

Explainable Deep Neural Network Based Multiclass Classification of Tomato Leaf Disease: A Systematic Review

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Abstract

Tomato leaf diseases pose a major threat to agricultural productivity and global food security. Early detection is essential to minimize crop loss and improve yield quality. In recent years, artificial intelligence (AI), particularly deep learning, has emerged as a powerful tool for automated plant disease detection using image-based approaches. This paper presents a comprehensive systematic review of AI-based techniques for tomato leaf disease classification, covering convolutional neural networks (CNNs), transfer learning methods, transformer-based architectures, and hybrid models. Furthermore, the study critically examines the role of explainable artificial intelligence (XAI) techniques, including Grad-CAM, LIME, and SHAP, in enhancing model transparency and interpretability. A detailed evaluation of widely used datasets, such as PlantVillage and real-world field datasets, is conducted to assess model generalization. Comparative analysis highlights the strengths and limitations of different approaches. Key challenges, including dataset bias, lack of real-world robustness, and computational constraints, are discussed. Finally, future research directions focusing on lightweight architectures, edge AI, and multimodal learning are proposed to bridge the gap between research and practical agricultural deployment.

The review reveals that CNN-based models achieve up to 99% accuracy on benchmark datasets; however, their performance significantly decreases under real-world conditions due to dataset bias and environmental variability. These findings highlight the need for robust and generalizable AI solutions for real-world agricultural deployment.

Keywords

Tomato leaf disease, Deep learning, Explainable AI, CNN, Transfer learning, Vision Transformer, Precision agriculture

1. Introduction

Tomato is one of the most widely cultivated crops worldwide [4], [35] and serves as a vital component of global food systems. However, tomato plants are highly susceptible to a variety of leaf diseases, including early blight, late blight, bacterial spot, and leaf mold, which significantly affect crop yield and quality. Traditional disease identification methods rely on manual inspection by agricultural experts, which is often time-consuming, subjective, and impractical for large-scale farming environments.

The advancement of artificial intelligence (AI) has revolutionized many domains, including agriculture. In

particular, deep learning techniques have shown remarkable success in image classification tasks. Convolutional neural networks (CNNs) have demonstrated superior performance in extracting hierarchical features from leaf images, enabling accurate disease classification without the need for handcrafted features [1], [2]. Early work by Mohanty et al. [1] showed that deep learning models trained on the PlantVillage dataset could achieve classification accuracy exceeding 99%. Similarly, Sladojevic et al. [2] demonstrated the effectiveness of deep neural networks for plant disease recognition.

Subsequent research has focused on improving model performance through advanced architectures such as ResNet [12], DenseNet [11], and Inception networks [14]. These models enhance feature extraction and improve classification accuracy. Transfer learning techniques have also been widely adopted to address the challenge of limited labeled datasets by leveraging pretrained models [3], [6]. More recently, transformer-based models, such as Vision Transformers (ViT), have been introduced to capture global relationships in images, offering new opportunities for improving classification accuracy [7], [38].

Despite these advancements, several challenges remain. Most existing studies rely on controlled datasets, such as PlantVillage, which do not adequately represent real-world agricultural environments [30]. As a result, models often fail to generalize when deployed in field conditions. This gap between laboratory accuracy and real-world performance remains a critical challenge in practical agricultural applications. Additionally, deep learning models are often considered “black boxes,” making it difficult to interpret their predictions. This lack of transparency limits their adoption in practical agricultural applications [36].

To address these issues, explainable artificial intelligence (XAI) techniques have been introduced to provide insights into model decision-making processes. Methods such as Grad-CAM [9] and LIME [10] enable visualization of important regions in input images, improving model interpretability and user trust.

This paper aims to provide a comprehensive systematic review of AI-based approaches for tomato leaf disease classification.

1.1 Contributions of this review

- A detailed analysis of datasets used in tomato disease detection

- A comprehensive review of deep learning architectures
- An evaluation of explainable AI techniques
- A comparative analysis of existing methods
- Identification of key challenges and future research directions

2. Methodology

This study follows a systematic literature review ensuring the reliability and comprehensiveness of the existing research. The selected databases ensure comprehensive coverage of both engineering and agricultural research, thereby ensuring the reliability and comprehensiveness of the review process.

