Artificial Intelligence-based Autonomous Pesticide Spraying Drone Management for Sustainable Agriculture

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Abstract. Precision agriculture has greatly progressed by increasing crop output in recent years. Unfortunately, diseases caused by pests and insects often lead to big losses in fields, reducing crop yield. To fix this, fertilizers and pesticides improve crops and control insects and pests. People are worried about the harmful impact of pests on human health, food security, and the environment. Drones operated by people are being used more and more to spray pesticides, reducing the health risks of doing it by hand. The drone uses advanced path planning and GPS to move through complicated areas, covering big areas and treating infested regions well. A cloud-based system for control, monitoring, and data analysis gives useful information through data analysis, letting people follow pest population changes, find repeating patterns, and use good pest control methods. The autonomous pest control drone fixes the problems with traditional pest control methods.

Keywords: Precision agriculture, Pest Management, Drone technology, Artificial intelligence, Environmental impact, Autonomous system.

1 Introduction

According to the 2023 Food and Agriculture Organization (FAO) Statistical Yearbook, over 42% of the global population has selected agriculture as their primary occupation[1]. In agriculture, a lot of challenges have been faced by the farmers working in greenhouses and commercial types of farming[2]. The challenges such as the hazards to human health stemming from exposure to pesticides and other chemicals used in farming will impact both livelihoods and health [3]. Apart from these challenges, insects contribute a lot in posing a threat to crops by consuming and damaging crops. Plant diseases like bacterial rot, fire blight, and crown gall are caused by pathogens in the environment, which can have a significant impact on farmers. These hazards lead to economic losses for farmers due to the handling of pesticides, damage caused by insects, and plant diseases [4], [5]. Over the past decade, farmers have implemented various control measures to minimize the impact of pest and disease management, aiming to mitigate these risks and ensure crop safety. The advancement of robotics technology has led to farmers using rovers to monitor crop health and control pesticide spraying [6], [7]. However, there are many limitations associated with using

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robots in agriculture, such as soil conditions, crop types, and environmental constraints. Further technological developments, such as drones, are expected to solve these problems [8], [9]. In recent years, the development of drones has prompted researchers to create more efficient and adaptable vehicles. These drone vehicles can be used for pest control management and can eliminate chemical hazards to human beings by automatically handling pesticide spraying systems [10], [11]. Developing countries like India are actively promoting using drones in agriculture, especially for crop assessment, digitisation of land records, and spraying of insecticides and nutrients [12]. The Indian National Drone Policy and the Drone Rules 2021 for drone technology make it easier for people and companies to own and operate drones in the country. The Kisan Drone Scheme by the Indian government provides financial assistance to institutions, individual farmers, and entrepreneurs to procure and use drones for agricultural purposes. While drone technology development has helped solve many challenges faced by farmers, a new challenge has arisen in the form of drone handling[13]. Farmers often struggle with operating drones in constrained environments due to a lack of skill and knowledge in drone operation. Certified drone pilots are the only ones capable of effectively operating drones in such environments. Nowadays, many researchers are exploring the use of autonomous drones for pest control management and integrating Artificial Intelligence (AI) into traditional farming practices. This innovative use of AI-based autonomous pesticide-spraying drones is a transformative solution for sustainable agriculture. By digitizing land records and employing machine learning algorithms, precise navigation and target detection can be achieved[14]. CNN and machine learning algorithms are utilized to improve drone capabilities for automated control, data collection, and real-time analysis, making drones invaluable tools in modern agriculture and other fields. Advanced object detection systems in modern autonomous drones utilize AI algorithms to identify the target in agricultural fields that require pesticide spraying. With this AI technology, drones can adapt spray patterns based on the specific needs of different crops[15]. Factors such as plant height, growth stage, and the presence of insects are also considered to optimize the application of pesticides. This customization ensures that the right amount of pesticide is applied to the right areas at the right time, crucial for effective pest management[16], [17], [18]. The integration of autonomous drones in agricultural practices significantly contributes to sustainable farming methods by reducing chemical runoff. Autonomous drones allow for precise application only in the targeted areas that require treatment, reducing the overall volume of pesticides used and minimizing the potential impact on surrounding ecosystems. In summary, the evolution of drone technology signifies a shift towards more intelligent and efficient agricultural practices, promoting sustainable agricultural practices through advanced technologies [19], [20], [21], [22], [23]. This paper explores the deployment of AI-powered drones as a transformative solution for sustainable agriculture, highlighting technological advancements, operational efficiencies, and environmental benefits. While challenges such as regulatory frameworks, data security, and technological accessibility exist, continued research and collaboration among stakeholders are crucial for widespread adoption.

