Deep learning based mechanical fault detection and diagnosis of electric motors using directional characteristics of acoustic signals

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ABSTRACT

Early identification of rotating machinery faults is crucial to avoid catastrophic failures upon installation. Contact-based vibration acquisition approaches are traditionally used for the purpose of machine health monitoring and end-of-line quality control. In complex working conditions, it can be difficult to perform an accurate accelerometer based vibration test. Acoustic signals (sound pressure and particle velocity) also contain important information about the operating state of mechanical equipment and can be used to detect different faults. A deep learning approach, namely one-dimensional Convolution Neural Networks (1D-CNN) can directly process raw time signals thereby eliminating the human dependance on fault feature extraction. An experimental research study is conducted to test the proposed 1D-CNN methodology on three different electric motor faults. The results from the study indicate that the fault detection performance from the acoustic-based measurement method is very effective and thus can be a good replacement to the conventional accelerometer-based methods for detection and diagnosis of mechanical faults in electric motors.

1. INTRODUCTION

Electric motors play a crucial role in various industries, and it is critical for them to function safely and efficiently for extended periods. Often, machines are used until they break down, but this approach can lead to negative outcomes such as compromised safety, decreased production efficiency, and increased expenses for repairs. Therefore, it is crucial to incorporate intelligent, effective, and accurate fault diagnosis and quality control methods for electric motors.

Presently, vibration measurements are the main method used for monitoring and diagnosing motor mechanical faults [1]. This technology has advantages, including inexpensive sensors and content rich information about equipment status. However, accelerometers mass load equipment and must be mounted to the structure.

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Acoustic methods are useful when machinery cannot be accessed directly, as measurements can be taken from a distance without sensors being mounted on the machine. This can be particularly helpful in industrial settings where a contact based sensor installation is not feasible or when required to quality test a large sample of manufactured parts in a short time. Using acoustic techniques can greatly improve fault diagnosis in these scenarios. Most acoustic work in the past only focused on sound pressure measurements. Those measurements are negatively affected by background noise and noise from equipment in manufacturing plants. Acoustic particle velocity sensors [2] which can provide both magnitude and directional information can be useful to overcome this problem.

Deep Learning (DL) has gained attention in many industries as it has demonstrated its potential in analyzing and identifying underlying data patterns eliminating human expertise dependence on feature extraction. It is being explored as a complement to physics-based models in several areas, including machine condition monitoring, fault diagnosis, complex manufacturing process modeling, and quality inspection [3]. Convolutional Neural Networks (CNNs) is a type of deep learning algorithm that has been widely used in image and signal processing tasks, including fault diagnosis. The importance of CNNs in fault diagnosis lies in its ability to automate the process of fault detection and diagnosis, which can save time, reduce costs, and improve the accuracy and reliability of the diagnosis. In recent years, 1D-CNNs [4] particularly demonstrated their ability in effectively analyzing and processing sequential time-series data directly.

Acoustic particle velocity based measurements can be used together with 1D-CNNs for performing electric motor fault diagnosis. This method is attractive because the acoustic data in time domain from different motor fault types can be used directly to train a 1D-CNN model without the need to transform it to the frequency domain. This paper investigates the fault classification performance across four different electric motor conditions, where data is acquired using a motor fault simulator at multiple speeds. The results from this experimental study indicated comparable diagnosis when sound intensity data is used instead of traditional accelerometer data.

2. THEORY

2.1. Sound Intensity

Sound intensity is a measure of the amount of sound energy passing through a given area per unit time. It is defined as the power per unit area, expressed in Watts per square meter (W/m²). Sound intensity is a vector quantity, meaning that it has both a magnitude and a direction. The measurement of sound intensity can be done using sound intensity probes. A PU probe [2] can capture both sound pressure and acoustic particle velocity at the same time using single device, across a wide frequency range from a few Hz up to 20k Hz.

