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Enhancing Smart Agriculture Based on UAV-Assisted Spraying Route Planning Optimization

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Abstract

Agriculture is the efficient use of different technologies and methods to cultivate land, raise crops, and rear animals to produce food, fuel, fibre, and other necessities for human survival. The application of Unmanned Aerial Vehicle (UAV) technologies to smart farming transforms yield planning, precision spraying, and crop monitoring, resulting in improved resource management and higher production for farmers globally. There is a labor shortage as a consequence of the growing technology that has reduced the number of people working in agriculture. This issue can be resolved with the use of agricultural machinery, such as drones, to spray pesticides. Unfortunately, spraying pesticides in the mountainous orchards is difficult due to the environment, culture, and limitations in operation. The Bellman-Ford technique is used to update the distance estimates until resolution to find the optimal route in weighted elements. We suggest smart agriculture instructing drones to avoid obstructions and choose the most optimal routes for spraying pesticides in an approach that minimizes battery usage, pesticide costs, and operational challenges by fusing reinforcement learning (RL) using the Policy Gradient Method (PG) and the Gaussian filter using data preprocessing. This research conducted experiments using various reward systems, flying direction granularities, and settings to develop a strategy appropriate for slope orchards. When handling path planning problems in complicated contexts, RL works more accurately than the accurate in PG methods.

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Keywords: Smart agriculture, Policy Gradient Method (PG), Spraying, Unmanned Aerial Vehicle (UAV), Route Planning.

1 Introduction

The agriculture to improve soil health, improve yields of crops, and support sustainable farming with long-term environmental and financial advantages, integrated pest control techniques and the use of organic fertilizers are suggested (Balavandi, 2017). Using technology and data-driven approaches, smart agriculture guarantees profitable and sustainable farming by streamlining agricultural procedures, increasing crop yields, and optimizing resource usage (Zheng, 2022). To improve farming methods and boost yields, smart agriculture makes use of UAVs to conduct surveillance flights. The technology provides farmers access to real-time information on the health of crops, soil conditions, and insect activity. In the scenario, smart agriculture represents an essential technological advancement to preserve crop quality and output. The technology used to spray pesticides includes drones for spraying (Maksumkhanova, 2025). The efficiency of pest control is increased as farmers do not have to handle pesticide tanks and spend time in areas where pesticides are prevalent (Lin et al., 2020). There are a lot of unanswered questions about drone spraying technologies. In orchards, complicated operation situations such as buildings, generator towers, nylon nets for crop management, and others are encountered while deploying a crop-sprayed drone for plant protection. Additionally, the majority of orchards are situated on hillsides that have various slopes and tree heights. Too many farmers cultivate a range of crops on the hill (Cavalaris et al., 2022). Currently, most drones used for spraying are controlled manually. Drone pilots have a variety of challenges, and when objects are out of sight, it is difficult for them to make quick decisions to avoid them, which can lead to aircraft mishaps. Applying distinct insecticides to various crops is another challenge; the aforementioned issues might be resolved if the spraying drones could autonomously spray after taking off and reaching the target based on the input position. To develop a drone route planning platform that can autonomously determine the optimal pesticide spraying path by using the suggested path algorithm and taking into account various environmental factors such as orchard terrain, tree density, insect frequency, and more (Son et al., 2024) (Anna et al., 2025). The system automatically identifies the crucial spots and calculates the optimal path based on the various weights, though, despite its cost-effectiveness, dynamic choices are unable to take into account every environmental element (Singh et al., 2020). The UAVs are essential to smart farming since they travel fields with collecting high-resolution aerial data and visuals using sophisticated route planning techniques (Balasm et al., 2025). By effectively monitoring crop health, identifying stress or infested regions, and making decisions based on data for optimal farming, fertilization, and pest management measures, farmers can eventually increase crop yields and promote sustainable farming, using UAVs. To determine the most effective pesticide spraying path and minimize the use of pesticides and UAV batteries on hilly terrain, when examining the crop density, the height of the slope, and the exact spot of pest infestations (Singh et al., 2024). The objective of the research project is to increase agricultural productivity by applying UAVs to spraying path planning optimization (Ghulam & Farman, 2025). Improve yields of crops and the environmental impact in smart agricultural practices, which entails creating algorithms and procedures to maximize crop coverage while minimizing resource utilization.

The UAVs have a plethora of applications in intelligent agriculture. The main factors encouraging farmers to adopt UAVs in smart farming are their affordability and simplicity of operation. Remote controllers that use radio waves are mostly used to operate UAVs (Maddikunta et al., 2021). The research investigates the varieties of sensors that are appropriate for smart farming, as well as the possible needs and difficulties associated with using UAVs for smart agriculture. A novel approach is to use agricultural sensor charging to address the primary research issue. Wireless soil data transfer to a centralized server, which is made possible by the deployment of the energy-constrained device (ECD) (Chittoor et al., 2023). Improved allocation of resources, immediate decision-making, precision agriculture, remote observation, and control are made possible by the suggested ECD. The ECDs are charged using a unidirectional wireless charging drone.

