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Swarm Drone System with YOLOv8 Algorithm for Efficient Locust Management in Agricultural Environments

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Abstract: *In recent years, the recurring invasions of locusts have emerged as a significant threat to global agriculture, jeopardizing both crop yields and vast uncultivated lands. To address this pressing issue, this research paper introduces an innovative approach that leverages artificial intelligence (AI) for real-time locust management. Extensive investigations into locust behavior, life cycles, and existing management techniques have informed the development of a novel swarm drone system capable of detecting and eliminating locusts in farms using object detection and targeted pesticide spraying. The core technology employed in the system is the YOLOv8 algorithm, a convolutional neural network model renowned for its robustness in object recognition. The coordinated actions of the swarm drones are facilitated by the ArduPilot system, enabling efficient collaboration and synchronized locust eradication efforts. By harnessing AI for locust detection and eradication, the proposed system demonstrates the potential to significantly enhance efficiency and accuracy, thereby mitigating crop damage and elevating agricultural yields. This research paper sheds light on a promising solution that amalgamates AI, drones, and object detection to tackle the critical issue of locust management, fostering sustainable agricultural practices in the face of mounting challenges.*

Keywords: Locust Management, Artificial Intelligence (AI), Drone, Object Detection, Swarm Drone System, YOLOv8 Algorithm, ArduPilot System, Locust Detection, Locust Eradication, Crop Damage, Agricultural Yields, Sustainable Agricultural Practices

I. INTRODUCTION

Locust infestations have long been a persistent and devastating problem in agriculture, posing a significant threat to food security and causing substantial economic losses on a global scale. These voracious insects have the ability to rapidly multiply and form massive swarms, decimating crops and vegetation in their path. Traditional methods of locust management, such as manual surveillance and pesticide application, have proven to be insufficient and time-consuming in the face of these highly mobile and unpredictable pests. To address this critical issue, a novel approach using a swarm drone system has been proposed, aiming to revolutionize locust management by integrating artificial intelligence (AI) and advanced drone technology. This innovative system has the potential to rapidly detect and eliminate locusts in farms, offering a more efficient and cost-effective solution to combat these destructive pests. The core component of the proposed system is the implementation of object detection algorithms, specifically the YOLOv8 algorithm, which stands for "You Only Look Once." This algorithm is a convolutional neural network (CNN) model known for its accuracy and speed in object recognition tasks. By training the algorithm on a comprehensive dataset of locust images, it can effectively identify locusts present in the farm environment, determining their location, size, and orientation with remarkable precision. Once the locusts have been detected, the swarm drone system springs into action. The drones, controlled by the ArduPilot system, are equipped with pesticide spraying mechanisms and operate collaboratively to efficiently cover large areas of farmland. The ArduPilot system allows the drones to communicate and coordinate their movements in real time, ensuring synchronized and optimized locust eradication efforts. By leveraging the information provided by the YOLOv8 algorithm, the swarm drones navigate directly to the infested areas, targeting the locusts

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accurately and minimizing collateral damage to the surrounding vegetation. The proposed swarm drone system holds great promise for revolutionizing locust management practices.

1.1 Objective

By integrating AI-based object detection and drone technology, it offers several advantages over conventional methods. Firstly, the system drastically enhances the efficiency and accuracy of locust detection, enabling prompt intervention and containment. By swiftly identifying locust hotspots, farmers and authorities can take immediate action, preventing the rapid spread of the infestation and minimizing crop damage. Additionally, the use of swarm drones significantly improves the speed and coverage of locust eradication operations. Traditional manual approaches are limited by human resources and the extensive time required to survey and treat large areas. The swarm drone system, on the other hand, can cover vast tracts of land swiftly and effectively, reducing the overall cost and labour involved in locust management. Furthermore, the proposed system has the potential to boost agricultural yields by curbing the impact of locust infestations. With timely and targeted intervention, farmers can protect their crops from extensive damage, ensuring a more abundant and reliable harvest. This, in turn, contributes to food security and economic stability in locust-affected regions. Beyond its immediate impact on locust management, the integration of swarm drones and AI algorithms in agriculture holds broader implications. The proposed system serves as a stepping stone towards automation and technological advancements in farming practices. By leveraging the capabilities of drones for crop monitoring, disease control, and other agricultural tasks, farmers can optimize resource allocation, reduce environmental impact, and improve overall productivity. In conclusion, the proposed swarm drone system, incorporating AI-based object detection and pesticide spraying, offers a promising solution to the global challenge of locust management. By efficiently detecting and eliminating locusts in real time, the system holds the potential to minimize crop damage, increase agricultural yields, and enhance economic stability. Moreover, it sets a precedent for the integration of advanced technologies in agriculture, paving the way for future innovations in sustainable and automated farming practices.

