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Research Article

A Deep Learning Approach for Motor Fault Detection using Mobile Accelerometer Data

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ABSTRACT

Electrical machines, which provide many conveniences in our daily life, may experience malfunctions that may adversely affect their performance and the general functioning of the industrial processes in which they are used. These failures often require maintenance or repair work, which can be expensive and time consuming. Therefore, minimizing the risk of malfunctions and failures and ensuring that these machines operate reliably and efficiently play a critical role for the industry. In this study, a one-dimensional convolutional neural network (1D-CNN) based fault diagnosis model is proposed for electric motor fault detection. Motor vibration data was chosen as the input data of the 1D-CNN model. Motor vibration data was obtained from a mobile application developed by using the three-axis accelerometer of the mobile phone. Three-axis data (X-axis, Y-axis and Z-axis) were fed to the model, both separately and together, to perform motor fault detection. The results showed that even a single axis data provides error-free diagnostics. With this fault detection method, which does not require any connection on or inside the motor, the fault condition in an electric motor has been detected with high accuracy.

1. INTRODUCTION

Electrical machines are indispensable for industry, especially in power generation, manufacturing and transportation. In these applications, they play a critical role in the conversion and control of energy and are essential to meeting the energy demands of modern society. Due to occasional malfunctions in electrical machines, they do not operate at high efficiency and may consume more energy than necessary. This leads to higher operating costs. Failures that occur can create safety hazards for workers, such as electric shock or fire. These hazards can cause injury, equipment damage, or even death. For these reasons, it is necessary to detect faults before they progress and to implement preventive maintenance and monitoring programs.

Electric motors have complex internal structures and mechanisms that make it difficult for humans to visually inspect and identify faults. Many faults occur in motor parts or electrical windings that are not easily accessible or visible without disassembling the motor. Many motor failures present as subtle changes in performance or behavior that are not immediately noticeable to humans [1]. Identifying motor failures often requires a deep understanding of motor operation, performance characteristics and failure patterns. Some faults in motor may occur intermittently or under certain operating conditions. Detecting such errors in real time requires constant monitoring of various parameters and being able to analyze large volumes of data quickly. People can find it difficult to constantly monitor motors at such high frequencies and to analyze complex data patterns effectively. In contrast, machine-learning models can overcome these challenges by analyzing large amounts of data from engines, detecting fine patterns, and identifying error signatures more accurately and efficiently. These models process data in real time, providing continuous monitoring and timely fault detection, increasing overall motor reliability and minimizing downtime. Deep learning methods are based on the use of raw input data, unlike traditional approaches where it is necessary to manually extract the properties of the input data. Thus, the need for expert knowledge is minimized [2]. Due to these advantages, deep learning models have been applied in many different fields such as detecting brain abnormalities from magnetic resonance images (MRI) [3], diagnosing heart diseases from electrocardiography (ECG) signals [4, 5], face recognition [6], speech recognition [7], as well as motor fault detection [8-16], and successful results have been obtained.

The most preferred input data for detecting faults in motor bearings are current [8-10] and vibration [11-16] data. Vibration signals are very sensitive to the presence of bearing

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defects or anomalies. Within the realm of deep learning models, convolutional neural networks (CNN) excel at learning features from mechanical vibration signals. As a result, many studies have utilized CNNs for intelligent fault diagnosis of machines [11-14].

Jia et al. [11] proposed an approach called deep normalized convolutional neural network (DNCNN) to solve the problem that CNNs do not take into account the unbalanced distribution of machine health conditions. In this approach, normalized layers based on weight normalization strategy and ReLU activation function are used to improve the training process. A weighted softmax loss has been developed to deal with the unbalanced distribution data problem. In addition, a neuron activation maximization (NAM) algorithm was developed to understand how DNCNN learns features from vibrational signals.

Machine learning models trained with data previously collected from another machine may not perform satisfactorily when the environment and operating conditions change on different machine instances. Asutkar et al. [12] presented a transfer-learning model to address this deficiency. With 1D-CNN and transfer learning, it has been determined that the accuracy rates are high even if datasets from different machines are used in training and testing. Shen et al. [14] developed an approach that embed the physical knowledge of bearing faults into the model training process. Fault detection has been successfully achieved with this deep learning approach, which consists of a simple threshold model and CNN model for error detection. In addition, generative adversarial networks (GAN) [15], long-short-term-memory (LSTM) [16] models were also used in motor fault diagnosis and motivating results were obtained.