Instantaneous sound intensity is the time averaged product of the instantaneous sound pressure $p(t)$ and the corresponding instantaneous particle velocity $u(t)$ at the same position:

$$I = \frac{1}{T}\int_{0}^{T} p(t) \cdot u(t) dt \tag{1}$$

where T is the period of the measurement.

2.2. 1D-Convolutional Neural Networks (1D-CNNs)

DL is a learning structure that utilizes both multilayer artificial neural networks and specialized network architectures to learn hierarchical representations of input data [5]. The early layers of the networks learn low-level features, while the later layers combine these features to create high-level representations of the objects being analyzed. Since DL models have many free parameters, specialized architectures like CNNs have been developed to exploit known structures in the input data. CNNs have been particularly successful in image processing because they use convolutions to search for smaller patterns within larger inputs, creating new channels that represent extracted patterns. These outputs are compressed using pooling, which reduces the number of parameters to be tuned and improves computational efficiency. DL models use hierarchical stacks of convolutional and pooling layers as feature extraction layers and end with a fully-connected network for classification or regression on the learned features.

CNNs have shown remarkable performance in recognizing images which are 2-dimensional inputs, while 1D-CNNs [4] have been proven effective in handling sequential inputs like vibration signals. The convolution operation for 1D inputs and kernels can be expressed as:

$$y_c(n) = \sum_{k=0}^{L-1} w(k)x(nS_c + k) \tag{2}$$

where x is the input signal of length N and w is the convolutional kernel of length L. The kernel moves across the input signal by a stride S_c, which indicates the number of data points it moves per step. To ensure that the bounds of n remain within the original signal length (including zero-padded regions on the sides of the input), the values can be set accordingly. Once the convolutional output $y_c(n)$ is obtained, it can be passed through an activation function like the rectified linear unit (ReLU) to introduce nonlinearity as follows:

$$y_a(n) = \max\big(0, y_c(n)\big) \tag{3}$$

where $y_a(n)$ is the output of the activation function subjected to pooling. The maximum value within a sliding window of length M is commonly selected using a technique called Max pooling:

$$y(n) = \max_{0\leq k\leq M-1} \Big(y_a\big(nS_p + k\big)\Big) \tag{4}$$

The stride S_p defines the spacing between adjacent pooling windows as they move across the features obtained from convolutional operations. By stacking multiple convolutional and pooling layers in sequence, a feature extraction network can be constructed, and its outputs can be fed into a multilayer, fully-connected network for final classification. To train CNNs, traditional backpropagation techniques like stochastic gradient descent (SGD) and the RMSProp-based Adam algorithm can be employed.

3. DATA ACQUISITION – MOTOR FAULT SIMULATOR

This section describes the experimental setup that was used for present analysis. This research study used a SpectraQuest motor fault simulator [6] to generate a dataset featuring four distinct motor conditions, which includes a healthy motor (Good) and three mechanically faulty motors. The first fault corresponds to a bowed rotor (BR) , while the second involves a built-in rotor unbalance (BRU) that results from an unequal weight distribution about its rotating centerline. The third faulty motor incorporates a bearing (BF) with a hole on the outer race.

To facilitate data acquisition, two acoustic transducers, a microphone, and a PU probe were installed to detect acoustic signals. The microphone was positioned half a meter away from the motor, while the PU probe was placed just 0.5in above the motor, measuring pressure and particle velocity simultaneously in the upward (+Z) direction. Additionally, two accelerometers were mounted, one placed on the top (+Z) and the other on the side (+Y) of the motor for measuring vibration. The accelerometers were included in the experiments for comparison with the acoustic sensors in terms of fault detection performance. Vibration and acoustic measurements were collected at sampling rates of 12800 Hz and 25600 Hz, respectively. Data acquisition was performed using Siemens SCADAS hardware and TestLab software, at five constant speeds: 1000, 1500, 2000, 2500, and 3000 RPM, resulting in a total of 20 distinct operating conditions. Each of these operating conditions was recorded for a duration of 60 seconds and saved as WAV files. The WAV files were subjected to min-max normalization to bring them within the range of [0, 1], and then divided into windows of 512 points, in order to prepare the data for use in the 1D-CNN. The test setup can be seen in Figure 1. Finally, all the collected data is partitioned with a goal to use 70% of the signals for training data, 15% for validation data and 15% for testing data, respectively.

