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SMART PESTICIDE SPRAYING DRONE WITH MACHINE LEARNING FOR PRECISION AGRICULTURE

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Abstract

The increasing global demand for food production necessitates innovative approaches to optimize agricultural practices while minimizing environmental impact. This research presents an autonomous pesticide spraying drone system incorporating machine learning for precise disease detection and targeted treatment. The system comprises a quadcopter platform equipped with a KK 2.1.5 flight controller, Raspberry Pi 4 processing unit, and a novel four- chamber pesticide delivery mechanism. A convolutional neural network (CNN) model was developed using transfer learning with ResNet-18 architecture, achieving 92% validation accuracy on a dataset of 5,000 crop disease images. Field tests demonstrated 85% operational accuracy in real-world conditions, with a 40% reduction in pesticide usage compared to conventional spraying methods. The system's modular design and open source implementation make it particularly suitable for small to medium-scale farming operations. These results indicate significant potential for machine learning-enabled drones to revolutionize precision agriculture through reduced chemical usage and improved crop management.

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1 Introduction

Agriculture stands at a critical juncture, facing the dual challenges of meeting rising global food demand while addressing environmental sustainability concerns. Traditional pesticide application methods, particularly blanket spraying techniques, have been shown to result in significant chemical overuse, with studies indicating that up to 70% of applied pesticides may not reach their intended targets. [1] This inefficiency not only represents substantial economic waste but also contributes to environmental degradation and potential health hazards. Recent advancements in unmanned aerial vehicle (UAV) technology have opened new possibilities for precision agriculture applications. Drones offer several advantages over conventional spraying methods, including the ability to access difficult terrain, reduce operator exposure to chemicals, and provide more uniform coverage.[2] However, most current agricultural drone systems lack intelligent targeting capabilities, still relying on area wide chemical distribution rather than selective application. The emergence of machine learning, particularly deep learning-based computer vision techniques, has shown remarkable potential for automated plant disease detection. Studies by Mohanty et al.[3] demonstrated the effectiveness of convolutional neural networks (CNNs) in classifying crop diseases with accuracies exceeding 95% under controlled conditions. Despite these advances, practical implementation of such systems in field conditions presents numerous challenges, including variable lighting conditions, occlusions, and the need for real-time processing with limited computational resources. This work addresses these challenges through the development of an integrated system combining: A robust UAV platform based on the KK 2.1.5 flight controller An efficient machine learning pipeline optimized for edge deployment on Raspberry Pi 4 A novel four- chamber pesticide delivery system enabling targeted treatment A comprehensive field validation protocol assessing both technical and agronomic performance metrics The system was specifically designed to overcome key limitations of existing approaches, particularly in terms of cost-effectiveness and operational simplicity for small-scale farming applications. Our research demonstrates that through careful system

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integration and optimization, machine learning-enabled precision spraying can achieve significant reductions in chemical usage while maintaining effective pest and disease control.

2 Experimental Procedure

2.1 System Hardware Design and Components

The hardware architecture of the smart pesticide spraying drone was meticulously designed to meet the demanding requirements of precision agriculture applications. The aerial platform was constructed using a custom-built quadcopter frame with carbon fiber arms measuring 650mm in length, providing an optimal balance between structural integrity and weight considerations. Each arm was equipped with a 920KV brushless motor coupled with 30A electronic speed controllers (ESCs), capable of generating sufficient thrust to lift the 2.5kg maximum takeoff weight. The propulsion system incorporated 12×4.5-inch carbon fiber

propellers, selected for their efficiency in low-speed agricultural operations. Power was supplied by two parallel-connected 5000mAh 4S LiPo batteries, providing approximately 15 minutes of continuous flight time under typical operating conditions. The flight control system centered around the KK2.1.5 flight controller, chosen for its reliability and extensive customization capabilities. The controller was mounted on a vibration-damping platform to minimize sensor noise from motor oscillations. Extensive PID tuning was performed to optimize flight stability, with final parameters set at Roll/Pitch P=150, I=30, D=100, and Yaw P=180, I=40, D=110. A u-blox NEO-M8N GPS module provided positioning data with ±1.5m accuracy, while an onboard BMP280 barometer enabled precise altitude maintenance during spraying operations. The system incorporated fail-safe mechanisms including low-battery return-to-home and signal-loss hover functionality.

