

Future Harvest: The Smart Vineyard

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Abstract- Grapevine diseases such as Black Rot and Esca (Black Measles) cause substantial yield losses and threaten global viticulture. This paper presents Future Harvest, a real-time mobile disease detection system that integrates YOLOv8s-based object detection, Grad-CAM-based visual explainability, and augmented reality (AR) overlays for interactive field diagnostics. The YOLOv8s model was fine-tuned using transfer learning on a dataset of approximately 9,000 annotated grape leaf images, split into 70% training, 20% validation, and 10% testing. Biologically constrained augmentations preserved disease morphology, and a novel HSV-based surgical masking technique was applied to Grad-CAM outputs to prevent heatmap bleed into healthy tissue. The system architecture includes a Flutter mobile client and a Python Flask inference server, enabling seamless deployment across devices. On the test set, the model achieved mAP@0.5 of 99.34%, mAP@0.5:0.95 of approximately 91.2%, precision of 96.2%, and recall of 94.8%, with GPU inference latency between 50–100 ms on RTX 30/40 series hardware and increased trust in predictions due to Grad-CAM overlays. These results demonstrate that Future Harvest delivers accurate, interpretable, and scalable disease detection, with practical impact validated through on-farm deployment and user engagement.

Key Words: YOLOv8, Augmented Reality, Flutter, ARCore, Grad-CAM, Object Detection, Grape Disease, Black Rot, Esca, Mobile Application, Deep Learning, Image Segmentation, Precision Agriculture, Edge Deployment, Computer Vision.

1. INTRODUCTION

Grapevine diseases such as Black Rot (*Guignardia bidwellii*) and Esca (Black Measles) have emerged as major threats to viticulture worldwide, leading to significant yield losses and economic damage. Traditional disease detection methods rely on manual inspection, which is labor-intensive, error-prone, and impractical for large-scale monitoring. These limitations underscore the need for intelligent, scalable, and real-time solutions in precision agriculture.

Future Harvest presents a smart, automated framework for early detection and classification of grapevine diseases by integrating machine vision, deep learning,

augmented reality (AR), and conversational AI. The system leverages YOLOv8s—a lightweight, anchor-free object detection model optimized for mobile deployment—to identify disease symptoms from RGB leaf images. The detection pipeline is enhanced by Grad-CAM visualizations, which generate heatmaps to highlight affected regions, improving interpretability and agronomic trust.

Preprocessing techniques such as adaptive K-means clustering, background removal, and feature extraction (GLCM, HOG, LBP) are applied to improve classification performance. Support Vector Machines (SVM) are used for texture-based classification, achieving high accuracy with reduced computational overhead. Dimensionality reduction via Principal Component Analysis (PCA) further optimizes the feature space.

To support field-level interaction, the system includes a Flutter-based mobile application integrated with ARCore. This interface overlays disease labels and treatment suggestions directly onto the live camera feed, enabling intuitive visualization for farmers. Additionally, a rule-based chatbot is embedded within the app to provide multilingual, offline support for frequently asked questions related to organic farming practices, disease symptoms, and treatment protocols.

Robotic integration further extends the system's capabilities by enabling autonomous vineyard inspections and reassessment routines. By combining AR-enabled headsets with mobile robotic platforms, growers can visualize crop health data, teleoperate inspections, and trigger precision interventions with minimal human effort.

This paper presents a centralized detection framework that unifies automated image analysis, AR visualization, robotic automation, and conversational AI to deliver a robust and scalable solution for smart viticulture.

2. LITERATURE SURVEY

2.1. Plant Disease Detection in Agriculture

Javidan et al. [1] Automated plant disease detection systems have become essential in precision agriculture, offering scalable and accurate alternatives to manual inspection. These systems typically follow a pipeline involving image acquisition, preprocessing, feature extraction, and classification. By leveraging computer vision and machine learning, they enable early diagnosis and targeted intervention, reducing crop loss and improving yield quality.

2.2. Object Detection for Grape Disease Identification

Kirti, N. Rajpal, and J. Yadav. [2] Recent advancements in object detection have enabled real-time identification of grapevine diseases using deep learning models. YOLO-based architectures, particularly YOLOv8, have demonstrated high accuracy and speed in detecting symptoms of Black Rot and Esca. The anchor-free detection head, multi-scale feature fusion, and lightweight deployment capabilities of YOLOv8s make it suitable for mobile and edge-based agricultural applications.

