Fırat Üniversitesi Deneysel ve Hesaplamalı Mühendislik Dergisi

Dalgacık Dönüşümü Tabanlı Özellikler Kullanarak Fırçasız DC Motor Seslerinin Makine Öğrenmesi Yöntemleri ile Analizi

Bilal TEKİN[1], Turgay KAYA[2*]

[1,2]Elektrik-Elektronik Mühendisliği Bölümü, Mühendislik Fakültesi, Fırat Üniversitesi, Elazığ, Türkiye.
[1]bilaltekin4931@gmail.com, [2]tkaya@firat.edu.tr

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Öz

Fırçasız DA (BLDC) motorlar, yüksek verimlilikleri, güvenilirlikleri ve düşük bakım gereksinimleri nedeniyle çeşitli uygulamalarda yaygın olarak kullanılmaktadır. Bu motorlar, mekanik fırçaların bulunmaması nedeniyle daha az aşınma ve düşük bakım gereksinimi sağlar. Bu özellikleri, özellikle endüstriyel otomasyon, elektrikli araçlar, robotik sistemler gibi birçok alanda tercih edilmelerini sağlar. Makine öğrenimi (MÖ) ile BLDC motorlarının entegrasyonu, bu motorların verimliliğini, güvenilirliğini ve performansını önemli ölçüde artırabilir. ML algoritmaları, motorun performans verilerini analiz ederek arızaların önceden tespit edilmesine yardımcı olabilir. Motorun normal çalışma koşullarından sapmalarını izleyen ML algoritmaları, arızalı durumları hızlı bir şekilde tanımlayabilir. Makine öğrenimi, motorun çalışma koşullarına bağlı olarak en verimli çalışma noktalarını öğrenebilir ve buna göre motorun hızını veya diğer parametrelerini dinamik olarak optimize edebilir. Bu çalışmada ses analizi ile BLDC motorlarındaki mekanik arızaların tespit edilmesini sağlayan bir yöntem önerilmektedir. Ses analizi ile normal ve arızalı motorların ses kayıtlarından Ayrık Dalgacık Dönüşümü (ADD) tabanlı özellikler çıkarılmış ve elde edilen özellikler makine öğrenimi yöntemleriyle sınıflandırılmıştır. Burada, ADD ile veri boyutu azaltılmıştır, istenmeyen ve önemsiz katsayılar baskılanmıştır. Elde edilen yeni verilerle aşırı uyumdan kaçınacak Bagging trees kullanılmıştır. Bagging, birden fazla karar ağacını birleştirerek her ağacın aşırı uyum sağlama eğilimini dengelemeye çalışır ve modelin genelleme kapasitesi artar. Ayrıca, her model bağımsız olarak eğitildiği için paralel hesaplamaya imkân sağlar. Elde edilen model ile %89.205 doğruluk, 0.821 kappa değeri elde edilmiştir.

Anahtar kelimeler: Fırçasız doğru akım motoru, Ayrık dalgacık dönüşümü, Makine öğrenmesi, Arıza tespiti

*Yazışılan Yazar

İntihal Kontrol:Evet– Turnitin
Şikayet: fujece@firat.edu.tr
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Analysis of Brushless DC Motor Sounds with Machine Learning Methods Using Wavelet Transform Based Features

Bilal TEKİN[1], Turgay KAYA[2*]

[1,2]Electrical and Electronics Engineering Department , Faculty of Engineering, Firat University, Elazig, Türkiye.

[1]bilaltekin4931@gmail.com, [2]tkaya@firat.edu.tr

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Abstract

Brushless DC (BLDC) motors are widely used in various applications due to their high efficiency, reliability and low maintenance requirements. The absence of mechanical brushes reduces wear and minimizes maintenance. These features make them preferred in many areas, especially industrial automation, electric vehicles, and robotic systems. Integration of a BLDC motors with machine learning (ML) can significantly increase the efficiency, reliability and performance of these motors. ML algorithms can help detect faults in advance by analyzing the performance data of the motor. ML algorithms, which monitor deviations from the normal operating conditions of the motor, can quickly identify faulty situations. ML can learn the most efficient operating points depending on the operating conditions of the motor and dynamically optimize the speed or other parameters of the motor accordingly. In this study, a method is proposed that enables the detection of mechanical faults in a BLDC motors with sound analysis. With sound analysis, Discrete Wavelet Transform (DWT) based features were extracted from the sound recordings of normal and faulty motors and the obtained features were classified with machine learning methods. Here, the data size is reduced with DWT, unwanted and unimportant coefficients are suppressed. Bagging trees are used to avoid overfitting with extracted statistical features. Bagging tries to balance the overfitting tendency of each tree by combining multiple decision trees and the generalization capacity of the model increases. In addition, since each model is trained independently, it allows parallel calculation. With the obtained model, 89.205% accuracy and 0.821 kappa value were obtained.

