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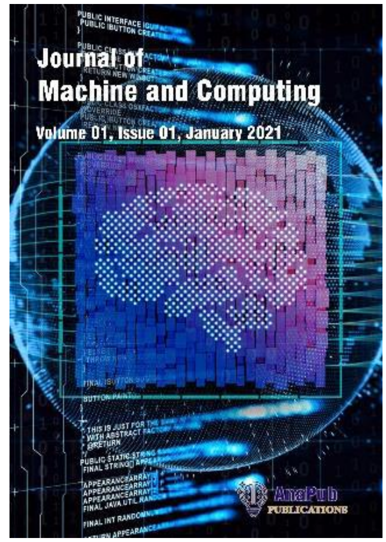

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The Deployment of Machine Learning and On-Board Vision Systems for an Unmanned Aerial Sprayer for Pesticides

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Abstract: In the Smart Farming (SF) domain, integrating autonomous systems is revolutionizing the efficiency and sustainability of Crop Management (CM) practices. This paper introduces an approach to Pest Control (PC) in Tea Plantations (TP), focusing on using an autonomous Unmanned Aerial Vehicle (UAV) equipped with a Pest Detection (PD) and precision spraying system. Leveraging the capabilities of the DJI Agras T40, a UAV specifically engineered for agricultural use, this system incorporates a Deep Learning (DL) built on the DenseNet-121 architecture. This model is refined to accurately detect and accurately evaluate the infection rates of six prevalent tea pests. In order to intelligently identify pesticide dispersion, the UAV uses advanced technology. This provides targeted deployment, optimizes the utilization of resources, and minimizes impact on the environment. The method's effectiveness has been proved by simulation experiments, recommending that it has real-world possibilities. A sustainable and flexible approach to several pest cases can be achieved by pairing the Sprayer Control Module (SCM) with the PD. Such integration significantly advances autonomous Pest Control Systems (PCS), enhances PC precision and performance, and minimizes the environmental impact.

Keywords: Sprayer Control Module, UAV, Smart Agriculture, Intelligent Autonomous Systems, Crop Management, Smart and Precision Agriculture

1. Introduction

Precision Agriculture (PA) and Smart Farming (SF) have transformed the landscape of agriculture by integrating innovative technology and novel methods to approach agriculture to enhance productivity, lifespan, and sustainability. Applying data-driven conclusions, PA provides practical application of resources, accurate monitoring of agricultural performance, and effective oversight of conditions in the soil. The productivity of crops, reduced waste, and input optimum performance have all been substantially improved by integrating autonomous systems into SF techniques. Systems that are automated like these factors have grown fundamental in many processes related to agriculture, rapid the sector's progress towards more successful and sustainable approaches. Recent developments in fields such as soil testing, collection of information, and precise fertilizer and water application have revolutionized conventional agricultural operations. As a result, agriculturalists can reduce costs, improve productivity, and optimize Decision-Making Systems (DMS).

By providing an innovative method of using Chemicals used for pest-reducing tasks related to hand spraying, permitting precise and accurate control across different environments, and sustaining agricultural products productivity and health, Unmanned Aerial Vehicles (UAVs) have transformed the Pest Control System (PCS). Instead of being time-consuming and susceptible to mistakes, autonomous UAV sprayers enhance the efficacy and accuracy of protecting crops while minimizing human monitoring necessities.

The invention of an intelligent autonomous Pest Detection (PD) and spraying system has been rendered more challenging by recognizing that autonomous UAV sprayers, fitted with complex algorithms and sensors, can execute challenging tasks without human involvement, boosting the productivity of PCS. Machine Learning (ML), Computer Vision (CV), and autonomous accuracy are required for an entire system to navigate productively, identify bug-afflicted areas, and react fast in order to evolve to new surroundings and pest types.

The present research describes an experimental UAV-based PCS for Munnar Tea Plantations (TP) in south India. The research utilizes the capabilities of the DJI Agras T40, a powerful and accurate UAV sprayer, to maximize TP's business operations. The DJI Agras T40 UAV uses a DenseNet-121 learning model to detect and quantify pest infection rates across six tea cultivation pest types. Its intelligent Sprayer Control Module (SCM) guides the drone to the precise location for targeted pesticide application. The model demonstrated promising performance in simulation trials, meeting and exceeding expectations, showcasing a significant leap forward in PA, and presenting a sign into a future where innovative technology and SF practices intersect.

Integrating UAVs for agricultural PCS faces challenges such as model accuracy, real-time processing, sensor calibration, navigation safety, regulatory compliance, environmental impact, deployment infrastructure, and system maintenance. A proposed approach addresses these issues by ensuring accurate PD, instantaneous processing, calibrated sensors, focused spraying, and adherence to rules. This includes regulatory compliance, advanced obstacle detection, operator training, real-time monitoring, environmental impact mitigation, system redundancy, and regular maintenance.

