, https://doi.org/10.1007/s11042-022-14272-2.

[7] V. Shwetha, A. Bhagwat, and V. Laxmi, "LeafSpotNet: A deep learning framework for detecting leaf spot disease in jasmine plants," *Artificial Intelligence in Agriculture*, vol. 12, pp. 1–18, Jun. 2024, https://doi.org/10.1016/j.aiia.2024.02.002.

[8] A. Gatla *et al.*, "Optimizing Edge AI for Tomato Leaf Disease Identification," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 16061–16068, Aug. 2024, https://doi.org/10.48084/etasr.7802.

[9] R. Rajamohanan and B. C. Latha, "An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12033–12038, Dec. 2023, https://doi.org/10.48084/etasr.6377.

[10] R. Ahmed and E. H. Abd-Elkawy, "Improved Tomato Disease Detection with YOLOv5 and YOLOv8," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 13922–13928, Jun. 2024, https://doi.org/10.48084/etasr.7262.

[11] A. Abdullah, G. A. Amran, S. M. A. Tahmid, A. Alabrah, A. A. AL-Bakhrani, and A. Ali, "A Deep-Learning-Based Model for the Detection of Diseased Tomato Leaves," *Agronomy*, vol. 14, no. 7, Jul. 2024, Art. no. 1593, https://doi.org/10.3390/agronomy14071593.

[12] X. Wang and J. Liu, "An efficient deep learning model for tomato disease detection," *Plant Methods*, vol. 20, no. 1, May 2024, Art. no. 61, https://doi.org/10.1186/s13007-024-01188-1.

[13] M. B. Yildiz, M. F. Hafif, E. K. Koksoy, and R. Kurşun, "Classification of Diseases in Tomato Leaves Using Deep Learning Methods," *Intelligent Methods In Engineering Sciences*, vol. 3, no. 1, pp. 22–36, Mar. 2024, https://doi.org/10.58190/imiens.2024.84.

[14] M. Umar, S. Altaf, S. Ahmad, H. Mahmoud, A. S. N. Mohamed, and R. Ayub, "Precision Agriculture Through Deep Learning: Tomato Plant Multiple Diseases Recognition With CNN and Improved YOLOv7," *IEEE Access*, vol. 12, pp. 49167–49183, Jan. 2024, https://doi.org/10.1109/ACCESS.2024.3383154.

[15] X. Guo, "Automatic detection of tomato leaf disease using an adopted deep learning algorithm," *Journal of Intelligent & Fuzzy Systems*, vol. 46, no. 4, pp. 7909–7921, Jan. 2024, https://doi.org/10.3233/JIFS-236905.

[16] P. K. Nalli, D. P. Garapati, M. V. Subbarao, E. Katta, A. S. Krishna, and N. Deevi, "Comparative Study of Deep Learning Techniques for Detecting Tomato Plant Leaf Diseases Using Transfer Learning," in *International Conference on Distributed Computing and Optimization Techniques*, Bengaluru, India, Mar. 2024, pp. 1–7, https://doi.org/10.1109/ICDCOT61034.2024.10516123.

[17] L. Upadhyay and A. Saxena, "Evaluation of Enhanced Resnet-50 Based Deep Learning Classifier for Tomato Leaf Disease Detection and Classification," *Journal of Electrical Systems*, vol. 20, no. 3s, pp. 2270–2282, Mar. 2024, https://doi.org/10.52783/jes.1856.

[18] B. Khan *et al.*, "Bayesian optimized multimodal deep hybrid learning approach for tomato leaf disease classification," *Scientific Reports*, vol. 14, no. 1, Sep. 2024, Art. no. 21525, https://doi.org/10.1038/s41598-024-72237-x.

[19] A. N. Jabbar and H. Koyuncu, "Deep learning and grey wolf optimization technique for plant disease detection: a novel methodology for improved agricultural health," *Traitement du Signal*, vol. 40, no. 5, pp. 1961–1972, 2023, https://doi.org/10.18280/ts.400515.

[20] E. Gangadevi, R. S. Rani, R. K. Dhanaraj, and A. Nayyar, "Spot-out fruit fly algorithm with simulated annealing optimized SVM for detecting tomato plant diseases," *Neural Computing and Applications*, vol. 36, no. 8, pp. 4349–4375, Mar. 2024, https://doi.org/10.1007/s00521-023-09295-1.

