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Condition monitoring of internal combustion engines with vibration signals and fault detection by using machine learning techniques

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ABSTRACT

Internal combustion engines are frequently used in transportation, power plants, and in many other applications for industrial purposes. For this reason, it is very important that the maintenance is done systematically and that the faults are detected correctly. In this study, two different methods were used for the detection of the healthy internal combustion engine (H) and faulty internal combustion engines (single-cylinder misfire-F1, two-cylinder misfire-F2). In the first method, classical signal features were extracted from engine vibration measurements and used in the training of artificial neural networks (ANNs) and support vector machine (SVM). In the second method, convolutional neural networks (CNNs), a deep learning method in which features are extracted automatically, are used. Spectrograms of engine vibration signals were used to train pre-trained CNNs with different structures. Spectrograms were obtained by applying short-time Fourier transform (STFT) to vibration signals. The results of GoogleNet and ResNet-50 models trained with spectrograms were compared with the results obtained from models based on ANNs and SVM.

Keywords: Fault detection, Internal Combustion Engines, Neural Networks, Deep Learning, Condition Monitoring, Vibration Signals

1. Introduction

Internal combustion engines are used in many vehicles such as cars, trucks, ships, submarines, and aircraft. They are also preferred in applications such as agriculture, transportation, and electricity generation facilities. For this reason, the maintenance of internal combustion engines and the exact detection of their faults are extremely critical issues for performance, safety, and reliability.

The processes that take place inside the internal combustion engine are extremely complicated and hard to model analytically. Therefore, modern techniques of machine learning (supervised learning, unsupervised learning, reinforcement learning, and deep learning) are used in combustion control and optimization, estimation of emission values, and design or optimization of engine elements in internal combustion engines [1].

2. Literature Review

In the literature, there are a limited number of studies on the detection of faults such as knocking, misfiring, or deterioration of engine elements in the internal combustion engine with machine learning techniques. In their study, Jafarian et al. [2] placed four vibration sensors in different positions of an automobile engine and investigated various faults, including misfire and valve clearance, using the data obtained by the sensors under various operating conditions. They also classified the engine state using various machine learning techniques with the signal features obtained using fast Fourier transform (FFT). Li et al. [3] developed an intelligent diagnostic method for marine diesel engines using instantaneous angular velocity information. In their work, they performed the implementation and evaluation of a technique based on the combination of empirical mode decomposition, independent component analysis, and support vector machine (SVM). Moosavian et al. [4] developed an intelligent diagnostic approach based on acoustic and vibration signals using a combination of sensor fusion and classifier and used artificial neural networks (ANN) and SVM techniques to diagnose spark plug faults in an internal combustion engine. Saharma et al. [5] performed the detection of misfire faults in an internal combustion engine using the features extracted from the vibration signals and the decision tree algorithm. Devasenapati et al. [6] used decision trees for feature selection and classification to identify misfire faults in a four-stroke four-cylinder internal combustion gasoline engine. Castresana et al. [7] utilized a multi-output ANN model to obtain a complete performance map of a ship's diesel engine. Wang et al. [8] proposed a new diagnostic method through hybrid algorithm-based multidimensional feature extraction for the detection of undiagnosed engine faults that affect the normal operation of vehicles. Cai et al. [9] presented a new method for diagnosing diesel engines by combining back propagation neural networks, known as Bayesian networks, with a rule-based algorithm. Kowalski et al. [10] used the extracted features by monitoring various signals produced by the engine as inputs for a feedforward neural network-based classification algorithm. Karatuğ and Arslanoğlu [11] developed a condition-based maintenance system for fault diagnosis in ship engine systems using ANN and illustrated three scenarios. Flett and Bone [12] used machine learning methods to detect valve spring and valve clearance faults in diesel engines and compared their methods with each other in terms of performance. Wang et al. [13] diagnosed the faults of a diesel engine based on adaptive wavelet packets and empirical mode decomposition and used fractal dimension features for this purpose. Basurkoa and Uriondo [14] developed a condition-based maintenance strategy for medium-speed diesel engines used on ships. They trained a feed-forward neural network to build the engine performance model and detected the engine's fuel consumption and fault condition. In the study by Küçüksarıyıldız et al. [15], specific fuel consumption for a 60 HP tractor was evaluated under different conditions of axle load, tire pressure, and drawbar force. The results were also predicted using ANN, with the best model demonstrating high accuracy in its predictions. Togun and Baysec [16] developed an ANN model to predict torque and brake specific fuel consumption of a gasoline engine using spark advance, throttle position, and engine speed. Based on experimental data, the model was trained and tested, showing satisfactory accuracy. The ANN model is also presented as an explicit mathematical function. Çay et al. [17] developed an ANN model to predict brake specific fuel consumption, effective power, average effective pressure, and exhaust gas temperature of a methanol engine. Based on experimental data from a four-cylinder engine, the model achieved regression values close to 1, RMS values below 0.015, and mean errors under 3.8%, demonstrating its effectiveness in predicting engine performance. Parlak et al. [18] studied an ANN model using a back propagation algorithm to predict specific fuel consumption and exhaust temperature of a Diesel engine at different injection timings. The model achieved a mean absolute relative error of less than 2% compared to experimental results, indicating strong consistency and making it a useful tool for preliminary thermal engineering analyses.