Keywords: Brushless DC motors, Discrete wavelet transform, Machine learning, Fault detection

*Corresponding author

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1. Introduction

Troubleshooting is critical to the continued and smooth operation of an industrial system. A brushless DC electric motor is a synchronous motor that uses direct current (DC).It is also known as a commutated motor. It started to become widespread in the 1960s [1]. A BLDC motor offers high power density, efficiency, and low noise levels. For this reason, they are used in industrial control systems, automotive, robots and white goods areas [2-4]. The presence of permanent magnets instead of windings in the rotor has reduced the weight and volume of the motor in addition to reducing losses [5]. In addition, BLDCs have complex control circuits and are expensive. They also need location information [6-8]. In these motors, where precise speed and position control can be made, it is important to detect the fault in advance so that any fault does not affect the sensitivity of the motor.

BLDC motor is frequently preferred in variable speed applications because it has high starting torque. It emits low acoustic noise due to the absence of brush friction [1,9]. A BLDC Motor is used in devices such as Electric vehicles, Hybrid vehicles, Industrial robots, Washing machines, Conveyors, Fans. Malfunctions occur in a BLDC Motor, just like other machines, and it is very important to follow these malfunctions in order to return them to normal operating conditions as soon as possible [10]. Intelligent techniques (AI) have been successfully used for fault diagnosis in machines.

In the study Ref. [11], NN classifies healthy and faulty conditions by analyzing the stator current and rotation speed of the motor. In [12], stator current and lateral vibration measurements were used to extract meaningful features by wavelet transform to identify bearing faults in BLDC under variable operating conditions. [13] presents a bearing failure analysis of BLDC motors. The vibration signal of both healthy and defective bearings was analyzed by identifying specific frequencies in the vibration spectrum. A recurrent neural network was then used to detect and classify the presence of bearing faults. Khan et al has contributed to the detection and classification of faults in electric vehicle interface connections by ML tools [14].

Sarman et al. presents a fault diagnosis method for brushless direct current motor drives using hybrid ML models, achieving 98.8% accuracy in detecting open circuit and short circuit faults [15].

In [16], SAC-DM technique was applied to diagnose malfunctions in electromechanical systems from audio signals through tests performed on a small BLDC motor. Wavelet Multiresolution Analysis (WMA) has been used to separate a chaotic signal component from the noise emitted by the engine. Similarly, 92% accuracy rate was achieved in the prediction of BLDC motors by using audio signal processing and ML models for preventive maintenance planning [17]. To estimate the remaining service life of BLDC motors, a prediction with 88% accuracy was made using the Random Forest algorithm [18].

In this proposed study, high and low frequency components in data will be separated by using DWT. Then, statistical features will be obtained, data size will be reduced and new features will be extracted. The new features obtained will be analyzed with ML methods, success metrics for the BLDC failure situation will be obtained and interpreted.

The workflow consists of the material and method part (dataset, used method steps) in section 2, the experimental results part in section 3 and finally the conclusions part.

2. Material and Method

2.1. Dataset

The dataset, used in this work, comprises of 43 .wav files and approximately 10 seconds each. In addition, sampling frequency is 16 kHz containing the sound of four A2212 BLDC motors [19]. Dataset comprises of healthy motors, propeller failure and bearing failure types. These categories number of file sizes are listed in Table 1 and samples are shown in Figure 1. The sound of an engine varies depending on whether the various components are working properly. The sounds of normal, bearing faulty and propeller faulty engines are different as each type of fault affects the operating dynamics of the engine differently. The sound of a properly operating engine is constant and smooth (Figure 1a). The sound of a Propeller Faulty Engine is low, muffled, irregular and may have increased vibration (Figure 1b). The sound of a bearing faulty engine is high-pitched, humming and irregular (Figure 1c).