2 Methodology

2.1 Methodology Overview

Drone development and testing consist of different layers, as shown in Figure 1. Conducted a detailed survey on existing drone technology design and their performance based on the functionality. Using the Simulink toolbox of MATLAB software the design was created and studied its flight dynamic characteristics. The created Simulink model was optimised based on the recorded real-world data to improve its performance. High-quality components are procured from the vendors as per the design specifications of the model. In a well-suitable environment, the procured drone components are assembled, at every stage of the drone assembly section it undergoes performance testing to ensure the proper working conditions. For real-world testing, a detailed testing plan was developed to evaluate the drone's performance such as flight control, autonomous navigation, sensor accuracy, and communication reliability. During this initial stage of testing safety measures and contingency plans are to be followed to mitigate risks. Data were collected from these test flights and were analysed to find the areas of improvement predicted through simulation. The final stage of drone development methodologies consists of an iterative real-world testing process, based on this iterative testing process problems happened in remote control and autonomous interventions were observed. Observations are recorded for immediate decision-making analysis such as making design improvements.

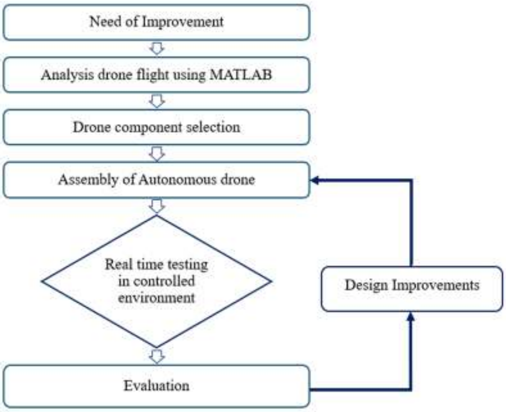

Fig. 1. Methodology Overview

2.2 Mathematical Model of Quadcopter

A mathematical model of a quadcopter was developed to simulate the propeller movements using a control algorithm. A mathematical model is an initial step in understanding the mathematical principles and physical laws applied to the quadcopter system as shown in Figure 2. The created mathematical model accurately describes the behavior of the quadcopter and can be modified to apply to similar multi-rotor aerial vehicles [24]. The model first defines the coordinate systems and then establishes the relationship between the drone coordinates and the earth coordinates shown in Figure

3. The kinematics (torque and forces) of the quadrotor setup are calculated using the Newton-Euler relation. The final derived equation is in the form of Newton's second law of motion in matrix notation. These equations are then utilized in the simulation of the quadrotor in MATLAB.

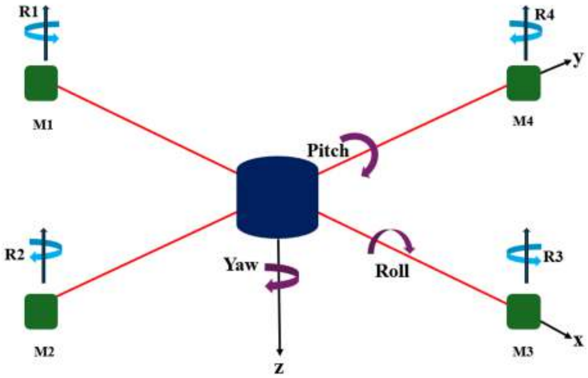

Fig. 2. Quadcopter structure[25]

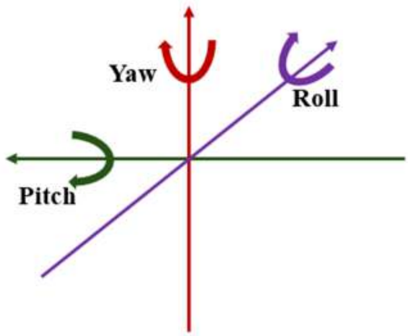

Fig. 3. Earth and body coordinate system of the quadrotor[24].

