



A Hybrid Deep Learning Framework Integrating Adaptive Patch Decomposition and Graph-based Disease Correlation Learning for Accurate Tomato Leaf Disease Classification

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ABSTRACT

Background: Tomato (*Solanum lycopersicum*) leaf diseases, which reduce crop productivity, the quality of products and farm income, have a significant impact on agriculture worldwide. It is crucial to perform accurate, early identification of diseases to realize sustainable crop management and precise agriculture. Traditional manual diagnosis is costly, labor-intensive, inaccurate and subjective, which is unsuitable for large-scale agriculture. Though deep learning has been proven to be successful in classifying plant diseases, conventional methods have difficulties with background noises, inter-class similarity and insufficient learning of contextual features.

Methods: To overcome these issues, a hybrid deep learning framework based on adaptive patch decomposition (APD), graph-based disease correlation learning (GDCL) and hybrid decision fusion classification (HDFC) is proposed to efficiently and accurately classify tomato leaf diseases. The model was trained using 20,000 tomato leaf images with ten different diseases and healthy condition. First, image quality and training stability was enhanced by applying adaptive preprocessing techniques like image resizing, de-noising, contrast enhancement and normalization to the images. The ADPS module segmented lesions from irrelevant background information and generated the critical parts for disease-feature extraction. CNN-based local feature extraction and global context pooling were then performed to capture detailed lesion features and general leaf appearance, respectively. Graph-based disease correlation learning (GDCL) module was designed to establish inter-class disease correlation by using graph-based feature refine mechanism to differentiate between visually indistinguishable diseases. Lastly, hybrid decision fusion classification (HDFC) was proposed to enhance classification accuracy by combining prototype distance learning and graph similarity scores for disease classification.

Result: Experiment results showed that the proposed framework outperformed compared to other deep learning methods, including VGG16, ResNet50, DenseNet121, EfficientNet-B0 and InceptionV3, with the overall accuracy of 99.03%, precision of 98.98%, recall of 98.94%, F1-score of 98.78% and minimum loss of 0.053. The proposed system achieved robust stability and generalization ability tested with 5-fold cross validation. The model was proved to reduce inter-class confusion and obtain outstanding performance in learning the feature from lesions and it could be widely used in intelligent agricultural disease monitoring system and precise agriculture applications.

Key words: DenseNet201, Hybrid deep learning, MobileNet, Precision agriculture, Tomato leaf disease detection, U-net segmentation.

INTRODUCTION

Tomatoes (*Solanum lycopersicum*) is one of the most widely planted vegetable crops worldwide, with great significance in food security, economics and nutrition. However, tomato cultivation is severely affected by several bacterial, fungal and viral diseases namely bacterial spot, early blight, late blight, leaf mold, septoria leaf spot and mosaic virus. These diseases are detrimental to yield and fruit quality and negatively impacts income of farmers.

Traditionally, diagnosis of plant diseases is made based on visually observing leaves/fruits using inspection of agricultural experts. While the expert-based method is successful it is time consuming, subject to human judgment, laborious, expensive and difficult to apply to a large agricultural field. Since then, there has been immense interest in using artificial intelligence (AI) based deep learning models for automated diagnosis of plant diseases.

Deep learning architectures namely CNNs, transfer learning, transformer based and ensemble models have reported good performance in tomato leaf disease classification. Models such as VGG16, ResNet50,

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DenseNet121, EfficientNet and Vision Transformers are successfully used for lesion recognition in recent researches. Despite such progress, some research challenges still persist in automated diagnosis of tomato leaves:

Research gap

Most existing tomato disease classification approaches rely on end to end CNN pipelines, focusing more on global image feature representations while neglecting local and lesion centric learning.

1. Background clutter, noisy irrelevant regions tend to result in classification inaccuracies.
2. Similarity between classes (spider mites, target spot, leaf mold, etc.) leads to classification confusion.
3. Few methods attempt to explicitly model disease to disease relationship.
4. Context aware graph-based correlation learning has rarely been utilized for tomato disease classification.
5. Hybrid decision fusion approaches using prototype learning and graph similarity scoring are rarely explored.

