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Comparison of Classification Models and Accelerometer Sensors for VTOL UAV Flight Condition Detection

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ABSTRACT

This study develops a classification model for detecting multiple flight conditions of VTOL (Vertical Take-Off and Landing) UAVs using accelerometer data, with a motion capture system included for comparison. The objective is to identify the most effective machine learning model for classifying various flight conditions, such as healthy and faulty propellers, different payloads, and windy environments. Initially, various machine learning models, including Quadratic Support Vector Machine (QSVM), Neural Networks, and Naive Bayes, were trained using acceleration and displacement data. QSVM was identified as the best-performing model, achieving 87.5% training accuracy with acceleration data and 79.3% with displacement data. Following this, data from two accelerometers (an iPhone SE 2020 and an ADXL345) were used exclusively with the QSVM model for further comparison. The iPhone SE sensor achieved 97.73% training accuracy, while the ADXL345 attained 93.06%. While the iPhone sensor demonstrates superior performance, it serves only as a benchmark, as it is not intended for onboard UAV applications. The results indicate that affordable sensors, like the ADXL345, can achieve sufficient accuracy, making them viable for practical UAV deployments. The study concludes by recommending higher-quality sensors and advanced machine learning techniques for enhanced UAV fault detection.

Keywords: VTOL, Acceleration sensor, positional camera, fault prediction, classification algorithm

I. INTRODUCTION

A. BACKGROUND

Unmanned Aerial Vehicles (UAVs) are utilized in various applications, including parcel delivery, search and rescue missions, structural inspections, geographic mapping, and even passenger transport [1]. Proper maintenance is crucial to ensure UAVs' safety, reliability, and longevity. Regular inspections and maintenance help identify wear and tear, such as motor degradation or sensor malfunctions, before they lead to critical failures. An early warning system could minimize the risk of system failures, leading to costly damage, operational downtime, and, in the worst-case scenarios, accidents that jeopardize public

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safety and assets.

The primary importance of an early warning system lies in its real-time ability to identify emerging problems, such as propeller damage, battery degradation, or navigation errors, before they result in operational failures or accidents. By continuously monitoring the flight performance, early warning systems can provide immediate alerts to operators, enabling swift corrective actions to prevent crashes, service disruptions, or loss of valuable payloads. This research focuses on propeller damage, particularly at the tip of the blade [2]. Such damage can result from various factors, including fatigue wear, accidental impacts, and collisions with debris, which can alter the propeller's aerodynamic profile [3].

UAV flight monitoring systems should consider four key functions: communication with the operator, sensor capabilities to detect its surroundings, interfacing with the operational mission, and possessing reliable positioning and navigation capabilities [4]. These capabilities are desirable and essential for the effective and safe operation of the UAV. Fault diagnosis (FD) techniques are vital in ensuring the safety and reliability standards of autonomous and remotely controlled systems [5] through multiple sensors integrated into the UAV system. FD techniques involving fault detection estimators and fault isolation methods [6] contribute to UAV operations' long-term reliability and sustainability. For industries that rely heavily on drones for time-sensitive tasks, an early warning system helps avoid costly delays and ensures consistent performance.

Developing an intelligent early warning system for drone monitoring necessitates gathering data from various flying conditions. This approach is critical for ensuring the system can accurately detect faults and malfunctions across different operational scenarios where external factors such as wind speed, temperature, altitude, and payload variations can impact performance. Training machine learning models requires a large and varied dataset to effectively learn the drone's standard operating patterns and distinguish between typical fluctuations and true signs of failure. For instance, to effectively train neural networks for UAV fault detection, it is necessary to collect vibration data from the quadcopter during flights under various operating conditions [7]. Data from sensors under different conditions, such as high winds, carrying payloads, or navigating in challenging terrains, allow the system to make accurate predictions and deliver timely alerts, regardless of the specific flight environment.

B. LITERATURE REVIEW

UAVs are rapidly becoming a key asset in applications such as search & rescue, surveillance, inspection, and precision farming. The necessity of integrating UAVs in urban scenarios requires an increase in reliability and capability of predicting faults, especially when these unmanned vehicles must be certified to fly in populated areas[1]. During the quadcopter's flight, anomalous and unforeseen events including actuator failure, sensor failure, and structural failure could happen. For UAVs to fly safely, real-time online fault detection and identification (FDI) of the abnormal state of the quadcopter is essential [2].

In [3], the origins of failures in drones can be numerous, ranging from manufacturing errors to in-flight failures. These experiments were conducted as a preliminary, unfunded study to establish the baseline performance of the UAV under failure conditions. The main objective is to build upon this set of flight tests to generate an increasingly rich set of failures under various flight conditions as well as to design, develop, and validate flight control algorithms that can detect, identify, and accommodate for such failures. In [4], the experiment approach is simplistic, but it’s a useful fault emulation technique for the study of fault detection and diagnosis methods in a controlled environment. The modelling of a quadcopter with propeller faults has been investigated. The assumption for the control strategy was that complete propeller failure had occurred and the vehicle was allowed to rotate about an axis. This approach has been used to capture the deformation of a flexible rotor blade and estimate the rotation angles of moving objects.

In an aircraft, faults can be classified as actuator faults, sensor faults and plant (or component or parameter) faults. Actuator faults include partial or total loss of an actuator’s control, which can result in a constant output (e.g., a stuck rudder or an engine failure), change in the actuator gains (e.g., partial loss of engine power), or drift in output values (e.g., change in the trim of the elevator). Sensor faults represent wrong measurement readings by the sensors, which can result in total faults (e.g., a random output from a faulty sensor), bias faults (e.g., bias in gyroscope reading), gain faults (e.g., in an uncalibrated range sensor) and outlier faults (e.g., jumps in GPS reading). Plant faults include problems that change the dynamic properties of the system (e.g., a damaged wing) and the complete loss of communication between the controller and a component[5]. Common anomalies in UAVs encompass a range of issues that can affect their performance and reliability. One prevalent anomaly is GPS signal loss, resulting from interference or environmental conditions, which can compromise navigation accuracy. Motor failures, including issues like overheating, misalignment, or electronic speed controller malfunctions, can lead to unstable flight or crashes.

