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Application of low-cost ADXL1002 accelerometer for vehicle engine misfire detection using a novel hybrid EMD-based image processing and DCNN-LSTM model

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Abstract Engine misfires significantly impact vehicle performance and efficiency. This paper presents a novel misfire detection method using vibration data from an ADXL1002 accelerometer. The proposed approach employs Empirical Mode Decomposition (EMD) to effectively extract relevant frequency components from vibration signals, enhancing feature separation. The processed data is then transformed into 2D grayscale images and fed into a hybrid Deep Convolutional Neural Network–Long Short-Term Memory (DCNN-LSTM) model for classification. Experimental results showcase outstanding performances, achieving 100% training accuracy and 98.7% test accuracy. Comprehensive evaluation metrics—including sensitivity, specificity, balanced accuracy (BA), and geometric mean (GM)—validate the model's robustness in detecting misfires across diverse operating conditions.

Keywords: Vehicle engine, vibration signals, empirical mode decomposition (EMD), ADXL1002 accelerometer, hybrid Deep Convolutional Neural Network–Long Short-Term Memory (DCNN-LSTM).

1. Introduction

Engine misfires present a frequent and problematic issue that disrupts the normal combustion process within vehicle engines, severely affecting performance and reliability. Studies such as those in [1] highlight the prevalence of this issue, which occurs when the fuel-air mixture in a cylinder fails to ignite properly. This problem has a broad impact on various engine functions, making it essential in automotive engineering to detect and resolve misfires promptly.

Researchers in [2] emphasize the critical need for swift and accurate identification and resolution of misfires. Addressing this problem is not merely about fixing an error but is essential for maintaining optimal engine performance and environmental stewardship.

Utilizing vibration signals offers a practical and non-intrusive method for assessing engine health [1, 3]. Analyzing these vibrations provides a window into the engine's internal workings, despite their complexity, as they carry valuable performance data [3, 4]. Consequently, vibration signal examination is a vital diagnostic tool, especially for pinpointing specific engine misfires [1, 3].

The majority of research has explored the use of various sensors, including MEMS accelerometers, acoustic sensors, and knock sensors, to capture these vibrations [5, 6]. Digital signal processing techniques applied to noisy vibration data have shown promise and are extensively used in monitoring equipment like pumps, ball bearings, and gearboxes [7, 8]. However, challenges arise when applying these methods to vehicle engines due to the instability of the signals under conventional analysis techniques [9].

Alternatively, machine learning (ML) technologies have been employed to train algorithms to recognize patterns in vibration signals. These methods involve learning from labeled data to identify faults, utilizing approaches such as clustering, decision trees, neural networks, and support vector machines [10–14]. Advanced diagnostic systems for rotating machinery typically involve two stages: feature extraction using neural networks or signal processing, followed by pattern recognition-based classification [11].

In the current industrial era, researchers are continually exploring innovative techniques to assess the health of industrial machines and vehicles. Despite this progress, precision and sensitivity in tools like vibration analysis, digital signal processing, and machine learning remain challenged by operational changes, limited sensor data, excessive noise, or complex vibration patterns.

This paper makes a significant contribution to the field by introducing a novel method for classifying engine conditions using vibration data from the ADXL1002 accelerometer. A notable innovation is the application of Empirical Mode Decomposition (EMD) as a preprocessing step, which effectively isolates relevant information within specific frequency components of the vibration signals. Moreover, the study improves classification accuracy by transforming the cleaned vibration data into 2D grayscale images for the proposed DCNN-LSTM model. The results demonstrate exceptional performance, with a training accuracy of 100% and a test accuracy of 98.7%. Additionally, a thorough evaluation of the DCNN-LSTM architecture is conducted using custom test sets for the misfire dataset, employing various performance metrics such as accuracy, sensitivity, specificity, Balanced Accuracy (BA), and Geometric Mean (GM) to provide comprehensive insights into the model's classification capabilities and effectiveness.

2. Material and methods

2.1. Vibration dataset

We gathered our data utilizing an ADXL1002 accelerometer, a MEMS sensor, which was integrated with the BeagleBone Black control system. This setup enabled us to analyze the vibrational behavior of a vehicle's engine under various conditions. For an in-depth examination of the ADXL1002 accelerometer's calibration when connected to the BeagleBone Black, please refer to our prior publication at [15].