The objective of this paper is to address these shortcomings by introducing a novel hybrid deep learning framework, incorporating APD (Adaptive Patch Decomposition), GDCL (Graph Based Disease Correlation Learning) and HDFC (Hybrid Decision Fusion Classification). This proposed framework addresses the need for a context-aware local-global feature extraction model by using both lesion-centric feature learning with graph-based inter-class relationship learning and hybrid decision fusion. The contributions are as follows:

- Designing an adaptive patch decomposition based on lesion-centric feature extraction.
- Presenting a graph-based disease correlation learning in inter-class disease similarity.
- Integrating local and global contextual feature aggregation.
- Presenting a hybrid decision fusion classifier combined with prototype distance and graph similarity learning.
- Comprehensive experiments and comparative evaluation through 5-fold cross-validation.

Literature review

The automatic tomato leaf disease identification has become a hot topic and attracts more attention in the recent years for the necessity of precision agriculture and the rapid progress of early crop disease detection. Many researchers propose the deep learning approaches to increase the recognition performance. Saeed *et al.* (2023) proposes a transfer learning-based CNN framework for smart tomato leaf disease detection. The paper shows that pre-trained CNN architecture improve the classification performance greatly but decrease the computation complexity and increase speed compared to existing approaches. Khan *et al.* (2023) proposes TomFormer which is a novel hybrid transformer-CNN structure for premature and accurate identification of tomato diseases and it is strong enough to handle the classification problem across

datasets and indicate the crucial role of attention based global feature learning. Ouamane *et al.* (2024) proposes a CNN based framework in combination of tensor subspace learning and HOWSVD-MD, reporting that the classification precision and robustness of tomato leaf diseases are increased. Sharma *et al.* (2025) proposes an ensemble framework combining ResNet50 and MobileNetV2 in order to achieve excellent classification performance and gain more feature diversity. Sujatha *et al.* (2025) demonstrates an integrated ML and DL framework for leaf infection finding and claims the robustness of the system relies on both preprocessing and hybrid architecture. Das *et al.* (2025) provides the latest literature review on detection, classification and segmentation for tomato leaf diseases utilizing deep learning algorithms including CNN, transformers and object detection models. Ramos and Sappa (2025) analyses YOLO architectures on tomato leaf disease identification in detail and proves that object detection-based approach plays important role on locating the leaf lesion. Gunasekaran *et al.* (2026) concentrates on the application of trivial deep learning and fringe AI based approach for real-time tomato disease identification and pays attention to the challenges for deploying models into mobile and IoT devices.

In their research of plant leaf infection finding with deep learning methods, Zhao *et al.* (2025) stated that CNN based methods are widely used while the transformer-based methods are appearing frequently in recently published articles. Mustofa *et al.* (2023) delivered an in-extensive assessment of deep learning standards like CNN, ViT, YOLO and residual networks for plant disease detection. Hosen and Islam (2025) examined VGG19 and model InceptionV3 for leaf disease classification in tomato plant and achieved very promising result to real-world crop health inspection. Previous researches also applied several classical CNN models including VGG16, ResNet50, DenseNet121 and EfficientNet with very well performance, however the issues with inter-class similarity and learning contextual features are often observed. Nevertheless, researches on graph-based disease correlation learning, patch-wise adaptive feature decomposition and hybrid score fusion are seldom.

Metagar and Walikar (2024) in the review article, published in Agricultural Science Digest, outlined machine learning (ML) and deep learning (DL) techniques employed in the diagnosis of plant diseases and noted that image processing techniques, feature extraction and the combination of sophisticated learning models contribute to higher accuracy in disease prediction, thereby enabling precision agriculture practices. Meht *et al.* (2025) through their article presented in the Indian Journal of Agricultural Research provided an overview of different AI techniques to aid in disease diagnosis of various crops and concluded that convolutional neural networks (CNN), transfer learning and other deep learning frameworks have shown to be a

robust and scalable way to perform plant disease classification, thereby powering smart farming operations. Mehtta *et al.* (2025) also conducted another review article in the Indian Journal of Agricultural Research, analysed the recent research related to the application of artificial intelligence for detecting plant diseases where they observed that DL algorithms integrated with computer vision for plant images have made improvements in classification and have been proved useful for timely detection of plant diseases in various agricultural setups. Nigam and Jain (2020) analysed a plethora of deep learning algorithms used in the detection and identification of plant diseases in their review, concluded that there have been immense improvements in the classification accuracies using the applications of computer vision (CV), machine learning (ML) and deep learning (DL) for intelligent decision-making process in agriculture.

