

Battery Condition Monitoring of Quadrotor UAV using Machine Learning Classification Algorithm

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Abstract— Unmanned aerial vehicle flight performance and efficiency rely on various factors. Flight instabilities can happen due to malfunctions inside the system and disturbances from the external environment. Battery status plays a significant role towards healthy flight conditions. A weak battery will affect the performance of propellers and motors, and the presence of wind disturbance can contribute towards inefficient flying capabilities. Therefore, investigation of fault at the early stage is crucial to maintain the great performance of the UAV. This paper aims to investigate the best prediction system from the existing machine learning algorithm such as Decision Tree (DT), Linear Discriminant (LD), Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Neural Network (NN) to classify the battery condition of the quadrotor by extracting the features from the displacement time series dataset. By using recorded flight data, it will be statistically analyzed to extract the flying condition features. The extracted features are the Euclidian distance (ED), speed, acceleration, Periodogram Power spectral density (PSD) and Fast Fourier Transform (FFT) of the signal. The result shows that the two best classifier algorithms are the Decision Tree and Neural Network models with training accuracy of 98% and 93% in Set A and B, respectively.

Keywords— Machine Learning Algorithm; Classification Learner; Unmanned Aerial Vehicle (UAV); battery capacity.

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I. INTRODUCTION

Unmanned aerial vehicles (UAV) are widely used nowadays. The multipurpose UAV gives people more convenient ways to do aerial photography, videography, precise agriculture, real-time monitoring, and delivery system. Despite the massive increase in applications of UAVs, it is crucial to maintain stable and safe flight during take-off and landing, especially in windy outdoor environments. Quadrotor UAVs are known to be vulnerable to wind gusts. Most quadrotors are electric vehicles with onboard batteries. The quadrotor needs more power to overcome the wind disturbance, resulting in faster battery drainage.

Consequently, the performance of the quadrotor deteriorates as the battery becomes weak. In 2018, the experiment on the power consumption with a different flight conditions on widely used flying mission planning was proposed. Viranga et al. [1] concluded that power consumption has increased even though the UAV is in the hovering position because the efforts of the UAV to retain stability are averse to environmental conditions changing with the altitude. This situation shows that the external environment affects the battery condition during flight.

Extensive recording of sensor signal analysis could provide helpful information to predict the battery performance. Integrating quadrotor signals analysis from a data-driven fault detection and identification (FDI) algorithm with machine learning techniques enables the classification of the battery condition. In 2018, Pourpanah et al. [2] introduced the development of anomaly detection system using Fuzzy Adaptive Resonance Theory Neural Network for UAV motor and propeller faulty. In the same year, Lu et al. [3] also developed the fault detection system using machine learning but this time using reinforcement learning-based motor-temperature measurement. However, both studies do not consider the battery capacity of the UAV.

Motor fault detection techniques are usually based on electrical or mechanical techniques, which is known as model-based fault detection and identification approach. For example, Hu et al. (2021) [4] have proposed experimental research on UAV stability by analysing mechanical vibration data measured from the UAV motors. Compared to data-driven algorithms, model-based and knowledge-based algorithms include a lot of rule and model dependencies [5][6][7]. Due to model-free analysis, the data-driven analysis demonstrated greater flexibility. This paper will use the data-driven FDI method to detect anomalies and designate them as flaws.

The flying condition of a quadrotor UAV should be in stable condition to achieve the full performance of the functional capabilities. A quadrotor's flying quality and reliability are affected by various parameters from the external environment and the internal part of the system. Fault or failure in any part may lead to catastrophic consequences. The conditions that prevent the quadrotor from stable and safe flight include insufficient battery capacity, faults in the motors or propellers, wind conditions and loss of communication [8].

Vibration signal analysis is widely used in condition monitoring and fault diagnosis system of rotating machinery. Good airframe vibrations in the flying course contain a large amount of information for fault detection and identification. Effective vibration signal extraction techniques are crucial for rapidly diagnosing a quadrotor UAV's flying status. Proper flight positioning data recording provides helpful information with equal diagnosis quality comparable to vibration signal analysis [9][10].