The paper is divided into six sections: Section 2 discusses related work, Section 3 presents methods and study area, Section 4 presents architecture and process explanation, Section 5 presents results and simulation, and Section 6 concludes the work.

2. Literature Review

Integrating UAVs in agriculture, particularly pesticide application, significantly shifts towards PA. Excessive pesticide use has adverse effects on soil fertility and resistant pest species. UAVs can address these challenges by employing semi-automatic approaches and specialized control systems with advanced sensors and hardware, enhancing precision spraying.

[11] introduces a cost-effective, robot-assisted pesticide application solution guided by a color sensor and microcontroller. This precision-driven wheeled robot enhances efficiency and reduces environmental and human health hazards associated with pesticide overuse.

The study emphasizes the importance of accurate target recognition for UAV sprayers, highlighting the use of Deep Learning (DL) for real-time identification of spraying areas in coriander croplands, resulting in high F1 scores, potentially improving the precision of UAV-based spraying.

[13] test various modules for PCM using an autonomous UAV system. Based on the results of this investigation, these techniques are more accurate than conventional approaches to distributing chemical substances, which might decrease the number of chemical products consumed.

Given the results obtained from the research project, a modular system was suggested for equipping traditional sprayers with CV and specific nozzle controls [14-16]. This strategy provides improvements to both the natural environment and economic growth. Also, research analyses the impact of droplet size and wind speed on the likelihood of drift by UAVs, consequently feeding regulatory guidelines with helpful information and reinforcing the environmental security of UAV spraying compared to standard approaches.

The study introduces a visionary UAV sprayer system that uses RGB cameras to assess vegetation vigor and adjust pesticide flow, highlighting the adaptability of UAV technology for responsive and PA applications.

The study by [17-20] examines the use of UAVs in agriculture, particularly in developing countries like India. They highlight challenges like farm size, income, knowledge transfer, and infrastructure. However, their research on a Drone as a Service (DaaS model demonstrates UAVs' potential for efficient weedicide application and suggests a significant increase in agricultural UAV markets.

3. Materials Used

3.1 UAV Architecture

In our research, we utilized the DJI Agras T40 M/s. Shenzhen DJI Sciences and Technologies Ltd., Guangdong, China, is a UAV designed to apply agricultural pesticide spraying. The drone architecture is shown in Figure 1. The drone features a 40-liter spray tank and can cover an area of approximately 52 acres per hour, which is suitable for efficient pesticide application in large fields. Its structural design includes a coaxial twin-rotor system, each arm with dual motors and propellers, which ensures stability during flight.

The drone is equipped with advanced atomizing nozzles, which create a fine mist to ensure even distribution of the chemicals, optimizing the application efficiency and minimizing waste. The T40 is equipped with a 12-megapixel camera, which facilitates the creation of local maps essential for precise spraying operations, especially in varied terrains such as orchards and hilly regions. The mapping process involves outlining a target area and allowing the drone to photograph and stitch together images for a comprehensive 2D map. The rapid-charging battery supports extensive use with up to 1,500 charge cycles and can recharge in nearly 10 minutes using a compatible high-voltage outlet. The drone can handle up to 50 kg for dry material spreading with an efficient discharge system that maximizes coverage while minimizing refill frequency. An enhanced obstacle avoidance system with an active phased array radar and a binocular vision system for 3D mapping significantly reduces the risk of in-flight collisions, contributing to the safe deployment of the UAV in complex agricultural environments. Table 1 presents the specifications of the UAV.

Figure 1: DJI Agras T40 UAV

Table 1: Specification for the DJI Agras T40

Category	Specifications
Weight	38 kg (no battery), 50 kg (with battery)
Max Takeoff Weights	Spraying: 90 kg, Spreading: 101 kg
Dimensions (mm)	Operational: 2800×3150×780, Compact: 1125×750×[illegible]50
Hovering Accuracy	RTK enabled: ±10 cm, RTK disabled (radar): ±[illegible] cm H
Max Flight Radius	2000 m
Max Wind Resistance	6 m/s
Motor Power	4000 W/rotor
Propeller Diameter	54 inches
Rotor Quantity	8
Tank Capacity	Liquids: 40 L, Solids: 70 L
Spray/Spread Width	Spray: 1[illegible] m, Spread: 7 m
Operating Temperature	0°C to 40°C
Radar System	Omnidirectional with obstacle avoidance
Vision System Range	0.4-25 m
Remote Controller Display	7.02-inch touch LCD, 1920×1200 resolution
Operating Frequency	2.4000-2.4835 GHz, 5.725-5.850 GHz
Battery Life	Internal: 3.3 hrs, External: 2.7 hrs
Battery Capacity	30000 mAh
Voltage	52.22 V
Charging Time	Approx. 10 mins
Generator Output	DC and AC outputs
Fuel Tank Capacity	30 L
Fuel Efficiency	Approx. 500 ml/kWh