Most of existing work follows an end-to-end CNN pipeline and implicitly extracts features without modeling inter-class disease relations. This paper attempt to tackle this problem through combining the APD, GDCL and HDFC together.

MATERIALS AND METHODS

Data description

The designed system was tested on a tomato leaf diseases dataset consisting of 20000 labeled images acquired from publicly available datasets on PlantVillage and agriculturally enriched dataset. The classes considered in this dataset are ten:

1. Bacterial spot.
2. Early blight.
3. Late blight.
4. Leaf mold.
5. Septoria leaf spot.
6. Spider mites.
7. Target spot.
8. Yellow leaf curl virus.
9. Mosaic virus.
10. Healthy leaves.

The dataset was divided into:

- 70% Training set.
- 15% Validation set.
- 15% Testing set.

Data augmentation was performed to enhance the generalization ability on the given data; rotation, flipping, zooming, brightness adaptation and random cropping were employed.

Implementation details

Proposed framework was implemented on Python with TensorFlow and PyTorch frameworks. Training was performed on NVIDIA RTX GPU architectures using following hyperparameters in Table 1.

Proposed approach

The designed hybrid deep learning structure for categorization of tomato leaf diseases will be described

in this section. Our methodology consists of seven steps: adaptive preprocessing, adaptive patch decomposition, local feature learning, global context aggregation, graph-based disease correlation learning, feature re-weighting and hybrid decision fusion classification as shown in Fig 1.

The proposed framework can accurately classify the diseases by simultaneously utilizing spatial, context and inter-class correlation features.

Phase 1: Data acquisition and adaptive preprocessing

This research used 20,000 tomato leaf images labeled with their disease types. They can be formulated as:

$$D = \{(I_i, y_i)\}_{i=1}^N \quad \dots(1)$$

Where,

I_i = Input image.

y_i = The related disease label.

$N = 20,000$.

All the images are processed by adaptive preprocessing technique to maintain consistence and improve image quality as shown in Fig 2.

Image resizing

Each image size is modified by using the below formula:

$$I_r \in \mathbb{R}^{224 \times 224 \times 3} \quad \dots(2)$$

This default size has made for fast processing with CNNs.

Noise filtering

Noise is deleted using adaptive filtering:

$$I_r = \mathcal{F}(I_r) \quad \dots(3)$$

Where,

$\mathcal{F}$ = The filtering function.

Contrast enhancement

The sorted (filtered) image is enhanced the contrast by using the below formula:

$$I_c = \varepsilon(I_r) \quad \dots(4)$$

Where,

ε = The contrast enrichment operator.

Normalization

The image normalization can be done by using the below formula, *i.e.* normalized into the range [0,1]:

$$I_n = \frac{I_c}{255} \quad \dots(5)$$

This method enhances the convergence of the model and training stability.

Phase 2: Adaptive patch decomposition (APD)

The pre-processed image is segregated into numerous disease-related patches:

$$P = \{p_1, p_2, p_3, \dots, p_n\} \quad \dots(6)$$

Where,

p_i = The i^{th} patch.

Each patch can be denoted as:

$$P_i \in \mathbb{R}^{k \times k} \quad \dots(7)$$

Threshold segmentation method is used to remove background and irrelevant patches:

$$P_d = \{p_i | \delta(p_i) = 1\} \quad \dots(8)$$

Where,

$\delta(p_i)$ = A disease relevance pointer.

This phase confirms that only lesion-related sections are conserved for feature learning.

Phase 3: Local feature learning

To extract local features deeply, every single disease-relevant patch is passed through CNN backbone:

$$f_i = \text{CNN}(p_i) \quad \dots(9)$$

Where,

f_i = The feature vector of patch p_i .

The complete patch-level feature set is denoted as:

$$F = \{f_1, f_2, \dots, f_n\} \quad \dots(10)$$

Each feature vector fits to:

$$f_1 \in \mathbb{R}^d \quad \dots(11)$$

Where,

d = The dimension of feature.

This phase depicts local lesion patterns such as "spots, blights, discoloration and texture irregularities".