With the advancement of the ML classification method, reliable quadrotor fault identification is feasible by using positioning data [9]. The data needs to go through appropriate pre-processing to emphasize valuable and informative features before moving through the next level of the feature extraction method. With detailed data analysis, the machine learning approach will eventually promise a reliable model for classifying quadrotor performance. This paper uses position and displacement data to provide informative features to monitor and predict the stability of a flying quadrotor UAV affected by both the external environment and internal battery conditions. The classification learner algorithms will then be compared to identify the most suitable classifier for predicting the quadrotor flight performance.

II. LITERATURE REVIEW

Fixed wing, rotary wing and flapping wing are the three categories of unmanned aerial vehicles (UAV). This paper will focus on the rotary wing of UAV, specifically the quadrotor. The quadrotor's absolute position is defined by its coordinates x , y , and z , and its attitude is defined by the Euler angles, which are roll angle, ϕ , pitch angle, θ and yaw angle, ψ . Roll angle is defined as rotation around the x -axis; pitch angle is defined as rotation around the y -axis; and yaw angle is defined as rotation around the z -axis [11].

A flaw in the drone's propellers could lead the aircraft to crash to the ground, resulting in its destruction, and pose a safety risk to objects and people in the aerial vehicle's area of action. People frequently use vibration signals to detect machine part defects to reduce machine damage and keep the equipment working at its best. As a result, some researchers have attempted to examine the subject from various perspectives, including comparable theoretical background of vibration analysis for UAV condition monitoring and performance analysis [12].

Most of the studies stated that the VTOL UAV's faults come from the malfunctions of its fundamental parts. Altinors et al. [13] proposed that faulty of VTOL UAV mostly come

from the propeller, eccentric and bearing malfunctions. The literature surveys show minimal studies on the quadrotor UAVs' battery performance [14]. In 2017, Bondyra et al. [15] presented a signal processing and machine learning algorithm, Support Vector Machine (SVM), to detect faults in the rotor of the UAV. Iannace et al. [16] proposed that to construct a system capable of detecting an imbalance in a quadrotor's propeller, data acquired from acoustic measurements of the noise from UAV can be utilized to train a model based on neural networks. Both of these used the vibrations signal to conduct the FDI method.

However, recent studies did not consider the battery capacity of the UAV in conducting the FDI using a data-driven method integrated with the ML algorithm [6][7]. The previous study on the battery consumption of the UAV was conducted in 2018 when Viranga et al. [1] proposed a comprehensive energy consumption model for UAV mission planning by analyzing the power consumption of the UAV in different conditions of the environment. This paper will investigate how to classify battery level based on displacement features using classification learning algorithm.

The flight data is obtained from the previous research on developing and testing open jet wind tunnels for quadrotor flight testing [17]. Wind speed is manipulated by frequency of the wind tunnel motor frequency due to its linear relationship. The data sets contain informative features that will be extracted and categorized into several groups to start classification learning. The summary of parametric features extracted by the previous studies can be observed in Table I.

TABLE I
SUMMARY OF PARAMETRIC FEATURES FROM PREVIOUS STUDIES.

Feature	Reference
Mean	Do et al. (2011)
Standard deviation	[18]
Root Mean Square	
Energy	
Spectral Mean	
Displacement of X and Y	Chen et al. (2017)
Mean value	[19]
Self-covariance	
Wavelet packet transform (WPT)	Shaheryar et al.
Fast Fourier Transform (FFT)	(2017) [20]
Cepstrum information	
Short Time Fourier Transform (STFT)	
Empirical mode decomposition (EMD)	
Time-domain statistical features (TDSEF)	
mean (M), rootmean square (RMS) standard deviation (SD), Skewness (S), Kurtosis (K), Crest factor (CF), Latitude factor (LF), Shapefactor (SF) Impulse factor (IF)	Pourpanah et al. (2018) [2]
Frequency	Li et al. (2019) [21]
Displacement	
Maximum amplitude	Hu et al. (2021) [4]
Minimum amplitude	

