RESEARCH ARTICLE

Smart Ground Robot for Real-Time Detection of Tomato Diseases Using Deep Learning and IoT Technologies

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Abstract

This study presents an intelligent automated system for real-time detection and classification of tomato diseases using a Convolutional Neural Network (CNN) integrated within an Internet of Things (IoT) based unmanned ground vehicle (UGV). The CNN was trained and evaluated using a dataset comprising over 20,000 images of tomato leaves categorized into ten distinct diseases—Late Blight, Early Blight, Septoria Leaf Spot, Tomato Yellow Leaf Curl Virus, Bacterial Spot, Target Spot, Tomato Mosaic Virus, Leaf Mold, Spider Mites Two-Spotted Spider Mite, Powdery Mildew—and healthy leaves. The developed CNN architecture, optimized for lightweight deployment on edge devices like Raspberry Pi 4, achieved an overall validation accuracy of approximately 83%, with notable variations across classes in precision, recall, and F1-score. Specifically, high precision scores (above 80%) were obtained for diseases such as Bacterial Spot, Late Blight, and Tomato Yellow Leaf Curl Virus, while moderate scores in diseases exhibiting subtle visual symptoms underscored areas for future refinement. The UGV autonomously navigates tomato fields, captures high-resolution images of leaves, and conducts on-site real-time disease classification, significantly reducing the labor, human error, and time associated with traditional manual inspections. Comprehensive quantitative analyses, including confusion matrices and visual assessments of classified samples, validate the practical viability and robustness of the proposed system, although certain misclassifications highlight opportunities to enhance training data diversity and model generalizability in future work. The integration of deep learning and IoT technologies demonstrated in this study substantially advances precision agriculture, improving disease management practices and promoting sustainable agricultural productivity.

Keywords: automated systems, agricultural robotics, internet of things (IoT), deep learning, tomato disease detection, raspberry Pi 4.

1 Introduction

The global agriculture industry is undergoing significant transformations driven by the rapid development of the Internet of Things (IoT) and

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advanced technological integration. IoT has enabled substantial improvements in agricultural efficiency, cost reductions, service accessibility, and operational management, even in remote or resource-limited regions [1]. Particularly in precision agriculture, IoT applications such as real-time monitoring, predictive analytics, and precision farm management have gained momentum, enabling optimized decision-making and sustainable crop cultivation through data-driven approaches [2]. However, despite the evident benefits, several challenges remain, especially related to network infrastructure, data management, and the adoption of open-source IoT technologies in agriculture [3].

The need for automation in agriculture has intensified due to rising global food demands and labor shortages, driving the agricultural sector toward increased reliance on artificial intelligence (AI), robotic systems, and deep learning, which has demonstrated transformative potential across diverse agricultural tasks [4]. Recent advancements in machine learning (ML), especially deep learning (DL), have significantly improved automation in agricultural tasks such as disease detection, tomato leaf disease classification, fruit counting, and precision crop monitoring [5]. Convolutional neural networks (CNNs), a particular DL architecture, have consistently demonstrated superior accuracy over traditional ML methods like Random Forest (RF) and Support Vector Machine (SVM) across various agricultural applications [6].

Despite these advancements, agricultural practices in developing countries remain heavily dependent on labor-intensive methods requiring continuous manual monitoring, highlighting a critical gap in technological adoption and automation capabilities. To address this gap, recent studies propose deep learning-driven systems that automate disease identification processes directly in field conditions, enabling accurate real-time detection of diseases and pests across diverse crop environments [7]. Moreover, the rise of IoT-enabled smart agriculture ecosystems, incorporating technologies like wireless sensor networks, big data analytics, and cloud computing, signifies a broader trend towards sustainable agricultural practices designed to address food security challenges arising from population growth, resource scarcity, and environmental unpredictability [8].