Looking at the studies in the literature, it can be seen that vibration analysis is the prominent approach in diagnosing the faults of internal combustion engines. In addition, studies using modern machine learning techniques in the detection of engine faults are also extremely limited. With the effective use of modern machine learning techniques, engine faults can be diagnosed. Therefore, in this study, two methods based on machine learning and vibration analysis are utilized for the detection of internal combustion engine faults. Accordingly, vibration signals were classified using two different machine-learning methods. In the first method, ANN and SVM models are trained with classical features extracted from their signals. In the second method, spectrograms were obtained from vibration signals and CNN models were used to detect engine faults. Engine vibration data shared by Randall in his Vibration-based Condition Monitoring book [19] were utilized to validate the two methods presented. Finally, the results obtained from the methods were compared in terms of performance.

3. Materials and Methods

3.1 General information

In a diesel engine, the thermodynamic energy obtained by the ignition of the air-fuel mixture in the cylinder is converted into mechanical energy via the slider-crank mechanism. Fig. 1 shows an inline 6-cylinder internal combustion engine with a 1-5-3-6-2-4 ignition pattern.

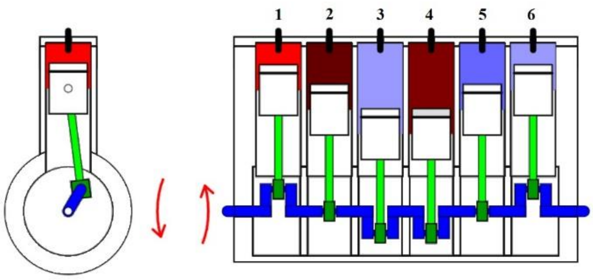

Fig. 1 6-cylinder internal combustion engine

Significant vibrations occur in engines due to factors such as oscillating and rotating parts, cyclical changing of gas pressure due to combustion, and inertia forces of moving parts. These vibrations usually occur as torsional vibration, longitudinal vibration, and mixed vibrations. Torsional vibrations are mainly caused by the cyclic gas pressure in the cylinder as a result of combustion and the mass forces of the moving parts. That is, changing the crankshaft rotational speed causes velocity fluctuations, hence torsional vibrations [19,20]. Therefore, torsional vibrations can contain information about engine malfunctions that affect gas pressure, such as misfires and valve clearance. Fig. 2 shows angular velocity fluctuations for a misfire in a cylinder of an inline 6-cylinder engine with a 1-5-3-6-2-4 ignition pattern. There are six uniform fluctuations in normal operation. As shown in the figure, if one of the cylinders misfires, the speed drops significantly and must be gradually rebuilt by the following cylinders [19].

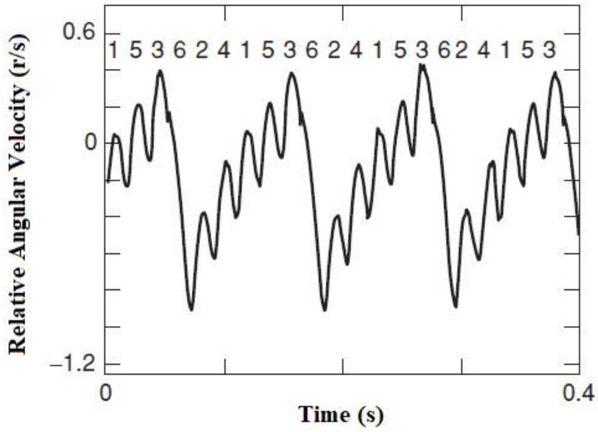

Fig. 2 The misfire in one cylinder and angular velocity fluctuates [19].