Minimum amplitude	Chen et al. (2021) [22]
Maximum amplitude	
Mean	
Variance	
Mean Square	
Root Mean Square Value	
Euclidian distance	
Mahalanobis distance	

Artificial Intelligence (AI) is broadly defined as any approach that allows computers to emulate human behaviour and recreate or outperform human decision-making to handle complicated tasks autonomously or with slight human interaction [23]. AI is a subset of data science that comprehends traditional programming and ML. Deep learning (DL) and artificial neural networks (ANN) are two instances of ML models and methodologies [24]. This paper will apply the conventional machine learning algorithm to compare the performance of classification models, which is Decision Tree (DT), Linear Discriminant (LD), Naïve Bayes (NB), SVM, k-nearest neighbors (KNN) and Neural Network (NN) in the prediction of battery capacity of the quadrotor using recorded flight data.

DT is a type of tree structure that resembles a flowchart, where each internal node represents a test on an attribute, each branch a test result, and each leaf node (terminal node) a class label [24]. LD is a supervised learning classification algorithm. This model is beneficial for a linear combination of features, hence helpful in searching for linear transformation that maximizes class separability in the reduced dimensional space [25]. NB Classifiers are stochastic classifiers with an assumption that different features are unrelated [26]. It is based on Bayes' Theorem, and the conditional independence assumption is based on the conditional independence principle. It first learns the joint probability distribution of the input and output using the conditional probability distribution. SVM is a computational learning method for classifying small data. SVM solves a limited quadratic optimization problem based on structural risk minimization (SRM) to build optimal separation hyperplane $f(x) = 0$ between data sets [27]. The KNN algorithm is an instance-based learning technique based on the idea that cases in a dataset will often be found in close proximity to other instances with similar attributes [28]. An artificial neural network is a collection of connected nodes known as artificial neurons that imitate the neurons in a biological neural network. NN is a collection of algorithms that work together to recognize underlying relationships in a batch of data [24].

III. METHODOLOGY

The methodology and the procedures taken to achieve the objectives of this research will be explained in this part. Figure 1 shows the project flowchart showing major steps implemented to predict the fault using ML algorithm. The process started by reviewing past research papers on the flying condition monitoring of UAVs. There are several related research on the flying monitoring of the UAV, as explained in the literature survey section. This study will focus on the movement signal analysis of a quadrotor

comparable to the vibration analysis for machine condition monitoring techniques. In addition, the survey is conducted to discover the frequently used methods in ML, and the relevant and informative features will be selected for performance classification.

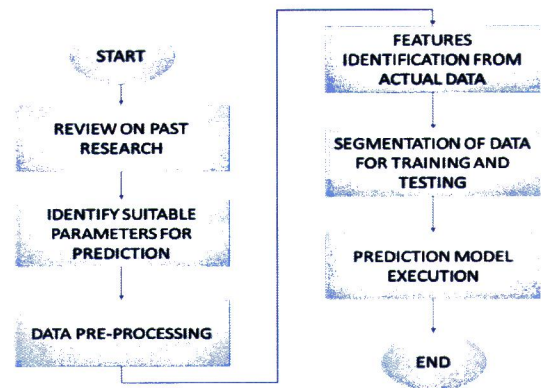


Fig. 1 Project Flowchart.

A. Parameter review and selection.

The commonly used parameter in vibration signal analysis is frequency, period, displacement, velocity, acceleration, root mean square amplitude, mean, variance, skewness, kurtosis, median and range [25], [29]–[31]. Vibration signals acquired with vibration transducers from a rotating machine are frequently in the time domain. Vibration signals frequently consist of many responses from various sources within the rotating machine and some background noise. Using the obtained vibration signals directly for fault diagnosis is challenging, whether through physical inspection or automatic monitoring.