The first data point in our collection captures the engine running smoothly at 2500 RPM. The second point documents an engine misfire occurring at a reduced speed of 1500 RPM. The third sample records another misfire, this time at 2500 RPM, providing a contrast to the initial healthy engine state. The fourth and final data point captures a misfire at an increased speed of 3000 RPM. Detailed descriptions of these misfire events can be found in Table 1.

Table 1. Description of the vehicle engine vibration dataset.

Sr. no.	Health condition	Value
1	Healthy	2500 RPM
2	Misfire	1500 RPM
3	Misfire	2500 RPM
4	Misfire	3000 RPM

This comprehensive dataset allows for a thorough analysis of the accelerometer's responsiveness to different engine conditions, providing insights into the subtle vibrational patterns of both normal and malfunctioning states at varying RPMs.

2.2. Preprocessing

To diagnose misfire conditions in vehicle engines using vibration data from MEMS sensors like the ADXL1002 accelerometer, it is crucial to preprocess the data to mitigate unwanted signals and external noise from the engine's complex structure. Resonance frequencies from various engine components further complicate this task, necessitating effective data cleaning methods.

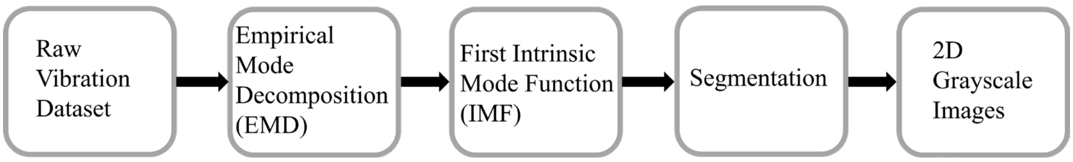

Figure 1. Block diagram of preprocessing steps.

Our methodology involves the use of Empirical Mode Decomposition (EMD) as a pivotal preprocessing step. EMD is a signal processing method that decomposes complex vibration signals into simpler components known as Intrinsic Mode Functions (IMFs). Each IMF captures a distinct frequency component of the original signal, facilitating the isolation and analysis of pertinent information. The first IMF extracted from each vibration signal is particularly significant, as it represents the most dominant and fundamental frequency components. This extraction allows us to concentrate on key features linked to misfire conditions. The block diagram of the preprocessing steps is depicted in Figure 1.

Next, we transform the first IMF into 2D grayscale images, which are then used as input for our DCNNLSTM (Deep Convolutional Neural Network - Long Short-Term Memory) model. Figure 2 displays a random visualization of the 2D grayscale images created from the preprocessing steps for various engine health conditions. By converting the vibration data into visual formats, our model can effectively learn and distinguish patterns associated with misfire conditions at different RPMs, thereby improving the diagnostic accuracy and robustness.