Many recent works deal with actuator fault estimation and tolerance in multirotor UAVs. Among the traditional model-based methods, we can find both linear and nonlinear failure detection validated with experimental results. Although the most common approaches are model based, artificial intelligence is applied as well to estimate the fault magnitude, in the recent work a fault estimation scheme based on recurrent neural networks was proposed. The work injected the fault at a software level, and the experiment validated the fault estimation with indoor experiments[6]. In [7], the experiment allows for determining several parameters necessary to certify these devices, such as hovering accuracy, positioning accuracy, device position drift, positioning repeatability, variability of the positioning accuracy, deviation, and repeatability of the distance. Additionally, the collected data can be used for post-flight analysis, enabling researchers to refine algorithms,

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improve flight performance, and enhance the capabilities of UAVs in various applications. The information is fundamental for precise navigation, obstacle avoidance, mapping, and even understanding the environment the UAV operates.

Displacement and acceleration data are vital for developing a reliable UAV flight classification model. Displacement data tracks the movement through space, capturing its position, velocity, and orientation in multiple flying conditions[8]. Deviations from expected displacement patterns can indicate potential faults. This information is vital for training the classification model to recognize specific faults based on how they affect the movement. Acceleration data complements displacement data by providing detailed information about the forces acting on the drone during flight[9]. Accelerometers capture changes in speed and direction across three axes (X, Y, and Z), offering insights into the flight's stability and responsiveness. When faults occur, the drone's acceleration profile will show abnormal fluctuations, which can then be used to classify specific types of faults. Both types of data can provide a detailed and multi-dimensional view of the drone's behavior, enabling early fault detection and enhancing the reliability and safety of UAV operations.

Accelerometer is an automatic tool for measuring acceleration, detecting, and measuring vibration and measuring acceleration due to the body (inclination). Acceleration creates a state of speed over time. Direction movements are changes of objects that will also cause acceleration. There are two main principles of the accelerometer measurement system where one is to measure the displacement of the mass and the other one measures the frequency of a vibrating element changing (mass) it's caused because of tension changes. The accelerometer measures linear acceleration and by integrating the signal twice we can obtain the position[10]. By analysing vibration patterns, they can optimize the UAV's design and configuration, mitigate excessive vibrations that might compromise performance or data quality, and ultimately enhance flight safety and efficiency. With regards to accelerometers sensor, their usage as a gravity sense is hampered by the fact that accelerometer measurements contain not only information of the gravity field, but also vehicular accelerations. The usage of the sensor to detect gravity in attitude estimation is therefore always accompanied by the associated problem of compensating for vehicular accelerations [11] engineers and researchers to assess the structural integrity of the UAV, detect potential issues or malfunctions in its components, and ensure the accuracy of gathered sensor data.

The primary importance of a motion capture system lies in its ability to measure even the smallest deviations in UAV displacement accurately. By capturing real-time displacement data, motion capture systems enable the creation of highly detailed flight profiles, which serve as benchmarks for multiple flight conditions. The tracking quality of a motion capture system using passive markers is strictly related to placement and a calibration process. High-precision systems are mostly based on markers and infrared lighters. The object, which often is a rigid body, has multiple markers attached. That allows us to track the object effectively. It is important to note that properly chosen and placed markers increase the visibility of the object[12]. Overall, a motion capture system (MCS) functions by recording the positions of markers from multiple camera perspectives and processing this information to reconstruct precise three-dimensional movement data. This data is then used for a wide array of applications across different industries. To evaluate the performance and stability of VTOL UAVs, an indoor flight test in a multiple-flying environment is necessary. The fundamental measurements of UAV flight are the position displacement and rotation angle an understanding of these parameters is essential for the development of indoor flight test rigs. The quadcopter movement is controlled by variations of the relative thrusts over four degrees of freedom yaw, roll, pitch, and altitude where two opposite rotors rotate in a clockwise direction and the remaining pair rotates in a counter clockwise direction for flight balance; each degree of freedom can be controlled by adjusting the thrusts of each rotor individually[13]. The data collected from the positional cameras provide real-time feedback, allowing for adjustments in flight paths, aiding in accurate positioning for tasks like surveying or inspection, and contributing to the overall safety and efficiency of the UAV operation.

In [14], a fault detection and classification algorithm based on deep learning (DL) and time-frequency analysis (TFA) is designed to detect and classify sensor faults of the Drone UAV. In[15], the experiment proposed a machine learning-based real-time failure prediction and classification framework for its eventual deployment with actual autonomous flights. The results showed that after initial pre-processing to prepare data for applying recurrent neural networks, stacked long short-term memory (LSTM) generated intelligent insights for failure identification.

II. OBJECTIVES AND CONTRIBUTIONS

In recent years, with the development of UAV technology, more and more UAVs have been developed and employed for various practical applications, such as payload transportation, aerial surveillance, and border monitoring. An adaptive fault-tolerant flight controller is presented for a VTOL tail-sitter UAV and validated through experiment tests. A fault tolerance control (FTC) scheme is proposed for a tilt-rotor UAV developed by the Korea Aerospace Research Institute to compensate for the adverse effect of actuator faults[16]. UAVs, commonly known as drones, can experience faults that compromise their functionality and performance. These faults may range from mechanical issues to electronic malfunctions. Motor problems, a prevalent fault, can stem from factors such as seized or stalled motors, uneven motor speeds, or overheating due to continuous operation. The most common UAV faults include insufficient battery capacity, loss of communication, motors, and propeller problems. Among them, the probability of faults occurring in motors and propellers is higher than in other parts when a UAV is

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flying. However, there is little research on UAV motors and propeller fault detection[17]. Furthermore, what is even more interesting is to see if a classical machine learning algorithm would achieve the required performance within the complications of the real world. Therefore, Support Vector Machine (SVM), a supervised classification algorithm, has been implemented for the problem of fault diagnosis to predict faults online [18].