As an alternative to processing vibration signals, a popular strategy is to compute specific raw signal properties that can effectively characterize the signal. In machine learning, this type of characteristic is named by features. Thus, the feature selection must be conducted to process this collected signal into a machine learning classification algorithm. There are two forms of manual inspection of vibration signals as part of time domain defect diagnosis: visual inspection and feature-based inspection. The visual inspection is conducted by plotting the raw signal and observing the signal's pattern. From the flight data, the movement signals obtained from optical cameras are in discrete positions where x , y , and z values are observed.

B. Data Pre-processing

Data pre-processing is the crucial step in the data-driven FDI technique. The presence of irrelevant characteristics in the data can reduce model accuracy and cause the model to train based on irrelevant features. Feature selection is the process of selecting the features that contribute the most to the prediction variable or output that the study expected, either automatically or manually.

Table II shows the information on UAV data obtained from the previous research on developing and testing open jet wind tunnels for quadrotor flight testing [17]. The total data point

is a summation of shortened data points from each sample after the take-off and landing data cut-off. Wind speed is manipulated by frequency of the wind tunnel motor frequency due to its linear relationship.

TABLE II:
FLIGHT DATA LENGTH INFORMATION

Wind tunnel motor frequency (Hz)	Sampling frequency (Hz)	Sample	Total Data Point
15	120	Set A	14,000
25	120	Set B	22,300

The threshold for false and normal vibration of a quadrotor with different battery capacities is calculated using statistical analysis. Threshold calculation in Eq. 1 is essential for the decision part of the fault detection and identification method.

$$X(t) = \begin{cases} \text{false,} & x(t) \geq Q_3 \\ \text{normal,} & \text{otherwise} \end{cases} \quad (\text{Eq. 1})$$

Q_3 is the threshold calculated using the mean and quartile values of the flight data. The threshold calculation is the same as calculating outliers in statistical knowledge. Initially, the measures of the spread of the data are essential to detect the outliers. Outliers are commonly removed when the analysis is done. However, this research found that the data's outlier occurred repeatedly and is considered a fault [32]. The quartile of each dataset group determines the outliers, which are defined as all datapoint above the threshold of the third quartile. Q_i indicates i^{th} quartile calculated by Eq. 2

$$Q_i = L + \frac{h}{f} \left(\frac{iN}{4} - f_c \right) \quad (\text{Eq. 2})$$

where N is the total frequency, L is the lower limit of Q_i , h is the class size, f is the frequency of Q_i , and f_c is the cumulative frequency.

Table III shows the UAV battery level classified based on the Euclidian distance threshold calculated from UAV displacement measurement. From Fig. 2 and Fig. 3, it is shown that there is various condition of flight data available for Set A and Set B. Both set of data were recorded at similar hovering altitude of 2m. Flight data from Set B shows higher fluctuations compared to Set A due to stronger wind disturbance. In addition, the flight data in both figures is the flight data at the hovering state where the take-off and landing of the quadrotor have been cut off.

TABLE III:
THE CLASSIFICATION OF DATA BASED ON DISPLACEMENT DATA

Condition	Euclidian Distance (m)	Classification group
Low Battery capacity	>0.04	1
Optimum Battery capacity	<0.04	2

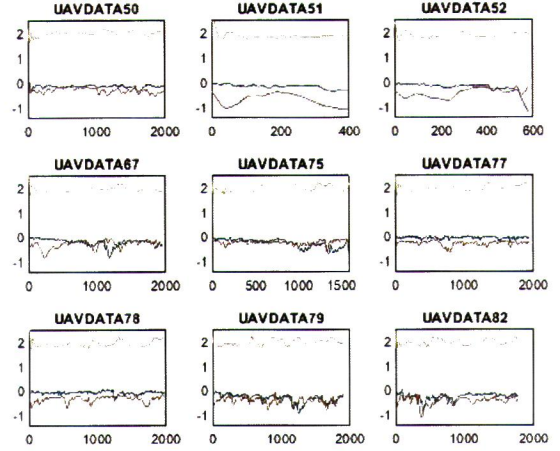


Fig. 2 Shortened flight data from Set A with displacement reading (m) versus 120Hz data points. (Red line: x-displacement, Blue line: y-displacement, Yellow line: z-displacement)

