Real-Time Rice Crop Disease Monitoring: YOLOv11-Powered System with Voice Alerts and Health Scoring

Kirtirajsinh Zala
Department of Information Technology
Marwadi University
Rajkot, India
kirtirajsinh.zala@marwadieducation.edu.in

Mrudurajsinh Chudasama
Department of Electrical Engineering
Marwadi University
Rajkot, India
mrudurajsinh.chudasama@marwadieducation.edu.in

Jivesh Poddar
Northeastern University
Boston
Poddar.j@northeastern.edu

Hemant Patel
Department of Computer Engineering
Dr.Subhash University
Junagadh, India
hemant.patel@dsuni.ac.in

2025 Artificial Intelligence and Smart Technologies for Sustainability Conference (AISTS) | 979-8-3315-9852-5/25/$31.00 ©2025 IEEE | DOI: 10.1109/AISTS66100.2025.11232999

***Abstract*—This paper presents a cost-efficient, AI-driven framework for real-time detection and alerting of rice crop diseases using YOLOv11. The proposed system addresses the limitations of existing solutions by leveraging existing low-cost field cameras or drone/UAV-captured images with geotagged metadata, eliminating the need for new camera infrastructure and reducing costs significantly. The YOLOv11 model is employed for multi-class detection of Bacterial Blight, Rice Blast, and Brown Spot, achieving a Box Precision (P) of 0.649, Box Recall (R) of 0.569, mAP50 of 0.626. The system integrates with a localized Interactive Voice Response (IVR) system for voice alerts and includes a field health scoring mechanism to provide actionable insights to farmers. The web-based dashboard health scores, upcoming risks like disease and alert logs, enabling farmers to monitor crop health remotely. Simulated case studies demonstrate the system's effectiveness in generating relevant alerts and tracking health scores over time. Future work will focus on improving model recall and mAP50-95 through further training with augmented datasets and expanding detection capabilities to include more diseases. This framework represents a significant advancement in AI-driven agricultural solutions for small-scale farmers, offering a powerful tool to enhance rice crop management and improve food security.**

***Index Terms*—Yolo, Computer vision, Agriculture, Crop disease**

I. Introduction

For millions of farmers worldwide, rice production is vital to their livelihoods and global food security. However, rice crops are threatened by diseases such as Brown Spot, Rice Blast, and Bacterial Blight, which cause significant yield losses and reduce produce quality. Bacterial Blight, caused by Xanthomonas oryzae pv. oryzae, can reduce yields by over 50% under extreme conditions [1]. Rice Blast, caused by the fungus Magnaporthe oryzae, also leads to substantial yield losses [2]. Brown Spot, caused by Bipolaris oryzae, can reduce yields by 10%–58% and has historically contributed to severe famines, such as the 1942 "Great Bengal Famine" [3].

Small-scale farmers, who make up a large portion of the agricultural workforce in less developed countries, are particularly vulnerable to these diseases. They often lack access to advanced detection technologies due to high costs and technical barriers. Existing solutions, such as mobile app-based detection systems and drones, have limitations. Current drones are cost-prohibitive to acquire as well as maintain and the mobile applications that are in the market right now cannot provide reliable real-time alerting.

Additionally these apps can be very cumbersome when handled by people without any writing and reading skills. In most instances, the abilities of such systems to provide actionable information and position clinical observation in a broad field-wide context are also lacking. New AI-powered crop disease recognizing developments, especially, those based on the YOLO approach, e.g. YOLOv3, YOLOv5, YOLOv7 have shown high accuracy in plant disease detection. Still, implementation of such systems necessitates the use of specialized hardware and is not fully assimilated into the farmer-centric warning procedures. This paper is aimed on filling these bottom lines with a suggestion of a cost effective AI based real time rice crop disease recognition and pro-active alerting model.