The urgency to mitigate the impacts of agricultural diseases, which substantially threaten global food production, further accentuates the need for technological solutions. Emerging plant disease pandemics account for significant economic losses and pose persistent risks to environmental health, food security, and global supply chain stability [9]. Consequently, deep learning models, particularly CNNs, have demonstrated strong capability in automated plant disease detection, offering high classification accuracy across diverse disease categories. Deploying such models within IoT-based robotic platforms presents a highly promising direction for scalable, real-time disease management in vulnerable crops such as tomatoes [10].

Automated plant disease detection, particularly leaf disease identification, has increasingly emerged as an essential area of research due to its potential economic impact on agricultural productivity [11]. Techniques leveraging multispectral and hyperspectral imaging combined with advanced machine learning (ML) and deep learning (DL) algorithms, such as Convolutional Neural Networks (CNNs), ResNet, and VGG architectures, have proven effective in accurately identifying leaf diseases across various plant species. These computational methods typically outperform traditional ML classifiers, including Support Vector Machines (SVMs) and Random Forests (RF), offering significant accuracy improvements and demonstrating robust performance metrics like precision, recall, and F1-score [12].

Early and precise detection of crop diseases using DL methods has shown remarkable success in real-time agricultural applications. Notably, advanced CNN models, when integrated with powerful embedded hardware platforms, have achieved impressive real-world classification accuracies, validating their suitability for field deployment [13]. Despite these technological advancements, several open issues persist, including model generalizability across diverse crops, computational efficiency for real-time inference, and the scarcity of comprehensive, publicly available datasets. Addressing these gaps requires datasets that encompass various crop types, disease classes, and environmental conditions to enhance the robustness and effectiveness of disease detection models [14].

In response to the necessity for more efficient computational performance suitable for edge computing environments, researchers have developed lightweight CNN architectures. For instance, the VGG-ICNN model has demonstrated

outstanding results. Its significantly reduced number of parameters positions this architecture as an optimal solution for real-time disease detection tasks in resource-constrained agricultural environments [15]. Concurrently, advancements in agricultural autonomous navigation technologies, tailored for the complexity and unpredictability of farming environments, underline the importance of integrating precise, efficient navigation systems into automated agricultural equipment. Future research in this domain highlights key trends such as multi-dimensional perception, selective autonomous navigation technologies, multi-agent cooperative systems, and fault diagnostic capabilities, all essential to enhancing the practicality and reliability of autonomous agricultural vehicles [16].

IoT-based solutions offer promising approaches to tackling these challenges through innovative applications such as smart irrigation, precision farming, crop health monitoring, pest management, agricultural drones, and supply chain management [17]. Nevertheless, widespread adoption of IoT in agriculture necessitates addressing fundamental issues related to connectivity, scalability, data privacy, cost management, and enhancing awareness among stakeholders. Effective collaboration between farmers, technology providers, academia, and policymakers is crucial to unlocking the full potential of IoT-driven agricultural practices, ultimately contributing to sustainable agricultural productivity and resilience amidst global challenges such as climate change and resource scarcity [18].

This study proposes an autonomous, intelligent system leveraging CNNs integrated with IoT devices (a Raspberry Pi 4-powered unmanned ground vehicle, UGV) for real-time tomato disease detection. The CNN model is trained on a publicly available dataset consisting of over 20,000 images capturing ten common tomato diseases and healthy plants [19]. The developed system achieves robust disease classification accuracy and near real-time performance suitable for practical agricultural deployment, addressing the previously mentioned limitations of traditional methods.

The contributions of this work include:

- Designing a low-cost Unmanned Ground Vehicle (UGV) specifically for tomato disease detection tasks, enabling accessibility and practical feasibility for small-scale farmers.
- Developing a computationally efficient and robust Convolutional Neural Network (CNN) model capable of accurately identifying and classifying major tomato leaf diseases.
- Integrating IoT and edge-computing technologies by deploying the developed CNN model onto a Raspberry Pi 4-based UGV, enabling near real-time disease identification and classification with minimal computational resources.
- Successfully identifying and classifying major tomato diseases, thus demonstrating the system's potential applicability in precision agriculture.

The remainder of this paper is structured as follows: Section 2 presents detailed methodology and system architecture; Section 3 reports experimental results and discussions, followed by concluding remarks and suggestions for future work in Section 4.

