AI-Enabled Reconfigurable Edge Device for Plant Health Assessment in Greenhouse Environment

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Abstract

Timely detection of plant diseases in greenhouse environments is essential for minimizing crop loss, reducing chemical use, and supporting sustainable production. This paper presents an AI-enabled, reconfigurable edge device designed for leaf-level disease assessment using multimodal sensing and embedded intelligence. A 3D-printed handheld prototype was developed with a custom PCB integrating VIS/NIR spectral sensors, a thermal module, and an RGB camera for noninvasive measurement of physiological stress. A lightweight deep learning model combined with handcrafted spectral indices performs fully on-device analysis to detect early indicators such as abnormal thermal patterns, pigment loss, and reflectance changes linked to infections. The system is built on a low-power Raspberry Pi platform and supports model reconfiguration for rapid adaptation to different crops and disease types. Real-time inference is achieved through a segmentation-based pipeline deployed on both an Android app and an Ubuntu graphical interface. Validation trials demonstrated early disease detection with 86.4% accuracy with previously collected images and an average latency of 2.52 seconds on Android and 2.19 seconds on Ubuntu. We are currently calibrating our framework in the greenhouse environment for real-time assessments. A web dashboard provides live visualization of thermal overlays, spectral response, and health scores. By combining custom hardware, multimodal sensing, and on-device AI, the system offers a portable and scalable solution for early disease detection in greenhouse crops.

Introduction

Accurate plant health monitoring is essential in modern greenhouse farming, which plays a key role in global food security. While greenhouses support year-round cultivation, high humidity and poor airflow can accelerate disease spread. Early detection is therefore critical to prevent crop loss, reduce chemical use, and maintain yield quality (Allali et al. 2025). Keeping plants healthy boosts productivity and sustainability by reducing water, nutrient, and pesticide use, which is increasingly important as global food demands rise (Xing, Wang, and Mustafa 2025). Modern tools such as computer vision, multispectral and thermal imaging, and environmental sensors provide real-time stress detection and can identify early disease or nutrient issues before visible symptoms appear (Borah et al. 2025). Traditional monitoring depends on visual checks and lab tests, which are slow and error-prone (Buja et al. 2021), highlighting the need for faster automated systems. AI and edge computing address this gap. Deep learning models can assess health, detect weeds, and classify diseases accurately (Karunathilake et al. 2023), while edge devices process data locally to reduce delays and bandwidth needs (Gill et al. 2025). These systems can give immediate alerts or adjust irrigation and lighting in real time (Borah, Khanal, and Sundaravadivel 2024). Advances now enable AI on compact hardware like Raspberry Pi, NVIDIA Jetson, and FPGA-based accelerators, offering faster results with lower energy use (Bansal et al. 2025). Reconfigurable hardware such as FPGAs and SoCs can adjust to changing greenhouse conditions, making them effective for real-time plant health management.

Therefore, this paper introduces an AI-powered, reconfigurable edge device designed for early leaf-level disease detection in greenhouse crops. The handheld system combines visible (VIS), near-infrared (NIR), and thermal imaging sensors to capture detailed physiological signals from plants. By analyzing patterns such as abnormal heat distribution, pigment loss, and spectral changes, the device can identify early signs of disease, even before visible symptoms appear. With on-device AI processing and adaptable hardware, it offers real-time, actionable feedback to growers, supporting faster decisions and promoting more sustainable and efficient greenhouse management.

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Related Work

AI and deep learning have greatly improved plant disease diagnosis. Convolutional Neural Networks (CNNs) are now widely used because they can automatically extract key features from leaf images (Natarajan, Chakrabarti, and Margala 2024). Early studies showed high accuracy in identifying plant diseases under controlled conditions using models like AlexNet, GoogLeNet, and VGG on crops such as cucumbers, bananas, cassava, and tomatoes (Sladojevic et al. 2016; Lu, Tan, and Jiang 2021; Bhuyan and Singh 2024). However, performance often declines in real-world settings due to changing light, overlapping leaves, and faint early symptoms (Khan et al. 2024). To address this, researchers use transfer learning to adapt pre-trained models for specific plant datasets, cutting training time and improving accuracy (Shafik et al. 2024). Lightweight models such as MobileNetV2 and MobileNetV3-small also make on-field deployment feasible by using fewer resources (Chen et al. 2024). These advances are helping shift plant disease detection from cloud-based systems to faster, device-level processing in the field. Edge computing plays an important role by handling data close to where it is collected (Mohith et al. 2025). In smart greenhouses, edge devices locally process data from environmental sensors to enable immediate control actions and efficient plant health monitoring (Nguyen, Nguyen, and Gia 2024). Most existing studies rely on cloud-based processing and do not integrate multimodal imaging with reconfigurable edge hardware, limiting scalability and real-time responsiveness. This gap highlights the need for low-power, on-device systems capable of localized sensing and decision-making.

