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RESEARCH ARTICLE

TOMTO-NET: TOMATO LEAF DISEASE DETECTION USING DEEP LEARNING-BASED DUAL-ATTENTION BASED MOBILE NETWORK

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Abstract – Tomato leaf diseases (TLD) have a significant impact on tomato cultivation modernization. However, traditional diagnostic approaches suffer from low efficiency, misclassification, and inability to adapt to complex field environments. Additionally, existing models struggle with intra-class variability and inter-class similarity, reducing their reliability in real-world disease management. This research aims to address these challenges by introducing a novel TOMTO-NET for accurate TLD detection using Dual-MoNet. A Gaussian Star Filter (GaSF) is employed to reduce noise while preserving essential disease features in tomato leaf images. A MobileNet backbone integrated with a Dual Attention Block (Dual-MoNet) is used for efficient feature extraction, where channel-wise and spatial attention mechanisms enhance fine-grained disease representation. A Spiking Neural Network (SNN) is then utilized for biologically inspired classification of tomato leaves into Healthy and Diseased categories. The effectiveness of the TOMTO-NET approach was evaluated using F1 score, recall, accuracy, specificity, and precision. The experimental results demonstrate the TOMTO-NET achieves an overall accuracy of 98.98%. The TOMTO-NET method improves the accuracy by 1.15%, 2.55%, and 4.15% compared to DM-YOLO, ToLeD, and PLPNet, respectively.

Keywords *– Tomato leaf diseases, Gaussian Star Filter, Dual-MoNet, Spiking Neural Network, Dual Attention Block.*

1. INTRODUCTION

Tomato leaf diseases have a major influence on the modernization of tomato cultivation. It is susceptible to several illnesses that reduce tomato output and quality and result in large financial losses [1]. A widespread disease called tomato grey leaf spot damages and kills tomato leaves, making it impossible for the plants to develop and bear fruit [2]. It is difficult to eradicate the illness that causes tomatoes to have grey leaf patches. The pathogen's four stages of infection responsible for tomato grey leaf spot are contact, invasion, latency, and onset. Early prevention and control measures are therefore required prior to a widespread pandemic [3]. The quality, safety, and health of tomatoes as well as the use of pesticides and pollutants can all be decreased with early disease diagnosis [4].

Large-scale planting demands cannot be met by traditional disease detection systems because of their poor diagnostic efficiency, rapid disease transmission, and tendency for plants to miss the proper management period [5]. The difficulties with tomatoes can be separated into two categories: 16 diseases caused by bacteria, fungi, or improper production practices, and 5 other types of diseases caused by sects. The bacteria Ralstonia solanacearum is responsible for a dangerous type of bacterial wilt [6]. This bacterium may survive for a very long time in soil and penetrate roots through artificial wounds formed during cultivation, transplanting, or even insects, or naturally occurring wounds created during the formation of secondary roots. Disease development is favored by high temperatures and dampness [7].

Deep learning (DL) [9]-based object identification methods in machine learning (ML) [8] provide benefits such improved generalization capabilities, higher accuracy, and faster detection speeds. These days, popular object identification algorithms include traditional models like SSD, YOLO series, and Faster R-CNN [10]. In order to show the potential of object detection algorithms in agricultural disease detection, researchers have conducted several experimental detection tasks.

However, traditional diagnostic approaches suffer from low efficiency, misclassification, and inability to adapt to complex field environments. Additionally, existing models struggle with intra-class variability and inter-class similarity, reducing their reliability in real-world disease management. The main research contributions are mentioned below:

- The main goal of this research is to develop an efficient DL-based approach for accurate TLD detection using a Dual-MoNet framework.
- GaSF is utilized during preprocessing to reduce noise while preserving critical disease-related patterns in tomato leaf images.
- MobileNet integrated with a Dual Attention Block is employed for feature extraction, where channel-wise and spatial attention mechanisms enhance fine-grained feature representation.
- A Spiking Neural Network (SNN) is utilized for final classification, leveraging spike-based temporal dynamics to accurately distinguish between Healthy and Diseased tomato leaves.