Table 1. Number of file sizes dataset

Sound Type	Number of File Sizes
Healthy Motor	20
Bearing Motor	7
Propeller Motor	16

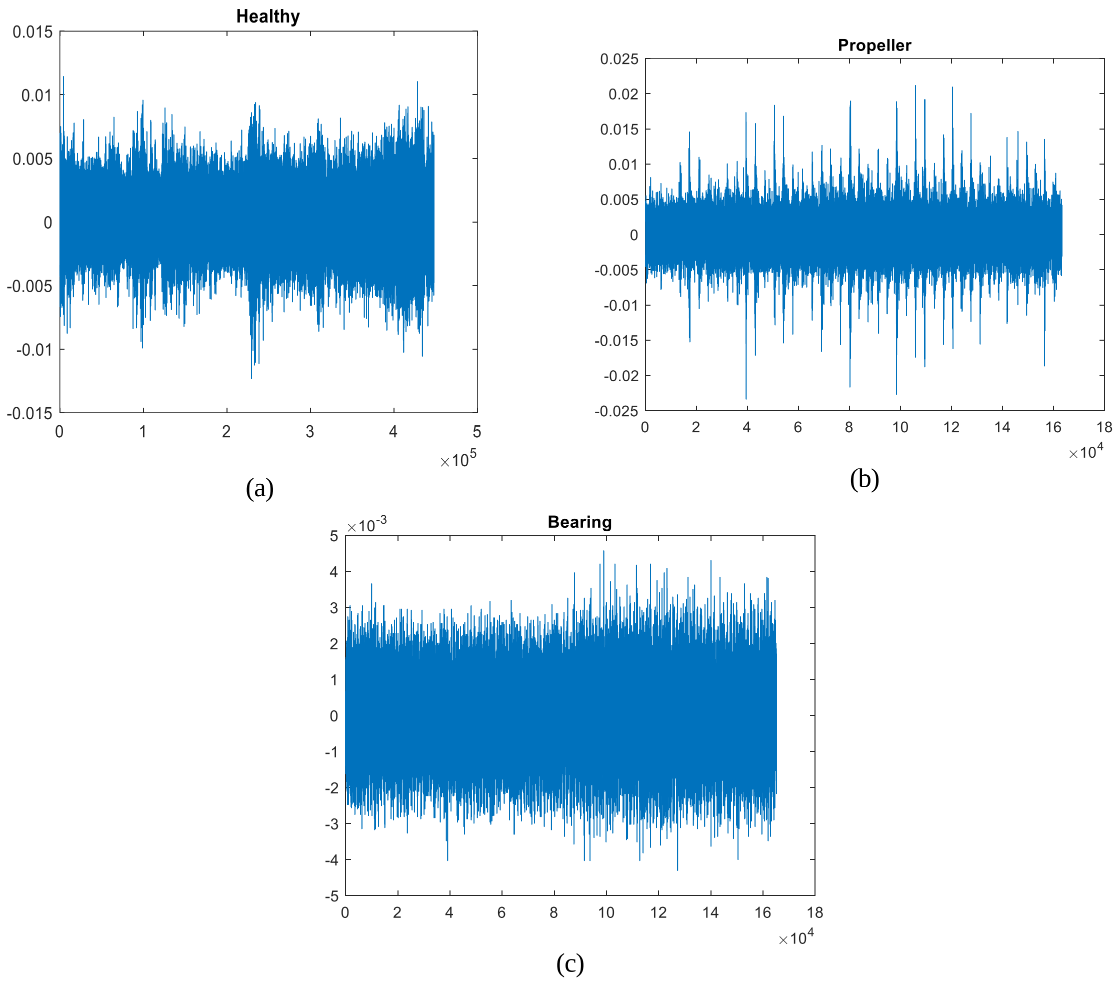


Figure 1. (a) Healthy, (b) propeller failure and (c) bearing failure motor sound samples

2.2. Application of flow chart

The dataset used in the study was taken as ready. In case of using a real-time system, external factors such as ambient noise will affect the analysis. Filtering techniques can be used to minimize these factors, increase the reliability of the system and reduce errors (low pass, Kalman filter, Wiener filter). To reduce electromagnetic noise, devices and sensors can be protected with special shields, the signal can be converted to the frequency domain and unwanted frequency components can be separated. Each approach can be customized according to the application area and the characteristics of the system.