Various sensor equipment and platforms installed around the motor are used to obtain vibration signals for motor fault diagnosis [10]. These platforms are both costly and impractical to use. In this study, motor vibration data were collected with a non-invasive mobile application in order to evaluate motor health with an easy method that does not require the use of expensive sensors and minimizes the need for expert knowledge. Today, the possibilities of smartphones, which are available to almost everyone, are used in motor fault diagnosis and the motor health status is evaluated without any cost. With the CNN model, which is one of the deep learning methods and has proven to be successful in diagnosis and classification in many areas, motor fault diagnosis has been carried out without error. Thus, a low-cost and practical method for the problem is presented.

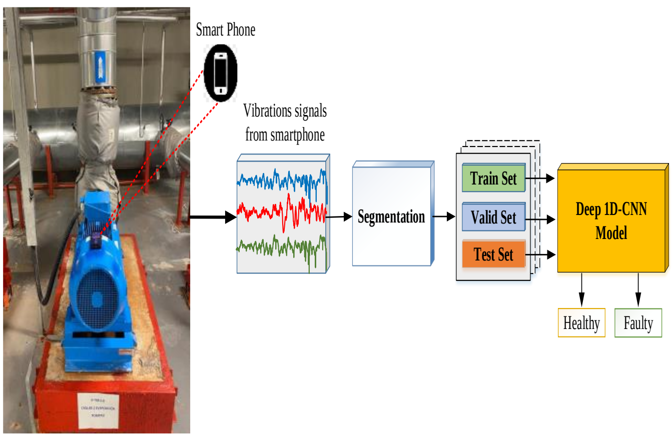


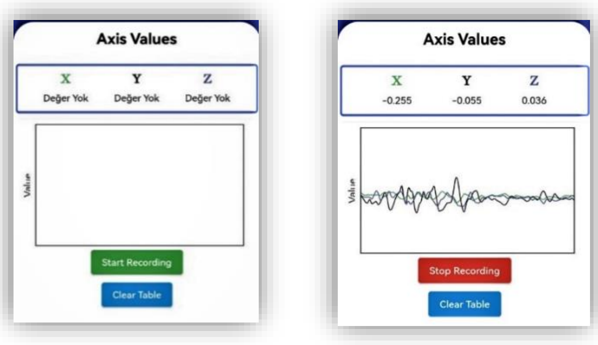
Figure 1. Illustration of the flowchart to build proposed approach.

2. MATERYAL VE METOD

In this study, a mobile application has been developed to detect motor failures from vibration data with 1D-CNN model. Illustration of the flowchart to build proposed approach is given in Figure 1. The phone, on which the mobile application was installed, was placed on the motor and data acquisition was performed in three axes (X, Y, Z). The data is segmented and divided into train set, validation set and test set. The 1D-CNN model was trained with the vibration data received, and then the performance of the model was evaluated with the test data.

2.1. Mobile Application

The mobile application used to get vibration data from the electric motor was realized with Flutter based on Dart language. Developed in 2011 by Google, Dart is defined as an object programming language. Flutter, developed by Google, makes it possible to develop applications for Android, iOS and web through a single toolkit. The reason why Flutter environment was preferred in this study is that Flutter enables the development of applications for different operating systems and devices through a single code base. The interface of the mobile application is as shown in Figure 2. Vibration data in the X-, Y- and Z-axes can be easily obtained by placing the phone with the application installed on it on an electric motor, opening the application screen and pressing the "Start Recording" button shown in Figure 2 (a). After starting the application, the application can show the vibrations in the X-, Y- and Z-axes both graphically and numerically as shown in Figure 2 (b). When the "Stop Recording" button is pressed, the application stops receiving vibration data and saves the received data in an excel spreadsheet. To delete the received data from the excel table, press the "Clear Table" button. Thus, the application becomes ready again to receive new data.



(a) (b)

Figure 2. Visual interfaces of the mobile application (a) Application opening screen (b) When receiving real-time vibration data.

2.2. Proposed 1D-CNN Model

The CNN model proposed in this study is realized with an end-to-end learning structure. With this model, which does not require any feature extraction step, it is aimed to detect the motor health status. Since the vibration signals are one-dimensional, a 1D-CNN model is used.

