A Sound Based Method for Fault Classification with Support Vector Machines in UAV Motors

Ferhat Yol[1], Ayhan Altınors[2], Orhan Yaman[3,*]
[1,2]Department of Electronics and Automation, Vocational School of Technical Sciences, Firat University, Elazig, Turkey
[3]Department of Digital Forensics Engineering, Technology Faculty, Firat University, Elazig, Turkey

***Abstract*—In this study, a machine learning-based method is proposed for Brushless DC (BLDC) motors used in unmanned aerial vehicles (UAV). Shaft failure, magnet failure, propeller failure, and bearing failure are common failures in BLDC motors. These fault types are created on UAV engines. Sound recordings were taken from the engines for each failure type. While collecting the dataset, the motors were run at a constant speed. First of all, sound data was collected for the sound engine. Then, fixed time-length audio recordings were taken for 4 fault classes at a constant speed and a data set was created. This dataset consists of five classes. In order to reduce the data size in these sounds, Average Filter, Average Polling, and Normalization processes were applied, respectively. Then, the Chi2 Method was used for feature selection. In the next step, the Support Vector Machine (SVM) algorithm is used to classify the obtained features. In classification, 96.70% accuracy was calculated with the Cubic SVM algorithm.**

***Index Terms*— Brushless motors, Fault detection, Machine learning, Support vector machines, Unmanned aerial vehicles.**

I. INTRODUCTION

BLDC motors are used frequently especially in UAVs due to their simple and frequent maintenance-free structures and high power-volume ratios. High-speed motors are used in propeller UAVs such as quadcopters, octocopters, helicopters and other open-wing electrically operated UAVs. Due to the developing technologies, high speed BLDC motors can be produced. These developments also increase the usage areas of UAVs. UAVs are used in areas such as Military reconnaissance, Cargo transportation, Meteorological Observation and Civil aerial photography [1–3]. The high cost of UAVs and other electronic equipment such as cameras they carry can lead to huge economic losses in a possible accident. In addition, the fact that UAVs fly in regions with high human population creates a huge potential risk for a possible accident. In addition, the malfunction of UAVs used for military purposes is undesirable and leads to strategic losses. For these reasons, condition monitoring and fault detection is an important issue in UAVs. There are many studies in the literature for fault detection and diagnosis of BLDC motors. In these studies, generally current, voltage, vibration and sound based methods have been developed. Cheng et al. [2] developed a vibration-based method for diagnosing quadcopter failures in his study. In the model he developed, he extracted features from the three axis vibration data he received from the Accelerometer using RMS, Sample Entropy and Standard Deviation algorithms. Later, he achieved an accuracy of 96.98% and 99.24% in the Self Organization Map (SOM) model, which he developed using 3 axis accelerometer data. Sadhu et al. [4] developed a Neural Network-based method for Fault Detection and Identification. Using Bi-LTSM and CNN, flight data were classified and diagnosed. In the experiments, it was possible to detect malfunctions with 99.00% accuracy in simulation data and 85.00% in real time experimental data. Lu et al. [5] proposed a deep learning-based method for troubleshooting UAVs. In the method he developed, the increase in motor temperatures and acceleration were monitored and fault predictions were made. Pourpanah et al. [6] made a diagnosis by using motor currents in their study named "Anomaly Detection and Condition Monitoring of UAV Motors and Propellers". In the developed method, feature extraction from harmonics of motor currents was classified by methods such as CART, KNN, NB and QFAM-GA. 95.34% accuracy was achieved in the proposed method. Keipour et al. [7] used the Recursive Least Squares method to detect abnormalities in UAVs. In the method he developed, an accuracy of 88.23% was obtained. Titouna et al. [8] used Kullback-Leiler Divergence (KLD) and Artificial Neural Networks to detect errors in UAVs. Liu et al. [9] used Convolutional Neural Networks (CNN) to detect the damage of the propellers due to the noise created by the propellers in the method he proposed in his study named "Audio-Based Fault Diagnosis Method for Quadrotors". He achieved 90% accuracy in the model developed. Bondyra et al. [10] used signal processing methods using SVM with IMU data for Fault Diagnostic and Condition monitoring. In the literature, many similar methods such as motor current measurement, vibration measurement and sound measurement are used for motor fault detection [11–15]. In sound-based methods, motor sounds are listened continuously by placing a microphone close to the motor. Various malfunctions that may occur in the motor can be detected by analyzing the obtained sound data.