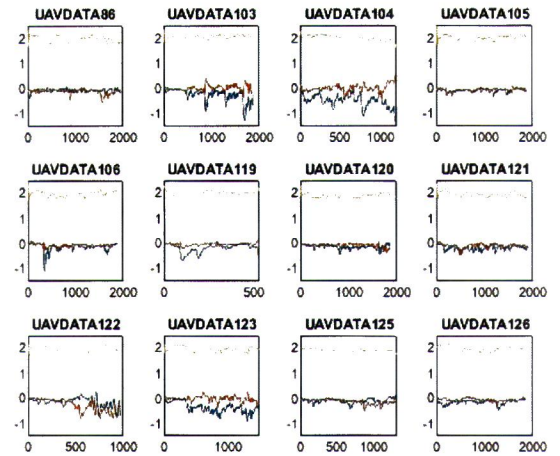


Fig. 3 Shortened flight data from Set B with displacement reading (m) versus 120Hz data points. (Red line: x-displacement, Blue line: y-displacement, Yellow line: z-displacement)

Fig. 4 shows the sample of data that contains more frequency of higher displacement occurred during the hovering state. In contrast, Fig. 5 displays the sample data which is more stable and contains the standard displacement of the quadrotor flight. The displacement of the quadrotor at a hovering state should be in a stable range, and the forces acting on it should be perfectly balanced. The pressures acting on a UAV remain steady over time in ideal environmental circumstances. As a result, the forces generated by rotating the UAV's propellers remain constant over time. However, the observations from Fig. 4 plotted in the signal analyzer MATLAB show that fluctuation happens in the hovering state.

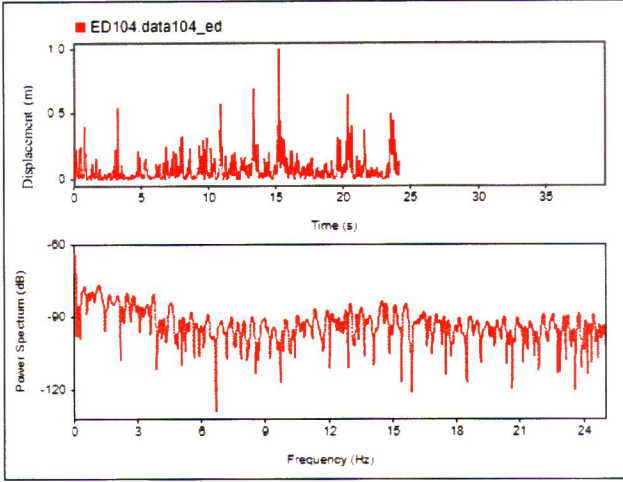


Fig. 4 Flight data with higher displacement during the hovering state.

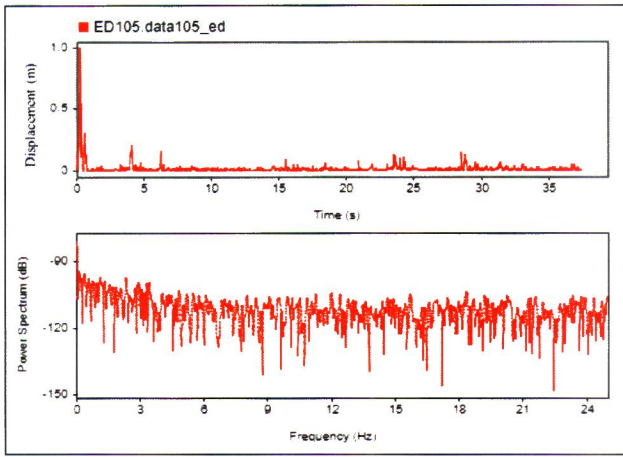


Fig. 5 Flight data with normal displacement during the hovering state.