The designed deep network model consists of 13 layers. The model has 1D Convolution (Conv1D), MaxPooling (MaxPool), flatten and dense layers. Figure 3 shows the structure of the proposed model for electric motor fault detection. Table I shows the parameters of the model in detail.

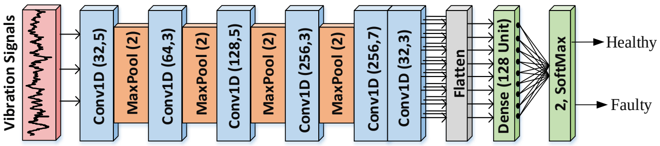


Figure 3. Architecture of proposed 1D-CNN model

TABLE I
DETAILED LAYERS AND PARAMETERS OF THE PROPOSED 1D-CNN MODEL

Layer	Layer Name	Kernel×Unit	Other Layer Parameters
1	Conv1D	5×32	Activation = ReLu, Strides = 1
2	MaxPooling1D	-	Strides = 2
3	Conv1D	3×64	Activation = ReLu, Strides = 1
4	MaxPooling1D	-	Strides = 2
5	Conv1D	5×128	Activation = ReLu, Strides = 1
6	MaxPooling1D	-	Strides = 2
7	Conv1D	3×256	Activation = ReLu, Strides = 1
8	MaxPooling1D	-	Strides = 2
9	Conv1D	7×256	Activation = ReLu, Strides = 1
10	Conv1D	3×32	Activation = ReLu, Strides = 1
11	Flatten	-	-
12	Dense	1×128	ReLu
13	Dense	1×2	Softmax

Convolutional layers are the fundamental building blocks of CNNs. Convolutional layers consist of filters that slide over the input image, scanning for relevant patterns and features. Pooling layers reduce the spatial dimensions of feature maps while preserving important information. Flatten layer flattens the feature maps into a 1D vector before transferring the data to the dense layers. The dense layer, also known as the fully connected layer, connects every neuron (or node) in the previous layer to every neuron in the current layer, creating a dense, fully connected network of neurons. In the last layer of the network, the softmax layer is used to predict the class to which the input signals belong. The optimizer selected was the Adam optimizer, and loss function was selected as the binary cross-entropy. After developing the model, the layer numbers, types and parameters of the deep algorithm are changed by brute force technique and the performance of the CNN model are observed.

2.3. Dataset

A three-phase, two-pole, 50 Hz, 5.5 kW asynchronous motor was selected for data acquisition. Firstly, data was obtained from the faulty motor and then the motor was repaired and data was obtained from the healthy motor in three axes (X, Y, Z). At 40 Hz operating frequency, vibration data of 64000×3 (1280 seconds) from the faulty motor (F) and 64000×3 (1280 seconds) from the healthy motor (H) were taken. These data were segmented in 500×3 dimension with 50 sample shifts. Thus, 1270 samples were obtained from each of the H and F classes, 2540 data samples in total. Then 80% of all data was used for training, 10% for validation and 10% for testing.

Figure 4 shows the X-, Y- and Z-axes vibration signal samples from the faulty and healthy motor. When the vibration samples are analyzed, it is seen that the peak value of the vibration amplitude of the defective motor is approximately 1.7 and the peak value of the vibration amplitude of the healthy motor is approximately 0.9.