2.1 Data Sources

2.3 Inclusion Criteria

Studies were included based on the following criteria:

- Published between 2015 and 2025
- Focus on image-based plant or tomato disease detection
- Use of machine learning or deep learning techniques
- Availability of experimental results

2.4 Exclusion Criteria

The following studies were excluded:

- Non-peer-reviewed articles
- Studies without experimental validation

Relevant literature was collected from major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. These databases were selected due to their comprehensive coverage of high-quality research publications in artificial intelligence and agricultural applications.

2.2 Search Strategy

The search was conducted using combinations of keywords such as:

- “tomato leaf disease detection”
- “plant disease classification deep learning”
- “CNN agriculture disease detection”
- “explainable AI plant disease”

Boolean operators (AND, OR) were used to refine the search results.

- Duplicate publications
- Non-image-based disease detection methods

2.5 Study Selection Process

A total of 250 papers were initially identified. After removing duplicates and screening titles and abstracts, 120 papers were retained. Further full-text analysis resulted in 65 eligible studies. Finally, 50 high-quality papers were selected for detailed review. PRISMA flow diagram of the study selection process as shown in Fig. 1.

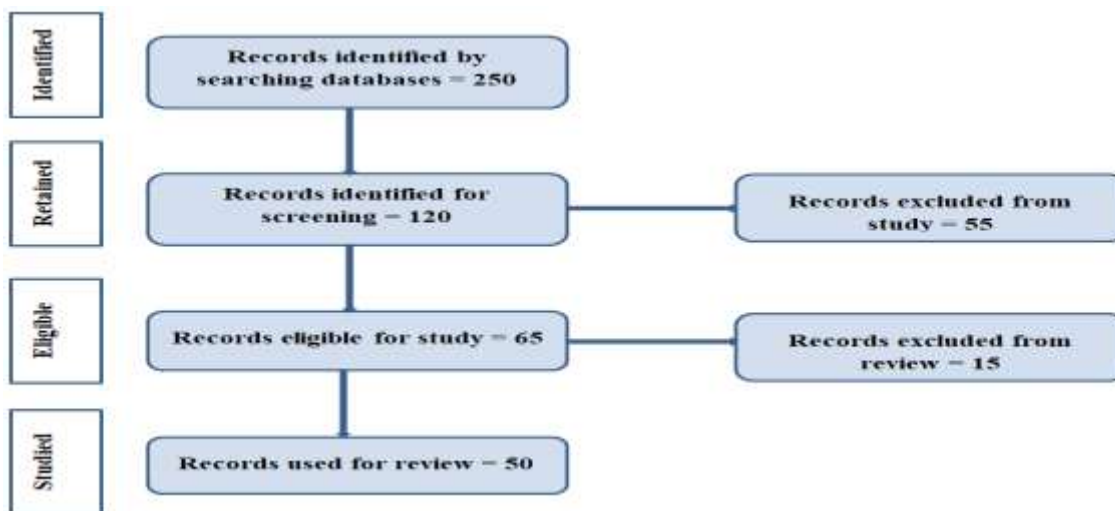


Fig. 1. PRISMA flow diagram of the study selection process.

3. Dataset Analysis

3.1 PlantVillage Dataset

The PlantVillage dataset is one of the most widely used datasets for plant disease classification research [30]. It contains over 50,000 labeled images of healthy and diseased plant leaves captured under controlled conditions. The dataset includes multiple classes of tomato leaf diseases, making it a popular benchmark for evaluating model performance. Several studies have reported high classification accuracy using this dataset. For example, Mohanty et al. [1] achieved over

99% accuracy using deep CNN models. Similarly, Ferentinos [5] demonstrated that deep learning models outperform traditional machine learning techniques on this dataset. This indicates that high accuracy reported on benchmark datasets may not reflect real-world performance, raising concerns about model reliability in practical agricultural applications.

This limitation reduces the practical applicability of models trained solely on such datasets. The images are captured under uniform lighting conditions with clean backgrounds, which do not

reflect real-world agricultural environments. As a result, models trained on this dataset often fail to generalize when applied to field conditions [29].