The remaining of this work was divided into the sections that follow. Section 2 provides an overview of the latest works of AMD detection, Section-3 introduces the TOMTO-NET approach in practical aspect, Section-4 demonstrates the experimental arrangement and the findings of the TOMTO-NET, finally Section 5 includes a conclusion and future work.

2. LITERATURE SURVEY

Several computer-based methods have been developed by researchers for classifying TLD. Advanced DL, and ML approaches to increase the dependability of categorizing the illness of tomato leaves types. Some of these methods are examined in this section.

In 2024 Wang, Y., et al., [10] examined a method that makes use of attention processes and multi-scale feature fusion to identify TLD. The BiRepGFPN replaces the Path Aggregation Feature Pyramid Network (PAFPN) in the Yolov6 model to efficiently merge deep semantic and superficial spatial information.

In 2024 Khan, R., et al., [11] examined an automated TLD identification using GLCM and SIFT features in an image SVM-based method. The suggested method uses an SVM in conjunction with reliable feature extraction techniques, such as the GLCM and SIFT, to achieve sufficient classification. The experimental findings demonstrate the remarkable accuracy and dependability of our suggested method, greatly enhancing the classification and diagnosis of illnesses affecting tomato leaves.

In 2025 Abulizi, A., et al., [12] introduced a DM-YOLO approach YOLOv9 model for identifying TLD. According to the testing data, this model's accuracy rose by 2.2%, 1.7%, 2.3%, 2%, and 2.1% when compared to several mainstream better models.

In 2020 Agarwal, M., et al., [13] proposed a ToLeD approach for TLD detection using convolution neural network. With regard to classes, the accuracy of the classification varies between 76% and 100%. For the nine disease classes and one healthy class, the recommended model's average accuracy is 91.2%.

In 2023 Tang, Z., et al., [14] presented a PLPNet-based method for detecting illness of tomato leaves. Using a self-constructed dataset, the experimental findings demonstrate that PLPNet achieved 54.4% average recall (AR), 94.5% mean average accuracy with 50% thresholds (mAP50) and 25.45 frames per second (FPS).

In 2022 Nagamani, H.S. and Sarojadevi, H., [15] presented a DL method for identifying TLD. In contrast to the other classification methods, the most remarkable accuracy of 96.735 percent is achieved by the R-CNN-based Classifier.

In 2025 Sun, H., et al., [16] introduced an E-TomatoDet for increases the efficacy of detection of TLD by combining and enhancing local and global feature perception skills. By integrating CSWinTransformer into the detection network's core, TLD ability to capture global features is significantly enhanced. The TLD dataset E-TomatoDet outperformed the sophisticated real-time detection network YOLOv10s, increasing the mean Average Precision (mAP50) by 4.7% over the baseline model to 97.2%.

However, traditional diagnostic approaches suffer from low efficiency, misclassification, and inability to adapt to complex field environments. Additionally, existing models struggle with intra-class variability and inter-class similarity, reducing their reliability in real-world disease management. To overcome these challenges a novel TOMTO-NET approach for accurate TLD detection using Dual-MoNet.

3. PROPOSED METHODOLOGY

In this research, a novel TOMTO-NET model is proposed for accurate TLD detection using Dual-MoNet. Figure 1 demonstrates the overall process of the TOMTO-NET methodology.

