AI-Based 3D Simulation for Drone Flight Dynamics

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***Abstract*—Unmanned aerial vehicles (drones) have provided new potential in areas like surveillance, transportation, construction, and agriculture. Simulating drone dynamics is vital in these domains, as it allows researchers to test drones in complex or risky circumstances. However, evaluating drone behavior is complicated because to the various elements involved. Traditional models based on Newtonian and fluid dynamics use parameters including force, gravity, propeller characteristics, and air density. While these models can replicate a generic drone, they are not realistic for replicating the dynamics of a specific drone due to the complex nature of the parameters. An AI-based technique gives a simpler way to model drone dynamics compared to these older methods. This approach leverages advanced AI models trained on massive datasets from real-world flight events. The datasets cover a range of flight maneuvers, including figure-eight, circular, and lazy-eight patterns, illustrating several sorts of drone motions. Several methods were utilized to develop the models, including multi-output regression, support vector machines (SVM), neural networks (NN), and convolutional neural networks (CNN). The CNN model achieved the highest accuracy at 78%. To validate the models, anticipated drone shifts were compared with real-world flight data. Future work will focus on further refining the CNN-based model and integrating it with a virtual reality environment for improved simulation.**

***Index Terms*—Artificial Intelligence, Conventional Neural Networks, Drone Dynamics, Simulation, Three-Dimensional Space**

I. Introduction

Unmanned Aerial Vehicles (UAVs), regularly known as drones, have become popular over the past two decades because of their numerous uses in surveillance, disaster management [1] ,pollution monitoring, cinematography, archaeology [2], delivery and military reconnaissance [3]. The development of drones begins a revolutionary period that alters the potential of hovering technology [4]. On the other hand, the UAV market has rapidly grown during the previous five years. Figure 1 shows forecasted revenue through 2025 as well as the global commercial UAV revenue from 2016 to 2023 [5].

The demand for knowledgeable and experienced human resources is critical as drone technology develops. For this technology to be used effectively, the workforce must possess both theoretical knowledge and practical abilities. Due to this, comprehensive training programs are necessary to cultivate a proficient workforce [6]. The use of drone simulators is a key component of this training program. These simulation programs provide a safe setting for aspiring drone pilots to improve their abilities and get comfortable with the specifics of flying drones. It is impossible to overstate the value of drone simulation, particularly since some drone activities are very dangerous. Before real-world deployment, professionals can evaluate and improve their abilities by simulating drone operations. Through simulation, factors that are unavailable in real systems can be observed, and model parameter adjustments can be made easily. This makes it easier to evaluate multiple options for optimizing system design. One essential element that sticks out is drone simulation, which offers drone pilots significant training and hands-on experience. Simulators can minimize costs and training duration while reducing the risks and damages resulting from improper processes [7].

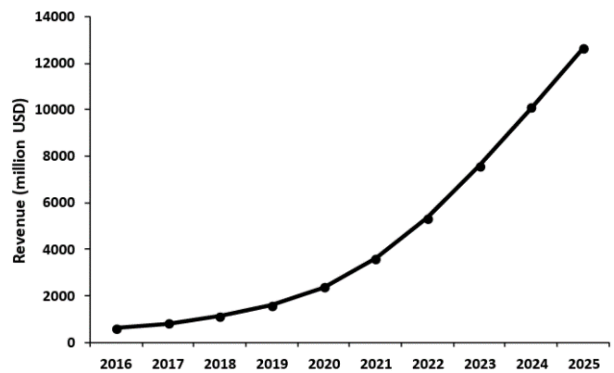

Fig. 1: Commercial UAV revenue worldwide from 2016 to 2025

Tools like the DJI (Da-Jiang Innovations) drone simulator, Zephyr, and FPV Air 2 drone simulators can simulate real-time drone behavior [8]. These simulators only imitate drones sold by manufacturers. On the other hand, it is difficult to simulate drone dynamics using simulation models based on fluid and Newtonian dynamics. It requires applying specific knowledge, conducting several trials under ideal environmental circumstances, analyzing practical challenges, and assessing the many parameters of the customized drone.

Compared to conventional techniques like fluid and Newtonian dynamics models, machine learning, a sub field of artificial intelligence, offers a simplified strategy for

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simulating drones. Machine learning uses fewer parameters than these traditional methods for accurately imitating drone behavior. When compared to the difficulties inherent in fluid and Newtonian dynamics models, machine learning models are a more effective option for generating realistic and accurate drone simulations. Therefore, this paper proposed a method for the simulation of drone dynamics using machine learning.

The following are the specific objectives of the study:

- To conduct a comprehensive analysis of the current state-of-the-art techniques used for simulating UAV movements.
- To gather necessary data on real flight scenarios for building the model.
- To develop an AI-based model that can accurately simulate the movements of UAVs.
- To validate the AI-based simulation model by comparing its predictions with real-world drone flight data.

The remaining parts of this paper are organized in the following manner: Section II provides a thorough assessment of the most advanced drone simulation models currently available. Section III provides a comprehensive explanation of the original study methodology, encompassing the processes of data gathering, preprocessing, and model building techniques. The evaluation and outcomes of the created models are reported in Section IV. Section V addresses the conclusions drawn from this investigation. Section VI,VII addresses the limitations and concludes the paper along with propective research directions.

II. Related work

As a subclass of UAVs, drone contains a variety of models, including tri copters, hexacopters, quadcopters, and helicopters. An effective simulator should include the capability to deal with a diverse range of these drone models [8]. UAV simulators serve three main functions: evaluating new technology, providing affordable training, and supporting research and development activities [4].

In 1910, pilots were trained on the first flying simulator that didn't depend on wind. Figure 2 shows that it was made up of two halves of a barrel that were mounted and moved by hand by a pilot sitting in the upper half of the barrel. The pilots had to line up the reference bar of the simulator that shows the sky [9].

Fig. 2: First Flight Simulator

A UAV simulation method using numerical techniques was introduced by David Orbea et al. They include numerical approximations in their mathematical model, which includes several Single Input Single Output (SISO) systems. These systems have relationships between altitude, pitch, roll, yaw angles as input parameters and x, y, z axis speeds as output parameters [10] . Identifying the complicated relationships between the aircraft's speed on the X-axis and the pitch angle, its speed on the Y-axis and the roll angle, and its speed on the Z-axis and the yaw angle are the main objectives of this mathematical analysis. Figure 3 shows the aircraft's angles and orientations. This method adjusts the pitch angles and motor speeds based on assumptions about the multi-rotor system, leading to unpredictable behavior when wind conditions change.

Using the Newton-Euler method, Fernando H.C.T.E et al. have provided an approach for simulating quadrotor dynamics [11]. The model predicts the effects of the forces and torques generated by the four propellers on the quadrotor motion. The main objectives are to streamline the creation of control algorithms for autonomous navigation and trajectory planning. An experimental flight is conducted using a quadrotor prototype to evaluate the dynamic model. The results obtained from these flights are compared with simulation data to verify their accuracy. Several research and development projects have utilized machine-related theories to produce ICT solutions for drones [12], [13], [14]. However, most of these applications are for the creation and advancement of autonomous UAV and the target tracking in both outdoor and indoor settings.