To address these gaps, this paper proposes a cost-efficient, AI-driven framework for real-time detection and alerting of rice crop diseases using YOLOv11. The framework leverages existing low-cost field cameras or already available camera systems, eliminating the need to implement an entirely new system. It integrates with a localized Interactive Voice Response (IVR) system for voice alerts and includes a field health scoring mechanism. This approach aims to provide a scalable and user-friendly solution that is accessible to small-

Fig. 1. Rice Bacterial

Fig. 2. Rice Blast

Fig. 3. Rice Brown

scale farmers, enabling them to detect diseases early and take timely actions to mitigate losses.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive review of existing literature, highlighting the advancements and limitations of current solutions. Section 3 details the proposed methodology, including the system architecture and key components. Section 4 discusses the system components in depth, focusing on the innovations and practical implementation of each part. Section 5 presents the experimental setup and evaluation, showcasing the effectiveness of the proposed framework. Section 6 offers a discussion on the benefits and limitations of the system compared to existing research. Finally, Section 7 concludes the paper by summarizing the value of the framework to farmers and its potential to make deep learning accessible and affordable for small-scale agriculture.

II. Literature Review

A new development in AI crop disease detection on the other hand promises to significantly lift agricultural output and allow farmers to always have an eye on their crops health. Deep learning models have been dilligently proven towards the effectiveness and precision in detecting varied plant diseases. In particular, model built on Convolutional Neural Network (CNN) and the YOLO (You Only Look Once) family of object detection algorithm are subject to this problem.

A two phase recognition framework which combined YOLOX and a Siamese Net was reported for rice leaf disease detection and reached 95.58% over mAP [4]. An improved YOLOv7 model incorporating MobileNetV3 for feature extraction, Coordinate Attention (CA), and SIoU loss function [5] achieved a mAP@0.5 of 93.7% and an accuracy of 92.3%. For example, a ResNet34 based model with self attention mechanisms gives 98.54% accuracy in multiclass rice leaf disease classification [6]. To identify four rice leaf diseases, a deep learning method in combination with support vector machines provided promising results [7]. A hybrid of deep learning model with the adaptive feature selection for detection of paddy leaf disease resulted in 98.86 % classification accuracy [7].

Recent interest in lightweight models is due to their suitability for low resource environments. For the application of crop classification, an improved CNN architecture was proposed with respect to effectiveness and adaptability in a low resource environment [9]. An artificial hummingbird based AX-RetinaNet approach was optimized for detection of rice plant disease, where we show the potential of lightweight architectures [10]. In addition, with the merger of edge computing and IoT devices, new real time disease detection opportunities have been made available. To address the challenges of deploying deep learning models on edge devices, a lightweight hybrid model, Tiny-LeViT, built by hybridizing CNN and transformer architectures is introduced [11].

Despite these advancements, several challenges remain. Many existing systems require high-end hardware, limiting their accessibility to small-scale farmers. Mobile app-based solutions, while more accessible, may not be user-friendly for non-literate users and often lack real-time alerting capabilities. Furthermore, the integration of disease detection with farmer-centric alerting mechanisms and field-wide context remains underexplored.

The following table provides a comparison of different models used in rice disease detection:

To address these gaps, this paper proposes a cost-efficient, AI-driven framework leveraging existing low-cost field cameras or already available camera systems. The framework integrates with a localized Interactive Voice Response (IVR) system for voice alerts and includes a field health scoring mechanism. This approach aims to provide a scalable and user-friendly solution that enhances accessibility for small-scale farmers, enabling early disease detection and timely interventions.