This research advances the development of a multiple flying condition detection system for UAVs by proposing a method that leverages multiple sensors to identify the best classification model and the best sensor for UAV malfunctions identification. The study focuses on analyzing sensor outputs, with two primary objectives:

a) To compare machine learning classification models across different flight conditions using displacement and acceleration data.

b) To evaluate classification accuracy using different types of accelerometer sensors.

In a previous study [19], fault detection relied on audio sensors under a single flight condition involving faulty propellers. In this experiment, both acceleration sensors and a positional camera are used. We utilize a motion capture system due to the high accuracy, precision, and consistency in capturing movement data over time, ensuring reliable representation of the ground truth UAV movement [20,21]. Statistical features are extracted from the sensor data and supplied to a classification model, which assesses the accuracy of predictions based on features derived from acceleration and displacement data. The most effective machine learning classifier model is then used to compare the classification accuracy between two accelerometer sensors.

The analysis evaluates each sensor's ability to provide informative features across varying flight conditions, including propeller faults, flights with additional load, and windy environments. A total of eight flight condition groups are created, and the recorded data from all conditions are gathered from multiple sensors. This enables a comparative assessment of the classification performance between different acceleration sensors.

III. SETUP AND METHODOLOGY

3.1 FLOWCHART

The flowchart in Figure 1 represents a process for the classification of VTOL flight conditions, involving multiple steps from data collection to model evaluation.

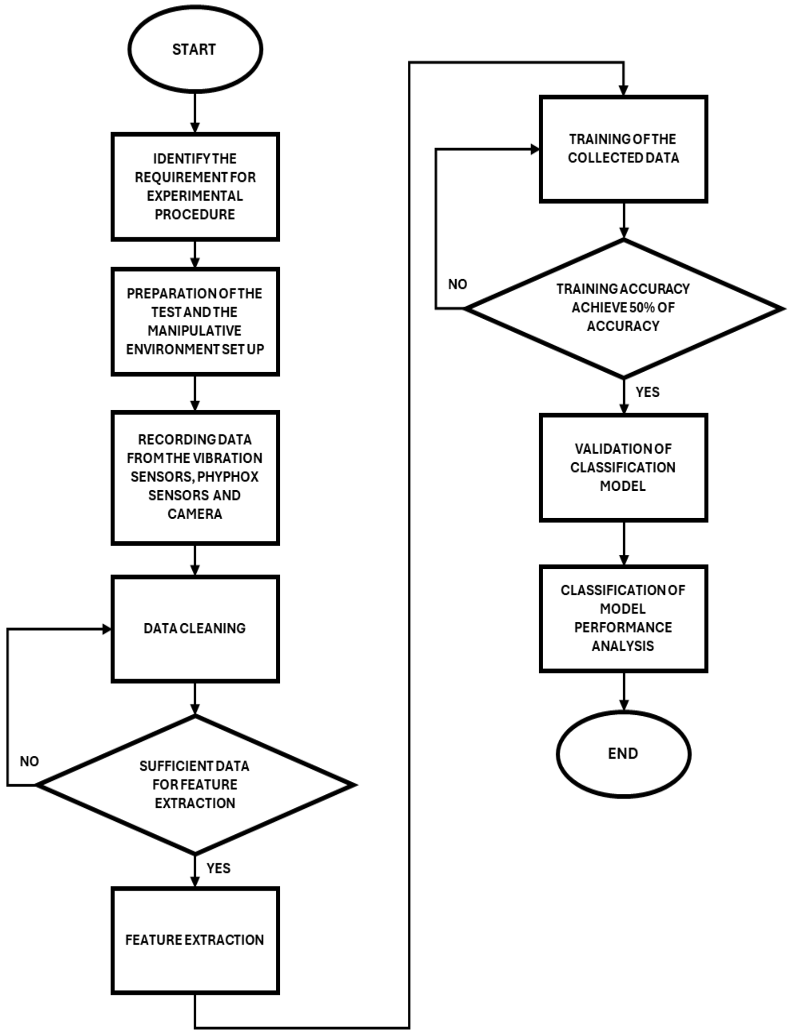

Figure 1 Flowchart for the classification of VTOL flight conditions

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The initial process is to identify the requirements of the experimental procedures including the placement of vibration sensors and positional cameras. Then, the manipulative environment is configured to be in windy and non-windy, with load and without load, in healthy and faulty propeller conditions. The positional cameras capture real-time motion tracking, allowing 3D linear movement analysis to detect irregularities in the UAV flight movements. The acceleration sensors capture real-time acceleration data that allows the sensor to capture any change in the drone's movement.

Data gathering consists of two types of input: acceleration sensor data and positional camera data. These raw data are then processed in a feature extraction step, where statistical features are derived from both sensors data.

Next, the extracted features are fed into classification model, where machine learning is applied to detect or predict potential flying conditions. Following the classification step, the performance of various models is compared to identify the most accurate classification model. Determining whether the recorded data is sufficient for developing a classifier model involves two considerations: the number of samples in each class and the complexity of the classifier model. First, it is crucial to have enough data from each class for proper feature extraction. Then, the dataset should have larger number of samples compared to the number of features.

Finally, the experiment will continue with further investigation for comparison between different acceleration sensor setups to determine the most effective configuration by integrating the best classifier model with the best acceleration sensor for classification of VTOL flight multiple flying conditions.

3.2 EXPERIMENTAL SETUP

Using complex monitoring and postprocessing algorithms helps reduce the inaccuracy introduced by measurements. A diverse collection of sensing methods can identify proper motion, resulting in various applications in autonomous systems. The experimental setup for this study is shown in Figure 2. A group of infrared cameras is positioned all around the measurement area, focusing on either passive or retro-reflective markers. This allows them to triangulate the exact three-dimensional position of the marker. Images of high contrast reflecting markers can be recorded at up to 2 kHz using infrared lighting.

The acceleration sensors used to measure the acceleration value due to vibration are then attached to the drone, and a solid base is set to ensure the sensor is attached correctly. The acceleration sensor will collect data when the drone starts flying in multiple conditions and environments. The multiple environments are then set up to be wind and non-windy environments.