Table 1. Key hardware components and specifications.

Component	Specification	Purpose
Raspberry Pi 4 Model B	ARM Cortex-A72 Quad-Core 1.5 GHz CPU, 4GB RAM, Bluetooth 5.0, Dual-band Wi-Fi (2.4 GHz/5 GHz)	CNN inference, image capturing, and cloud communication
ESP32 Microcontroller	Dual-core, 240 MHz, Integrated Wi-Fi and Bluetooth (BLE)	Motor control, sensor interfacing, obstacle avoidance
Web Camera	A4Tech 925HD, Resolution: 1920×1080 pixels, 30 fps	Capturing high-resolution leaf images
Ultrasonic Sensor	Waterproof, Detection range: up to 60 cm	Real-time obstacle detection
8-Channel Relay Module	8 separate relay switches, 5V DC operating voltage	Control and isolation of DC motors
DC Motors	8 motors, Operating voltage: 12V DC	Robot mobility and navigation
Buck Converters	Input: 12V DC, Output: 5V DC, Max Current: 3A	Voltage regulation and power management
DC Battery	12V, 7Ah rechargeable battery	Primary power source for field operations
Mechanical Frame and Tires	Custom-made frame, 8 robotic tires, and 2 shock absorbers	Robust navigation through agricultural fields

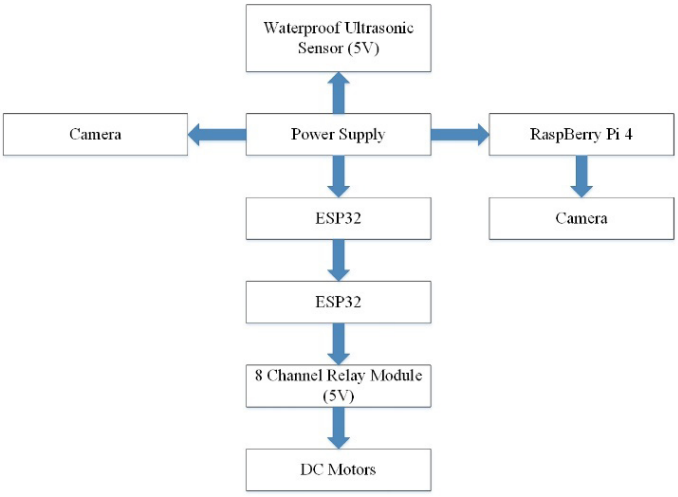

Figure 1. Block diagram of the robot.

2 Methodology

This section details the systematic approach taken to develop, train, evaluate, and deploy the intelligent automated tomato disease detection system. The methodology includes Hardware Description and Integration, dataset description, CNN model architecture, model training, performance evaluation metrics, and system implementation.

2.1 Hardware Description

A low-cost autonomous UGV was designed featuring a Raspberry Pi 4 as the computational core, an ESP32 microcontroller for motor and sensor control, ultrasonic distance sensors for obstacle avoidance, and a high-resolution web camera (A4Tech 925HD) for image capturing. Table 1 provides the summary of the key hardware components and their specifications.

Figure 1 presents a block diagram showing the relationship between different hardware components. The block diagram depicts a robotic system integrating various sensors and control units. At the core, an ESP32 microcontroller connects to a relay that controls motors, facilitating motion. The ESP32 receives inputs from an ultrasonic sensor for distance measurement and two cameras for visual feedback. Power is supplied to the entire system, including the ESP32, cameras, and Raspberry Pi 4. The Raspberry Pi 4 processes additional camera data, enhancing visual and computational capabilities. This configuration allows the robot to navigate, capture real-time data, and interact with its environment through sensor feedback and motor control, ensuring precise operation.

Figure 2 shows the detailed structural design of the robot. The robot is meant especially for use in agriculture for tomato disease detection. Emphasizing stability and adaptability, the 8×8 robotic car design lets it negotiate easily in agricultural fields. Equipped with shock absorbers and dampers, the robot reduces the effect of uneven terrain, thereby enabling smooth mobility that protects the delicate onboard equipment vital for disease diagnosis. Small tires help the robot to be more maneuverable and to minimize soil compaction so it may pass exactly between rows of tomato plants.

