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An Agricultural Skid-Steering Robot for Tomato Leaf Disease Detection and Targeted Pesticide Spraying: An Updated Prototype and Current Technology

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Abstract: *Agricultural workers may be exposed to pesticides during conventional crop-protection operations, while timely identification of leaf diseases remains important for effective crop management. This paper presents an updated discussion of an agricultural skid-steering robot originally developed for tomato-leaf disease identification and targeted pesticide spraying. The prototype combines a four-wheel skid-steering platform, ultrasonic sensing, an MPU6050 inertial sensor, Arduino Nano control, ZigBee communication, MATLAB-based image processing, K-means clustering and an artificial neural network (ANN) classifier. Tomato-leaf images representing healthy leaves, bacterial spot, early blight, late blight and leaf mold are processed through image acquisition, preprocessing, colour-space transformation, clustering, segmentation, feature extraction and classification. The detected disease condition is then communicated to the robot controller, which activates the pump for the corresponding programmed spraying interval. The original prototype demonstrated the feasibility of integrating image-based disease recognition with a mobile agricultural platform. The present manuscript retains the original prototype observations while adding a current technology perspective. Recent studies show a transition toward YOLO-family detectors, lightweight deep-learning models, edge AI, autonomous navigation, multi-sensor perception and variable-rate robotic spraying. These developments identify practical pathways for extending the prototype toward real-time field deployment without claiming that such newer technologies were implemented in the original system.*

Keywords: agricultural robotics, ANN, computer vision, edge AI, image processing, K-means clustering, precision spraying, skid steering, tomato leaf disease.

I. INTRODUCTION

Agricultural automation has expanded from isolated sensing and monitoring systems toward integrated platforms capable of perception, decision support and physical intervention. Plant disease detection is one of the important computer-vision applications in this area because visible symptoms can provide an early indication of crop stress or infection. The earlier prototype underlying this manuscript was designed for tomato (Solanum lycopersicum) crops and combined a mobile skid-steering platform with image-based disease recognition and targeted pesticide spraying.

The original system used an Arduino Nano for locomotion and actuator control, an MPU6050 accelerometer/gyroscope module for attitude-related measurements, an ultrasonic sensor for crop and distance sensing, and ZigBee for wireless

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communication. Image analysis was performed in MATLAB through preprocessing, colour-space conversion, K-means clustering, segmentation, feature extraction and ANN classification. The prototype reported tests for bacterial spot, early blight, late blight, leaf mold and healthy tomato leaves.

The purpose of this revised manuscript is not to claim that the original prototype contained current deep-learning or autonomous-robotics capabilities. Instead, the original implementation is retained as the baseline and is discussed alongside recent research directions. This distinction is important for accurate reporting of prior work and for identifying meaningful future extensions.

II. RELATED WORK AND TECHNOLOGY EVOLUTION

A. Traditional Image Processing and ANN

The original system represents a classical computer-vision pipeline. RGB leaf images were preprocessed, transformed into L*a*b* colour space, filtered, clustered with K-means and segmented before classification. A feed-forward ANN was used as the classifier. Such a pipeline separates image processing into interpretable stages and can operate with modest computational requirements, but it depends on engineered processing steps and can be sensitive to image acquisition conditions.

B. Deep-Learning-Based Disease Detection

Recent research increasingly uses end-to-end deep-learning detectors. Studies have evaluated multiple YOLO generations for tomato leaf disease identification and have examined the trade-offs among accuracy, latency and model size [8]. Other recent work has proposed lightweight YOLO-based architectures to improve small-lesion detection while limiting computational cost [9]. These approaches reduce the dependence on manually designed segmentation and feature-extraction stages.

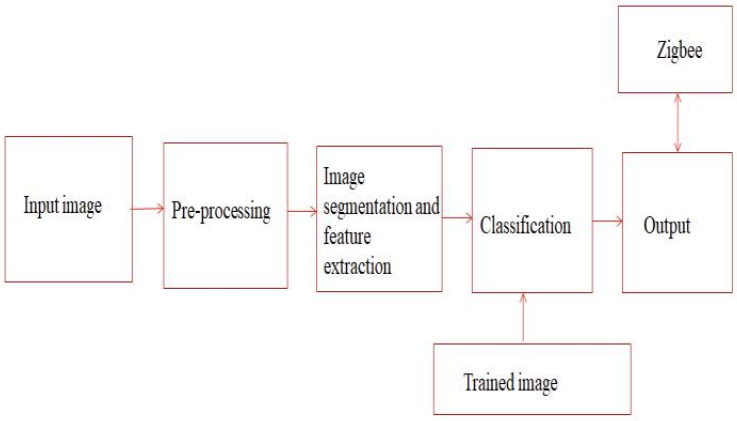


Fig. 1. Original image-processing and classification workflow.

C. Lightweight and Edge-Oriented AI

Agricultural robots have limited power and computing resources compared with laboratory workstations. Recent work such as AgriLiteNet combines lightweight convolutional features with streamlined transformer components and is specifically oriented toward agricultural-robot deployment [10]. The direction is therefore moving from PC-dependent image processing toward local inference on edge hardware.