The reducing sensor energy consumption, that examines cooperative clustering and multi-UAV-assisted methods in the present research. To convey the information to cluster heads, they construct a theoretical lower bound for sensor consumption of energy (Nguyen et al., 2023). That also demonstrated the clusters are balanced in energy consumption, with sensor energy consumption approaching the theoretical lower bound. As a result, finding balanced clusters in terms of energy consumption is a crucial component of the suggested heuristic multi-UAV systems known as Gathering data Assisted by Multi-UAV using Balanced Clustering (GAMBAC). A fog technology-based architecture for smart farming, which uses a UAV to collect information from Internet of Things (IoT) sensors placed across farms and then transfer it to fog sites established at the network interface (Kavitha, 2024). The system uses a charged tokens approach, where UAVs get tokens at the fog nodes. The UAVs can be charged for their upcoming missions by exchanging these tokens subsequently. The fog nodes form a system to detect intrusions to identify UAV behavior as benign or malicious using machine learning (ML) techniques (Sajid et al., 2023). They wirelessly obtain certain medical data from IoT nodes connected to herding livestock through the use of UAVs in an increasingly significant family of applications called cow monitoring apps. The drone-captured videos and photos are being used widely to monitor the behavior and diagnose livestock diseases, among other Livestock Management uses for UAVs. Such applications for livestock data gathering face several difficulties (Benalaya et al., 2022). The problem of utility maximization by concurrently minimizing energy usage and maximizing information gathering by UAV and Unmanned Ground Vehicles (UGV) (Singh et al., 2023). They utilized a modified form of the Greedy Randomized Adaptive Search Procedure (GRASP) technique to defeat the above difficulty and forecast an effective route for UAVs and UGVs to agricultural areas. The effectiveness of the suggested algorithm is demonstrated theoretically and empirically, compared to other cutting-edge techniques using real-world data. A hybrid path planning (HPP) method that ensured a UAV's quick collision-free route in situations of crisis, hence facilitating efficient data collecting. The shortest route map is created in the suggested HPP scheme using the probabilistic roadmap (PRM) method, and various path restrictions are improved for a three-dimensional environment using the enhanced automated bee colony (ABC) method (Poudel & Moh, 2021). According to simulation results, the suggested HPP performs considerably better in terms of flight duration, consumption of energy, converging time, and path of flying than both the PRM and traditional ABC approaches. The artificial intelligence (AI) models assist in diagnosing crop lesions more accurately, providing prompt, astute, and quick action to stop a recurrence and guarantee farmers get their money back. The scientific basis for increasing crop yields by related mechano-biosynthesis was addressed in the research, an attempt to lessen the impact of the current worldwide agricultural crisis. By enhancing the constraints of UAVs and AI models, convergence technology can enable integrated intelligence for smart farming and economical agro-allied results (Huo et al., 2024).

Motivation of the research

The motivation behind this work is to address the labor shortage and operational challenges in agriculture by leveraging UAV technologies for efficient pesticide spraying. Effective route planning is minimize resource waste, increases spraying accuracy, and drastically saves operating costs. To increase yield, guarantee consistent crop treatment, and develop sustainable agriculture practices is ultimately to help farmers and the environment by utilizing cutting-edge optimization techniques.

Contributions of the Research

- Developed a novel method for optimizing drone-based pesticide spraying in the mountains. Gaussian filter to preprocess data to enhance route selection and decision-making.
- Bellman-Ford method to determine the most efficient routes for drones in weighted environments and to update distance estimations. Improved path planning by combining the Policy Gradient (PG) approach with reinforcement learning (RL) allowed drones to effectively avoid obstacles.
- Experimental Validation is to fine-tune the method for complicated environments, an assortment of extensive tests were conducted with various reward systems, flying direction granularities, and settings.

The system is specifically designed to address the unique issues associated with pesticide spraying in mountainous areas, advancing UAV applications in smart farming.

The rest of the work is divided into several parts. Part 2 covers methodology, Part 3 focuses on result analysis, and Part 4 covers the conclusion.

2 Materials and Methods

This section describes the environmental conditions that the investigation observed in mountain orchards to greater understand the types of obstacles that drones can confront when operating in high terrain. A system environment is introduced since real-world assisted learning is the primary focus of the work, Tensor Flow is used to create UAV simulators.

Environmental Data Collection

The algorithm plans the optimal flying paths for drones by prioritizing spraying based on environmental information. To gather environmental sensing data by training drones to regulate their motion using a UAV technique. According to the energy consumption and data constraints delay, each location is given a distinct color to prioritize the data and ensure its rapid transfer with a minimum delay. It uses real-time monitoring of temperature, humidity, and wind speed to improve spraying precision. UAV employs multispectral and thermal imagery to monitor crop health and insect infestation levels. This data-driven method enhances decision-making, resulting in more efficient pesticide application while minimizing environmental effects. The simulation environment accurately simulates UAV operations in mountainous orchards, including dynamic wind effects, high-resolution topography data, and UAV limitations. Wind conditions, like as turbulence and crosswinds, affect navigation and spraying accuracy, while terrain models handle height changes and obstacle avoidance. UAV constraints, such as battery life, cargo capacity, and collision avoidance, improve operating feasibility and spraying efficiency. Figure 1 shows the prioritizing areas based on color.