2.2 Dataset Description

The CNN model was trained and evaluated on a publicly available Tomato Leaf Disease Classification dataset, comprising over 20,000 labeled images across ten distinct tomato diseases and one healthy class: Late Blight, Early Blight, Septoria Leaf Spot, Tomato Yellow Leaf Curl Virus, Bacterial Spot, Target Spot, Tomato Mosaic Virus, Leaf Mold, Spider Mites Two-Spotted Spider Mite, Powdery Mildew, and Healthy Leaves. Images were captured from diverse environmental conditions, including both controlled laboratory settings and natural outdoor environments. Dataset images were resized to a uniform resolution of 128×128 pixels for optimal computational efficiency and consistency in training and inference.

2.3 CNN Model Architecture

A lightweight CNN model architecture was developed for computational efficiency suitable for deployment on resource-constrained edge devices. The model consists of four convolutional layers with increasing filter depths (32, 64, 128, and 256 filters, respectively), each followed by batch normalization and ReLU activation. Max pooling layers follow each convolutional block for dimensionality reduction. A global average pooling layer reduces model complexity and mitigates overfitting. Finally, fully connected dense layers with dropout regularization and a softmax output layer perform multi-class classification into 11 categories. Figure 3 presents the detailed CNN model architecture summary, highlighting layer types, dimensions, and parameter count clearly.

2.4 Training and Evaluation Procedure

The dataset was split into 80% training and 20% validation subsets. The CNN was trained using categorical cross-entropy loss and the Adam optimizer (learning rate: 0.001) over 15 epochs. Model performance was evaluated using comprehensive quantitative metrics, including accuracy, precision,