3.1. Pre-processing using GSF

GaSF is used effectively reducing noise while preserving TLD information in areas. This process is generally applied in scenarios where the leaf image might contain noise that is periodic or quasi-periodic and is brought on by scanning artifacts, the environment, or other causes. The mathematical representation for the frequency domain representation of the GaSLF is as follows:

$$GaSLF(u,v) = \begin{cases} max\big(R_1(u,v), R_2(u,v)\big) & if\ R_1(u,v) > 0\ and\ R_2(u,v) > 0, \\ R_1(u,v) & if\ R_1(u,v) > 0\ and\ R_2(u,v) = 0, \\ R_2(u,v) & if\ R_1(u,v) = 0\ and\ R_2(u,v) > 0, \\ 0 & otherwise. \end{cases} \quad (1)$$

Where $R_1(u,v)$ and $R_2(u,v)$ represent the two orthogonal Gaussian filters applied at point (u,v) in the frequency domain, the filter outputs the maximum of the two Gaussian filters value if both filters are greater than zero at (u,v), indicating the presence of significant data in both directions. $R_1(u,v) = \sum_n e^{-D_1(u,v)^2/N}, R_2(u,v) = \sum_n e^{-D_2(u,v)^2/N}$, and $D_1(u,v)$ and $D_2(u,v)$ are the distances from the center of the noise peaks:

$$D_1(u,v) = \sqrt{(u-u_{1n})^2 + (v-v_{1n})^2}, D_2(u,v) = \sqrt{(u-u_{2n})^2 + (v-v_{2n})^2}, \quad (2)$$

Finally, the GaSF is defined as:

$$GaSF(u, v) = 1 - GaSLF(u, v)(2) \quad (3)$$

Where $GaSF(u, v)$ is the output of the GaSF at the frequency at the frequency coordinates (u, v), $GaSF(u, v)$ is the Low-Pass Filter, which is designed to detect and suppress noise, $1 - GaSLF(u, v)$ensure that the filter removes noise where the $GaSLF(u, v)$ detects high noise presence, while noise is reduced. The GaSF effectively reducing noise while preserving image information in areas where both filters are active.