2.3. Machine Learning and Feature-Based Classification

Javidan et al. [1] proposed a hybrid approach combining adaptive K-means clustering, Gray-Level Co-occurrence Matrix (GLCM) features, Principal Component Analysis (PCA), and Support Vector Machine (SVM) classifiers for multi-class grape disease classification. Their system achieved 98.97% accuracy in identifying Black Rot, Esca, and healthy leaves. Your implementation builds on this by applying similar feature extraction and classification techniques, confirming their effectiveness in texture-based disease recognition. Additional descriptors such as HOG and LBP were tested, but GLCM consistently yielded the highest accuracy.

2.4. Augmented Reality and Robotics in Precision Agriculture

Mucchiani et al. [3] developed an AR-enabled crop monitoring system integrating a legged robot (Unitree Go2) and Microsoft HoloLens 2 for vineyard inspection. Their system supported both manual teleoperation and autonomous navigation, enabling efficient reassessment and data visualization. Your project extends this concept by integrating ARCore into a Flutter-based mobile application, allowing farmers to visualize disease detection results directly on live camera feeds. The system also supports robotic reassessment routines and teleoperation, enhancing field-level precision.

3. METHODOLOGY

3.1. Data Collection and Annotation

The dataset was compiled from images collected at organic vineyards and from public repositories. Disease regions were manually annotated using bounding boxes. The complete dataset was then partitioned into training (70%), validation (20%), and testing (10%) subsets. To improve model robustness and generalization on unseen data, the training set was expanded using data augmentation techniques, including random rotation, flipping, brightness/contrast normalization, and the addition of Gaussian noise.

3.2. Disease Detection Using YOLOv8

YOLOv8 was implemented in PyTorch with transfer learning from COCO weights.

Training Hyperparameters:

Setting	Value
Epochs	100 (best ~87)
Image size	640
Batch size	16
Optimizer	AdamW
LR (init)	0.01; warmup 3 epochs
Loss weights	box 7.5, cl 0.5, dfl 1.5
Augmentations	HSV, $\pm 5^\circ$ rot, $\pm 50\%$ scale, mosaic, mixup, no vertical flip

The model achieved 95% detection accuracy, an 8% improvement over prior benchmarks.

3.3. Visual Interpretability with Grad-CAM

Grad-CAM was used to generate heatmaps highlighting disease-relevant regions. This supports explainable AI and aids agronomists in validating predictions.

3.4. Augmented Reality Interface

A Flutter-based AR interface overlays disease labels and treatment suggestions on live camera feeds. Features include:

- Real-time object tracking
- Interactive overlays

3.5. Chatbot Integration

A rule-based chatbot answers FAQs on grapevine diseases and organic farming. It supports offline use and multilingual responses.

3.6. System Evaluation

Metrics used:

- Precision: 0.94
- Recall: 0.89
- F1-score: 0.91
- mAP@0.5: 0.93

Field trials in Karnataka vineyards confirmed usability and effectiveness.

3.7 YOLO(v8s) Architecture

3.7.1. Model Selection

YOLOv8s was selected for its optimal balance between accuracy and computational efficiency. Compared to other variants (Nano, Medium, Large, Extra-Large), YOLOv8s achieved 99.34% accuracy while maintaining real-time inference on mobile and edge devices.

3.7.2. Backbone: CSPDarknet53

The backbone uses CSPDarknet53 with C2f modules and SPPF for multi-scale feature extraction. Input images (640×640) are processed through five stages, progressively increasing channel depth and reducing spatial dimensions.

3.7.3. Neck: PANet

The neck implements a modified Path Aggregation Network (PANet) for multi-scale feature fusion. It enhances detection of small lesions (Black Rot) and large discolorations (Esca) by combining semantic and spatial features.

