EarlyCropGuard: A Risk-Adaptive Edge AI Framework for Early Crop Disease Prediction and Real-Time Detection Using Computer Vision: A Review

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Abstract

Crop diseases significantly affect agricultural productivity, crop quality, and food security. Artificial Intelligence (AI), Deep Learning, and Computer Vision have shown strong potential for automated crop disease detection. However, existing methods often apply the same computational complexity to every image, resulting in higher processing time and resource consumption, especially in real-time and edge-based applications.

This paper proposes **EarlyCropGuard**, a risk-adaptive Edge AI framework for early crop disease prediction and real-time detection using Computer Vision. The framework first performs image quality assessment and lightweight AI-based screening, followed by risk estimation based on prediction confidence. Images are categorized into low-, medium-, or high-risk levels, enabling adaptive selection of the required analysis.

Low-risk images receive rapid processing, while medium- and high-risk cases undergo detailed disease classification, localization, severity assessment, and explainable AI-based analysis. By integrating adaptive processing, lightweight Edge AI, disease assessment, and explainability, EarlyCropGuard aims to reduce unnecessary computation while providing an efficient, interpretable, scalable, and real-time solution for crop disease monitoring on resource-constrained edge devices.

Keywords
Crop Disease Detection, Computer Vision, Edge AI, Deep Learning, Risk-Adaptive Framework, Early Disease Detection, Real-Time Detection, Disease Severity Assessment, Explainable AI.

INTRODUCTION

Agriculture plays an important role in food production and economic development, but crop diseases significantly affect crop yield and quality. Traditional disease identification mainly depends on visual inspection by farmers and agricultural experts, which can be time-consuming and subjective. Early identification of crop diseases is therefore essential for reducing crop damage and improving agricultural productivity [1], [2].

Recent advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision have enabled automated crop disease detection using plant and leaf images. Convolutional Neural Networks (CNNs) have demonstrated strong performance in learning disease-related visual features and classifying plant diseases automatically [1], [2], [3].

However, many existing crop disease detection systems are evaluated using controlled datasets with clear leaf images and simple backgrounds. Their performance can be affected in real-world agricultural environments due to variations in lighting, shadows, image quality, complex backgrounds, and early-stage disease symptoms [4], [5].

Another major challenge is the computational complexity of deep learning models used for real-time disease detection. Edge AI and lightweight models provide a promising solution by enabling faster local processing on resource-constrained devices such as smartphones and embedded systems, reducing dependency on cloud-based infrastructure [3], [6].

Based on these challenges, this review proposes **EarlyCropGuard**, a risk-adaptive Edge AI framework for early crop disease prediction and real-time detection using Computer Vision. The framework aims to combine fast AI screening, adaptive risk analysis, detailed disease detection, and efficient processing to support reliable and scalable crop disease monitoring.

REVIEW METHODOLOGY

This review paper follows a structured approach to analyze existing research related to crop disease detection using Artificial Intelligence, Deep Learning, Computer Vision, Edge AI, and real-time monitoring. The review focuses on identifying commonly used techniques, existing limitations, and research gaps in crop disease detection systems [5], [7].

Relevant research papers were identified using academic sources such as Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, and other recognized scientific databases. The literature search was performed using keywords including *crop disease detection*, *plant disease detection*, *deep learning*, *computer vision*, *Edge AI*, *real-time detection*, and *disease severity assessment*.

The selected studies primarily include journal and conference papers related to AI-based crop disease detection, disease classification, localization, real-world image analysis, lightweight deep learning models, and Explainable AI. Priority was given to highly relevant and recent studies, while foundational research papers were also included to understand the development of this research area [1], [2], [3].

The selected papers were analyzed and categorized based on their methodology, AI model, dataset, application area, major contribution, and limitations. Special attention was given to challenges related to early disease detection, field image variability, computational complexity, Edge AI deployment, disease severity assessment, and model interpretability [4], [5].

Based on the comparative analysis of the selected studies, major research gaps were identified and used to develop the proposed **EarlyCropGuard** framework. The proposed framework introduces a risk-adaptive approach that aims to provide efficient processing by combining fast Edge AI screening with detailed analysis for medium- and high-risk crop images.

LITERATURE REVIEW

Crop disease detection has significantly advanced with the development of Artificial Intelligence (AI), Deep Learning, and Computer Vision. Early studies by Mohanty et al. [1] and Sladojevic et al. [2] demonstrated the effectiveness of Deep Learning for automatic plant disease identification from leaf images. Ferentinos [3] further evaluated Deep Learning models for multiple crops and diseases, while Too et al. [4] compared fine-tuned architectures for disease classification. Recent review studies [5], [6] highlighted the growing use of Machine Learning and Deep Learning while identifying challenges related to dataset diversity, model generalization, and real-world agricultural environments.

Research has gradually moved from controlled image classification toward real-time and field-based disease detection. Fuentes et al. [7], Picon et al. [8], [9], and DeChant et al. [10] demonstrated the application of Deep Learning using real-field and mobile-captured crop images. Recent Computer Vision surveys and reviews [11]–[13] further explored advanced AI techniques for crop disease monitoring. Lightweight architectures such as MobileNet [14] and EfficientNet

[15], along with recent research on efficient models [16], have created opportunities for mobile and Edge AI-based disease detection with reduced computational requirements.