Our motivation in this study is to collect acoustic dataset from Brushless DC motors and propose a machine learning based method. The dataset obtained from the motors consists of five different classes. Noise reduction and size reduction were performed on these sound signals with Mean Filter, Average Polling and Normalization. Then, feature extraction was made with the Chi2 method. After the feature selection step, the classification was made using the SVM algorithm. One of the main contributions of the proposed method is that

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*Corresponding author: orhanyaman@firat.edu.tr

it is a lightweight method. Thus, an architecture that can work in real time on the embedded system is presented.

II. MATERIALS

In this study, 820KV BLDC motors are used to create the sound dataset. These BLDC motors are commonly used 2212 Series BLDC motors those are generally used in drones, model aircraft and other UAVs. These motors accelerate to approximately 820 RPM per volt. Since motors with higher KV values go to higher rpm with the same voltage, the current required by the motor increases. Since the high current requirement will cause the motor and drivers to heat up during the tests, motors with low KV values have been specially selected. The low KV value of the motors reduced the current required by the motor during the tests. The technical characteristics of the motor used are given in Table 1.

TABLE 1. TECHNICAL SPECIFICATIONS OF THE USED MOTOR

Operating voltage	2-3S Lipo (7.4V-11.1V)
Max. Operating Current	12A
Max. Power	144W
KV Value	820KV
Max. RPM	9840RPM
Weight	50gr
Sizes	28x29mm
Shaft Diameter	3.17mm

In UAVs, according to the size of the aircraft, the amount of load will be carried and the purpose of use, different sized propellers are used. Generally, propellers such as 8x4.5, 10x4.5 or 12x4.5 are used. The first parameter given in the propellers represents the propeller diameter and the second parameter represents the pitch angle. In the researches, the most common faults occur in BLDC are Bearing Failure, Balance Failure, Propeller Failure, Magnet Failure. In particular, the propellers are damaged in the event of a possible accident and cause vibrations on the UAV. Also, the motor shaft can be bent in case of severe impact. On the other hand, since BLDC motors operate at very high speeds and the motor windings and bearings come into direct contact with air, the bearings can be damaged in a short time. In Fig.1, the most common balance failure and bearing failure can be seen.

Android phones have been preferred to receive audio data due to the stereo sound recording feature and the ability to change the recording parameters, AAC (M4A) format, Sample Rate 16000Hz and Encoder Bit Rate 128 kbps are used for audio recording. For this application, 5 different classes were determined, the first one being a healthy motor and the other four belonging to defective motors. In the first step, the robust motor without any malfunction was operated for five minutes and sound recording was taken. The characteristics of the sound data sets received from motors are given in Table 2.