D. Robotic and Precision Spraying

Recent studies increasingly integrate disease detection with robotic spraying rather than treating vision as a standalone classification task. An improved YOLOv8 system has been investigated for precision tomato leaf disease detection and

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targeted application [11]. This is closely related to the original prototype, whose classification output was already connected to a pump-control stage. The newer direction adds more precise localization, real-time inference and opportunities for variable-rate application.

E. Technology Evolution Summary

TABLE I: Technology Evolution Summary

Subsystem	Original prototype	Current research direction
Image analysis	MATLAB preprocessing + K-means	Deep learning / detection
Classifier	Feed-forward ANN	YOLO / CNN / transformer
Processing	Host PC / MATLAB	Edge AI device
Communication	ZigBee	IoT / Wi-Fi / MQTT
Navigation	Controlled movement	Autonomous navigation
Disease output	Disease category	Detection + localization + severity
Spraying	Programmed interval	Precision / variable-rate control
Sensing	Ultrasonic + IMU	Camera + LiDAR/depth + IMU

III. ORIGINAL PROTOTYPE ARCHITECTURE

The original prototype established a perception-to-actuation chain consisting of image acquisition, image processing, ANN classification, communication, Arduino control and pump activation. The robot platform used four driven wheels with DC motors controlled through an L293D motor-driver module. The Arduino Nano handled locomotion and actuator commands. The MPU6050 supplied accelerometer and gyroscope measurements used to calculate pitch and roll, while the ultrasonic sensor supported crop and distance sensing. ZigBee provided wireless serial communication between the robot and the host/control side.

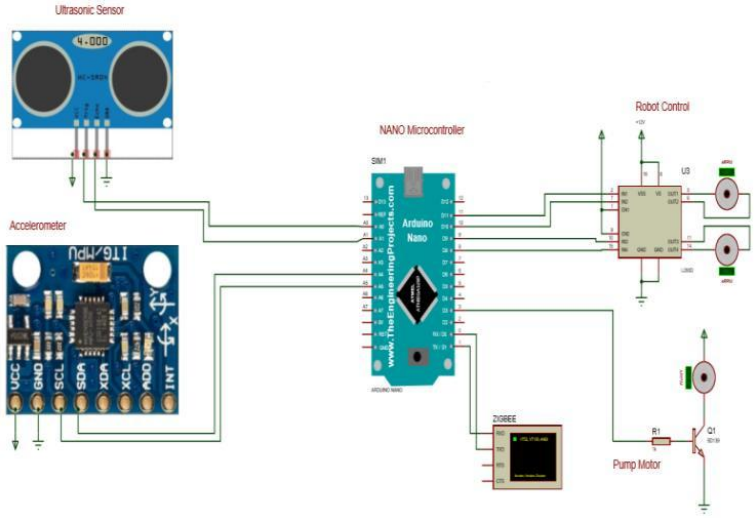


Fig. 2. Hardware interconnection of the prototype.

The image-processing sequence consisted of RGB image acquisition, preprocessing, conversion to L*a*b* colour space, filtering, K-means clustering, segmentation, feature extraction and ANN classification. The classification output was associated with a treatment output and approximate spraying interval. The original project therefore connected computer vision to a physical agricultural actuator rather than stopping at disease classification.

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IV. IMPLEMENTATION AND INTERFACING

The robot chassis used four wheels driven by DC motors and controlled through an L293D motor driver. The Arduino Nano was responsible for locomotion and actuator commands. The MPU6050 accelerometer and gyroscope supported balance-related measurements, and the ultrasonic sensor was used for crop and distance sensing. ZigBee modules provided wireless serial communication.



Fig. 3. Example tomato leaf input used in the prototype.

The MATLAB graphical user interface provided controls for communication-port selection, baud-rate configuration, maximum travel distance, sensor-data reception, data storage and directional movement. The classification result was transferred through the serial/ZigBee path to the Arduino, which controlled the pump and robot actuators.

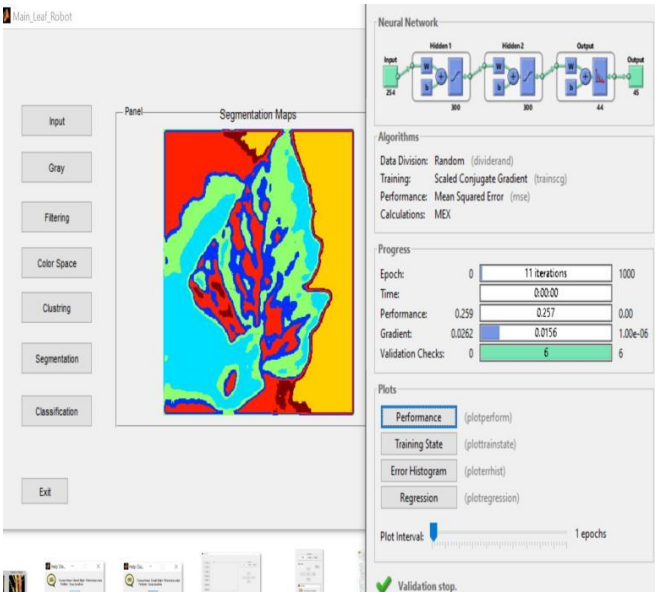


Fig. 4. MATLAB classification and control interface.