System Architecture

Overview of the Proposed System

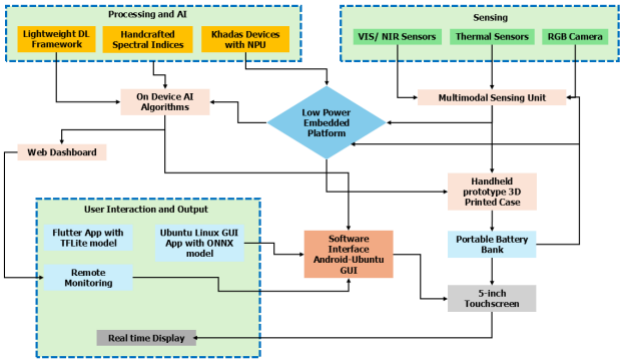


Figure 1: Architecture of an edge device combining sensors, local processing, and real-time interaction for greenhouse plant monitoring.

The system architecture (Figure 1) comprises four layers: sensing, processing, AI integration, and user interaction. A multimodal sensing unit combining VIS/NIR, thermal, and RGB sensors captures plant-level spectral and temperature data, which are processed on a low-power Khadas platform with an integrated NPU for efficient on-device inference. Lightweight deep learning models and handcrafted spectral indices extract features and detect disease symptoms without cloud dependency. A reconfigurable software interface supports deployment on Android and Ubuntu systems with GUI-based visualization and dashboard integration. Results are displayed on a 5-inch touchscreen, and the portable, battery-powered, 3D-printed design ensures suitability for greenhouse environments.

AI Model Integration on Hardware

The AI models are integrated into the hardware prototype using two methods. The first is a Flutter-based mobile application that runs TensorFlow Lite (TFLite) models on low-power Android devices. The second uses an Ubuntu Linux setup on the prototype to run ONNX models for functional testing and software development. This configuration includes a GUI that manages the main application workflow and communicates with the AI models.

Flutter Application

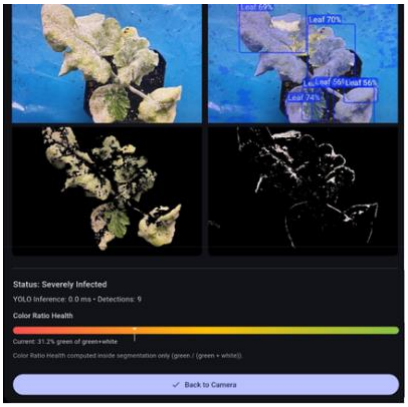


Figure 2: Mobile app interface displaying original image, leaf detection, segmentation, and color-based health score.

The mobile interface is built as a cross-platform Flutter application, allowing deployment on Android while remaining compatible with iOS, Linux, and other platforms. The app integrates a TFLite segmentation model to perform on-device YOLO inference for plant health analysis. It supports real-time camera capture, plant segmentation, and calculation of a color-based health score using the green-to-white pixel ratio. Images and processed outputs are stored locally, with options to import external images and export results to the public gallery. A built-in gallery lets users review and analyze previous captures, and the preview

screen displays inference results, overlays, processing times, and health indicators. Field testing showed stable, low-latency performance, and Flutter's cross-platform design supports future scalability. Figure 2 illustrates the real-time analysis interface showing detection, segmentation, and health scoring on previously collected images. Performance may be affected by lighting variations, and the color-ratio method can underestimate severe infections when mixed yellow-green regions are present. To improve reliability, AI-based scores are combined with color-ratio outputs for final assessment.

Ubuntu Linux GUI application

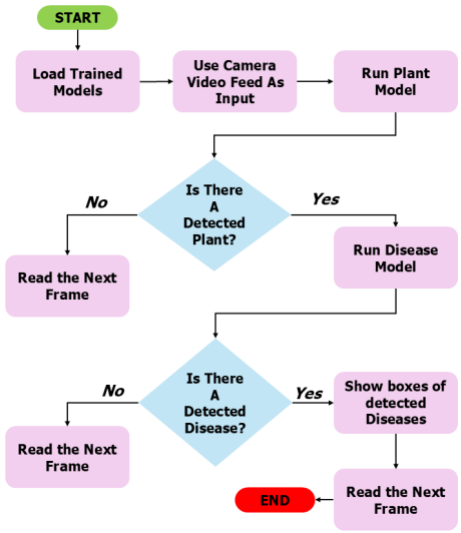


Figure 3: Workflow of the real-time plant and disease detection pipeline using video feed input.