Sample images of tomato leaf diseases as shown in Fig. 2,

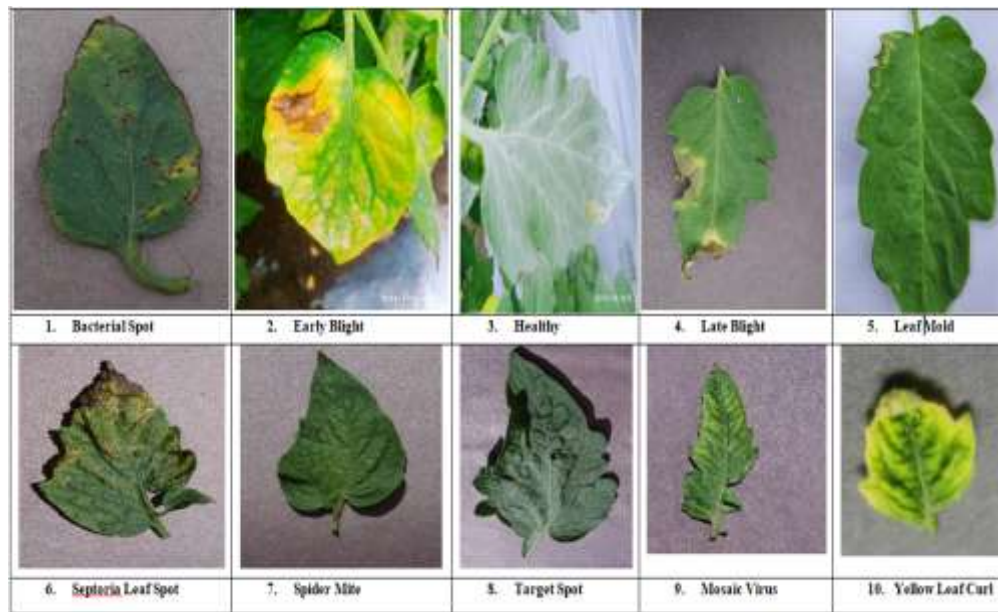


Fig. 2. Sample images of tomato leaf diseases.

3.2 Field-Based Datasets

To address the limitations of controlled datasets, several studies have used field-collected datasets that include real-world variations such as lighting changes, background clutter, and leaf occlusion [31]. These datasets provide a more realistic evaluation of model performance but are often smaller and more challenging to annotate.

Recent studies have emphasized the importance of using diverse datasets to improve model generalization. For instance, Nguyen et al. [49] proposed a lightweight transformer-based model trained on real-world data, demonstrating improved robustness compared to traditional CNN models.

3.3 Dataset Challenges

The major challenges associated with datasets include:

- Limited availability of labeled real-world data

- Class imbalance
- Variability in environmental conditions
- Annotation complexity

These challenges significantly impact model performance and highlight the need for more robust dataset collection strategies.

4. Deep Learning Approaches for Tomato Leaf Disease Classification

Deep learning has become the dominant paradigm for plant disease detection due to its ability to automatically learn discriminative features from raw image data. This section provides a detailed analysis of major deep learning approaches, including CNN-based models, transfer learning, transformer-based architectures, and hybrid models. Workflow of tomato leaf disease classification as shown in Fig. 3,



Fig. 3. Workflow of tomato leaf disease classification.

4.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are the most widely used models for image-based plant disease detection. CNNs consist of multiple layers, including

Despite high accuracy, CNN models suffer from limited generalization due to their reliance on local feature extraction, which restricts their effectiveness in complex real-world environments [29], [34]. This