V. EXPERIMENTAL OBSERVATIONS

The original project tested representative images of bacterial spot, early blight, late blight, leaf mold and healthy tomato leaves. The image-processing stages included grayscale conversion, filtering, colour-space transformation, clustering, segmentation and final classification. The MATLAB neural-network interface generated performance, training-state, error-histogram and regression visualizations during classification.

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Fig. 5. K-means cluster representation used during segmentation.

The reported prototype outputs included a disease name, a treatment output and an approximate spraying interval. The robot was subsequently commanded through the Arduino-MATLAB interface to activate the pump. The prototype therefore demonstrated a complete physical proof of concept from image analysis to spraying.



Fig. 6. Agricultural robot during spraying demonstration.

Because the original project report does not provide a standardized train/test split, dataset size, precision, recall, F1-score, mean average precision or controlled field-trial statistics, those metrics are not reconstructed or invented in this revised manuscript. A rigorous modernization experiment should report these measures on a clearly defined dataset and under representative field conditions.

VI. CURRENT RESEARCH GAP AND POSSIBLE EXTENSIONS

A. Deep-Learning Replacement

The classical K-means and ANN pipeline can be replaced in a future implementation with a lightweight YOLO/CNN detector. Current literature shows active evaluation of YOLO-family models for tomato disease recognition and the development of lightweight architectures for agricultural robots [8]–[10].

B. Edge Deployment

A Raspberry Pi-class device or an NVIDIA Jetson-class edge computer could host the inference pipeline. Model compression, quantization and optimized inference could be evaluated using accuracy, latency, memory consumption and power consumption as complementary metrics.

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C. Autonomous Navigation

The skid-steering platform can be extended with camera, LiDAR or depth sensing and IMU fusion. A future implementation could use crop-row detection, waypoint planning and obstacle avoidance so that scanning requires less manual control.

D. Disease Severity and Precision Spraying

Instead of mapping only disease class to a fixed spraying interval, a future system can estimate the affected region and disease severity, then combine the estimate with nozzle characteristics, robot speed and plant distance to determine an experimentally calibrated spray command. Such a system should be validated with agronomic guidance and measured chemical usage rather than assuming that a particular duration is universally appropriate.

E. IoT-Based Monitoring

A networked version could record disease class, confidence, severity, location, timestamp, battery state and spray events. MQTT or a similar protocol could connect the robot to a backend and dashboard for monitoring and historical analysis.

VII. DISCUSSION

The principal value of the original prototype is the integration of multiple subsystems rather than any single algorithm. The project connects image processing with a mobile platform and an actuator, which is an important step toward agricultural automation. Current literature indicates that the same integration problem is now being approached with more capable visual models, edge hardware and targeted spraying [10], [11].

However, improved algorithmic accuracy alone does not guarantee field performance. A practical agricultural robot must consider changing illumination, leaf orientation, occlusion, wind, motion blur, camera-to-plant distance, network reliability, battery capacity and safe actuator operation. Therefore, future evaluation should include end-to-end latency and field-level measurements in addition to image-classification metrics.

A useful modernization experiment would evaluate the original ANN pipeline against one or more modern lightweight detectors using the same test images where possible. The comparison should include precision, recall, F1-score, inference time, model size and energy/power requirements. This would convert the present prototype review into a reproducible modernization study without altering the historical implementation.

VIII. CONCLUSION

This paper revisits an agricultural skid-steering robot developed for tomato leaf disease detection and targeted pesticide spraying. The original prototype integrated MATLAB image processing, K-means segmentation, ANN classification, Arduino-based control, ZigBee communication, inertial sensing, ultrasonic sensing and a pump actuator. The system demonstrated a complete proof-of-concept path from crop image analysis to physical spraying.

The updated technology review shows a clear research trajectory from classical image processing toward deep-learning detection, lightweight edge inference, autonomous navigation, disease-severity estimation, IoT monitoring and precision or variable-rate spraying. These developments provide a practical roadmap for future enhancement of the prototype. The present paper deliberately distinguishes the original implemented components from technologies reported in subsequent research and therefore does not attribute modern AI or autonomous capabilities to the earlier prototype.

Disclosure on Prior Work

The core robot design, image-processing pipeline, hardware integration and prototype observations summarized in this manuscript originate from the authors' earlier BE project work. This manuscript is prepared as a substantially revised and contextualized publication-practice version, with an updated technology discussion and recent literature. Before

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submission, the authors should disclose the earlier publication/project report to the editor and confirm that the target journal permits substantially revised versions of previously published work. The manuscript should not be submitted simultaneously to multiple journals.

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