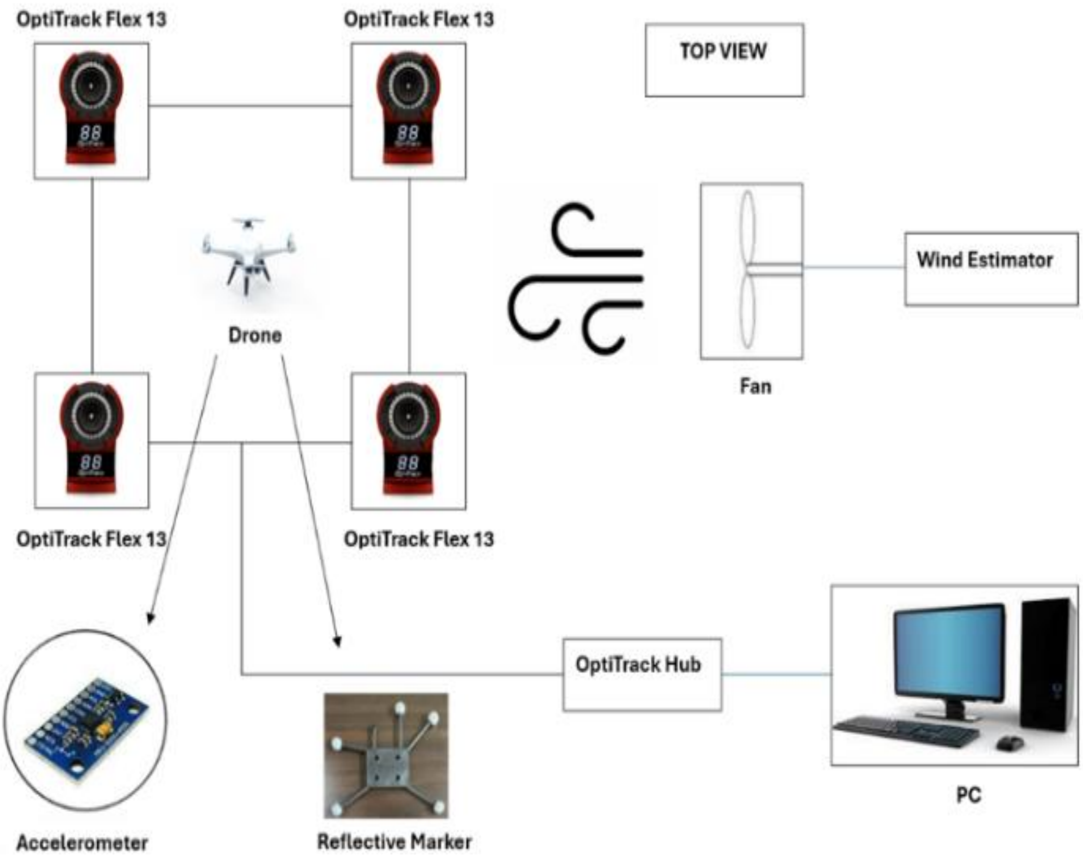

Figure 2 Experimental setup

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3.3 EXPERIMENT CONDITION

The multiple conditions of the experiment are manipulated from the propeller, flying with load, and windy conditions as shown in Figure 3-5. The propeller conditions come from healthy and faulty conditions. Then, flying conditions are manipulated from load and no-load flying conditions. The windy and non-windy conditions will be the other flying conditions.

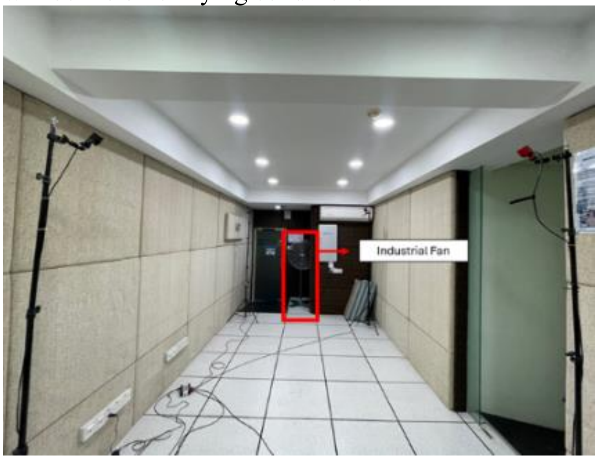

Figure 4 The 500g load attached to the drone

Figure 5 Healthy and faulty propeller. The faulty propeller's tip is cut by 15mm to simulate faults

The flying with load conditions is set for 500g for the weight, which remains constant in every flight. Then, the faulty propeller conditions are set to 2 of 4 propellers being cut at the propeller's tip.

3.4 OPTITRACK FLEX 13

To conduct the UAV tracking study, a minimum of 4 low-cost OptiTrack cameras as shown in Figure 6 should be securely mounted on a stable stand. It is crucial to ensure that the cameras do not vibrate during the flight test to maintain accurate data. However, it is worth noting that the low-cost OptiTrack system is vulnerable to infrared sunlight reflection, which can affect the precision of the rigid body streaming data and lead to ghosting marker recording.

Figure 6 OptiTrack Flex 13

3.5 ACCELEROMETER ADXL 345

Accelerometers measure acceleration forces, including those caused by vibrations. They detect changes in motion and can be used to measure the frequency, amplitude, and direction of vibrations in various objects or structures. An accelerometer typically provides data in three-dimensional along the X, Y, and Z axes. The accelerometer ADXL 345 used in this study is shown in Figure 7, which is a light-weight and low-cost and can be purchased off-the-shelf.

Figure 7 ADXL 345 Acceleration sensor

3.6 ACCELEROMETER WITH PHYPHOX APPLICATION

Phyphox mobile applications is used for acceleration measurement to measure the total acceleration acting on mobile device without the influence of the gravity. Accelerometer data was collected using the Phyphox app (Figure 8) on an iPhone SE 2020. The smartphone is tightly mounted on top of the VTOL UAV to avoid additional vibrations from the mobile phone. This application enables monitoring the real-time acceleration data from the other devices through Wi-Fi internet connection.