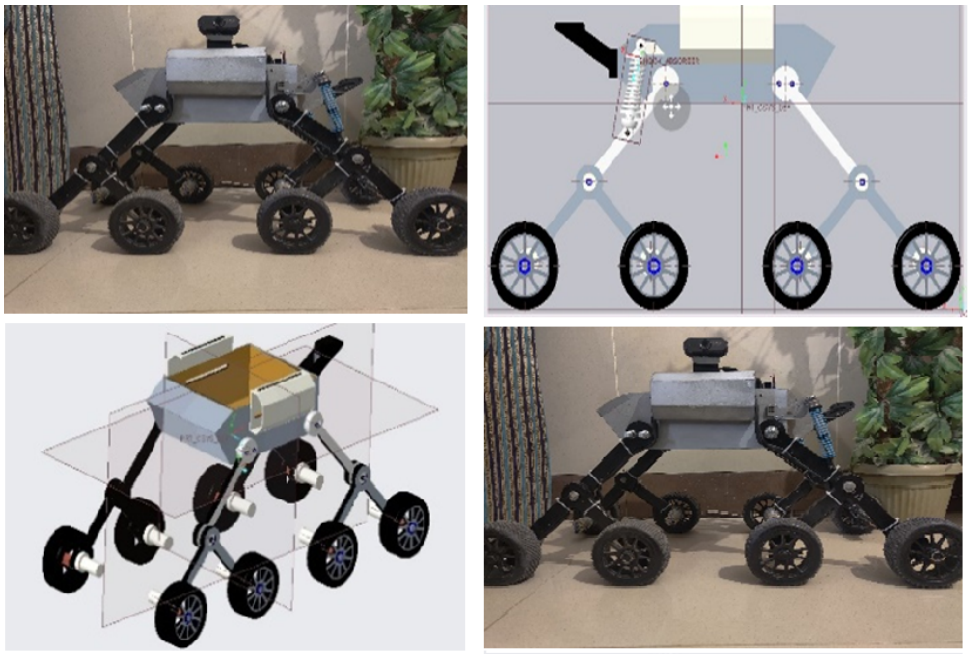

Figure 2. Structure of the robot.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 126, 126, 32)	896
batch_normalization_4 (BatchNormalization)	(None, 126, 126, 32)	128
max_pooling2d_4 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_5 (Conv2D)	(None, 61, 61, 64)	18,496
batch_normalization_5 (BatchNormalization)	(None, 61, 61, 64)	256
max_pooling2d_5 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_6 (Conv2D)	(None, 28, 28, 128)	73,856
batch_normalization_6 (BatchNormalization)	(None, 28, 28, 128)	512
max_pooling2d_6 (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_7 (Conv2D)	(None, 12, 12, 256)	295,168
batch_normalization_7 (BatchNormalization)	(None, 12, 12, 256)	1,024
max_pooling2d_7 (MaxPooling2D)	(None, 6, 6, 256)	0
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 256)	0
dense_6 (Dense)	(None, 256)	65,792
dropout_3 (Dropout)	(None, 256)	0
dense_7 (Dense)	(None, 11)	2,827

Total params: 1,374,947 (5.25 MB)
Trainable params: 457,995 (1.75 MB)
Non-trainable params: 960 (3.75 KB)
Optimizer params: 915,992 (3.49 MB)

Figure 3. Model summary.

recall, F1-score, and a confusion matrix for detailed class-wise analysis. The inference speed was benchmarked against MobileNetV2 to validate real-time performance.

2.5 System Operation Workflow

Figure 4 presents the operational workflow of the system. The system enables semi-autonomous navigation through agricultural fields, capturing high-resolution tomato leaf images, which are resized to 128×128 pixels onboard. A real-time CNN model performs disease classification onsite, with the results uploaded to Firebase cloud storage. These classification results are then displayed via user-friendly mobile or web interfaces, ensuring accessibility for end-users.

3 Results and Discussion

This section presents a detailed evaluation of the proposed intelligent automated tomato disease detection system, focusing on the developed CNN model's performance metrics and the robot's operational efficacy.

The proposed lightweight CNN model demonstrated strong classification capabilities, achieving an overall validation accuracy of approximately 83% on the held-out 20% validation subset. The performance was further comprehensively assessed using precision, recall, and F1-score, providing detailed class-wise insights into the model's effectiveness. Figure 5 shows the precision, recall, and F1-score for each class.

Specifically, the CNN model achieved precision exceeding 80% for diseases such as Bacterial Spot,

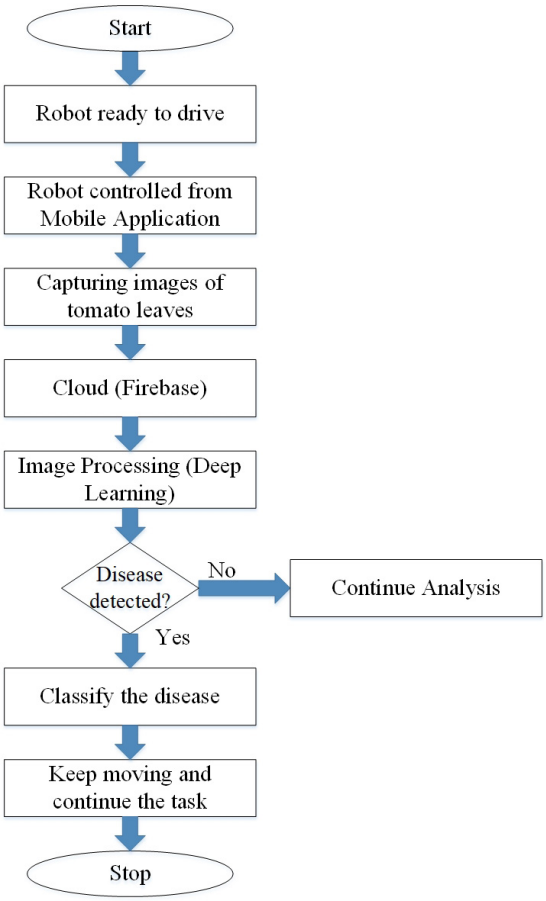

Figure 4. Operational flowchart.