As the dataset comprises audio signals, numerical conversion is required for feature extraction. Feature extraction is performed with DWT from signals belonging to different categories received from the

BLDC motor. After the signals are processed, the features obtained are classified with ML methods and engine error detection is made. Performance evaluation is made for new data entry with the model obtained by ML. The flow chart of the proposed model is given in Figure 2. WT is a signal processing method used in the analysis of stationary and non-stationary signals. While only frequency information is obtained with this analysis performed in Fourier Transform, frequency and time information of the signal can be obtained with WT [20-22]. Since optimum time-frequency resolution can be achieved in all frequency ranges of WT, it enables the analysis of systems with time-varying frequencies and temporal analyzes to be performed precisely. This allows analysis to be done quickly and easily [23]. DWT is an important tool in signal processing applications because it can efficiently capture local and global features of signals [24]. DWT separates the signal at each level into an approximation and detail component using wavelet functions. This provides the opportunity to discard the less informative part of the data for each level. If DWT is applied at more than one level, it gradually reduces the data size. Approximation coefficients at lower levels carry more information and detail coefficients at higher levels usually contain unnecessary details. It is possible to compress the data by resetting these details.
The detail coefficients obtained after DWT can usually be noise or very low frequency details. These coefficients can be reduced to zero or low values. Coefficient thresholding serves to remove such low value coefficients and keep only the most significant components. After the unnecessary coefficients are zeroed out, the data is reconstructed using inverse DWT. The reconstructed data is reduced in size and compressed but retains important information.

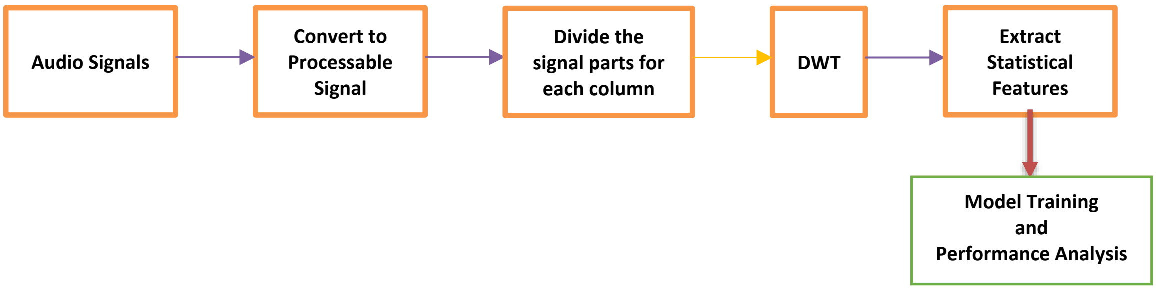
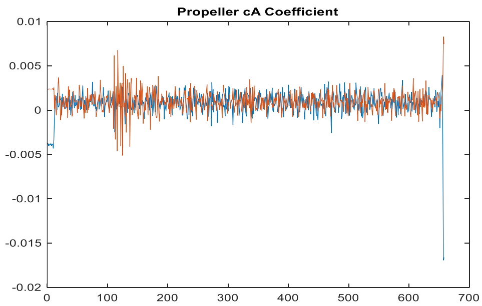
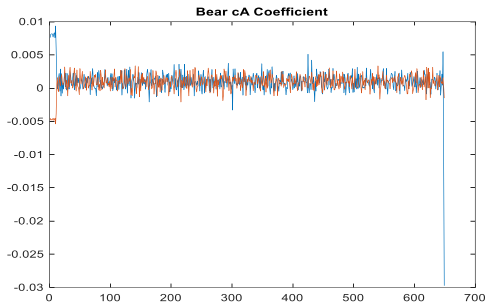


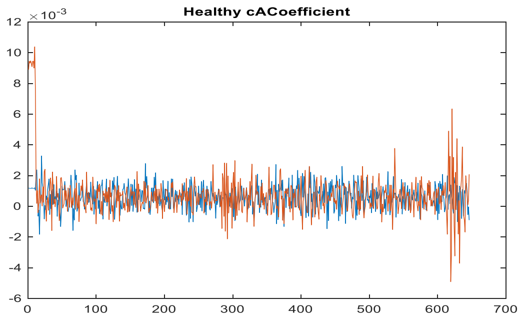
Figure 2. The flow chart of the proposed model



(a)



(b)



(c)

Figure 3. Wavelet coefficients of each data types ((a) propeller (b) bearing and (c) healthy)

In this work, to have a large number of features and to obtain efficient results with ML, each of the two-column data entries was divided into two segments for feature extraction. Wavelet transform was applied to four separate parts and their statistical properties were obtained. 7. Level Db7 is used. Wavelet coefficients of each data types are given in the Figure 3. Since there were different numbers of files for each species in the original data set, the data numbers were obtained as in the Table 2.