Figure 8 Phyphox applications logo

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3.7 FEATURE EXTRACTION

Many statistical techniques are utilized to extract features from drone flight test data. They help to identify important patterns, relationships, or characteristics within the collected data. The four feature extraction keys of mean, standard deviation (STD), kurtosis (K), and interquartile range (IQR) are frequently applied in problem identification.

$$Mean = \frac{\sum x}{n} \quad (1)$$

$$Std = \sqrt{\frac{\sum(x-\bar{x})}{n-1}} \quad (2)$$

$$K = E\left[\frac{x-E(x)}{\sqrt{Var(x)}}\right] \quad (3)$$

$$IQR = Q3 - Q1 \quad (4)$$

where x represents each individual data point and n is total number of data points.

The data from various UAV flying conditions and multiple sensors are used for statistical feature extraction as shown in Equation (1) until Equation (4). Equation (1) is the average of a group of data points is called the mean. Calculating the mean of sensor readings or other relevant parameters over a specific period provides a central tendency measure, offering insight into the typical behaviour of the drone during flight Equation (2) is the standard deviation (Std) quantifies how widely distributed the data are around the mean. A higher standard deviation indicates greater dataset variability. It can signify fluctuations or irregularities in sensor readings or performance metrics during flight. Equation (3) is the Kurtosis that measures the shape of the distribution curve. High kurtosis indicates a more peaked distribution with heavy tails, suggesting outliers or extreme values in the dataset. Equation (4) is the interquartile range (IQR) that stands for the range of values in the data between the first quartile (25th percentile) and the third quartile (75th percentile). Compared to the range or standard deviation, it measures the dispersion of the middle 50% of the sample and is less susceptible to outliers.

3.8 DATA TRAINING USING CLASSIFICATION MODEL

Creating a classification model for data training involves using supervised learning algorithms to classify input data into different categories or classes based on labelled training data. This process starts by gathering data where each sample is labelled with its corresponding class. The model uses this labelled data along with the provided statistical parameters to learn the relationship between the input features and the output classes they are associated with. The model undergoes training iterations, adjusting its internal parameters to minimize errors in predicting the correct classes. The labelled data is shown in Table 1.

3.9 CLASSIFICATION MODEL ACCURACY COMPARISON

Once trained, the model's performance is evaluated on new, unseen data to ensure it can generalize well to make accurate predictions. This iterative process of learning from labelled data, creating patterns, and making predictions defines the essence of training a classification model. The choice of the best training algorithm depends on various factors, including the dataset's characteristics and the specific requirements of the problem at hand. This article discusses the comparison of supervised learning algorithms available in MATLAB's Classification Learner app. It compares the classification models within the app and evaluates the three best-performing algorithms. This study compares classification model accuracy and confusion matrix parameters between Naïve Bayes, Neural Networks, and Support Vector Machines.

3.10 CLASSIFICATION ACCURACY COMPARISON BETWEEN ACCELEROMETER SENSORS

The best classification model will be used to compare the classification accuracy using different accelerometer sensors. Finally, classification accuracy is compared between features extracted from low cost ADXL 345 sensor and decent sensor embedded in an iPhone SE 2020. Comparison between sensors is crucial to determine the best sensor for UAV flight condition monitoring. Accuracy is the key factor to consider for sensor quality in classifying the drone's flying condition. Accuracy measures the overall effectiveness of the classification model by indicating the proportion of correct classes out of all classifications.

IV. RESULTS AND DISCUSSION

4.1 RECORDED DATA

Recorded data is organized according to its flying conditions as shown in Table 1. Group 1 until group 8 are determined based on three conditions: windy or non-windy conditions, faulty or healthy propeller, and load or no-load flying conditions. Wind conditions can significantly impact the performance and stability of aerial platforms, and the classification model's efficiency needs to be evaluated under both scenarios.

When the UAV flies with a load, it can have several effects on its flying capabilities. Due to the additional weight, a UAV consumes more energy to maintain flight. This can result in reduced flight time and range compared to when the UAV is flying without a load.

4.2 CLASSIFICATION MODEL ACCURACY

The statistical features extracted for various propeller types and flight conditions based on Table 1 were used for training and comparison across three different classifiers. The training process involved two sensors: an accelerometer and a camera. As shown in Figure 1, after the feature extraction process, the extracted statistical data is trained for evaluation classifier's performance between two sensors. This comparison classifier performance is to determine the best sensor for UAV flight condition

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monitoring. Based on Table 2, the QSVM scored the highest classification percentage for both sensors. A QSVM is a type of SVM classifier that uses a quadratic kernel to map input features into a higher-dimensional space where a quadratic decision boundary can be constructed to separate classes.

Table 1 Group label for UAV flight conditions

Group	Load / No-Load	Windy / Non-Windy	Faulty / Non-Faulty	Time (min)	Samples (vibration)	Samples (position)
1	Load	No-Windy	Faulty	3	1,200	22,000
2	Load	No-Windy	Healthy	3	1,200	22,000
3	Load	Windy	Faulty	3	1,200	22,000
4	Load	Windy	Healthy	3	1,200	22,000
5	No-Load	No-Windy	Faulty	3	1,200	22,000
6	No-Load	No-Windy	Healthy	3	1,200	22,000
7	No-Load	Windy	Faulty	3	1,200	22,000
8	No-Load	Windy	Healthy	3	1,200	22,000
Total				24	9,600	176,000

Table 2 Classification Learner Accuracy

Acceleration Data		
Classifier	Train (%)	Test (%)
Quadratic SVM	87.5	78.13
Wide Neural Network	73.61	72.92
Kernel Naïve Bayes	72.92	72.92
Position Data		
Classifier	Train (%)	Test (%)
Quadratic SVM	79.31	78.95
Wide Neural Network	63.79	52.63
Kernel Naïve Bayes	70.69	65.79

Based on the training and test classification accuracy, the results have shown that acceleration data leads to higher scores in classification accuracy, as shown in Figures 9 and 10.

