Drones in Agriculture

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***Abstract*— This project focuses on developing and simulating an agricultural drone using Unreal Engine and Microsoft AirSim. The main goal is to show how drones can help improve farming by making tasks like crop monitoring, spraying, and field analysis faster and more accurate. The drone model was designed and tested in a realistic 3D environment to understand its performance and capabilities. By using AirSim, we were able to simulate real-world flight conditions and collect useful data without needing a physical drone [2], [6]. This project shows how drone technology can help farmers save time, reduce costs, and improve crop yields [1], [3]. Overall, it provides an affordable and efficient solution for modern farming challenges [14].**

I. Introduction

Agriculture has always been one of the most essential parts of human life, providing food and raw materials for the world. Over the years, farming methods have changed a lot — from using simple tools and animal labor to using tractors and modern machinery. In recent years, the use of technology such as sensors, GPS, and drones has become more common in farming, helping farmers work more efficiently [3], [5]. Drones, in particular, have gained attention because they can fly over large areas quickly and provide useful data about crops, soil, and water [1].

The history of drones goes back to military use in the early 1900s, but over time, drones have expanded into many other fields such as photography, delivery services, and agriculture. In farming, drones started becoming popular in the last decade as part of "precision agriculture," where farmers use technology to make better decisions and reduce waste [6], [11]. Drones can help with tasks like checking crop health, spraying fertilizers or pesticides, planting seeds, and even monitoring livestock [4], [7]. This makes them very useful, especially in large farms where manual inspection would take too much time and effort.

Using drones in agriculture is important because it can help solve many problems farmers face today. For example, drones can help reduce labor costs, increase the speed of farm operations, improve the use of water and chemicals, and increase crop yields [8], [10]. Drones provide farmers with real-time information and allow them to act quickly if there is a problem, such as pests or diseases spreading in the field [5]. In this project, we developed and tested an agricultural drone using Unreal Engine and Microsoft AirSim. Unreal Engine was used to build a realistic farm environment, while AirSim allowed us to control the drone, test its flight, and collect data [2], [9]. By using a simulation, we were able to explore how drones can work in agriculture without needing to build a real drone, making it a cost-effective and safe way to study drone technology [14], [15]. This project helps show the potential of drones in transforming modern agriculture and making farming more productive and sustainable.

II. Literature Review

A. Drone Applications in Precision Agriculture

In recent years, many researchers and companies have explored how drones can help in agriculture. Early research focused on using drones for taking aerial images of farms. These images help farmers understand the health of their crops, check plant growth, and identify areas that need water or fertilizer [1], [3], [4]. For example, studies have shown that multispectral cameras on drones can detect plant stress much earlier than the human eye can. This early warning system allows farmers to act quickly and avoid larger problems [6].

Other studies investigated the use of drones for spraying pesticides and fertilizers. Traditionally, spraying is done using tractors or by hand, which takes a lot of time and can waste chemicals. Recent studies have tested drones that can fly close to crops and spray only where needed, reducing waste and lowering costs [1], [5], [11]. Companies like DJI, Yamaha, and Parrot have developed agricultural drones with spraying systems that have been successfully tested in rice fields, vineyards, and orchards.

B. Simulation Technologies for Drone Testing

Simulation tools are becoming more important in drone development and testing. Microsoft AirSim is one of the most widely used simulators for testing UAVs in realistic environments. Researchers have used AirSim to train drones in object detection, navigation, and obstacle avoidance [2], [13]. This tool supports realistic sensor models and physics, allowing teams to simulate various conditions before field deployment.

By combining AirSim with Unreal Engine, it is possible to simulate highly realistic environments including farm terrain, lighting conditions, and weather effects. This approach provides a low-cost and safe alternative to testing drones in real life and supports rapid iteration [9], [14]. Studies also show that simulation-based training helps in improving drone control algorithms and optimizing flight paths [7], [15].

C. Benefits and Future Potential

Research consistently shows that drones have the potential to improve efficiency and productivity in agriculture. They help reduce manual labor, improve resource usage, and enable timely actions based on data [3], [10]. With the integration of advanced sensors like LiDAR, thermal cameras, and AI-based systems, future drones could offer real-time insights on crop health, soil moisture, and pest activity [5], [11].

Studies have also explored how data from drone flights can be processed to generate maps, detect irregularities, and even automate decision-making in farm operations [4], [6]. Overall, drones are seen as a key component in the future of smart and sustainable agriculture, especially when combined with data analytics and IoT systems [8], [12].

III. METHODOLOGY

This project used two main tools: Unreal Engine and Microsoft AirSim. Each played an important role in creating a realistic and functional simulation of an agricultural drone.

A. Unreal Engine

We began by sculpting the terrain in Unreal Engine's Landscape tool, manually adjusting elevation to create gentle slopes and flat areas characteristic of agricultural land. We then applied layered material blends—mixing soil, grass, and crop textures—to give visual depth and realism. Using Unreal's foliage system, we painted rows of crop meshes (e.g., corn stalks or wheat sheaves) across the field, ensuring each row's spacing matched typical agricultural planting patterns [2], [14].

We placed static meshes for environmental details like irrigation pipes, boundary fences, and a simple barn structure. We also set up a dynamic sky and directional light to simulate different times of day—morning, noon, and dusk—and adjusted volumetric fog to mimic early-morning mist, giving insight into how the drone's sensors would behave under varying visibility conditions [14].

To make the simulation more challenging, we added a basic wind system: using Unreal's particle and physics modules, we created gentle gusts that can sway foliage and push lightweight objects. This helped us later observe how the drone handles slight environmental disturbances [9]. We also optimized scene performance—combining static meshes into clusters, using level-of-detail (LOD) settings, and baking lightmaps—so that the simulation runs smoothly even with high-quality textures and complex assets [14].