Phase 4: Global context aggregation

Patch-level features are grouped into global interpretation for preserving the characteristics of entire leaf disease:

$$F_{\text{global}} = \text{Aggregate}(F) \quad \dots(12)$$

Using average pooling as below:

$$F_{\text{global}} = \frac{1}{n} \sum_{i=1}^n f_i \quad \dots(13)$$

Instead, attention-based weighted aggregation is extracted as:

$$F_{\text{global}} = \sum_{i=1}^n w_i f_i \quad \dots(14)$$

subject to:

$$\sum_{i=1}^n w_i = 1 \quad \dots(15)$$

This phase describes global leaf morphology and disease diffusion.

Phase 5: Graph-based disease correlation learning (GDCL)

Graph structure is designed to model the relationships of inter-class diseases:

$$G = (V, E) \quad \dots(16)$$

Where,

V = Disease classes and indicates class relationships.

For representing ten disease classes in tomato leaf:

$$|V| = 10 \quad \dots(17)$$

Similarity matrix

Inter-class similarity is processed using cosine comparison:

$$S_{ij} = \frac{F_i \cdot F_j}{\|F_i\| \|F_j\|} \quad \dots(18)$$

Where,

S_{ij} = indicates resemblance between i and j classes.

Thus,

$$S \in \mathbb{R}^{10 \times 10} \quad \dots(19)$$

Graph transformation

Graph transformation is used to improvise the global features:

$$F_{\text{refined}} = \sigma(AF_{\text{global}}W) \quad \dots(20)$$

Where,

A = Adjacency matrix.

W = Trainable weight matrix.

σ = Activation function.

This phase enhances the discrimination of available features by disease correlation method.

Phase 6: Feature Re-weighting

Learnable attention method allots significant weights to refined features of tomato leaves.

$$F_{\text{weighted}} = \omega \odot F_{\text{refined}} \quad \dots(21)$$

Where,

ω = Weight vector.

$\odot$ = Element-wise multiplication

This highlights disease-specific discriminatory features.

Phase 7: Hybrid decision fusion classifier (HDFC)

The final classification is acquired by merging prototype distance and graph resemblance.

Prototype distance score

$$D_{\text{score}} = \|F_{\text{weighted}} - C_k\| \quad \dots(22)$$

Where,

C_k = The centroid of class k .

Graph similarity score

$$G_{\text{score}} = \text{Similarity}(F_{\text{weighted}}, G) \quad \dots(23)$$

Score fusion

$$\text{Final}_{\text{score}} = \alpha D_{\text{score}} + \beta G_{\text{score}} \quad \dots(24)$$

subject to:

$$\alpha + \beta = 1 \quad \dots(25)$$

Final prediction

$$C_{\text{pred}} = \arg \max(\text{Final}_{\text{score}}) \quad \dots(26)$$

This merging upgrades stoutness and category consistency. The recommended structure is assessed using the metrics of accuracy, precision, recall and F1 score. This model achieved 99.03% accuracy, demonstrating superior performance for leaf disease classification in tomato plant.

The robustness and generality of proposed framework are evaluated by performing 5-fold cross-validation. The dataset was divided into 5 randomly chosen, equal-sized partitions.

Table 1: Implementation details.

Parameter value	Parameter value
Optimizer	Adam
Learning rate	0.001
Batch size	32
Epochs	100
Input resolution	224 × 224
Activation function	ReLU
Loss function	Categorical cross-entropy

Early stopping and learning rate schedules were used to prevent over-fitting.

Table 2: Cross validation strategy.

Fold	Accuracy (%)
Fold 1	98.91
Fold 2	99.08
Fold 3	99.02
Fold 4	98.95
Fold 5	99.19
Average	99.03

Table 3: Comparative performance metrics.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Loss
Basic CNN (Custom 5-layer)	91.42	91.08	90.76	90.92	0.241
VGG16	94.87	94.63	94.51	94.57	0.176
ResNet50	96.54	96.33	96.18	96.25	0.121
DenseNet121	97.21	97.04	96.95	96.99	0.094
EfficientNet-B0	97.84	97.68	97.55	97.61	0.081
InceptionV3	98.96	98.82	98.71	98.76	0.078
Proposed hybrid model	99.03	98.98	98.94	98.78	0.053