3.2 Area of Study

Located on the green hills of Munnar, the southern state of Kerala, the study station is a private TP that covers about 20 ha. The Munnar tea estates, situated 1,500 and 2,500 meters above the ocean's surface, are renowned for their gently undulating hills adorned with green tea plants. At these planned elevations, this specific farm experiences a unique environment that is perfect for producing tea but, alas, is infested by pests. The environmental conditions have been defined by substantial rainfall along with periodic clouds. The estate management team maintains the highest priority on SF procedure, focusing on chemical consumption and sustainability. The plantation thus provides an optimal location for the autonomous, accurate use of chemicals through an autonomous UAV system. In support of the estate's focus on SF, the research investigation will demonstrate how this technology may improve efficiency while reducing its environmental impact.

3.3 Pest Threats in Munnar's TPs

The green tea plantations of Munnar are unparalleled and serve as centers for pests and an attraction for tea lovers owing to their flavorful, tasty tea and the pleasant climate that nurtures plants. Two major insects that may cause severe damage to tea plants are the red spotted spider mite (Oligonychus coffee) and the leaf-eating mosquito bug (Helopeltis theivora). Because it eats on sap from trees, the tea-consuming mosquito insect reduces production and curls the leaf surfaces of tea plants. On the other hand, lack of moisture is good for red-colored spider mites, which may trigger the plant's health to decline and foliage to turn yellow. The looming looper caterpillar (Biston Suppressaria) is a pest that may decrease the production and quality of crops by devouring plants. Dangerous crop arterial networks, insects, and bugs such as shot hole borer (Xyleborus Fornicatus) burrow into stems.

The tea tortrix can impair a tea garden's aesthetics and the health of the plants, and it is additionally referred to as the tea leaf roller (Homona Coffearia). Despite proper management, fungal illnesses like blister rot (Exobasidium Vexans) can remove plantations and inflict significant losses. Blister blight is a bacterial illness, and tea tortrix, which safeguards itself by wrapping the leaf, is a different possible factor. In Figure 2, images of each of the unwanted insects are shown.

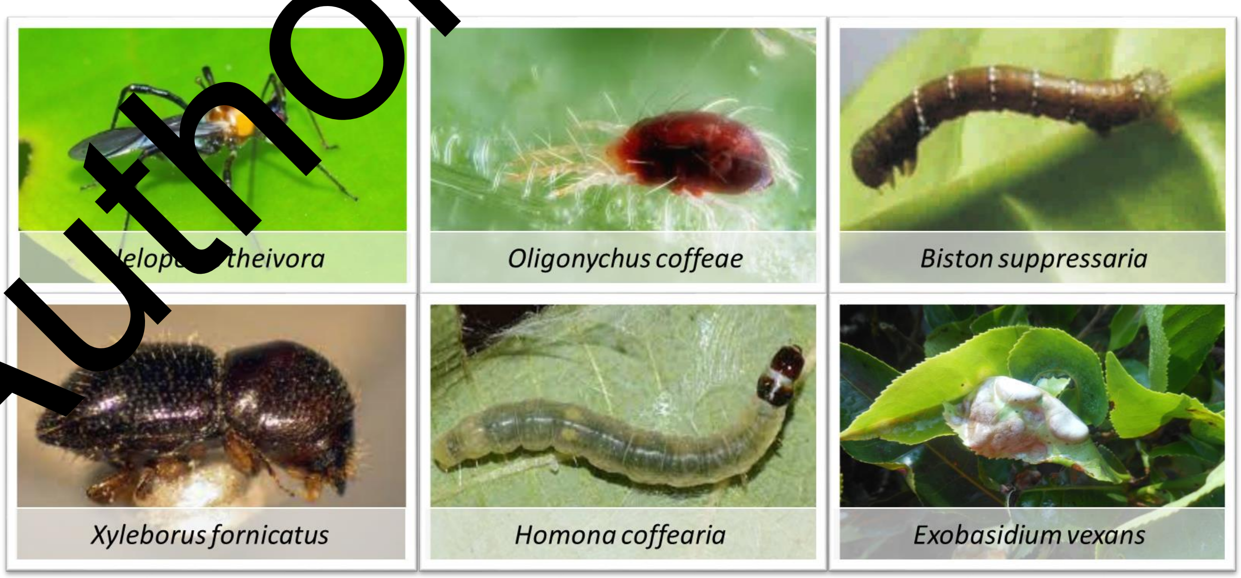


Figure 2: Pest Images

4. Proposed Model

The proposed Pesticide Spray Model (PSM) is presented in Figure 3. The detailed description of the components are discussed in the following sections:

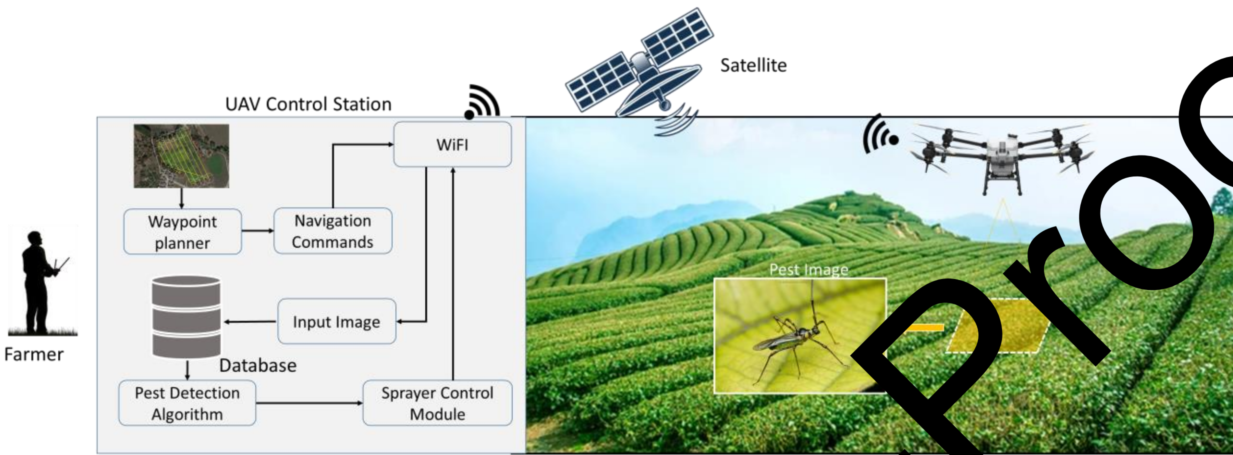


Figure 3: UAV-based PD and PSM

4.1 Waypoint Planner

To implement the proposed PSM, a plantation segment should be divided into multiple zones. The waypoint planner in the proposed PSM employs Mission Planner Software (MPS) to create the autonomous flight path for the UAV (Fig. 4). The defined segment, marked by the red boundary in the image provided, targets the area of interest for the UAV's operation. Within the MPS, the initial task is to import the segment's acquired geospatial data. This data is the foundational layer upon which the UAV's flight path is made. The software enables the setting of precise coordinates for each waypoint, effectively translating the 2-D map data into a 3-D flight plan by incorporating altitude data specific to the plantation's geography.

Waypoints are strategically aligned with the rows of tea bushes, creating an efficient navigation grid that enhances the UAV's coverage over the entire area. Setting waypoints that match the sloping terrain's elevations optimizes the drone's path for uniform pesticide application. MPS indicates if the UAV should be sprayed, sped up, or elevated at every route. These rules are essential for pesticide control in areas classified as "No-Spray Zones," such as the borders of plantations or locations close to rivers. Achieving Pest Control (PC) and environmental safety requires this level of precise UAV control. The precision of the UAV assures sustainability and PC protection.

Figure 4: Waypoint planning using MPS

Automatic mode route selection, which applies algorithms to develop effective path for particular regions, is also possible in UAV software, unlike manual route setup. The control unit of the UAV provides preliminary directions for GPS-guided self-piloting and provides terminal landmarks; the monitoring software of the UAV enables rapid intervention according to changes or impediments in surroundings, thereby ensuring objective Success Rate (SR) and accuracy.

4.2 Data Collection and Pre-Processing

Accurate PD can be found by obtaining high-resolution images of TP leaves using the 12-megapixel video cameras on the DJI Agras T40 UAV. The AI model uses specific leaf features. Before subsequent research, the images receive preliminary processing to ensure reliability and quality by removing highly fuzzy images with poor brightness. In order to encompass the geographical region that has been targeted, the UAV moves following a path that MPS has set.

The ML model examines a dataset that includes images of green tea leaves in order to identify signs of a pest problem. It performs this by juxtaposing these images to the sequences of pest features it discovered, thereby detecting particular signs such as coloration or structural flaws. Precise health of plant tests is made feasible by this non-invasive technique, enabling precise and fast PCS. By restricting the use of pesticides to specific regions, this technique improves productivity while also lowering the usage of pesticides and promoting a more sustainable approach to plantation health monitoring.