TABLE I
COMPARISON OF DIFFERENT MODELS USED IN RICE DISEASE DETECTION [2], [5], [7], [10]

Model/Method	Dataset Characteristics	Key Innovations
Two-phase YOLOX + Siamese	2800 images (complex backgrounds)	Hybrid framework for small-sample disease detection
Improved YOLOv7	4500 images (multiple disease co-occurrence)	MobileNetV3 lightweight design; CA attention; SIoU loss function
ResNet34 + Self-attention	3200 images (natural field conditions)	Self-attention for gradient vanishing mitigation; multiclass classification
DCF-YOLOv8	IP102 dataset (complex lighting/backgrounds)	DenseBlock-based DCF module; Mish activation for nonlinear feature extraction
FHTW-Net (ViT + BERT)	Multimodal dataset (image-text pairs)	Cross-modal retrieval; TMS attention; FNE-HNM strategy; WBA optimization

III. PROPOSED METHODOLOGY

Addressing existing solution limitations, the proposed framework presents a cost efficient and AI driven framework for real time rice crop disease detection and alerting. In contrast to prior systems that need expensive hardware or do not have the farmer interaction features, our proposed framework utilizes current low cost field cameras or the drone/UAV collected images that include geo positioned metadata. It means no new camera infrastructure is needed and that can save you a ton of money.

This diagram illustrates the detailed interaction between the farmer, camera system, YOLOv11 model, GPS module, IVR system, health scoring module, and web dashboard. It shows the flow of data and control throughout the system.

A. Input and Preprocessing

The system utilizes video or images captured from existing field cameras, drones, or UAVs. These inputs often contain geotagged metadata, which is leveraged for spatial context. The input data is preprocessed to enhance quality, including normalization, resizing, and augmentation, ensuring it is suitable for the YOLOv11 model [15].

B. YOLOv11 Model for Disease Detection

The YOLOv11 model is employed for multi-class detection of Bacterial Blight, Rice Blast, and Brown Spot. Trained on diverse datasets like the Rice Object Detection Dataset from Roboflow, the model detects diseases in real-time, providing bounding boxes and confidence scores. This enables precise identification and localization of diseases within the captured images.

C. Disease Classification and Severity Scoring

Detected diseases are classified, and a severity score is calculated based on disease prevalence and intensity. This score is instrumental in generating appropriate alerts and recommendations, reflecting the urgency and extent of the disease outbreak.

D. Voice Alert Generation

Localized voice alerts are generated in the farmers' native language using an IVR system. These alerts provide real-time information on disease detection and recommended actions, ensuring accessibility for non-literate users and timely response to outbreaks.

E. Health Score Generation

A field health score is computed using disease severity, frequency, and weather risk factors. Categorized into Healthy, At-Risk, and Critical, this score guides farmers in making informed decisions about their fields, facilitating proactive crop management.

F. Web-based Dashboard

A web-based dashboard developed using Gradio displays disease maps, health scores, upcoming risks, and alert logs. If images are captured using drones or UAVs, geotagged metadata enables the display of disease maps. This dashboard is accessible from any browser, allowing remote monitoring of crop health.

This comprehensive framework enables early disease detection, timely interventions, and effective crop management, addressing previous limitations and providing farmers with a powerful tool to enhance their agricultural productivity.

IV. SYSTEM COMPONENTS

A. Reusing Existing Camera System

The system reuses existing surveillance cameras, drones or UAVs for real-time frame extraction, offering a cost-effective alternative to dedicated agricultural monitoring systems. This approach eliminates the need for farmers to invest in new camera infrastructure, significantly reducing initial costs in many cases. A cost comparison with drone and smartphone-based systems is provided in Table 2. OpenCV is utilized for capturing and processing RTSP video feeds, enabling seamless integration with YOLOv11 for object detection. This technology stack ensures real-time video manipulation and frame extraction, making it ideal for disease detection applications [16], [17].