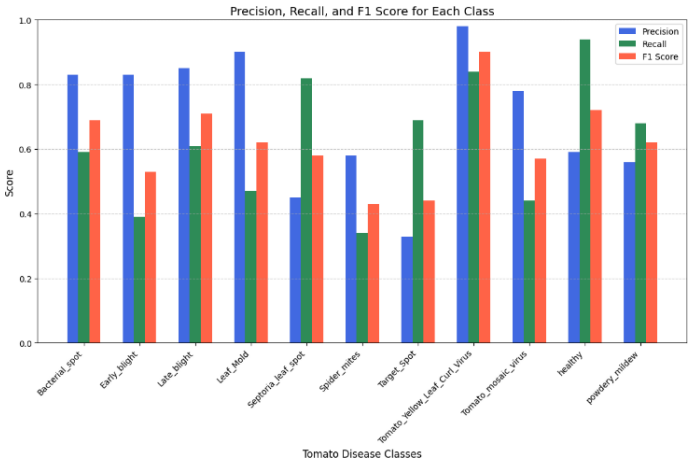

Figure 5. Precision, Recall, and F1 Score.

Late Blight, and Tomato Yellow Leaf Curl Virus, demonstrating robust performance in distinguishing clearly visible diseases. However, relatively moderate performance was observed for diseases such as Spider Mites Two-Spotted Spider Mite and Target Spot, highlighting challenges in recognizing subtle visual symptoms. These results underscore the need for further dataset diversification and targeted model enhancements.

Figure 6 illustrates the training accuracy and loss curves over 15 epochs, showing stable convergence behavior. The model accuracy steadily increased, whereas the loss consistently decreased, indicating successful learning and minimal overfitting.

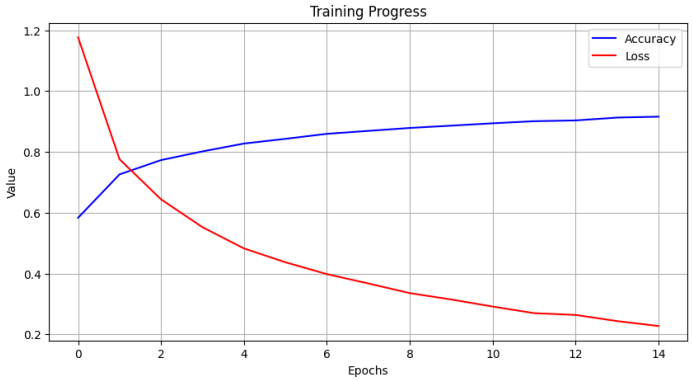

Figure 6. Training accuracy and loss.

Figure 7 presents the confusion matrix. To gain deeper insights into model performance, a normalized confusion matrix was evaluated. It revealed robust class predictions for "healthy" leaves, with minimal misclassification. However, significant confusion was noted between visually similar disease classes (e.g., Leaf Mold and Target Spot), guiding areas for future improvement.

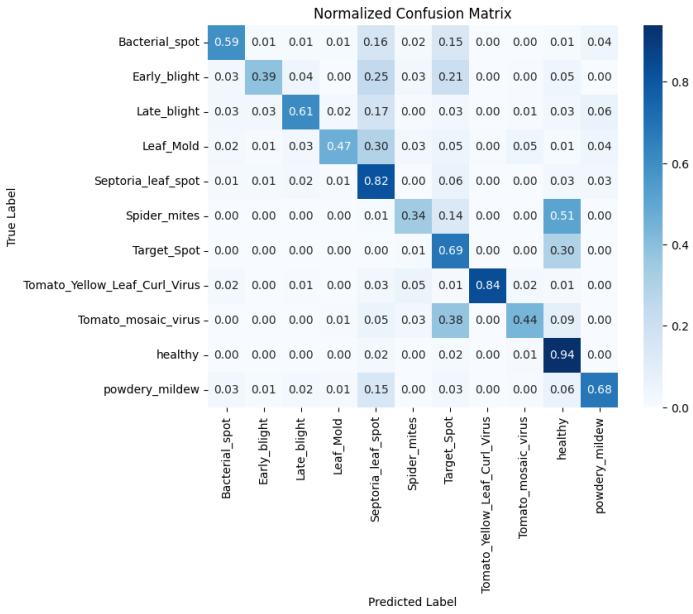

Figure 7. Confusion matrix.