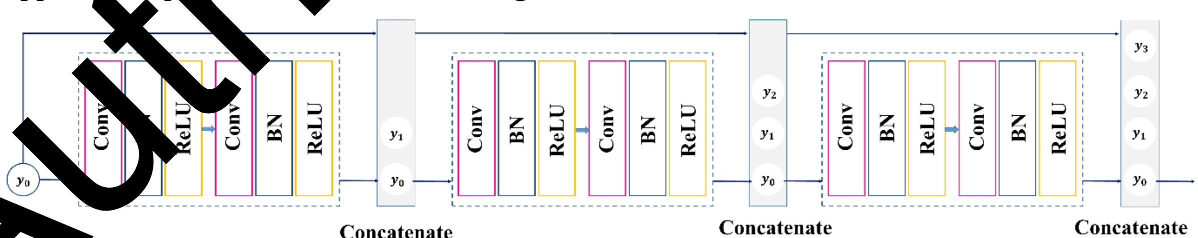


Figure 5: Structure of Denseblock

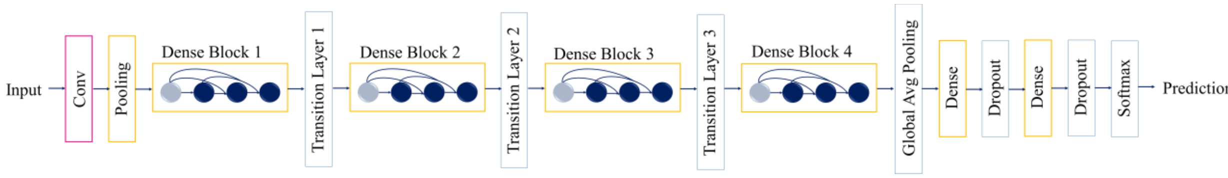


Figure 6. Densenet network's model

4.3 PD Algorithm

Leveraging a DL model to extract basic features, the research focuses on PD in TP image representations. To detect pests on tea leaves, the simulation must be equipped to discern their spectral and textural patterns. The above model is more adept at coping with diverse problems with pests and is more applicable than DeepCNN. Having stated that there is a greater chance of it being an overfit. Data processing, failure, batch standardization, and transfer learning are a few of the techniques integrated into the framework to improve its generalization capabilities. These methods enhance the model's value in precisely recognizing pests over various crop conditions.

The revolutionary design referred to as DenseNet, which has its foundation in the ResNet design, uses layer-wise direct connections to optimize the performance of data analysis. In a feed-forward method, DenseNet links all of the layers directly with each other, compared to traditional networks. Identical to ResNet's identity relationships, DenseNet partitions its framework into "Dense Blocks," where the total filters are dynamic, but the geographical dimensions of the feature maps remain fixed. A novel model is found within these dense blocks: the data inputs and results of the following layers are integrated. All of the 'd' layers in a DenseNet of 'D' layers perform a nonlinear function. 'T_d', a composite function that embraces batch normalization, ReLU activation, and a 3 × 3 convolution, EQU (1).

$$y_d = T_d(\{y_0, y_1, \dots, y_{d-1}\}) \quad (1)$$

In this EQU (1), ' y_0 ' signifies the stating data input image to the network, ' y_d ' is the result of the ' d th layer, the ' {.} ' specify the integrated feature maps formed in the previous layers.' y_i ', and ' T_d ' is the composite function significant to the functions at layer ' d '. This connection allows DenseNet to avoid the explosion gradient problem common in deep networks and permits a more robust feature propagation.

DenseNet models integrate unique transition layers positioned between the dense blocks. Their core function is to perform dimensionality reduction through a sequence of operations that includes batch normalization, a 1×11×1 convolution, followed by a 2×22×2 average pooling process. The dense pairing of feature maps has a chance to substantially elevate a network's confusion, considering these transition layers vital to complexity monitoring. The strengths of

DenseNet are manifold. Foremost, it addresses the challenge of vanishing and exploding gradients, a common hindrance in standard deep neural networks. Additionally, it facilitates the reutilization of features across the network. Unlike conventional networks that rely solely on the most abstract feature set for classification tasks, DenseNet leverages a composite feature pool from different levels of abstraction, significantly reducing the model's parameters and enhancing the efficacy of the network.

In this study, we adapt the DenseNet-121 framework, recognized for its depth and efficiency in feature extraction, to suit our needs in PD from high-resolution images of TP leaves. This model comprises four dense blocks, processing input images of size 224×224 pixels. This study introduces two fully connected layers after the global average pooling layer to further enhance our network's ability to classify and discern pest-infected regions. This modification aims to refine the representation of high-level features specific to leaf conditions. The output layer employs a SoftMax activation function, which provides a probabilistic estimation of pest presence. Figures 5 and 6 illustrate the architecture of the adapted model and an example of connectivity within a dense block. Comprehensive details of the architecture, including layer configurations, are presented in the following Table 2.