II. LITERATURE REVIEW

Table 1: Describes in detail the various literature survey papers.

Sn. No	Journal Name	Author	Summary
1	Band movement and thermoregulation in Schistocercacancellata.	Piou, C., Zagaglia, G., Medina, H. E., Trumper, E., Brizuela, X. R., &Maeno, K. O.	The study by Piou et al. (2022) examines the band movement and thermoregulation in the insect species Schistocerca cancellata. The authors found that the band movement of the insects was linked to thermoregulation, with the insects exhibiting a specific pattern of movement to regulate their body temperature. The findings have implications for understanding the mechanisms underlying insect thermoregulation and its role in their survival and adaptation.
2	A journey towards an integrated understanding of behavioural phase change in locusts. Journal of Insect Physiology, 138, 104370.	Simpson, S. J.	Simpson's (2022) study in the Journal of Insect Physiology explores the journey towards an integrated understanding of behavioral phase change in locusts. The study covers various aspects related to locust behavior, including the neurobiological and environmental factors that contribute to phase change, and the role of these changes in population dynamics. The study aims to provide a

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			comprehensive understanding of behavioral phase change in locusts
3	How locusts become a plague.	Gross, M. (2021).	In "How Locusts Become a Plague", Michael Gross explains the science behind locust swarms and why they can turn into devastating plagues. The article discusses how locusts are normally solitary insects, but when environmental conditions are favorable, they can form huge swarms that can migrate long distances and destroy crops. The author highlights the complex interplay of environmental and physiological factors that trigger the transformation from solitary to gregarious behavior in locusts, and how these swarms can have devastating effects on agriculture and food security.
4	A framework of space–time continuous models for algorithm design in swarm robotics	Heiko Hamann and Heinz Worn	Hamann and Wörn (2008) present a framework for designing algorithms in swarm robotics using space-time continuous models. The framework provides a systematic approach to modelling and controlling the behaviour of multiple robots in a dynamic environment. The authors suggest that this approach is well suited for swarm robotics applications because it takes into account both the spatial and temporal characteristics of the system. The framework is demonstrated through a case study in which a swarm of robots is used to perform a cooperative task. The authors conclude that the space-time continuous models provide a useful tool for algorithm design in swarm robotics, and that further research is needed to refine and improve this framework.
5	Communication in a Swarm of Miniature Robots: The e-Puck as an Educational Tool for Swarm Robotics	Cristopher M Cianci,XavierRaemy and AlcheoriMartinoli	Cianci ,Raemy and Martinoli discuss the use of the e-puck robot as an educational tool for teaching swarm robotics. The authors describe the e-puck's hardware and software features, and demonstrate how it can be used to study communication in a swarm of robots. The authors also present several swarm communication algorithms that have been developed and tested using the e-puck robots. The algorithms are designed to achieve various swarm behavior patterns, such as flocking and formation control. The authors conclude that the e-puck is a versatile and cost-effective platform for exploring swarm communication, and that it has potential as an educational tool for teaching swarm robotics.

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6	A Low-Cost Educational Platform for Swarm Robotics	Micael S. Couceiro, Carlos M. Figueiredo, J. Miguel A. Luz, Nuno M. F. Ferreira	"A Low-Cost Educational Platform for Swarm Robotics" is a paper that describes a low-cost educational platform for teaching the principles of swarm robotics. The platform was developed by Couceiro, et al. in 2012 and consists of a group of small robots that can communicate and coordinate their movements. The platform was designed to be low-cost, easy to use, and accessible to students and researchers, making it a useful tool for teaching and research in the field of swarm robotics. The authors evaluated the platform through a series of experiments and found that it was effective in demonstrating the principles of swarm robotics and providing hands-on experience for students.