The real-time applicability was evaluated by measuring the inference time per image on the Raspberry Pi 4 platform, using TensorFlow as the inference framework with an input resolution of 128×128 pixels. Under identical experimental conditions, the proposed lightweight CNN model

Table 2. Comparison with related CNN-based plant disease detection systems on embedded platforms.

Study	Platform	Accuracy	Inference Time	Key Feature
Gajjar et al. [13] (2022)	NVIDIA Jetson TX1	96.88%	<0.1 s	Real-time CNN, embedded
González-Huitrón et al. [20] (2021)	Raspberry Pi 4	Up to 100%[a]	–[b]	Lightweight CNN, tomato
Proposed	**Raspberry Pi 4**	**≈83%**	**0.101 s**	**IoT+UGV+CNN, 11 classes**

[a] Best result using Xception on PlantVillage-derived tomato dataset; other models range from ∼92% to 100%.
[b] Inference time not explicitly reported in the original study.

achieved an average inference time of 0.101 seconds per image, compared to 0.111 seconds per image for MobileNetV2 evaluated under the same hardware and software configuration. The proposed model thus demonstrated approximately 9% faster inference than MobileNetV2, confirming its suitability for near real-time field deployment on resource-constrained edge devices.

Table 2 presents a comparative summary of the proposed system against representative related works on CNN-based tomato or plant leaf disease detection deployed on embedded platforms. It should be noted that the lower validation accuracy of the proposed model (≈83%) relative to prior works is attributable to the higher task difficulty: our dataset encompasses 11 classes drawn from a more diverse set of environmental conditions, including both controlled and outdoor field images, whereas prior works primarily used the curated PlantVillage dataset under controlled conditions. The proposed system nevertheless demonstrates the additional advantage of full IoT integration with autonomous UGV navigation, which is absent in prior embedded-only implementations [13, 20].

Figure 8 presents sample visual classification outputs obtained from the CNN model. The model produced accurate classifications for visually distinct diseases, as shown, whereas subtle cases posed challenges, aligning closely with the confusion matrix results.

The low-cost UGV platform demonstrated effective operational capabilities. Equipped with an 8-channel relay module for motor control and a waterproof ultrasonic sensor with a detection range of up to 60 cm for real-time obstacle avoidance, the robot navigated test environments smoothly. During controlled field trials, the robot successfully detected and avoided obstacles within the sensor's operational range and maintained continuous image capture at the designated inter-row spacing of tomato plant rows. It should be noted that formal quantitative navigation metrics—such as path accuracy, obstacle avoidance success rate, and area coverage speed—were not recorded in the current study and are identified as priorities for evaluation in future field deployment trials.

The deployment of lightweight CNN models on low-cost embedded platforms such as Raspberry Pi 4 has been demonstrated to achieve effective real-time tomato disease classification, validating the feasibility of edge-computing-based disease detection in practical agricultural field conditions [20]. The use of energy-efficient components in the proposed UGV further reduces power consumption, enhancing system sustainability and economic viability for small-scale farmers.

Despite promising results, limitations exist, including occasional misclassifications between visually similar disease classes. Future improvements involve enhancing dataset diversity, optimizing CNN architecture further, and conducting more extensive field trials for improved reliability and generalizability.

4 Conclusion

This study presented an intelligent, automated tomato disease detection system combining a lightweight Convolutional Neural Network (CNN) with a low-cost IoT-based unmanned ground vehicle (UGV). The developed CNN model was trained on a publicly available dataset of over 20,000 tomato leaf images and successfully classified ten common tomato diseases and healthy leaves with an overall validation accuracy of approximately 83%. Comprehensive quantitative evaluations, including precision, recall, F1-score, and confusion matrix analysis, demonstrated strong performance for diseases with distinct visual features (precision exceeding 80%), while highlighting classification challenges among diseases exhibiting subtle symptom variations. Real-time applicability was demonstrated by achieving an average inference time of 0.101 seconds per image,