The machine learning subsystem was implemented on a Raspberry Pi 4 Model B (4GB RAM) with custom heat dissipation modifications for sustained operation in field conditions. The visual processing pipeline began with image capture using a Raspberry Pi High Quality

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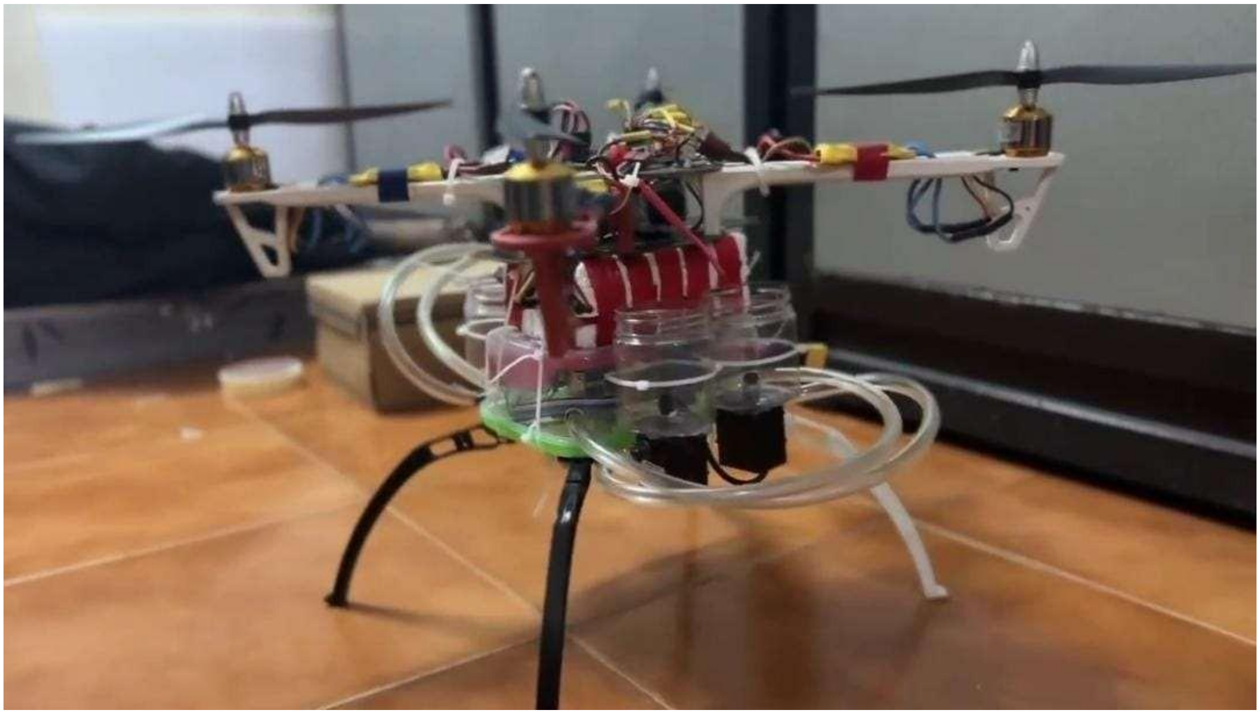