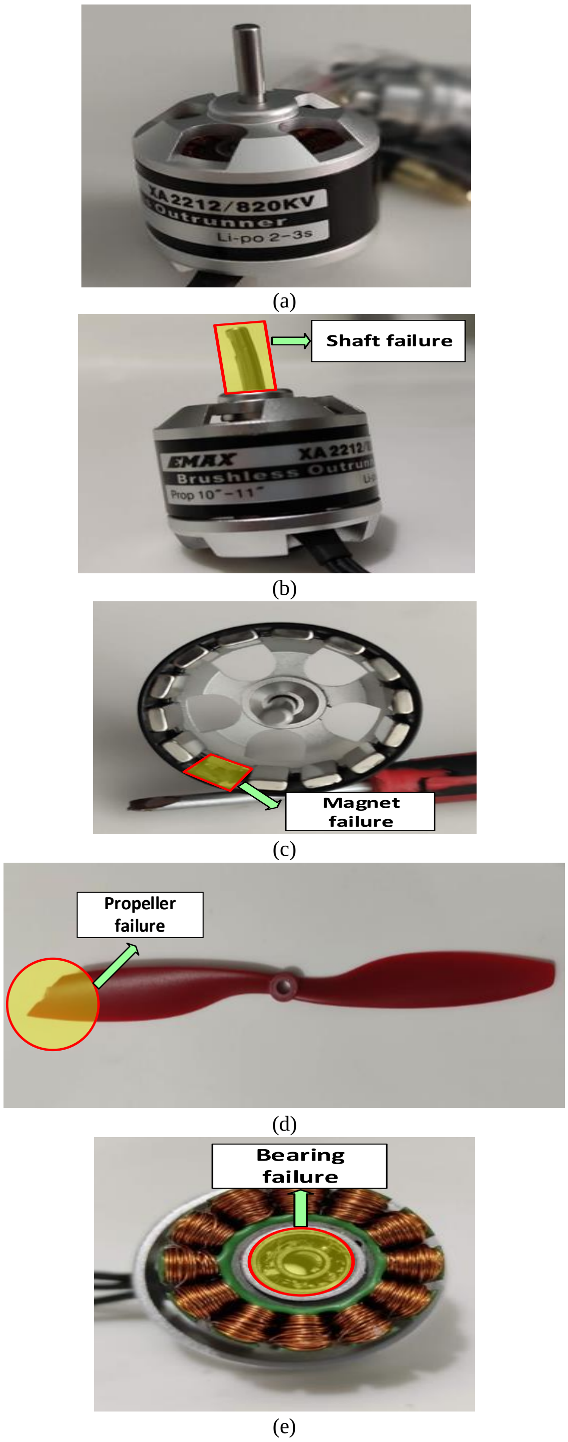
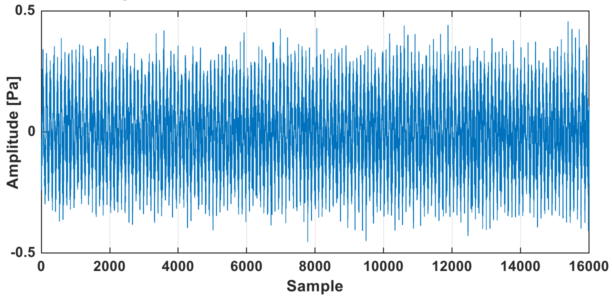


Fig.1. Images of the healthy and the defective motors (a) Healthy motor (b) Balance (Shaft) failure (c) Magnet failure (d) Propeller failure (e) Bearing failure

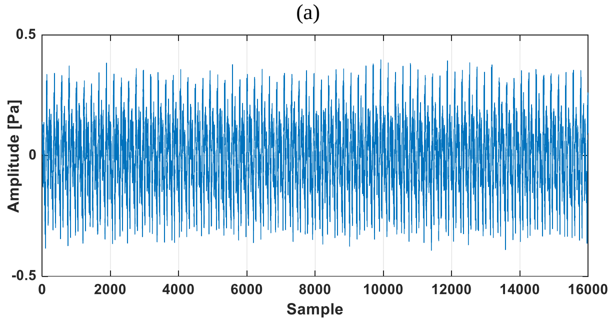
TABLE 2. CHARACTERISTICS AND CLASS INFORMATION OF THE COLLECTED SOUND DATA SET

Class Number	Class Definition	Duration (min)	Number of samples
Class 1	Healthy	5	300
Class 2	Balance Failure	5	300
Class 3	Magnet Failure	5	300
Class 4	Propeller Failure	5	300
Class 5	Bearing Failure	5	300

