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Detection of Fault from Acoustic Signals in Automobile Engines using Deep Learning Techniques

Fatih Alperen ERDOĞAN [1], Ayhan KÜÇÜKMANİSA [2], Zeynep Hilal KİLİMCİ [3,*]

[1] *Department of Electronics and Communication Engineering, Kocaeli University, Kocaeli, 41001, Turkey,* ***ORCID:*** *0000-0001-9871-6784*
[2] *Department of Electronics and Communication Engineering, Kocaeli University, Kocaeli, 41001, Turkey,* ***ORCID:*** *0000-0002-1886-1250*
[3] *Department of Information Systems Engineering, Kocaeli University, Kocaeli, 41001, Turkey,* ***ORCID:*** *0000-0003-1497-305X*

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Abstract

Detecting faults in automobile engines from sound signals is a challenging task in the production phase of automobiles. That is why it attracts engineers and researchers to handle this issue thereby applying various solutions. In this work, we propose a deep learning-based fault detection mechanism in automobile engines from different sound resources. In the dataset collection phase, various vehicle breakdown sounds are gathered from social media environments by constructing our own customized crawler. Moreover, noise addition is applied to increase the amount of data. Subsequently, raw audio files are processed at the feature extraction step employing mel-frequency cepstral coefficients. To detect the vehicle breakdown sounds, 1-D and 2-D convolutional neural networks, long short-term memory networks, artificial neural networks, and support vector machines are modeled. Experiment results show that the usage of a 1-D convolutional neural network is transcendent with 99% accuracy compared to the other techniques, especially, state-of-the-art studies are considered.

1. Introduction

With the rapid growth of the automobile industry, the detection of possible engine faults both during the production phase and individual use has crucial importance due to ensuring matutinal caution about the engine's situation of operation. There are so many reasons related to engine faults that can be arisen from the different parts of the automobile. For instance, flooded engine failure, ball failure, brake pedal failure, radiator water boiling failure, ripping motor failure, timing belt failure, engine failure due to lack of oil, etc. In this work, we concentrate on detecting automobile engine faults from sound signals.

Fault detection and condition monitoring of such engines using acoustic signals has been the object of many studies and has attracted interest from researchers and engineers. In [1], a visual point model is introduced to diagnose acoustic emission and vibration signals for fault detection in an internal combustion engine and drive axle shaft. With the help of the template matching method, the proposed system can detect error states. The study concluded that the use of a visual model point model provides effective fault detection in an internal combustion engine and drive axle shaft. In [2], the authors propose to detect faults in an automobile engine by observing the acoustic emission status. Principal component analysis and discrete wavelet transform technique are performed to construct the feature space. Then, a support vector machine was used for classification in 300 sound samples, 150 of which were intact and the rest were faulty motors. The experimental results show that the proposed model can detect engine failures with an accuracy of 72.64%. In [3], a continuous wavelet transform model is proposed for the purpose of detecting faults in internal combustion engines. The authors concentrate on three different categories namely, slightly different form normal, clearly different form normal, and sound signal without fault. They report that the wavelet technique is efficient to diagnose faults in internal combustion engines. In [4], the authors investigate the combination of discrete wavelet transform (DWT) and neural networks in the detection of engine faults. With the

* Corresponding Author: zeynep.kilimci@kocaeli.edu.tr

help of DWT, time and frequency domain information is also included unlike the other literature studies. In addition to DWT, Parseval's theorem is also utilized in the feature extraction step. After that, the classification task is performed by the neural network. The experimental results show that the proposed framework is capable to categorize different failures of engines.

In [5], the authors introduce a wavelet-based support vector machine for induction machine fault detection. In the first stage, feature space is constructed from a transient current signal with the help of a discrete wavelet transform. To perform the dimension reduction process, principal component analysis (PCA) and kernel PCA are implemented. After that, an SVM classifier is employed for the classification task to detect faults. Experiment results indicate that the utilization of W-SVM with Daubechies and Symlet kernels results in high accuracy. In [6], automobile fault detection is proposed using Fast Fourier Transform (FFT) on acoustic emission thereby distinguishing various operational states of a machine. With the usage of FFT, the fault within the ignition system of the engines can be detected from acoustic signals. Therefore, the frequency differences in the energy of FFT coefficients are the indicator of the resource of the faults that reflects the importance of features called representative attributes for the fault detection system. Then, PCA is carried out to provide for reducing the dimension of feature space. The authors inform that SVM classifier exhibits approximately 80% of accuracy. In [7], authors propose to categorize faulty and healthy sound signals from automobile engines using wavelet transformation at the feature extraction step. The sound signals are gathered from ignition system of four different automobile engines. After performing wavelet transformation at the feature extraction stage, more relevant features are picked up employing correlation-based feature selection (CFS) algorithm. Then, k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), and multi-layer perceptron (MLP) method are utilized for the classification task. Experiment results show that k-NN technique with 5 neighbors outperforms other models for all datasets.