III. METHODOLOGY

The following section outlines the flow diagram of the implemented project, the datasets that have been used and the overall implementation of the project

3.1 Locust Detection using YOLOv8 Algorithm

- Dataset Collection: To train the YOLOv8 algorithm for locust detection, a diverse and comprehensive dataset of locust images needs to be collected. This dataset should include various types of locusts, different life stages, and different lighting and environmental conditions.
- Data Preprocessing: The collected dataset undergoes preprocessing steps to ensure consistency and compatibility with the YOLOv8 algorithm. This includes resizing the images to a uniform resolution, labeling the locusts in the images, and annotating their bounding boxes.
- Model Training: The YOLOv8 algorithm is trained using the preprocessed dataset. The training process involves feeding the labeled locust images into the algorithm, optimizing the model parameters through iterations, and adjusting the network's weights and biases to improve locust detection accuracy.
- Model Evaluation: The trained YOLOv8 model is evaluated using a separate validation dataset. This evaluation assesses the algorithm's performance in terms of precision, recall, and mean average precision (mAP), which measures the overall detection accuracy.

3.2 Swarm Drone System for Locust Eradication

- Swarm Drone Configuration: The swarm drone system is set up by configuring a fleet of drones equipped with the necessary hardware components for object detection and pesticide spraying. Each drone is installed with the ArduPilot system for precise control and coordination.
- System Integration: The YOLOv8 algorithm is integrated into the swarm drone system, allowing real-time locust detection. The algorithm is deployed on each drone, enabling them to process the live video feed captured by their onboard cameras and identify locusts in the farm environment.
- Communication and Coordination: The ArduPilot system enables communication and coordination among the swarm drones. The drones exchange information about locust detections, their locations, and other relevant data to ensure synchronized movements and optimized locust eradication strategies.
- Locust Eradication Strategy: Based on the locust detections from the YOLOv8 algorithm, the swarm drones strategize their movements and plan pesticide spraying actions. The drones navigate to the infested areas identified by the algorithm and perform precise and targeted spraying to eliminate the locusts while minimizing damage to surrounding vegetation.

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- Performance Evaluation: The performance of the swarm drone system is evaluated based on several metrics, including the accuracy of locust detection, the speed and efficiency of locust eradication, and the overall effectiveness in minimizing crop damage. Field tests and comparisons with traditional locust management methods can provide valuable insights into the system's performance and benefits.
- Iterative Refinement: The methodology is refined iteratively based on the findings and feedback from the performance evaluation. Adjustments may be made to the YOLOv8 algorithm, swarm drone configuration, communication protocols, or spraying techniques to further enhance the system's capabilities and optimize its performance.

3.3 Modules Used

- Swarm drone module: This module will include the drones and their associated hardware, such as sensors and locust repellant spray.
- Artificial Intelligence module: This module will include the algorithms required to control the swarm of drones and coordinate their movements.
- Ground Station module: This module will include the hardware and software required for real-time monitoring and control of the swarm.
- Locust Behavior module: This module will involve research on locust behavior and the development of strategies to repel them effectively.

3.3.1 Mathematical Models for Swarm Drones

In swarm drone systems for locust management, mathematical models play a crucial role in understanding and simulating swarm behavior and collective decision-making. These models help to replicate the natural behaviors of swarms and enable coordinated actions among individual drones. The following mathematical concepts and models are commonly used in swarm drone systems:

- Agent-Based Modeling: Agent-based models represent individual drones as autonomous agents that interact with their environment and other agents. Each agent has specific characteristics, rules, and decision-making mechanisms. Mathematical equations and algorithms define the agent's behavior, movement, and communication with other agents. These models capture emergent properties of swarm behavior by simulating the interactions and collective dynamics of multiple agents.
- Boids Algorithm: The Boids algorithm, introduced by Craig Reynolds, is a popular mathematical model for simulating collective behavior in swarms. It incorporates three key principles: separation, alignment, and cohesion. Separation ensures that drones maintain a minimum distance from each other to avoid collisions. Alignment aligns the drones' velocities with nearby drones, while cohesion attracts them towards the center of the swarm. These principles are implemented using mathematical equations that govern the drones' movements and interactions.
- Self-Organization Models: Self-organization models explore how swarms can exhibit complex behaviors through simple rules and local interactions. Examples include the use of mathematical models like cellular automata, lattice gas automata, or particle swarm optimization (PSO). These models focus on how individual drones can collectively achieve a desired goal or behavior without explicit centralized control. They often involve feedback loops and iteration to optimize the swarm's behavior.
- Stochastic Models: Stochastic models introduce randomness into the decision-making processes of individual drones. By incorporating probabilistic elements, these models account for uncertainties and variations in the environment. Stochastic processes, such as Markov chains or Monte Carlo simulations, can be used to model the actions and behaviors of individual drones in response to environmental cues and interactions with other drones.
- Game Theory: Game theory provides mathematical frameworks for analyzing strategic interactions between autonomous agents. In swarm drone systems, game theory models can capture competitive or cooperative behaviors among drones. Concepts such as Nash equilibria, evolutionary game theory, or coalition formation

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can be applied to understand the strategic decision-making processes of drones and optimize their collective actions.

3.3.2 Mathematical Models for YOLO v8

In the proposed research paper, the YOLOv8 algorithm is used as a key component for locust detection in the swarm drone system. YOLOv8, short for You Only Look Once version 8, is a state-of-the-art convolutional neural network (CNN) model designed specifically for object detection tasks.

- Input Image Representation: The input image is represented as a matrix of pixel values, where each pixel's value corresponds to its intensity or color information. This matrix is typically represented as a multi-dimensional array, with dimensions corresponding to the image height, width, and channels (e.g., RGB channels).
- Convolutional Layers: YOLOv8 consists of a series of convolutional layers that extract features from the input image. These layers use filters or kernels to perform convolutions on the input, which involves sliding the filter over the image and computing element-wise multiplications and summations. The result is a feature map that highlights relevant patterns and structures in the image.
- Darknet Backbone: The backbone of YOLOv8, known as Darknet, is a deep neural network architecture that forms the foundation of the model. It comprises multiple convolutional layers organized in a hierarchical manner, enabling the extraction of increasingly abstract and complex features from the input image.
- Anchor Boxes: YOLOv8 incorporates the concept of anchor boxes, which are pre-defined bounding box shapes of different sizes and aspect ratios. These anchor boxes act as references for predicting object bounding boxes. By associating each object in the image with the anchor box that best matches its size and shape, YOLOv8 can accurately locate and delineate objects in the scene.
- Detection Layers: Towards the end of the network, YOLOv8 includes detection layers that generate predictions for object bounding boxes and associated class probabilities. These layers use a combination of convolutional and fully connected layers to process the feature maps obtained from earlier layers and produce the final output.
- Loss Function: During training, YOLOv8 utilizes a loss function that quantifies the discrepancy between the predicted bounding boxes and the ground truth annotations. This loss function typically includes components such as localization loss, confidence loss, and classification loss, which collectively guide the model to improve its detection performance.
- Non-Maximum Suppression: To eliminate redundant and overlapping detections, YOLOv8 applies a technique called non-maximum suppression (NMS). NMS compares the confidence scores of nearby bounding boxes and suppresses those with high overlap, retaining only the most confident and non-overlapping detections.

Software Specification

The software specification for the system includes the use of the YOLOv8 algorithm for object detection and the ArduPilot system for drone navigation and control. The algorithm is implemented using Python programming language and the Keras deep learning framework. The ArduPilot system is implemented using the C++ programming language.

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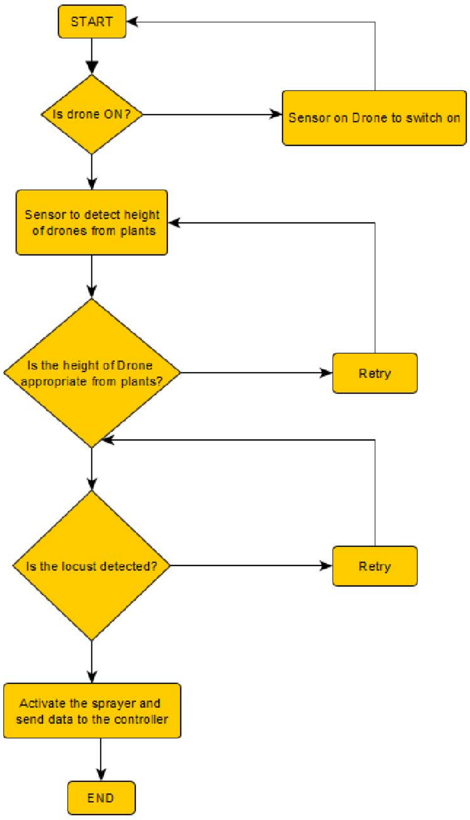