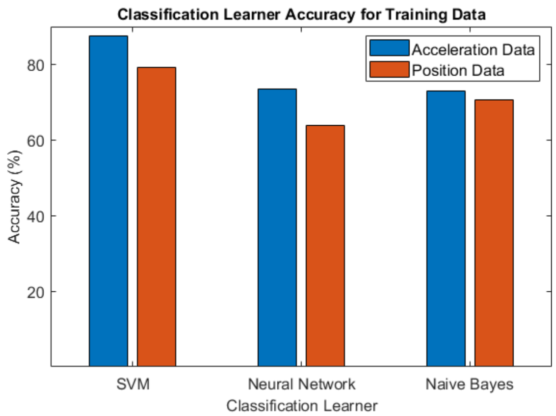

Figure 9 Classification Learner Accuracy for training

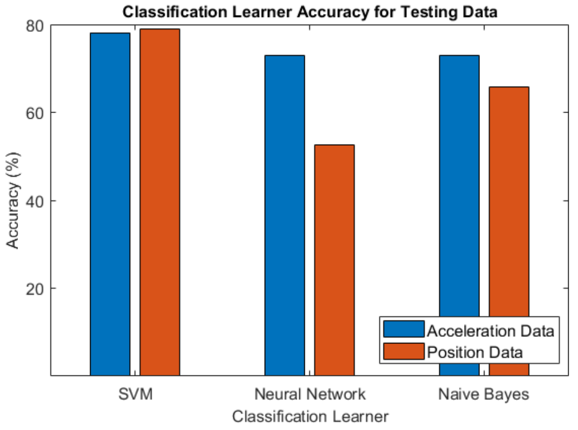

Figure 10 Classification Learner Accuracy for test

The validation accuracy for acceleration data is higher than positional displacement data by 8.71%. Based on our observation, acceleration sensor data provides better statistical features than position data for propeller fault classification. Furthermore, we found that QSVM is the best model for differentiating flight conditions using both sensors.

4.3 CONFUSION MATRIX FOR QSVM MODEL

Figure 11 and Figure 12 show the confusion matrix for QSVM for both positional camera and acceleration data, representing that the model correctly predicts most instances. Confusion Matrix provides a detailed information the efficiency of the classifier's performance. Its purpose is to determine which of the two sensors has the better classifier performance based on the UAV flying condition in Table 1. Positive predictive value (PPV) and false discovery rate (FDR) are the common metrics to evaluate the classifier's performance. A high PPV indicates the model correctly identifies the flying

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condition leading to efficient fault detection while a low FDR indicates fewer false positives, ensuring accurate diagnosis of flying conditions.

The confusion matrix of the QSVM classifier for the acceleration sensor shows that the highest false discovery rate (FDR) was 25% for Group 1, and the highest score positive predictive value (PPV) was 100% for Group 5.

Meanwhile, the confusion matrix of the QSVM classifier for the positional camera shows that the highest false discovery rate (FDR) was 66.7% for Group 1, and the highest score positive predictive value (PPV) was 100% for Groups 3, 5, and 7. Hence, the data for positional cameras and acceleration sensor shows that Group 5 had a 100% PPV score. The prediction for acceleration data shows more accurate data prediction due to PPV and FDR percentage compared to the positional camera.