Javier Maldonado et al. suggested another simulator to do dynamic simulations, this method first obtains a comprehensive dynamic model of the UAV using a quadcopter. Next, using Unity 3D, a virtual three-dimensional representation of the quadrotor and its operational environment is created [15]. In this method, six generalized coordinates can be used to describe the position and orientation of the quadrotor at any given time. This coordinator system is used to generate equations for quadrotor dynamics modeling. The framework is complicated because it has a lot of model parameters.

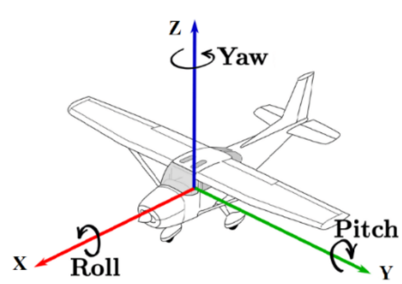

Fig. 3: Pitch, Yaw, and Roll Angles of an Aircraft

Commercial simulators can be effectively utilized for drone simulation. Real Flight drone/flight simulator [16] , Simpro drone simulator [17], Liftoff by Immersion RC [18] and HELIX professional R/C flight simulator [19] are some of the reviewed commercial drone simulators which can be employed to imitate certain commercial drone. One of the most notable situations is the DJI flight simulator, which is recognized for modeling various types of commercial drones [20]. This software simulator lets users mimic the actions of several DJI-branded UAVs and controllers. The weather and sunshine settings can be customized, and the simulator offers a variety of 3D scenarios. Using DJI's advanced flight control technology, DJI Flight Simulator is a professional pilot training program that simulates the feeling of really being in the air. It supports a large selection of DJI drones and is designed for business users. But this simulator is not flexible for addressing specific research and development. The primary problem with DJI Flight Simulators is their proprietary software, which means that the remote operation devices and simulated UAVs have limitations and cannot be expanded [15]. Furthermore, it is a very difficult challenge to simulate custom-built drone simulator with these generalized drone dynamics.

Jemin et al. proposed a strategy for regulating a quadrotor via a neural network provided via reinforcement learning methods [21]. They proved the efficiency of the training method in both simulated situations and with an actual quadrotor. Additionally, the trained policy displayed outstanding performance while preserving computational economy. Additionally, it emphasized several advantages of neural network rules beyond their adaptability. However, this experiment was restricted to a confined area, spanning around 2 meters in each dimension.

Jackson et al. applied machine learning approaches to develop a dynamic model for a rotorcraft [22]. They suggest that standard rotorcraft dynamic models, which rely on well-established physical laws and are generally correct, often require simplification for real-time motion predictions. This simplification might lead to mistakes in motion predictions compared to real vehicle behavior. In their research, machine learning approaches were utilized to train a dynamic model specifically for predicting on-axis motion responses such as pitch rate, roll rate, and yaw. The machine learning approach utilized a Gaussian Process (GP) non-linear autoregressive model [23]. Their findings illustrate the successful application of machine learning in forecasting on-axis motions of a rotorcraft, with generally higher accuracy compared to physics-based dynamic models.

Punjani suggested a method for helicopter dynamic modeling using a Rectified Linear Unit (ReLU) network [24]. This approach was chosen due to the helicopter's complicated dynamics, including rigid body dynamics, aerodynamics, engine dynamics, and vibration, as well as numerous maneuvering patterns. Their study examined numerous baseline models and found that the ReLU network greatly outperformed them. It also improved acceleration forecasts over current state-of-the-art approaches, with more performance benefits possible through hyperparameter adjustment. They tested the model on a range of maneuvers, including forward and sideways flight, vertical and inverted vertical sweeps, stop-and-go, flips, loops, spins, circles,evading, orientation sweeps, and both gentle and violent freestyle.

Sandaruwan et al. suggested a machine learning-based approach to model drone dynamics related to the figure of Eight Maneuvering pattern [25]. Authors have produced satisfactory findings and proved that the machine-learning approach can be successfully applied to anticipate drone motions. However, they have not released the evaluation of the built drone dynamic model and simulation environment.

Shehan et al. performed a comprehensive review study on diverse simulation models that employ mathematical and machine learning methodologies [26]. The authors claim that most current drone simulators lack generalizability and frequently depending on many model parameters. Additionally, researchers highlight an absence of studies that utilize artificial intelligence (AI) techniques to accurately replicate the flight dynamics of drones based on three-dimensional flight data.

III. Methodology

This chapter covers the methods of data collecting, the process of building the model, evaluation approaches, and the outcomes of the derived model. Figure 5 indicates the basic steps of research methodology.

A. Data Collection

Four-rotor drones are a subclass of multirotor systems, and these drones employ four rotors to keep them hovering. A prominent example of these multirotor drones is the regularly used DJI Mavic mini drone developed by the SZ DJI Technology Co. Ltd [27]. Data collection for the present research was performed using a DJI Mavic Mini drone, as shown in figure 4. The drone's position and orientation are determined by the inputs it gets from the radio controller. The main goal of this project is to utilize machine learning

Fig. 4: DJI Mavic Mini Drone and Remote Controller

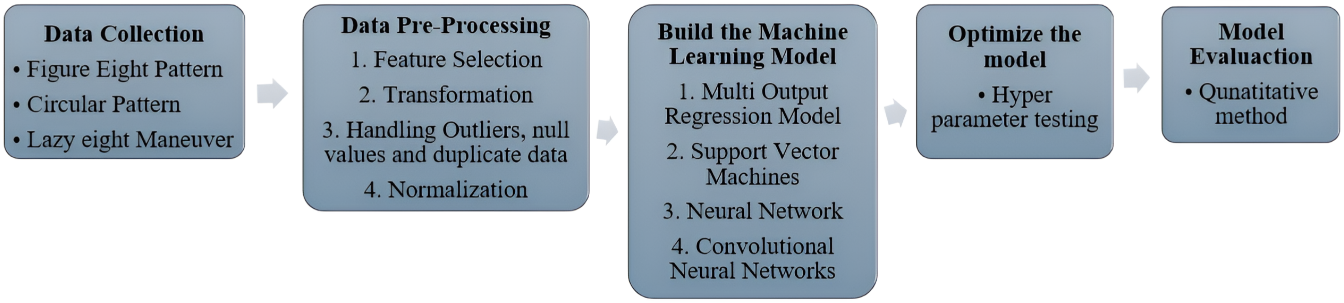

Fig. 5: Research Methodology

methods to create a flexible model for a quadcopter drone. The objective of this model is to develop a relationship between the movements and orientation adjustments of the drone, and the inputs received from the operator's radio controller. Six degrees of freedom are available to the drone for movement, which includes three rotational and three transnational motions.

The drone's movements in three dimensions are controlled by the remote controller utilizing four main configurable factors outlined below. Adjusting these variables enables the drone to move in complicated patterns inside three-dimensional space. A radio controller with these important adjustable variables is shown in figure 6.

- Throttle: Controls the vertical motion. Adjusting the throttle upwards causes the drone to climb while reducing it causes the drone to fall.
- Yaw: Controls rotation around the vertical axis. Clockwise rotation turns the drone right, counterclockwise turns it left.
- Pitch: Controls forward and backward tilt. Sliding forward pushes the drone forward, and sliding backward moves it backwards.
- Roll: Controls side-to-side tilt. The rolling left pushes the drone left, rolling right moves it right.