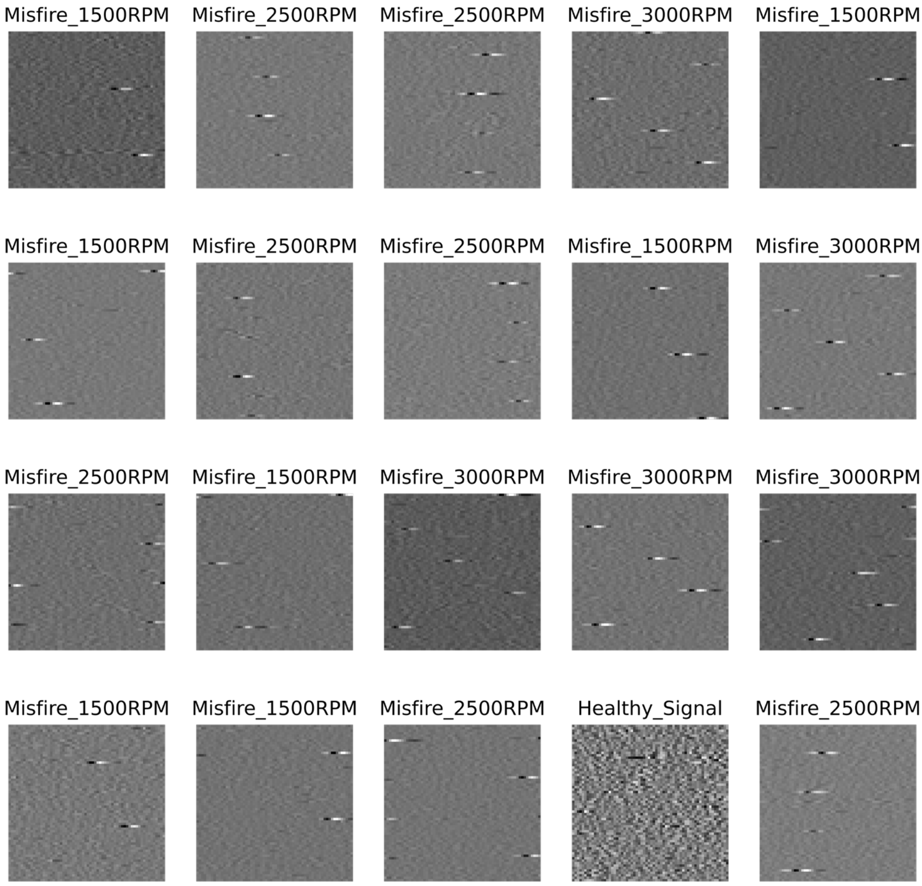

Figure 2. 2D grayscale images of random vibration signals.

2.3. Proposed model

The developed model for detecting engine misfires utilizes a hybrid structure that integrates Deep Convolutional Neural Networks (DCNN) with Long Short-Term Memory (LSTM) networks. This innovative approach focuses on effectively interpreting 2D grayscale images generated from processed vibration signals. Named the DCNN-LSTM, our model is tailored for identifying misfires in vehicle engines by analyzing vibration signals recorded at various engine speeds (1500 RPM, 2500 RPM, 3000 RPM) in addition to normal, healthy signals. The model categorizes the data into four distinct classes and employs an initial Convolutional Neural Network (CNN) component, which is succeeded by LSTM layers for handling sequential data learning.

The CNN segment of the model consists of several convolutional layers, each tuned to capture distinct features from the input images. The first layer utilizes 32 filters with a kernel size of (6, 6) and employs the Rectified Linear Unit (ReLU) activation function to introduce non-linearity. Subsequent max pooling layers help reduce spatial dimensions while preserving important features. The network's depth and complexity increase gradually through additional convolutional layers, culminating in a total of nine convolutional layers that enable the model to learn hierarchical representations of the input data.

Following the CNN layers, a flattening operation is employed to transition to densely connected layers. A dense layer with 128 neurons and ReLU activation is incorporated to further extract relevant features. Integration of LSTM layers is a distinctive feature of the proposed model. The input is reshaped for compatibility with the sequential nature of LSTM, followed by two LSTM layers with 64 and 32 units, respectively. These layers enable the model to capture temporal dependencies and long-term patterns within the vibration signals.

To facilitate classification, the model employs a final dense layer with a softmax activation function, producing probabilities for each class. The final dense layer, activated by softmax, outputs probabilities across the specified number of classes (number classes = 4), representing different engine conditions (1500 RPM, 2500 RPM, 3000 RPM, and a healthy signal). The model is compiled using categorical cross-entropy as the loss function, Adam optimizer for parameter optimization, and accuracy as the evaluation metric. Table 2 illustrates the overall proposed model described above.

Table 2. Proposed DCNN-LSTM model

Layer (Type)	Output shape	No. of parameters
Layer 1 (2D convolution)	(None, 64, 64, 32)	1184
Layer 2 (2D max pooling)	(None, 22, 22, 32)	0
Layer 3 (2D convolution)	(None, 11, 11, 40)	46120
Layer 4 (2D max pooling)	(None, 11, 11, 40)	0
Layer 5 (2D convolution)	(None, 6, 6, 40)	14440
Layer 6 (2D max pooling)	(None, 6, 6, 40)	0
Layer 7 (2D convolution)	(None, 3, 3, 40)	14440
Layer 8 (2D max pooling)	(None, 3, 3, 40)	0
Layer 9 (2D convolution)	(None, 2, 2, 80)	51280
Layer 10 (flatten)	(None, 320)	0
Layer 11 (fully connected)	(None, 128)	41088
Layer 12 (reshape)	(None, 1, 128)	0
Layer 13 (LSTM)	(None, 1, 64)	49408
Layer 14 (LSTM)	(None, 1 32)	12416
Layer 15 (flatten)	(None, 32)	0
Layer 16 (fully connected)	(None, 4)	132

3. Experimental results and discussions

In this study, we analyzed a vehicle engine vibration dataset collected using the ADXL1002 accelerometer, as described in Table I. Before implementing the DCNN-LSTM model presented in Table 2, we preprocessed the data to remove unwanted signals and external noise resulting from the complex behavior of the vehicle engine. After cleaning, the vibration data was converted into 2D grayscale images to be used as inputs for the DCNN-LSTM model. Figure 3 shows that the training accuracy achieved 100%, while the test accuracy was 98.7%.