In the motor failure data set, 300x16000 data were obtained by recording five minutes, ie 300 seconds, for each class. Thus, 1500x16000 data were obtained for 5 classes. Sample sound signals obtained from the microphone are shown in Fig.2



(a)



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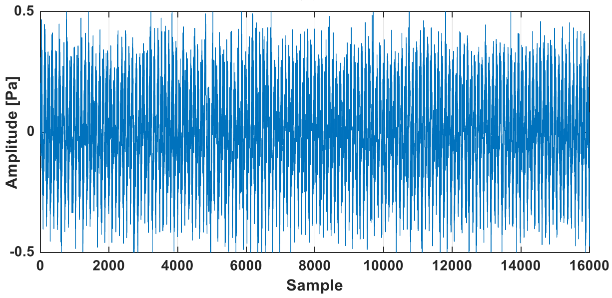

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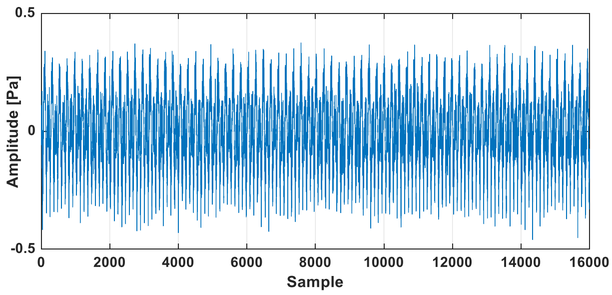

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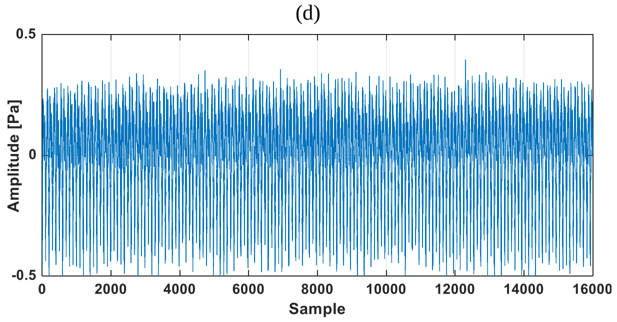

(e)

Fig. 2. Sound samples collected for fault detection (a) Healthy, (b) Balance Failure, (c) Magnet Failure, (d) Propeller Failure, (e) Bearing Failure

III. PROPOSED METHOD

In this study, a sound based fault detection method is proposed for brushless motors which are widely used in UAV motors. First of all, balance, magnet, propeller and bearing failures were created in 820 KV brushless motors. Then, the operating sounds of the healthy and the defective motors were collected using a microphone. The block diagram of the proposed method is shown in Fig.3.