The DJI Mavic Mini drone is equipped with a variety of integrated sensors that are intended to guarantee accurate flying and consistent performance. The sensors, such as accelerometers, GPS, and GLONASS, work together to ensure precise location, navigation, and flight stability. The Mavic Mini offers a flight log that documents flight position, orientation data, and radio controller input data. The log records 10 data points per second (10Hz), providing detailed insights into the drone's flying patterns and pilot commands. While the Mavic Mini maintains a baseline location accuracy of roughly 0.5 meters using its built-in GPS sensors, customers can boost this accuracy up to 1 centimetre by installing extra sensors. This feature enables enhanced accuracy in tasks like surveying or mapping.

In pilot training, fundamental maneuvers including steep power turns, steep spirals about a point, chandelle turns, lazy eights, and eights-on-pylons are often utilized to build pilots' skills and abilities [28]. Most of these training techniques contain six degrees of freedom motions, providing for the dynamic interaction between the drone and the operator [29]. The figure-eight maneuvering pattern, or its variations is extensively employed across several areas to imitate real-world circumstances and test essential maneuverability features [30]. Below main maneuvering patterns were selected for collecting drone flight data.

- Figure-Eight Pattern: This pattern involves flying the drone in a figure-eight configuration, which can assist pilots learn coordinated turns, maintaining altitude, and controlling speed. Pattern performed on a flat plane without significant changes in altitude.
- Circular Pattern: Flying the drone in a circular path around a fixed point.
- Lazy eight Maneuver: The Lazy Eight maneuver is an advanced aviation technique comprising two subsequent 180-degree turns in opposite directions, along with

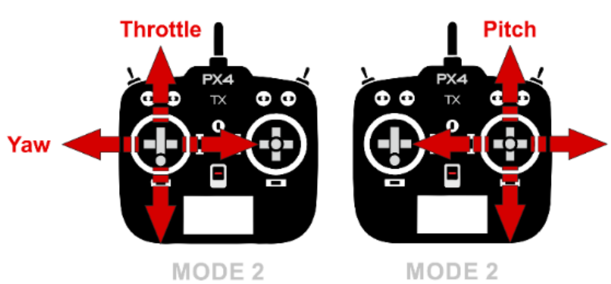

Fig. 6: A Remote Controller with Key Controllable Variables

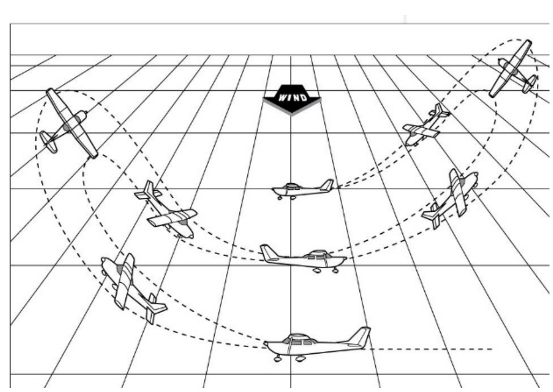

Fig. 7: Lazy eight pattern

smooth climbs and descents. The aircraft increase altitude during the first 90 degrees of each turn, then descends during the second 90 degrees.The figure 7 shows the lazy eight pattern.

These maneuvering patterns give a dataset covering a wide spectrum of drone motions, from basic maneuvers to more complex flight tactics. These specific patterns are chosen over random patterns because they inherently include varied dynamics within their structured movements, providing a comprehensive overview of the drone's capabilities and pilot ability.

Nearly 100 drone flights were done over a period of nearly three months to obtain the data, totaling 8 hours of flying time covering 10 kilometers. This distributed strategy was adopted instead of gathering data in a single session to ensure a more comprehensive understanding of diverse flight situations over time. Each experiment completed by a single drone pilot involves nearly thousands of data points, while the overall dataset contains over 100,000 data points. These flight logs are stored either on the mobile phone linked to the remote controller or on the SD card installed into the drone. The duration of each flight varied from 2 minutes to 10 minutes. Figure 8 illustrates an actual aerial image acquired during a data gathering period held on university premises.

Accurately maneuvering the drone in three-dimensional space without any visible indicators according to these three pattern shapes is a difficult challenge. To attain accurate shapes, researchers employ physical markers placed on the ground to direct the trajectory of the drone. By operating the drone and utilizing these markings as visual references, it's able to maintain its original form. To ensure that the acquired data of the drone matches with the real flight path, the researcher examined the size and shape of the recorded pattern with real markers on the ground. It verified there was no GPS error in the recorded data. Additionally, the experienced drone pilots visually observed the drone's position relative to these landmarks on the ground.

B. Data Pre-Processing

The data saved on either the mobile phone or SD card is kept as a text file. The initial stage involved translating the string values of the text file data into numerical numbers. DJI provides a flight log viewer on their website, which makes the transformation of all text files into CSV (Comma Separated Values) format [31] . Each flight log covers 184 features and covers nearly 1000 data points, with an approximate flight length of 10 minutes. Starting from a battery level between 97% and 100% carrying out all operations with fully charged batteries that helps to prevent the risk of performance variations in the drone due to variances in battery power [32]. Several conclusions about the parameters and implications were drawn from the analysis of the raw data set:

- Positional Parameters: The drone's position in three dimensions is indicated by parameters like latitude, longitude, and altitude. The drone's geographic location can be described by the combination of these connected factors.
- Time Stamp Consistency: Every data point was recorded at consistent intervals, with a fixed amount of time elapsed between each capture. This guarantees the temporal component of the data's uniformity and consistency, enabling precise analysis throughout time.
- Velocity Parameters: In three dimensions, the drone's velocity components are represented by VelocityX, VelocityY, and VelocityZ. These values aid in understanding the drone's movement and trajectory over time, much like location parameters do.
- Constant Parameters: Some sets of parameters don't change much or don't change at all during the experiment. For instance, unless there are notable alterations or problems with the drone's power source, parameters like GpsCount, GpsLevel, Battery Power (%), Battery Voltage, Battery Voltage Deviation, and Battery Cell Voltages usually stay constant.
- Static Parameters: Some parameters don't change based on the drone's specified settings, or they offer advice and warnings in place of dynamic data. Examples of such parameters are App Tip, App Warning, App Message, and Flight Mode, which provide information or notifications on how the drone is operating but don't change much while in flight.

In considering the these variables, the following crucial parameters were chosen for selection from the dataset:

- Time (seconds): This option shows how long it has been since the drone was turned on. It functions as a foundational measure for monitoring the flight data's time component.
- RcAileron: The radio controller signals used to control the drone's roll are represented by this parameter. It offers information on how the drone's horizontal tilting is changed by the pilot.
- RcElevator: The drone's horizontal pitch attitude is controlled by these signals from the radio controller. They show that the drone's forward or backward tilt has been adjusted.
- RcRudder: The drone's rotation around its vertical axis is controlled by the yaw, which is determined by these signals from the radio controller.
- RcThrottle: The engine's speed is controlled by these signals from the radio controller, which affect how quickly

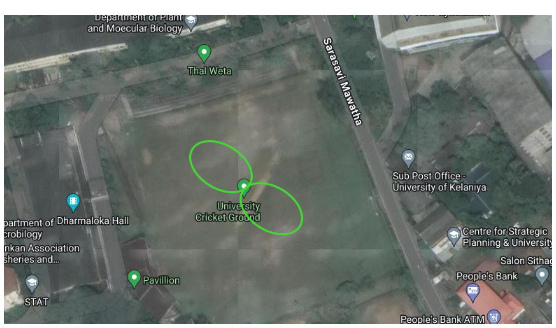

Fig. 8: Actual aerial view of a sample drone pilot drill

the drone climbs or falls. They provide details regarding the drone's total speed of movement.
- Cartesian coordinates: These three parameters (x, y, z) stand for the Cartesian coordinates that are obtained from latitude and longitude measurements. They enable analysis in three dimensions by giving a spatial representation of the drone's position.
- Orientation: The drone's head's degree of bearing is indicated by this parameter. It means pitch , yaw and raw angles of drone. It helps to comprehend the orientation of the drone in relation to its surroundings by providing information about which way it is facing.