The Euler angles describe the orientation of a rigid body within a coordinate system and the relationship between two reference frames. It is represented as ϕ_1, ϕ_2, and ϕ_3,which correspond to the roll, pitch, and yaw angles, respectively. These angles describe the rotations of a body around the axes of a coordinate system.The motion equation was derived based on the earth's inertial frame of reference. This equation can be utilized to simulate the aircraft's position in MATLAB to the earth's frame. The trajectory can then be mapped using online path-planning algorithms. Generated equations can be used for making a mathematical model in MATLAB and the drone's motion can be analysed. This ensures that corrections of any sort are made beforehand while visualising the simulations made with the help of several MATLAB functions as shown in Figure 4. Hence testing the drone is made safer when tested in real real-time environment.

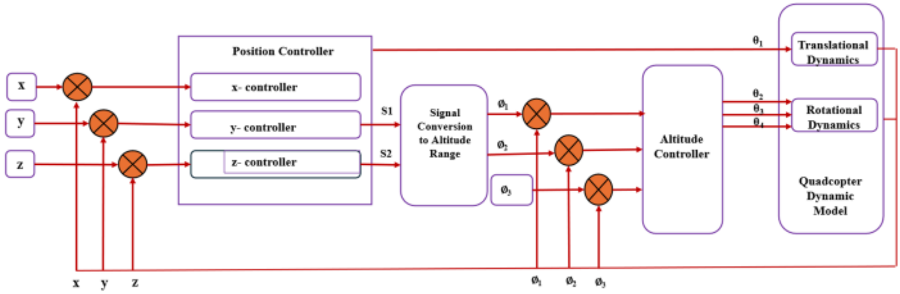

Fig. 4. Control Architecture for the drone simulation

2.3 MATLAB Simulation

The behaviour of the mathematical model's outputs is dependent on the input values and the MATLAB simulation of these mathematical models is shown in Figure 5.

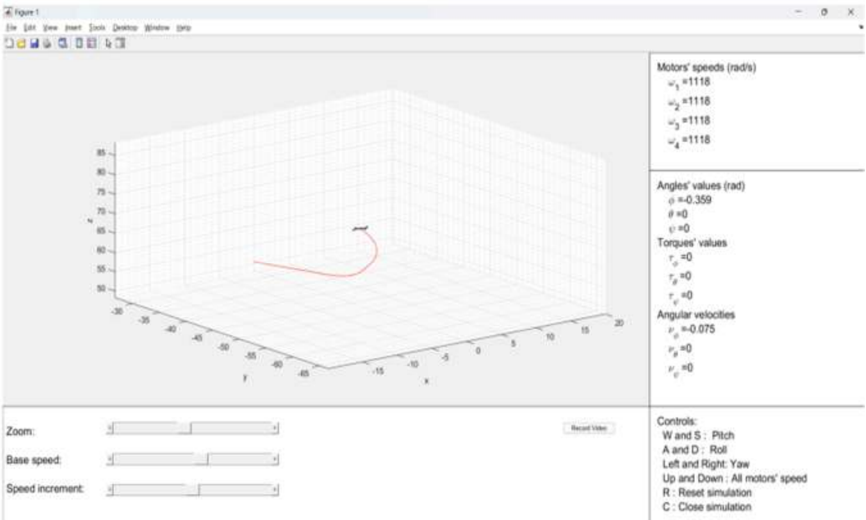

Fig. 5. Simulation window designed in MATLAB

3 Design and Assembly of Drone

3.1 Design Process

Design loop is the circular nature of the design process often used in the drone designing process as shown in Figure 6. Initially, the drones are built based on certain assumptions.