Furthermore, recent research has expanded beyond simple disease classification toward disease severity assessment and Explainable AI. The study in [17] highlighted the importance of severity assessment, while Grad-CAM [18] and recent XAI studies [19], [20] emphasized the need for transparent and understandable AI predictions. Overall, the reviewed literature demonstrates significant progress in classification, real-time detection, Computer Vision, Edge AI, severity assessment, and explainability. However, these capabilities are often addressed separately, which highlights the need for an integrated and risk-adaptive framework such as the proposed EarlyCropGuard system.

EVOLUTION OF CROP DISEASE DETECTION

Crop disease detection has evolved significantly from traditional manual inspection to automated Artificial Intelligence and Computer Vision-based approaches. Initially, farmers and agricultural experts identified diseases by observing visible symptoms such as leaf spots, discoloration, and changes in plant appearance. However, manual identification is time-consuming, subjective, and highly dependent on expert knowledge [1], [2].

Traditional image processing and Machine Learning techniques were later introduced to automate disease detection. These approaches used image features such as color, texture, and shape, followed by classification algorithms to identify plant diseases. Although these methods improved automation, their performance often depended on manually selected features and controlled image conditions [2], [3].

The introduction of Deep Learning significantly improved automated crop disease detection by enabling models to learn important visual features directly from images. Convolutional Neural Networks (CNNs) and transfer learning approaches demonstrated high performance for identifying multiple plant diseases and reduced the requirement for manual feature extraction [1], [3], [4].

Recent research has expanded crop disease detection beyond simple classification by using advanced Computer Vision techniques for real-world applications. Object detection, localization, and segmentation approaches can identify disease types and affected regions, making automated systems more useful for practical agricultural monitoring under complex field conditions [3], [4].

Currently, crop disease research is moving toward lightweight AI models, real-time processing, Edge AI deployment, early disease detection, and more intelligent analysis. These developments aim to address computational limitations and real-world challenges while providing a foundation for adaptive frameworks such as the proposed **EarlyCropGuard** system.

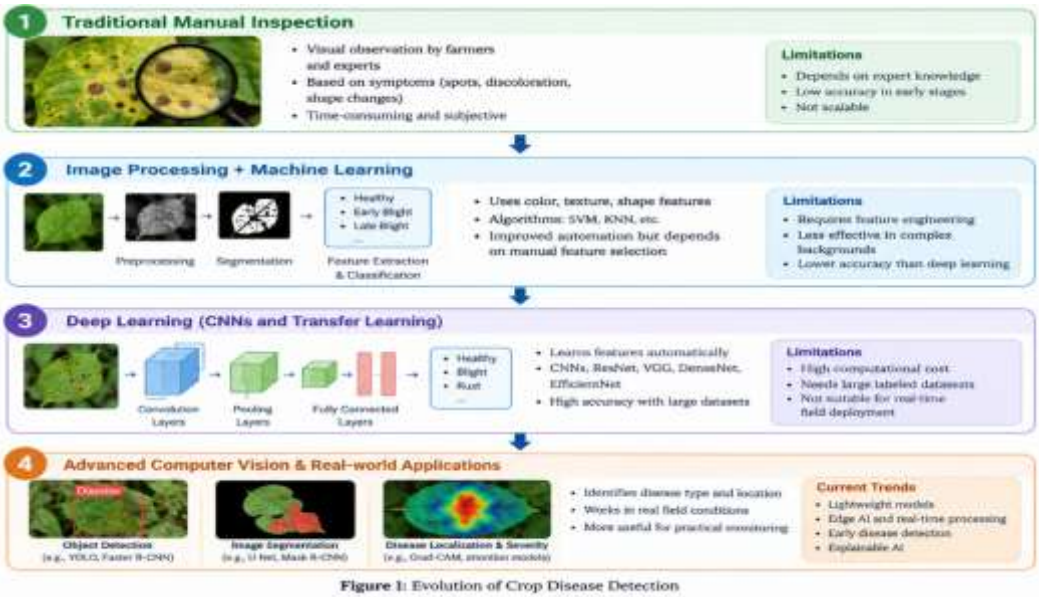


Figure 1: Evolution of Crop Disease Detection

4.AI AND COMPUTER VISION TECHNIQUES FOR CROP DISEASE DETECTION

Artificial Intelligence and Computer Vision have significantly improved automated crop disease detection by enabling systems to analyze plant images and identify disease-related patterns. These technologies reduce dependence on manual inspection and support faster and more consistent disease diagnosis. Machine Learning and Deep Learning techniques have been widely applied for disease classification using crop and leaf images [1], [2], [3].

4.1 CNN-Based Disease Classification

Convolutional Neural Networks (CNNs) are widely used for crop disease classification because they can automatically learn important visual features from plant images. CNN-based models have demonstrated strong performance in identifying multiple crop diseases without requiring manual feature extraction. Advanced architectures such as VGG, ResNet, DenseNet, and EfficientNet have further improved classification performance [1], [2], [3], [4].

4.2 Object Detection and Localization

Object detection techniques extend disease analysis beyond classification by identifying both the disease type and its location within an image. Models such as YOLO and Faster R-CNN can detect affected regions using bounding boxes, making them useful for images captured in real agricultural environments [5], [6].

4.3 Image Segmentation and Severity Analysis

Image segmentation techniques are used to identify precise disease-affected regions at the pixel level. This helps in separating healthy and diseased areas and can support disease severity assessment based on the proportion of affected crop or leaf area. Segmentation approaches provide more detailed information than simple image classification [7], [8].