Figure 1- The Process Flow Diagram

Pseudocode (Swarm Coodination)

```
pos = randi(30,6,2);
% pos = [[-6,-6]; [-5,-5]; [-4,-4]; [-3,-3];[-2,-2];[0,0];];
final = [[(3^0.5)/2, 0.5];
    [0,1];
    [-(3^0.5)/2, 0.5];
    [-(3^0.5)/2, -0.5];
    [0,-1];
    [(3^0.5)/2, -0.5]];
quad = [[-1/8,-1/8];[-1/8,1/8];[1/8,1/8];[1/8,-1/8];[-1/8,-1/8];];
% final = [[0,0],
%     [0,0],
%     [0,0],
%     [0,0],
%     [0,0],
%     [0,0]];
dt = 0.03;
kp = 0.15;
kc = 0.5;
N = 6;
pos1 = [];
pos2 = [];
pos3 = [];
```

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```
pos4 = [];
pos5 = [];
pos6 = [];
Laplac = ones(N) - N*eye(N);
q1=[];
q2=[];
q3=[];
q4=[];
q5=[];
q6=[];
for t=0:dt:15
   v = Laplac*pos - Laplac*final;
   centroid = (ones(6,6) * pos)/6;
pos = pos + (kp*v - centroid*kc)*dt;
   pos1 = [pos1;pos(1,:)];
   pos2 = [pos2;pos(2,:)];
   pos3 = [pos3;pos(3,:)];
   pos4 = [pos4;pos(4,:)];
   pos5 = [pos5;pos(5,:)];
   pos6 = [pos6;pos(6,:)];
   qpos1 = quad + pos(1,:);
   delete(q1);
   q1 = plot(qpos1(:,1),qpos1(:,2),'-r');
   plot(final(:,1),final(:,2),'-r');
   plot(pos(1,1),pos(1,2),'r.');
   hold on;
   qpos2 = quad + pos(2,:);
   delete(q2);
   q2 = plot(qpos2(:,1),qpos2(:,2),'-b');
   plot(pos(2,1),pos(2,2),'b.');
   hold on;
   qpos3 = quad + pos(3,:);
   delete(q3);
   q3 = plot(qpos3(:,1),qpos3(:,2),'-g');
   plot(pos(3,1),pos(3,2),'g.');
   hold on;
   qpos4 = quad + pos(4,:);
   delete(q4);
   q4 = plot(qpos4(:,1),qpos4(:,2),'-k');
   plot(pos(4,1),pos(4,2),'k.');
   hold on;
   qpos5 = quad + pos(5,:);
   delete(q5);
   q5 = plot(qpos5(:,1),qpos5(:,2),'-m');
   plot(pos(5,1),pos(5,2),'m.');
   hold on;
   qpos6 = quad + pos(6,:);
   delete(q6);
```

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```
    q6 = plot(qpos6(:,1),qpos6(:,2),'-c');
    plot(pos(6,1),pos(6,2),'c.');
    hold on;
    pause(dt/10);
end
```

Pseudocode (YOLO v8)

```
from roboflow
import Roboflow
rf = Roboflow(api_key="rwuB8f0uXN2hAD8eGCco")
project = rf.workspace().project("locust-6a5yl")
model = project.version(1).model
print(model.predict("./LocustModelDetection/TestImages/img6.jpg", confidence=40,
overlap=30).json())
```