In [8], noise-based engine fault diagnosis is introduced thereby consolidating wavelet packet analysis, artificial neural network, and intensity analysis of sound (WPA-ANN). The noises of the engine-fault-diagnosis system are classified as normal and faulty using an artificial neural network after carrying out the feature extraction step with the discrete wavelet transform technique. Experiment results demonstrate that the proposed WPA-ANN method under nine different states is capable to detect faults in the engine. In [9], authors investigate fault detection in motors of unmanned aerial vehicle (UAV). Because brushless DC (BLDC) motors employed in UAVs operate at high speed bringing about failures, authors mainly focus on the propeller, eccentric and bearing faults in UAV motors by analyzing sound data. The statistical-based feature extraction techniques are applied to the sound data obtaining average, standard deviation, variance, correlation, kurtosis, and skewness scores. After that, decision tree (DT), SVM, and k-NN algorithms are utilized for the purpose of detecting faults. Authors report that SVM and k-NN exhibit similar classification results with nearly 99.75% of accuracy while DT performs approximately 99.16% of accuracy. In [10], the authors concentrate on the detection of failures in diesel engine components by performing classification tasks on the vibration and acoustic signals with the help of machine learning methodology. The signals are analyzed in the frequency-domain, time-domain, and time–frequency domain employing fast Fourier transform (FFT) and short-time Fourier transform (STFT) techniques. To perform the classification task, Artificial Neural Network (ANN) is modeled. Experiment results show that ANN efficaciously categorizes the scuffing faults in the components of diesel engine with 100% of accuracy. In [11], the authors present the vibration-based diagnosis of gear failures in internal combustion (IC) engine gearboxes utilizing the K star technique. At first, features are extracted from the vibration signals utilizing discrete wavelet transform. Furthermore, feature space is extended by more representative features with the aid of the decision tree method. Next, the classification task is considered as driving gear with a healthy state and gradual tooth failure states. K-NN algorithm, K-star algorithm, and locally weighted learning algorithm are assessed for the categorization task. Experimental results indicate that the classification performance of the K-star algorithm outperforms others with 97.5% of accuracy.

Recently, the application of deep learning algorithms in different research areas attracts researchers due to ensuring better results compared to the conventional machine learning models. The main reason behind of it is performing feature extraction process is carried out automatically. Thence, more representative features of the dataset are gathered with the help of deep networks, which strengthens the generalization capability of the system during the training stage.

In recent years, the application of deep learning methodology in a different type of motors for the purpose of detecting failures have become popular. In [12], Autoencoder -based unsupervised machine failure detection is proposed from acoustic signals for noisy domain adaptation. Authors concentrate on the proposed approach because of lacking research on functional adaptation models across different noisy domains and the necessary bulky computational space. For this purpose, a noisy domain adaptive marginal stacking denoising auto-encoder (NDAmSDA) is proposed to address this problem on acoustic signals. To demonstrate the contribution of the proposed framework, datasets blended with additive white Gaussian noise (AWGN) and binary masking noise (BMN) from the motor tests and gear tests are evaluated. Experiment results show that the inclusion of auto-encoder-based fault detection model cuts across other models. In [13], authors introduce an efficient failure detection model employing convolutional attention neural network (CANN) model and continuous wavelet transform. At the data collection step, vibration signals are gathered and tagged into five classes namely, normal condition, outer ring fault, inner ring fault, misalignment condition, and broken rotor bar for induction motors. After that, vibration signals are converted into scalogram feature images with the aid of continuous wavelet transform. Next, the time-frequency images are constructed. The features of the images are evaluated as input of the proposed CANN model to diagnose the faults of the induction motor. The authors conclude the paper that the usage of the proposed framework exhibits superior performance with 99.43% accuracy compared to the literature studies. In [14], an approach is introduced for failure detection of hydraulic piston pumps with acoustic images, called adaptive convolutional neural network. Firstly, acoustic signals are transformed into time–frequency features by employing continuous wavelet transform. After constructing a base convolutional neural network, the architecture is improved providing parameter tuning with Bayesian optimization. After that, an improved model (CNN-BO) is used for classification purposes for detecting failures. Experiment results show that CNN-BO performs well and ensures better robustness in failure detection for a hydraulic piston pump.