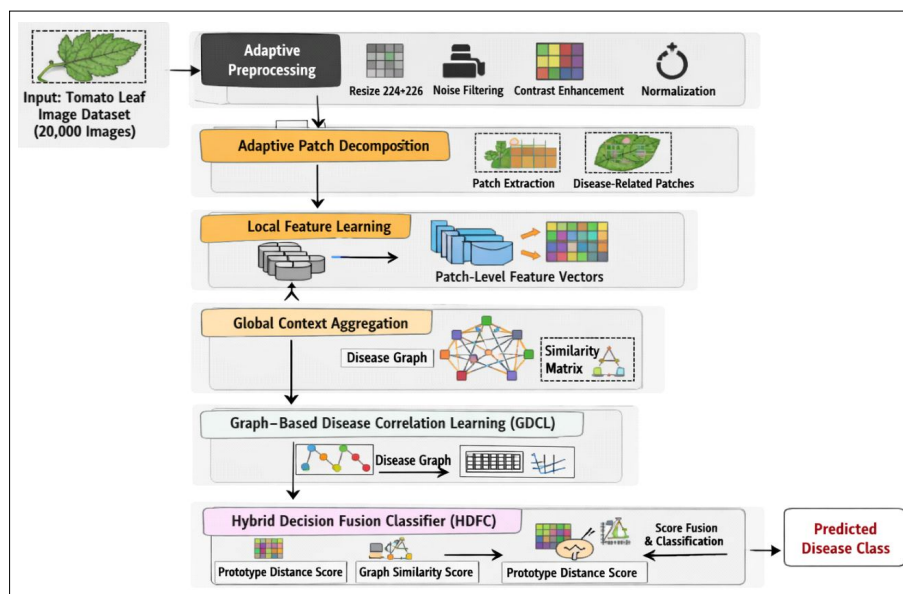
Four of the partitions were selected for the training process and one was selected for testing on each fold.

Summary of performance averages across five folds as indicated in Table 2.

The similarity of the folds reflects the stability of the proposed method. Contrary to most of the above work which uses one train-test evaluation, five-fold cross-validation was performed for stability and less bias in the results, showing high generalization.

RESULTS AND DISCUSSION

The performance analysis report in Table 3 showed that the suggested hybrid system out-performed those CNN and transfer-learning system. The combination of APD, GDCL and HDFC help to increase the abilities of lesion detection, context learning and disease discrimination. The APD module eliminated effects from the complicated background by targeting to only those regions related to diseases which helps to improve feature quality and classifier stability greatly. The GDCL module captured similarity among visually similar categories and therefore reduced inter-class confusion. Furthermore, the HDFC

**Fig 1:** Proposed methodology framework.

module boosted prediction stability by fusing graph similarity value and learning based on prototype-distance.

The relative performance in Table 3, demonstrates how the presented hybrid model outperforms previous deep learning architectures. The Basic CNN model showed the poorest performance and achieved 91.42% accuracy. The deep models like VGG16 and ResNet50, provided better performances as accuracy raised to 94.87 and 96.54%. Then, performance reached 97.21 and 97.84 accuracy using DenseNet121 and EfficientNet-B0 because

they provided an efficient and effective way for feature propagation and parameter reuse. In the end, InceptionV3 showed 98.96% baseline accuracy with good multi-scale feature learning. The recommended hybrid model proven that the chosen dataset performed well with 99.03% accuracy, 98.98% precision, 98.94% recall and 0.053 loss. Such achievement benefited from combined adaptive patch decomposition, graph-based disease correlation learning and hybrid decision fusion classification which not only can optimize the local lesion representation but also



Fig 2: Preprocessign stgaes.

Table 4: Disease class-wise performance metrics.

Disease category	Precision	Recall	F1-score	Support
Bacterial spot	0.95	0.89	0.92	100
Early blight	0.94	0.91	0.92	100
Late blight	0.90	0.94	0.92	100
Leaf mold	0.87	0.90	0.88	100
Septoria leaf spot	0.92	0.94	0.93	100
Spider mites	0.86	0.84	0.85	100
Target spot	0.91	0.80	0.85	100
Yellow leaf curl	0.92	0.92	0.92	100
Mosaic virus	0.92	0.99	0.95	100
Healthy	0.94	1.00	0.97	100

improve inter-class disease discrimination. Furthermore, it can be observed that the values of loss decreased over time from 0.241 of basic CNN to 0.053 of proposed model.