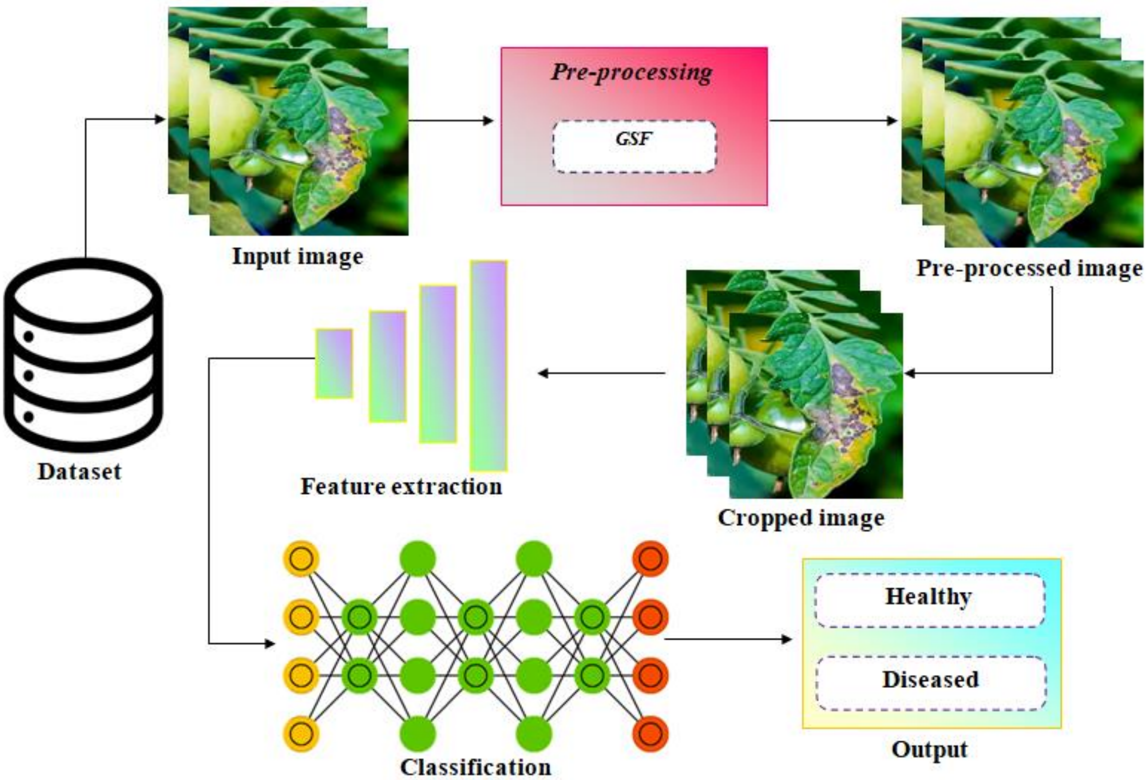

Figure 1. Proposed TOMTO-NET approach

3.2. Feature extraction

Dual-MoNet method is used for identifying a diseased in Tomato leaf images to extract the features. MobileNet combined with a Dual Attention Block involves leveraging the efficiency of MobileNet architecture to obtain feature maps and then enhancing these features with advanced attention mechanisms. MobileNet is designed for computational efficiency, using depthwise separable convolutions to reduce the model size and computation requirements while preserving the ability to capture hierarchical features from input images. It processes the image through a series of depth wise and pointwise convolutions, yielding a set of feature maps that represent different levels of image abstraction.

The features are extracted and the Dual Attention Block refines these feature maps to improve their quality and relevance. This block applies two types of attention mechanisms: spatial and channel-wise. The channel attention mechanism emphasizes the significance of several feature channels, learning to weigh the significance of each channel based on global context. Meanwhile, the spatial attention mechanism emphasizes crucial regions within the feature maps, allowing the model to concentrate on important spatial locations. By combining these attentions, the Dual Attention Block enhances the representational power of the features, making them more discriminative for subsequent classification. Thus, integrating MobileNet with a Dual Attention Block results in a strong and efficient feature extraction pipeline, optimizing both computational efficiency and feature quality. The mathematical representation of the process of feature extraction using the Dual-MoNet method. Depthwise separable convolutions are used by MobileNet to lower computational complexity. It consists of two main types of convolutions:

For every input channel, depthwise convolution applies a convolution process separately, reducing the computation. If $I \in \mathbb{R}^{H \times W \times C}$ is the input feature map, for every channel, the depthwise convolution applies a filter separately.

$$F_c = I_c * K_c, \forall_c \in \{1,2, \dots, C\} \quad (4)$$

Where I_c is the c-th input channel, K_c is the convolution kernel for the c-th channel, and F_c is the output for that channel.

Pointwise convolution 1×1 convolution that mixes the information across channels. This is represented by:

$$O = \sum_{c=1}^{C} F_c * K_c' \quad (5)$$

WhereK_c' is the 1×1 convolution kernel applied to each depthwise output. After applying several depthwise and pointwise convolutions, MobileNet produces feature maps, $F \in \mathbb{R}^{H' \times W' \times C'}$.The Dual attention block applies channel-wise attention and spatial attention to refine the feature maps. In the final output feature map, the Dual attention block is

$$F'' = \beta.(\alpha.F) \quad (6)$$

Here, α is the channel attention vector applied element-wise to the feature map, and β is the spatial attention matrix. The output of the MobileNet feature extractor combined with the Dual Attention Block are represented as:

$$F_{output} = DualAttention(F_{MobileNet}) \quad (7)$$

This final feature map used for classification from the computational efficiency of MobileNet and the refined attention mechanisms from the Dual Attention Block.

3.3. Classification

Spike neural network (SNN) is employed to classify types of tomato leaf into Healthy and Diseased. SNN is type of neural network, which are more biologically plausible compared to traditional artificial neural networks, process on information using discrete events (spikes) rather than continuous values. Hidden layers consist of spiking neurons, adjusted based on learning rules. The output layer aggregates spikes and classifies tomato leaf health or disease.