In this work, unlike the studies done so far, we focus on the detection of different faults in automobile engines by using various deep-learning techniques that have not been tried before in the literature. At first, the dataset is constructed by gathering sounds of different faults from online video-sharing platforms. The sounds capture flooded engine failure, ball failure, brake pedal failure, radiator water boiling failure, ripping motor failure, timing belt failure, and engine failure due to lack of oil. Then, sound signals are extracted using mel-frequency cepstral coefficients to feed into the deep learning architectures. To detect the failure, 1-D and 2-D convolutional neural networks, long short-term memory networks, artificial neural networks, and support vector machines are modeled. Experiment results demonstrate that the 1-D convolutional neural network outperforms other models achieving a 98.5% of accuracy score.

This paper is organized as follows: Section 2 gives the methodology and proposed framework. Section 3 presents the experimental setup and results. Section 4 summarizes and discusses results and outlines future research directions.

2. Proposed Method

This work proposes a deep learning-based automobile engine fault detection system. The proposed method uses engine sounds as input data. Input data is preprocessed with the Mel-frequency Cepstrum Coefficient method for feature extraction. Then, features are fed to Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) based approaches to classify engine sounds. Also, the proposed method is implemented on a mobile platform. The block diagram of the proposed method is shown in Figure 1.

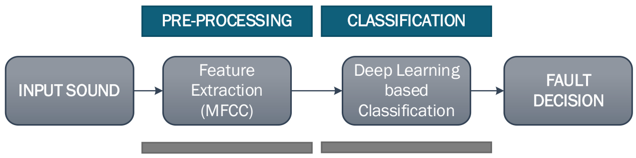


Figure 1. The block diagram of the proposed framework.

2.1. Pre-processing

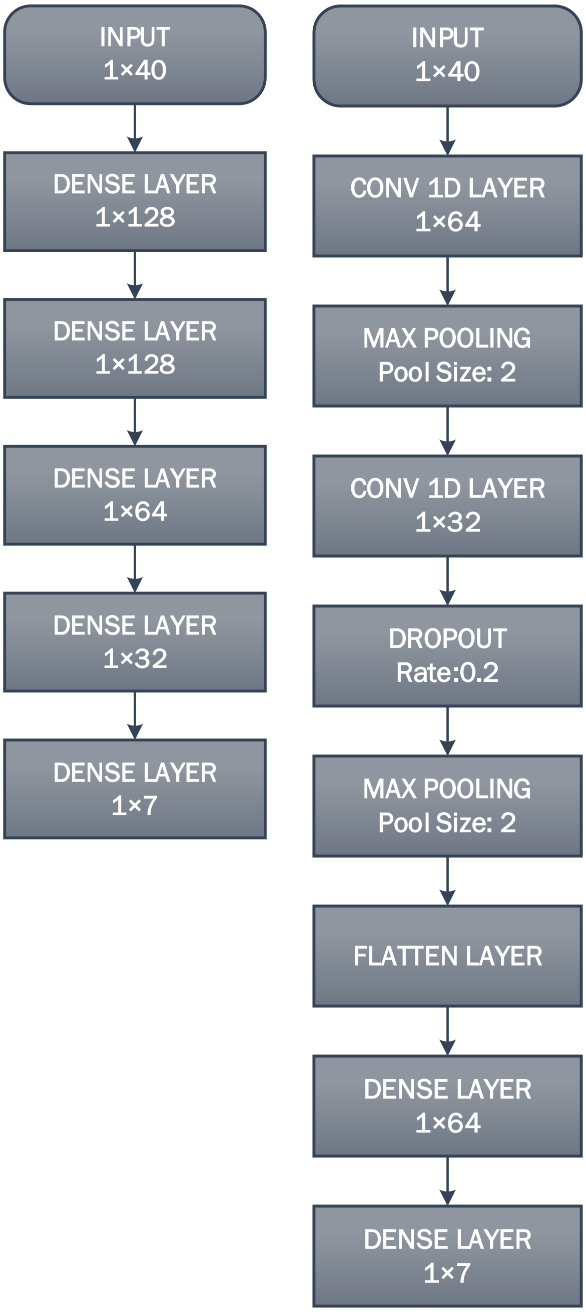
Deep learning-based approaches have the capacity to perform feature extraction and classification together. However, in general, a large amount of training data is needed to perform these two functions together. In the case of limited training data as in the proposed method, features are extracted from the data with another process and these features are used as input data.