Experimental Parameters and Test Conditions

The research examines critical environmental characteristics such as temperature, humidity, wind speed, and terrain elevation to determine their influence on UAV spraying efficiency. Variable pest infestation levels, varying terrain slopes, and changing weather conditions are used to assess UAV adaptability and accuracy. These controlled investigations ensure that the suggested strategy optimizes flight trajectories and spraying intensity, resulting in more efficient pesticide application and resource usage.

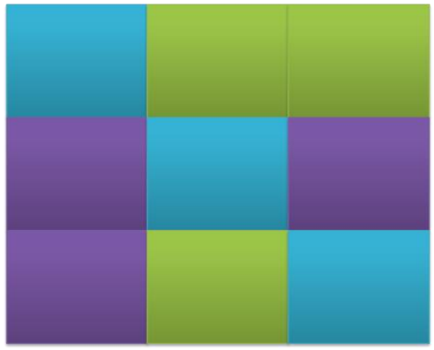

Figure 1: Prioritizing Areas Based on Color

Environment of Mountain Orchard

The team observed the field of studies on fruit plants in the highlands and visited the slope orchards, for more studies on drones that would spray pesticides effectively. There are many different kinds of structures and buildings in the orchard, and the trees range greatly in size, height, and species. The drone pilots' tasks are made more difficult by these factors together.

Data preprocessing using Gaussian filter

The smoothing of sensor data, the optimization of navigation paths, and the facilitation of effective crop, pest, and resource management across a range of terrains, the integration of Gaussian filters into UAV path planning methods in smart agriculture improves precision and promotes high-yield and profitable agricultural activities. A technique used to filter the picture before classification is the Gaussian filter. This approach is the linear filter, depending on the form of the Gaussian function, has a weighted average for every element.t can be determined to get the values of each component of the Gaussian smoothing filter to create. It enhances UAV state estimation by lowering sensor noise and increasing localization accuracy, which is required for steady flying. It is commonly utilized in sensor fusion, target tracking, and terrain mapping to ensure accurate data interpretation during navigation. This filtering approach is critical in GPS-denied conditions, allowing UAVs to function efficiently with onboard sensors and inertial measurements.

$$g(w,z) = \frac{1}{d} f^{\frac{w^{2+}\ z^{2}}{2\sigma^{2}}} \quad (1)$$

Where d is the normalization constant and σ is the Gaussian Kernel standard deviation using equation (1).

Software Environment

The TensorFlow Flow team designed Google Brain, an open-source application development framework. Focused on training and inference applications, this symbolic mathematics toolkit leverages DataStream and differentiable techniques. Figure 2 shows the Tensor Flow architecture, which Tensor Flow uses to put up DataStream graphs and structures. Another crucial component of TensorFlow is the Tensor Board, a visual and graphical monitoring tool for TensorFlow processes.

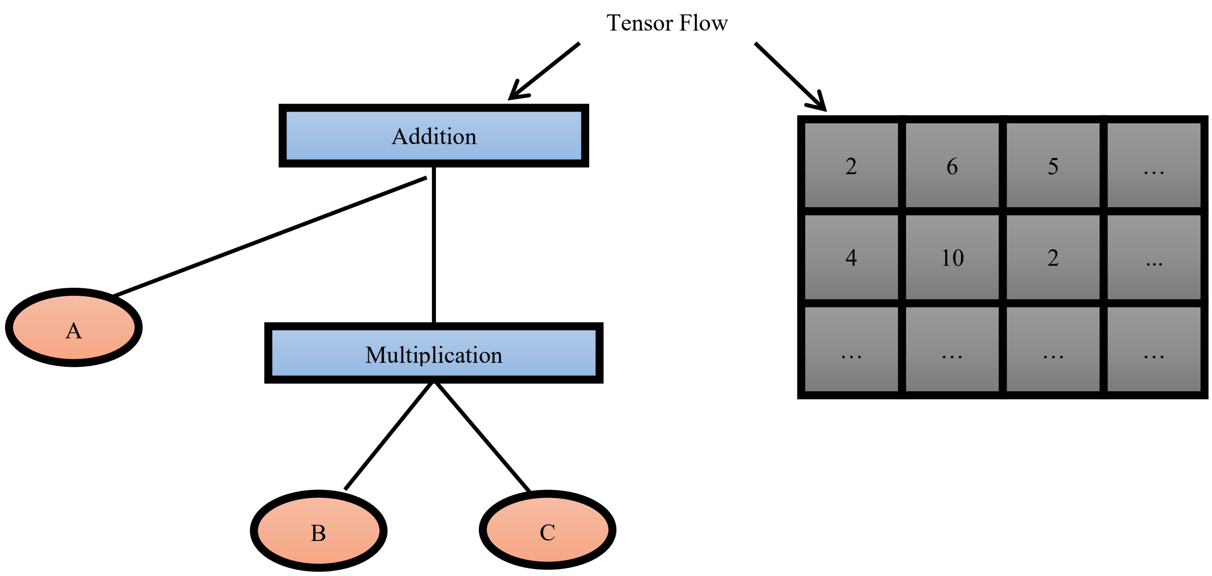

Figure 2: Tensor Flow Structure

System Design

The UAV architecture for the drone application is described in the subsection. They provided reward information for a sample of training in UAV to determine the drone's flying directions after establishing the environment and making environment maps. Then analyzed the data and produced a drone flight route.