els capable of al information.
Fig. 4,

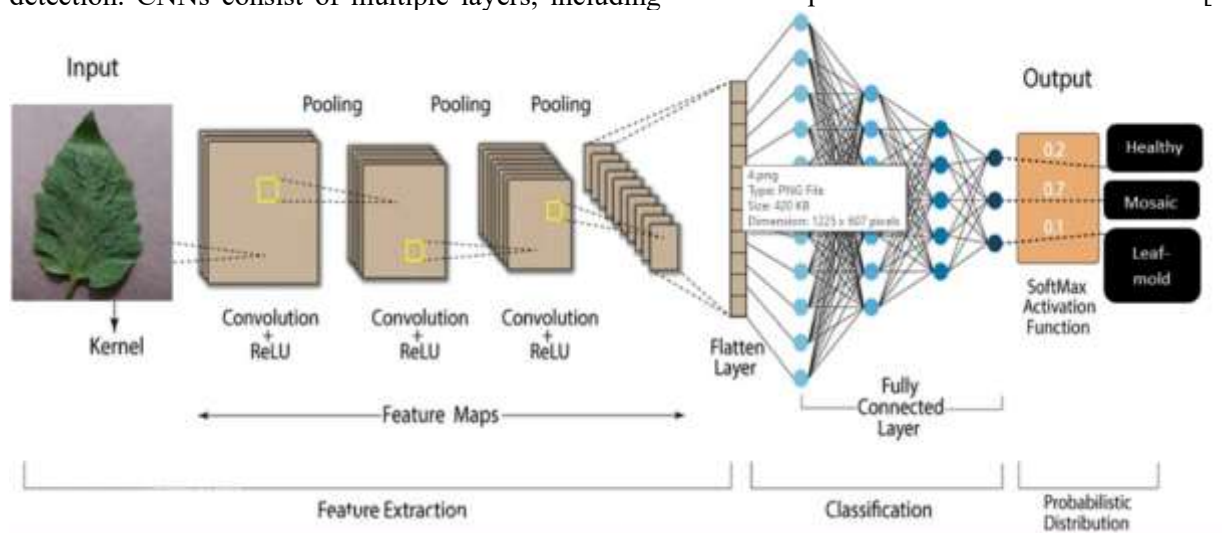


Fig. 4. Architecture of CNN model.

Early work by Krizhevsky et al. [13] introduced AlexNet, which demonstrated the effectiveness of deep learning for image classification. Building on this, several architectures such as VGGNet [6], ResNet [12], and DenseNet [11] have been widely adopted for plant disease detection tasks.

Mohanty et al. [1] utilized deep CNN architectures to classify plant diseases and achieved high accuracy on the PlantVillage dataset. Similarly, Sladojevic et al. [2] demonstrated that CNNs outperform traditional machine learning techniques such as Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN).

More recent studies have explored deeper architectures to improve performance. For example, Ferentinos [5] evaluated multiple CNN architectures and reported that

deeper models achieve higher accuracy due to improved feature representation capabilities. However, increasing model depth also introduces challenges such as overfitting and higher computational cost.

Advantages of CNNs

- Automatic feature extraction
- High classification accuracy
- Robust performance on large datasets

Limitations of CNNs

- Sensitive to dataset bias
- Require large labeled datasets
- Limited ability to capture global context

4.2 Transfer Learning

Transfer learning has emerged as an effective approach to address the challenge of limited labeled data in agricultural applications. Instead of training a model from scratch, transfer learning leverages pretrained models trained on large datasets such as ImageNet.

Too et al. [3] conducted a comparative study of transfer learning techniques and demonstrated that fine-tuning pretrained models significantly improves classification accuracy. Similarly, Chouhan et al. [26] showed that transfer learning reduces training time while maintaining high performance.

Transfer learning is particularly useful in scenarios where collecting labeled data is expensive or time-consuming. It also helps mitigate overfitting by utilizing pretrained feature representations.

Advantages

- Reduced training time
- Improved performance with limited data

However, transformer models require large datasets for effective training and are computationally intensive. Recent work by Nguyen et al. [49] has focused on developing lightweight transformer models suitable for deployment on mobile devices.

Although transformer-based models capture global dependencies, their requirement for large datasets limits their applicability in agricultural domains with limited labeled data [38].

Advantages

- Captures global context
- Improved feature representation

Limitations

- High computational cost
- Requires large datasets

5. Explainable Artificial Intelligence

The adoption of AI in agriculture requires models to be transparent and interpretable. Explainable AI (XAI) techniques aim to provide insights into model decision-making processes, enabling users to understand and trust the predictions.

5.1 Importance of Explainability

Deep learning models are often considered “black boxes,” as their internal decision-making processes are not easily interpretable. This lack of transparency poses a significant challenge in critical applications such as agriculture, where incorrect predictions can lead to economic losses.