Statistical features refer to various measurements used to summarize and analyze a data set. After DWT, extracted statistical features which are mean, median, max, min, range, std, mad and norm as shown in Table 2. Mean is the value obtained by dividing the sum of all values in a data set by the number of observations. The mean indicates the central tendency of the data set. Median is the middle value when the values in a data set are ranked. The median determines the central tendency of the data set and is not affected by outliers. Mode is the most frequently occurring value in a data set. The mode is frequently used for categorical data. Standard Deviation measures how much the values in a data set spread around the mean. A higher standard deviation indicates that the values in the data set are more dispersed than the mean. Variance is the square of the standard deviation. It refers to the overall variability of the distribution of the data set. Minimum and Maximum Values are the smallest and largest values in the data set. The norm of a matrix is a scalar that gives some measure of the magnitude of the elements of the matrix. After statistical properties are obtained, normalization is performed to make the data uniform. Z-score was used as normalization. The normalized values are shown in Figure 4. The extracted features size is listed in Table 2, after DWT and extracted statistical features. Also, the related labels are given in Table 2.

Table 2. The extracted features size and used statistical features

Sound Type	Extracted Statistical Features Sizes	Label	Used Statistical Features	
Bearing Motor	28*11	0	Mean	Range
Healthy Motor	88*11	1	Median	Std
Propeller Motor	60*11	2	Maximum	Mad
Total	176*11		Minimum	Norm

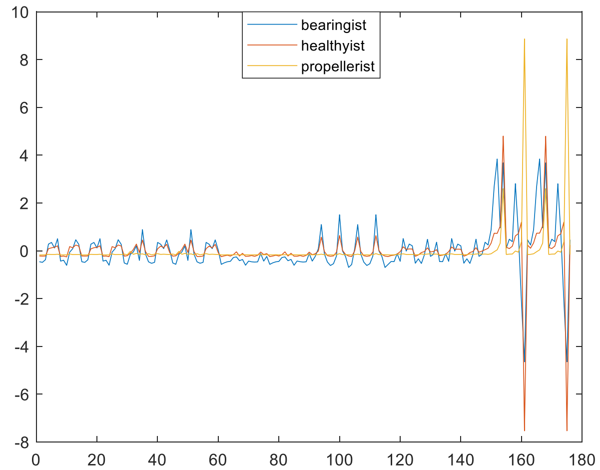


Figure 4. The normalized values for each data

ML is a field that enables AI to use data and different algorithms to mimic the human learning process and improve its accuracy. ML system; It consists of the steps of decision making, generating error function and updating weights. Classification, one of the ML applications, is a supervised ML process. With ML, a classification problem can be performed on used or unused data to accurately predict whether the data will fall into relevant categories. Classification algorithms refer to ML algorithms used to classify data into specific categories. Each of these algorithms may be more suitable for a specific data set and application. Logistic regression is a linear classification model and is usually used in binary classification problems [25]. Decision trees are a model that classifies data by dividing it into branches, there is a risk of overfitting. Random forests are a method consisting of the combination of multiple decision trees [26]. Each tree is trained independently and the results are combined by majority voting. Support vector machines try to find the most appropriate hyperplane that separates data points into different classes.It can be used for two or multi-class problems [27]. Artificial neural networks process data with structures based on the working principle of the human brain. It performs very well with high accuracy and large data sets. LDA projects the data to a lower-dimensional space in order to distinguish classes [28]. It maximizes the differences between classes while minimizing the variance within the class, and is effective in working with high-dimensional data.