Structure of the System

Two components comprise this system architecture; the UAV automated path planning system's enhanced training is covered first. The crowd proceeded through the phases of the experiment.

System Structure for UAV Route Planning

The overall design of the UAV autonomous route planning system is shown in Figure 3. The length of the treetops, the concentration of the species targeted, and the extent of the pest infestations were important variables in the region that needed to be sprayed with pesticides. That produced the incentives required for the UAV. Throughout training, this incentive enables one to understand which flying direction is most appropriate. A penalty is applied if a direction is considered inappropriate, the acceptable direction, the greater the reward, following the whole train session, the weights are preserved. The overall design of the UAV's autonomous route planning system is shown in Figure 3.

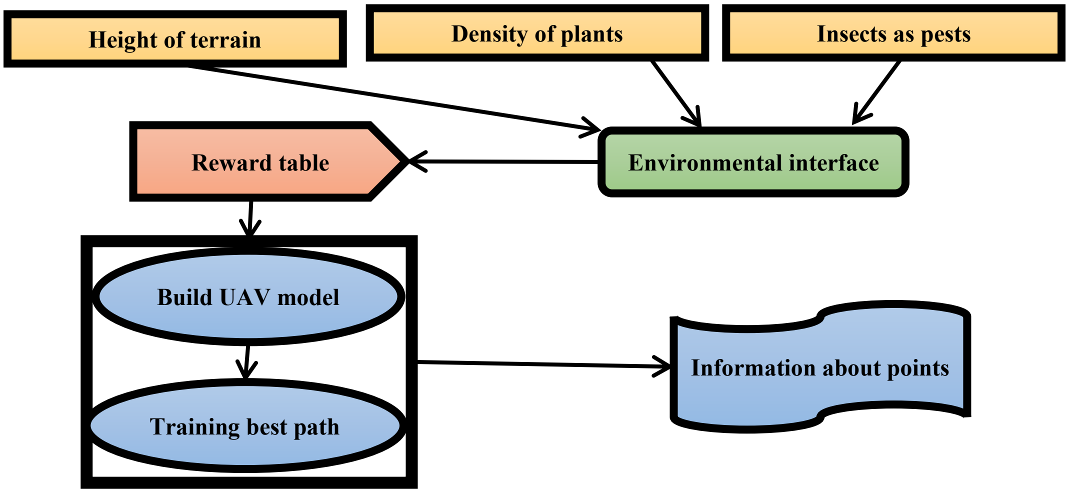

Figure 3: Overall Design of The UAV's Automatic Route Planning System

UAV- Enhanced Smart Agriculture Using Bellman-Ford Algorithm with Policy Gradient

Method (BF-PG)

The UAV-enhanced smart agriculture system using the BF-PG technique optimizes resource allocation and decision-making in farming by improving efficiency and precision in smart agriculture management and environmental monitoring.

Policy Gradient Method (PG)

A potent RL technique called the PG method is combined with path-planning techniques designed specifically for UAVs that operate in smart farming environments. This advanced fusion ensures accurate and effective aerial tasks by optimizing UAV guidance by utilizing real-time data components, environmental conditions, and crop-specific constraints. The PGs are employed in the system to modify UAV paths, establishing a balance between exploration and extraction to optimize productivity, reduce resource consumption and improve overall farming operations. This integrated strategy is a prime example of the latest developments in agricultural technology, transforming the way UAVs are used to monitor, evaluate, and maximize crop health and yield an intelligent environmental approach. The PG techniques use $\nabla_\theta \mathrm{I}(\pi_\theta)$ to maximize$\mathrm{I}(\pi_\theta)$given the policy gradient, these techniques assert using equation (2).

$$\nabla_\theta \mathrm{I}(\pi_\theta) = \mathbb{E}_{\sigma\pi_\theta}[R^{\pi_\theta}(t,b).\nabla_\theta \log \pi_\theta(\mathrm{b}|\mathrm{t})] \qquad (2)$$

Where the visitation measure for state action is specified in$\sigma\pi_\theta$. The expressed total reward gradient rise is maximized by the PG based to be more precise, it can produce a series of policy variables in$\{\theta i\}_{i\geq 1}$denote in equation (3).

$$\theta_{j+1\leftarrow}\theta_j + \eta.\nabla_\theta \mathrm{I}(\pi_{\theta_j}) \qquad (3)$$

The learning rate is represented by $\eta > 0$. Natural gradient ascent is used by natural PG and is independent of policy parameterization. About policy π_θ, let $E(\theta)$ have the data matrix provided in equation (4).

$$E(\theta) = \mathbb{E}_{\sigma\pi_\theta}[\nabla_\theta \log \pi_\theta(\mathrm{b}|\mathrm{t})(\nabla_\theta \log \pi_\theta(\mathrm{b}|\mathrm{t})^{\mathrm{S}}] \qquad (4)$$

Naturally occurring PG functions at every iteration.

$$\theta_{j+1\leftarrow}\theta_j + \eta.\left(E\left(\theta_j\right)\right)^{-1}.\nabla_\theta.I(\pi_\theta) \quad (5)$$

In this case, η represents the learning rate, and $E\left(\theta_j\right))^{-1}$ is the inversion of$E\left(\theta_j\right)$. In actuality, the policy enhancement steps are estimated by remaining to calculating both $I(\pi_\theta)$ and $E(\theta)$ using equation (4). The reward measurements are shown in Table 1.