4.4 Advanced Computer Vision Approaches

Recent studies have introduced advanced techniques such as attention-based models, Vision Transformers, and hybrid deep learning architectures for crop disease analysis. These approaches aim to improve feature extraction and model performance under complex field conditions involving variations in lighting, backgrounds, and disease symptoms [9], [10].

Overall, AI and Computer Vision techniques provide different levels of crop disease analysis, including classification, localization, and segmentation. However, selecting an appropriate model requires balancing accuracy, computational complexity, and real-time performance, particularly for Edge AI-based applications.

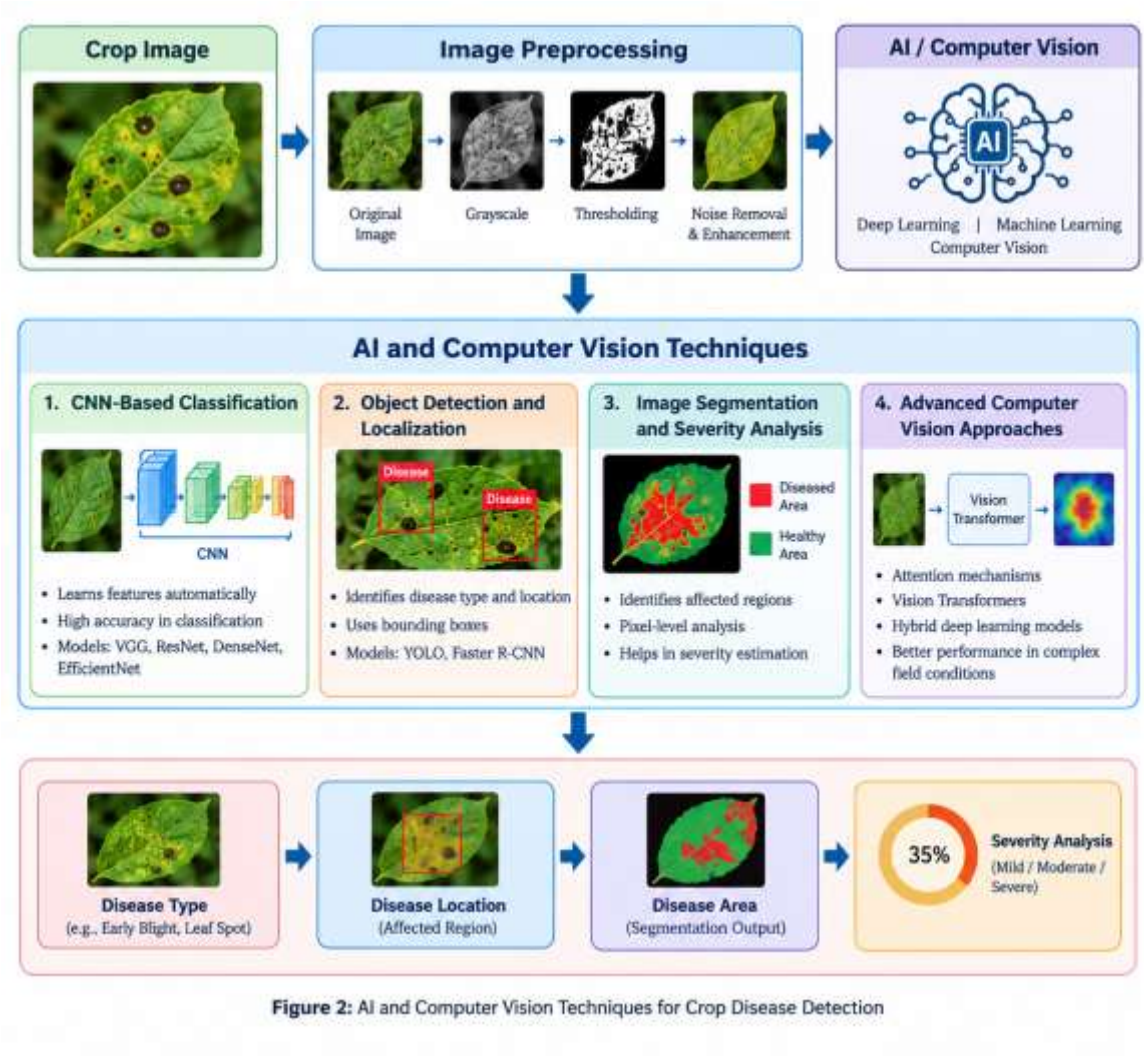


Figure 2: AI and Computer Vision Techniques for Crop Disease Detection

Figure 4.1: AI and Computer Vision Techniques for Crop Disease Detection

5. EDGE AI AND REAL-TIME DISEASE DETECTION

The increasing use of Artificial Intelligence in agriculture has created a need for crop disease detection systems that can provide accurate results with minimal processing delay. Traditional cloud-based approaches require crop images to be transmitted to remote servers for analysis, which may increase latency and depend on stable internet connectivity. Edge AI has emerged as an alternative approach by enabling AI models to perform inference closer to the data source [11], [12].

5.1 Edge AI for Crop Disease Detection

Edge AI refers to the deployment of AI models on local devices such as smartphones, embedded systems, and other resource-constrained computing platforms. Existing studies indicate that Edge AI can reduce communication delays and support faster decision-making by processing crop images locally. However, the limited computational resources of Edge devices create challenges in deploying large and complex deep learning models [11], [13].

