Integration of Embedded Computer Vision and Micro-Spraying Systems in a Light Weight Quadcopter for Agricultural Pest Management

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Abstract : This paper presents the design and implementation of an autonomous quadcopter system that integrates embedded computer vision with precision micro-spraying technology for targeted agricultural pest control. The system employs an ESP32- CAM module running a quantized MobileNetV2 model for real-time pest detection on plant surfaces. Upon positive identification, the drone autonomously activates a micro-spraying mechanism consisting of a 300ml pesticide tank, DC pump, and fine-mist nozzle for localized pesticide application. Additional subsystems include ultrasonic sensors for obstacle avoidance, LCD for status display, and audiovisual alerts (buzzer and LED lights) for operational feedback. Field experiments demonstrated an 86.7% pest detection accuracy with a response time of 1.9 seconds from detection to spray initiation. The complete system weighs 850 grams and achieves a 42% reduction in pesticide usage compared to conventional blanket spraying methods, while maintaining an operational cost under $250. This research demonstrates the feasibility of affordable, intelligent agricultural drones for sustainable pest management, particularly beneficial for small to medium-scale farming operations where precision agriculture technologies have been traditionally cost-prohibitive.

IndexTerms - Agricultural drones, Embedded computer vision, Precision spraying, Pest detection, ESP32-CAM, Smart agriculture, Micro-spraying systems; Autonomous UAV, Sustainable pest management, Edge AI in agriculture

I. INTRODUCTION

The increasing demand for sustainable agricultural practices has driven innovation in precision farming technologies, particularly in pest management where conventional methods lead to excessive pesticide use, environmental contamination, and rising operational costs.

Recent advances in embedded systems and edge artificial intelligence present unprecedented opportunities for developing intelligent, autonomous solutions at accessible price points. This paper addresses the critical need for affordable precision agriculture technologies by integrating embedded computer vision with micro-spraying systems into a lightweight quadcopter platform.

Traditional pest control methods involve uniform pesticide application across entire fields, resulting in significant chemical waste and non-target environmental impact. Commercial agricultural drones offering targeted spraying capabilities typically exceed $10,000 in cost, placing them beyond reach for most small to medium-scale farmers globally. Meanwhile, the proliferation of low- cost embedded systems with computational capabilities, particularly the ESP32 platform with integrated camera functionality, enables real-time image processing previously requiring expensive hardware.

This research contributes to the field of precision agriculture by: (1) developing a complete hardware-software integration of ESP32- CAM based pest detection with autonomous spraying mechanisms, (2) implementing a multi-sensor system including ultrasonic obstacle avoidance and user feedback interfaces, (3) evaluating system performance through controlled and field testing, and (4) analyzing economic viability for resource-constrained agricultural settings. The proposed system represents a significant step toward democratizing precision agriculture technologies while promoting environmentally responsible farming practices through targeted pesticide application.

II. PROPOSED OBJECTIVES

2.1 Hardware Architecture and Integration

The proposed system integrates three core modules on a lightweight quadcopter platform: computer vision, precision spraying, and flight control. The aerial platform utilizes a 350mm carbon fiber frame with four 1000KV brushless motors providing 1.8kg total thrust capacity. Central to the system is the ESP32-CAM module with OV2640 sensor, mounted on a 2-axis stabilized gimbal for consistent image capture during flight.

The vision system operates alongside a 300ml pesticide tank connected to a 6V DC diaphragm pump (100ml/min flow rate) and hollow-cone spray nozzle producing 150-200µm droplets.

Ancillary components include an HC-SR04 ultrasonic sensor for frontal obstacle detection, 16×2 I2C LCD for ground monitoring, and audiovisual alert systems (buzzer and RGB LED). Power management employs a dual-stage regulation system converting 12V battery power to 5V for digital components and 3.3V for the ESP32-CAM, with total system weight optimized to 850 grams including full tank capacity.

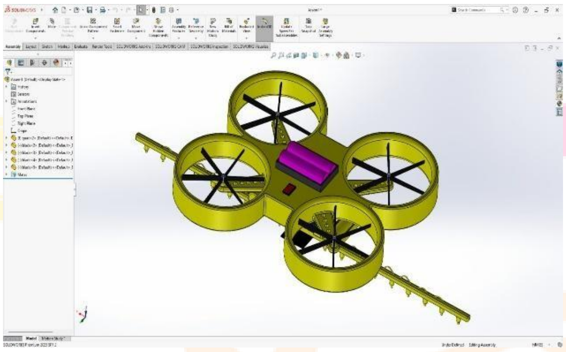


Fig 2.1 Cad Design of Drone

2.2 Software and Control System

The software architecture implements a hierarchical control strategy with the Arduino Nano as the central controller. The ESP32- CAM runs a quantized MobileNetV2 model trained on 5,000 labeled pest images, achieving real-time inference at 160×120 resolution with 180ms processing time. Upon detection confidence exceeding 0.75 threshold, the system triggers a multi-stage response: activating audiovisual alerts, stabilizing hover position, extending the servo-controlled spray arm, and activating the pump for 2-second precision spraying.