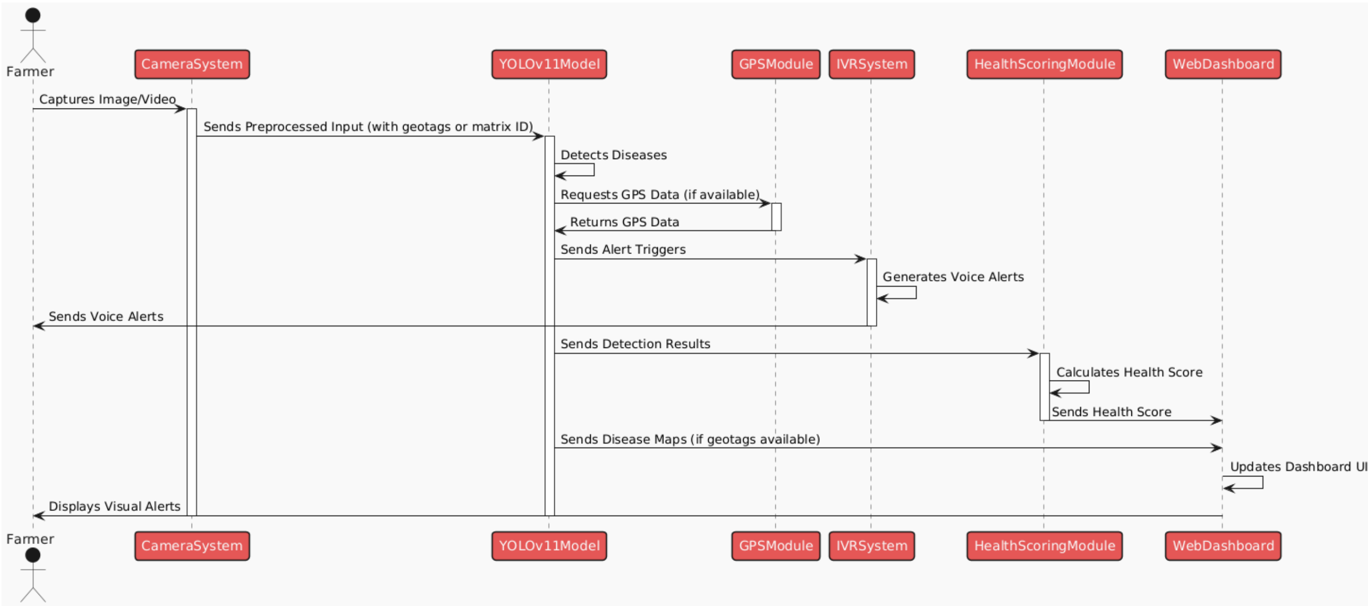

Fig. 4. Detailed Workflow of Proposed System

B. Voice Alert System via IVR

The IVR system generates voice alerts in local languages, ensuring accessibility for non-literate users. The alert logic and message flow are illustrated in the figure 2 below. The IVR system uses text-to-speech technology to convert alert messages into voice calls. The system is designed to handle multiple languages, ensuring it can be deployed in diverse linguistic environments.

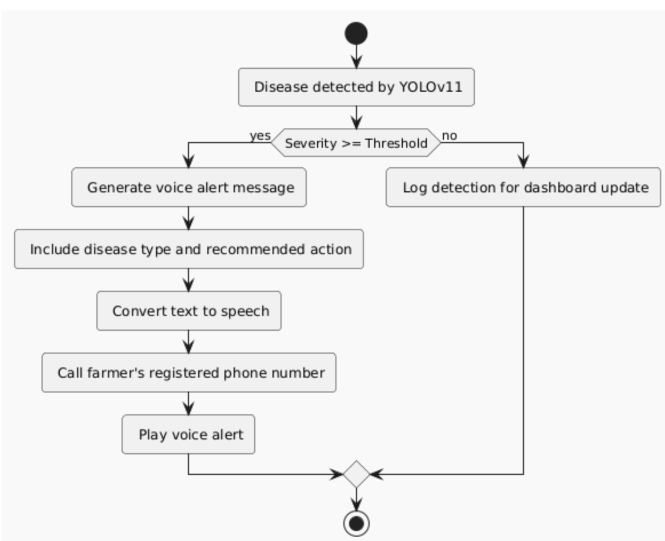

Fig. 5. Alert logic and message flow for proposed system

C. Field Health Scoring Mechanism

The health scoring mechanism uses a combination of disease severity, frequency, and weather risk factors to compute a field health score. The score is categorized into Healthy, At-Risk, and Critical to guide farmers in making informed decisions. The scoring logic is detailed in Table 3.