These parameters capture the location and orientation of the drone when changing the input parameter of the radio controller. After combining these parameters, it provides a complete dataset for the creation of a machine-learning drone dynamic model. Together, these parameters capture important facets of drone operation, allowing the model to efficiently learn and simulate the drone's behavior. In response to radio controller input, the machine learning-based drone dynamic model need to predict the position and orientation of the drone. Hence, the data can be categorized into two main groups: input parameters and output parameters, as demonstrated in table I.

Before training the model one important step is data transformation.These are data transformation steps. The time in the CSV file is formatted as a string, for example, "12m 15.1s". Before proceeding, the time values in string format need to be transformed to numerical format in total seconds. To identify the drone position latitude and longitude values are used in CSV files. For simple calculation of machine learning model, it is necessary to convert latitude and longitude values into local Cartesian system. There are numerous global ways for translating latitude and longitude into Cartesian coordinate systems [33]. But the study focuses on a specific local area rather than a bigger region because local coordinate systems is used for small-scale mapping projects [34]. In this coordinate system, choosing the drone's home location as the initial point (0,0) simplifies calculations and permits accurate distance measurements over smaller regions. This procedure effectively turns geographic coordinates into a local Cartesian coordinate system, enabling calculations and measurements inside a specific area.

Out of the 100,998 data points represented in the dataset, 42,023 were determined to be outliers. Removal of these extreme values greatly impeded the performance of the model and also decreased the size and diversity of the dataset, therefore potentially weakening the ability to generalize and resulting in skewed estimations. Xiuzhen Jiao et al. discovered a technique to handle the high number of outliers contained in drone flight data [35]. They proposed the application of the Two-sided median filtering strategy, which greatly minimizes the amount of outlier data points. This approach is used to smooth the data by replacing outlier values with the median value of surrounding items within a specified interval. The approach is particularly beneficial when working with time-series data or data where outliers might reflect noise. After following the application of this approach, the dataset had just 6088 outlier points.

TABLE I: Input and Output Features

Input Features	Output Features
OSD.flyTime	Cartesian coordinates:
RC.aileron	OSD.longitude
RC.elevator	OSD.latitude
RC.throttle	OSD.height
RC.rudder	Orientation:
	OSD.pitch
	OSD.roll
	OSD.yaw

Duplicate data points can occur when drones hover or stay still because their sensors keep recording readings even when there is no movement. This phenomenon happens because sensors, such as GPS receivers and IMUs(Inertial Measurement Unit), continuously send data to flight log including position, orientation, and velocity every 0.1 seconds, regardless of whether the drone is moving. Thus, during periods of hovering or stationary flight, repeated sensor readings may produce identical or almost identical values, resulting in duplicate entries in the dataset. Removing duplicate entries from drone flight datasets is critical to ensure the accuracy and reliability of the data. Also, duplicate entries might develop due to different factors such as sensor noise, signal interference, or limitations in sensor precision. By recognizing and deleting these duplicates, researchers can receive a more precise representation of the drone's behavior. This method helps prevent skewed analysis, false insights, and errors in model training. In this dataset, 6014 duplicate data points have been eliminated to improve the quality of the data.

Normalization is a fundamental step in the data prepossessing phase of machine learning. It is applied to translate features inside a dataset that may reside on various ranges of values into a standardized scale. This standardization is crucial as considerable discrepancies in feature ranges might adversely affect the learning process. The min-max scaling strategy entails this project scaling each feature independently using the minimum and maximum values provided in the dataset. Normalization of specified columns of a data frame is a prepossessing step in machine learning workflows to ensure that features are on the same size. Before normalization, the values of each feature ranged from -250 to 1750. After normalization, these values were scaled down to a range between -15 and 15. Figure 9 and figure 10 demonstrate the data points before and after scaling, respectively.

C. Build the Machine Learning Model

Machine learning with simulating drone dynamics involves utilizing computational techniques and statistical models to enable drones to learn and adjust based on data, rather than depending on explicit programming. Given the dynamic and

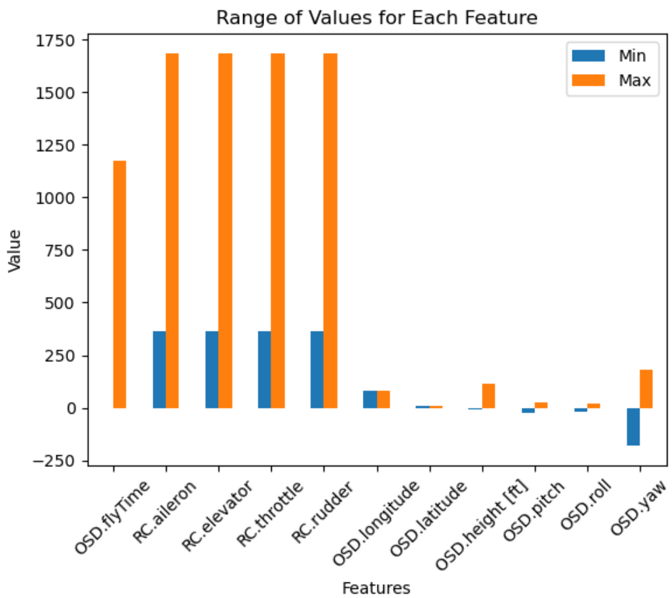

Fig. 9: Range of values before scaling

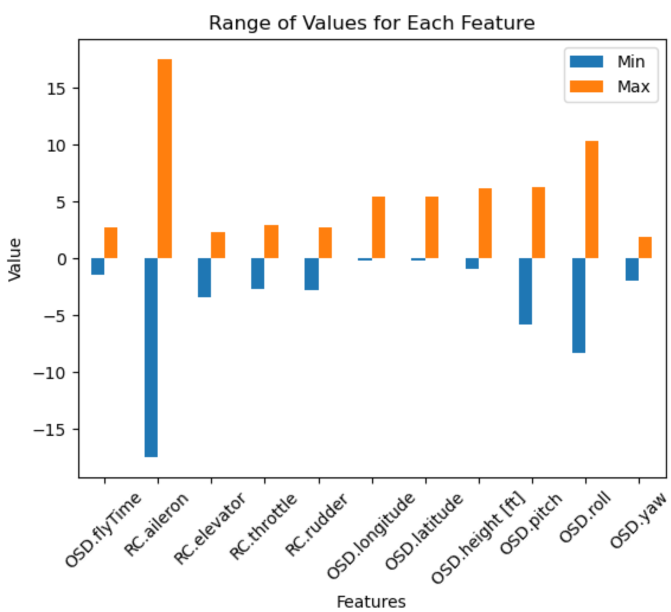

Fig. 10: Range of values after scaling

nonlinear character of both the input and output datasets, which involve the drone pilot's radio controller inputs and the drone's position and orientation, there are various acceptable models to explore. These models should be capable of handling the quick changes in the data and capturing the complex relationships between the inputs and outputs. Below are some potential models that can be utilized to simulate drone movements simultaneously [36].