Table 1: Reward Measurements

Reward	Color	Reward
In the direction of the end endpoint	Blue Pink Green Red	52
Moderate pest infestation		121
Slight pest infestation		82
Severe pest infestation		151
Higher terrain areas		-12
Endpoint		201
Outside boundary		-11

The reward measurements in Table 1 are designed to guide UAVs toward the best spraying paths by rewarding useful behaviors and penalizing inefficiency. Positive rewards stimulate travel towards the endpoint and priority of severe pest infestations, but negative rewards discourage flying over higher terrain or beyond bounds to maximize pesticide consumption and battery life. Empirical validation entailed testing several incentive systems in simulated orchard settings, assessing UAV performance, pesticide distribution, and energy usage. The results showed that the proposed incentive system efficiently balances operational restrictions, resulting in precise and cost-effective UAV-assisted spraying.

Optimal Path Identification Using the Bellman-Ford Algorithm (BF)

The Bellman-Ford algorithm optimizes UAV-assisted spraying routes in challenging environments in the Mountains by determining the shortest paths between waypoints while considering obstacles such as steep terrain and natural barriers. Using TensorFlow for UAV models allows for accurate modeling of the conditions, enhancing the planning of efficient and effective routes for spraying operations. The accurate perception of complicated terrain and the optimization of flight paths employed in this approach enhance resource utilization and operational efficiency in smart agriculture. Optimizing UAV routes over large farmlands is made easy with this approach, which quickly finds the shortest possible route from the starting site to every other site in a balanced network. UAVs can monitor crops, evaluate soil conditions, and administer treatments as much as possible by using this algorithm to navigate around farms. Bellman-Ford integration with smart agricultural systems facilitates accurate and fast gathering of information, which enhances crop yields and promotes sustainable farming methods. But the conventional approach functions in the case where all the initial distance estimations are overestimates, where s_0 is the start of time for all j denoted in equation (6).

$$\hat{C}_s(s_0) \geq c_j \quad (6)$$

This approach calculates the distance to the closest individual in a group of source nodes instead of being heavily based on the traditional Bellman-Ford method. Furthermore, we want to accommodate scenarios in which the graph and the collection of sources could alter a node while simply employing the minimal triangular inequality restrictions imposed by its neighbours Specifically, let $\hat{C}_s(s)$ represent the estimated distance j has the original set, the following is the algorithm using equation (7):

$$\hat{C}_s(s+1) = \begin{cases} min_{i\epsilon M(j)}\{\hat{C}_s(s) + c_{ij}\} & j \nexists T \\ 0 & j \in T \end{cases}, \forall s \geq s_0 \tag{7}$$

In the situation when there is a single source node and additionally the source or graph changes, the behaviour of this method approaches that of a traditional Bellman-Ford. The Bellman-Ford algorithm effectively handles graphs with negative weights to maximize shortest path computations. Finding the shortest path from a single source to every vertex and identifying negative-weight cycles are two of its robust and precise path-finding features.

Pseudocode 1: shows the BF-PG Pseudocode.

```
Initialize:
   - Graph G with vertices V and edges E
   - Distance array dist[] with initial values ∞ (except start_vertex)
   - Policy π
   - Learning rate α
   - Number of iterations N
Function BF-PG(Graph G, Policy π, α, γ, N):
  Step 1: Bellman-Ford to find shortest paths
dist[start_vertex] = 0
for i from 1 to |V| − 1:
for each edge (u, v) in E:
ifdist[u] + weight(u, v) < dist[v]:
                    dist[v] = dist[u] + weight(u, v)
  Step 2: Policy Gradient Updates
for iteration from 1 to N:
for each vertex v in V:
value[v] = compute_policy_value(v, π)
for each edge (u, v) in E:
new_policy_action = select_action_based_on_value(value[u], value[v], π)
π[u] = new_policy_action
Function compute_policy_value(vertex v, Policy π):
   # Return value based on policy π (simplified)
return value
Function select_action_based_on_value(value_u, value_v, Policy π):
   # Return new policy action based on values (simplified)
returnnew_action
```

BR- PG method enhances crop yields and minimize environmental impact through smart agricultural practices, utilizing algorithms and procedures to maximize crop coverage while minimizing resource application. BF effectively maintains lower weights and is located in the shortest processes in the path, which is essential for optimizing resource allocation and UAV navigation in intelligent agriculture. PG enhances the ability of UAVs to make decisions in dynamic contexts, allowing them to adjust to changing circumstances and maximize agricultural techniques through using acquired regulations, and BF-PG optimizes UAV-based smart agriculture for precision and efficacy.

3 Results and Discussion

In this research, we analyzed smart agriculture based on UAV to spraying route planning using the PG method. The improved PG approach uses path planning and examine the outcomes.