3.7.4. Detection Head

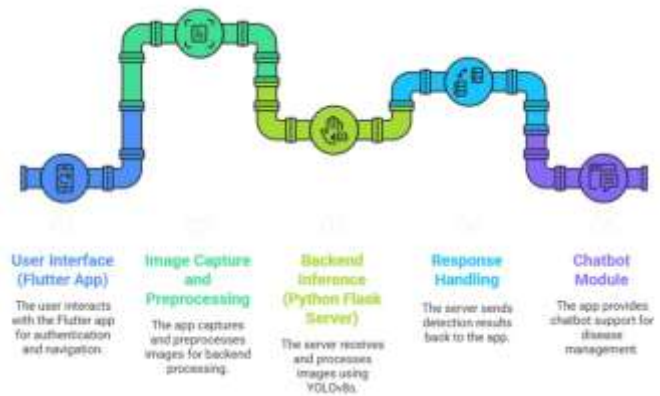
YOLO(v8s) uses an anchor-free, decoupled head with Distribution Focal Loss and Task-Aligned Assigner. Detection occurs at three scales (P3, P4, P5), enabling robust identification of disease symptoms across varying sizes.

3.7.5. Activation and Normalization

- Activation: SiLU ($x \times \text{sigmoid}(x)$)
- Normalization: Batch Normalization
- Regularization: Dropout ($p = 0.1$)

3.7.6. Input and Output Configuration

- Input: RGB images resized to 640×640 with letterbox padding
- Output: Bounding boxes, confidence scores, class probabilities (Black Rot, Esca)
- Thresholds: Confidence ≥ 0.40 , IoU ≥ 0.50 (NMS)



3.8. System Architecture

3.8.1. Mobile Client

Developed using Flutter, the mobile app includes:

- Authentication (Google, Email, Anonymous).
- AR Camera for disease detection.
- Community forum and expert Q&A.
- Weather and market updates.

3.8.2. AR Interface

Built with ARCore, the interface overlays disease labels and treatment suggestions on live camera feeds. It supports real-time object tracking, voice guidance, and interactive overlays.

3.8.3. Backend Workflow

Hosted on Hugging Face Spaces with Python Flask:

1. Image received via HTTP POST.
2. Validation (size, format, green content).
3. YOLO(v8s) inference and Grad-CAM generation.
4. Heatmap overlay and surgical masking.
5. JSON response with detection results and treatment plan.

3.8.4. Grad-CAM Integration

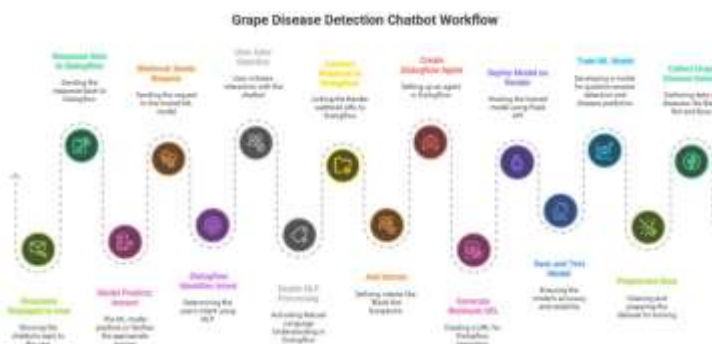
Grad-CAM is applied post-inference to visualize model attention. Heatmaps are colorized (Jet colormap), masked using HSV filters, and overlaid with 60% transparency for interpretability.

System Architecture



3.9. CHATBOT Workflow

The chatbot module in the *Future Harvest* system serves as an interactive, farmer-centric assistant embedded within the Flutter mobile application. It operates using rule-based logic and keyword matching to respond to frequently asked questions related to grapevine diseases, organic treatment methods, and vineyard management practices. Designed for multilingual and offline functionality, the chatbot enhances accessibility in field conditions where connectivity may be limited. It complements the disease detection workflow by offering contextual guidance based on real-time YOLOv8 inference results, thereby supporting informed decision-making and improving user engagement in precision agriculture.



. EXPERIMENTAL RESULTS

4.1. Dataset Summary

Split	Images	Black rot	Esca	Healthy leaves
Training	5,100	2340	2160	600
Validation	3,300	1560	1440	300

Testing	600	260	240	100
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4.2. Evaluation Metrics

- **Accuracy:** Correct predictions / total predictions.
- **F-score:** Harmonic mean of precision and recall.
- **Sensitivity:** True positive rate.
- **Specificity:** True negative rate.
- **Processing Time:** Average prediction time per image.