TABLE II
CONCEPT OF HEALTH SCORING MECHANISM

Score Category	**Thresholds**	**Recommended Action**
Healthy	Low disease severity and frequency	Monitor regularly
At-Risk	Moderate disease severity or frequency	Take preventive measures
Critical	High disease severity and frequency	Immediate intervention required

TABLE III
COST COMPARISON WITH DRONE AND SMARTPHONE-BASED SYSTEMS

System Type	**Cost Range**	**Maintenance Requirements**
Reused Surveillance Cameras	Low to Moderate	Minimal
Drone-based Systems	High	High
Smartphone-based Systems	Moderate to High	Minimal

D. Farmer Dashboard

With the dashboard, farmers are able to use a user-friendly interface to monitor their fields. All these features are supported: Disease Maps, health scores, upcoming risks and alert logs. Access via any browser gives the farmers a complete view at all their fields. This enables farmers to drill down into a particular area of the field and see a specific disease with information and suggested actions.

V. Experimental Setup and Evaluation

A. YOLOv11 Setup

The Rice Object Detection Public Dataset from Roboflow [18] contains three classes: Rice Blast, Rice Bacterial Blight, and Rice Brown Spot. This publicly available dataset comprises a total of over 1300 images, which are partitioned into a training set (70%), validation set (20%), and test set (10%). It includes 942 instances of these diseases. Our model, which has 100 layers, 2,582,737 parameters, and a 6.3 GFLOPs computational load, was carefully set up and trained using this dataset.The performance metrics during training the model were:

- Box Precision (P): 0.649
- Box Recall (R): 0.569
- mAP50: 0.626
- mAP50–95: 0.33

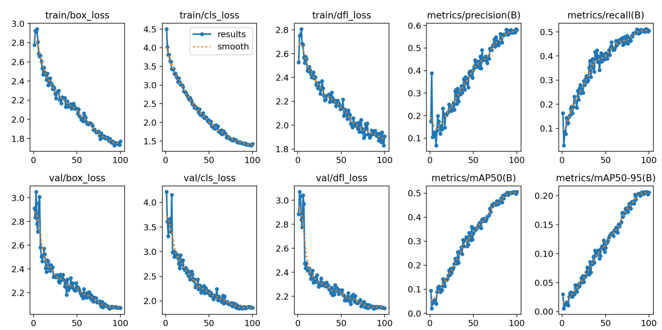

Fig. 6. Result graphs of Yolov11 training

All training process was done on a Tesla T4 GPU using Python 3.11.12, PyTorch 2.6.0+cu124. Importantly, the model was impressively fast, taking 0.2ms for preprocessing, 2.9ms for inference, 0.0ms for loss calculation, and 4.0ms for post-processing each image. The results show that the model can perform real time image processing, and hence is suitable for practical agricultural applications.

B. Simulated Case Studies

To comprehensively evaluate the system's effectiveness, we conducted three simulated case studies on virtual farms. Each study involved distinct scenarios to simulate diverse field conditions and disease distributions:

Case Study 1: Farm A: - Sample Images: Images are focused on Rice Blast, Rice Brownspot, and are 50 images total.

- Detection Outputs: The most prevalent was Rice Brownspot was detected at 120 instances.

- Alert Logs: It generated 15 alerts, all for Rice Brownspot and suggested treatment be done immediately.

- Health Score Evolution: Healthy as detection of Brownspot causes At Risk and simulation of treatment actions causes Healthy again.

Case Study 2: Farm B: - Sample Images: All three environments have been combined in 70 images.

- Detection Outputs: Detecting 180 instances, Rice Bacterial Blight and Rice Blast were equally prominent.

- Alert Logs: Produced 20 alerts, alerting users to the urgency of Bacterial Blight and recommending field quarantine measures.

- Health Score Evolution: Started as At-Risk, declined to Critical because of Bacterial Blight spread, and rebounded to At-Risk under simulated interventions.