Mel-Frequency Cepstrum Coefficients (MFCC) is one of the well-known and successful feature extraction methods. The MFCC algorithm splits an audio signal into frames by reshaping it into smaller windows using the Hamming window. The spectrum is generated for each frame using the Fast Fourier Transform and each spectrum is weighted using a filter bank. Finally, the MFCC vector is calculated using the Logarithm and the Discrete Cosine Transform [15]. As a result of this processes 39 features are obtained but the first 10 are used as feature vectors, considering that they provided sufficient discrimination. In this study, audio signals are divided into 4 equal parts and 10 coefficients are calculated for each audio segment. therefore, each audio signal has 40 MFCC feature vectors.

2.2. Classification

In the study, ANN and CNN-based architectures are used to classify engine sounds. 1×40 size MFCC features are used as input data with these approaches. Proposed classification architectures are given in Figure 2.

Artificial neural networks are a method inspired by biological neural networks in the human brain. Artificial nerve cells (artificial neurons) form the structure of ANN with the connections they create. There are three or more interconnected layers in an artificial neural network.



(a) (b)

Figure 2. Network architectures used in the proposed model (a) ANN based (b) CNN based

Neurons in the input layer compose the first layer. From the first to the last layer data transmission is carried out. The final layer is usually set up to output the desired result (classification, regression, etc.). The interconnected neural layer units attempt to learn about the information gathered by weighing it. As a result, the error is used to recalculate the weight of the ANN's unit connections to account for the difference between the desired and actual outcomes. Over time, the ANN will "learn" how to reduce this difference. The backpropagation algorithm is preferred to transfer the effect of this error calculated in the last layer to the previous layers and to update the weights depending on the error.

Deep learning approaches, as a continuation of artificial neural networks, have become popular in recent years. The concept of Deep Learning is developed with the aim of increasing the performance and effectiveness of artificial neural networks. Deep learning could be used in many tasks such as classification, object detection or regression. The deep neural network is a type of artificial neural network consisting of many hidden layers. Convolutional neural networks are the most widely used deep neural network. This network consists of one or more convolutional layers, a downsampling layer, a pooling layer and one or more connected layers like a standard multilayer neural network. The main advantage of CNNs is that it requires fewer parameters than a fully connected network with the same number of hidden units.

2.3. Mobile Platform Implementation

Systems created in traditional artificial intelligence studies are implemented in large-scale hardware environments such as computers. This approach has great benefits in the training, testing and analysis phases. However, it is not always possible to have high-capacity processing units when the developed methods are expected to be used in real life.

The deep learning model proposed in this study is implemented on a smartphone. Mobile application is developed on Android Studio using Flutter. The deep learning model trained on the computer is deployed to the mobile application using Tensorflow Lite. In Figure 3, a screenshot of the mobile device screen is shown while the proposed method is running on the mobile device.

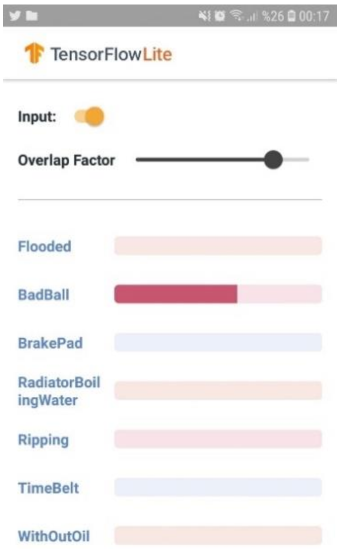


Figure 3. Screenshot of mobile device implementation of the proposed method

3. Experimental Results

The vehicle fault detection sound dataset used in this study is created manually from social media platforms (Instagram, YouTube, etc.). In total, 5000 1 second duration audio recordings are recorded. Recorded vehicle fault types and sample sizes for each type are given in Table 1.

