OPEN ACCESS

International
Journal
Of Modern Engineering Research (IJMER)

IoT-Enabled Early Blight Detection System for Tomatoes Using ESP32-CAM

Ahmet Bobrek
Burdur Mehmet Akif Ersoy University, Vocational School of Technical Sciences, TURKIYE.
Corresponding Author: Ahmet Bobrek

Around the world, tomato cultivation suffers substantial production and quality losses due to the tomato early blight disease (Alternaria solani). The disease can cause crop losses of 35% to 78% and shows up as brown-black patches on leaves, stem rot, and fruit rot. Reducing the use of chemicals and encouraging sustainable agriculture depend greatly on early disease identification. Expert knowledge-based visual assessment and laboratory tests are examples of classic sickness diagnosis procedures. These treatments have limitations, such as being expensive, time-consuming, and subject to subjective evaluations. The usage of ESP32-CAM, a low-cost embedded system, for real-time disease diagnosis was studied in this work, along with the use of AI-based image processing algorithms in agricultural decision support operations. Because of its low power consumption, wireless connectivity, and built-in camera capability, the ESP32-CAM module provides continuous monitoring capabilities in field circumstances. Using models constructed using deep learning techniques (CNN, MobileNet, etc.), the system can automatically detect disease symptoms and warn growers in real time. The results suggest that small- and medium-sized producers can benefit from economical smart agriculture systems. The recommended method optimizes spraying schedules and prevents superfluous chemical use by recognizing the disease early with good accuracy rates (85–95%). Additionally, it permits remote monitoring and data analysis through connectivity with IoT infrastructure, which helps precision agriculture techniques become more extensively adopted. This technique is seen as a vital step in promoting environmental and economic sustainability in the transition to digital agriculture.
KEYWORDS: Early Blight Detection, Esp32 Cam, TinyML, Embedded Systems

---

Date of Submission: 05-11-2025 Date of acceptance: 15-11-2025

I. INTRODUCTION

Tomato (Solanum lycopersicum L.) is among the most extensively cultivated and economically significant vegetable crops globally. Nonetheless, it is particularly vulnerable to various fungal infections, with Early Blight, induced by Alternaria solani, being one of the most devastating. The ailment first manifests as dark brown concentric lesions on mature leaves and proliferates swiftly in warm, humid environments, resulting in chlorosis, leaf drop, and a marked decrease in photosynthetic efficiency. Severe infections can result in yield losses of 30–80% [2], presenting a significant risk to both greenhouse and open-field production systems.

Conventional disease detection techniques, including visual field examinations and laboratory analysis, are laborious, costly, and necessitate specialized people, rendering them unfeasible for small-scale farmers. These constraints underscore the pressing want for automated, swift, and economical monitoring and decision-support systems proficient in identifying Early Blight in its nascent phases. Timely identification facilitates targeted treatment of affected regions, decreases pesticide application, and mitigates environmental pollution and financial losses, thereby promoting sustainable agricultural practices [11].