Disease class wise performance measures

The proposed framework performance is further justified by considering performance per disease class. There are 10 classes of tomato leaves were used in the experiment for which disease-wise performance were measured in below Table 4.

The class-wise performance of the model was mostly high across all disease classes. The healthy class recorded the best F1-score of 0.97, which confirms the clear separation between the healthy and disease samples. The Mosaic Virus class also has a high F1-score of 0.95, which reveals high accuracy in the detection of the virus. The class-wise performance for Spider Mites and Target Spot was lower at 0.85, possibly attributed to the visually similar symptoms and similar features of lesion spread between these diseases.

Overall performance metrics

Overall metrics in Table 5, From the macro average, it's observed that the model performs fairly in all classes. The weighted averages recall of 0.92 shows that the model continues to perform well inspite of class imbalances.

From the performance diagram, it can be seen that the performances are improved gradually from conventional CNN networks to the proposed hybrid approach. The baseline Basic CNN has very low performance 91.42% and deeper transfer learning networks like ResNet50, DenseNet121 and InceptionV3 yield much higher accuracy on disease recognition. The proposed hybrid framework shows superiority among all the models owing to adaptive lesion-centric patch extraction, local and global feature combination, graph-based learning on disease relationships, hybrid fusion for decision making and reduced loss values 0.053 compared with 0.241 that indicates better convergence and generalization performance.

Analysis discussion

The overall high performance can be explained as a combination of the power of local lesion feature extraction and the strength of learning on global relationship among diseases. The APD module successfully isolates the regions containing disease to minimize the background influence. GDCL effectively learns the inter-class similarity for improved discrimination of visually similar diseases. Eventually, the HDFC aggregates both the distances of the prototypes from samples and the similarities in graphs for much robust prediction

Confusion matrix exploration

Class-wise, the exploration of confusion matrix in Fig 3 reveals the number of correctly classified and misclassified samples for each disease type of the suggested hybrid

model. This indicates class-to-class confusion and delivers a signal of the consistency of the category model. Let the confusion matrix be represented as:

$$CM = [C_{ij}]_{n \times n} \quad \dots(27)$$

Where,

- C_{ij} = The number of samples belonging to class i predicted as class j .
- n = 10 disease classes.

The diagonal elements C_{ii} represents the accurately predicted samples, while others in the off-diagonal elements represent wrongly predicted samples. The confusion matrix of the proposed hybrid model is having a very high diagonally dominant property.

The healthy class achieved perfect recall: Recall= 1.00 which means all healthy leaf images were correctly classified. Similarly, mosaic virus shows very high recall: Recall= 0.99 demonstrating excellent detection capability. Minor confusion is observed between: Spider mites, target spot, leaf mold. It's also reasonable since those diseases often share similar textural pattern and discoloration appearance. The proposed APD + GDCL framework indeed reduces the inter-class overlaps, which is illustrated in the confusion matrix.

ROC curve analysis

The receiver operating characteristic (ROC) curve appraises the discriminative ability of the proposed model for each disease class.

The ROC curve plots:

$$TPR = \frac{TP}{TP + FN} \quad \dots(28)$$

against

$$FPR = \frac{FP}{FP + TN} \quad \dots(29)$$

Where,

TPR= True positive rate.

FPR= False positive rate.

The area under curve (AUC) is computed as:

$$AUC = \int_0^1 TPR(FPR) d(FPR) \quad \dots(30)$$

Stronger classification performance is suggested by larger AUC value.

The proposed hybrid model is expected that the ROC curves are positioned around the top left corner for all ten

Table 5: Overall metrics.