The system is shown to be able to detect disease, produce appropriate alerts, and track health scores over time via these case studies. Results point to the practical applicability of the proposed framework supporting farmers in more efficient management of crop health.

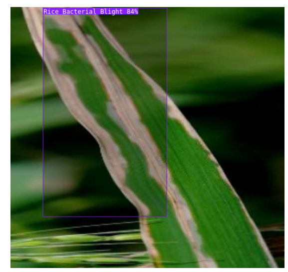

Fig. 7. Rice Bacterial detection in rice leaf

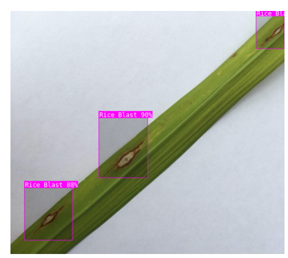

Fig. 8. Rice Blast Blast detection in rice leaf

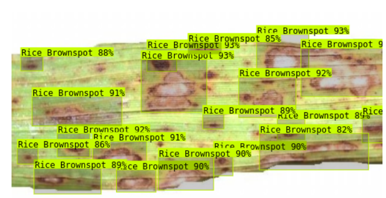

Fig. 9. Rice Brown detected in rice leaf

VI. Discussion

A. Analysis of Results

The results obtained from the YOLOv11 model demonstrate its effectiveness in detecting rice crop diseases with reasonable accuracy. The model achieved a Box Precision (P) of 0.649 and a Box Recall (R) of 0.569, indicating its ability to correctly identify and locate diseases within images. The mAP50 of

0.626 suggests that the model performs well when considering a 50% overlap threshold for true positives. However, the mAP50–95 of 0.33 indicates room for improvement in detecting diseases across a range of overlap thresholds.

B. Comparison with Existing Solutions

Compared to existing solutions, the proposed framework offers several advantages. Unlike drone-based systems, which are expensive to acquire and maintain, our system reuses existing low-cost field cameras or drone/UAV-captured images with geotagged metadata. This significantly reduces the initial investment required by farmers. Mobile app-based systems, while more accessible, often lack real-time alerting capabilities and may not be user-friendly for non-literate users. Our framework addresses this by incorporating a localized IVR system for voice alerts, ensuring accessibility for all farmers regardless of literacy level.

C. Benefits of the Proposed System

The proposed system provides farmers with a comprehensive solution for disease detection and management. The real-time detection capabilities enable early intervention, potentially reducing yield losses and improving crop quality. The voice alerts and health scoring system offer actionable insights, helping farmers make informed decisions about their fields. Furthermore, the system's ability to operate in low-bandwidth environments makes it suitable for rural areas where internet connectivity may be limited.

D. Limitations and Future Work

While the proposed system demonstrates promising results, there are limitations that need to be addressed. The model's recall and mAP50–95 can be improved with further training on augmented datasets and potential adjustments to the model architecture. Additionally, the system currently focuses on three major rice diseases. Future work could expand the detection capabilities to include more diseases. Real-world deployment and validation with farmers will also be crucial to ensure the system meets their practical needs.

E. Conclusion

The proposed framework represents a significant advancement in AI-driven agricultural solutions for small-scale farmers. By combining real-time disease detection, localized voice alerts, and field health monitoring, it provides a powerful tool for improving rice crop management. The system's cost-effectiveness, accessibility, and practicality position it as a valuable asset in the fight against crop diseases and food insecurity.