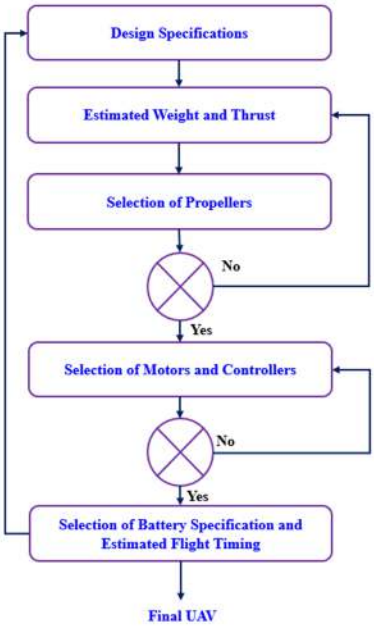

Fig. 6. Process Loop for Designing a Drone

The optimization process is a loop, so the first step is to start by making some assumptions. First, let's assume that the drone already flies with an existing design with known weight and battery size. Let's assume that the Gross Vehicle Weight of the drone for our use case is 1.5 Kgs, where GVW = Unladen weight + Payload. The payload is the weight of the spraying mechanism the drone has to carry to fulfil our requirements for the prototype under development. The unladen weight is the quadcopter's weight alone. The assumed weight is based on the components that will be assembled on the drone for the project. Since the designed drone is hovering, the thrust-to-weight ratio is kept lower than or equal to 2.[27] (Racing drones have a higher thrust-to-weight ratio to tear air and plunge quickly)

Table 1. Drone Components and Their Weight

Sl. No	Component	No. of Units	Individual weight (g)	Total weight (g)
1	Flight controller	1	40	40
2	ESC	1	25	25
3	BLDC motors	4	60	240
4	Frame	1	400	400
5	Battery	1	300	300
6	Propeller	4	10	40
7	Telemetry	1	60	60
8	GPS unit	1	30	30
			Total	1135

Table 2. Payload Components and Their Weight

Sl. No	Component	No. of Units	Individual weight (g)	Total weight (g)
1	Arduino Nano	1	40	40
2	3-6V submersible pump	1	25	25
3	Zigbee UART	2	60	240
4	9V battery	1	400	400
5	Tank (250 ml)	1	300	300
6	Breadboard	1	10	40
			Total	221

So, the Gross Vehicle Weight of the drone is the sum of the drone's components' weight and the spraying mechanism's weight. Hence, GVW = 1135(g)+221(g) = 1356(g) [Approximately 1500g] Thrust Calculation When a drone is hovering in place (in no-wind condition), the thrust is equal to the weight of the drone. Hence, Weight = Mass x Acceleration due to gravity Weight = 1.5(kg) x 9.8 = 14.7N (Approximately 15N) Thus the drone's propeller must produce 15N of force to hover the drone. Since we are building a quadcopter (4-motor propeller configuration), each propeller takes around one-fourth of the force required to hover the drone. Each propeller needs around 3.675 N of force to hover the drone.

3.2 Factor of Safety

The calculation mentioned earlier focused solely on hovering, but for overall flight, including take-off and loitering, a drone needs additional thrust. This accounts for factors like acceleration and maintaining stability, so to incorporate a safety margin into their designs to ensure the drone operates reliably under various conditions. Force/Propeller = 3.675 N or 4 N approximated (0.41kgf) Considering a FOS = 2, for stable flight control, Force/Propeller = 4 x 2 = 8 N per propeller (0.82kgf) Hence we need to confirm that the drone produces 0.82 Kg-f or 8 N thrust per propeller.

3.3 Compatibility Check - Motor & Propeller

To ensure propeller and motor compatibility by utilizing Mejzlik's static thrust calculator as shown in Figure 7. This tool helps determine the optimal combination of propeller size and motor specifications to achieve efficient performance. By inputting relevant data such as motor type, propeller dimensions, and desired thrust, builders can assess the suitability of components before assembly. This proactive approach ensures that the drone operates smoothly and efficiently during flight, enhancing overall performance and reliability.