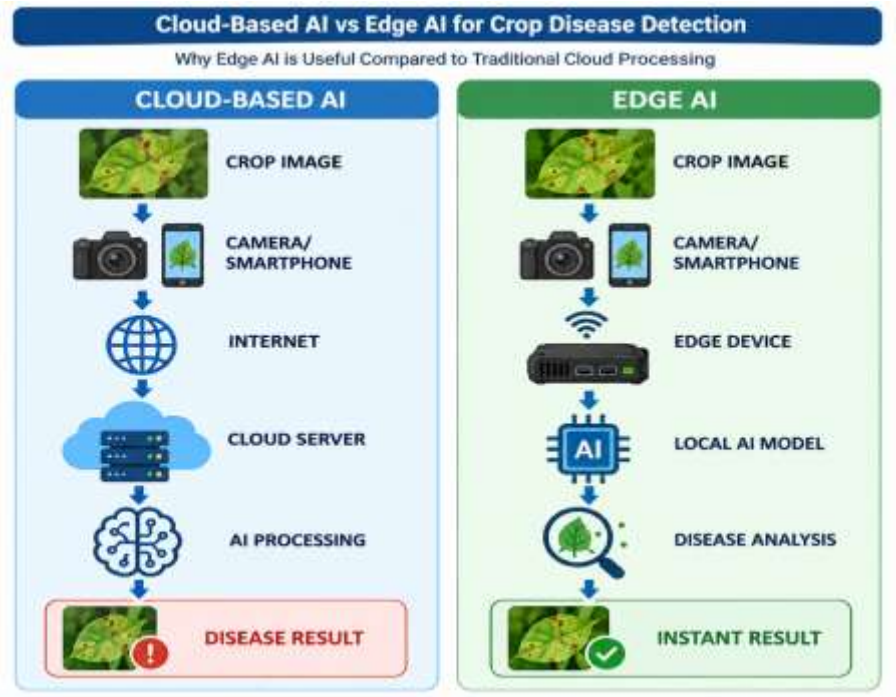


Figure 5.1: Cloud-based AI vs Edge AI for Crop Disease Detection

5.2 Lightweight Deep Learning Models

To address resource limitations, several studies have investigated lightweight deep learning architectures for efficient image classification and real-time applications. Models such as MobileNet, EfficientNet, and ShuffleNet are designed to reduce model size and computational requirements while maintaining acceptable performance. These approaches provide potential solutions for deploying crop disease detection models in practical Edge-based environments [6], [12], [14].

5.3 Real-Time Disease Detection Approaches

Real-time crop disease detection requires an appropriate balance between detection accuracy, inference speed, and computational complexity. Existing Computer Vision approaches, including lightweight CNNs and optimized object detection models, have demonstrated the potential for rapid disease analysis. However, real-world conditions such as varying illumination, complex backgrounds, image blur, and early-stage symptoms can significantly affect detection performance [3], [4], [15].

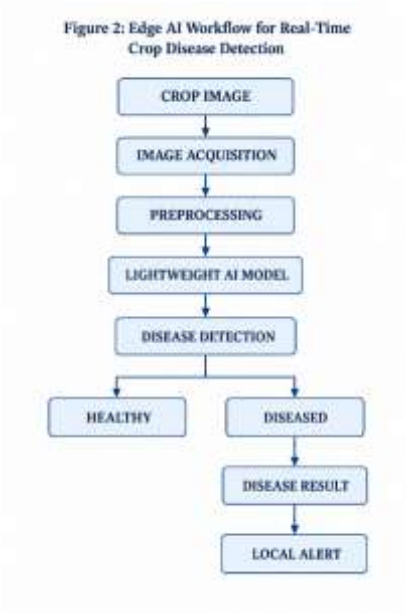


Figure 5.3: Edge AI Workflow for Real-Time Crop Disease Detection

5.4 Challenges and Research Gap

The reviewed studies show that Edge AI can improve the efficiency and accessibility of real-time crop disease detection; however, several limitations remain. Most existing systems use a fixed processing pipeline in which all images receive the same level of analysis, regardless of their disease risk or prediction confidence. This creates a research opportunity for risk-adaptive approaches that can perform fast screening for simple cases while applying detailed analysis only to uncertain or high-risk cases. Such a strategy forms the conceptual basis for the proposed EarlyCropGuard framework [5], [11], [16].

Table: Comparison of Cloud-Based and Edge-Based Disease Detection

Feature	**Cloud-Based AI**	**Edge AI**
Processing Location	Remote Server	Local Device
Internet Dependency	High	Low
Response Time	May have Delay	Faster
Data Transmission	Required	Limited
Computational Power	High	Limited
Real-Time Capability	Moderate	High
Privacy	Data sent externally	Local Processing
Device Limitation	Low	High

6. EARLY DISEASE DETECTION AND SEVERITY ASSESSMENT

Early detection of crop diseases is essential for reducing crop damage and supporting timely agricultural intervention. However, early-stage symptoms are often small, unclear, and visually similar to natural variations in leaves, making their identification more difficult than detecting severe disease symptoms. Existing studies have mainly focused on disease classification after visible symptoms become prominent, while early-stage detection remains an important research challenge [4], [5], [17].

