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# AI-Based Real-Time Crop Image Analytics for Crop Insurance

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**ABSTRACT:** Agriculture plays a crucial role in the economic stability of many developing countries, yet farmers continue to face significant challenges due to crop diseases, unpredictable climatic conditions, and inefficient insurance claim processes. Traditional crop monitoring systems, which rely on manual field inspection or expert analysis, often suffer from delays, human error, and lack of consistency in identifying early-stage diseases. Similarly, conventional insurance assessment methods involve time-consuming surveys and subjective evaluations, leading to inaccurate damage estimation and delayed compensation. These limitations result in reduced crop productivity, financial losses, and increased uncertainty for farmers, highlighting the need for an intelligent and efficient automated system.

This study presents an AI-based crop health analysis and insurance estimation system using deep learning and computer vision techniques to address these challenges. The system utilizes image-based input to detect crop diseases and assess plant health using a lightweight Convolutional Neural Network (MobileNetV2), along with OpenCV for image preprocessing and feature enhancement. By eliminating the dependency on manual inspection and integrating automated analysis, the proposed approach ensures improved accuracy, scalability, and real-time performance. A Flask-based web interface provides users with instant results, including disease classification, health score, damage estimation, and insurance claim prediction aligned with PMFBY schemes. The results demonstrate that the system achieves reliable performance under varying environmental conditions and offers a practical solution for smart agriculture and digital insurance applications.

**KEYWORDS:** Crop Health Analysis, Deep Learning, MobileNetV2, OpenCV, Computer Vision, Image Classification, Real-Time Monitoring, Crop Disease Detection, Image Processing, Flask, Smart Agriculture, Insurance Estimation

## I. INTRODUCTION

Managing crop health efficiently in modern agricultural environments has become a significant challenge, particularly with the increasing impact of climate change, plant diseases, and pest infestations. Traditional crop monitoring systems rely heavily on manual field inspections or expert supervision to assess plant conditions. While these approaches provide basic insights, they are often time-consuming, labor-intensive, and lack consistency in detecting early-stage diseases. As agricultural practices expand to support large-scale farming and smart agriculture initiatives, the complexity of monitoring crop conditions across vast areas has driven researchers to explore automated and intelligent solutions based on computer vision and artificial intelligence.

Recent developments in agricultural automation have introduced image-based systems that utilize captured crop images to detect plant diseases and monitor crop health. Early approaches focused on image processing techniques such as color analysis, segmentation, and edge detection to identify abnormalities in plant leaves [1], [2]. While these methods demonstrated initial success, they often struggled under varying lighting conditions, complex backgrounds, and environmental changes. To improve detection accuracy, machine learning techniques such as Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) were introduced, enabling better classification of crop diseases based on extracted image features [3], [4]. However, these methods required manual feature engineering and lacked the robustness needed for large-scale real-time agricultural applications.

More recently, deep learning-based models have gained significant attention for their ability to perform accurate and real-time image classification. Techniques based on Convolutional Neural Networks (CNNs) [13]–[15], particularly lightweight architectures such as MobileNetV2 [5], have demonstrated high efficiency in detecting crop diseases under complex environmental conditions. These models automatically extract relevant features from images, eliminating the need for manual feature engineering and improving scalability. Researchers have further enhanced these systems by integrating disease localization techniques, damage estimation metrics, and health scoring methods to provide more

detailed analysis of crop conditions [6], [7]. Additionally, combining these models with web-based platforms has enabled real-time visualization and accessibility for farmers, improving the usability of agricultural monitoring systems [8].

Despite these advancements, existing systems still face several limitations. Many approaches focus primarily on disease detection without providing a complete end-to-end solution that includes damage assessment, insurance estimation, and real-time reporting [9]. Furthermore, some systems require high computational resources or fail to maintain consistent performance under real-world conditions such as varying lighting, weather changes, and image quality variations [10]. These limitations highlight the need for an integrated and efficient system capable of delivering accurate, real-time crop analysis while remaining cost-effective and scalable.