Table 2: Configuration of the learning model

Layer name	Output size (pixels)	Layers
Input Image	224 x 224	-
Convolution + ReLU	112 x 112	Conv 7x7, stride 2
Max Pooling	56 x 56	3x3 max pool, stride 2
Dense Block (1)	56 x 56	6 x [1x1 conv + 3x3 conv]
Transition Layer (1)	28 x 28	1x1 conv + 2x2 avg pool, stride 2
Dense Block (2)	28 x 28	12 x [1x1 conv + 3x3 conv]
Transition Layer (2)	14 x 14	1x1 conv + 2x2 avg pool, stride 2
Dense Block (3)	14 x 14	24 x [1x1 conv + 3x3 conv]
Transition Layer (3)	7 x 7	1x1 conv + 2x2 avg pool, stride 2
Dense Block (4)	7 x 7	16 x [1x1 conv + 3x3 conv]
Global Average Pooling	1 x 1	-
Fully Connected + SoftMax	-	6 [pest types]

The pre-trained model used a 782 image dataset with 1-5 pest species to refine its ability to PD, utilizing the introduced dataset as a training ground.

4.4 Sprayer Control Module

The Sprayer Control Module (SCM) is a crucial component of the proposed UAV-PCS, regulating pesticide dispensing based on pest infection rate on tea plants. It integrates PD data with a precision spraying algorithm for optimal application.

1. **Infection Rate Determination:** The infection rate is calculated by the PD algorithm using the input from the leaf image data. The infection rate (I) is the ratio of the infected leaf area to the total surveyed leaf area within the image frame, EQU (2)

$$I = \frac{A_{\text{infected}}}{A_{\text{total}}} \times 100\% \tag{2}$$

where A_{infected} is the total area of detected pests on the leaves and A_{total} is the total leaf area in the image.

2. **Variable Rate Spraying:** The SCM adjusts the spray rate (R) based on the infection rate, using a pre-defined control function, $f(I)$, which determines the amount of pesticide needed, EQU (3)

$$R = f(I) = R_{\text{base}} + (I \times S_{\text{factor}}) \tag{3}$$

Here, R_{base} is the base spray rate, and S_{factor} is a sensitivity factor that scales the spray rate increase with infection severity.

3 **Real-Time Adjustments:** As the UAV traverses the plantation, the SCM continuously receives real-time data on infection rates. The control module uses this data to adjust the spray nozzle's flow rate. A feedback loop ensures that the amount of pesticide dispensed is responsive to the immediate requirements of the plants.

4 **Spray Pattern and Distribution:** The SCM is programmed to optimize the spray pattern to ensure maximum coverage with minimal waste. This is accomplished by adjusting the spray nozzles' angles and the UAV's altitude. A distribution algorithm, $D(x, y)$, accounts for the UAV's position and speed to adapt the spray pattern across the plantation grid.

5 **Pesticide Dosage and Flight Path Optimization:** Utilizing the infection rate data, the SCM optimizes the UAV's flight path to focus on areas with higher infection rates. The UAV follows a path that maximizes coverage of the infected regions while minimizing unnecessary spraying. This path optimization can be represented as a problem of reducing the function $P(x, y, I)$ over the plantation area, where P represents the path that the UAV will take given the coordinates (x, y) and infection rates I

Environmental and Safety Compliance: The SCM adheres to predefined thresholds for pesticide concentration to ensure environmental and human safety. If the required pesticide dosage exceeds safety levels, the system alerts the operator and adjusts the spray concentration to acceptable limits.

To ensure an effective and economical spray distribution, the SCM utilizes a mathematical model that correlates the pesticide dispensing rate with the UAV's speed (V), nozzle discharge coefficient (C_d), and the desired droplet size (D_s). The spray flow rate (Q) is determined as follows: EQU (4)

$$Q = C_d \times A_{\text{nozzle}} \times \sqrt{2 \times g \times H} \tag{4}$$

where A_{nozzle} is the nozzle cross-sectional area, g is the acceleration due to gravity, and H is the height of liquid pesticide in the tank, which decreases as spraying progresses.

4.5. Control Logic Implementation:

The SCM algorithm is implemented in the UAV's onboard computer, utilizing real-time data processing and actuator control to adjust the spray mechanisms.

The control logic includes the following steps:

(a) The PD system will be used to collect real-time infection data.

(b) The variable rate spraying algorithm computes the infection rate and determines the most suitable spray rate.

(c) The UAV's flight path will be adjusted using an optimized path algorithm for optimal coverage.

(d) The sprayer's flow rate and pattern are continuously adjusted in response to real-time infection data and UAV dynamics.