3.2 Experimental data

In this study, vibration signals obtained from 3 different cases of a 6-cylinder internal combustion engine were used [19]. Vibration signals were obtained from the engine block with an accelerometer located near the 6th cylinder. In the first case, the engine runs normally. In the second case, there is a misfire fault in one cylinder. In the third case, there are misfire faults in two cylinders. Misfire faults were achieved by removing the ignition cables. The firing order is 1–5–3–6–2–4. The sampling frequency for measurements in all cases is 24 000 Hz. Since the engine speed fluctuates, especially for faulty conditions, the signals containing the cycles are divided into shorter segments (32x1024). The average engine speed is nominally 1500 rpm. More detailed information can be found in the relevant reference [19].

3.3. Methodology

In this study, we applied two different methods for the detection of a healthy internal combustion engine (H) and faulty internal combustion engines (single-cylinder misfire-F1, two-cylinder misfire-F2). In the first method, we extracted classical features from engine vibration signals and used them in training ANN and SVM. These features are mean (M), root mean square (RMS), standard deviation (SD), variance (VAR), kurtosis (K), and skewness (S). In the second method, we used CNNs, a deep learning method, to detect engine faults. We utilized spectrograms of engine vibration signals to train pre-trained CNNs with different structures. We used the short-time Fourier transform (STFT) to obtain the spectrograms.

3.3.1. The first method based on classical machine learning algorithms

The main purpose of feature extraction is to determine a set of quantitative coefficients to describe the distinctive abilities of the vibration signal characteristics in order to diagnose internal combustion engine faults. The features extracted from the signals are shown in Table 1.

Table 1 Features of the engine vibration signals

Property Name	Formula
Mean (M)	$M=\frac{1}{N}\sum_{i=1}^{N}x_i$
Root mean square (RMS)	$RMS=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$
Standard deviation (σ, SD)	$SD=\sigma=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2}$
Variance (σ^2, VAR)	$VAR=\sigma^2=\frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2$
Skewness (S)	$S=\frac{\sum_{i=1}^{N}(x_i-\bar{x})^3}{(N-1)\sigma^3}$
Kurtosis (K)	$K=\frac{\sum_{i=1}^{N}(x_i-\bar{x})^4}{(N-1)\sigma^4}$

ANN and SVM, which are used to detect engine faults using features in the first method, are among the most well-known modern machine-learning algorithms. ANN was developed with inspiration from the human brain and nervous system. In the ANN algorithm, artificial neurons process the features determined as input in the hidden layer and produce output about the engine faults. A two-layer feedforward neural network is used for the detection of engine faults. The number of hidden neurons was determined as 10 and the network was trained with the Levenberg-Marquardt backpropagation algorithm. SVM is also applied to classification and fault detection problems. This study, it is aimed to minimize the loss function while classifying the engine faults with SVM and to obtain the optimal hyperplane separating the classes in the best way. Since there is a lot of work in the literature on the mathematical details of SVM and ANN [21], no further information is given here. Input and target data for both ANN and SVM were randomly divided into three partitions. 70% of the data was used for training and 15% for validation. Finally, 15% of the data was used for a completely separate test.

3.3.2. The second method based on deep learning

Traditional machine learning methods rely on predefined features, while deep learning techniques, especially Convolutional Neural Networks (CNNs), excel at automatically learning complex data structures. CNNs effectively extract hierarchical features from raw data without extensive manual feature engineering, enhancing accuracy and reducing processing time. Their capability to handle large datasets makes them ideal for applications like fault detection, leading to more accurate and reliable results. Consequently, CNNs are increasingly favored for engine fault detection tasks over classical approaches.

The second method applied in this study is based on the STFT, which is one of the time-frequency analysis methods. We obtained the spectrograms from the motor vibration signals with STFT and used them to generate the dataset for the deep learning algorithm.