1) Multi-Output Regression Model: A multi-output regression model is a potent analytical tool utilized to predict many continuous target variables simultaneously. This model allows for the simultaneous prediction of key factors in drone flight data processing, including geographical coordinates (latitude and longitude), altitude, and orientation (pitch, roll, yaw). The model can comprehensively understand the drone's flight dynamics by analyzing these variables collectively to capture the interactions and dependencies among them. This method simplifies the model, maintains uniformity in predictions, and improves resilience to missing data, making it well-suited for assessing drone flight data with numerous interrelated variables [37]. A multi-output regression model is a strong tool for assessing drone flight data by predicting numerous variables at once, but it may face difficulties in situations with complex and nonlinear drone motions. Because linear regression models often struggle to handle complex relationships, leading to poor performance. Considering the constraints in precision seen in simulated situations, this method may not be appropriate. Hence, different approaches must be investigated to accurately depict the complex dynamics of drone flights.

2) Support Vector Machines: Support Vector Machines (SVM), offer versatility in handling both classification and regression tasks effectively. Particularly in regression, SVM is more suitable, especially when dealing with high-dimensional datasets and nonlinear connections between variables. The kernel trick, an essential aspect of SVMs, allows for the transformation of input data into higher-dimensional spaces. This enables the more accurate representation of nonlinear relationships by creating decision boundaries. However, despite these advantages, it's crucial to realize that SVMs, like multi output regression model, may provide unsatisfactory results in certain cases. For instance, if the relationship between inputs and outputs in drone data is particularly complicated or non-linear, SVMs may struggle to capture it adequately. In such circumstances, deep learning algorithms might offer superior performance.

3) Neural Network: Traditional machine learning algorithms have difficulty in finding complicated connections within drone input and output data due to the so sophisticated nature of the data. However, neural network models offer a possible answer to this challenge. TensorFlow is deep learning framework developed by Google and released as open source, has gained prominence in the field since its inception in 2015 [38]. The Keras, a high-level neural network library developed on top of TensorFlow, stands out for its user-friendly interface and accelerated model construction process. Keras simplifies the building of artificial neural networks, offering developers an easy Python-based API for constructing and training models. With its seamless connection with TensorFlow, Keras enables developers to use the potential of deep learning without the complexity commonly associated with older neural network frameworks. Together, Keras and TensorFlow provide a formidable toolkit for addressing the difficulties of drone data analysis. By utilizing the power of neural networks, researchers may reveal insights from drone data that may have been challenging to extract using traditional machine learning methodologies. Optimizing machine learning models relies heavily on hyperparameter adjustment. The research utilizes Randomized Search Cross-Validation(RandomizedSearchCV) for this purpose. This approach efficiently explores hyperparameter space, leading to a well-optimized model capable of obtaining improved accuracy and better generalization on unseen data. Through the examination of each parameter, the performance measure is evaluated using a specific scoring metric, such as negative mean squared error. This approach discovers the configuration that offers the most optimal outcomes compared with traditional machine learning methods. However, additional implementation is necessary because of a low level of accuracy.

4) Convolutional Neural Networks: Convolutional Neural Network (CNN) is a unique form of neural network that is particularly excellent for processing organized grid-like data, such as images and sequential data. CNN and Neural Networks (NNs) differ fundamentally in their architecture and application domains. While NNs are made of fully connected layers where each neuron is linked to every neuron in the subsequent layer, CNNs integrate convolutional layers that apply learnable filters to extract features from grid-like data, such as images or time series [39]. The model acquired features in a hierarchical manner, starting from basic and progressing to more intricate, which enhances their ability to recognize patterns effectively. After using the appropriate settings, the model displayed improved performance compared to other models. Additionally, the model was tested across diverse maneuvering patterns, further verifying its accuracy.

Among these four models, the CNN model provided excellent findings, notably excelling in scenarios requiring intricate dynamics and large datasets. Next section explains the result of each model and overview of dataset.

IV. Evaluation and Results

In the context of an AI-based strategy to simulate drone dynamics in three-dimensional space, evaluation methodologies play a significant role in measuring the correctness and effectiveness of the simulation model. Quantitative validation methods are particularly valuable in this context since they provide objective measures to assess the accuracy of motion predictions. One often adopted quantitative validation method is comparing simulated outcomes with real-world scenarios. In this research, metrics such as mean squared error (MSE), root mean squared error (RMSE), or mean absolute error (MAE) is generated to measure the disagreement between simulated and observed drone movements.

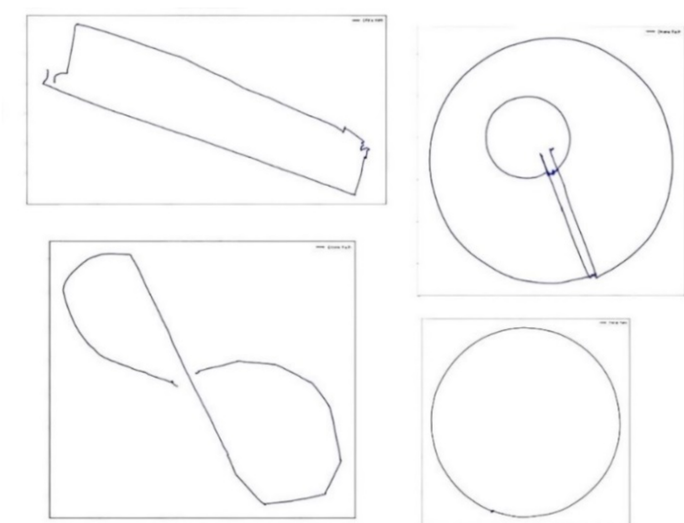

Fig. 11: Sample Drone Drills

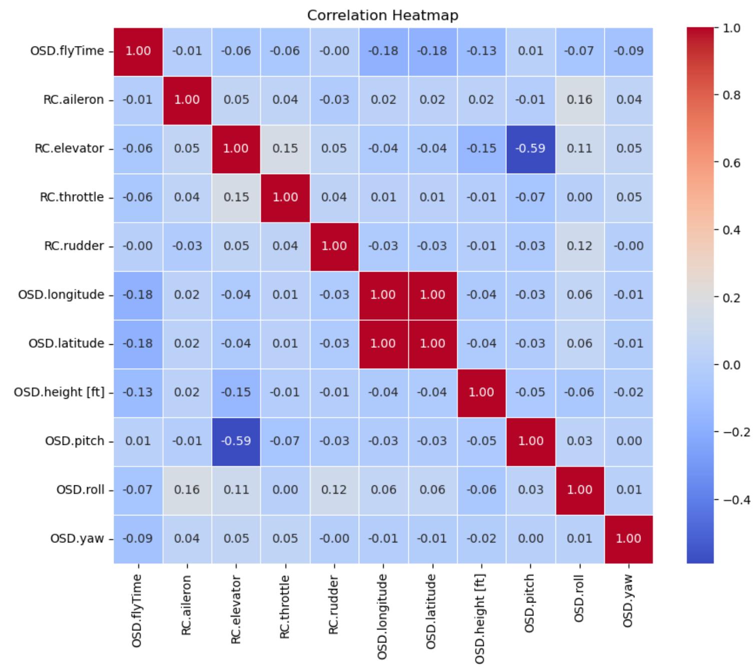

Fig. 12: Correlation Matrix of Features

A. Summary of Dataset

The collection comprises over 100,000 data points indicating diverse moving patterns observed during drone drills. Each practice was conducted under diverse conditions, including varying velocities and experienced drone pilots. Figure 11 shows the sample maneuvering patterns.