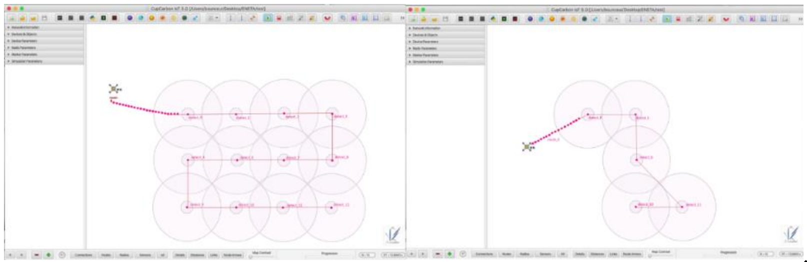
(e) The goal is to ensure environmental and safety compliance through intelligent thresholds and real-time adjustments.

Integrating SCM into our UAV-based PCS solution can significantly improve the precision and effectiveness of pesticide application in TPs, resulting in a sustainable and cost-effective approach that minimizes ecological footprint.

5. Simulation Setup

The study used the Cup Carbon 5.0 simulator to simulate IoT device and UAV behaviors in an SF framework. It created a virtual TP with distinct zones, varying in pest infection intensity, to replicate the heterogeneous nature of agricultural fields, allowing for realistic simulations of IoT devices and UAVs. UAVs were programmed to cover a field efficiently, using a bespoke PD algorithm to identify and geotag infected areas. They then spray precisely, deploying pesticides exclusively over the afflicted plants, mimicking the actions taken during an actual pest outbreak. This data provides valuable insights into PC measures' effectiveness and response times.

Clusters of UAVs' preliminary trajectory and the techniques of infection spraying are displayed in Figure 7. Researchers performed an extensive model with updated parameters to determine how numerous variables, such as speed, weight resources, atmospheric conditions, and chemical distribution sequences, impacted the PC's productivity.



(a) (b)

Figure 7: Cup Carbon Simulation: a) initial path navigation b) PD and spray navigation

5.1 Assumptions and Operation for UAV-Based PC

Certain presumptions form the core of the functional approach of the DJI Agras T40 UAV-based PCS for TPs. Such hypotheses are the backbone for study experiments, which represent imagined scenarios that can be amended according to the complexity of the real world.

A. Assumptions:

(a) *Optimized UAV Performance:* It is measured that the DJI Agras T40 UAV functions at its optimum effectiveness, fulfilling the manufacturer's standards for flight designs, chemical loads, and battery lifespan.

(b) *Stable Weather Conditions:* Unprecedented weather situations, such as severe winds, rain, or fluctuating humidity, will not mark the UAV's flight path or the pesticide spraying method; such variables have no significance in the function.

(c) *Uniform Crop Density:* The simulation attempts to consider unexpected anomalies, like crops' size, good health, or spacing, which may impact the frequency of pests and the success rate of the spraying method because it implies a constant TP distribution.

(d) *High Detection Accuracy:* The hypothesis of high accuracy and low false detection rates with the DJI Agras T40 UAV's embedded PD algorithm could fail to detect water in environments with dissimilar graphical limitations.

(e) *Practical Pesticide Application:* The research demonstrates that chemical pesticides, when distributed by UAV, effectively eradicate all of the detected pests, irrespective of whether or not they are robust or have several levels of vulnerability.

B. Operation: The single-UAV system's functioning approach is executed systematically following these hypotheses generated.

1. *Initial Reconnaissance:* A baseline crop study has been performed by the DJI Agras T40 UAV. It detects the initial symptoms of pest activity and defines areas within the plantation.
2. *Infestation Detection:* Targeted spraying treatments have been rendered feasible by the UAV's advanced PD, which uses regular flight data to pinpoint diseased regions.
3. *Precision Spraying:* By accurately spraying chemical compounds onto diseased regions, the UAV reduces resources and minimizes environmental impact.
4. *Monitoring and Adjustment:* The UAV maintains track of what was sprayed after the aerosol spray treatment concludes, providing valuable data for further operations and improving the PCS holistically.
5. *Data Synthesis and Review:* A process of investigation of statistics and performance, the UAV system enhances PCS and verifies farming legal compliance, resulting in overall productivity benefits. It accomplishes this through the production of precise information from each sortie.

5.2 Statistics Analysis

In order to evaluate how effectively a UAV simulation is employed, the study used statistical methods, including a One-Sample t-test, Repeated Measures ANOVA, and C-SGFT (C-Square Goodness of Fit Test). The studies confirmed if the measured PD-SR equaled predicted rates, evaluated the mean detection time to a target time, and analyzed reliability and potential to enhance across numerous UAVs.