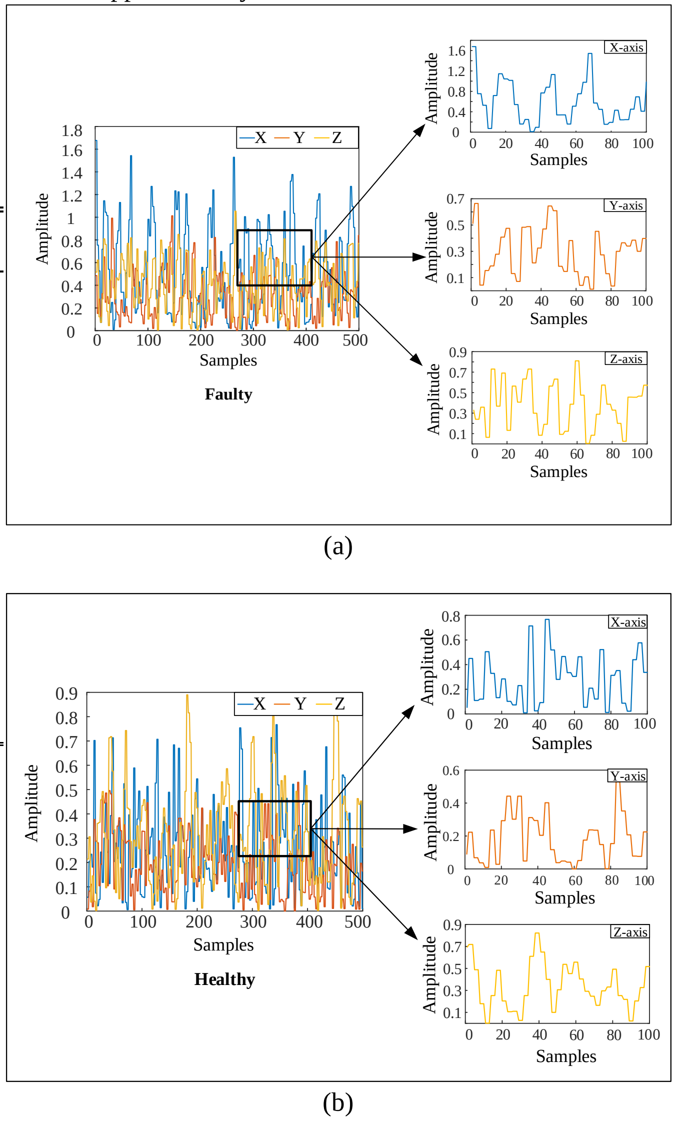


Figure 4. Vibration samples a) Faulty motor b) Healthy motor

In this study, the performance of the proposed CNN model in motor fault detection is tested with four different cases:

- Case 1: Motor fault detection using X-axis data.
- Case 2: Motor fault detection using Y-axis data.
- Case 3: Motor fault detection using Z-axis data.
- Case 4: X-axis, Y-axis, Z-axis data were given to the deep learning model as three different features and motor fault detection was performed.

3. EXPERIMENTAL RESULTS

The 1D-CNN model was first trained on each axis data separately to obtain loss and accuracy values. Figure 5 shows the changes in the accuracy and loss values of the model over 10 epochs for the cases where X-axis, Y-axis and Z-axis data are used, respectively. Looking at the performance graphs, it is seen that the model does not have an overfitting problem.

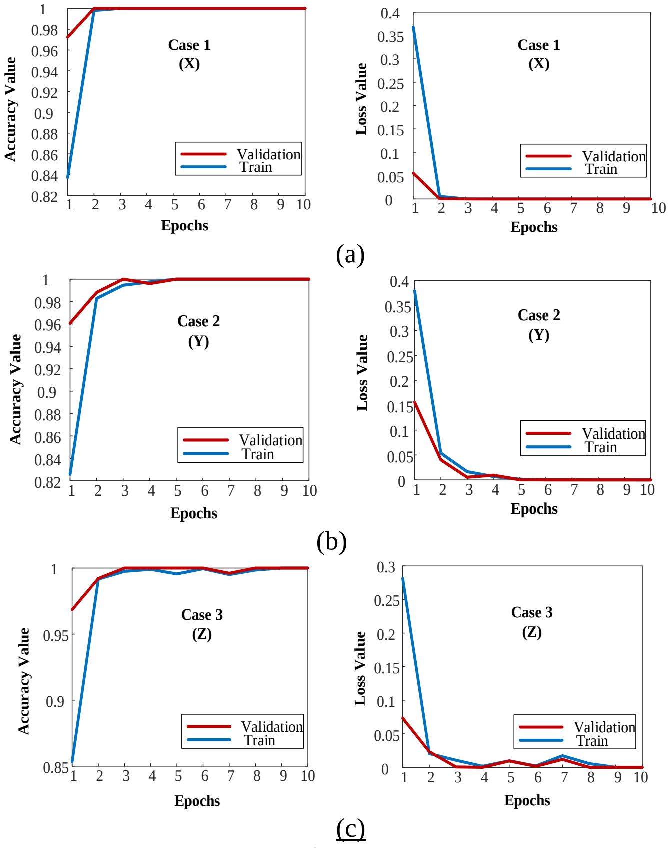


Figure 5. Accuracy and loss graphs for each case a) X-axis, b) Y-axis, c) Z-axis

The training performances of the model on each axis data were quite successful. However, considering the motor fault types, it was thought that providing all axis data to the model input would provide an even superior performance. In line with this idea, X-, Y- and Z-axes signals were combined and the training performance of the model was observed. Figure 6 shows the performance graphs obtained by combining X-axis, Y-axis and Z-axis signals and feeding them to the model input. As can be seen in the graphs, combining X-axis, Y-axis and Z-axis data provided similar performance in the performance measures of the model.