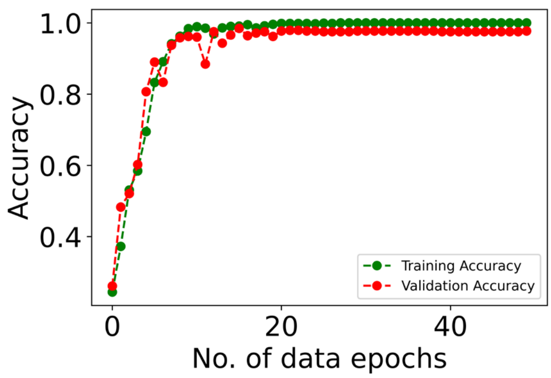

Figure 3. Accuracy of the proposed DCNN-LSTM model: training accuracy and validation accuracy.

Additionally, Figure 4 presents the confusion matrix, providing a visual representation of the accuracy for each class. According to the matrix, healthy signals were predicted with 99% accuracy, misfire at 1500RPM was predicted with 100% accuracy, misfire at 2500RPM with 98%, and misfire at 3000RPM with 100% accuracy. These results showcase the effectiveness of our model in accurately classifying different engine conditions based on vibration data.

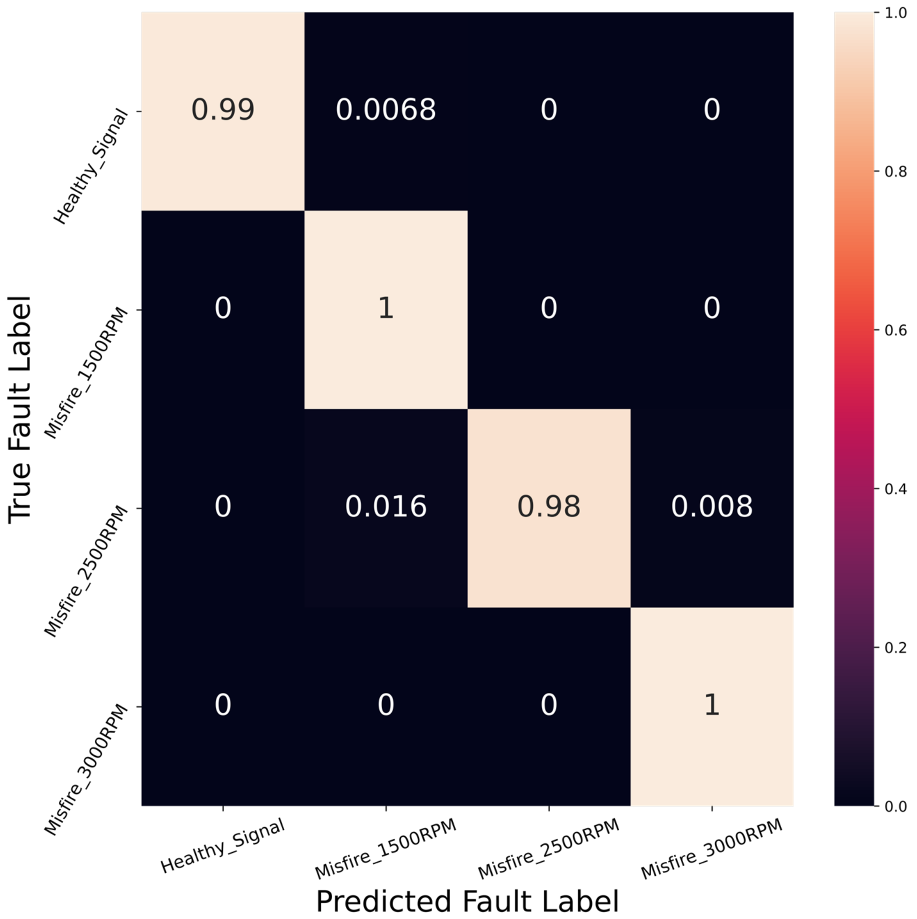

Figure 4. Confusion matrix representing the true faults versus predicted faults for engine misfire at different RPMs.

Moreover, in Table 3, we present a detailed analysis of the conclusive performance results attained by our system. The evaluation involved implementing the proposed DCNNLSTM architecture on test sets specifically tailored for the misfire dataset, as expounded in Table 1. To assess the system's efficacy comprehensively, we considered multiple performance indicators.