To address these challenges, this research proposes an AI-based crop health analysis and insurance estimation system using MobileNetV2 and OpenCV. The system leverages image-based input to detect crop diseases, evaluate plant health, and estimate damage severity through automated analysis techniques. By eliminating the dependency on manual inspection and integrating intelligent processing, the proposed approach offers a practical and scalable solution for modern agriculture. The integration of a Flask-based web interface further enhances accessibility, enabling users to monitor crop conditions and insurance estimates in real time. This work aims to contribute toward the development of intelligent, vision-based systems that support efficient crop management and digital agricultural insurance systems.

## **II. LITERATURE REVIEW**

### **2.1 Vision-Based Crop Health Monitoring Systems**

Research in agricultural monitoring has gradually shifted from manual inspection and sensor-based systems toward vision-based approaches that utilize image inputs for detecting crop diseases and assessing plant health. Traditional systems relied on manual observation or sensor-based techniques such as soil sensors and environmental monitoring devices to analyze crop conditions [1], [2]. While these systems provided basic support, they were often expensive to deploy, required continuous maintenance, and lacked the ability to provide accurate visual analysis of plant diseases. As a result, researchers began exploring image-based systems that eliminate dependency on physical sensors and provide scalable solutions for large agricultural fields. Vision-based systems utilize digital images of crops to detect diseases and monitor plant health, making them more flexible and cost-effective for real-world agricultural applications.

### **2.2 Image Processing and Machine Learning Approaches**

Early vision-based crop monitoring systems primarily relied on classical image processing techniques such as color analysis, segmentation, and edge detection to identify disease patterns in plant leaves [3], [4]. These approaches were effective in controlled environments but struggled under dynamic conditions such as varying lighting, background noise, and environmental changes. To improve performance, machine learning techniques such as Support Vector Machines (SVM) and k-Nearest Neighbors (KNN) were introduced for classifying crop diseases based on extracted features [5], [6]. Although these methods improved detection accuracy, they required manual feature extraction and were not suitable for real-time applications in large-scale agricultural environments.

### **2.3 Deep Learning-Based Crop Disease Detection Models**

Recent advancements in deep learning have significantly improved the accuracy and efficiency of crop disease detection systems. Convolutional Neural Networks (CNNs) and lightweight architectures such as MobileNetV2 have been widely adopted for image-based classification tasks [7], [8]. These models automatically extract complex features from images and provide high accuracy in detecting plant diseases under varying environmental conditions. MobileNetV2, in particular, is designed for efficiency and can operate on low-resource devices, making it suitable for agricultural applications. Researchers have further enhanced these systems by integrating disease localization techniques, health scoring methods, and damage estimation models to provide more detailed insights into crop conditions [9], [10]. These systems demonstrate strong performance in real-time environments and can handle diverse crop types and disease variations.

### **2.4 Integrated Smart Agriculture Systems and Limitations**

Despite significant progress, existing agricultural monitoring systems still face several limitations. Many approaches focus only on disease detection without integrating damage assessment, insurance estimation, and real-time reporting into a unified system [11]. Additionally, some systems require high computational resources or fail to perform consistently under challenging real-world conditions such as poor lighting, weather variations, and inconsistent image quality [12]. While web-based platforms and cloud integration have been introduced in some studies, a complete end-

to-end solution that combines detection, analysis, and real-time user interaction remains limited [13]. Therefore, there is a growing need for efficient, scalable, and cost-effective systems that integrate deep learning with real-time monitoring and user-friendly interfaces in agricultural environments.