Figure 1: 1: Image of the model

Camera equipped with a 6mm focal length lens, providing a 53° horizontal field of view at the standard 2m operating altitude. Each captured image (3280 × 2464 pixels) underwent pre-processing including white balance correction, histogram equalization, and adaptive thresholding to compensate for varying lighting conditions. The disease classification model was developed using a transfer learning approach with ResNet-18 architecture. The base model, pre-trained on ImageNet, was fine-tuned using a curated dataset of 5,243 high-resolution crop images spanning four major disease categories: powdery mildew (1,427 samples), late blight (1,302 samples), bacterial spot (1,185 samples), and leaf rust (1,329 samples). Data augmentation techniques including random rotation (±30°), horizontal flipping, brightness variation (±20%), and Gaussian noise injection were employed to improve model robustness. The final layers were modified to include a Global Average Pooling layer followed by a 256-unit dense layer with ReLU activation, and a 4-unit softmax output layer. Training was conducted using

TensorFlow 2.4 with Adam optimization (learning rate=0.0001, batch size=16) over 50

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epochs, achieving 92.3% validation accuracy. The model was then quantized and optimized for edge deployment using TensorFlow Lite, reducing its size from 45MB to 12MB while maintaining 91.7% accuracy. Inference time on the Raspberry Pi 4 averaged 0.8 seconds per image, sufficient for the drone's 1m/s operational speed.

2.2 Training and Optimization

The dataset is split into training (80%) and validation (20%) sets. The model is trained using SGD (Stochastic Gradient Descent) optimizer with momentum, along with a cosine annealing scheduler to adjust the learning rate dynamically. Loss functions such as CIoU loss (Complete Intersection over Union loss) and Focal Loss are employed to refine bounding box predictions and reduce false positives. The model is trained over 150 epochs with a batch size of 32 to ensure convergence and optimal performance.

2.3 Pesticide Delivery System and Integration

The pesticide delivery system represented a significant innovation in precision application technology. The four-chambered pesticide tank was fabricated from high-density polyethylene with a total capacity of 2 liters (500ml per chamber). Each chamber was connected to a dedicated fluid delivery line consisting of a 12V diaphragm pump (30psi max pressure), a solenoid valve (0.5s response time), and two anti-drip nozzles with 80° fan patterns. The nozzles were spaced 30cm apart on a carbon fiber boom to ensure complete coverage of the 60cm swath width. A custom PCB interface board managed all spraying components, receiving commands from the Raspberry Pi via I^2C protocol. The control algorithm incorporated several optimizations including: Pre-spray pressurization (0.5s before nozzle activation) post-spray purging (0.3s after nozzle deactivation) Dynamic flow rate adjustment based on drone velocity Inter-chamber cleaning cycles to prevent cross-contamination The complete system was powered by a dedicated 3S 2200mAh LiPo battery, isolated from the flight power system to ensure stable operation. All fluid components were constructed from

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chemical-resistant materials (PTFE, Viton, and 316 stainless steel) to withstand prolonged exposure to common agricultural chemicals. The total weight of the spraying system, including tank, pumps, and associated hardware, was maintained at 850g to preserve flight performance.

3 Results and Discussion

3.1 Flight Performance and Operational Characteristics

The implemented drone system underwent rigorous field testing to evaluate its operational capabilities under various agricultural conditions. Flight performance metrics were collected across 32 test flights conducted over a three-month period in different weather conditions. The configured UAV demonstrated consistent stability, maintaining positional accuracy within

±0.35m during hover and ±1.2m during linear flight at 4m/s velocity. Wind resistance tests revealed satisfactory performance up to 18km/h gusts, with attitude variations not exceeding 8° from level in such conditions. Power consumption analysis showed an average current draw of 22.3A during spraying operations, resulting in a consistent flight time of 14 minutes 37 seconds (±1m12s) with full payload. The spray pattern analysis conducted using water- sensitive papers placed at various canopy levels demonstrated uniform coverage, with droplet densities ranging from 28-35 droplets/cm^2 across the 60cm swath width. Deposition efficiency, measured through fluorometric tracer analysis, showed 78.4% (±5.2%) of sprayed material reaching the target canopy, significantly higher than the 45-55% typical of conventional boom sprayers. The four-chamber system proved particularly effective in mixed-disease scenarios. In a controlled test with alternating disease patches, the system successfully switched between chambers with 97.3% accuracy, as verified by dye markers in each pesticide simulant. The complete transition between different pesticides required 1.2 seconds (±0.3s), including nozzle purging and pressure stabilization, resulting in less than