The mathematical representation of liver cancer using an SNN involves encoding image features into spike trains, modeling neuron dynamics using equations like those in the model for synaptic weights based on spike timing-dependent plasticity and making classification decisions according to the output layer's spike activity. The intensity of a feature is encoded as the firing rate of spikes.

$$f_i = K.I_i \quad (8)$$

Where f_i is the firing rate of the ith input neuron, I_i is the intensity of the ith pixel or feature and K is a scaling factor that converts intensity to spike rate. The dynamic of it is possible to utilize an explanation of a spiking neuron using the model of Leaky Integrate and Fire.

$$T_m \frac{dV(t)}{dt} - V(t) + R.I(t) \quad (9)$$

Where $V(t)$ is the potential of the membrane at a certain time t, then $T_m$is the membrane resistance, and R is the membrane time constant. $I(t)$ is the input current, typically coming from the weighted sum of input spikes. SNN represented by coming the input encoding, neuron dynamics, weight updates, and decision-making.

$$Class = \arg max_j \left(\sum_i w_{ij} . \sigma \left(\int_0^T I_i\,(t)dt \right) \right) \quad (10)$$

Where $\sigma(.)$represents the spiking neuron model, typically implemented as model, T is the time window over which spikes are accumulated and $I_i(t)$ is the input to the ith neuron over time. This framework leverages the temporal dynamics and event-driven nature of SNN to classify the different types of tomato leaves.

4. RESULT AND DISCUSSION

In this section, the experimental arrangement of the TOMTO-NET approach was implemented using MATLAB 2022b. The TOMTO-NET was evaluated using a number of measures in this section including recall, specificity, precision, f1score, and accuracy depending on the gathered dataset. The experimental result of the TOMTO-NET is illustrated in Figure 4 for TLD detection.