Table 3: One-Sample t-Test:

Test	Mean UAV Detection Time (min)	Target Time (min)	t-Value	df	p-Value	Mean Difference (min)	95% CI Lower Bound	95% CI Upper Bound
1	3.5	4	-2.33	29	0.026	-0.5	-0.9	-0.1
2	3.8	4	-1.05	29	0.300	-0.2	-0.6	0.2
3	[illegible]	4	-2.00	29	0.054	-0.4	-0.8	0.0
4	3.7	4	-1.50	29	0.141	-0.3	-0.7	0.1
5	[illegible]	4	-2.80	29	0.008	-0.6	-1.0	-0.2

Employing a 4-minute PD target as a benchmark, the UAV's mean detection time varied between 3.4 to 3.8 minutes in five distinct experiments performed by the One-Sample t-test. In Tests 1, 3, and 5, the UAV consistently PD faster than the target time, with p-values of 0.026, 0.054 (marginally significant), and 0.008, respectively. These tests showed that the UAV detected faster than expected (-0.5, -0.4, -0.6 minutes). However, in Test 2 and Test 4, the mean detection times were not suggestively different from the target time (p-values of 0.300 and 0.141, respectively), indicating that the UAVs met the performance benchmark. The narrower confidence intervals in Test 1, Test 3, and Test 5 indicate a more precise mean difference from the target time, signifying reliable UAV performance.

Table 4: Repeated measures ANOVA

Flight	Detection Rate 1 (%)	Detection Rate 2 (%)	Detection Rate 3 (%)	Detection Rate 4 (%)	Detection Rate 5 (%)	F Value	df Between	df Within	p-Value
1	88	91	93	94	95	4.67	4	16	0.007
2	85	89	90	92	93	3.50	4	16	0.025
3	87	88	92	90	94	2.56	4	16	0.066
4	86	90	89	93	95	5.12	4	16	0.004
5	84	87	91	92	94	4.20	4	16	0.014

The Repeated Measures ANOVA for this UAV-PD rate over five separate flights indicates a trend of improvement, as shown in Table 4. The detection rates progressively increased from the initial 80s to the mid-90s. Statistically significant advancements are noted in Flights 1, 2, 4, and 5, with p-values well below the alpha level of 0.05 and F values ranging from 3.50 to 5.12, demonstrating a consistent enhancement in detection accuracy. Although Flight 3's p-value slightly exceeds the conventional threshold for significance, it still trends toward higher detection rates. The results imply that the UAV's detection algorithm might improve through repeated operations, highlighting a potential learning effect and the robustness and increasing efficiency of the PD system with successive deployments.

Table 5: Result of C-SGFT

Zone	Observed SR (%)	Expected SR (%)	χ^2 Value	df	p-Value
A	90	85	1.88	1	0.170
B	88	85	0.53	1	0.466
C	93	85	4.71	1	0.030
D	85	85	0.00	1	1.000
E	89	85	0.94	1	0.332

The C-SGFT applied to our UAV-PD-SR across five different zones reveals that, in most cases, the observed rates in Table 5 are in close agreement with what was expected, except for Zone C. Zones A, B, D, and E show no significant deviation from the expected SR of 85%, as indicated by p-values more effective than the alpha level of 0.05, with Zone D perfectly matching the expected rate. Zone C, with a p-value of 0.030, suggests a statistically significant higher SR than expected, which may imply that this zone's conditions are particularly conducive to detection or that some zone-specific factors are at play, enhancing the UAV's effectiveness. The model's performance is consistent with expectations, and Zone C's anomaly warrants further investigation to determine what's causing the higher SR.

Autonomous UAV systems in TPs can reduce labor costs, optimize pesticide usage, and minimize crop losses. Despite high initial investment, long-term savings and increased yields make it a financially viable sustainable agriculture solution. With a dynamic DL approach to several crops and pests, the approach is robust and adaptable, making it suitable for many farming uses.

6. Conclusion and Future Work

Applying a DenseNet-121 driven DL in a UAV, particularly the DJI Agras T40, the research shows how to autonomously detect pests and spray pesticides accurately in a tea plantation area. The system was adept at precisely detecting and quantifying six common pest problems based on computer simulations performed on a Munnar, India TP. This enabled the UAV to select treatment regions precisely, minimizing harm to the environment and consumption of pesticides. In Smart Farming, the Sprayer Control Module controls its functions based on PD stages, so chemical treatments are put down when required. This method promotes crops' performance and health while minimizing the environmental effects. Further investigation on autonomous UAV sprayers is feasible through this research, a significant advance step in SF.

By implementing ML and UAV technological devices, the farming industry may predict environmentally friendly approaches, which will impact PA, CM, the condition of the environment, and total efficiency and profitability.

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