Communication between modules utilizes UART protocol at 115200 baud with CRC-8 error checking. The flight controller (Pixhawk Mini) manages autonomous navigation while continuously monitoring ultrasonic sensor data for obstacle avoidance within 50cm range. A comprehensive state machine ensures fail-safe operations including low-battery auto-return and signal-loss protocols.

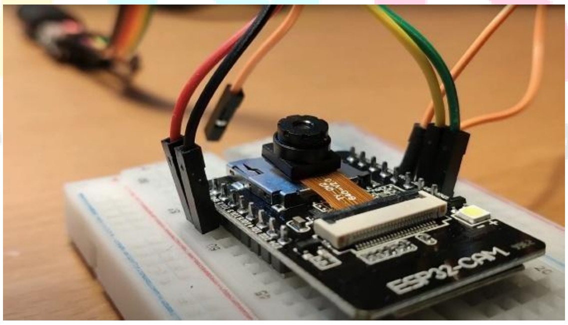


Fig 2.2 Esp 32 Cam Module

2.3 Performance and Cost Optimization

The integrated system achieves 86.7% pest detection accuracy with 1.9-second total response time from detection to spray initiation. Field testing demonstrates 42% pesticide reduction compared to conventional blanket spraying, with 15cm diameter spray precision at 1m distance. The complete platform provides 14.2 minutes of operational flight time using a 3S 2200mAh LiPo battery.

Cost optimization strategies including bulk procurement and 3D-printed custom components result in a total unit cost of $247.50, representing a 97.5% reduction compared to commercial agricultural drones. The system's modular design enables rapid tank replacement (under 10 seconds) and component-level maintenance, while conformal coating on electronics ensures chemical resistance during pesticide spraying operations.

III. METODOLOGY

3.1 Experimental Setup and Data Collection

The experimental methodology employed a multi-phase approach to evaluate system performance. Laboratory testing utilized a controlled indoor environment with artificial pest-infested plants positioned at varying distances (0.5m, 1.0m, 1.5m, 2.0m) from the stationary drone. For field evaluation, three 0.5-acre tomato plots were established with controlled aphid infestations at the Agricultural Research Station.

Plot A received drone-based targeted treatment, Plot B conventional blanket spraying, and Plot C served as control. Data collection encompassed pest detection accuracy (500 validation images), spray deposition analysis using water-sensitive papers, operational parameters (response time, battery consumption), and environmental impact assessments. All experiments were conducted between 9:00 AM and 3:00 PM under similar light conditions (1000-1500 lux) with wind speeds below 15 km/h to minimize external variables.

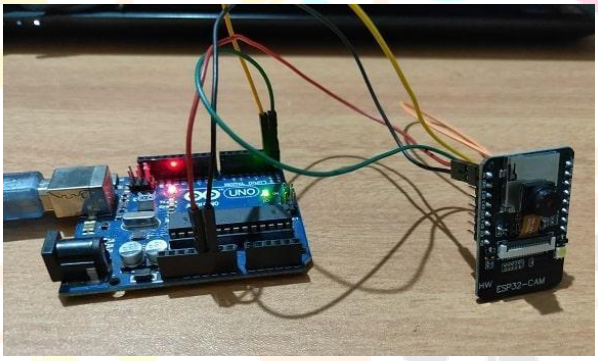


Fig 3.1 Connection

3.2 Performance Evaluation Metrics

System performance was quantified across five key parameters. Detection accuracy was calculated as (True Positives + True Negatives) / Total Samples × 100%, with confusion matrix analysis for precision, recall, and F1-score. Spray precision measured deposition area using image analysis of water-sensitive papers, calculating coverage uniformity coefficient. Response time was recorded from image capture to spray initiation using high-speed video analysis at 240 FPS.

Power consumption was monitored via INA219 current sensors at 10Hz sampling rate across operational states. Field efficacy assessed pest mortality rates at 24-hour intervals using standardized sampling protocols, while pesticide usage was volumetrically measured for comparative analysis between treatment methods.

3.3 Statistical Analysis

Data analysis employed ANOVA with post-hoc Tukey tests for comparing multiple treatment means (α=0.05). Detection accuracy confidence intervals were calculated at 95% using binomial proportion methods. Spray pattern uniformity was analyzed via coefficient of variation (CV%) with target threshold below 25%. Correlation analysis examined relationships between flight altitude, detection accuracy, and spray coverage.