C. Feature Identification

The vibration features can be identified by reviewing past research and journal literature as presented in Table I. There are plenty of ways to extract features. Pattern recognition can be implemented using time domain, frequency domain, and time-frequency domain analysis. Careful analysis is crucial to extract informative features from the flight data.

The extracted features in this study refer to time domain analysis and frequency domain analysis as shown in Table IV. The extracted features from time domain analysis are Euclidian distance, speed and acceleration. Meanwhile, from frequency domain analysis, the extracted features are the Fast Fourier Transform (FFT) value and Power Spectral Density of the signal in decibels(dB).

TABLE IV:
FEATURE PARAMETERS FROM TIME DOMAIN AND FREQUENCY DOMAIN ANALYSIS.

Time domain features extracted by:

Euclidian Distance

$$\sqrt{X_d^2 + Y_d^2 + Z_d^2}$$

$X_d = \text{Euclidian Distance of } X$
 $Y_d = \text{Euclidian Distance of } Y$
 $Z_d = \text{Euclidian Distance of } Z$

Speed

$$\sqrt{V_x(t)^2 + V_y(t)^2 + V_z(t)^2}$$

$V_x = \text{Speed on } X - \text{axis}$
 $V_y = \text{Speed on } Y - \text{axis}$
 $V_z = \text{Speed on } Z - \text{axis}$

Acceleration

$$\sqrt{\bar{a}_x(t)^2 + \bar{a}_y(t)^2 + \bar{a}_z(t)^2}$$

$\bar{a}_x = \text{acceleration on } X - \text{axis}$
 $\bar{a}_y = \text{acceleration on } Y - \text{axis}$
 $\bar{a}_z = \text{acceleration on } Z - \text{axis}$

Frequency domain features extracted by:

Fast Fourier Transform

$$\sum_{n=0}^{N-1} x[n]W_N^{nk}$$

Power Spectral Density

$$\lim_{n \rightarrow \infty} \frac{|X(W)|^2}{n}$$

Fig. 6 and Fig. 7 are the FFT signal and periodogram for power spectral density, respectively. Both are from the same sample of flight data.

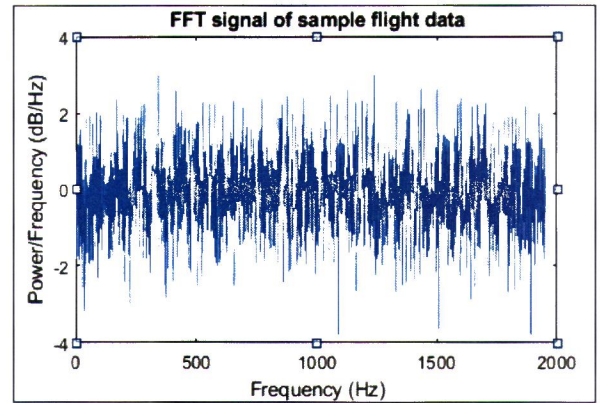


Fig. 6 The FFT signal of sample flight data.

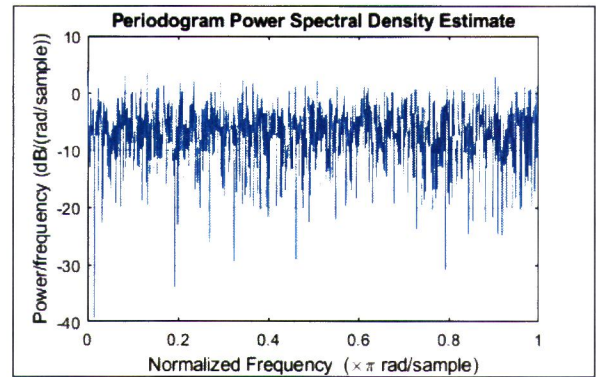


Fig. 7 The power spectral density of the same flight in Fig. 6.