Figure 12 depicts the link between input and output attributes. A correlation matrix is a tabular form exhibiting correlation coefficients between variables in a dataset. Each cell in the matrix denotes the correlation coefficient between two variables, indicating the strength and direction of their linear link. The correlation coefficient varies from -1 to 1: 1 shows a perfect positive linear link, where both variables increase together; -1 indicates a perfect negative linear relationship, where one variable increases as the other drops; and 0 indicates no linear relationship.

In the dataset, a correlation coefficient of 1.0 between latitude and longitude denotes a perfect positive linear relationship. This indicates that while latitude grows, longitude also increases correspondingly, and vice versa.

Additionally, there's a noteworthy relationship between the elevator control input (RC.elevator) and the pitch angle of the drone (OSD.pitch), albeit in different directions. Increasing the elevator control input by pullig back on the control stick to lift the nose of the drone actually results in a decrease in the pitch angle, causing the nose to point downward. Conversely, decreasing the elevator control input by pushing forward on the control stick to lower the nose leads in an increase in the pitch angle, causing the nose to point upward. This inverse relationship helps maintain the drone's stability during flight, as changes in the elevator input lead to matching modifications in pitch angle to counterbalance the aircraft's orientation [40].

Figure 13 shows the distribution of each feature. Based on the distribution, it appears that the dataset comprises a varied range of data, with certain variables demonstrating higher fluctuation than others. The concentration of values around certain ranges for aileron, elevator, throttle, and rudder suggests that these elements may have set or limited operational ranges, whereas the regularly distributed height, pitch, and roll values signal more variability in these aspects of drone flying.

B. Result of Models

The training of the models utilized an Intel Core i9 CPU running at a clock speed of 3.7 GHz, along with an RTX 3080 graphics card and 32 GB of DDR4 RAM. The training duration ranged from 15 minutes to 3 hours. The dataset is partitioned, with 80% allocated for training and 20% allocated for testing. The study comprised a range of patterns to comprehensively test the model's performance. Furthermore, a specific drone movement pattern was selected for the aim of testing each model. Figure 14 depicts the actual trajectory of the drone's maneuvering.

1) Multi-Output Regression Model: To assess the performance of the model, Mean Squared Error (MSE) is utilized,

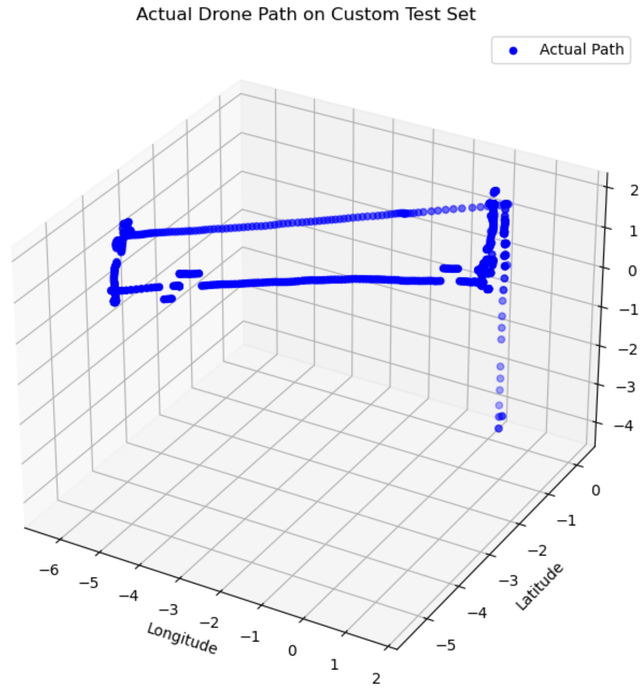

Fig. 14: Actual Trajectory of the drone

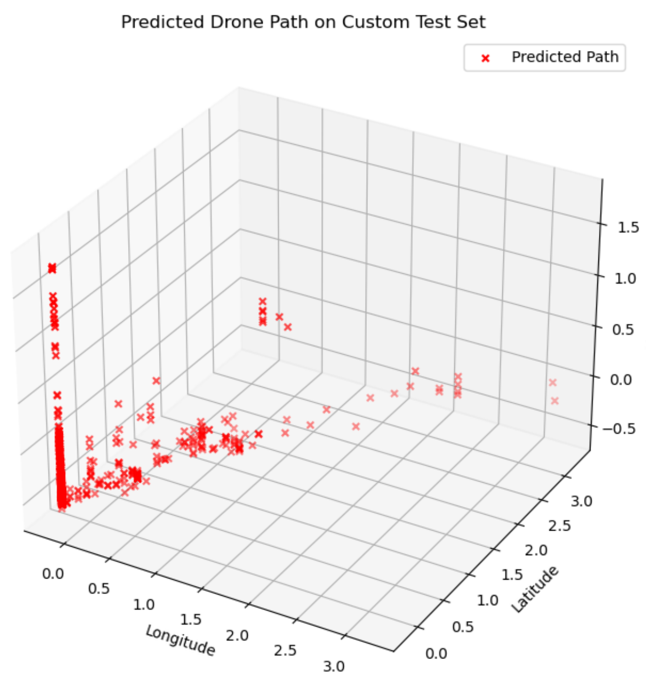

Fig. 15: Predicted path of multi-output regression model

which quantifies the average squared difference between the model's predictions and the actual values.

A lower MSE indicates higher performance, suggesting predictions that closely match actual results. Conversely, a greater MSE suggests bigger gaps between anticipated and actual values, indicating poorer model performance. In this situation, the MSE is 1541.7, suggesting the need for