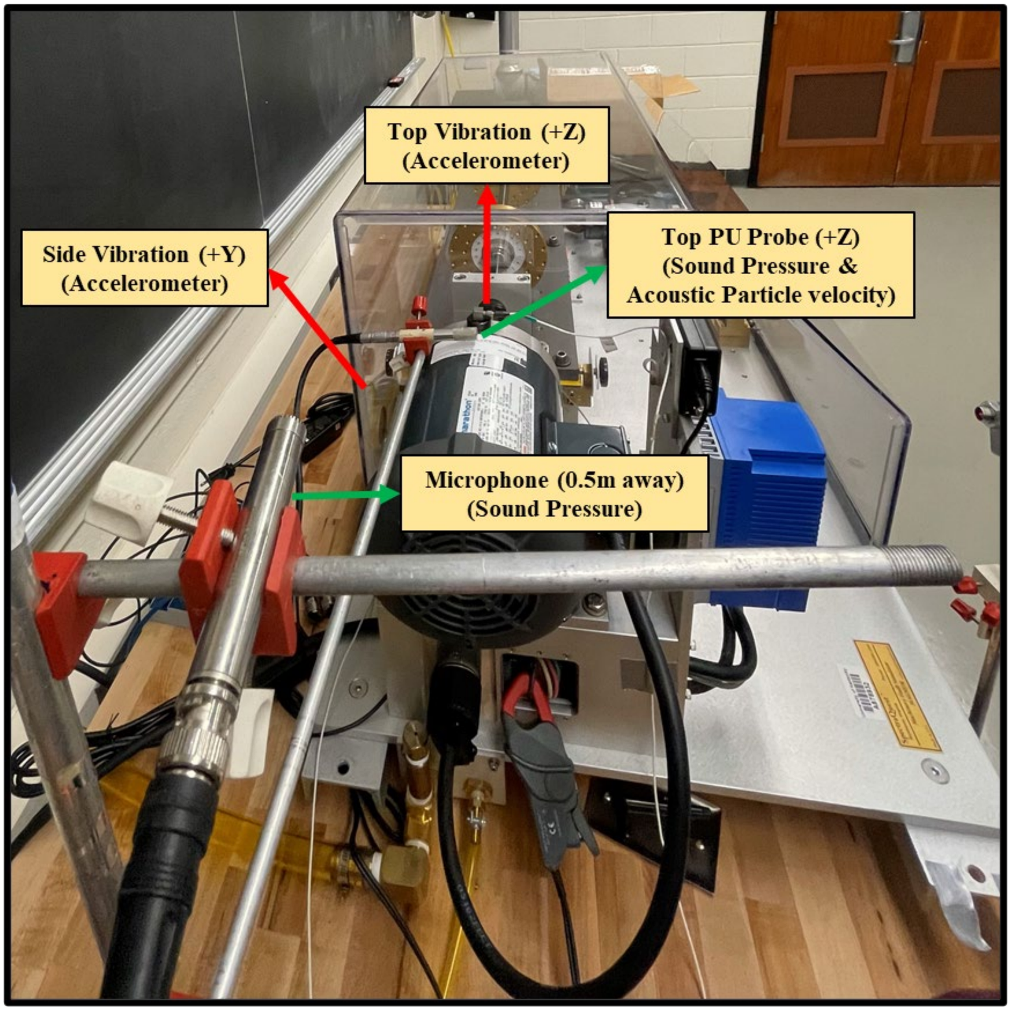

Figure 1: Motor fault simulator & measurement sensor set-up.

4. 1D-CNN BASED FAULT DIAGNOSIS

The network architecture flowchart of the 1D-CNN model designed for this study is shown in Figure 2. The collected dataset as described in Section 3 is used to pass through a series of convolution, pooling, and batch normalization layers. A total of 3 convolutional layers and 3 pooling layers were used to compute a total of 4096 features. Those features are then flattened through two fully connected layers where 4096 features are narrowed down to 64 features, and lastly, there are 4 outputs corresponding to four motor condition probabilities, which are used to calculate the multi-class classification accuracy.