STFT is a Fourier-based transform used to determine the frequency and phase of local parts of the signal that change over time. With STFT, a long-time signal is split into short segments and the Fourier transform is implemented for each short segment separately to obtain the spectrogram. Finally, spectrograms are plotted as a function of time. In Eq. 1, x(t) represents the time signal, τ is the time axis, and ω is the frequency [22].

$$P_{Spektrogram,x}(\tau,\omega)=\left|STFT_x(\tau,\omega)\right|^2 \quad (1)$$

We used the spectrograms obtained with STFT to train pre-trained CNNs with different structures to detect engine faults. CNNs are a special subclass of ANNs, and classification with CNN is mostly performed on images. CNNs are a specially developed version of multilayer perceptrons. In multilayer perceptrons, each neuron in one layer is connected to all neurons in the next layer. CNN consists of convolutional and subsampling layers. Each of these layers has a specific topographic structure, and each layer contains different clusters of neurons. Each neuron is also linked to neurons in previous layers [22]. In Fig. 3, a typical CNN architecture is given. The input layer in the figure represents the spectrograms in our problem, and the output layer is the engine fault. The mathematical details of CNNs will not be given here as they have been extensively discussed in the literature [22].

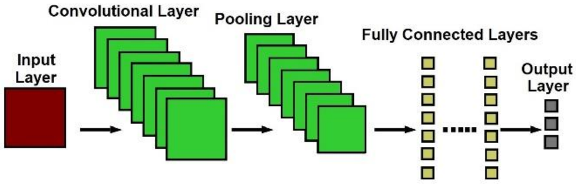

Fig. 3 Typical CNN architecture

Pre-trained CNNs are modified and applied to new classification problems. In this way, the time and effort required to train a network is much less than to train a network from scratch [23]. Detailed features of the pre-trained CNNs used in this study are given in Table 2. Also, Table 3 shows the training parameters.

Spectrograms of vibration signals for an healthy internal combustion engine (H) and faulty internal combustion engines (single-cylinder misfire-F1, two-cylinder misfire-F2) were obtained separately. The spectrograms obtained for each engine were divided into three groups as training (50%), test (25%), and validation (25%). CNN outputs are modified and changed to classify healthy and faulty engines. Using training and validation data, CNNs were trained on deep features, and faults were classified. Finally, the trained network was tested, and faults were diagnosed based on data labels.

4. Results and Discussion

4.1. Signal analysis

The representations of vibration signals obtained from H, F1, and F2 engines in the time and frequency domain can be seen in Fig. 4. Since the signal data is divided into 32 segments, these representations contain 1 out of 32 of the measurements used in the calculations. Accordingly, the frequency amplitudes of the vibration signals of the H engine are lower than the faulty engines. However, a more detailed examination can be made to extract the features of the signals.

Table 2 Features of the pre-trained CNNs

	GoogleNet	ResNet-50
Layer depth	22	50
Layer Number	144	177
Connection Number	170	192
Type of Input	Spectrogram	Spectrogram
Size of Input	224x224x3	224x224x3
Type of Output	Classification	Classification
Size of Output	3	3
Weight learning rate factor	10	10
Bias learning rate factor	10	10
The Loss Function	Cross-entropy	Cross-entropy

Table 3. Training parameters of pre-trained CNNs

	GoogleNet ResNet-50
Frequency of Validation	5 Hz
Rate of Learning	0.001
Maximum Epoch	5
Size of Mini Batch	10
Input Data Resolution	483 x 430 pixel

4.2. The Results of the First Method

Fig. 5 shows the different features of vibration signals of healthy and faulty internal combustion engines. Accordingly, looking at the M values, it can be seen that the F2 engine produces the highest features. The H engine produced the lowest M values. Looking at the RMS values, it can be seen that the H engine produces the highest features. The F1 engine produced the lowest RMS values. There is a similar trend for SD and VAR features. Looking at the S values, it can be seen that the F2 engine produces the highest features. The F1 engine produced the lowest S values. K features were close to each other for all three engines.

All these features are used to create the dataset that is organized to detect motor failure with ANN and SVM.