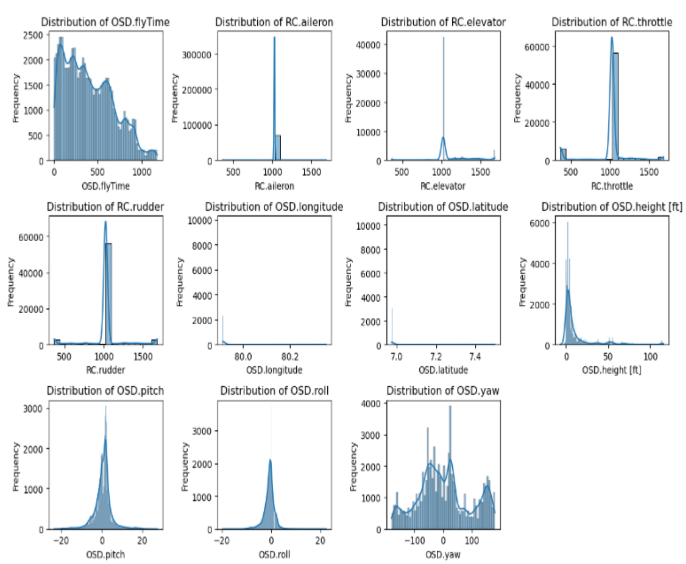

Fig. 13: Distribution of Dataset

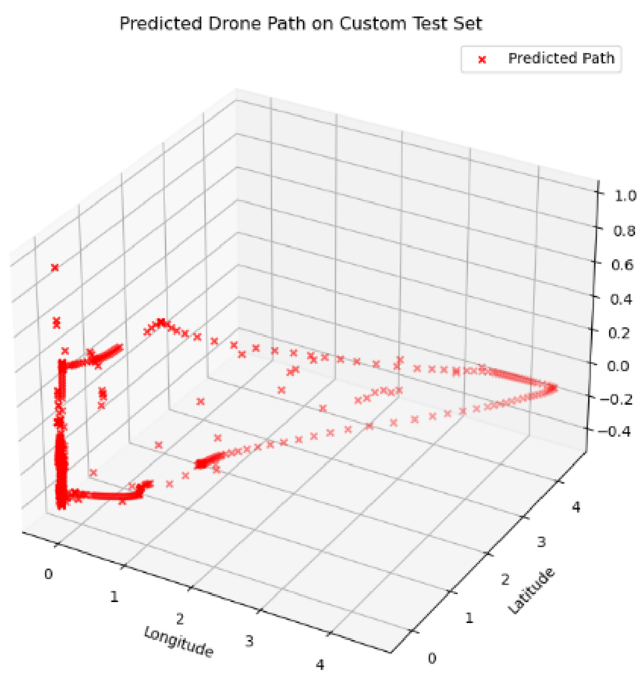

Fig. 16: Predicted path of SVM model

further improvement. Moreover, the reported accuracy is 2.5%, which is significantly low. Visual representations in figures 15 demonstrate the model's anticipated trajectory based on testing data. These graphics demonstrate the difference between the model's predictions and the real-world movement of the drone shown in figure '15. Overall, the model's performance is rated poor, indicating the need for modification and additional optimization.

2) Support Vector Machine Model: The SVM model generated similarly bad outputs, replicating the performance of the multi-output regression model. Reported accuracy on the test dataset stands at 4.99%, with an MSE of 1540.99. Figures 16 display the model's anticipated trajectory based on the testing data.

3) Neural Network Model: Hyper parameter adjusting is a vital step in optimizing neural network models. To do this, RandomizedSearchCV is applied to explore a range of hyper parameters and determine the optimum combination for the model. The results of this search, including the optimal parameters, are presented in table II. When compared to both the multi-output regression and SVM models, this model

TABLE II: Hyperparameters for NN model

Parameter	Value
neurons	64
learning_rate	0.001
layers	2
epochs	100
dropout_rate	0.3
batch_size	64

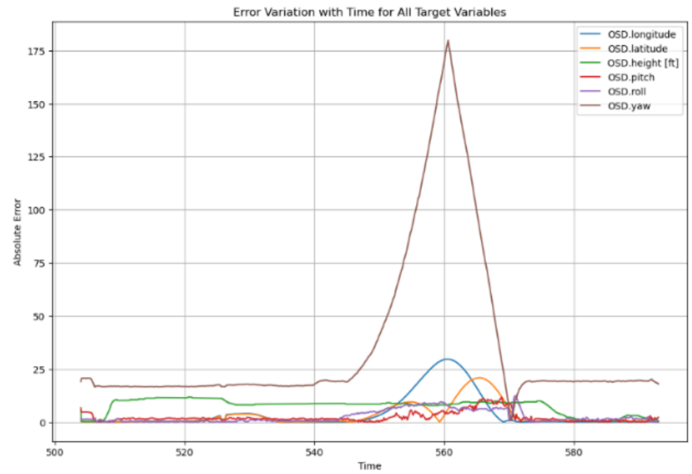

Fig. 17: Error variation of target features in NN model

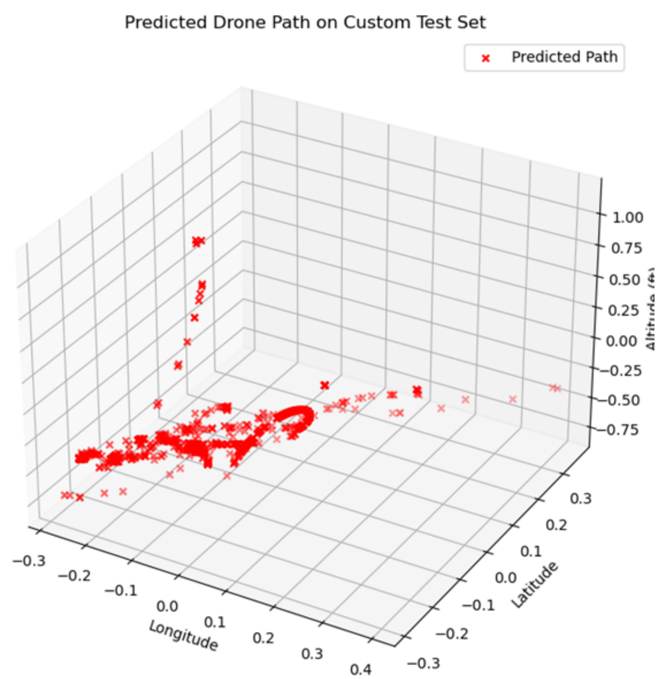

Fig. 18: Predicted Path of Neural Network Model

demonstrated significantly improved accuracy. With an MSE value of 0.72 and a model accuracy of 17%, it topped its counterparts. Figure 17 depicts the error variations of all output variables. It illustrates that yaw has a greater rate of error variation compared with other output variables. Figure '18 illustrates the expected trajectory of the drone maneuver.

4) Conventional Neural Network Model (CNN): Utilizing RandomizedSearchCV, appropriate hyperparameters were discovered for the CNN model. These optimal parameters are detailed in Table III. The variance in error across output characteristics is displayed in figure 19, suggesting successful prediction for all output aspects except yaw, which demonstrates significant error variation. This mismatch is related to the distribution of yaw values, as demonstrated in

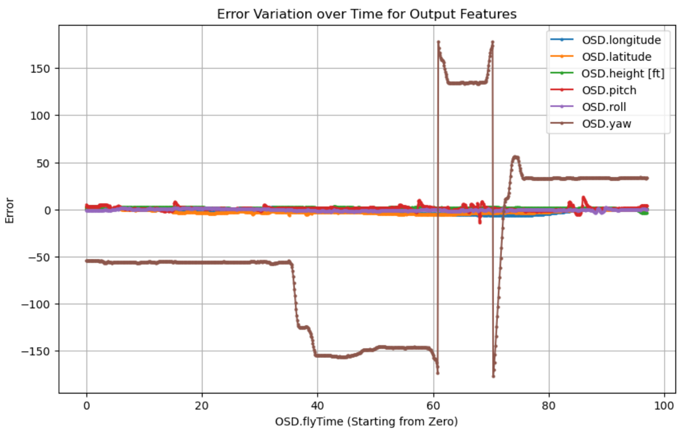

Fig. 19: Error variance of all target variables in the CNN model

TABLE III: Hyper Parameter for CNN model

Parameter	Value
filters	128
kernel_size	5
activation	relu
optimizer	adam
learning_rate	0.001
epochs	50
batch_size	32

TABLE IV: Comparison of Models

Model	Time takes for training	Accuracy	MSE
MOR	20 minutes	-1441.79%	1541.7
SVM	38 minutes	-1440.99%	1540.99
NN	97 minutes	17%	0.72
CNN	123 minutes	78%	0.65