#### Summary Synthesis

The literature indicates a clear transition from traditional manual and sensor-based crop monitoring systems to vision-based approaches for efficient and real-time agricultural analysis. Sensor-based methods, although useful, are expensive and difficult to maintain, while image processing techniques often struggle under dynamic environmental conditions such as lighting variations and background complexity [1]–[4]. Machine learning approaches improve detection accuracy but require manual feature extraction and are not well-suited for large-scale real-time applications [5], [6]. Recent advancements in deep learning, particularly CNN-based models such as MobileNetV2, have significantly enhanced real-time crop disease detection and analysis [7]–[10]. Additionally, integration with web-based platforms improves accessibility and usability for farmers [11]. However, most existing systems still lack a complete end-to-end solution that combines detection, damage assessment, and insurance estimation efficiently, highlighting the need for a unified, scalable, and cost-effective smart agriculture system [12]–[15].

### III. REVIEW-BASED METHODOLOGY

This section presents an image-based methodology for designing an intelligent crop health analysis and insurance estimation system using deep learning and computer vision techniques [19], [20]. Unlike traditional manual inspection methods, the proposed approach relies on image input and automated analysis to detect crop diseases and evaluate plant health. Building upon advancements in image classification and agricultural AI systems, this methodology integrates disease detection, damage estimation, and real-time visualization into a unified framework. The approach focuses on achieving accurate, scalable, and cost-effective crop monitoring suitable for real-world agricultural environments.

#### 3.1 System Approach and Comparative Selection

The methodology is based on a combination of deep learning models, image processing techniques, and web-based visualization tools. The selection of components prioritizes systems that:

- Detect crop diseases in real time using image classification models.
- Operate efficiently on standard devices without requiring specialized hardware.
- Provide scalable solutions adaptable to different crop types and environmental conditions.

Deep learning models such as MobileNetV2 are selected due to their ability to perform fast and accurate image classification in real-time scenarios [7], [8]. OpenCV is used for image preprocessing, including resizing, normalization, and enhancement of crop images [3], [4]. Additionally, Flask is incorporated as a backend framework to enable real-time data communication and visualization through a web interface [11]. This combination forms a robust foundation for building an end-to-end crop analysis and insurance estimation system.

Such categorization establishes a structured methodological framework, ensuring efficient integration of detection, analysis, and reporting components within the system.

#### 3.2 Crop Health Detection Workflow

The system follows a structured workflow for detecting and analyzing crop conditions. Initially, crop images are uploaded by users through a web interface. The input images are preprocessed using OpenCV techniques such as resizing, noise reduction, and normalization to ensure consistent quality. The processed images are then passed to the MobileNetV2 model, which classifies crop diseases and identifies affected patterns within the image [7].

Following classification, the system evaluates the health condition of the crop by calculating metrics such as health score and damage percentage. The extent of infection is analyzed based on visual patterns and model predictions, enabling accurate assessment of crop condition. This analytical approach ensures effective disease detection and severity estimation without requiring manual inspection. The workflow operates continuously, enabling real-time analysis and instant feedback to users.

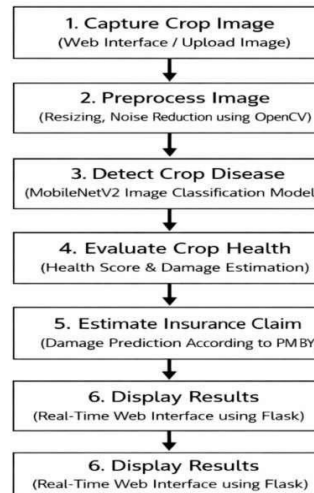
**Evaluation of AI-Based Crop Health Analysis and Insurance Imation Workflow**

Fig. 3.1 presents the workflow of the crop health analysis system, highlighting how image input is processed through multiple stages including preprocessing, disease classification, health evaluation, and damage estimation, enabling real-time monitoring and decision support.

**3.3 Real-Time Visualization and System Integration**

To enhance usability, the system integrates a web-based interface that displays crop analysis results in real time. The processed data, including detected disease, health score, damage percentage, and insurance estimation, is transmitted to a Flask backend server. The server provides APIs that allow the frontend interface to dynamically retrieve and display updated results [11].