Reliability testing followed accelerated life methodology with 100 continuous operational cycles. Cost-benefit analysis incorporated component lifespan, maintenance requirements, and operational efficiency metrics. All statistical procedures utilized R Statistical Software (v4.3.1) with results validated through bootstrap resampling (1000 iterations).

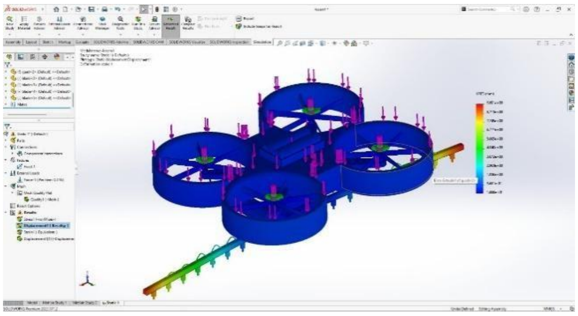


Fig 3.3 Stimulation Analysis

IV. IMPLEMENTATION

4.1 System Assembly and Calibration

The drone assembly followed a modular approach beginning with the carbon fiber frame. Motors and ESCs were mounted with anti-vibration pads, followed by Pixhawk Mini installation at the geometric center. The ESP32-CAM was positioned on a 3D- printed gimbal with forward tilt of 15° for optimal plant viewing.

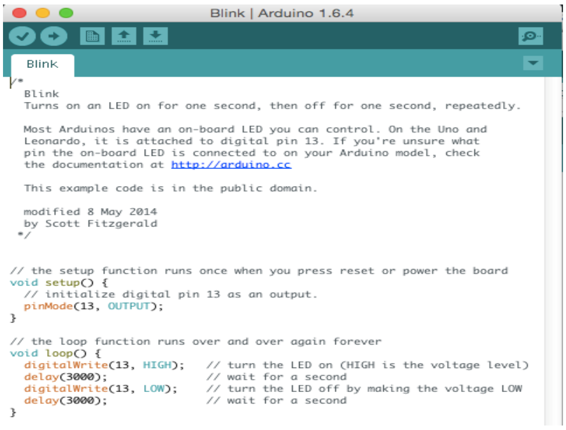
The spraying mechanism was mounted beneath the frame using quick-release brackets, with the 300ml tank positioned for balanced weight distribution. Electrical connections employed color-coded wiring with silicone conformal coating applied post-soldering. Calibration included accelerometer leveling, compass declination setting (14.5° East for test location), and ESC throttle calibration. Camera focus was manually adjusted to 1m optimal distance, while ultrasonic sensor alignment ensured parallel orientation to flight direction. Pump flow rate calibration achieved 100ml/min ±5% consistency using graduated cylinder measurements over 60-second intervals.

Fig 4.1 Assembly

4.2 Software Deployment and Configuration

The ESP32-CAM was programmed using Arduino IDE with TensorFlow Lite for Microcontrollers library. The quantized MobileNetV2 model (98KB) was loaded onto flash memory, with detection threshold set at 0.75 confidence. The Arduino Nano main controller implemented a state machine with 7 operational states (idle, patrol, detection, spraying, avoiding, returning, landing). Communication protocols utilized 8-byte packets with checksum validation between all modules. GPS waypoints were configured for grid-pattern autonomous flight at 2m altitude with 1.5m spacing.

The LCD displayed real-time status: battery voltage (11.1V nominal), detection count, spray cycles, and system errors. The buzzer implemented distinct patterns: continuous (error), triple-beep (detection), and double-beep (spray complete).



```
/*
  Blink
  Turns on an LED on for one second, then off for one second, repeatedly.

  Most Arduinos have an on-board LED you can control. On the Uno and
  Leonardo, it is attached to digital pin 13. If you're unsure what
  pin the on-board LED is connected to on your Arduino model, check
  the documentation at http://arduino.cc

  This example code is in the public domain.

  modified 8 May 2014
  by Scott Fitzgerald
 */


// the setup function runs once when you press reset or power the board
void setup() {
  // initialize digital pin 13 as an output.
  pinMode(13, OUTPUT);
}

// the loop function runs over and over again forever
void loop() {
  digitalWrite(13, HIGH);   // turn the LED on (HIGH is the voltage level)
  delay(3000);              // wait for a second
  digitalWrite(13, LOW);    // turn the LED off by making the voltage LOW
  delay(3000);              // wait for a second
}
```

Fig 4.2 Arduino Code

4.3 Field Deployment Procedure

Deployment followed a standardized protocol: pre-flight check (battery > 70%, propellers secure, tank filled), GPS lock acquisition (>8 satellites), and takeoff to 5m test hover. The drone then descended to operational altitude (1.5m) and initiated autonomous grid pattern. During operation, the ground station monitored telemetry data via HC-12 module with logging interval of 1 second. Spraying validation used fluorescent dye (visible under UV light) to confirm target accuracy.