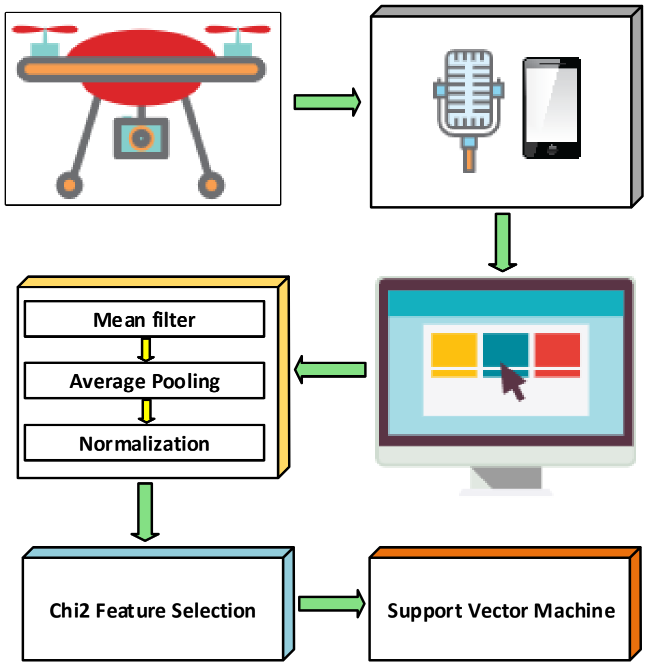

Fig. 3. Block diagram of the proposed method

As seen in Fig.3, the sound data is collected by mobile phone and transferred to the computer, and the proposed method has been applied. Five-minute sound recordings were collected separately for healthy and defective classes. Five-minute audio recordings were divided into one second each. Thus, 300 samples were obtained for each class. 16000Hz sampling was used while recording sounds. As a result, 300x16000 samples were obtained for each class. The proposed method consists of three stages. In the signal pre-processing step, noise cleaning, pooling and normalization are performed from the sound signals. Median Filter is used for noise removal. After the Median Filter process, the size of the signal was reduced by applying Average Pooling. As a result of the average pooling process, 300x2000 samples were obtained for each class. A total of 1500x2000 samples are available for the five classes. The purpose of applying Average pooling to sound signals is to increase the classification speed by decreasing the signal size. Normalization was applied after the average pooling process. Thus, both signal preprocessing and feature extraction were performed. After feature extraction, Chi2 method was used to calculate the best properties. Among the possible features that may affect the result, the highest quality ones are selected by certain mathematical operations and used in the classification process [16]. The observed (O) and expected (E) values are evaluated and the degrees of freedom (c) of the values are determined in the Chi-Square method. The mathematical equivalent of the Chi-Square algorithm is given in Equation 1.

$$x_c^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

Using the Chi2 feature selection method, the best 32, 64, 128, 256, 512 and 1024 features were selected among 2000 features. These selected features are classified with Quadratic SVM, Cubic SVM and Medium Gaussian SVM algorithms. Classification success is given in Fig.4.

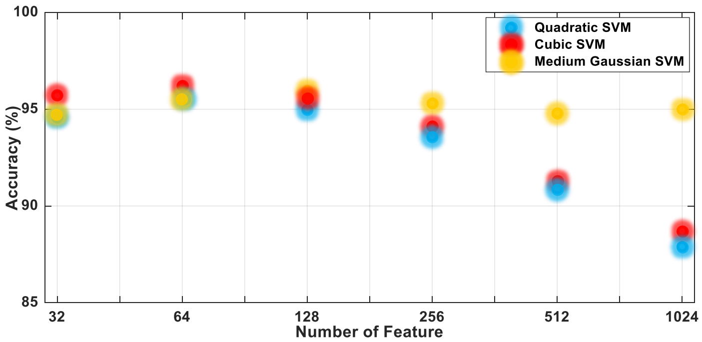

Fig. 4. Classification results of the most weighted features selected

As can be seen in Fig.4, the best success in classification algorithms was achieved when 64 features were selected. For this reason, the best 64 properties were selected while obtaining results in the proposed method.

IV. Results

In this study, MATLAB 2020A software was used for implementing the proposed method and calculating the results. Classification Learner Toolbox was used to obtain machine learning results. The results were obtained from a computer with 32GB RAM, Windows 10-64 bit with i7-3.00 GHz processor. Quadratic SVM, Cubic SVM and Medium Gaussian SVM are used in the proposed method. Box constraint level: 1, kernel scale mode: auto and multiclass method: one-vs-one parameters are used for Quadratic SVM. Box constraint level: 1, kernel scale mode: auto and multiclass method: one-vs-one parameters are used for Cubic SVM. Box constraint level: 1, kernel scale mode: manual, manual kernel scale: 8 and multiclass method: one-vs-one parameters are used for Medium Gaussian SVM [17–19]. Confusion matirx results obtained in the proposed method are shown in Fig.5.