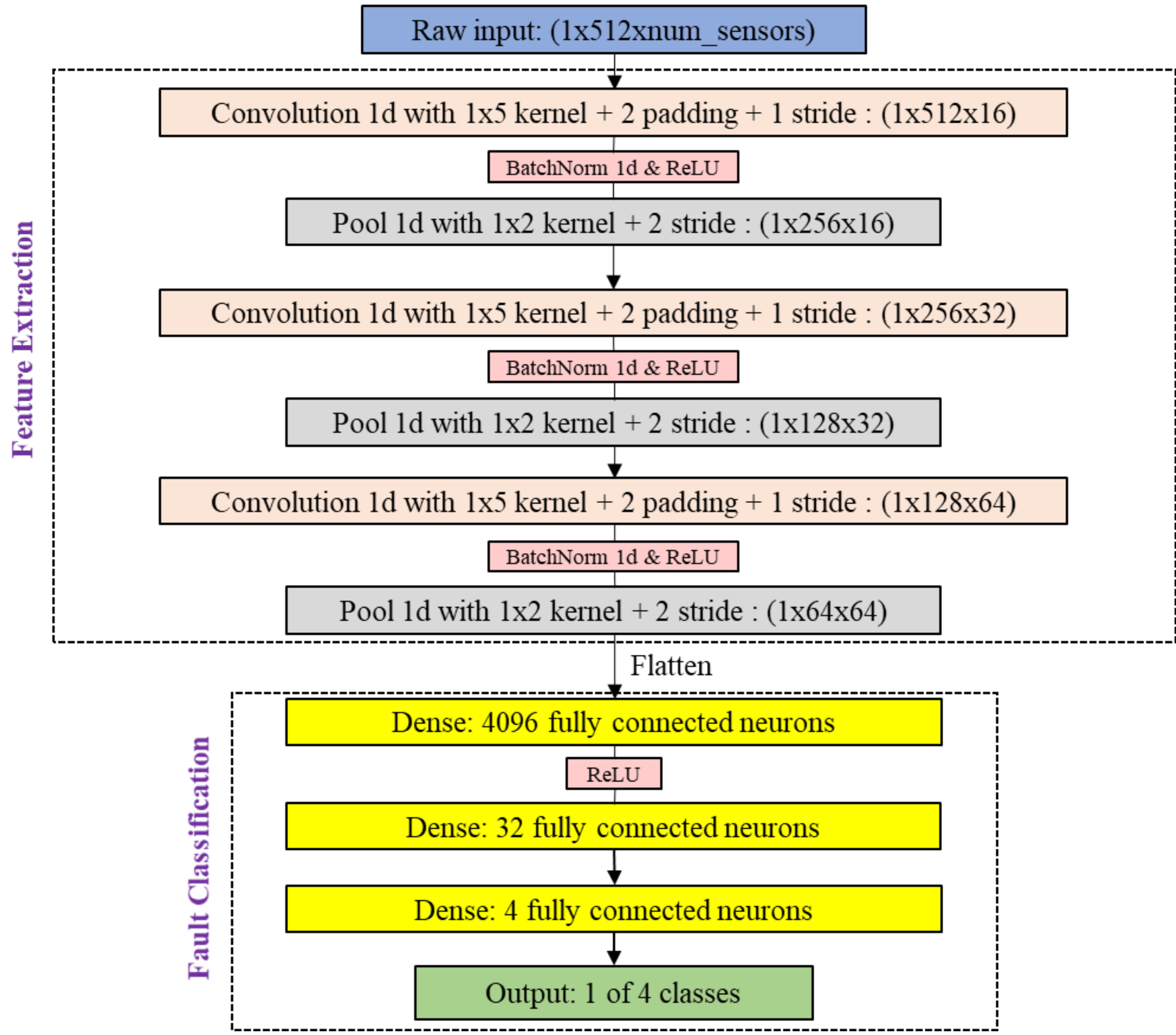

Figure 2: 1D-CNN network architecture for feature extraction and fault classification.