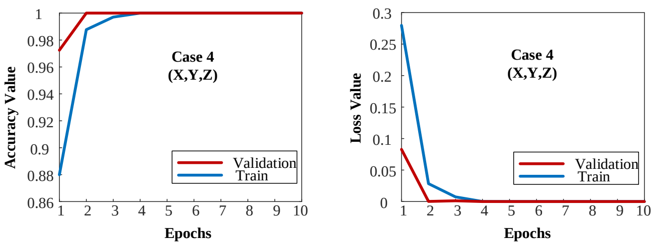


Figure 6. Accuracy and loss graphs for X-axis, Y-axis, Z-axis together

Accuracy, the most widely used performance evaluation metric, is used to evaluate the performance of the model. The accuracy value is calculated as in Equation 1:

$$Accuracy\ (\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (1)$$

In the equation, TP represents true positives and TN represents true negatives. Similarly, FP represents false positives and FN represents false negatives. Table II shows the validation accuracy values of the model at each epoch for the cases generated. When these values are analyzed, it is seen that the model quickly learns the motor fault condition.

TABLE II
VALIDATION ACCURACY VALUES OF THE 1D-CNN MODEL AT EACH EPOCH (%)

	X-axis	Y-axis	Z-axis	X,Y,Z-axis
Epoch 1	0.9724	0.9606	0.9685	0.9724
Epoch 2	1.0	0.9881	0.9921	1.0
Epoch 3	1.0	1.0	1.0	1.0
Epoch 4	1.0	0.9960	1.0	1.0
Epoch 5	1.0	1.0	1.0	1.0
Epoch 6	1.0	1.0	1.0	1.0
Epoch 7	1.0	1.0	0.9960	1.0
Epoch 8	1.0	1.0	1.0	1.0
Epoch 9	1.0	1.0	1.0	1.0
Epoch 10	1.0	1.0	1.0	1.0

The trained model was run on 254 test data. It was observed that the proposed model achieved 100% performance on the test data in all cases.

4. DISCUSSION

In this study, a deep learning model is trained using data obtained from a mobile platform to determine the motor fault status. The biggest advantage of the study is that it enables fault diagnosis only with the help of a smartphone without the need for any external sensor connection. Thus, fault conditions can be detected without the need for any platform installation inside or around the motor. The 1D-CNN model used in the study eliminates the need for any feature extraction step by providing end-to-end learning. The 1D-CNN model trained on the data obtained from the developed mobile application provided 100% accurate detection. In addition, fault recognition can be achieved by using any of the X-, Y- and Z-axes for the motor used.

In addition to its advantages, this study has several limitations. First of all, a single motor dataset was used for the study. Since the number of records in the dataset is limited, the number of data was increased with the 50-sample sliding window method. If more records are obtained, higher and more reliable accuracy values can be achieved. A single motor type was used in the study. The use of electric motors of different power and types will be useful in evaluating the generalizability of the proposed model.

In this study, only faulty and healthy motor diagnostics were performed. No classification of the type of failure was performed. The detection of different types of faults with the vibration information received from the mobile phone will be the subject of future studies.

5. CONCLUSION

In this study, motor vibration data is obtained from a mobile application and the health status of a motor is evaluated with a 1D-CNN model. The accuracy of the proposed 1D-CNN model is tested by first using the X-axis, Y-axis and Z-axis vibration data from the mobile application individually and then feeding these three axes data to the model simultaneously. In each case, the 1D-CNN model, which does not require any feature extraction and is easy to implement, performed an accurate classification with 100% accuracy rate. With this study, an experimental study is presented that the accelerometer sensors

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in mobile phones are useful for evaluating the motor health status, and that healthy and faulty motor states can be detected without the need for any sensor or vibration meter.

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BIOGRAPHIES

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Ahmet Orhan received the MSc. and PhD diploma in Electrical and Electronics Engineering from Firat University in 1987 and 1999 respectively. He is working as Associate Professor in Department of Electrical and Electronics Engineering at Firat University. His current research interests include synchronous motors, synchronous generators, induction motors, PM motors and generators, matrix converters.