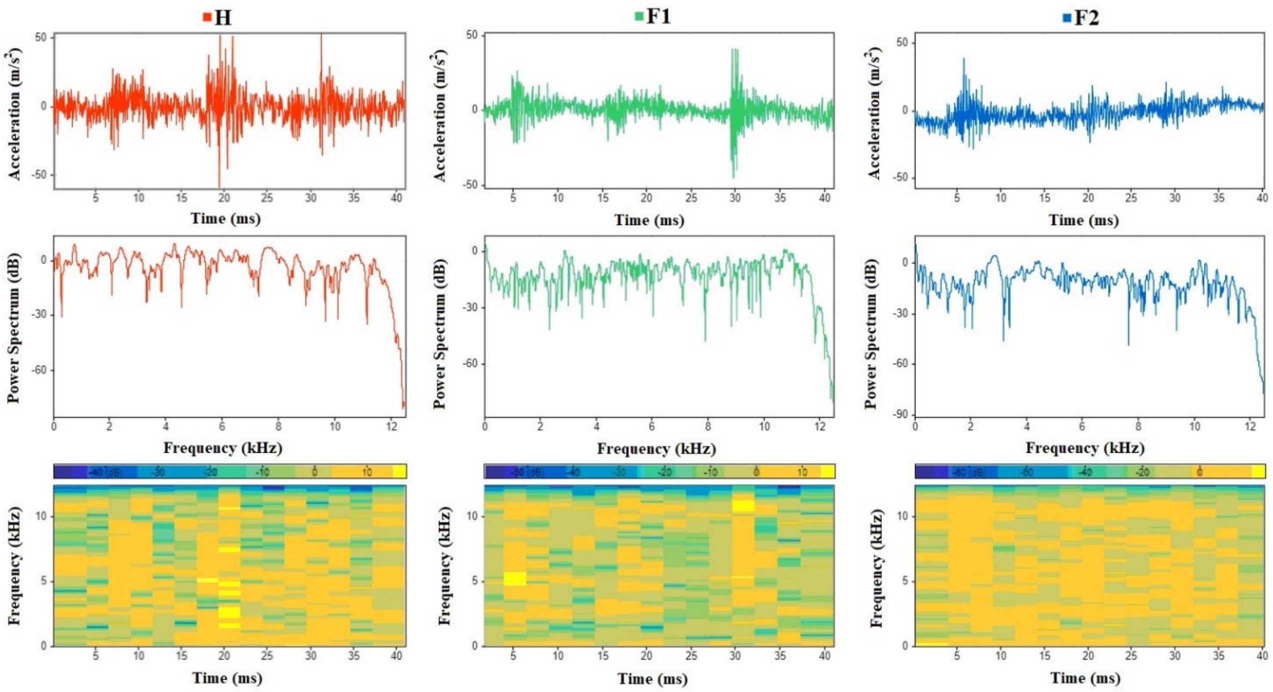

Fig. 4 Time and frequency domain representations and spectrograms of internal combustion engines vibration signals