Three 1D-CNN models are trained, Model-1 uses the accelerometers data from +Z and +Y directions to serve as a reference for comparison, Model-2 with two acoustic sensor inputs (sound pressure from microphone 0.5m away from motor, sound intensity waveform calculated from measured sound pressure and acoustic particle velocity waveforms collected using PU probe placed about 0.5in above the motor in +Z direction) and finally a Model-3 with just one acoustic sensor input comprised of a sound intensity waveform measured and calculated from PU probe alone. The training loss, validation loss and validation accuracy metrics are employed to verify the performance of the proposed network. The network is then trained until there is no significant decrease in the validation loss. Figure 3 shows how the aforementioned metrics improved over 50 epochs/iterations. An elbow shape within the loss curves indicates convergence of the respective model.

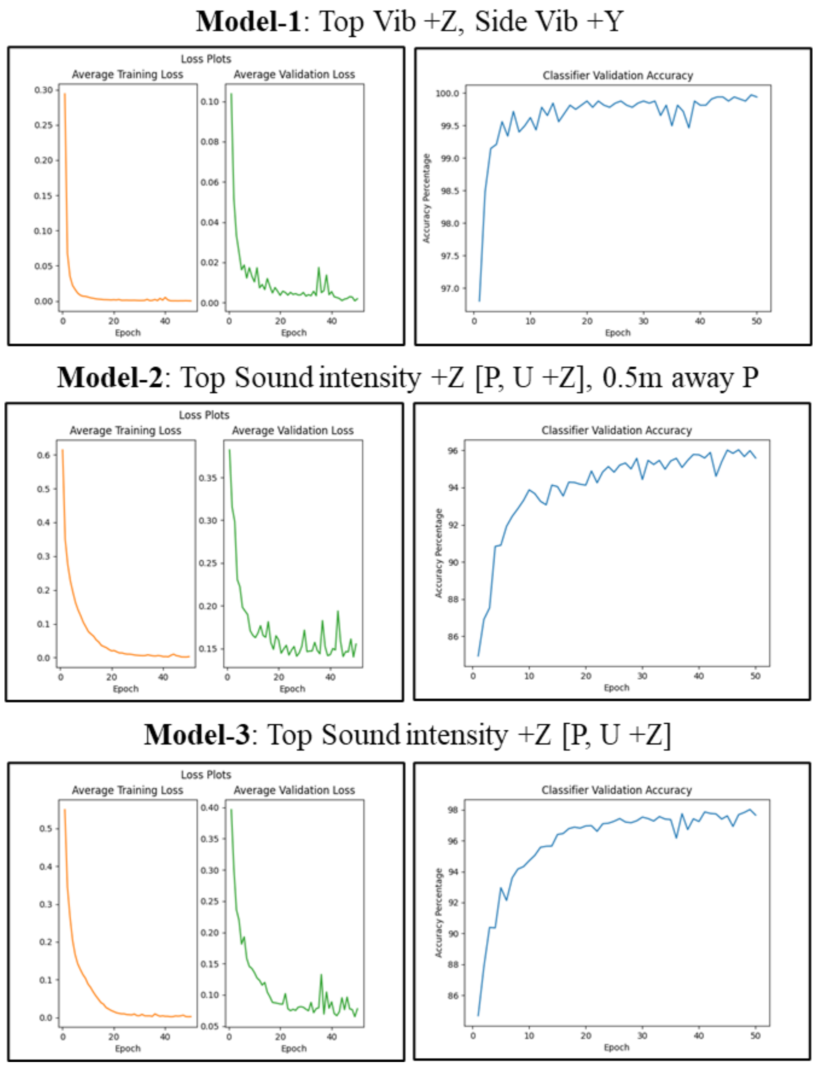

Figure 3: 1D-CNN models Training progression.