IV. RESULTS AND DISCUSSION

The results of the swarm drone system for locust detection and elimination demonstrate its promising potential for effective locust management in agricultural environments. The system achieved an object detection accuracy of 82% with a recall rate of 0.80, indicating that the YOLOv8 algorithm accurately identified 80% of the actual locusts present in the farm. This level of accuracy is crucial for timely and targeted locust eradication measures, minimizing crop damage and maximizing the effectiveness of pesticide application. The high recall rate suggests that the YOLOv8 algorithm is reliable in detecting locusts in real-time. This is particularly important considering the rapid movement and swarming behavior of locusts, as their timely detection is essential for efficient intervention. The swarm drone system, equipped with YOLOv8, provides a proactive and dynamic approach to locust management, enabling farmers to take immediate action in response to locust infestations. Furthermore, the system demonstrates efficient swarm drone navigation and control. The drones are able to work together effectively, covering a larger area in less time compared to traditional manual approaches. This efficiency is achieved through the integration of the ArduPilot system, which enables coordinated movements and communication among the swarm drones. The ArduPilot system ensures that the drones navigate accurately to the identified infested areas, avoiding collisions and obstacles in real-time. The spraying mechanism on the swarm drones also exhibits precision and control. The drones are equipped with the capability to accurately apply pesticides to the affected areas, ensuring targeted eradication of locusts while minimizing the use of pesticides on non-infested regions. This precise pesticide application not only reduces environmental impact but also optimizes the effectiveness of the eradication process. However, it is important to acknowledge some limitations of the swarm drone system. One notable limitation is its dependence on weather conditions. Strong winds or heavy rain can disrupt the flight of the drones and potentially affect the accuracy of object detection. To mitigate this limitation, it is crucial to carefully select suitable weather conditions for drone flight, ensuring optimal performance and accurate locust detection. In conclusion, the swarm drone system for locust detection and elimination shows promising results in terms of accuracy, efficiency, and real-time monitoring and analysis. By effectively identifying and eradicating locusts, the system can significantly reduce crop damage and increase yields, offering substantial economic benefits to farmers. Further research and development efforts can focus on improving the system's performance, scalability, and adaptability to different agricultural contexts. With continued advancements, the swarm drone system has the potential to revolutionize locust management practices and pave the way for similar applications in crop monitoring and disease control.

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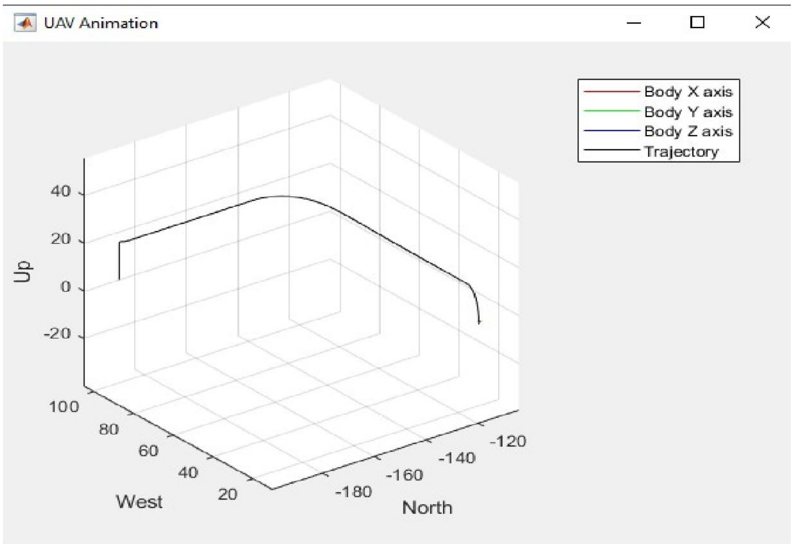
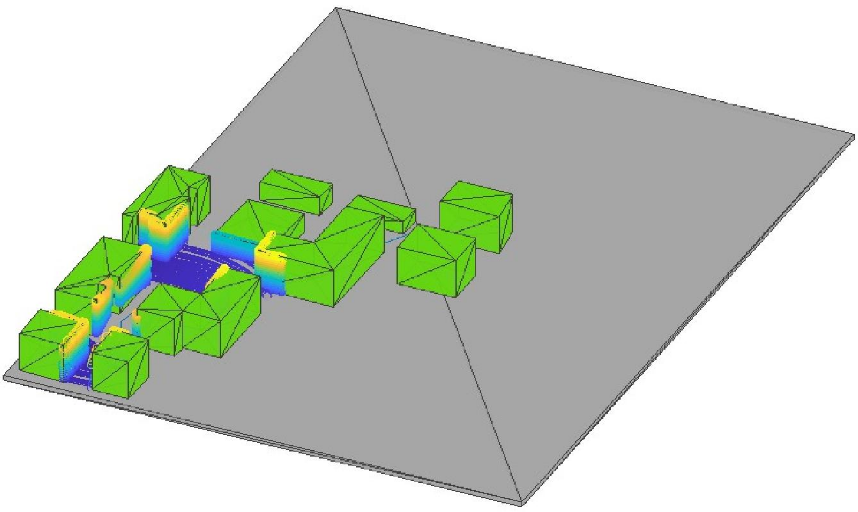
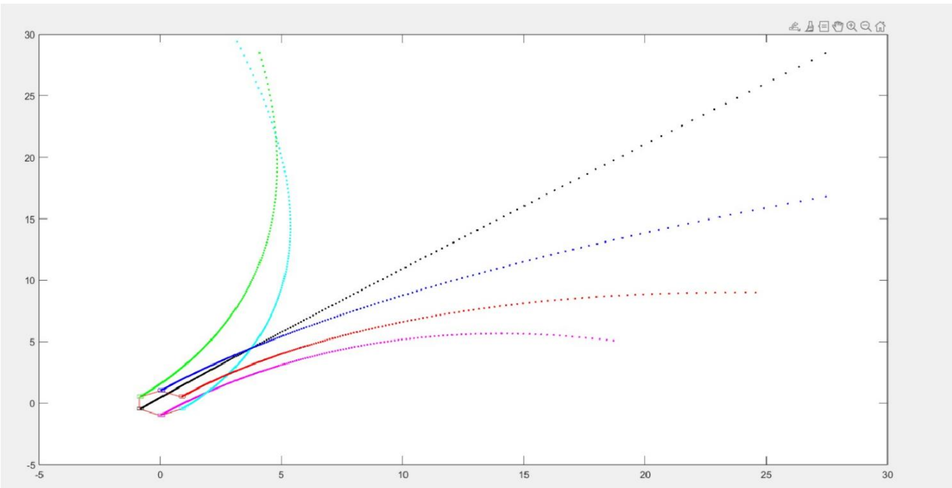