Table 3. Performance of the proposed DCNN-LSTM model.

Health condition	Accuracy (%)	Sensitivity (%)	Specificity (%)	BA (%)	GM (%)
Healthy signal	99.829	99.319	100	99.659	99.659
Misfire at 1500 RPM	99.429	100	99.239	99.619	99.619
Misfire at 2500 RPM	99.4	97.6	100	98.8	98.792
Misfire at 3000 RPM	99.8	100	99.733	99.867	99.866

Initially, our focus is on the accuracy metric, which serves as a yardstick for evaluating the correctness of our system's predictions. It reveals the proportion of correctly identified instances, providing insight into our system's overall performance. Sensitivity, also known as the true positive rate, delves into our system's ability to accurately detect positive instances among all actual positives. Conversely, specificity delves into our system's precision in pinpointing negative instances among all actual negatives. The Balanced Accuracy (BA) metric steps in for a more nuanced evaluation, striking a balance between sensitivity and specificity to ensure a fair assessment across different classes or outcomes. Furthermore, we incorporate the Geometric Mean (GM), a holistic measure derived from the square root of sensitivity multiplied by specificity. This metric offers a comprehensive view of our classification performance, particularly valuable in scenarios with class imbalances. Our computations are underpinned by specific formulas or algorithms outlined in the subsequent equations, showcasing our system's proficiency across various dimensions of accuracy and effectiveness in classification:

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

$$Sensitivity\ (\%) = \frac{TP}{TP + FN} \times 100, \tag{2}$$

$$Specificity\ (\%) = \frac{TN}{TN + FP} \times 100, \tag{3}$$

$$BA\ (\%) = \frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right) \times 100, \tag{4}$$

$$GM\ (\%) = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}} \times 100, \tag{5}$$

In evaluating the efficacy of our model on a dataset featuring distinct classes like healthy signals and various misfire RPMs, we delve into the realm of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). This involves a meticulous comparison between the predictions made by the model and the actual class labels assigned to each data point.

When our model accurately identifies positive cases for each class, such as pinpointing a misfire at 1500RPM correctly, we count it as a true positive. Conversely, false positives occur when the model erroneously labels a healthy signal as a misfire at 1500RPM. True negatives, on the other hand, depict instances where the model correctly identifies negative cases, like recognizing a healthy signal as not indicative of a misfire at 1500RPM.

However, false negatives emerge when the model wrongly predicts negative cases, such as mistaking a misfire at 1500RPM for a healthy signal. These numerical values serve as the basis for computing essential metrics like precision, recall, and accuracy, providing a comprehensive assessment of the model's performance across different classes.

In our exploration of DCNN-LSTM algorithms applied to vibration data obtained from vehicle engines, particularly in predicting misfires at varying RPMs using the ADXL1002 accelerometer, we've observed outstanding performance. Nevertheless, it's imperative to acknowledge the challenges inherent in preprocessing the vibration dataset due to the presence of unwanted signals and external noise, stemming from the complex nature of vehicle engine systems and the utilization of the cost-effective ADXL1002 accelerometer.

4. Conclusions

To summarize, this study utilized a dataset capturing vehicle engine vibrations, gathered using the ADXL1002 accelerometer. Before deploying our novel DCNN-LSTM model, we undertook a pivotal preprocessing stage to eliminate unwanted signals and external interferences stemming from the intricate engine dynamics. By employing EMD within our methodology, we decomposed the intricate vibration patterns into Intrinsic Mode Functions (IMFs), enabling focused examination of pertinent details within distinct frequency spectra. Post-cleansing, the vibration dataset underwent transformation into 2D grayscale representations, serving as inputs for our DCNN-LSTM model.

The outcomes of our research revealed notable achievements, with training accuracy reaching 100% and test accuracy at 98.7%. A detailed analysis, including the presentation of a confusion matrix, visually demonstrated the accuracy for each class. These results underscore the effectiveness of our model in accurately classifying diverse engine conditions based on vibration data.

Moreover, our extensive assessment encompassed the application of the DCNN-LSTM architecture on customized test datasets tailored for analyzing misfire occurrences. We meticulously computed various performance metrics, including accuracy, sensitivity, specificity, Balanced Accuracy (BA), and Geometric Mean (GM), to gain comprehensive insights into the model's classification accuracy and effectiveness across diverse dimensions.

Additional information

The authors declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

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