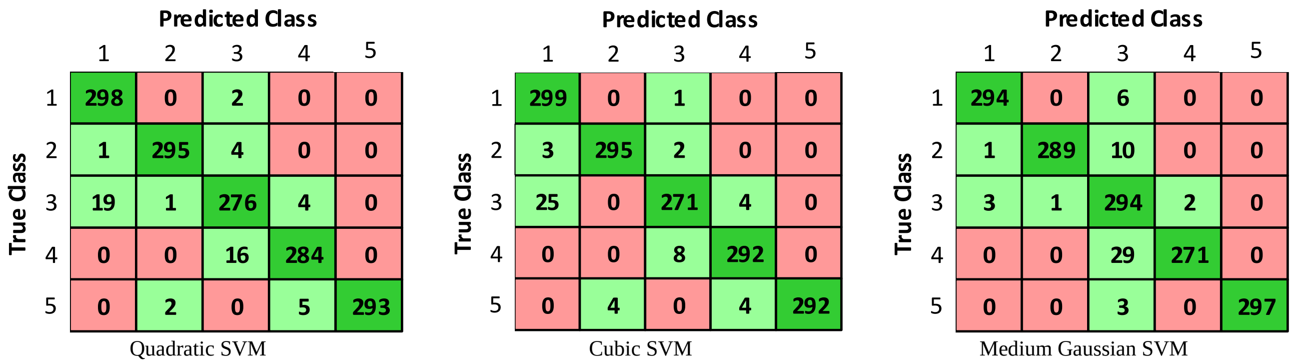

Fig. 5. Confusion matrix results obtained with the proposed method

In the confusion matrix given in Figure 5, the first class represents a healthy, the second class represents a balance failure, the third class represents a magnet failure, the fourth class represents a propeller failure, and the fifth class represents a bearing failure. As can be seen from the Confusion matrix, the best result for healthy motor and propeller failure is calculated with Cubic SVM. The best result for balance failure is calculated with both Quadratic SVM and Cubic SVM. The highest result for magnet and bearing failure was achieved with Medium Gaussian SVM. Accuracy, Precision, Recall, Geometric mean and F-Score results are calculated using True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) values obtained in Confusion matrix. These statistical parameters are given in equation 2-6.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$Geometric\_mean = \sqrt{\frac{TP * TN}{(TP + FN) * (TN + FP)}} \tag{5}$$

$$F - Measure = \frac{2TP}{2TP + FP + FN} \tag{6}$$

In the proposed method, the best Accuracy, Precision, Recall, Geometric mean and F-Score results were calculated by running the classification step of 1000 iterations. The results obtained are given in Table 3.

TABLE 3. ACCURACY, PRECISION, RECALL, GEOMETRIC MEAN AND F SCORE RESULTS OBTAINED BY RUNNING 1000 ITERATIONS

Classifiers	Statictic	Accuracy	Precision	Recall	Geometric mean	F-Score
Quadratic SVM	Max	96.40	96.44	96.40	96.36	96.42
	Min	94.66	95.49	95.40	95.34	95.44
	Mean	95.54	96.34	96.29	96.25	96.32
	Std	0.26	0.10	0.10	0.11	0.10
Cubic SVM	Max	96.60	96.70	96.60	96.54	96.65
	Min	95.26	96.27	96.13	96.05	96.20
	Mean	96.00	96.64	96.548	96.47	96.59
	Std	0.22	0.03	0.03	0.04	0.03
Medium Gaussian SVM	Max	96.33	96.70	96.33	96.28	96.52
	Min	94.93	95.98	95.46	95.40	95.72
	Mean	95.71	96.69	96.31	96.26	96.50
	Std	0.21	0.05	0.05	0.05	0.05

As seen in Table 3, the best result was calculated with the Cubic SVM algorithm with an accuracy of 96.6%. Accuracy was calculated as 96.4% with the Quadratic SVM algorithm and 96.33% with the Medium Gaussian SVM algorithm. The results calculated in Table 3 were obtained with 10 Fold Cross Validation. In the proposed method, the results obtained by running Fold by Fold are shown in Fig.6.