Oppenheim et al. [36] emphasized the importance of explainability in agricultural AI systems, highlighting

- Lower computational requirements

Limitations

- Domain mismatch between source and target datasets
- Limited flexibility in feature learning

4.3 Transformer-Based Models

Transformer architectures, originally developed for natural language processing, have recently been adapted for image classification tasks. Vision Transformers (ViT) divide images into patches and process them using self-attention mechanisms, enabling the model to capture global relationships within the image [7].

Zhao et al. [38] demonstrated that transformer-based models can achieve competitive performance in plant disease classification tasks. These models are particularly effective in capturing long-range dependencies, which are often missed by CNNs.

4.4 Hybrid Models

Hybrid models combine the strengths of CNNs and transformer-based architectures to improve performance. These models typically use CNNs for local feature extraction and attention mechanisms for capturing global dependencies.

Too and Yujian [27] proposed a hybrid model that integrates CNN and attention mechanisms, achieving improved classification accuracy. Similarly, Gupta et al. [45] introduced a CNN-attention hybrid model for tomato disease classification, demonstrating superior performance on real-world datasets.

Hybrid models represent a promising direction for future research, as they balance accuracy and computational efficiency.

the need for interpretable models to improve user trust and adoption.

5.2 Grad-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM) is one of the most widely used XAI techniques for visualizing model predictions. It generates heatmaps that highlight important regions in the input image that contribute to the classification decision [9]. Grad-CAM has been extensively used in plant disease detection to identify disease-affected regions in leaf images. It provides intuitive visual explanations, making it easier for users to interpret model predictions. Grad-CAM visualization of diseased regions as shown in Fig.5,



Fig. 5. Grad-CAM visualization of diseased regions.

5.3 LIME

Local Interpretable Model-Agnostic Explanations (LIME) is another popular XAI technique that explains model predictions by approximating the model locally with an interpretable model [10].

LIME is model-agnostic and can be applied to any machine learning model. It provides insights into feature importance, helping users understand the factors influencing the prediction.

5.4 SHAP

SHapley Additive exPlanations (SHAP) is a game-theoretic approach that assigns importance values to each feature based on its contribution to the prediction. SHAP provides both local and global interpretability, making it a powerful tool for understanding model behavior.

Recent studies have applied SHAP to plant disease detection, demonstrating its effectiveness in identifying important features and improving model transparency [44], [48].

5.5 Limitations of XAI

Despite their benefits, XAI techniques have certain limitations:

- Increased computational overhead
- Difficulty in interpreting complex explanations
- Lack of standard evaluation metrics

6. Comparative Analysis and Critical Evaluation

A comprehensive comparison of different AI-based approaches for tomato leaf disease classification is presented in Table 1 and Accuracy Comparisons of Deep Learning models as shown in Fig. 6,

Table 1. Comparative Analysis of Models

Study	Model	Dataset	Accuracy	XAI	Limitation
[1]	CNN	PlantVillage	99%	No	Dataset bias
[5]	CNN	PlantVillage	98%	No	Overfitting
[3]	Transfer Learning	PlantVillage	97%	No	Domain gap
[38]	ViT	Mixed	96%	No	Data requirement
[45]	Hybrid	Field	95%	Yes	Complexity
[49]	Lightweight Transformer	Field	94%	Yes	Lower accuracy