In recent years, the amalgamation of artificial intelligence (AI), deep learning (DL), and computer vision has transformed plant disease diagnostics. Convolutional Neural Networks (CNNs) and models based on transfer learning have demonstrated exceptional precision in identifying and categorizing leaf diseases across various situations. Kılıçarslan and Paçal (2023) performed a comparative analysis utilizing DenseNet-121, ResNet50v2, and MobileNet architectures trained on the PlantVillage dataset, attaining 99% accuracy and an F1-score of 0.9892, with DenseNet identified as the most dependable model [3].Özben and Güler (2025) created a MobileNet-based deep learning system utilizing 16,011 authentic tomato leaf photos, which include nine disease categories and healthy specimens. Of the evaluated models, MobileNetV3-Large attained the best accuracy at 99%, with both precision and recall surpassing 0.97 across all classes. The resultant model was effectively implemented in an Android mobile application for real-time, offline detection, showcasing the viability of edge-based smart agriculture [3]. Terzioğlu et al. (2025) proposed a hybrid approach that combines deep learning feature extraction with machine learning classifiers. The study utilized a dataset of 6,414 tomato photos across five categories (Late Blight, Early Blight, Gray Mold, Bacterial Canker, and healthy samples) to analyze 21 deep learning architectures in conjunction with feature selection algorithms like MRMR, Chi2, and ReliefF. The combination of EfficientNet-b0, Chi2, and Fine KNN attained an accuracy of 92%, underscoring the efficacy and cost-efficiency of hybrid learning methodologies [4]. Molina et al. (2014) previously presented a computer vision method utilizing MPEG-7 color descriptors for the identification of Early Blight. The Color Structure Descriptor (CSD) attained 100% accuracy with 190 expert-annotated leaf areas, demonstrating that even simple color characteristics may effectively differentiate between diseased and healthy tissues without the need for deep networks [6]. Nurlanuly (2024) conducted a comprehensive comparison of DenseNet, ResNet, and GoogleNet using 39,000 plant leaf pictures across 19 disease categories, including Tomato Early and Late Blight. DenseNet attained the best accuracy (99.8%) owing to its dense connectivity and effective feature reutilization, and the research highlighted its appropriateness for mobile, drone, and edge-deployed agricultural AI systems [7]. In addition to deep learning, Bal and Kayaalp (2023) investigated conventional machine learning methods by evaluating several SVM kernel functions on 4,000 tomato leaf images. The RBF kernel attained 90% accuracy, surpassing both linear and polynomial kernels, demonstrating that classical models retain efficacy in limited computing settings [8]. Conversely, Chakravarthy and Raman (2020) progressed beyond image-level categorization by utilizing object detection frameworks. Following the attainment of near-perfect classification accuracy with ResNet (99.73%) and Xception (99.95%), they deployed YOLOv3, YOLOv3-SPP, and YOLOv3-tiny for targeted lesion identification. YOLOv3-SPP attained a mean average precision (mAP) of 90.52%, but YOLOv3-tiny realized real-time inference at 12 ms per image, making it suitable for mobile or embedded systems [9]. Alternative computational methodologies have also arisen. Anam and Fitriah (2021) devised a hybrid Particle Swarm Optimization (PSO)–K-means segmentation method that attained an F-measure of 0.90, significantly surpassing the normal K-means performance of 0.418, and proficiently identifying sick areas in tomato leaves [10]. Xie et al. (2015) similarly shown that hyperspectral imaging (380–1023 nm) integrated with textural analysis could differentiate Early and Late Blight with 97.1% accuracy utilizing an Extreme Learning Machine (ELM) model and only five selected wavelengths (442, 508, 573, 696, 715 nm) [11]. Irmak and Saygılı (2020) developed a bespoke CNN model in Python/Keras utilizing a dataset including 18,345 tomato leaf pictures, categorized into nine disease classes and one healthy class. Their model attained a training accuracy of 97.05% with a test loss of 9.33%, and they proposed enhancing feature extraction to more effectively differentiate visually identical diseases, such as Early and Late Blight [5]. This research collectively indicates that deep learning frameworks, particularly lightweight CNN architectures like DenseNet, MobileNet, and EfficientNet, provide dependable, rapid, and scalable methods for the detection of tomato diseases. Incorporating these models into affordable, portable, and energy-efficient edge devices (e.g., ESP32-CAM or Raspberry Pi) can facilitate widespread AI use in agriculture, allowing for real-time, autonomous Early Blight detection and data-informed decision support for sustainable crop management.

II. MATERIAL AND METHOD

2.1 System Overview

This research presents an economical, edge-computing Early Blight detection system with an ESP32-CAM microcontroller. The system executes on-device inference via a lightweight convolutional neural network (CNN) model built through the Edge Impulse platform. The gadget processes data locally and transmits just categorization results, thereby greatly decreasing bandwidth usage, latency, and energy consumption, rather than sending high-resolution photos to cloud servers. The proposed configuration facilitates real-time disease detection in the field, offering instant input to cultivators and enabling targeted intervention tactics.

Key advantages of the system include:

- On-device inference: Eliminates the need for continuous internet access.
- INT8 quantization: Enhances inference speed and minimizes model memory footprint.
- Low power consumption: Ideal for battery or solar-powered deployments.
- Reduced data transmission: Only diagnostic results are sent, not raw images.

The main components of the tomato leaf disease detection system are summarized in Table 1, including the ESP32-CAM for image acquisition, a quantized Edge Impulse model for real-time classification, and MQTT-based communication with a remote dashboard.