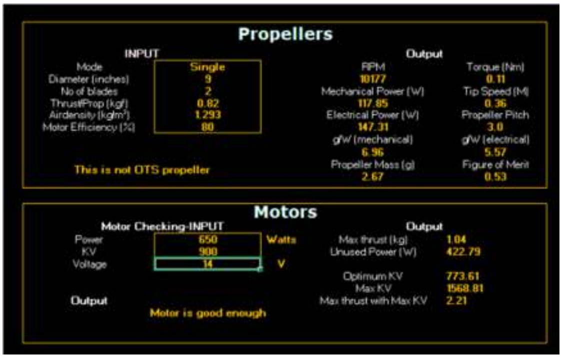

Fig. 7. Mejzlik’s static thrust calculator tool for checking compatibility

3.4 Assembly of Drone

The F450 frame, constructed from Polyamide (nylon), features motor mounting provisions designed for affixing motors on top of the frame. This layout facilitates easy installation and maintenance of motors, contributing to the frame's structural integrity and overall stability. Motor mounting on the F450 frame is facilitated by using an M3 compatible star screwdriver, ensuring secure fixation of the motors. The power module and ESCs are soldered directly onto the integrated PCB of the F450 frame, streamlining the electrical connections within the drone assembly. This integration enhances reliability by reducing the risk of loose connections and simplifies maintenance tasks. This approach eliminates the need for an external breadboard to distribute power from the battery to the drone's components, simplifying the wiring setup and reducing potential points of failure. The Pixhawk is a Flight Controller that acts as an ECU in providing stable flight conditions. The connections to the drone’s components are shown in Figure 8. The most common method for calibrating ESCs (Electronic Speed Controllers) for small electric aircraft is the max-throttle/min-throttle method.

Fig. 8. Assembled drone

4 Deep Learning in Agriculture

A dataset containing approximately four different hydroponic plant diseases has been acquired. Any image from this dataset can be used as a test image for the software. The training dataset is utilized to train the Convolutional Neural Network (CNN) so that it can identify the test image and the specific disease it exhibits. Epoch function is executed to reduce the loss in training and increase the model accuracy of the CNN as shown in Figures 9 and 10. The achieved accuracy of the model is more than 90% hence a satisfactory and fast responsive model is obtained.

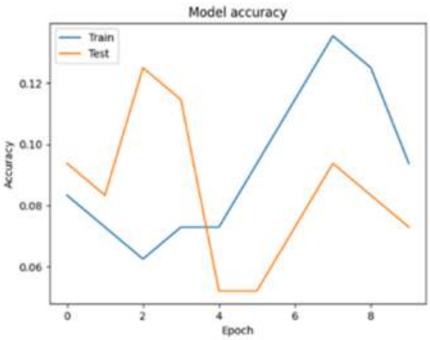

Fig. 9. Model Accuracy after every Epoch Pass

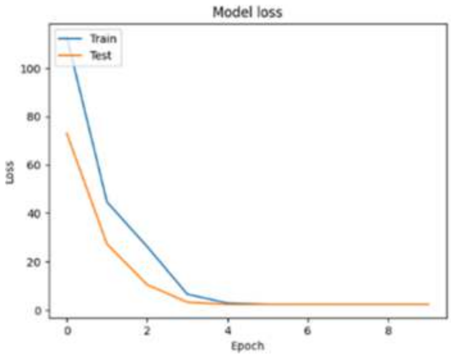

Fig. 10. Model Loss after every Epoch pass

4.1 Working Layers of the CNN Model

HereKeras pre-processing package to input images, which are then converted into array values using the Pillow package and its image-to-array function. The dataset containing classified tomato plant disease images is already established. Following this, the prediction function is employed to predict the disease affecting our tomato plants. As discussed above, the plant disease recognition method adopts a two-channel architecture capable of classifying plant diseases as shown in Figure 11. Plant disease images serve as input into the inception layer of CNN. During the training phase, feature extraction and classification are performed using convolutional neural networks (CNNs).