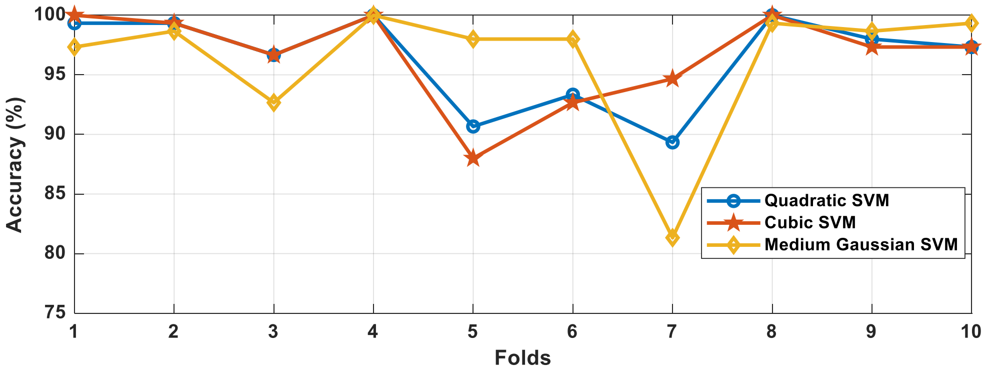

Fig. 6. Fold by Fold results of the proposed method

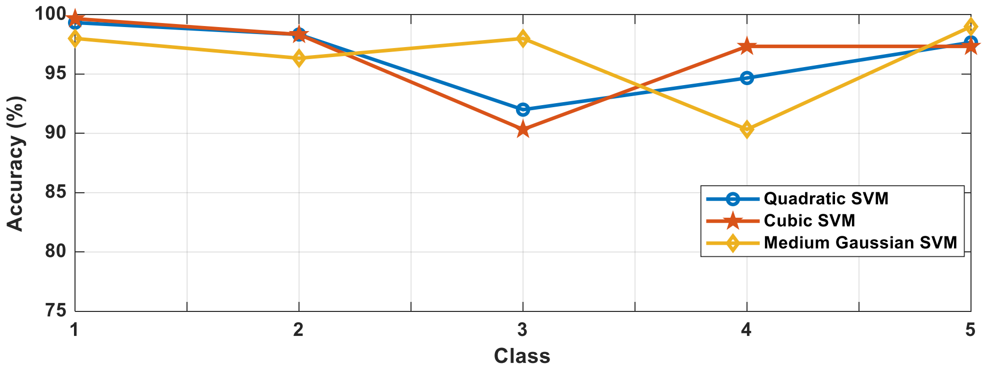

Fig. 7. Class by Class results of the proposed method

All of the Fold by Fold results given in Fig.6 are higher than 80%. Among the three classification algorithms, the best results were calculated in Fold-4 and Fold-8. In addition, accuracy values were calculated by running the proposed method Class by Class. Class by Class results are shown in Fig.7.

As can be seen in Fig.7, for all five classes, all results were calculated with an accuracy higher than 90%.

V. CONCLUSION

In this study, a method for detecting the failure of brushless motors used in Unmanned Aerial Vehicles (UAV) is proposed. Balance, magnet, propeller and bearing failures were created in 820 KV brushless motors. In addition, a data set was created for five classes by collecting sound data, including a healthy motor. Signal pre-processing was performed by applying a median filter, average pooling and normalization on the sound data. After the signal pre-processing step, the best 64 features were selected by using the Chi2 feature selection algorithm. Selected features are classified using the Support Vector Machine (SVM) algorithm. The accuracy was calculated 96.4% with Quadratic SVM, 96.6% with Cubic SVM and 96.33% with Medium Gaussian SVM. The proposed method was tested with many machine learning algorithms and the results were calculated. In the study, SVM algorithm was preferred because the highest accuracy value was calculated by SVM algorithm.

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