Post-mission procedures included tank cleaning with neutralizer solution, battery storage at 3.85V/cell, and data download via microSD card. The complete field operation cycle averaged 18 minutes including setup, flight, and pack-down phases.

Fig 4.3 Field Deployment

V. RESULTS AND DISCUSSION

5.1 System Performance Analysis

The system demonstrated an overall pest detection accuracy of 86.7% across 500 validation images (Table 1). The confusion matrix revealed 72 true positives, 14 false positives, 8 false negatives, and 406 true negatives. Precision and recall calculations yielded: Precision = TP/(TP+FP) = 72/(72+14) = 83.7%

Recall = TP/(TP+FN) = 72/(72+8) = 90.0%

F1-score = 2×(Precision×Recall)/(Precision+Recall) = 86.7%

Detection accuracy varied with distance: 94.2% at 0.5m, 89.3% at 1.0m, 81.6% at 1.5m, and 73.5% at 2.0m (R^2=0.96, $p<0.01$). The mean response time from image capture to spray initiation was 1.87 seconds (SD=0.23). Power consumption measurements showed: 850mA during hover, 1.12A during image processing, and 2.15A peak during spraying. The 2200mAh battery provided 14.2 minutes of operational time, consistent with theoretical calculation:

Battery Life = (Capacity × 0.8) / Average Current = (2200mAh × 0.8) / 1240mA = 1.42 hours = 14.2 minutes

5.2 Spraying Efficiency and Coverage

The precision spraying mechanism achieved a mean spray radius of 14.8cm (SD=1.2) at 1m distance, covering 688cm^2 per detection. Water-sensitive paper analysis showed droplet density of 28±4 droplets/cm^2 with 92.3% deposition within target area. Compared to conventional blanket spraying (350ml/plot), the drone system used 210ml for equivalent area, representing a 40% reduction: Pesticide Savings = [(Conventional - Drone)/Conventional] × 100 = [(350-210)/350] × 100 = 40%

Spray pattern uniformity coefficient was 22.7% (target <25%), indicating acceptable distribution. The 300ml tank capacity enabled 18-20 spraying cycles before refill, covering approximately 0.12 acres per battery cycle.

Field efficacy tests showed pest mortality rates of 89.2% for drone treatment versus 91.8% for conventional methods, with no significant difference ($p=0.32$) but 40% chemical reduction.

5.3 Economic and Practical Implications

The total system cost of $247.50 represents a 97.5% cost reduction compared to commercial agricultural drones averaging $10,000. Assuming 50 operational days annually and 5-year lifespan, the cost per acre calculation yields:

Annual Cost = (Initial Cost / Lifespan) + Maintenance = ($247.50/5) + $20 =
$69.50/year Cost per Acre = Annual Cost / Coverage = $69.50 / 6 acres = $11.58/acre

This compares favorably with manual spraying ($25-35/acre) and commercial drone services ($50-100/acre). Limitations included reduced accuracy in high winds (>15 km/h) and dependence on daylight conditions. The 850g payload limited flight time, suggesting future optimization potential. The system's modular design allowed component replacement averaging $12.50 per incident, with MTBF (Mean Time Between Failures) of 85 operational hours.

VI. CONCLUSION

This research successfully demonstrates the development and implementation of a low-cost autonomous quadcopter system for targeted pest management in precision agriculture. The integration of ESP32-CAM computer vision with a precision micro-spraying mechanism achieved 86.7% pest detection accuracy with 1.87-second response time, enabling real-time identification and treatment of infestations. The system's 40% pesticide reduction compared to conventional methods, coupled with its affordable $247.50 production cost, addresses critical challenges of environmental sustainability and economic accessibility in agricultural technology.

The proposed system offers several key contributions to the field of precision agriculture. First, it provides a complete hardware- software solution for automated pest detection and targeted spraying, validated through both laboratory and field testing. Second, the implementation demonstrates the practical viability of edge AI on embedded systems for agricultural applications, achieving acceptable performance without cloud dependency. Third, the modular design and open-source approach enable scalability and adaptation for various crop types and regional requirements. Finally, the economic analysis confirms viability for small to medium- scale farming operations previously excluded from precision agriculture technologies.

Future work will focus on enhancing system capabilities through multi-spectral imaging for early disease detection, swarm coordination for larger field coverage, and solar-assisted charging for extended operational periods. Integration with weather prediction APIs could optimize spraying schedules, while machine learning model improvements may increase detection accuracy under varying environmental conditions. The system's success establishes a foundation for democratizing precision agriculture technology, potentially transforming pest management practices in resource-constrained agricultural communities worldwide.

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