[21] U. Zahra, M. A. Khan, M. Alhaisoni, A. Alasiry, M. Marzougui, and A. Masood, "An Integrated Framework of Two-Stream Deep Learning Models Optimal Information Fusion for Fruits Disease Recognition," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 3038–3052, 2024, https://doi.org/10.1109/JSTARS.2023.3339297.

[22] A. Singh, S. Kumar, and D. Choudhury, "Tomato Leaf Disease Prediction Based on Deep Learning Techniques," in *International Conference on Computation of Artificial Intelligence & Machine Learning*, Jaipur, India, Jan. 2024, pp. 357–375, https://doi.org/10.1007/978-3-031-71481-8_28.

[23] T. Soujanya, S. Padmaja, D. Ramesh, Shabana, and S. Mohmmad, "An Optimized Deep Learning Technique for Enhance Disease Identification in Tomato Leaf to Promote Sustainable Agriculture," in *International Conference on Evolutionary Algorithms and Soft Computing Techniques*, Bengaluru, India, Oct. 2023, pp. 1–5, https://doi.org/10.1109/EASCT59475.2023.10392310.

[24] M. N. Shah, D. A. Gupta, D. A. Kumar, and D. D. S. Chouhan, "Optimized routing algorithm with AlexNet-ShuffleNet for plant leaf disease and infectious classification in IoT." Research Square, May 27, 2024, https://doi.org/10.21203/rs.3.rs-4398092/v1.

[25] K. Sundaramoorthi and M. Kamarasan, "Enhancing Tomato Fruit Disease Detection using Dung Beetle Optimization with Deep Transfer Learning based Feature Fusion Model," *International Journal of*

Engineering Trends and Technology, vol. 72, no. 9, pp. 127–138, Sep. 2024, https://doi.org/10.14445/22315381/IJETT-V72I9P111.

[26] C. Zhang, Y. Liu, and H. Liu, "Target localization and defect detection of distribution insulators based on ECA-SqueezeNet and CVAE-GAN," *IET Image Processing*, vol. 18, no. 13, pp. 3864–3877, 2024, https://doi.org/10.1049/ipr2.13213.

[27] Z. Zhang, X. Wang, and L. Cao, "FOX Optimization Algorithm Based on Adaptive Spiral Flight and Multi-Strategy Fusion," *Biomimetics*, vol. 9, no. 9, Sep. 2024, Art. no. 524, https://doi.org/10.3390/biomimetics 9090524.

[28] C. Zhu, W. Lin, H. Zhang, Y. Cao, Q. Fan, and H. Zhang, "Research on a Bearing Fault Diagnosis Method Based on an Improved Wasserstein Generative Adversarial Network," *Machines*, vol. 12, no. 8, Aug. 2024, Art. no. 587, https://doi.org/10.3390/machines12080587.

[29] "PlantVillage Dataset." [Online]. Available: https://www.kaggle.com/ datasets/emmarex/plantdisease.

[30] S. K and M. Kamarasan, "Improved Spider Monkey Optimization with Deep Learning Model for Tomato Leaf Disease Recognition," *International Journal of Engineering Trends and Technology*, vol. 72, no. 8, pp. 332–341, Aug. 2024, https://doi.org/10.14445/22315381/ IJETT-V72I8P131.

[31] M. T. Vasumathi and M. Kamarasan, "An Effective Pomegranate Fruit Classification Based On CNN-LSTM Deep Learning Models," *Indian Journal of Science and Technology*, vol. 14, no. 16, pp. 1310–1319, Apr. 2021, https://doi.org/10.17485/IJST/v14i16.432.

[32] Q.-H. Phan, V.-T. Nguyen, C.-H. Lien, T.-P. Duong, M. T.-K. Hou, and N.-B. Le, "Classification of Tomato Fruit Using Yolov5 and Convolutional Neural Network Models," *Plants*, vol. 12, no. 4, Jan. 2023, Art. no. 790, https://doi.org/10.3390/plants12040790.

[33] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, "Identification of Tomato Disease Types and Detection of Infected Areas Based on Deep Convolutional Neural Networks and Object Detection Techniques," *Computational Intelligence and Neuroscience*, vol. 2019, no. 1, 2019, Art. no. 9142753, https://doi.org/10.1155/2019/9142753.