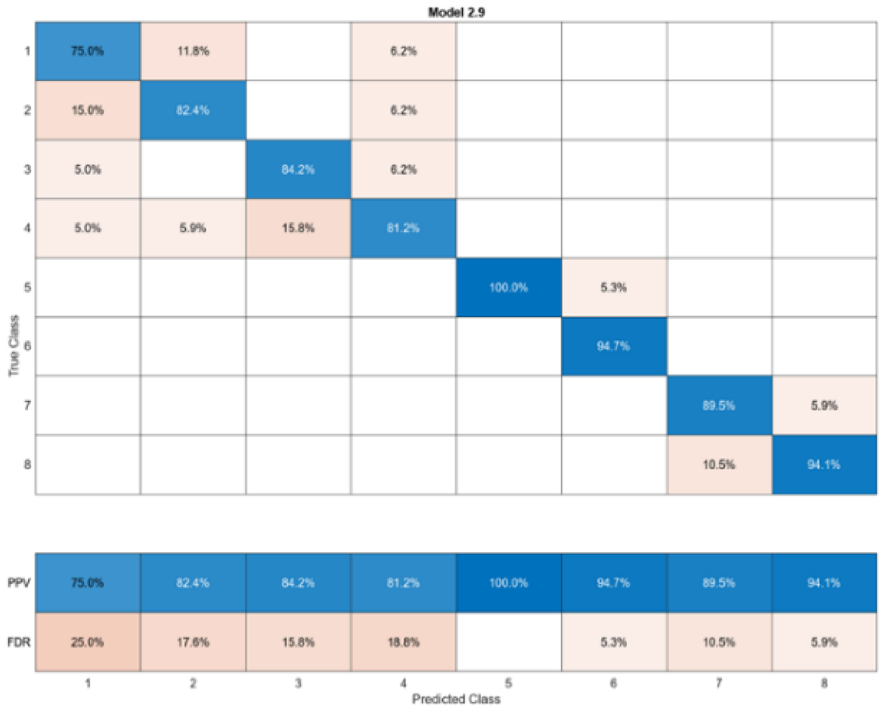

Figure 11 QSVM Confusion Matrix for acceleration data

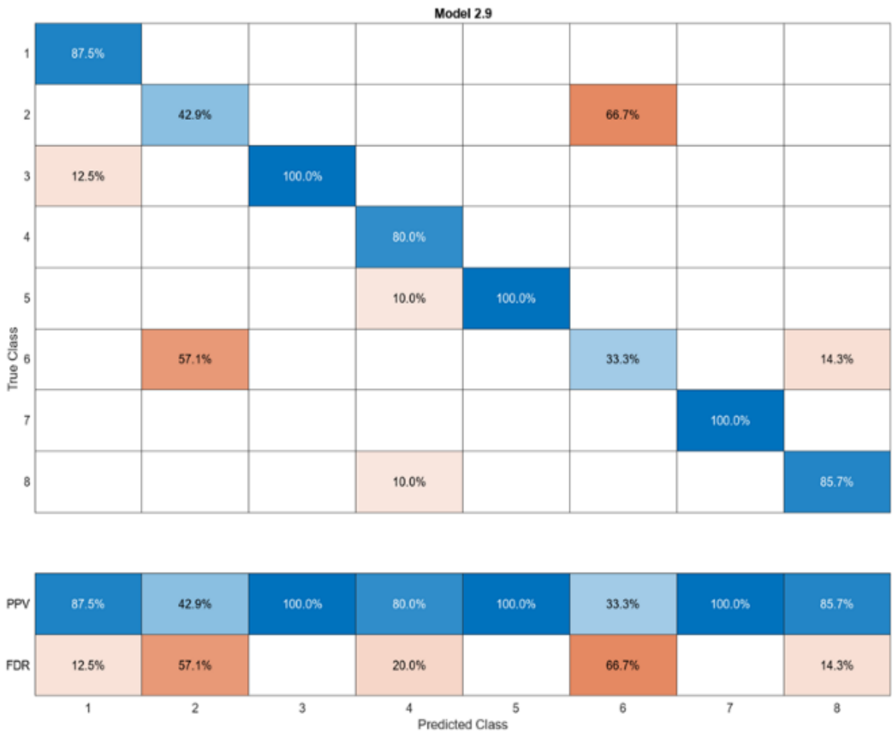

Figure 12 QSVM Confusion Matrix for positional data

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Data quality is a critical factor that significantly impacts a confusion matrix's effectiveness in evaluating a classification model's performance. High-quality data enhances the reliability of the confusion matrix, while poor-quality data can lead to misleading results and incorrect conclusions. Outliers are extreme values that differ significantly from most of the data. Outliers can distort the model's learning process, leading to poor performance and misclassifications. A machine vibration sensor might record an unusually high value due to a transient shock, affecting the model's accuracy. If some sensor readings are missing due to transmission errors, the model might fail to learn the correct patterns.

4.4 QSVM SCATTER PLOT FOR ACCELERATION DATA

Based on Figure 13 and Figure 14, the scatter plot results for the acceleration sensor data were shown.

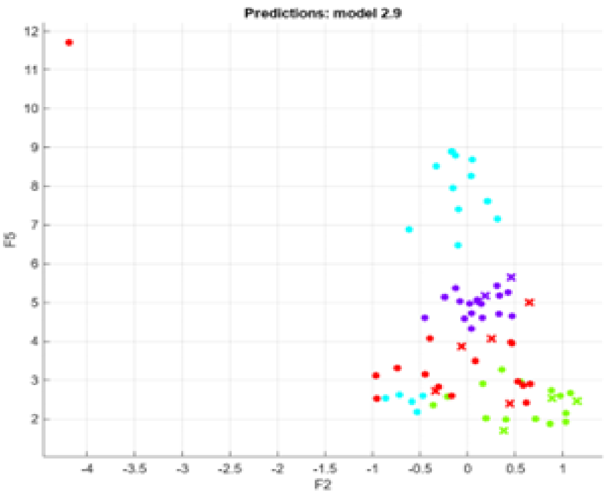

Figure 13 Scatter Plot in faulty propeller condition for acceleration data

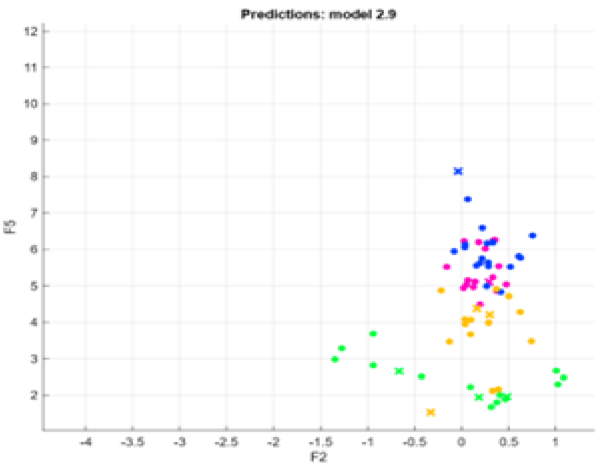

Figure 14 Scatter Plot in healthy propeller condition for acceleration data

The scatter plot extracted from MATLAB was based on the three different conditions that contribute to the various patterns of the scatter plot. A scatter plot visualizes individual data points based on two variables. It assists in analyzing class separation and misclassification. The clear separation indicates that the classification effectively differentiates the UAV flying condition.

Clusters in the context of scatter plots and data analysis refer to groups of data points that are closely packed together, suggesting that they have similar characteristics or share certain properties. A cluster is a collection of data points closer to each other in the feature space than points in other clusters. Based on the two selected features from the acceleration sensors data, the features contribute to a good class prediction due to obvious clusters produced in the scatter plot.

However, the two selected features from the acceleration sensor data also contribute to outliers in the scatter plot. Outliers are points far away from the main cluster of data points that are outliers and may require special attention. Outliers are data points that differ significantly from most observations in a dataset. For instance, outliers can be from the variability in the data and measurement error. They can arise due to variability in the data, measurement errors, or other factors. Outliers can significantly impact statistical analyses and provide important insights into the data, but they can also distort results if not handled properly. Outliers are values significantly higher or lower than the rest of the data. Based on the figures above, the outliers are seen when there were plots outside its cluster. The outliers will contribute to a mismatch for the classifier to predict data into the correct class based on the two selected features in the scatter plot.

4.5 CLASSIFICATION ACCURACY COMPARISON BETWEEN ACCELEROMETER SENSORS

The performance evaluation of the classifier using the Confusion Matrix is based on PPV and FDR. According to Confusion Matrix for QSVM model in Figure 11, the group with load (Group 1 to Group 4) presents higher FDR percentage compared to the group without load (Group 5 to Group 8). The group without load delivers better overall performance, making it more reliable for analysis due to its higher PPV and lower FDR. Therefore, the group without load was selected for the comparison between acceleration sensors.