Table 1. Description of system components involved in real-time edge-based tomato leaf classification using ESP32-CAM and Edge Impulse.

Component	Description
ESP32-CAM	Captures tomato leaf images in real-time
Edge Impulse Model	Pre-trained CNN model (quantized to INT8)
Local Inference Engine	Runs the model using TensorFlow Lite Micro
Wi-Fi/MQTT Module	Transmits results to remote dashboard
Mobile App / Web UI	Displays classification and timestamp

Figure 1 presents the complete processing pipeline for on-device plant disease classification using ESP32-CAM and Edge Impulse. The system integrates real-time inference, result visualization, and remote communication via MQTT in a resource-constrained edge environment.

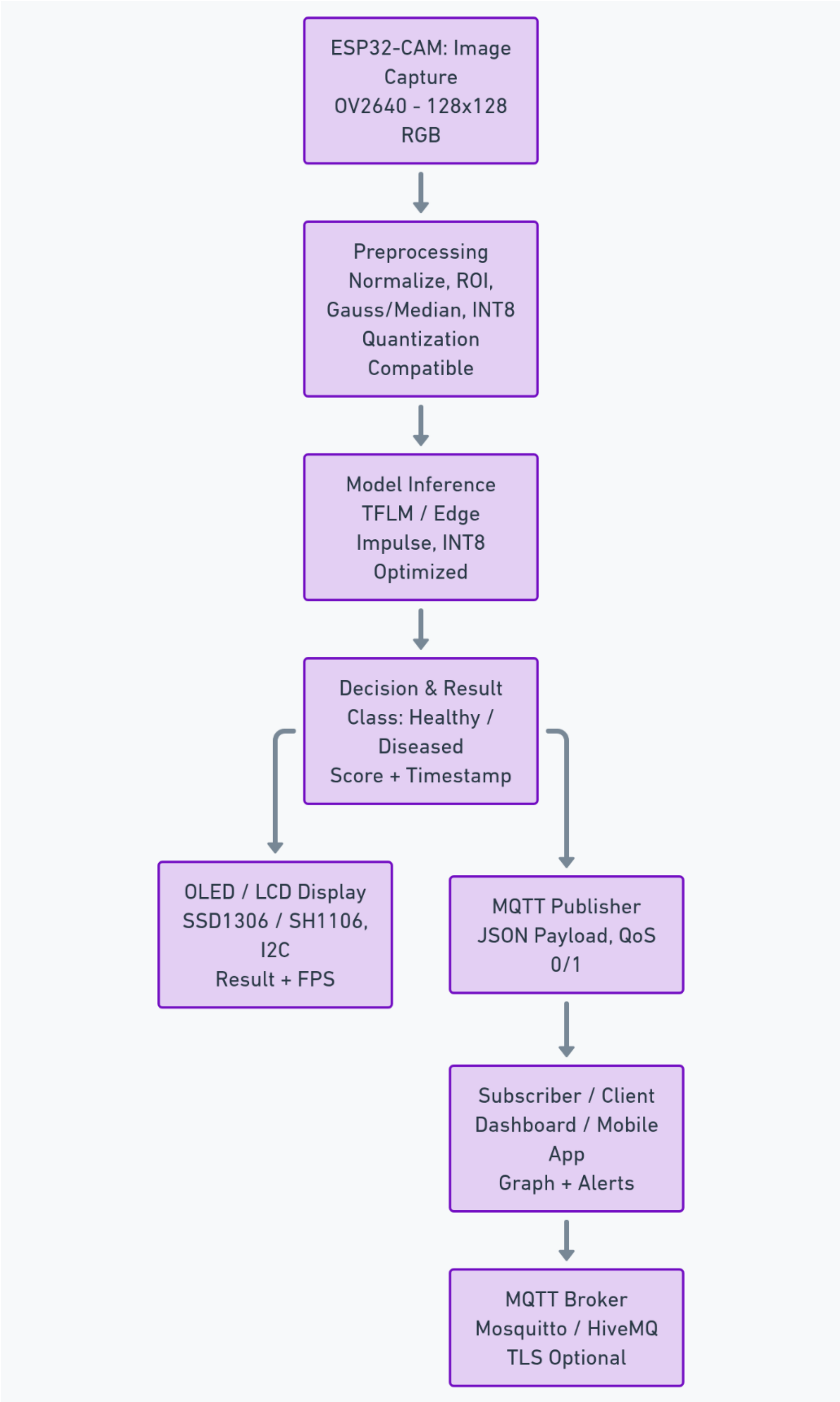

Figure 1. Block diagram of the proposed Early Blight detection system.