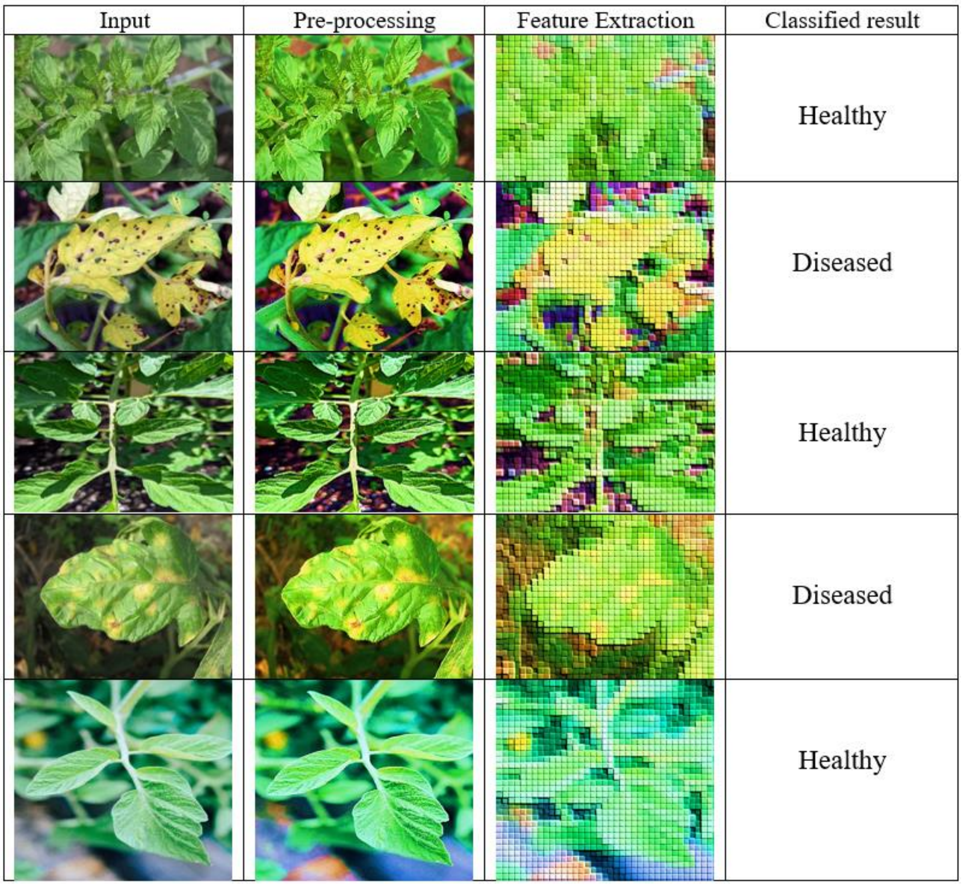

Figure 2. Experimental result of the TOMTO-NET

Figure 2 demonstrate the experimental results of the TOMTO-NET based on gathered publicly available images. Column 1 demonstrates the input TLD images. The pre-processed using GaSF to enhance the tomato leaf images quality by preserving edges while effectively reducing noise and improving visual clarity shown in column 2. The feature extraction using Dual-MoNet to extracting deep semantic features from the pre-processed images in column 3. Then SNN is used to classify into Healthy and Diseased illustrates in column 4.

4.1. Performance analysis

The TOMTO-NET was assessed in this section using a number of metrics, including specificity (Sp), accuracy (Ac), recall (Rc), F1 score (F1), and precision (Pr), on the gathered images.

$$Sp = \frac{TN}{TN+FP} \tag{11}$$

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

$$Pr = \frac{TP}{TP+FP} \tag{13}$$

$$Rc = \frac{TP}{TP+FN} \tag{14}$$

$$f1score = 2\left(\frac{precision*recall}{precision+recall}\right) \tag{15}$$

Where TP and TN indicate true positives and negatives of the sample images, FP and FN indicates false positives and negatives of the sample images.

Table 1. Performance analysis of TOMTO-NET

Classes	Ac	Pr	Sp	Re	F1
Healthy	99.22	98.45	98.61	99.05	98.98
Diseased	98.74	97.43	98.75	99.42	97.39

Table.1 displays the classification performance obtained by proposed model for TOMTO-NET classifying the LC. F1 score, precision, accuracy, recall and specificity are metrics that determine performance. A total accuracy of 98.98% is achieved by the TOMTO-NET using the dataset. The proposed TOMTO-NET model achieves 99.22% for Healthy, and 98.74% for Diseased.