References

[1] Bacterial Leaf Blight of Rice. (n.d.). Mechanism of Rice Resistance to Bacterial Leaf Blight via Phytohormones. MDPI. https://www.mdpi.com/2223-7747/13/18/2541
[2] Rice Blast Disease. (n.d.). Rice Blast. American Phytopathological Society. https://www.apsnet.org/edcenter/pdlessons/Pages/RiceBlast.aspx
[3] Brown Spot of Rice. (n.d.). GRDB. https://grdb.gy/wp-content/uploads/2016/09/Brown-Spot-of-Rice.pdf
[4] G. More, O. Patil, O. More, M. More, S. Suryavanshi, and M. Mali, 'Comparison of object detection algorithms CNN, YOLO and SSD'.
[5] S. Vijayan and C. L. Chowdhary, 'Hybrid feature optimized CNN for rice crop disease prediction', Sci. Rep., vol. 15, no. 1, p. 7904, Mar. 2025.
[6] Li, P.; Zhou, J.; Sun, H.; Zeng, J. RDRM-YOLO: A High-Accuracy and Lightweight Rice Disease Detection Model for Complex Field Environments Based on Improved YOLOv5. Agriculture 2025, 15, 479. https://doi.org/10.3390/agriculture15050479
[7] M. Islam, A. Azad, S. E. Arman, S. A. Alyami, and M. M. Hasan, 'PlantCareNet: an advanced system to recognize plant diseases with dual-mode recommendations for prevention', Plant Methods, vol. 21, no. 1, p. 52, Apr. 2025.
[8] Ngugi, H. N., Ezugwu, A. E., Akinyelu, A. A., & Abualigah, L. (2024). Revolutionizing crop disease detection with computational deep learning: a comprehensive review. Environmental monitoring and assessment, 196(3), 302. https://doi.org/10.1007/s10661-024-12454-z
[9] A. Batool, J. Kim, and Y.-C. Byun, 'A compact deep learning approach integrating depthwise convolutions and spatial attention for plant disease classification', Plant Methods, vol. 21, no. 1, p. 48, Apr. 2025.
[10] R. Mahbub, S. Shafiq Anuva, I. Towhid Khan, and Z. Islam, 'A comparative analysis of efficient convolutional neural network based methods for plant disease classification', in 2022 25th International Conference on Computer and Information Technology (ICCIT), Cox's Bazar, Bangladesh, 2022.
[11] Chakraborty, S.K., Chandel, N.S., Jat, D. et al. Deep learning approaches and interventions for futuristic engineering in agriculture. Neural Comput & Applic 34, 20539–20573 (2022). https://doi.org/10.1007/s00521-022-07744-x
[12] Diana Susan Joseph, Pranav M Pawar, and Rahul Pramanik. 2022. Intelligent plant disease diagnosis using convolutional neural network: a review. Multimedia Tools Appl. 82, 14 (Jun 2023), 21415–21481. https://doi.org/10.1007/s11042-022-14004-6
[13] M. Shoaib, A. Sadeghi-Niaraki, F. Ali, I. Hussain, and S. Khalid, 'Leveraging deep learning for plant disease and pest detection: a comprehensive review and future directions', Front. Plant Sci., vol. 16, p. 1538163, Feb. 2025.
[14] Upadhyay, A., Chandel, N.S., Singh, K.P. et al. Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. Artif Intell Rev 58, 92 (2025). https://doi.org/10.1007/s10462-024-11100-x
[15] GitHub - AsutoshDalei/Surveillance-Detection: A real-time object detection system using YOLOv5 and OpenCV. https://github.com/AsutoshDalei/Surveillance-Detection
[16] Rajan, M., Parameswaran, L. Key frame extraction algorithm for surveillance videos using an evolutionary approach. Sci Rep 15, 536 (2025). https://doi.org/10.1038/s41598-024-84324-0
[17] Pangavhane, M., Patil, R., Bharati, R., Gupta, D., Ahire, P., Patil, P., Rahane, W., Dharrao, D. (2025). Real-time deep learning-driven surveillance with spatiotemporal feature extraction for detection of anomalous human behavior across dynamic environments. International Journal of Safety and Security Engineering, Vol. 15, No. 1, pp. 105-111. https://doi.org/10.18280/ijsse.150112
[18] Aiad, 'rice Dataset', Roboflow Universe. Roboflow, Dec-2022. https://universe.roboflow.com/aiad-sr31k/rice-9zz0g