6.1 Early Disease Detection

Deep Learning and Computer Vision techniques have shown potential for identifying disease symptoms from crop images at different stages of infection. CNN-based models can learn visual patterns directly from images; however, their effectiveness depends on the availability of diverse datasets containing early-stage symptoms and real-field conditions. Variations in lighting, leaf appearance, and backgrounds can further affect detection performance [1], [2], [18].

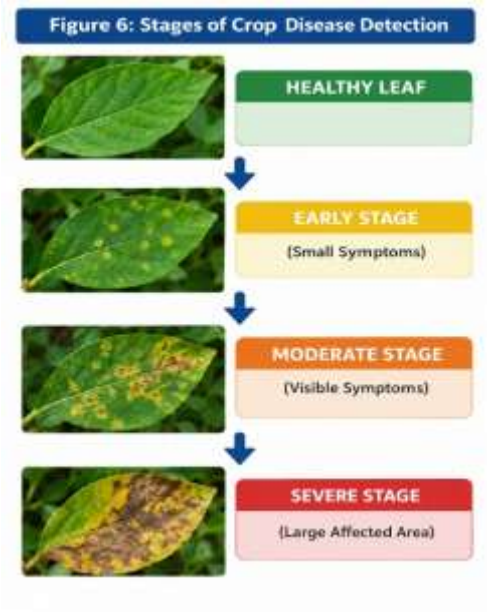


Figure 6.1: Stages of Crop Disease Detection

6.2 Disease Localization

Disease localization provides information about the position of affected regions within a crop image. Object detection methods can identify disease regions using bounding boxes, while image segmentation techniques provide more detailed pixel-level information. These approaches can improve disease analysis by identifying where symptoms are present instead of providing only a disease class [3], [7], [19].

6.3 Disease Severity Assessment

Disease severity assessment estimates the extent of infection by analyzing the proportion of affected plant or leaf area. Segmentation and image processing approaches are commonly used to separate healthy and diseased regions and calculate the affected area. Severity information can provide more useful insights for crop monitoring compared with disease classification alone [8], [17], [20].

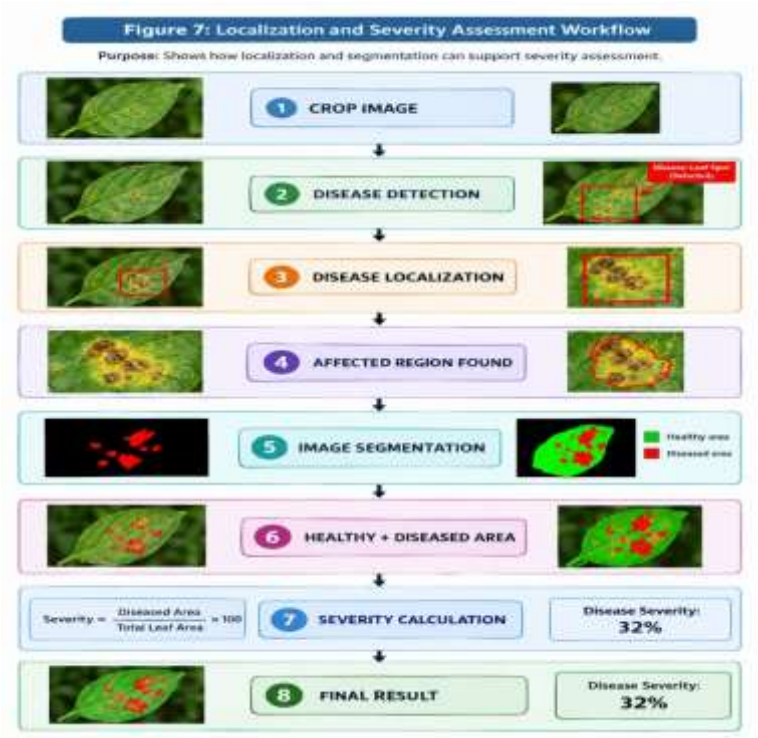


Figure 6.3: Localization and Severity Assessment Workflow

Table: Comparison of Major Crop Disease Analysis Tasks

Task	Main Purpose	Common Techniques	Output
Early Detection	Identify initial symptoms	CNN, Deep Learning	Healthy / Early Disease
Classification	Identify disease type	CNN, ResNet, EfficientNet	Disease Name
Localization	Find affected region	YOLO, Faster R-CNN	Bounding Box
Segmentation	Identify exact affected area	U-Net, Segmentation Models	Disease Mask
Severity Assessment	Measure infection level	Segmentation, Image Analysis	Severity Percentage

6.4 Challenges and Research Gap

The reviewed literature indicates that disease classification, localization, and severity assessment are often addressed as separate tasks. In addition, limited datasets containing early-stage symptoms and varying field conditions make reliable early detection challenging. Therefore, there is a need to further explore integrated approaches that combine early disease identification, localization, and severity assessment while maintaining computational efficiency for practical real-time applications [5], [17], [20].

7. EXPLAINABLE AI FOR CROP DISEASE DETECTION

Deep Learning models have demonstrated strong performance in crop disease classification; however, their predictions are often difficult to interpret. These models are commonly considered as “black-box” systems because they provide a prediction without clearly explaining which image features influenced the decision. Explainable Artificial Intelligence (XAI) aims to improve transparency and increase user confidence in AI-based crop disease detection systems [17], [18].