1.2 Data Collection and Model Development

The image dataset consisted of Early Blight–infected and healthy tomato leaves, collected under natural greenhouse lighting using the ESP32-CAM module and smartphone cameras for consistency. Images were resized to 96×96 pixels and uploaded to Edge Impulse Studio for preprocessing, labeling, and model training.Additionally, supplementary labeled images were incorporated from the publicly available *Tomato Leaf Disease Dataset* on Kaggle [13], which contains verified samples across multiple disease classes.

1.2.1 Preprocessing

To ensure optimal model performance and robustness, a series of image preprocessing steps were applied prior to training. These steps were designed to standardize input data, account for environmental variability, and improve the model's generalization capability. Specifically:

- Cropping and Resizing: All input images were cropped and resized to a uniform resolution of 96×96 pixels to match the input dimension of the MobileNetV2 architecture.
- Color Normalization: This step compensates for lighting differences across captured images, ensuring that features are not biased due to illumination variation.
- Data Augmentation: To further enhance generalization and reduce overfitting, augmentation techniques such as random rotation (±15°), brightness adjustment (±10%), and horizontal flipping were employed.

These preprocessing operations collectively contribute to the stability and accuracy of the inference process, particularly under varying field conditions where lighting and image composition can fluctuate.

1.2.2 Model Training on Edge Impulse

The neural network was developed using the Edge Impulse Impulse Design platform [12], which provides an end-to-end pipeline for data acquisition, feature extraction, model training, and deployment on embedded devices. Edge Impulse enables developers to create optimized TinyML models suitable for real-time inference on microcontrollers.

Training was conducted using the Adam optimizer with a learning rate of 0.001, batch size of 16, and 45 training cycles (epochs). The training process was executed on the CPU processor with data augmentation enabled to enhance generalization and prevent overfitting. Additionally, INT8 quantization profiling was applied to optimize the model for edge devices, such as the ESP32-CAM, ensuring efficient on-device inference with minimal resource consumption.

The model achieved remarkable performance with a validation accuracy of 98.5% and a loss value of 0.03. The confusion matrix revealed strong class separation, correctly identifying 97.9% of Early Blight and 99.0% of Healthy Leaf samples, with a weighted average F1-score of 0.98. Moreover, the Area Under the ROC Curve (AUC) reached 0.98, confirming the model's high discriminative capability. The data explorer visualization illustrated clear feature clustering between diseased and healthy samples, demonstrating effective feature extraction and decision boundary learning.

Overall, these results validate the quantized MobileNetV2 model's robustness and efficiency for real-time Early Blight detection on resource-limited embedded platforms, confirming its suitability for edge AI agricultural applications.The neural network training configuration and corresponding performance metrics are shown in Table 2.

Table 2. Neural Network Training Configuration and Performance Metrics

Parameter	Value / Setting
Architecture	MobileNetV2 (96×96×3 RGB, depth multiplier 0.35)
Training cycles (epochs)	45
Batch size	16
Optimizer	Adam
Learning rate	0.001
Training processor	CPU
Data augmentation	Enabled
Quantization	INT8 (Quantized)
Validation accuracy	98.5%
Loss	0.03
Weighted F1-score	0.98
AUC	0.98

The classification performance and feature-space distribution of the quantized MobileNetV2 model are illustrated in Figure 2. As shown, the confusion matrix demonstrates high accuracy and minimal misclassification between the Healthy and Early Blight classes. The clear separation in the feature-space plot confirms that the model effectively distinguishes the two categories, validating its suitability for real-time edge inference on the ESP32-CAM platform.