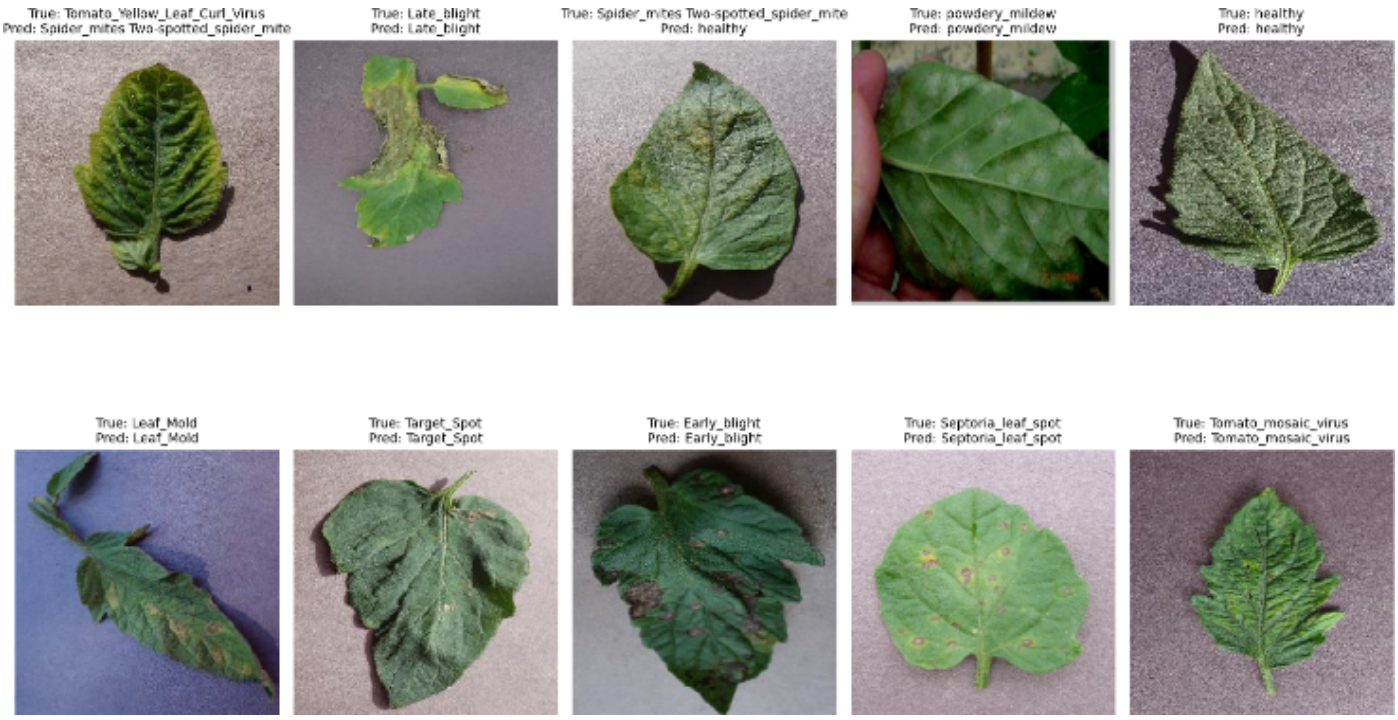

Figure 8. Classified images.

outperforming the benchmark MobileNetV2 model by approximately 9%. The proposed low-cost UGV design, integrating an 8-channel relay module and waterproof ultrasonic sensors for reliable obstacle avoidance and autonomous navigation, further enhances practical deployment feasibility. Despite promising results, limitations, such as occasional misclassification of visually similar diseases, were identified. Future improvements will include enhancing dataset diversity, refining CNN architectures, and conducting more extensive field evaluations to enhance reliability and generalizability. Overall, the integration of deep learning and IoT technologies demonstrated here significantly contributes toward practical precision agriculture solutions, promoting sustainable disease management practices and enhancing economic outcomes in agriculture.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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