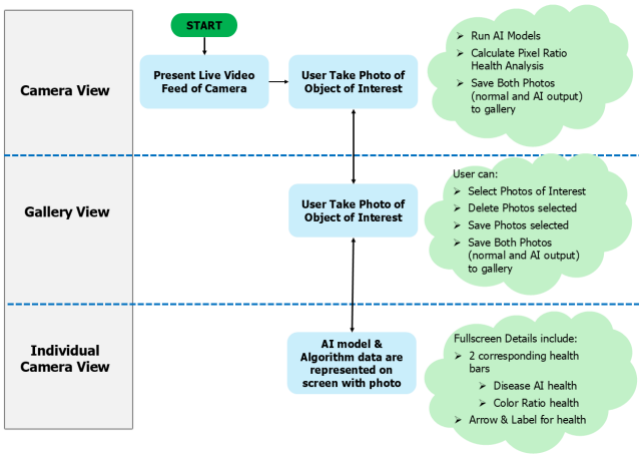


Figure 4: User interaction flow with AI-based plant health analysis and output visualization.

Figure 3 shows the real-time disease detection pipeline on the AI-enabled edge device. Live video frames from the RGB camera are processed on-device using a lightweight model, beginning with background removal and color segmentation. The segmented image is then analyzed for disease indicators such as powdery mildew. The YOLOv8 segmentation model classifies and highlights infected regions, producing visual overlays and an infection score that appear instantly on the touchscreen or remote dashboard. This enables real-time monitoring without cloud access. Figure 4 presents the user interface workflow. Users can capture new images or select existing ones from the gallery, after which the on-device AI model analyzes the leaf for disease symptoms. The system displays infec-tion masks, health scores, and severity levels on the touchscreen, with options to zoom, compare images, and view thermal or spectral overlays. This streamlined flow supports intuitive, interactive monitoring for growers and researchers in real-world greenhouse settings.

Materials and Methods

Data Acquisition

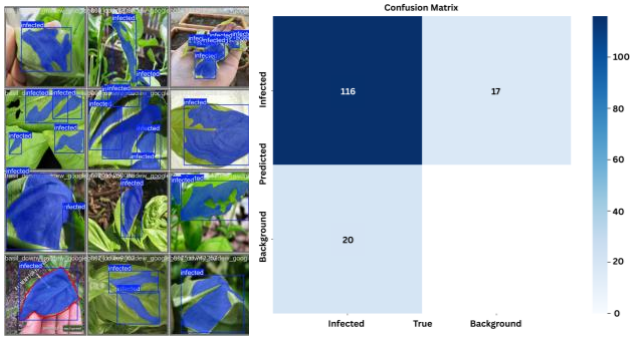
Figure 5: Annotated watermelon leaf with outlined regions.

The dataset consisted of RGB images of watermelon and tomato leaves captured under controlled greenhouse conditions to ensure consistent lighting and background. Both healthy and powdery mildew–infected plants were included, with images taken at various infection stages to support severity-level classification. Photographs were acquired using a high-resolution camera mounted on the AI-enabled handheld prototype, with fixed distance and orientation for uniformity. Each plant was imaged from multiple angles to improve robustness and account for variations in leaf position and appearance. Images were organized into separate folders representing different conditions and manually labeled into four health categories: very healthy, mildly infected, moderately infected, and severely infected, based on visual symptoms, color differences, and expert feedback. Annotation was performed using Labelme, which enables precise segmentation compared to box-based tools such as LabelImg. Segmentation outlines were drawn closely around each leaf to accurately measure pixel areas, supporting green-to-white ratio analysis and improving disease detection accuracy. The annotated dataset was used for both traditional image analysis and training the YOLOv8 segmentation model.

Figure 5 shows an example annotated leaf with diseased regions highlighted in red.