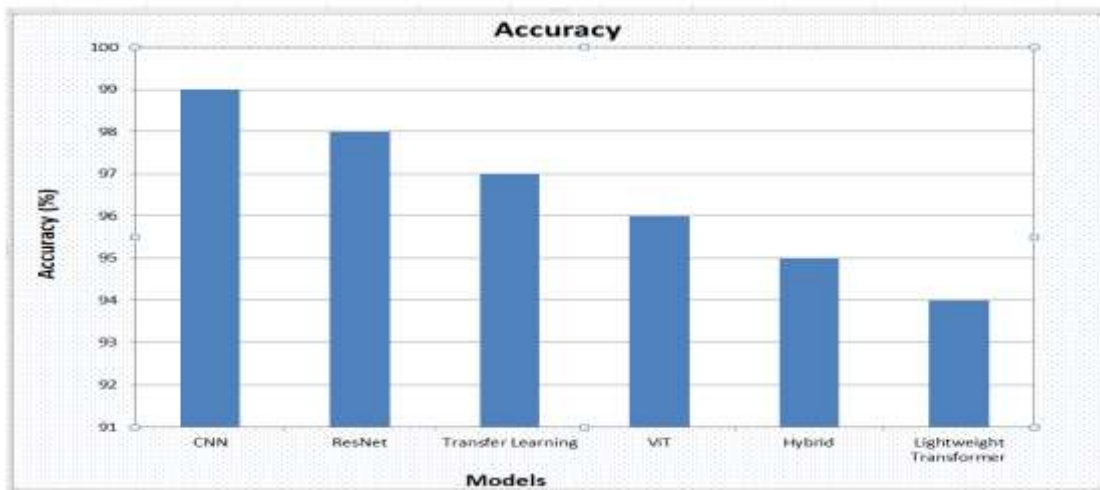


Fig. 6. Accuracy Comparisons of Deep Learning models.

6.1 Key Observations

1. CNN-based models dominate due to simplicity and high accuracy
2. Transfer learning improves performance with limited data
3. Transformer models show promise but require large datasets
4. Hybrid models provide a balance between accuracy and robustness

6.2 Critical Insights

- High accuracy reported in literature is often misleading due to dataset bias
- Real-world performance is significantly lower than reported results
- Lack of standardized evaluation metrics makes comparison difficult

Table 2. Summary of reviewed studies

Ref	Model	Dataset	Accuracy (%)	Key Contribution
[1]	CNN	PlantVillage	99	Early deep learning-based disease classification
[2]	CNN	Leaf Dataset	96	Automatic feature extraction approach
[3]	Transfer Learning	PlantVillage	97	Fine-tuning pretrained models
[5]	CNN	PlantVillage	98	Comparison of multiple DL architectures
[11]	DenseNet	PlantVillage	98	Improved feature reuse
[12]	ResNet	PlantVillage	98	Deep residual learning
[18]	CNN	Tomato Dataset	95	Disease visualization with CNN
[19]	CNN	Mobile Dataset	94	Mobile-based classification
[23]	CNN	Leaf Dataset	96	Understanding CNN decision process
[26]	Transfer Learning	PlantVillage	97	Reduced overfitting
[27]	Hybrid CNN + Attention	Field Dataset	95	Improved accuracy using attention
[37]	Attention CNN	Field Dataset	94	Better feature focus
[38]	Vision Transformer (ViT)	Mixed Dataset	96	Global feature extraction

[40]	Lightweight CNN	Mobile Dataset	93	Edge deployment optimization
[41]	EfficientNet	PlantVillage	98	Efficient scaling
[42]	Lightweight CNN	Real-time Data	94	Real-time detection
[43]	Transformer	Field Dataset	95	Transformer-based classification
[45]	Hybrid CNN + Attention	Field Dataset	96	Improved robustness
[46]	Edge AI Model	Real-world Data	94	On-device inference
[47]	Multimodal DL	Mixed Data	96	Image + sensor fusion
[49]	Lightweight Transformer	Field Dataset	94	Mobile-friendly transformer

7. Challenges in AI-Based Tomato Leaf Disease Detection

Despite significant advancements in deep learning for plant disease detection, several challenges continue to limit the practical applicability of these models.

7.1 Dataset Bias and Generalization Issues

One of the most critical challenges is dataset bias. Most existing models are trained on controlled datasets such as PlantVillage [30], which contain images captured under uniform conditions. While these datasets enable high classification accuracy, they fail to represent real-world variability.

Barbedo [29] demonstrated that models trained on controlled datasets often experience a significant drop in performance when applied to real-world images. This is primarily due to differences in lighting, background, and image quality. As a result, models that achieve near-perfect accuracy in laboratory settings may perform poorly in practical applications.

7.2 Limited Availability of Real-World Data

Collecting and annotating real-world datasets is a challenging and resource-intensive process. Field images often contain noise, occlusion, and overlapping leaves, making accurate annotation difficult. Hasan et al. [31] highlighted the need for large-scale, diverse datasets to improve model robustness.

7.3 Overfitting and Model Complexity

Deep learning models, particularly CNNs, are prone to overfitting when trained on small datasets. While

8.1 Environmental Variability

Field conditions introduce significant variability, including changes in lighting, weather, and background. These factors can negatively impact model performance. Studies have shown that models trained on controlled datasets fail to maintain accuracy under such conditions [34].

transfer learning helps mitigate this issue [3], it does not completely eliminate it. Additionally, deeper models such as ResNet [12] and DenseNet [11] introduce higher computational complexity, making them unsuitable for deployment on resource-constrained devices.