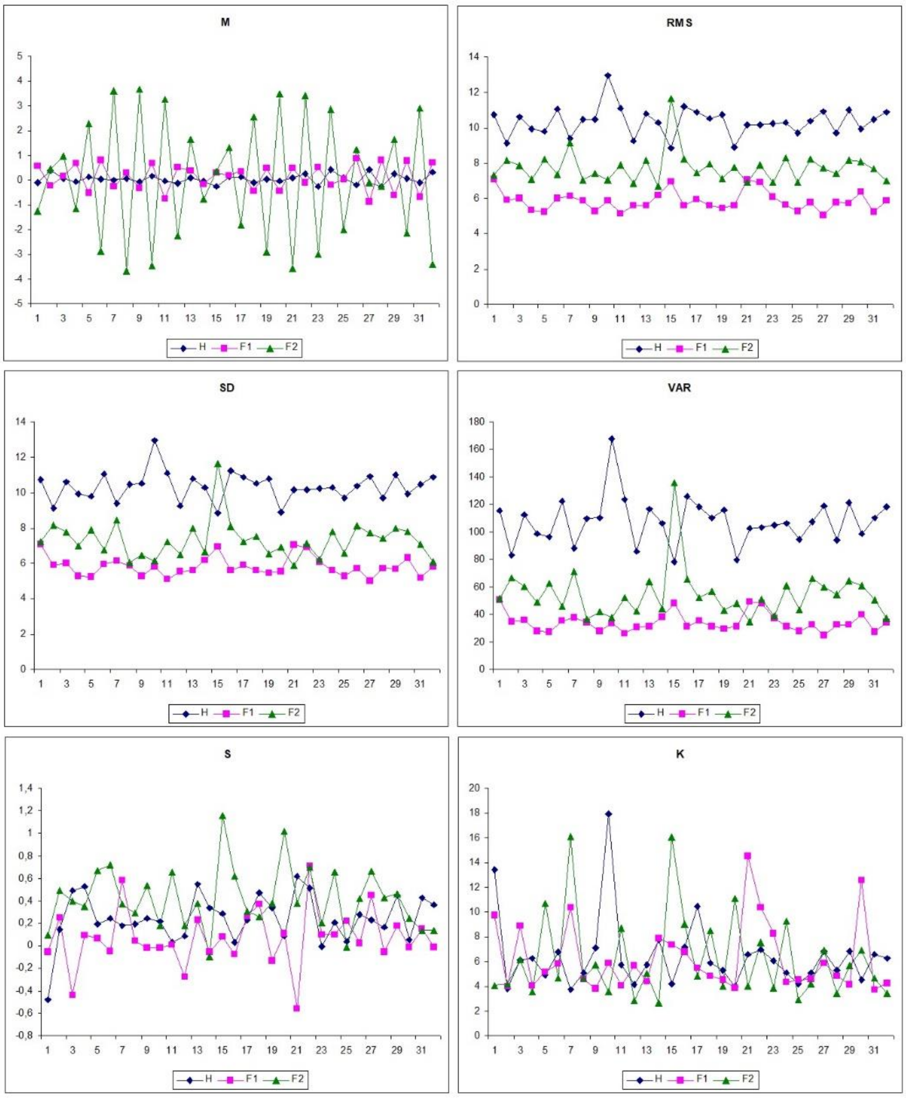

Fig. 5 Different features of vibration signals of healthy and faulty internal combustion engines

Fig. 6 shows the training, validation, and test performances of the ANN model. Accordingly, the best validation performance is 0.043846 at epoch 11. Fig. 7 shows the training, validation, and test confusion matrices of the ANN model. Looking at the all confusion matrix, it can be seen that the overall success rate of the model is 97.9%.

In this study, features extracted from the vibration signals of engines are also used in training SVM models. In order to avoid figure redundancy, the results of the SVM models are given directly. As can be seen from Table 4, all SVM models achieved a validation success of 95.8%.

4.3. The results of the second method

The CNNs used in this study were adapted to the problem of engine diagnostics and trained with spectrograms obtained from vibration signals. At the end of the training, validation success, loss, and gradient values were calculated. Finally, the successes of the tested CNNs with the data set reserved for the test were compared with each other. For CNN models, the goal is to identify healthy and faulty engines. Table 5 shows the class labels of the engines and the number of samples utilized for the training, validation, and test of different CNN models.

Table 4. Results of training of SVM models

SVM Models	Validation Accuracy (%)
Linear	95.8
Quadratic	95.8
Cubic	95.8
Gaussian	95.8

Table 5. Class labels and sample numbers

Class Label	H	F1	F2
Training Samples	22	22	22
Validation Samples	10	10	10
Test Samples	10	10	10

Fig. 8 demonstrates the accuracy rates for two different CNN models. Accordingly, GoogleNet and ResNet-50 models reached a 100% validation rate at the end of the training process. Since the number of layers and connections of the ResNet-50 model is higher, the training time is longer. With all other conditions remaining the same, the increase in complexity in the CNN architecture positively affects the accuracy rate and increases the training time.