Table 1. Vehicle fault detection sound dataset properties

Fault Type	Sample Size
Flooded Engine Failure	714
Ball Failure	715
Brake Pedal Failure	713
Radiator Water Boiling Failure	715
Ripping Motor Failure	713
Timing Belt Failure	715
Engine Failure Due to Lack of Oil	715

To test the performance of the proposed method more comprehensively, Urban Sound Dataset [16] is also used. The urban sound dataset is a very comprehensive data set consisting of sound samples that are frequently encountered in daily life. It contains sounds belonging to 10 different classes given below.

- Air Conditioning
- Car horn
- Children's playing
- Dog barking
- Drilling
- Vehicle engine
- Gun firing
- Drill
- Siren
- Street music

The performance of the proposed method is evaluated using the formulas given in (1), (2), (3) and (4). These measures are calculated using the confusion matrix shown in Table 2.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The classification performance of the proposed method on the custom vehicle fault dataset and Urban Sound Dataset is given in Table 3 and Table 4, respectively. There are not many methods in the literature on vehicle fault detection using audio signals. Thus, it was not possible to compare the proposed method with a method working on the same subject. Therefore, sound recognition methods like the proposed method are used for performance evaluation. These methods shared their results on Urban Sound Dataset in their publications. Also, in order to analyze their performance on vehicle fault detection audio datasets, these methods are implemented with respect to their provided information. The performance evaluation of [17], [18] and the proposed method on the Urban Sound Dataset is given in Table 3 and the custom vehicle fault dataset is given in Table 4. In Table 3, their results are shared in their publications, and the results with our implementation and proposed method results are compared. In Table 4, the results obtained with our implementation and proposed method results are compared. In Table 3 and Table 4, those marked with "*" represents our implementations.

Although the main objective of the proposed method is not urban sound classification, it should be noted that the proposed method has decent performance according to Table 3. As seen in Table 4, CNN based proposed method has the best results with all metrics. This shows that the proposed method has superior capabilities for vehicle engine fault detection.

Table 2. Confusion matrix of proposed method

		Actual	
		Positive	**Negative**
Predicted	**Positive**	True Positive	False Positive
	Negative	False Negative	True Negative

Table 3. Performance evaluation on Urban Sound Dataset

Method	Precision	Recall	F1-Score	Accuracy
SVM [17]	0,68	0,72	0,69	0,70
SVM [17]*	0,75	0,80	0,84	0,82
CNN [17]	0,83	0,81	0,82	0,81
CNN [17]*	0,83	0,75	0,79	0,78
LSTM [18]	0,85	0,85	0,85	0,83
LSTM [18]*	0,81	0,76	0,78	0,78
ANN based	0,71	0,66	0,67	0,77
CNN based	0,70	0,65	0,67	0,76

Table 4. Performance evaluation on Vehicle Fault Sound Dataset

Method	Precision	Recall	F1-Score	Accuracy
SVM [17]*	0,98	0,97	0,97	0,96
CNN [17]*	0,98	0,97	0,97	0,97
LSTM [18]*	0,98	0,96	0,98	0,98
ANN based	0,70	0,65	0,67	0,76
CNN based	**0,98**	**0,98**	**0,99**	**0,99**

4. Conclusion

In this study, a deep learning-based fault detection method from audio signals is proposed. Within the scope of the study, a total of 5000 sound data of 1-second engine failures are collected on social media. After the dataset is created, feature extraction is performed using the Mel-Frequency-Cepstrum-Coefficients (MFCC) then 2 different architectures consisting of CNN, ANN are evaluated. In addition to the custom vehicle fault sound dataset, Urban Sound Dataset, which is more popular in sound recognition, is used in the performance evaluation of the proposed method. Experimental results showed that the combination of MFCC and CNN gives the best results with 99 % accuracy when compared to studies in the literature. In the future, it is aimed to make improvements on the proposed method by using long-term dependencies with RNN architectures such as LSTM.

Declaration of Ethical Standards

The authors of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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