Accuracy

Accuracy is the degree to which a measurement or computation reflects the proximity of observations to the true value and relates to an accurate value or standard (equation 8). Improving crop management accuracy and effectiveness through route planning is a key component of enhancing smart agriculture using UAV-assisted spraying. When compared with the existing method, the proposed method achieved an accuracy of 95% when compared with SVM-KNN (Manikandan et al., 2024) (90%). It shows that the proposed technique is more efficient than other existing methods. Figure 4 shows the comparison of accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

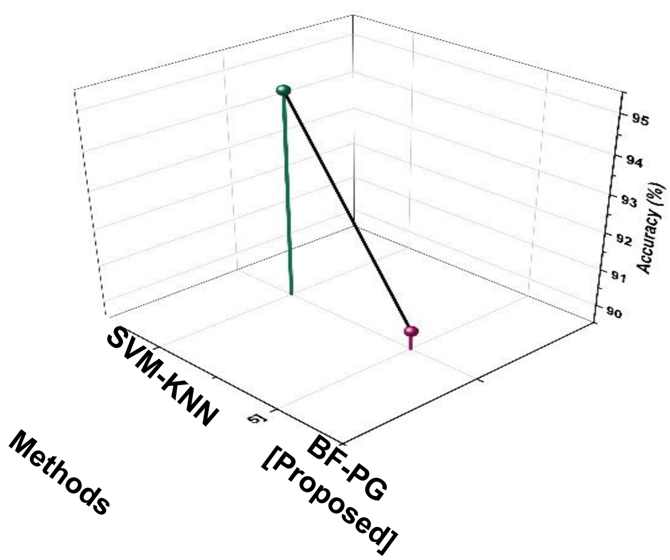

Figure 4: Comparison of Accuracy

Outcomes of Flight Direction

The ten instructions (up, top left, left, bottom left, bottom, bottom right, right, top right, horizontal, and vertical) can produce more cost-effective paths for the spraying drone's route planning compared with the straightforward four paths (up, left, bottom, and right). This is because cost considerations, such as battery life and drug quantity, are taken into consideration. In the four directions, increased point coverage is sprayed on the surrounding region, the blue areas having moderate infestation, and the pink portions with mild infestation. Ten Directions covers the green areas that have a substantial infestation, covers less of the blue and pink sections and puts their energy into creating shorter pathways. Consequently, for large-area applications, four directions are preferable to eight directions. Figure 5 illustrates the X-axis: horizontal distance in the spraying area, and the Y-axis: vertical distance in the spraying area. The optimal path in eight directions is shown in Figure 5.

Research used a UAV to plan the optimal pesticide application route automatically. Figure 6 represents a Comparison of accumulated flight distances between the BF-PG method and the existing method, Deep Q-Learning algorithm (DQN) (Chen et al., 2021) path algorithm. It showed that the BF-PG is better than the existing methods.

Comparison of the Iterative Curves

Iterative curves are dynamically changed pathways that are revised over numerous iterations to optimize trajectories. They are widely used in UAV path planning, robotics, and data fitting to enhance efficiency and accuracy. Figure 7 represents the comparison of the Iterative curves of BF-PG with the existing method, Dynamic Genetic Algorithm- Ant Colony Binary Iteration Optimization (DGA-ACBIO) (Liu et al., 2022).

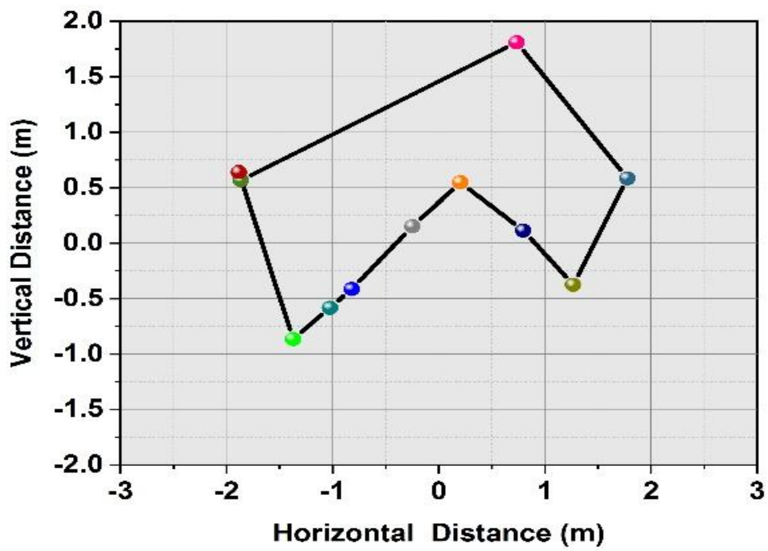

Figure 5: Optimal path in ten directions

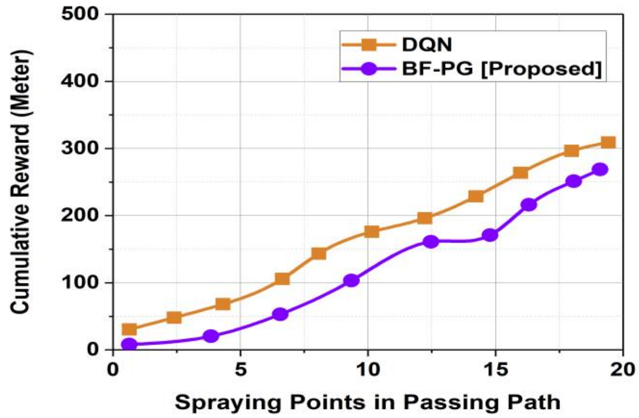

Figure 6: Comparison of Accumulated flight distances between BF-PG and DQN (Chen et al., 2021)