D. Data Segmentation for Training and Testing

The actual data for each set is divided by 70% and 30% for training and testing data, respectively. This research uses flight data from previous research for wind tunnel experiments [13]. The data contain flight displacement information collected using an optical image measurement system on different wind tunnel frequencies for quadrotor

flight stability testing. The segmented structure will then store input-output pairs of data important for the classifier. The headings of the segmented files contain the inputs and the output of the processed flight data according to the pre-defined groups. The training and testing file headings must be similar for the predictors and responses identification when uploading to the MATLAB.

E. Prediction Model Execution

The classification learner app in MATLAB is employed to utilize the machine learning algorithm. To estimate the performance of any model, the k-fold cross-validation method was used. In example, the data set D is distributed into k equal portions, d_1, d_2, \dots, d_k . Each portion is randomly divided into two partitions to train and validate the algorithm. The process is repeated k times, and each of the k-th portion is used just once for data validation. Finally, the k-fold results are averaged to get a global evaluation of classification accuracy. The k-fold cross-validation is implemented automatically in the classification learner app in the MATLAB.

IV. RESULTS AND DISCUSSION

This section presents and discusses all the results achieved from this project. Visual observation on both datasets shows that fluctuations randomly occur in the displacement signals. This research approach has locally evaluated the flight data sample to determine their features and employed it for classification learning. The visualization of sample flight data shows that repeating outliers occurred in the vibration signal indicating noise signal. The extracted features ensure that classification learning can learn without irrelevant information. The following section is the result for both sets of flight data in detail.

A. Classification Results for Set A.

The confusion matrix summarizes the classifier model accuracy, which can show the value of the data that is classified correctly or incorrectly. The confusion matrix in Fig. 8 shows the DT classifier model training. DT classifier and NN classifier in Fig. 9 are the most accurate model for the training datasets from set A with an accuracy percentage of 98%.

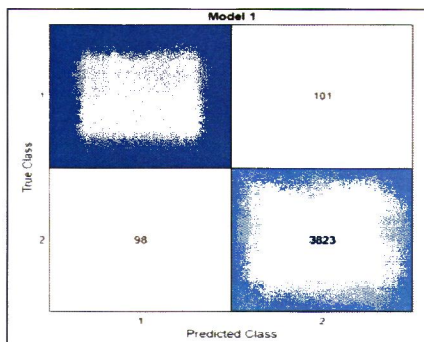


Fig. 8 The confusion matrix of Decision Tree model for Set A dataset.

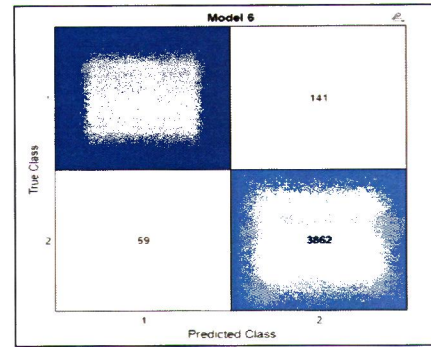


Fig. 9 The confusion matrix of NN model for Set A dataset.

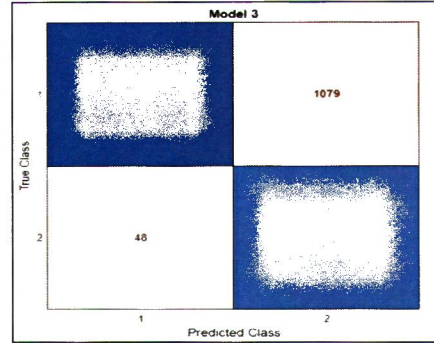


Fig. 10 The confusion matrix of LD model for Set A dataset.

However, the LD classifier model in Fig. 10 is not compatible with the classification of vibration signal data. The model misclassified the fault in the vibration signal as the normal vibration in the prediction model. This is because, despite being one of the most well-known classifiers, the classifier suffers from a singularity problem. If the dimensions are substantially more than the number of samples in each class, LD fails to calculate the discriminant functions in the singularity problem.