AI model Development

The YOLOv8-Seg model was trained on a manually annotated dataset of ~150 images of leaf samples using a standard train, validation, test split (70/20/10). During training, common augmentations such as brightness variation, rotation, and blur were used to improve robustness. The workflow begins by isolating the plant region, segmenting healthy (green) and infected (white) areas, and computing green-to-white pixel ratios that act as early health indicators. This traditional stage uses blob detection, morphological operations, and HSV-based segmentation, with masks stored in CSV format for quantitative analysis. This foundation is combined with an AI-based method using YOLOv8-Seg, trained for 250 epochs with a batch size of 16, achieving over 90 percent precision, about 83 percent recall, an mAP@0.5 above 89 percent, and an mAP@0.5–0.95 near 70 percent. The model captures complex disease patterns and generates accurate infection masks with metrics such as infected area, count, and healthy-to-diseased ratios, while keeping processing times between 1.2 and 1.9 milliseconds. PCA is applied to analyze variance trends and cluster samples by severity, and a final health score is assigned using AI outputs and color-ratio thresholds, categorized into very healthy, mildly infected, moderately infected, and severely infected. PCA was applied as an exploratory analysis tool to visualize how the features extracted from the segmented leaves separate across severity levels. Although not used for prediction, it helped confirm that healthy, mildly infected, moderately infected, and severely infected samples form distinct clusters, supporting the consistency of the scoring method.



(a) (b)

Figure 6: (a) YOLOv8-Seg leaf segmentation output highlighting infected regions used for leaf-level analysis, (b) Normalized confusion matrix from the test split showing distinguishing infected regions from background.

Figure 6(a) shows leaf segmentation results from the YOLOv8-Seg model, while Figure 6(b) presents the normalized confusion matrix for the YOLOv8-Seg infection detection model evaluated on the test dataset. The matrix illustrates the model's ability to correctly distinguish infected regions from background areas, highlighting the distribution of true positives, false positives, and false negatives. Figure 7 displays the GUI results, including the original image, color-based segmentation, and both AI-generated and ratio-based health scores, offering consistent visual and quantitative assessment.

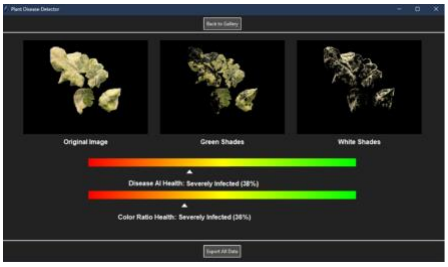
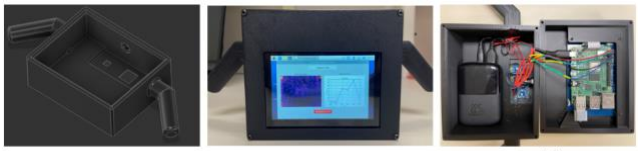


Figure 7: GUI showing original, green, and white leaf regions with predicted and color ratio-based health scores.

Hardware Implementation

A portable handheld device was developed with the primary goal of capturing plant images and running computer vision models locally as shown in Figure 8. The enclosure was 3D printed with PLA for quick prototyping and easy updates. It includes ergonomic handles for field use and a 5-inch touchscreen compatible with the Khadas VIM3 board, which has a built-in NPU for efficient edge processing. Power is supplied via a widely available portable battery bank, selected for its simplicity and suitability for early-stage prototyping. Future iterations are expected to integrate a custom battery solution. The RGB camera used in this version supports autofocus, ensuring high-quality image capture. A USB-C charging port was added to facilitate convenient charging. In the upcoming MildewID version, the device design has been improved for better grip and usability. A slot for the SparkFun Triad Multispectral Sensor was added to capture a wider spectral range. The case was slightly enlarged to fit new components, including the Arduino Nano, which processes sensor data for on-device analysis.



(a) (b) (c)

Figure 8: Prototype of handheld device showing (a) CAD design, (b) assembled unit with touchscreen and GUI, and (c) internal components including Khadas board, Arduino Nano, RGB camera, and battery.

Comparative Discussion

A comparison with earlier studies (Table 1) shows key differences in sensors, hardware, and applications. Tiny-LiteNet on Raspberry Pi 5 (Nyakuri et al. 2025) is fast (16 ms) with high accuracy (98.6%), but it relies only on RGB images. Thermal-based detection (Correa da Silva and Almeida 2025) works in low light and before symptoms appear, yet it performs only classification and lacks multi-sensor input. A multi-camera fusion method (Marco-Detchart et al. 2023) improves reliability but does not include spectral or thermal data. An IoT grapevine system (Morellos et al. 2024) achieves 92–94% accuracy with segmentation and classification on Raspberry Pi 4, though at slower speeds (330–390 ms). Studies on single-board computers (Routis, Michailidis, and Roussaki 2024) focus mainly on device performance instead of richer sensing. An AI-IoT irrigation system (Ibrahim et al. 2025) offers high accuracy with RGB but targets large farms rather than handheld tools. Low-power edge models for hydroponics (Musa et al. 2022; Kalbande et al. 2024) and MobileNetV3 on Raspberry Pi 4 (Tarek et al. 2022) also depend entirely on RGB. A cloud-based tomato disease detector (Yildiz et al. 2024) is user-friendly but requires internet access. In contrast, our system integrates RGB, VIS/NIR spectral, and thermal imaging in a single handheld edge device, performing both segmentation and classification in real time without cloud support. This multimodal design detects subtle plant health changes earlier and provides richer information than RGB-only systems while remaining practical for greenhouse use.