Simulated PG-based UAV Route Planning

The beginning point is the destination of the severe trajectory adjustment; it need not be on the center axis. The graphic shows that the ideal UAV spraying positions at each second are shown by pink stars. These positions are determined using the pesticide drift simulation in conjunction with the direction and speed of the wind measurements. The PG technique modified the spraying route, which is indicated by the green dotted line. The flight path indicates that in nine time steps, the UAV should perform four steering corrections. To make such a change in an implementation in the actual environment. The l^{th} control point is represented by Z_l, while the normalized time variable is represented by $s$both are denoted in equation (9). Figure 8 shows the PG-based UAV pesticide spraying routes. X-Axis: horizontal spatial coordinate along the direction of the UAV's flight path. Y-Axis: This axis usually represents the vertical spatial coordinate or position along the direction of the UAV's flight path.

$$Z\,(s) = \sum_{i=0}^{m} \left(\frac{m!}{l!(m-l)!}\right) Z_l\, s^l (1-s)^{m-l}, s \in [0,1] \qquad (9)$$

Outcomes for Various Environments

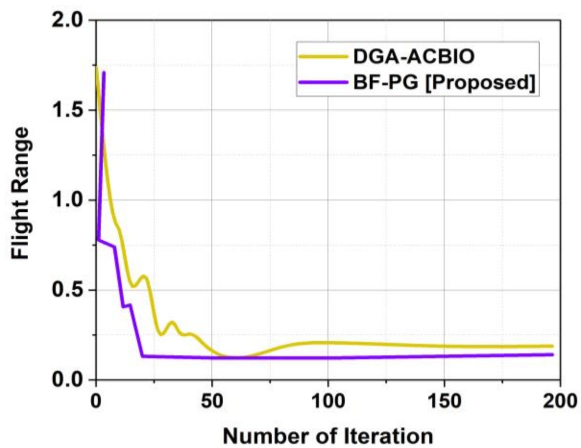

Figure 7: Comparison of the Iterative curves of BF-PG with DGA-ACBIO (Liu et al., 2022)

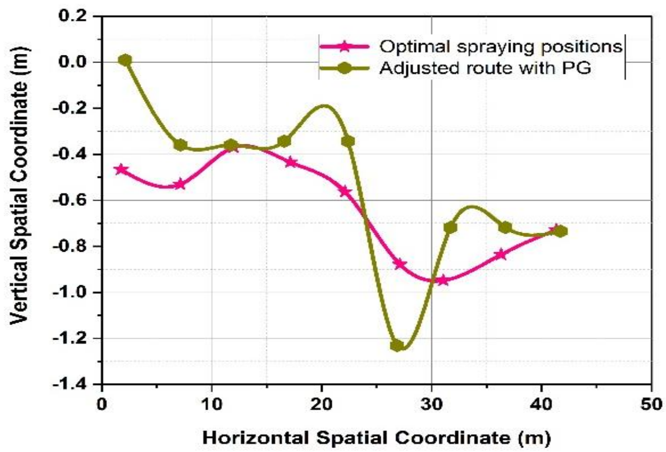

Figure 8: PG-based UAV pesticide spraying routes

The simulated establishment used in the investigation was a sloping orchard with steep topography and lots of flying drone obstacles. The selected tree species tended to attract pests, while the tree species that needed to be treated were dispersed. All of these variables need to be taken into account while creating a simulated path. Here, there are several environmental elements. A distinction based on the density of distinct tree species. The colors green, blue, and pink represent high, medium, and low tree densities, respectively. It is also observed that employing four flying directions results in a larger expense. When eight flying paths are more beneficial when the tree species density is the single factor to consider. The locations of pest infestations and the optimal species density for plan trees are shown in Figure 9.

The specific operational challenges of the proposed method are addressed to clarify its practical benefits. For instance, it tackles labor shortages in agriculture by automating pesticide spraying with UAVs, addresses difficult terrain in mountainous orchards using advanced path-planning algorithms, and optimizes resource management through reinforcement learning. It handles environmental data constraints by integrating Gaussian filters for precise navigation and decision-making. Highlighting the challenges and solutions could demonstrate the method's practical relevance and advantages, making its application and benefits clearer to readers. In agriculture, UAVs enhance efficiency in pesticide spraying but face challenges in mountainous terrains. Integrating reinforcement learning (RL) with the Policy Gradient (PG) method helps optimize UAV routes by learning to navigate obstacles and minimize battery usage. To improve route planning, reduce pesticide costs and operational issues. RL with PG effectively enhances battery life and operational efficiency compared to traditional methods.