Bagged trees are an ensemble learning technique in ML and attempts to balance the tendency of each tree to overfit by combining multiple decision trees [29]. It allows creating multiple decision trees from different subsets of training data. It also combines predictions to improve model performance. Samples are taken from the original training dataset and several new training sets are created. Each of these examples is used to train a separate decision tree. A decision tree is trained on each of these datasets. Once all trees are trained it combines the predictions. Bagging helps reduce overfitting in decision trees because the average of more than one tree is taken [30]. In addition, it reduces variance, which in turn affects performance. Bagging makes the more stable output by reducing sensitivity to variations in the training data, as better generalization performance against different datasets. It also offers parallel computing since each model is trained independently. This is a significant advantage when working with large datasets.

3. Experimental Results

In this work, bagged trees is chosen over other algorithms (such as SVM, CNN and LSTM) because they reduce the risk of overfitting, can give good results with less data, can make fast calculations thanks to their simple structure and generally have high generalization ability. In the classification made after feature extraction and feature selection, the parameters obtained with the confusion matrix, ROC curve and kappa coefficient were interpreted. Confusion matrix is shown in Figure 5. Figure 6 shows True Positive Rates (TPR) - False Negative Rates (FNR), and it indicates the ability of the model to correctly classify each class. Figure 7 shows Positive Predictive Values (PPV) and False Discovery Rates (FDR) respectively. PPV and FDR are used to understand the model's performance on false positives and false negatives. If the PPV is high, most of the cases that the model predicts as positive are actually positive. A low FDR indicates that fewer of the positive predictions are actually incorrect. Using these metrics together helps evaluate the model's performance more comprehensively.

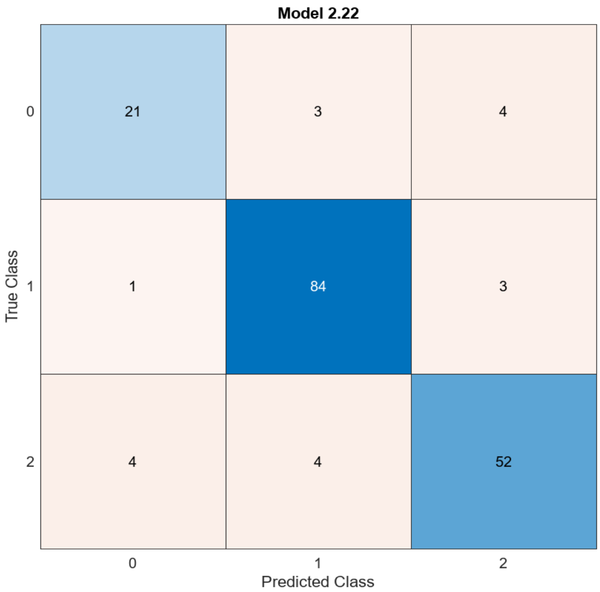


Figure 5. Confusion matrix of application

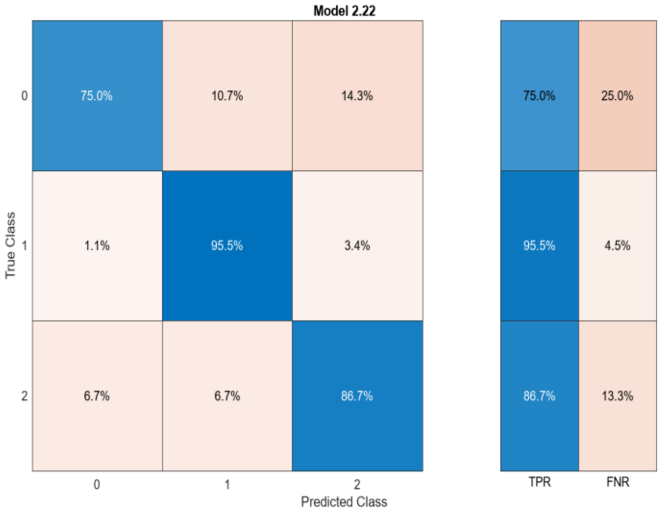


Figure 6. True Positive Rates (TPR) - False Negative Rates (FNR)

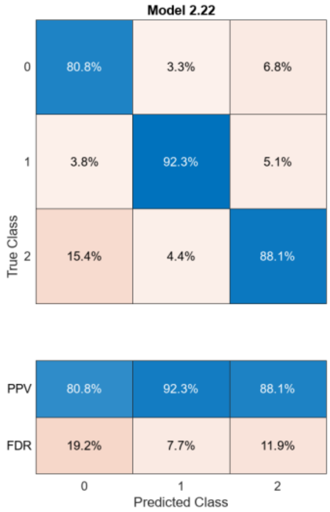


Figure 7. Positive Predictive Values (PPV) and False Discovery Rates (FDR)

Figure 8 and Figure 9 represent TPR-FNR and PPV-FDR bar graphs, respectively. These graphs allow the numerical visualization of the correct prediction performance of each class to be seen.