The final training loss, validation loss, and validation accuracy values for Model-1, Model-2 and Model-3 are summarized in Table 1, Table 2, and Table 3, respectively. While the final test accuracy obtained for Model-1 is 99.78%, Model-2 and Model-3 demonstrated test accuracies of 95.93% and 97.71%. The results from Model-3 in comparison to Model-2 confirmed that acoustic data from PU probe (sound pressure and particle velocity in +Z direction) alone is sufficient and in fact better than Model-2 which uses an additional acoustic measurement point from another microphone 0.5m away from motor.

Table 1: Model-1 (Top Vib +Z, Side Vib +Y) results.

Dataset	**Data Split (%)**	**Loss**	**Accuracy (%)**
Train	70	0.0002	--
Validation	15	0.002	99.94
Test	15	--	99.78

Table 2: Model-2 (Top Sound intensity +Z [P, U +Z], 0.5m away P) results.

Dataset	**Data Split (%)**	**Loss**	**Accuracy (%)**
Train	70	0.0028	--
Validation	15	0.1553	95.58
Test	15	--	95.93

Table 3: Model-3 (Top Sound intensity +Z [P, U +Z]) results.

Dataset	**Data Split (%)**	**Loss**	**Accuracy (%)**
Train	70	0.0023	--
Validation	15	0.0777	97.64
Test	15	--	97.71

The t-distributed stochastic neighbor embedding (t-SNE) technique is used in this study to gain a better understanding of the learning characteristics of the 1D-CNN model. t-SNE transforms high-dimensional data similarities into probabilities, allowing projection into a 2D space and enabling easier interpretation about the importance of the extracted features. The t-SNE plot (see Figure 4) for Model-3 shows that the features from the same motor condition cluster together to facilitate easy classification.

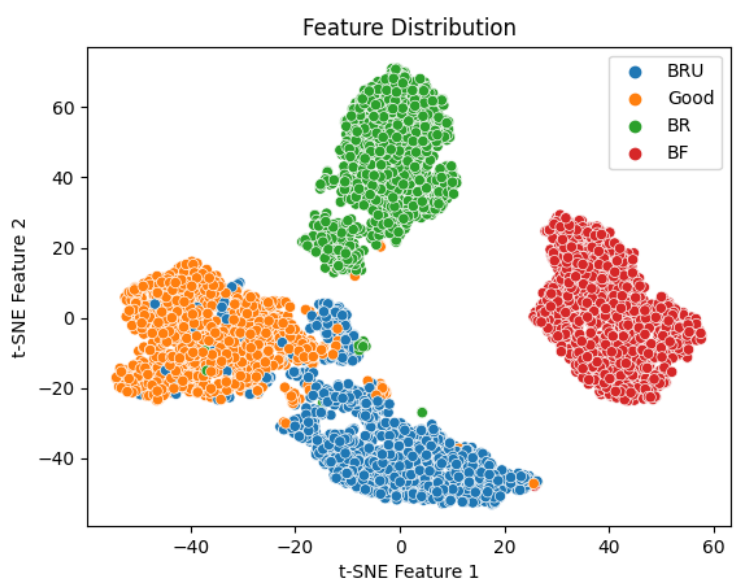

Figure 4: t-SNE (t-distributed Stochastic Neighbor Embedding) feature distribution.

5. CONCLUSIONS

In this paper, a method based on acoustic signals and 1D-CNN for fault diagnosis on electric motors is designed. The acoustic signals of electric motors measured using a PU probe (sound pressure and acoustic particle velocity simultaneously) can be used directly to calculate sound intensity waveforms, which can be directly fed into the 1D-CNN model in time domain. The method is verified experimentally using a dataset acquired from a four mechanical motor conditions. The fault classification results indicated excellent performance demonstrating that the proposed acoustic (non-contact) method is a promising alternative to conventional accelerometer-based (contact) acquisition techniques used when performing either predictive maintenance related machine health tests or quality assessments near the end of the production line.

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