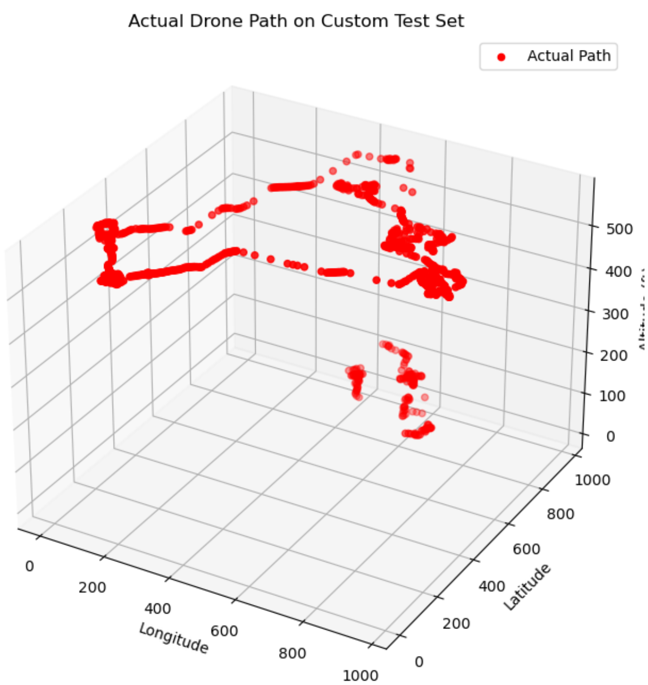

Fig. 20: Predicted path of CNN Model

Explained Variance, typically represented as a percentage, quantifies the proportion of the variance in the target variable that is explained by the model. Higher percentages indicate better model performance. These indicators together measure the accuracy and reliability of forecasts, driving future model development and decision-making processes. The box plot of the accuracy metric is displayed in figure 21.

These results demonstrate that the model works better for longitude, latitude, and height variables compared to pitch, roll, and yaw, as indicated by lower MSE, higher R-squared, and larger variance explained values. A comparison of each model is shown in table IV.

V. Conclusion

The recent development of unmanned aerial vehicles has significantly altered various industries, such as surveillance, transportation, construction, and agriculture. However, evaluating drone behavior provides substantial challenges due to the complex interplay of elements like speed, altitude, orientation, and trajectory. Simulating drone dynamics has become significant as it enables researchers to test drones in complex circumstances that are unsafe or impractical. Furthermore, by utilizing simulation, drone pilots can

figure 13, which is not normalized compared to other output features. The projected path of the test data reveals an MSE value of 0.65, with a model accuracy of 78% approximately. Significantly, the model displays greater accuracy compared to alternative models. Figure 20 displays the anticipated trajectory of the CNN model, which closely fits the actual journey.

Accuracy metrics in a CNN model assist in understanding its performance. R-squared (R2) quantifies the proportion of the target variable's variability that can be captured by the model. It is a numerical value between 0 and 1, where a higher value indicates a stronger fit. The Mean Absolute Error (MAE) quantifies the average discrepancy between projected and actual values, providing a measure of the typical deviation of predictions from the real values.

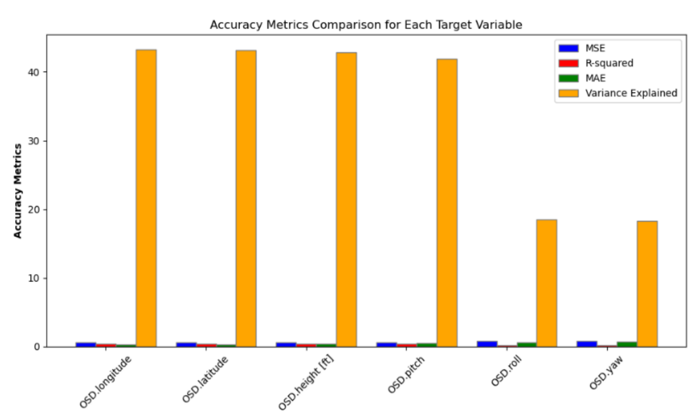

Fig. 21: Box plot of accuracy metrics

receive thorough training in effectively managing various circumstances.

Traditionally, drone dynamics have been investigated with Newtonian and fluid dynamics concepts, involving various parameters such as force, gravity, propeller characteristics, and air density. Replicating certain drones becomes problematic due to the number of parameters involved. However, the provided model can efficiently simulate generic drones.

The research proposed a machine learning-powered drone dynamic model capable of simulating drone behaviors without the necessity of specialist subject expertise or elaborate laboratory setups. This strategy utilizes advanced AI models trained on huge datasets including real-world flight conditions. These datasets offer a wide range of movements, such as eight, circular, and lazy-eight patterns, indicating numerous sorts of drone motions. Multiple modeling approaches, including multi-output regression, support vector machine, neural network, and convolutional neural network (CNN), were applied in building the model. Among these, the CNN model had the highest accuracy, achieving 78%. Quantitative validation was accomplished by comparing predicted patterns with real-world drone maneuvers. One notable observation from the experiment is the high-level shape of the real drone trajectory and the anticipated path produced by the CNN algorithm are the same.

In contrast to non-AI-based methodologies, which typically require more attention to diverse variables, the model streamlines the simulation process. This simplification not only accelerates the modeling technique but also mitigates the complexity associated with earlier methodologies. The fundamental adaptability and learning capabilities of AI models, of CNNs, enable them to detect underlying patterns and correlations in drone dynamics from raw data. Additionally, the employment of AI-driven methodologies has the potential to grow and adapt, enabling seamless interaction with multiple drone platforms and scenarios. The accessibility of drone simulation capabilities minimizes the necessity for specialist knowledge and sophisticated parameter calibration. This stimulates creativity and accelerates developments in the field of drone technology.

VI. Limitation

One of the most demanding components of this research was the collecting of data. It required the recording of numerous drone maneuvers, a task that was handled by expert drone pilots. Special care had to be taken to ensure that data collecting happened under calm weather conditions to avoid mistakes caused by wind disturbances, which could ultimately hinder the accuracy of the model. Moreover, gathering data for specialized flying patterns, such as figure eights, circles, and lazy eights, proved to be extremely problematic. These moves need perfect forms, making it required for substantial effort and competence from the drone pilots. Furthermore, the huge amount of data required for training the model presented another issue. Also, to manage such a vast dataset properly, high-performance computers are required.

VII. Future work

As a future step for this study, it would be helpful to integrate qualitative validation alongside the existing quantitative validation approaches. While quantitative validation focuses on numerical measures to assess model performance, qualitative validation involves visual inspection and subjective evaluation of simulated results against real-world observations. To strengthen qualitative validation, expanding the range of drone maneuvers and gathering more extensive information including varied drone dynamics is required. Additionally, combining the established model with simulation tools such as MATLAB or Unity gives an interesting option for future research. Furthermore, qualitative validation can be strengthened by comparing simulated trajectories, flying routes, and maneuvering patterns directly with real-world observations. This comparative analysis enables the discovery of any differences or inconsistencies between the simulation and actual drone behavior, offering significant insights into the model's accuracy and usefulness.

VIII. Data Availability Statement

The datasets utilized in the current study can be obtained from the corresponding author upon a reasonable request.

IX. Conflict of Interest

The authors state that they do not possess any identifiable conflicting financial interests or personal ties that could have potentially influenced the findings presented in this paper.

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