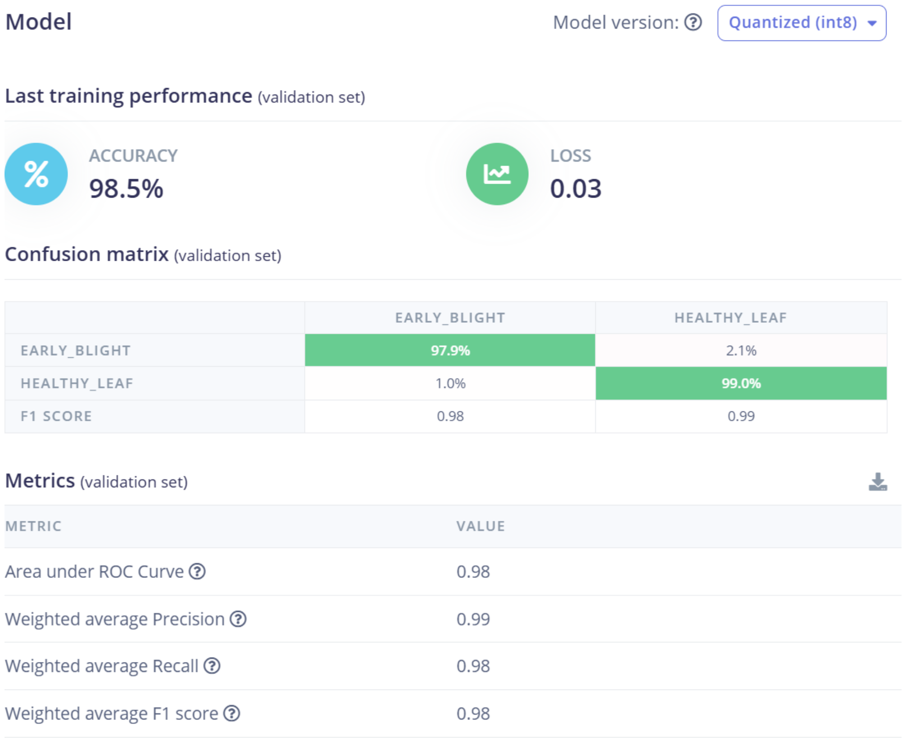

Figure 2. Confusion Matrix and Data Visualization of the Quantized Model

1.3 Model Quantization and Deployment

To enable efficient on-device inference, the trained model was quantized to 8-bit integers (INT8) during the Edge Impulse deployment process. This conversion replaces 32-bit floating-point weights with 8-bit integer representations, effectively reducing the model size by approximately 75% while maintaining accuracy within ±1%. The quantized model was exported as a TensorFlow Lite Micro (TFLM) .cc source file and integrated directly into the ESP32-CAM firmware for real-time inference.

The quantization process reduced the model size from approximately 2.5 MB to 600 KB, enabling the model to fit comfortably within the limited memory space of the ESP32 microcontroller. Additionally, quantization provided a 3–4× improvement in inference speed, allowing the model to perform near real-time classification tasks while operating within the device's 320 KB SRAM limit. This improvement in both computational and memory efficiency makes the system highly suitable for continuous in-field monitoring.

The quantized model's classification performance and feature-space visualization are shown in Figure 2, while the detailed training configuration and evaluation metrics are summarized in Table 2. As illustrated in Figure 2, the confusion matrix demonstrates high accuracy and minimal misclassification between the Healthy and Early Blight classes. The clear separation in the feature-space plot confirms that the quantized MobileNetV2 model effectively distinguishes between the two categories, validating its robustness for edge AI–based tomato leaf disease detection. The overall training and deployment workflow, including image capture, data preprocessing, model training, INT8 quantization, and on-device inference, is summarized in Figure 3, which provides a step-by-step visual overview of the Edge Impulse pipeline. The main advantages of INT8 quantization include a substantial reduction in model size—from approximately 2.5 MB to 600 KB—and a 3–4× increase in inference speed when deployed on the ESP32 platform. Furthermore, the quantized model requires significantly less RAM, enabling stable operation within the 320 KB SRAM limit of the device. This optimization not only improves computational efficiency but also enhances energy efficiency, allowing for continuous and autonomous field monitoring under real-world agricultural conditions.