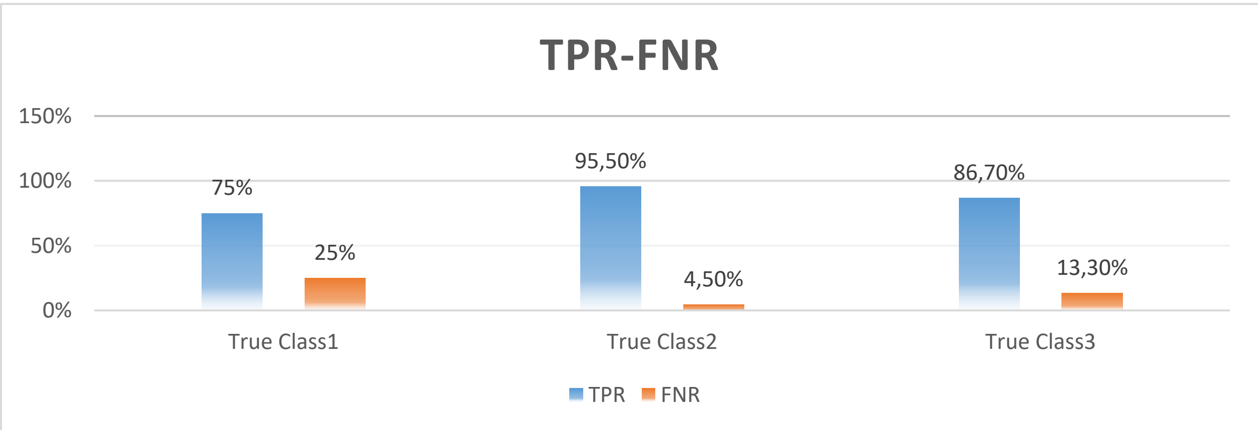


Figure 8. Numerical visualization of TPR-FNR values for each class

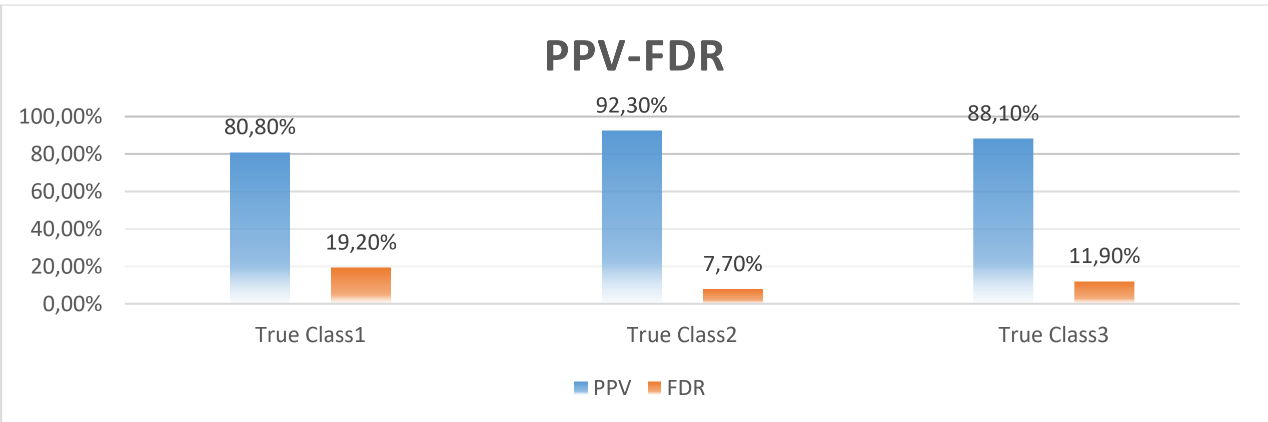


Figure 9. Numerical visualization of PPV-FDR values for each class

Table 3. Performance metrics

		Truth Data				
Classifier Results		***Class 1***	***Class 2***	***Class 3***	***Overall classification***	***Precision (%)***
	Class 1	21	3	4	28	75
	Class 2	1	84	3	88	95.455
	Class3	4	4	52	60	86.667
	Truth Overall	26	91	59	176	
	Recall (%)	80.769	92.308	88.136		
Overall Accuracy	%89.205					
Kappa	0.821					