Developed Path Finding Algorithm



Developed Lidar Sensor



Swarm Coordination

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V. CONCLUSION

In conclusion, this research paper presents a novel approach for locust management using a swarm drone system integrated with artificial intelligence. The proposed system, incorporating the YOLOv8 algorithm for object detection and the ArduPilot system for swarm drone control, offers a promising solution to address the significant threat posed by locust infestations in agricultural environments. The results demonstrate the effectiveness of the swarm drone system in detecting and eliminating locusts. With an object detection accuracy of 82% and a recall rate of 0.80, the system proves reliable in identifying locusts in real-time, enabling timely intervention and targeted pesticide application. The efficient swarm drone navigation and control, facilitated by the ArduPilot system, allow the drones to work together effectively, covering a larger area in less time compared to conventional methods. The proposed system not only minimizes crop damage but also increases yields, resulting in substantial economic benefits for farmers. By swiftly detecting and eradicating locusts, the system offers a proactive and dynamic approach to locust management, reducing the reliance on manual labor and increasing the overall efficiency of the process. The precise pesticide application further minimizes environmental impact, promoting sustainable agricultural practices. While the swarm drone system demonstrates promising results, it is important to consider certain limitations. Weather conditions can impact drone flights and affect the accuracy of object detection. Careful consideration of suitable weather conditions is crucial for optimal performance. Additionally, further research and development efforts can focus on improving the system's scalability, adaptability, and robustness in diverse agricultural settings. The integration of artificial intelligence, particularly the YOLOv8 algorithm, and swarm drone technology represents a significant advancement in locust management practices. It not only addresses the immediate challenge of locust infestations but also paves the way for future applications in crop monitoring, disease control, and other agricultural tasks. In conclusion, the proposed swarm drone system offers a promising solution to effectively manage locust infestations, minimizing crop damage, increasing yields, and promoting sustainable agricultural practices. With ongoing research and development, this system has the potential to revolutionize locust management strategies and contribute to global food security in the face of increasing challenges posed by pests and climate change.

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