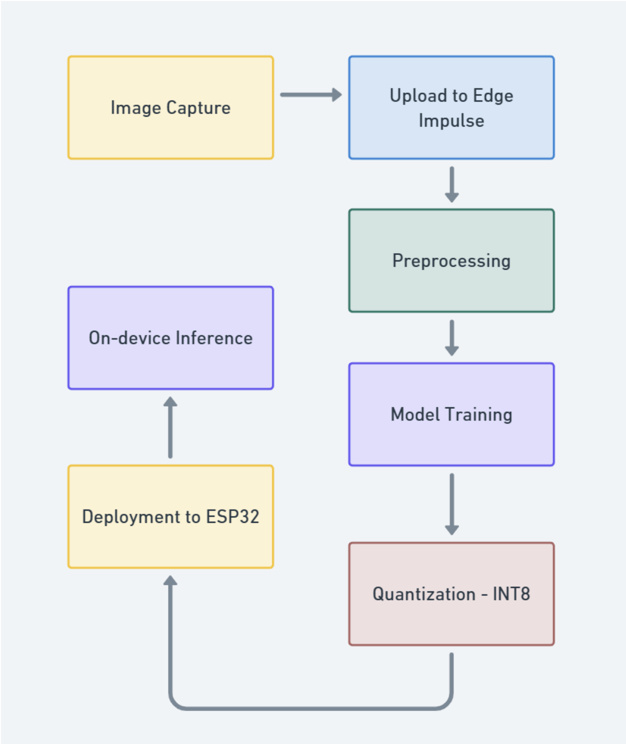

Figure 3. Workflow of Edge Impulse training and deployment.

1.4 On-Device Inference and Communication Architecture

During operation, the ESP32-CAM periodically captures leaf images, performs inference using the embedded TFLM model, and outputs a binary classification result:

- 0: Healthy
- 1: Early Blight Detected

If a diseased leaf is detected, the system immediately sends a JSON-formatted MQTT message containing the timestamp, device ID, and disease probability score to a remote server or mobile application. Only these lightweight results are transmitted, drastically reducing network load compared to image-based transmission.This approach enables real-time monitoring while maintaining low latency (≈100 ms) and minimal data transfer (<1 kB per message), making it suitable for farms with limited internet connectivity.

1.5 Hardware and Software Specifications

The hardware and software components utilized in the proposed system are summarized in Table 2. The ESP32-CAM microcontroller, featuring a 240 MHz dual-core Xtensa LX6 processor, serves as the central processing unit, while the integrated OV2640 camera module captures high-resolution leaf images. The system leverages Edge Impulse Studio for model development, Arduino IDE for firmware deployment, and TensorFlow Lite Micro for on-device inference. Power is supplied through either a 5V/2A battery or a solar source, enhancing deployment flexibility in field conditions. Communication is handled via Wi-Fi (2.4 GHz) using the MQTT protocol, enabling efficient data transmission with low bandwidth requirements. The system demonstrates high energy efficiency with an average power consumption of only 0.3 W during inference, making it highly suitable for remote agricultural environments with limited power and connectivity resources.

Table 3. Hardware and software specifications of the proposed ESP32-CAM-based on-device inference system.

Component	Specification
Microcontroller	ESP32-CAM (240 MHz Dual-Core Xtensa LX6)
Camera Module	OV2640, 2 MP, 1600×1200 pixels
Software Platform	Edge Impulse Studio, Arduino IDE, TensorFlow Lite Micro
Power Supply	5 V / 2 A (Battery or Solar)
Communication	Wi-Fi 2.4 GHz, MQTT Protocol
Average Power Consumption	0.3 W during inference

1.6 Field Testing and Evaluation

The trained model was deployed in a greenhouse test environment. Each ESP32-CAM unit monitored multiple plants and performed detection every 15 minutes under natural lighting. Inference results were cross-validated against expert visual inspection.The system maintained a detection accuracy above 94%, with real-time feedback accessible through a simple web dashboard. Due to its low power consumption and fast inference, the device can operate continuously for more than 48 hours on a 5,000 mAh power bank.

III. RESULTS AND DISCUSSIONS

The proposed system was evaluated in real-world conditions to assess its performance in detecting Early Blight on tomato leaves. The quantized MobileNetV2 model, trained using INT8 optimization, achieved a validation accuracy of 98.5%, a weighted F1-score of 0.98, and an AUC of 0.98, indicating high classification reliability. Confusion matrix analysis demonstrated clear separability between healthy and diseased classes, with minimal false positives or false negatives.