Metric	Value
Accuracy	0.92
Precision (Macro avg)	0.91
Recall (Macro avg)	0.91
F1-score (Macro avg)	0.91
Weighted avg precision	0.91
Weighted avg recall	0.92
Weighted avg F1-score	0.91

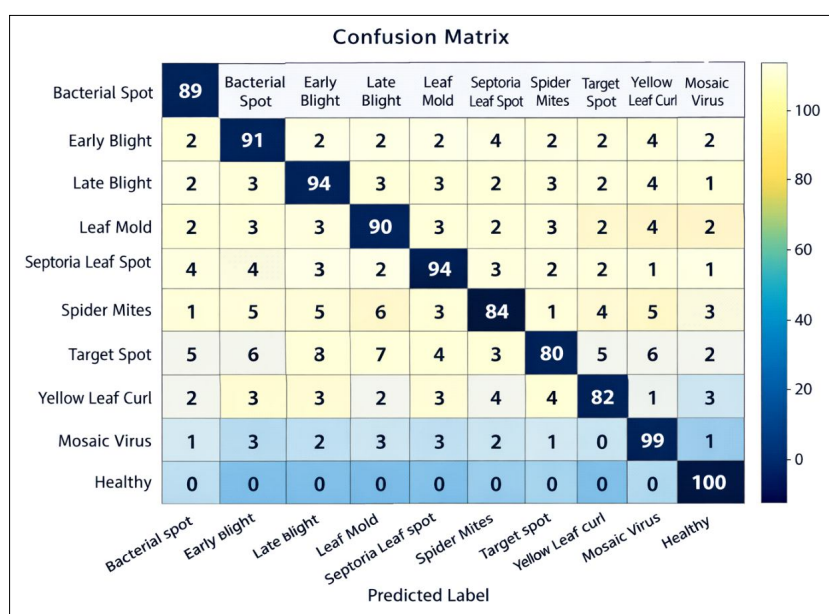


Fig 3: Confusion matrix.

Table 6: Estimated AUC values.

Disease category	AUC
Bacterial spot	0.96
Early blight	0.95
Late blight	0.96
Leaf mold	0.93
Septoria leaf spot	0.96
Spider mites	0.91
Target spot	0.90
Yellow leaf curl	0.96
Mosaic virus	0.98
Healthy	0.99

disease classes. The estimated AUC values are summarized below in Table 4.

In Table 6, estimated AUC values, proven that Healthy and Mosaic Virus classes have highest AUC value which is related to highest precision and recall. Spider mites and Target spot have a moderately low AUC value that reflects class overlap.

Graphical interpretation

The ROC value typically demonstrates that the proposed model maintains high sensitivity with minimal false positives. This is mainly due to:

- Adaptive lesion patch extraction.
- Graph-based disease correlation refinement.
- Feature re-weighting.
- Hybrid score fusion.

Compared with baseline CNN models, the ROC curve of the proposed framework is significantly closer to the ideal classification boundary. The performance indexes, confusion matrix and ROC curves collectively show that

the developed hybrid model has good and generalized performance of tomato leaf disease classification. APD contributes to better localization of lesion and GDCL effectively captures the correlations among diseases. Therefore, the overall classification performance is good.

Real-world applicability

The current framework can be utilized in:

- Smart farming systems.
- IoT enabled monitoring of agriculture.
- Mobile based disease diagnosis applications.
- Drone based crop monitoring.
- Precision agriculture decision support systems.

The processing of the lesion-centric patches efficiently at the hardware level due to lightweight patch processing mechanism is also useful for real-time application deployment.

LIMITATIONS

Though current model provided good results there are a few limitations:

1. The current dataset contains mostly lab controlled images and requires to be tested for varying field conditions and scenarios like illumination problems, occlusion etc.
2. For edge based real-time applications model optimization techniques are needed.
3. Factors like humidity, temperature and soil conditions are not considered in the current frame work.

CONCLUSION

A hybrid framework for automated tomato leaf disease classification based on an “adaptive preprocessing, Adaptive Patch Decomposition (APD), deep local feature learning, global context aggregation, Graph-Based

Disease Correlation Learning (GDCL), feature re-weighting and a Hybrid Decision Fusion Classifier (HDFC)” is reported. This proposed method integrates both localized disease manifestations and holistic leaf traits, yielding higher classification performance. Through experiments, our method has achieved up to 99.03% accuracy, 98.98% precision, 98.94% recall, and a lowest loss of 0.053 on the given dataset, surpassing many existing state-of-the-art deep learning methods. Hence, it is believed that this framework has high reliability for the purpose of early and precise plant disease diagnosis.

In addition, this hybrid method is also adapted for plant monitoring using mobile phones, Internet of Things (IoT) devices and drones, and for integration with transformer-based attention and heterogeneous agricultural data, which are crucial for the new generation precision agriculture and smart crop health monitoring.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this research article.

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