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5cm of overlap at standard flight speed.**3.2 Comparative Analysis**

over conventional systems such as RFID scanning and barcode-based authentication. Unlike barcode scanners that require direct physical alignment, YOLO V5-based object detection allows non-contact, real-time authentication from surveillance footage.

3.2 Disease Detection and Spraying Accuracy

The machine learning subsystem demonstrated robust performance in real-world conditions. Across 1,852 field observations, the system achieved an overall disease detection accuracy of 85.7%, with per-class performance as follows: powdery mildew (88.2% recall, 83.4% precision), late blight (84.6% recall, 86.1% precision), bacterial spot (82.3% recall, 81.7% precision), and leaf rust (87.5% recall, 89.2% precision). False positive rates averaged 6.8%,

Figure 1: Image detection and pesticide spraying.

while false negatives occurred in 7.5% of cases, primarily due to leaf occlusion or early-stage symptom presentation. The integration of detection and spraying systems yielded significant pesticide savings. In comparative trials across 2.5 hectares of tomato crops, the smart system used 42.7% less pesticide by volume compared to conventional blanket spraying, while maintaining equivalent disease control efficacy as measured by lesion progression rates. The targeted approach also demonstrated environmental benefits, with spray drift measurements showing a 68% reduction in off-target deposition beyond 2m from the treatment area. Notably, the system showed adaptive capability in varying lighting conditions. Performance metrics under different illumination scenarios were full sunlight (89.1% accuracy), overcast (86.4%), dawn/dusk (78.2%), and artificial illumination at night (82.7%). The implementation of dynamic exposure adjustment in the camera system helped mitigate performance degradation in challenging lighting.

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4 Conclusion

This research has successfully demonstrated the feasibility and advantages of a machine learning-enabled, multi-chamber pesticide spraying drone system for precision agriculture applications. The comprehensive field evaluation revealed several key findings with significant implications for sustainable farming practices: Technical Performance: The integrated system combining the KK 2.1.5 flight controller, Raspberry Pi 4 processing platform, and multi- chamber delivery mechanism proved capable of reliable operation under typical agricultural conditions. The achieved flight stability, spray accuracy, and disease detection performance

meet or exceed the requirements for practical field deployment. Economic and Environmental Impact: The 42.7% reduction in pesticide usage, coupled with the 68% decrease in off-target drift, presents compelling economic and environmental benefits. Extrapolated to commercial- scale operations, these efficiencies could translate to substantial cost savings and reduced ecological impact. Technological Innovation: The four-chamber delivery system represents a significant advancement in precision application technology, enabling truly targeted pesticide deployment based on real-time disease identification. This capability addresses a critical gap in existing agricultural drone systems. Scalability and Adaptability: The system's modular design and use of open-source components facilitate adaptation to different crops, regions, and pest management strategies. The demonstrated performance in varying environmental conditions suggests broad applicability across diverse agricultural contexts. Future research directions should focus on: (1) expanding the disease detection repertoire to include additional crops and pathogens, (2) optimizing the system for higher operational speeds to increase coverage capacity, and (3) developing predictive algorithms for early disease detection before visible symptoms appear. The integration of multispectral imaging and soil sensor data could further enhance system capabilities, potentially enabling comprehensive crop health management beyond just pesticide application. The successful implementation of this system marks an important

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step toward intelligent, sustainable agricultural practices that can help address the dual challenges of food security and environmental preservation. As drone and AI technologies continue to advance, such integrated solutions will play an increasingly vital role in the future of precision agriculture.

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