Table 1: Comparison with earlier related plant health monitoring studies.

Ref.	Sensing	Model Approach	Edge Hardware	Dataset/ Classes	Accuracy/ mAP	Latency
(Nyakuri et al. 2025)	RGB camera	Tiny-LiteNet (1.2MB; 1.48M params)	Raspberry Pi 5	Pests + diseases, multi-crop	98.6% acc; F1 98.4%	16ms
(Correa da Silva and Almeida 2025)	Thermal camera (8-14 µm)	InceptionV3, MobileNetV1/V2, VGG16	RPi 4B + Coral USB TPU + Intel NCS2	New thermal dataset: 15,444 imgs, 7 classes	-	Up to 2.13× speed-up (NCS2); 1.48× (Edge TPU)
(Marco-Detchart et al. 2023)	Multi-camera (multi-view RGB); fusion	Choquet integral fusion over CNN outputs	Edge-AI device (custom)	PlantVillage (87,000 imgs, 38 classes)	-	-
(Morellos et al. 2024)	RGB (field) + Mobile-UNet pre-seg.	MobileNetV2, EfficientNet-B0 + Mobile-UNet	RPi 4	Field videos; winery	94.1% (MV2); 92.4% (EN-B0)	330ms (MV2); 390ms (EN-B0)
(Routis, Michailidis, and Roussaki 2024)	RGB	Custom CNN (33 classes)	RPi3B+, RPi4B, Jetson Nano, Coral TPU	PlantVillage (33 classes)	Focus on device metrics	Inference speed profiled
(Ibrahim et al. 2025)	RGB (pivot system)	ResNet50 (11 classes)	IoT pivot rig	25,940 images	99.8% acc; P/R/F1 ≈ 100%	-
(Musa et al. 2022)	RGB (hydroponics)	KD-compressed shallow network	Embedded/IoT	PlantVillage (39 classes)	99.4% acc	-
(Kalbande et al. 2024)	RGB	MobileNetV2	Sipeed Maixduino (K210)	Tomato (10 classes)	94% (validation)	-
(Tarek et al. 2022)	RGB	MobileNetV3-Small/Large	RPi 4 (and workstation)	Tomato leaves	98.99% (MNV3-S); 99.81% (MNV3-L)	251ms (S), 348ms (L) on RPi 4
(Yildiz et al. 2024)	RGB (mobile app→cloud)	Custom DL (server-side)	AWS Lambda (cloud)	Tomato (Kaggle)	≈96% acc (DL model)	Network-bound
This work	**RGB+VIS/NIR spectral+ Thermal**	**Lightweight DL + spectral indices (on-device)**	**Raspberry Pi (handheld prototype)**	**Greenhouse (watermelon)**	**86.4%**	**Flutter App (Samsung device): 2522 ms (~2.52 s) Ubuntu GUI: 2192 ms (~2.19 s)**

Conclusion

In this work, we presented a portable, AI-enabled, reconfigurable edge device for early detection of plant diseases in greenhouse environments. The system integrates multimodal sensing, VIS/NIR and thermal imaging, together with on-device deep learning to produce real-time leaf-level health assessments. A custom 3D-printed prototype was developed using a Khadas VIM3 board with an integrated NPU, a touchscreen interface, and modular support for future sensors. By combining lightweight deep models with handcrafted spectral indices, the device achieves accurate, low-latency inference suitable for greenhouse deployment without any cloud dependency. The results demonstrate the potential of coupling flexible hardware with AI-driven analysis for scalable and proactive plant-health monitoring. We are currently evaluating the prototype with real-time observations from greenhouse plants, and its reconfigurable design allows adaptation across different crops and disease types. Future work will expand the sensor suite to full-range multispectral and hyperspectral imaging for more precise characterization of

early stress signatures. The findings in this paper are based on a preliminary dataset collected in our UT Tyler facility, with broader real-world validation now in progress. As the current dataset includes only two crops, future studies will incorporate larger multispecies collections and dedicated experiments to quantify the individual contribution of the VIS/NIR and thermal channels.

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