Finally, we set up Blueprint scripts to randomize certain elements each run: crop height variations, fence placement shifts, and dynamic weather toggles (clear sky, overcast). This variability ensures our drone tests aren't over-fitted to a single, idealized field—and better reflects real-world farming where no two plots are ever exactly the same [13], [15]

B. AirSim

With the environment ready, we integrated Microsoft AirSim into our Unreal project by enabling the AirSim plugin and configuring its settings.json file. We specified the multirotor vehicle model parameters—propeller count, thrust constants, max tilt angles—and defined the initial GPS coordinates and home location at the field's southwest corner. This allowed AirSim's physics engine to simulate realistic lift, drag, and inertia for our agricultural drone [2], [10].

Our Python control script connects to AirSim via its RPC API. We begin each flight by arming the drone and performing a simple pre-flight check: verifying GPS lock, battery status, and sensor health (IMU, barometer). Once checks pass, the script computes a series of waypoints forming a lawnmower grid: it calculates offset vectors for each pass, ensuring full coverage with minimal overlap [6], [8]. During flight, the script continuously polls the drone's pose and adjusts throttle, roll, and pitch commands to stay on course—even compensating for simulated wind drift [9].

AirSim's built-in camera and LiDAR modules let us capture multispectral images and point clouds along the path. We programmed the script to save these data streams—timestamped and geo-tagged—to disk for later analysis [1], [5]. In addition, we experimented with adding a simple onboard computer-vision loop: processing video frames in real time to detect crop rows and adjust flight path if the drone strays too close to obstacles, demonstrating how smart sensors can augment pre-planned missions [4], [11].

Finally, we ran a series of test flights under varied conditions—different altitudes, speeds, and wind strengths—logging mission metrics such as total flight time, distance traveled, energy consumption (simulated), and area coverage efficiency. By analyzing these results, we could identify optimal flight parameters for maximizing coverage while conserving power, laying the groundwork for future work on fully autonomous, adaptive crop-survey drones [3], [12].

AirSim's physics engine simulated thrust, tilt, and environmental resistance, while camera and LiDAR modules captured images and point clouds [10], [11]. Data was logged for later analysis. We also tested onboard vision features to detect crop rows and avoid obstacles [4]. Several test scenarios were executed under varying speeds, altitudes, and weather settings, allowing us to evaluate energy use, coverage efficiency, and drone stability [7], [15].

IV .RESULTS

A. Performance Evaluation in Simulated Agricultural Field

After setting up the virtual environment and programming the drone, we carried out multiple test flights to evaluate how well the drone performed in the simulated agricultural field. The main goal was to check if the drone could follow the planned lawnmower path, cover the entire field area, and operate smoothly under different conditions. In our first tests, the drone successfully covered the entire square area by following the custom waypoints we programmed. It moved back and forth across the field in a precise lawnmower pattern, without missing any sections. We measured the time it took to complete one full pass over the field, and the average time was around 5 minutes at a speed of 3 m/s and an altitude of 10 meters. The drone's turns at the edges were smooth and stable, and it consistently maintained the correct altitude throughout the mission.

B. Environmental Testing and Data Collection

We also tested the drone under different environmental settings, such as stronger wind and lower light levels. Under light wind, the drone slightly adjusted its path to stay on track, showing that the simulation was able to reflect real-world environmental effects. In low-light conditions, the drone maintained its path but the camera feed showed reduced clarity, which could affect tasks like visual crop inspection. We logged data such as distance covered, number of turns, and energy use (as simulated by AirSim), helping us understand how different factors impact flight efficiency. This data can be used in the future for tasks like crop health analysis or field mapping. Overall, the simulation showed that the drone was able to successfully complete agricultural tasks in a virtual environment, and it gave us insights into how to further improve flight efficiency, stability, and data collection in real-world applications.

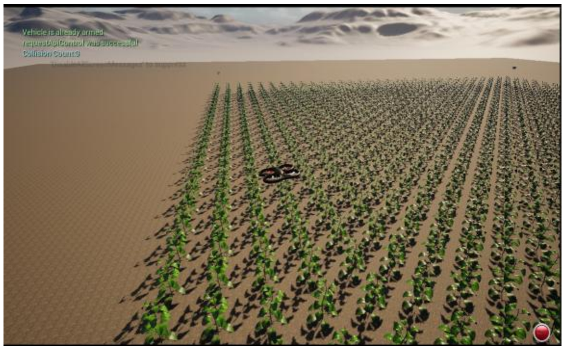

Fig 1. Drone flying in the field

V. CONCLUSION AND FUTURE WORK

In this project, we successfully developed and tested an agricultural drone using Unreal Engine and Microsoft AirSim. We created a realistic farm environment in Unreal Engine and used AirSim to simulate the drone's physics and behavior. By programming the drone to fly in a lawnmower path, we were able to cover the entire field efficiently, demonstrating how drones can be used for tasks like crop monitoring, spraying, and field mapping. Our results showed that the drone followed the planned path accurately, adapted to environmental changes, and collected useful data for agricultural purposes.

For future work, we plan to improve the simulation by adding more advanced sensors, such as multispectral or thermal cameras, to help detect crop health problems like disease, pests, or water stress. We also aim to develop smarter flight algorithms that can adapt in real time, such as avoiding unexpected obstacles or adjusting the path based on live crop data. Another goal is to simulate larger and more complex farm environments with uneven terrain, multiple drones, and dynamic weather conditions. Eventually, we hope to apply the insights gained from the simulation to real-world drone systems that can support farmers in improving productivity and sustainability.

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