As shown in Table 3, performance metrics are listed for this work. While the overall accuracy is 89.205%, the Recall values for each class are %, 80.769, % 92.308, % 88.136 and Precision values are % 75, % 95.455, % 86.667. Additionally, the Kappa coefficient was found to be 0.821%. Kappa is used to evaluate the performance of classification models. It measures the agreement between observed and predicted classes in the classification model. The kappa value is between -1 and 1, and the closer it is to 1, the better the model performance. Figure 10 expresses ROC Curve and Area Under Curve (AUC). AUC is used to compare the performance of classification models, especially in unbalanced classification problems. Its value varies between 0-1. The closer a model's AUC value is to 1, the better the performance. If it closes to 0.5, the classification ability of the model consists of random guesses. The ROC curve shows the relationship between sensitivity and specificity at different cutoff points of the classification model.

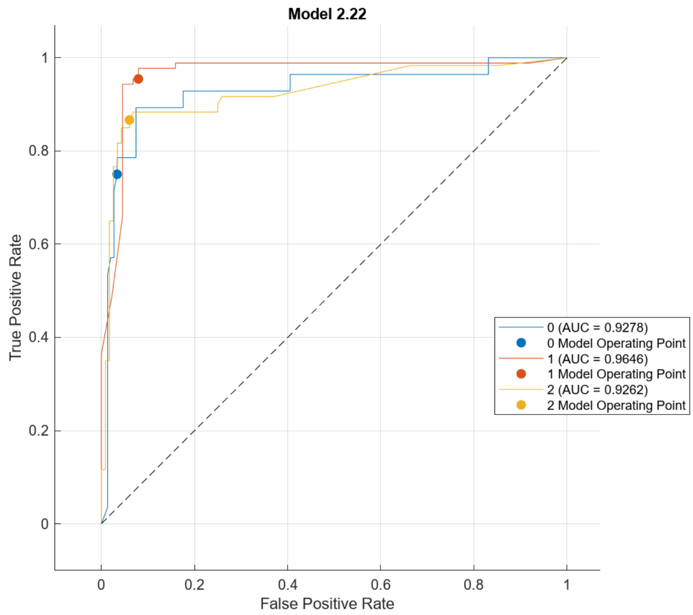


Figure 10. ROC Graphics

4. Conclusions

Classification of healthy and bad states in a BLDC motor and the use of data reduction methods provide practical benefits in many industries. Industrial robots using BLDC motors make precise and powerful movements. Motor failures can cause production errors and stoppages. Hence, continuous monitoring is essential to ensure early fault detection. Data reduction allows only critical data to be transmitted without affecting the processing speed of the robots and helps to detect motor failures more quickly.

Another area of use is in electric vehicles, where motor failures can negatively affect the performance of the vehicle and pose safety risks. In EVs, data reduction and healthy/bad classification techniques can be important in terms of battery consumption and processor load. Predictions of motor health allow users and maintenance teams to make timely interventions.

Three types of data were used in this study for a BLDC. Each data consists of 2 columns. Each column was divided into 2 parts and wavelet coefficients were determined with the db7 wavelet. Statistical features were extracted for 4 tracks. These features are mean, median, max, min, range, std, mad and norm. The obtained features were classified with the bagged trees algorithm. The probability of correct prediction of each class was examined with performance metrics. Recall, precision, accuracy, kappa, Roc Curve, AUC are used as the metric.

5. Discussion

Although the dataset is relatively small, future studies could explore real-time deployments or augment data with sensor fusion.

6. Contributions of the Authors

The authors' contributions to the paper are equal.

7. Statement of Research and Publication Ethics

The study is complied with research and publication ethics. There is no conflict of interest between the authors.

8. Acknowledgment

This study is produced from the first author's master's thesis titled "Analysis of Acoustic Data with Intelligent Computational Methods".

9. Ethical Statement Regarding the Use of Artificial Intelligence

No artificial intelligence-based tools or applications were used in the preparation of this study. The entire content of the study was produced by the author in accordance with scientific research methods and academic ethical principles.

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