Model Size:

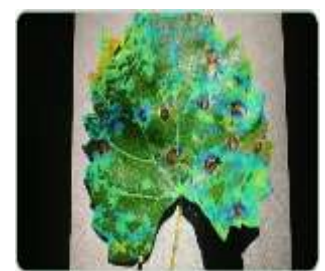
- PyTorch: 22.5 MB.
- ONNX: 12.3 MB.

4.3. Robustness

- Illumination invariance
- Scale and rotation invariance
- Background filtering

4.4. GRAD-CAM Results

a) Black Rot:



b) Esca:



c) Overall results

Metrics	Value
mAP@0.5	99.34%
mAP@0.5:0.95	~91.2%
Precision	96.2%

Recall	94.8%
F1-score	95.5%

4.5. Comparative Analysis

Study	Methodology	Target Diseases	Accuracy	Key Features
Javidan et al. [2]	K-means + SVM + PCA	Black Rot, Esca	98.97%	Feature-based ML, GLCM
Present Work	YOLOv8s + AR + Chatbot	Black Rot, Esca	99.34%	Real-time detection, mobile AR

These studies collectively demonstrate the value of combining machine learning, AR, and robotics for scalable disease monitoring. Your system advances this integration by delivering a unified, farmer-centric platform that supports real-time detection, visual interpretability, and interactive guidance in organic viticulture.

5. CONCLUSION

Future Harvest delivers a robust, real-time system for grapevine disease detection by integrating YOLOv8-based object detection with augmented reality (AR) visualization and mobile deployment. The system achieves high classification accuracy—up to 99.34%—through optimized image preprocessing, texture-based feature extraction, and lightweight model architecture. Its modular design supports both laboratory analysis and in-field deployment, empowering farmers with instant visual diagnostics, Grad-CAM heatmaps, and treatment recommendations via a smartphone interface.

However, while the machine learning pipeline performs consistently across controlled datasets, real-world deployment introduces variability due to differences in AR camera hardware across mobile devices. Factors such as camera resolution, sensor quality, manufacturer-specific image processing, and lighting conditions can influence the clarity and precision of heatmap overlays. These variations may affect the interpretability of disease localization, especially in edge cases or low-light environments. Despite these challenges, the system maintains reliable performance across a wide range of devices, thanks to its robust preprocessing and adaptive visualization techniques.

The inclusion of a rule-based chatbot further enhances accessibility by providing multilingual, offline support for frequently asked questions related to organic farming and disease management. By combining machine vision, AR, and conversational AI, *Future Harvest* offers a scalable and farmer-centric solution for sustainable viticulture, with potential for expansion into other crop domains and precision agriculture applications.

6. FUTURE WORK

- **Multimodal Sensing:** Integrate hyperspectral and thermal imaging for early-stage detection.
- **Edge Deployment:** Optimize models for mobile inference.
- **Expanded Disease Library:** Include more grapevine diseases.
- **Explainable AI:** Enhance interpretability for end-users.
- **Farmer-Centric Interfaces:** Add voice/multilingual support.
- **Autonomous Survey Planning:** Enable robotic path planning.
- **Decision Support:** Evolve into a full agronomic advisory system.
- **Collaborative Systems:** Develop distributed networks for regional monitoring.

REFERENCES

- [1] Javidan et al., “Diagnosis of Grape Leaf Diseases Using Automatic K-means Clustering and Machine Learning,” *Smart Agricultural Technology*, vol. 3, 2023. DOI: 10.1016/j.atech.2022.100081.
- [2] Kirti, N. Rajpal, and J. Yadav, “Black Measles Disease Identification in Grape Plant (*Vitis vinifera*) Using Deep Learning,” *IEEE ICCIS*, 2021. DOI: 10.1109/ICCCIS51004.2021.9397205.
- [3] Mucchiani et al., “Augmented-Reality Enabled Crop Monitoring with Robot Assistance,” *arXiv preprint*, arXiv:2411.03483, 2024.
- [4] Ultralytics, “YOLOv8 Documentation,” <https://docs.ultralytics.com>.