7.1 Importance of Explainable AI

Explainability is particularly important in agricultural applications because farmers and agricultural experts need to understand and verify AI-generated predictions. XAI techniques can highlight the image regions that influenced a model's decision and help determine whether the model is focusing on actual disease symptoms. This can improve trust and support more reliable decision-making [17], [19].

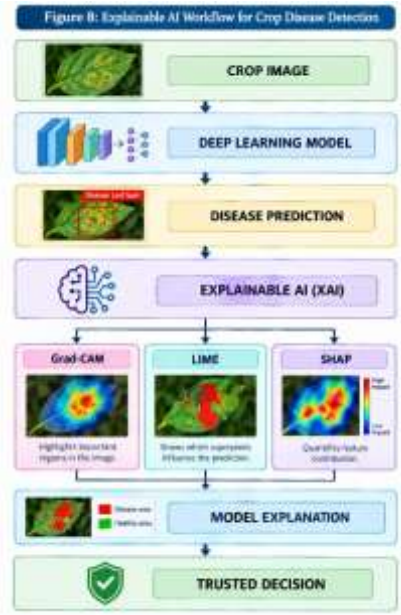


Figure 7.1: Explainable AI Workflow for Crop Disease Detection

7.2 Explainable AI Techniques

Several XAI techniques have been used to interpret Deep Learning models. Grad-CAM generates visual heatmaps to highlight important regions in an image, while LIME and SHAP provide explanations regarding the contribution of input features to model predictions. These techniques can help researchers analyze and understand the behavior of AI models used for crop disease classification [18], [19], [20].

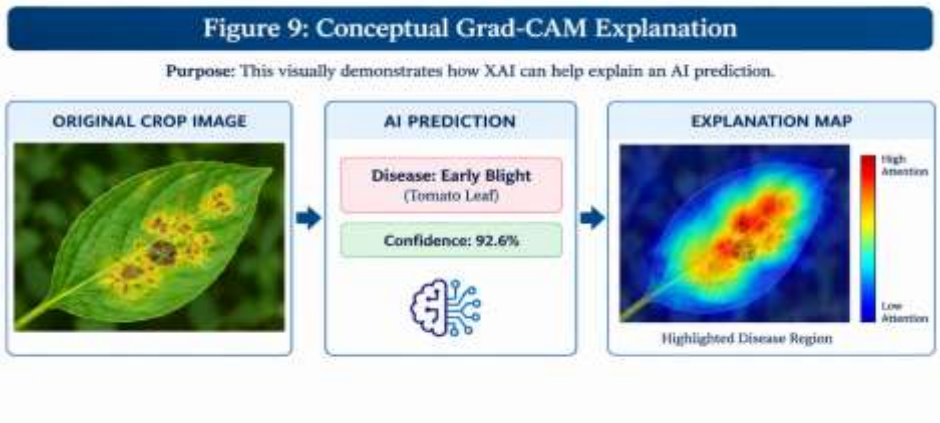


Figure 7.2: Conceptual Grad-CAM Explanation

7.3 Challenges of Explainable AI

Although XAI improves model transparency, several challenges remain in evaluating the quality and reliability of explanations. Different XAI methods may generate different explanations for the same prediction, and generating

explanations can increase computational requirements. These limitations are particularly important when XAI techniques are considered for real-time and Edge AI-based crop disease detection [17], [20].

7.4 Research Gap

The reviewed literature indicates that many crop disease detection systems primarily focus on improving classification accuracy, while model explainability receives comparatively less attention. The integration of XAI with lightweight and real-time crop disease detection systems therefore remains an important research direction. Future studies can explore adaptive approaches in which detailed explanations are generated only for uncertain or high-risk predictions, reducing unnecessary computational overhead while improving transparency.

8. COMPARATIVE ANALYSIS OF EXISTING STUDIES

This section presents a comparative analysis of the selected studies related to crop disease detection using Artificial Intelligence, Deep Learning, Computer Vision, and Edge AI. The reviewed studies differ in terms of datasets, AI models, detection techniques, deployment environments, and output capabilities. Therefore, comparing studies only on the basis of accuracy may not provide a complete understanding of their practical applicability [5], [9], [17].

8.1 Comparative Analysis of AI and Computer Vision Approaches

The reviewed studies demonstrate a clear transition from traditional Machine Learning methods to Deep Learning-based approaches. CNN-based models are widely used for disease classification, while advanced Computer Vision techniques such as object detection and segmentation provide additional information regarding disease location and affected regions. However, model performance may vary depending on the dataset, crop type, image conditions, and evaluation methodology [1], [2], [3], [4].

8.2 Comparative Analysis of Deployment and Real-Time Capability

Most existing studies primarily focus on improving disease classification accuracy using powerful Deep Learning models. However, practical deployment requires consideration of additional factors such as model size, computational complexity, inference speed, and internet dependency. Lightweight models and Edge AI approaches show potential for real-time applications, but maintaining accuracy under resource-constrained and real-field conditions remains challenging [6], [11], [12], [14].

8.3 Comparative Analysis of Advanced Disease Analysis

The reviewed literature indicates that disease classification is the most commonly addressed task, whereas localization, segmentation, early detection, severity assessment, and Explainable AI receive comparatively less attention. Some studies provide detailed analysis of affected regions, but these capabilities are often developed separately rather than as part of an integrated disease monitoring approach [7], [8], [17], [19], [20].