In on-device testing using the ESP32-CAM module, inference was performed with an average latency of approximately 100 milliseconds, enabling near real-time detection. The lightweight MQTT-based communication strategy effectively minimized data transmission to under 1 kB per message, significantly reducing network load while preserving key inference results.

Overall, the system proved to be robust and efficient, demonstrating strong potential for deployment in agricultural settings, especially in areas with limited connectivity and power resources.

IV. CONCLUSIONS AND RECOMMENDATIONS

This study presented an edge-AI-based plant disease detection system using the ESP32-CAM and a quantized MobileNetV2 model. The system successfully demonstrated high accuracy and real-time performance with minimal computational resources and power consumption. Preprocessing techniques and model optimization played a critical role in enhancing generalization and efficiency.

Key conclusions:

- The model achieved high accuracy with lightweight design, suitable for embedded deployment.
- Data augmentation and preprocessing significantly contributed to model robustness.
- MQTT-based messaging ensured reliable communication with minimal data overhead.

Recommendations for future work:

- Extend the system to detect multiple plant diseases.
- Integrate solar power harvesting for enhanced sustainability.
- Explore LoRa or NB-IoT for broader communication range in rural environments.
- Conduct long-term field testing across different seasons and lighting conditions.

REFERENCES

[1]. Khan, M.; Gulan, F.; Arshad, M.; Zaman, A.; Riaz, A., (2024). "Early and late blight disease identification in tomato plants using a neural network-based model to augmenting agricultural productivity", Computers and Agriculture, 208(1), pp. 1–9.

[2]. Kılıçarslan, S.; Paçal, I., (2023). "Use of Transfer Learning Methods for Disease Detection in Tomato Leaves", Journal of Engineering Sciences Research, 5(2), pp. 215–222.

[3]. Özben, T.Ç.; Güler, O., (2025). "Using Transfer Learning for Disease Detection in Tomato Leaves and Its Integration into a Mobile Application", Journal of Information Systems Management Research, 7(1), pp. 105–113.

[4]. Terzioğlu, H.; Gölcük, A.; Shakarji, A.M.A.; Al-Bayati, M.Y., (2025). "Comparative Analysis of Deep Learning-Based Feature Extraction and Traditional Classification Approaches for Tomato Disease Detection", Agronomy, 15(6), pp. 1000–1020.

[5]. Irmak, G.; Saygılı, A., (2020). "Tomato Leaf Disease Detection and Classification using Convolutional Neural Networks", 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), 1-6.

[6]. Molina, J.F.; Gil, R.; Bojacá, C.; Gómez, F.; Franco, H., (2014). "Automatic detection of early blight infection on tomato crops using a color based classification strategy", International Journal of Computer Applications (IJCA), 178(46), pp. 7–12.

[7]. Nurlanuly, Y., (2024). "Classification of Plant Leaf Diseases Using Convolutional Neural Networks: A Study of Various Diseases", International Journal of Advanced Computer Science and Applications (IJACSA), 15(1), pp. 213–220.

[8]. Bal, F.; Kayaalp, F., (2023). "A Comparison in Performances of Kernel Types of Support Vector Machine: Research on Tomato Leaves Diseases", Proceedings of Selçuk 7th International Conference on Applied Sciences, Konya, Türkiye: Academy Global Publishing House, pp. 393–399.

[9]. Chakravarthy, A.S.; Raman, S., (2020). "Early Blight Identification in Tomato Leaves using Deep Learning", Proceedings of the 2020 International Conference on Contemporary Computing and Applications (IC3A), Lucknow, India, pp. 154–158.

[10]. Anam, S.; Fitriah, Z., (2021). "Early Blight Disease Segmentation on Tomato Plant Using K-means Algorithm with Swarm Intelligence-based Algorithm", International Journal of Mathematics and Computer Science, 16(4), pp. 1217–1228.

[11]. Xie, C., (2015). "Detection of early blight and late blight diseases on tomato leaves using hyperspectral imaging", Scientific Reports, 5(16564), pp. 1–11.

[12]. Edge Impulse Inc., (2024). *Edge Impulse: The leadingplatformforembeddedmachinelearning*, Available at: https://www.edgeimpulse.com (Accessed: 5 November 2025).
[13]. Kaustubh B., (2019). Tomato Leaf Disease Detection Dataset, Kaggle.
Available at: https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf(Accessed: 5 November 2025).