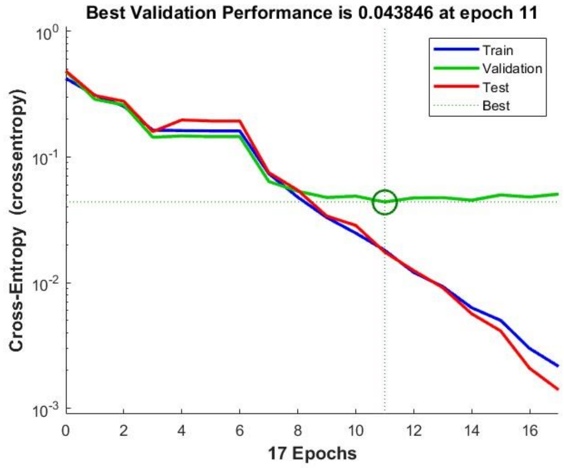

Fig. 6 Training, validation, and test performances of the ANN model

Fig. 7 Training, validation, and test confusion matrices of the ANN model

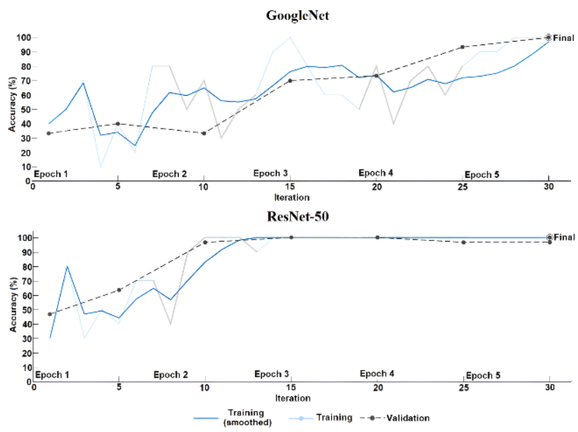

Fig. 8 Accuracies for different CNN models

The losses in training and validation processes for different CNN models can be seen in Fig. 9. Losses are a measure of the difference between the estimated output and the actual output. Losses decrease with the number of iterations. The loss values of the models decreased over time due to the variation in the validation rates during the training period.

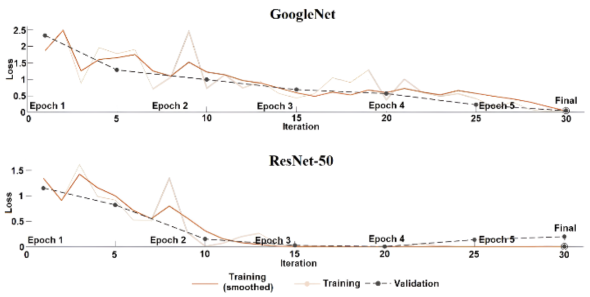

Fig. 9 Losses for different CNN approaches

The success rates of CNN models trained and tested with different numbers of samples can be seen in Table 6. Accordingly, as the number of samples increases, the validation and test successes, and training times of the two CNN models increase. It can be seen from the table that the training time of CNNs with more complex architecture such as Resnet-50 will be longer.

The performance of the CNN models, as shown in the table, indicates that both GoogleNet-CNN and ResNet-CNN achieve 100% validation success with an increase in training samples, which is a promising result. However, strong correlations between input and output data can sometimes lead to success without overfitting, especially with smaller datasets—this raises concerns about the models' generalization ability. The tendency of the models to memorize training data may limit their performance on different engine types or fault conditions. Therefore, it is crucial to consider strategies that enhance robustness and generalizability, such as adding more data or employing regularization techniques, to ensure reliable performance across diverse scenarios and validate results against various datasets.

In this context, the study contributes to the diagnosis of internal combustion engine faults by utilizing both classical machine learning methods (SVM and ANN) and deep learning techniques (CNN). It was observed that ANN achieved a success rate of 97%, outperforming SVM, while the ResNet-50 architecture also achieved a diagnostic performance of 100%. This underscores the potential of deep learning methods in this field. In contrast to most existing literature, such as Jafarian et al. [2] and Moosavian et al. [4], which primarily focus on classical machine learning approaches, this study suggests that integrating both classical and modern methods may enhance fault detection capabilities.

5. Conclusions

In this study, classical machine learning methods and CNNs were used for the diagnosis of internal combustion engines with different faults. While SVM and ANN are applied for fault diagnosis, classical features obtained from vibration signals are used for training purposes. Spectrograms were preferred when applying CNN models. The results obtained from the ANN and SVM models were compared. Accordingly, ANN performed better than SVM (97%). Two CNN models with different architectures showed similar diagnostic performance (100%). However, higher test success was achieved with the more complex Resnet-50. This model, which has a more complex architecture, has a longer training duration. As a result, it is seen that classical machine learning and deep learning algorithms can effectively classify the misfire faults of internal combustion engines.

Table 6 Sample number effect on CNN performance

CNNs	Number of Training Samples	Validation Success (%)	Test Success (%)	Training Duration (s)
GoogleNet-CNN	11	85	80	40
GoogleNet-CNN	22	100	95	81
GoogleNet-CNN	44	100	100	160
ResNet-50-CNN	11	90	90	90
ResNet-50-CNN	22	100	100	180
ResNet-50-CNN	44	100	100	160

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