Technology-Wise Comparison of Existing Approaches

Approach	Main Strength	Main Limitation	Real-Time Suitability	Edge Suitability
Traditional ML	Simple implementation	Manual feature extraction	Medium	High
CNN	High classification performance	Computational complexity	Medium	Medium
Object Detection	Disease + location	Higher computation	High	Medium
Segmentation	Precise affected area	Complex processing	Medium	Low/Medium

Approach	Main Strength	Main Limitation	Real-Time Suitability	Edge Suitability
Lightweight CNN	Fast processing	Possible accuracy trade-off	High	High
Edge AI	Local real-time processing	Limited resources	High	High
XAI	Better transparency	Additional processing	Medium	Medium



Figure 8.3: Reviewed Papers

8.4 Key Findings from the Comparative Analysis

The comparative analysis shows that existing approaches have achieved significant progress in automated crop disease detection. However, several limitations remain related to real-world image conditions, early-stage symptom detection, computational efficiency, model explainability, and integrated disease analysis. These findings indicate the need for adaptive approaches that can balance processing requirements with the complexity and risk level of the input image.

Based on the reviewed studies, an important research gap exists in combining fast initial screening with detailed analysis only when required. This observation provides the conceptual motivation for the EarlyCropGuard framework, which proposes a risk-adaptive strategy for future investigation involving efficient screening, disease analysis, severity assessment, and explainability.

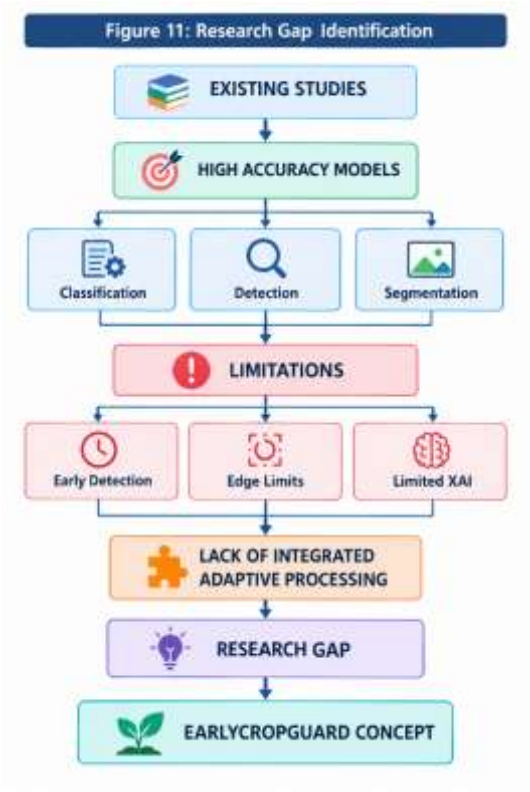


Figure 8.4: Research Gap Identification

9. RESEARCH GAPS AND PROPOSED EARLYCROPGUARD FRAMEWORK

The comparative analysis of existing studies shows that Artificial Intelligence, Deep Learning, and Computer Vision have significantly improved crop disease detection. However, several challenges still remain in practical crop disease monitoring, particularly in early-stage disease detection, computational efficiency, real-world image analysis, disease severity assessment, and model explainability [5], [17], [20].

One major research gap is related to early disease detection. Many existing studies focus on identifying diseases when visible symptoms are already clear and prominent. Early-stage symptoms may be small and difficult to distinguish from normal leaf variations. In addition, limited availability of early-stage disease images and real-field datasets can affect the reliability of existing AI-based detection approaches [4], [5].

Another limitation is the use of fixed processing pipelines in many existing systems. Most approaches apply the same AI model and level of processing to every input image, regardless of whether the crop is healthy, uncertain, or severely affected. This can result in unnecessary computational processing, especially when deploying AI models on resource-constrained Edge devices.

The reviewed studies also indicate that disease classification, localization, segmentation, severity assessment, and Explainable AI are often addressed as separate tasks. While some approaches provide detailed information about disease regions or severity, there is limited integration of these capabilities into a single efficient workflow. Similarly, Explainable AI techniques can improve transparency, but their integration with real-time and lightweight disease detection systems requires further investigation [17], [18], [20].

Based on these identified research gaps, this review proposes **EarlyCropGuard: A Risk-Adaptive Edge AI Framework for Early Crop Disease Prediction and Real-Time Detection Using Computer Vision**. The proposed framework is conceptual and is intended to provide a future research direction for developing more efficient and integrated crop disease monitoring systems.

The EarlyCropGuard framework begins with crop image acquisition and image quality assessment, followed by fast initial screening using a lightweight AI model. The screening results can be used to estimate the risk level of the input

image. Based on this analysis, crop images can be categorized into low-risk, medium-risk, or high-risk conditions, allowing different levels of processing to be applied.

Low-risk images can receive a quick result through fast screening, reducing unnecessary computational requirements. Medium-risk images can undergo additional disease verification, while high-risk or uncertain images can be directed toward advanced analysis. This detailed analysis may include disease classification, localization of affected regions, severity assessment, and Explainable AI-based interpretation.

The main contribution of EarlyCropGuard is its proposed **risk-adaptive processing strategy**. Instead of applying detailed and computationally expensive analysis to every crop image, the framework conceptually adjusts the processing level according to the estimated disease risk. This approach can be investigated in future research to balance real-time performance, computational efficiency, detailed disease analysis, and model transparency in practical crop disease monitoring applications.

10. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite significant advancements in Artificial Intelligence, Deep Learning, Computer Vision, and Edge AI, several challenges remain in developing reliable crop disease detection systems. The reviewed studies indicate that model performance is often influenced by dataset quality, real-world environmental conditions, computational limitations, and the availability of early-stage disease images [5], [17], [20].

One major challenge is the limited availability of diverse datasets captured under real agricultural conditions. Many existing datasets contain images with controlled backgrounds and clear disease symptoms, whereas real-field images may include variations in lighting, shadows, occlusion, complex backgrounds, and multiple leaves. Future research should focus on developing larger and more diverse datasets containing different crops, disease stages, and environmental conditions.

Another important challenge is early-stage disease detection. Early symptoms can be small and visually similar to natural variations in leaves, making accurate identification difficult. Future research can investigate advanced feature extraction techniques, attention-based models, and improved datasets specifically focused on early disease symptoms.

Computational efficiency also remains an important concern, particularly for real-time and Edge AI-based applications. Large Deep Learning models may provide high accuracy but require significant memory and processing resources. Future research should investigate lightweight models, model compression, optimization techniques, and adaptive processing strategies to achieve an effective balance between accuracy and inference speed [11], [12], [14].

Model explainability and reliability require further attention in practical agricultural applications. Explainable AI techniques can help users understand why a particular prediction was generated; however, generating explanations may increase computational requirements. Future research can explore efficient Explainable AI approaches that provide explanations when required, particularly for uncertain or high-risk disease predictions.

Another future direction is the development of integrated crop disease monitoring systems. Rather than focusing only on disease classification, future approaches can combine early detection, disease localization, severity assessment, real-time processing, and Explainable AI within a unified framework. Such integrated approaches can provide more meaningful information for farmers and agricultural experts.

Finally, future research can investigate the proposed **EarlyCropGuard** framework through practical implementation and experimental evaluation. The risk-adaptive processing strategy can be evaluated using different crop datasets and Edge devices to analyze its performance, computational efficiency, and suitability for real-world agricultural environments. These future directions can contribute toward the development of more accurate, efficient, transparent, and practical AI-based crop disease monitoring systems.

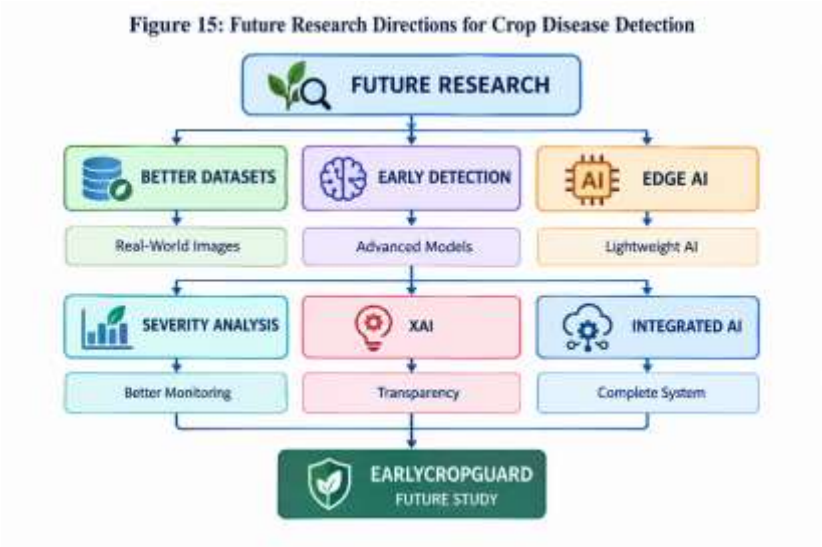


Figure 10: Future Research Directions for Crop Disease Detection

11. CONCLUSION

This review examined recent research on AI-based crop disease detection using Deep Learning, Computer Vision, Edge AI, disease localization, severity assessment, and Explainable AI. The reviewed studies demonstrate that AI-based approaches have significantly improved automated disease identification compared with traditional manual inspection methods. CNN-based models, object detection, and image segmentation techniques have provided effective solutions for disease classification and affected-region analysis.

However, the review also identified several important challenges in existing approaches. These include limited early-stage disease datasets, poor performance under real-field conditions, high computational requirements, fixed processing pipelines, limited severity assessment, and insufficient model explainability. In addition, many existing studies address classification, localization, severity analysis, and explainability as separate tasks rather than providing an integrated approach.

Based on the comparative analysis and identified research gaps, this review proposed **EarlyCropGuard: A Risk-Adaptive Edge AI Framework for Early Crop Disease Prediction and Real-Time Detection Using Computer Vision** as a conceptual framework for future research. The framework introduces a risk-adaptive processing strategy in which crop images can receive different levels of analysis according to their estimated risk and prediction characteristics.

The proposed framework conceptually combines fast initial screening, risk analysis, detailed disease classification, localization, severity assessment, and Explainable AI. Rather than applying computationally intensive analysis to every image, detailed processing can be directed toward medium-risk, high-risk, or uncertain cases. This approach provides a potential direction for balancing computational efficiency with detailed disease analysis.

In conclusion, the reviewed literature confirms the growing potential of AI and Computer Vision for intelligent crop disease monitoring. Future work can focus on implementing and experimentally evaluating the EarlyCropGuard framework using diverse real-world datasets and Edge devices. Such research can contribute toward the development of more efficient, adaptive, transparent, and practical crop disease detection systems for modern agriculture.

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