Table V shows the results of prediction model accuracy for training and testing. The best classifiers are the DT and NN models.

TABLE V:
SET A PREDICTION MODEL RESULT.

Classification model	Training	Testing
	accuracy results (%)	accuracy results (%)
Decision Tree	98.0	91.0
Linear Discriminant	64.2	51.6
Naïve Bayes	88.6	78.1
SVM	96.5	91.2
KNN	95.3	91.1
Neural Network	98.0	90.3

B. Classification Results for Set B.

The confusion matrix for the Set B training results is presented in Fig. 11 and Fig. 12. The latter is the lowest classifier score, the LD model. Set B contain a large amount of data compared to Set A. So, the classifier can learn more about the features and will be able to classify the data based on relevant features.

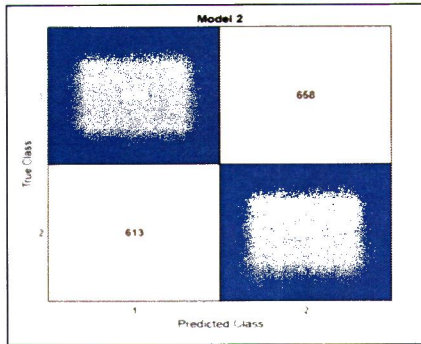


Fig. 11 The confusion matrix of the highest score for Set B - DT model.

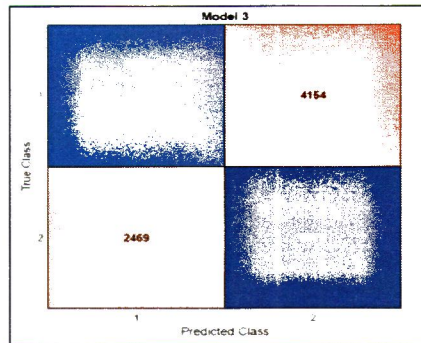


Fig. 12 The confusion matrix of the lowest score for Set B - LD model

Table VI shows the results of prediction model accuracy for the training and testing of set B for all classifiers. The most accurate is the Decision Tree classifier, with 93.3% accuracy for training and 94.7% accuracy for testing.

TABLE VI:
SET B PREDICTION MODEL RESULT.

Classification model	Training accuracy results (%)	Testing accuracy results (%)
Decision Tree	93.3	94.7
Linear Discriminant	65.0	74.9
Naïve Bayes	87.2	96.7
SVM	92.8	78.0
KNN	92.3	93.5
Neural Network	93.0	89.3

C. Results Comparison between Set A And Set B.

The results obtained for the Set A and Set B datasets are comparable. The amount of data in both sets differs, where Set B has more extensive data than Set A. The smaller number of data impacts the classifier by reducing the model's accuracy or causing the model to be overfitting and underfitting. Overfitting happens when the training result has a low error rate but testing data employed to the model gives a higher error rate. Then, the underfitting happens when the model can neither learn the training data perfectly nor generalize to the new data. The most accurate classifier model for both data sets is the DT and NN.

V. CONCLUSION

UAV flight performance and efficiency rely on various factors. Flight instabilities can happen due to malfunctions inside the system and disturbances from the external

environment. Battery status plays a significant role towards healthy flight conditions. A weak battery will affect the performance of propellers and motors, and the presence of wind disturbance can contribute towards inefficient flying capabilities. Therefore, investigation of fault at the early stage is crucial to maintain the great performance of the UAV. This paper investigates how to classify battery level based on displacement features using classification learning algorithm. Informative features for the flight condition have been classified using time and frequency domain parameters. The extracted features include Euclidian distance, speed, acceleration, Periodogram Power spectral density, and Fast Fourier Transform. The result shows that the best classifier algorithms for the selected features are the Decision Tree and Neural Network models.

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