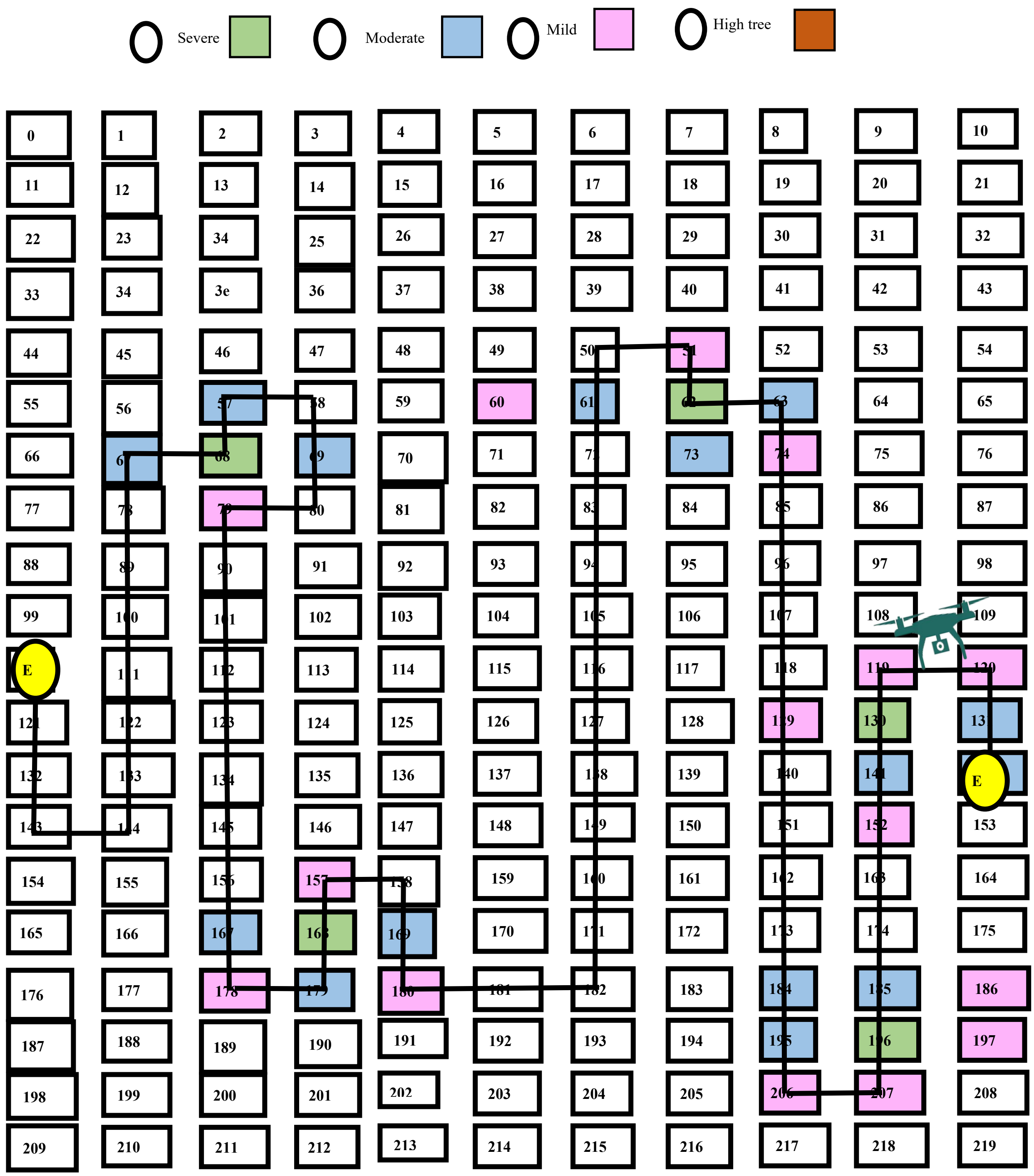

Figure 9: Locations of pest infestations and the optimal species density for plan trees

4 Conclusion

Smart agriculture that uses UAVs makes it feasible to plan a path to spray plants more efficiently. Advanced technology-equipped drones are needed to determine the optimal spraying routes, improve precision, use fewer assets, and promote sustainable agriculture approaches. We suggest using PG based on RL for drone path planning. By using smart agricultural techniques and sparingly applying pesticides to certain target species, we plan to lower the expense of pesticides. The drone navigates complicated settings autonomously and avoids obstacles by training the model using known environmental data. To determine the most optimal path in graphs with weighted edges, the Bellman-Ford approach continually changes distance estimates until a solution is found. It has experimented with various reward methods, flying directions, granularities and habitats to train the PG model to a strategy that takes into consideration the conditions with trees on a slope. This results in the system straying off course and avoiding regions that need to be sprayed in preference for the less-used path. Research suggested path planning works greater in straightforward environments. The PG approach helps with path modifications in the green line. Furthermore, all of the simulations were two-dimensional, switching to three-dimensional simulations, and combining the findings with the UAV flying control system for path planning, which represents field circumstances in the actual world. As indicated by the pink stars, the starting point is essential for path modifications in UAV spraying. When compared with the existing method, the proposed method achieved an accuracy of 95% when compared with SVM-KNN (Manikandan et al., 2024) (90%). The proposed method is scalable for large-scale farms and diverse crop situations as it uses UAV-based path planning to adapt to changing terrains and maximize pesticide use. Efficient obstacle avoidance and route optimization reduce resource waste and increase coverage. By modifying flying parameters and reward functions, the technique can be used in a variety of agricultural environments. The future scope of UAV-sprayed path planning optimization is the way for smart farming, which uses AI techniques to improve accuracy, use fewer resources, and have a smaller environmental effect. With its promises of greater yields of crops, financial savings, and environmentally friendly farming methods, this strategy is expected to spur productivity and innovation in the agricultural industry.

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