This integration ensures that users can access crop health information through standard web browsers without requiring additional software or technical expertise. The system is designed to operate efficiently on standard computing devices, making it suitable for deployment in agricultural fields, academic environments, and rural areas. By combining detection, analysis, and reporting, the methodology delivers a complete end-to-end solution.

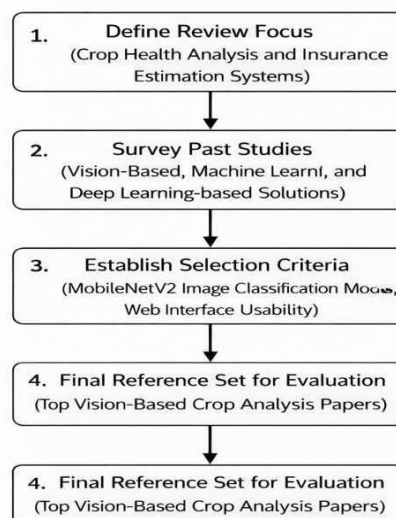
**Review Approach and Comparative Selection**

Fig. 3.2 presents the approach adopted for designing the crop health analysis system, highlighting stages such as problem identification, model selection, system integration, and evaluation, emphasizing the development of an efficient and scalable agricultural solution

### 3.4 Summary of Methodological Insights

The proposed methodology highlights the transition from traditional manual and sensor-based approaches to vision-driven intelligent agricultural solutions. Deep learning models such as MobileNetV2 enable accurate and real-time crop disease detection, while OpenCV facilitates efficient image preprocessing and analysis [7]–[10]. The integration of web-based interfaces further improves accessibility and user interaction [11]. Unlike existing approaches that focus on isolated functionalities, this methodology provides a unified framework that combines detection, analysis, and insurance estimation.

Overall, the approach demonstrates that an integrated, image-based system can achieve efficient crop monitoring while maintaining scalability and cost-effectiveness [16]–[18]. This methodology forms the foundation for developing intelligent agricultural systems aligned with modern smart farming requirements.

## IV. CONCLUSION

Recent advancements in agricultural monitoring systems indicate that vision-based approaches have significantly improved the efficiency of crop disease detection and plant health analysis. Techniques based on image processing and machine learning have contributed to automating crop monitoring; however, their performance is often limited under dynamic environmental conditions such as lighting variations, background complexity, and image quality differences [3], [4], [5]. The introduction of deep learning models, particularly MobileNetV2, has enhanced real-time crop disease detection by providing higher accuracy and faster processing capabilities [7], [8]. Additionally, the integration of health scoring methods and damage estimation techniques has enabled more precise evaluation of crop conditions in complex agricultural environments [9], [10].

Despite these advancements, several limitations remain across existing systems. Many approaches focus primarily on disease detection without offering a complete end-to-end solution that integrates real-time analysis, insurance estimation, and user interaction [11]. Furthermore, some systems require high computational resources or fail to maintain consistent performance under real-world conditions such as varying weather, lighting, and image inconsistencies, limiting their scalability and practical deployment [12]. These challenges highlight the need for a unified system that combines efficient detection, robust processing, and real-time accessibility within a single framework.

The proposed AI-based crop health analysis and insurance estimation system using MobileNetV2 and OpenCV provides an effective solution by integrating real-time disease detection, damage assessment, and automated insurance estimation. By eliminating the dependency on manual inspection and leveraging image-based analysis, the system ensures improved accuracy, cost-effectiveness, and scalability. The inclusion of a Flask-based web interface further enhances usability by enabling continuous monitoring and easy access to crop analysis results and insurance reports. Overall, this approach demonstrates the potential of AI-driven systems in addressing modern agricultural challenges and contributes toward the development of intelligent, scalable solutions suitable for smart farming and digital insurance systems.

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