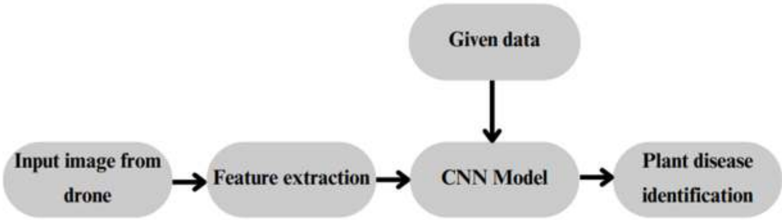

Fig. 11. Flow chart for CNN model

As the drone hovers over the field, it autonomously navigates towards individual plants, guided by its onboard systems. Upon reaching a plant of interest, the drone activates its onboard camera to capture an image of the crop. Once the image is obtained, it is swiftly transmitted using the TS832 48CH 5.8G wireless audio-video transmitter, facilitating real-time data transfer. Subsequently, the captured image is inputted into the CNN model for analysis to predict the plant's health status. This processing occurs within the drone's processing unit, enabling rapid assessment and decision-making based on the image data. Once the decision is made, it is transmitted to the drone's Zigbee module from the processing unit's Zigbee using the UART protocol. The pump motor is then activated using the H-bridge and Arduino Uno in conjunction, implementing the necessary actions dictated by the decision. Future enhancements could include implementing preset levels of pesticide spraying based on the assessed quality of the affected crop. Figure 12 shows the working of the autonomous spraying mechanism. This advanced feature would enable the drone to automatically adjust the spraying intensity, ensuring targeted treatment tailored to the specific needs of the crop, thereby optimizing pesticide usage and minimizing environmental impact.

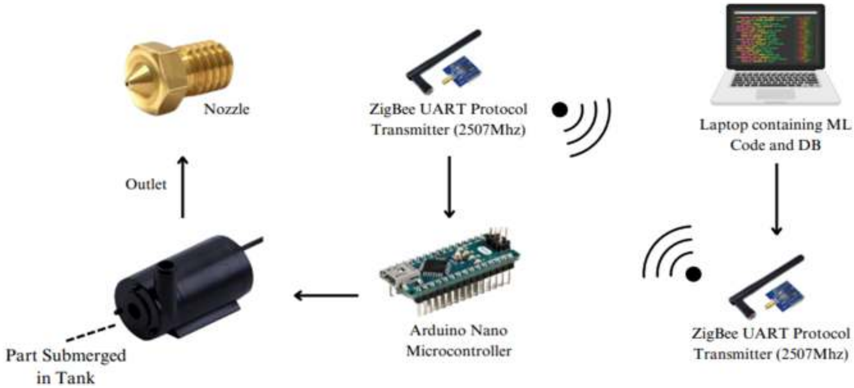

Fig. 12. Working of the autonomous spraying mechanism

5 Conclusion

The following conclusion arrived on developing autonomous pesticide spraying drone management,

- Developed drones can be operated autonomously with the integration of PIXHAWK-ECU and IoT sensors.
- Problems that arise in conventional methods of pesticide spraying are hazardous to humans, handling of pesticide while spraying, labour requirements, and expense involved in spraying are resolved through this autonomous spraying drone.
- Advanced technologies implementation in drone pesticide spraying management resulted in a substantial enhancement of operational efficiency. By automating the process of pest detection, monitoring, and pesticide application, the drone streamlines pest control operations, reducing the need for manual labour and associated costs.
- Apart from these operational benefits, the autonomous pesticide spraying drone's environmentally conscious approach significantly contributes to sustainability efforts by reducing pesticide usage and preventing over-spraying, thereby mitigating potential harm to non-target organisms and ecosystems.
- Integrating machine learning approaches such as CNN models were used to detect the categories of plants and their respective diseases. Moreover, advancements could be made to accurately determine the optimal amount of pesticide required for each

specific crop and disease scenario. This tailored approach would minimize pesticide usage, reduce environmental impact, and optimize crop health outcomes.

Overall, the advancements involved in these autonomous pesticide spraying drones contribute to sustainable and efficient pest management practices in agriculture.

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