In this analysis, 4 groups will be classified using QSVM model as shown in Table 3. The classification accuracy analysis for both acceleration sensors is compared based on wind and propeller conditions. The total 3-minutes data consists of 4,800 samples from the ADXL345 and 88,000 samples from the iPhone SE 2020 with a total duration of 12 minutes.

Figure 15 shows that both training and testing accuracy of iPhone SE 2020 is higher than ADXL345 with difference of 4.67% for training and 5.06% for testing using QSVM model. Integration of the best classification model with higher specification acceleration sensor

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significantly increases the training accuracy.

Table 4 Group label for Classification Learner model accuracy comparison using different acceleration sensor

Group	Windy / Non-windy	Faulty / Healthy	Time (min)	Samples (ADXL345)	Samples (iPhone SE 2020)
1	Non-Windy	Healthy	3	1,200	22,000
2	Windy	Healthy	3	1,200	22,000
3	Non-Windy	Faulty	3	1,200	22,000
4	Windy	Faulty	3	1,200	22,000
Total			12	4,800	88,000

Based on Table 4, the iPhone SE 2020 sensor has higher training and testing accuracy compared to the ADXL345, with train accuracies of 97.73% and 93.06%, and test accuracies of 94.64% and 89.58%, respectively.

The ADXL 345 acceleration sensor can have its sampling time shortened to 30 seconds while maintaining good classification performance. In contrast, the iPhone SE 2020 accelerometer can achieve high accuracy classification in a shorter 5 seconds sampling time.

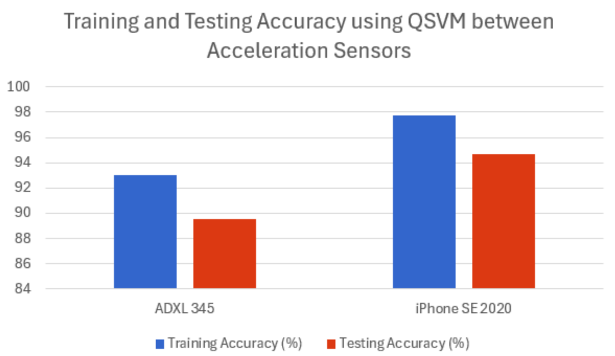

Figure 15 Comparison train and test accuracy using QSVM between acceleration sensors

Table 4 Classification Learner Accuracy of Accelerations Sensors

Sensors	Train Accuracy (%)	Test Accuracy (%)	Sampling time (sec)	Shorten Sampling Time (sec)
ADXL 345	93.06	89.58	180	30
iPhone SE 2020	97.73	94.64	180	5

Figure 16 shows classification of four different group conditions recorded by iPhone SE 2020 acceleration sensor. The figure provides a clear separation in the plot, illustrating that the QSVM model is performing well in classifying the data points based on the extracted features. The blue points represent Group 1, the red points represent Group 2, the yellow points represent Group 3, and the purple points represent Group 4, as illustrated in the scatter plot.

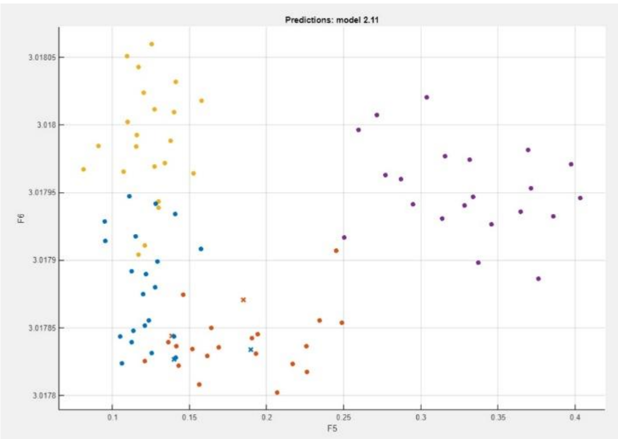

Figure 16 Scatter plot of acceleration sensor

Based on the results, acceleration data recorded using iPhone SE 2020 acceleration sensor shows better performance to predict VTOL UAV flying conditions, with QSVM being the most effective classification model. By using the same model, it can be concluded that prediction accuracy improves with better accelerometers within shorter prediction time.

V. CONCLUSIONS

In this study, we developed and evaluated a classification model to detect multiple flight conditions of VTOL UAVs using data from accelerometer sensors, with a motion capture system included for comparison. After testing various machine learning models, including Quadratic Support Vector Machine (QSVM), Neural Networks, and Naive Bayes, the QSVM model was identified as the best-performing model. The results showed that acceleration data provided significantly higher accuracy compared to positional data, with an 8.71% improvement in validation accuracy when using QSVM. The motion capture system was used to compare displacement data but showed lower classification accuracy than the accelerometer-based data.

Subsequently, data from two accelerometers (iPhone SE 2020 and ADXL345) were used to further evaluate the QSVM model. The iPhone SE sensor demonstrated superior classification accuracy with 97.73% training

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accuracy, compared to 93.06% for the ADXL345. However, the iPhone SE sensor was used primarily as a benchmark, as it is not intended for practical UAV onboard applications. The ADXL345 sensor, despite being a low-cost alternative, delivered satisfactory performance, demonstrating that affordable sensors can still provide sufficient accuracy for UAV fault detection in real-world scenarios.

The study emphasizes the potential for enhancing fault detection accuracy by using higher-resolution and more sensitive accelerometers, which could improve the detection of minor faults that might be missed by conventional sensors. Moreover, future work could explore advanced machine learning techniques, such as deep learning algorithms, to further refine classification accuracy. Additionally, the implementation of unsupervised learning algorithms for anomaly detection, such as autoencoders, isolation forests, and clustering methods, could help identify outliers and abnormal patterns in the acceleration data. Feature importance analysis will also guide optimal sensor placement and data collection strategies for UAV fault detection systems.

By combining these approaches, UAV fault detection systems can be further optimized, leading to more accurate and effective early warning systems for improved UAV performance and reliability.

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