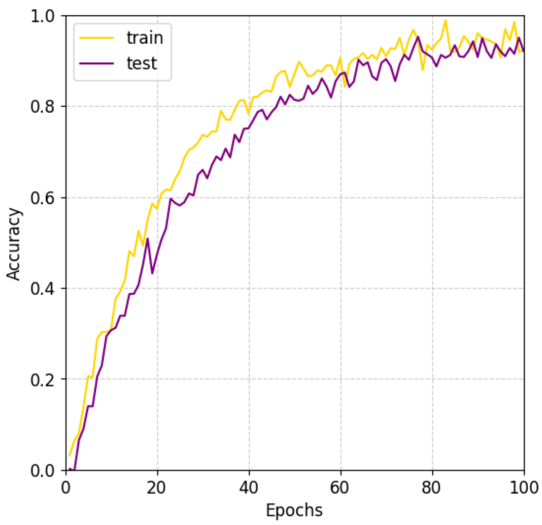

Figure 3. Accuracy curve of TOMTO-NET approach

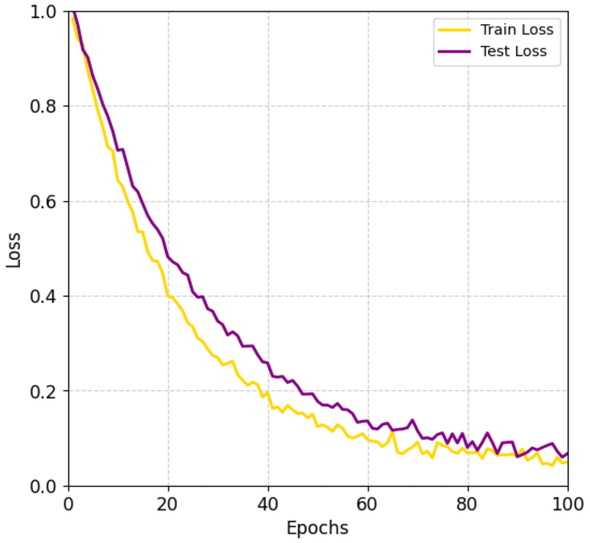

Figure 4. Loss curve of TOMTO-NET method

Figure 3 demonstrates the accuracy curve of the TOMTO-NET approach. The proposed TOMTO-NET accuracy curve for training and testing shows a high degree of 98.98%. The proposed TOMTO-NET model loss curve, which displays 100 epochs loss y axis and epochs on x axis is shown in Figure 4. The final loss value achieved by the TOMTO-NET model was 1.02%, demonstrating high model accuracy and stability.

4.2. Comparative analysis

The effectiveness of existing techniques was shown the TOMTO-NET approach output is superior for tomato leaf detection. The TOMTO-NET model performance is determined by its accuracy, recall, specificity, f1 score, and precision. Compared to the existing approach the accuracy level achieved by the combination of Multi-modal Dual-MoNet is more efficient. This section also includes a comparison of the proposed TOMTO-NET approach with conventional ML and DL techniques.

Table 2. Comparison between existing vs proposed classification networks

Networks	Ac%	F1%	Re%	Pr%	Sp%
RNN	93.82	84.58	83.92	87.64	89.15
CNN	95.67	91.34	86.45	84.67	87.87
DBN	97.04	93.89	94.88	92.12	90.59
Proposed SNN	98.98	97.75	95.39	94.97	94.86

Table 2 comparison of the proposed SNN model and current methods like CNN, DBN, and RNN. The proposed model achieves 5.49%, 3.45%, and 1.99% better than the conventional models, such as RNN, CNN, DBN for TLD detection. The SNN achieves better result compared to current networks, with a precision rate of 98.98% for the detection of TLD.

Table 3. Comparison of existing approaches and proposed approach

Authors	Methods	Accuracy
Abulizi, A., et al., (2025) [12]	DM-YOLO	97.85%
Agarwal, M., et al., (2020) [13]	ToLeD	96.51%
Tang, Z., et al., (2023) [14]	PLPNet	95.03%
Proposed	TOMTO-NET	98.98%

Figure 3 demonstrates the accuracy curve of the TOMTO-NET approach. The proposed TOMTO-NET accuracy curve for training and testing shows a high degree of 98.98%. The proposed TOMTO-NET model loss curve, which displays 100 epochs loss y axis and epochs on x axis is shown in Figure 4. The final loss value achieved by the TOMTO-NET model was 1.02%, demonstrating high model accuracy and stability.

5. CONCLUSION

This research introduced novel TOMTO-NET approach for precise diagnosis of TLD using Dual-MoNet. A GaSF is employed to reduce noise while preserving essential disease features in tomato leaf images. A MobileNet backbone integrated with a Dual Attention Block is used for efficient feature extraction, where channel-wise and spatial attention mechanisms enhance fine-grained disease representation. A SNN is then utilized for biologically inspired classification of tomato leaves into Healthy and Diseased categories. The effectiveness of the TOMTO-NET was evaluated using recall, specificity, precision, F1 score, and accuracy. The experimental results demonstrate that the TOMTO-NET attains an overall accuracy of 98.98%. The TOMTO-NET improves the accuracy by 1.15%, 2.55%, and 4.15% compared to DM-YOLO, ToLeD, and PLPNet, respectively. Future work will focus on extending the proposed model to multi-class classification for identifying specific TLD rather than binary detection. Additionally, integration with IoT-enabled devices and mobile applications will be explored to support real-time field deployment for farmers.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