7.4 Lack of Interpretability

The “black-box” nature of deep learning models remains a major concern. Although XAI techniques such as Grad-CAM [9] and LIME [10] provide insights into model predictions, they are not always sufficient to fully explain complex decision-making processes. Oppenheim et al. [36] emphasized that improving interpretability is essential for increasing user trust.

7.5 Computational Constraints

Many deep learning models require significant computational resources for training and inference. This limits their deployment in real-world agricultural settings, particularly in developing regions where access to high-performance hardware is limited. Edge computing solutions have been proposed to address this issue [46], but further research is needed.

8. Real-World Deployment Considerations

The transition from laboratory research to real-world deployment presents several practical challenges that must be addressed for successful implementation.

8.2 Device Constraints and Edge Deployment

Deploying AI models on mobile or edge devices requires lightweight architectures with low computational requirements. Recent research has focused on developing efficient models suitable for real-time applications. For example, Singh et al. [46] explored edge AI solutions for plant disease detection, demonstrating the feasibility of on-device inference.

Kaur et al. [40] proposed lightweight CNN models optimized for mobile platforms, achieving a balance between accuracy and efficiency.

8.3 Integration with Smart Farming Systems

AI-based disease detection systems can be integrated with Internet of Things (IoT) devices to enable real-time monitoring of crop health. Nguyen et al. [39] highlighted the potential of edge AI combined with IoT for precision agriculture.

8.4 User Trust and Adoption

For widespread adoption, farmers must trust the predictions generated by AI systems. Explainable AI techniques play a crucial role in building this trust by providing transparent and interpretable results [44].

9. Future Research Directions

To overcome existing challenges and improve the practical applicability of AI-based disease detection systems, several research directions should be explored.

9.1 Development of Lightweight Models

Future research should focus on designing lightweight deep learning models that can be deployed on resource-constrained devices. Techniques such as model pruning, quantization, and knowledge distillation can be used to reduce model complexity without significantly compromising accuracy [40], [46].

9.2 Edge AI and Real-Time Processing

Edge AI enables real-time processing of data directly on devices, reducing latency and dependence on cloud infrastructure. This is particularly important for agricultural applications, where timely decision-making is critical [46], [39].

9.3 Multimodal Learning

Combining image data with other sources of information, such as environmental sensors and weather data, can improve disease detection accuracy. Wang et al. [47] demonstrated that multimodal approaches provide better performance compared to single-modality models.

9.4 Advanced Explainable AI Techniques

While existing XAI methods provide useful insights, there is a need for more advanced techniques that offer deeper understanding of model behavior. Recent

studies have explored the use of SHAP and other methods for improved interpretability [48].

9.5 Large-Scale Real-World Dataset Creation

Developing large, diverse datasets that accurately represent real-world conditions is essential for improving model generalization. Collaborative efforts between researchers, farmers, and agricultural organizations can facilitate dataset collection and annotation.

9.6 Transformer and Hybrid Model Optimization

Future research should focus on optimizing transformer-based and hybrid models to reduce computational complexity while maintaining high accuracy. Lightweight transformer architectures [49] show promise in this direction.

10. Conclusion

This paper presents a comprehensive systematic review of AI-based approaches for tomato leaf disease classification. Deep learning models, particularly CNN-based architectures, have demonstrated remarkable success in achieving high classification accuracy. However, their performance is often limited by dataset bias and lack of generalization to real-world conditions.

The integration of explainable AI techniques has improved model transparency and interpretability, addressing one of the key challenges in deploying AI systems in agriculture. Despite these advancements, several issues remain, including limited availability of real-world datasets, computational constraints, and challenges in model deployment.

Future research should focus on developing robust, lightweight, and interpretable models that can operate effectively in real-world environments. The integration of edge AI, multimodal learning, and advanced explainability techniques will play a crucial role in advancing the field.

Overall, AI-based tomato leaf disease detection systems have significant potential to enhance agricultural productivity and sustainability. However, bridging the gap between laboratory performance and real-world deployment remains a critical challenge that must be addressed in future research.

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