[1] Y. Shen, Z. Yang, Z. Khan, H. Liu, W. Chen, and S. Duan, "Optimization of improved YOLOv8 for precision tomato leaf disease detection in sustainable

agriculture," *Sensors*, vol. 25, no. 5, pp. 1398, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Q. Wang, N. Yan, Y. Qin, X. Zhang, and X. Li, "BED-YOLO: An Enhanced YOLOv10n-Based Tomato Leaf Disease Detection Algorithm," *Sensors*, vol. 25, no. 9, pp. 2882, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] D. Karimanzira, "Context-aware tomato leaf disease detection using deep learning in an operational framework," *Electronics*, vol. 14, no. 4, pp. 661, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Z. Liu, X. Guo, T. Zhao, and S. Liang, "YOLO-BSMamba: A YOLOv8s-Based Model for Tomato Leaf Disease Detection in Complex Backgrounds," *Agronomy*, vol. 15, no. 4, pp. 870, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] H.A. Shehu, A. Ackley, M. Marvellous, and O.E. Eteng, "Early detection of tomato leaf diseases using transformers and transfer learning," *European Journal of Agronomy*, vol. 168, pp. 127625, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Z. Osmenaj, E.M. Tseliki, S.H. Kapellaki, G. Tselikis, and N.D. Tselikas, "From Pixels to Diagnosis: Implementing and Evaluating a CNN Model for Tomato Leaf Disease Detection," *Information*, vol. 16, no. 3, pp. 231, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] A. Imtiaz, F.B.I. Swapnil, S.R. Masud, and D. Karmaker, "Tomato leaf dataset: A dataset for multiclass disease detection and classification," *Data in Brief*, vol. 60, pp. 111520, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] D.L. Shanthi, K. Vinutha, and N. Ashwini, "Tomato leaf disease detection using CNN," *Procedia Computer Science*, vol. 235, pp. 2975-2984, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] V. Cheemaladinne, and S. Reddy, "Tomato leaf disease detection and management using VARMAx-CNN-GAN integration," *Journal of King Saud University-Science*, vol. 36, no. 8, pp. 103340, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Y. Wang, P. Zhang, and S. Tian, "Tomato leaf disease detection based on attention mechanism and multi-scale feature fusion," *Frontiers in Plant Science*, vol. 15, pp. 1382802, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] R. Khan, N. Ud Din, A. Zaman, and B. Huang, "Automated Tomato Leaf Disease Detection Using Image Processing: An SVM-Based Approach with GLCM and SIFT Features," *Journal of Engineering*, vol. 2024, no. 1, pp. 9918296, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] A. Abulizi, J. Ye, H. Abudukelimu, and W. Guo, "DM-YOLO: Improved YOLOv9 model for tomato leaf disease detection," *Frontiers in Plant Science*, vol. 15, pp. 1473928, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato leaf disease detection using convolution neural network," *Procedia Computer Science*, vol. 167, pp. 293-301, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Z. Tang, X. He, G. Zhou, A. Chen, Y. Wang, L. Li, and Y. Hu, "A precise image-based tomato leaf disease detection approach using PLPNet," *Plant Phenomics*, vol. 5, pp. 0042, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] H.S. Nagamani, and H. Sarojadevi, "Tomato leaf disease detection using deep learning techniques," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 1, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] H. Sun, R. Fu, X. Wang, Y. Wu, M.A. Al-Absi, Z. Cheng, Q. Chen, and Y. Sun, "Efficient deep learning-based tomato leaf disease detection through global and local feature fusion," *BMC Plant Biology*, vol. 25, no. 1, pp. 311, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] G. Wang, R. Xie, L. Mo, F. Ye, X. Yi, and P. Wu, "Multifactorial tomato leaf disease detection based on improved YOLOV5," *Symmetry*, vol. 16, no. 6, pp. 723, 2024. [CrossRef] [Google Scholar] [Publisher Link]

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