

## RESEARCH ARTICLE

# Evaluating Sensor Placement in Vibration-Based Engine Misfire Detection Using Artificial Neural Networks

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**ABSTRACT** – This paper examines the effect of sensor positioning on the ability of artificial neural networks (ANN) to classify engine misfires using vibration signals. When it faces misfires that can affect engine performance, fuel economy, and emissions, these events create specific vibration patterns that can be analyzed for diagnostic purposes. However, vibration-based diagnostics only work if the sensors are placed in a way that allows for precise and representative signals to be obtained. Using a 4-cylinder engine as the test rig, vibration data are acquired at four different sensor locations with various misfire conditions. The signals were subjected to pre-processing and feature extraction, resulting in an optimized subset of features for building an ANN. Separate neural networks were then created for each sensor location, and their accuracy and classification performance were evaluated using validation and testing metrics. According to the outcomes, diagnostic accuracy varied significantly depending on sensor placement, with the highest test accuracy of 82.36% achieved by placing the sensor close to the engine's central components. This site recorded vibration signals with the most diagnostic characteristics, highlighting its importance for credible fault recognition. The results also showed that the true positive rate differed for each classification according to different sensor positions, highlighting the importance of considering the unique characteristics of each individual cylinder. This work emphasizes the need for vibration diagnostics in conjunction with machine learning as a non-intrusive, low-cost event detection process that also provides a base for necessary design guidance towards advanced real-time fault detection systems. Future work focuses on improving multi-signal integration to improve diagnostic technology. These findings support the development of more effective and reliable engine fault detection systems.

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## 1. INTRODUCTION

Detecting engine misfires is a crucial feature in maintaining engine performance, fuel economy, and emissions [1, 2]. These misfires affect the supply of air and fuel to the engine, which can cause higher fuel consumption, increased pollutant emissions, and even damage to engine components [3, 4]. Crankshaft speed monitoring is a traditional misfire detection method, and although it is accurate under certain conditions, it cannot be sensitive enough to detect minor or unusual misfires [5]. This reduction in emissions has consequently led to a change in the respective automotive diagnostic methodologies, which tend to be more direct and, most often, through engine vibration analysis [6]. However, vibration analysis is one of the most effective methods, as it is non-destructive, and recent vibration sensors can detect real-time data and accurately reflect the exact engine behavior [7]. Monitoring of vibration signals from different engine parts enables the identification of distinctive patterns corresponding to an engine's normal and defective operation [8]. The success of this method, however, is heavily dependent on the placement of the sensors. Misfire events trigger vibrations that are best sensed on the engine, and the effectiveness of the applied system in collecting high-quality, relevant data depends significantly on the position of the vibration sensors on the engine. Thus, the strategic placement of sensors can significantly improve diagnostic accuracy.

The primary work in vibration-based misfire detection is to achieve high diagnostic accuracy across all engine types and misfire conditions. Although artificial intelligence—more precisely, ANN—has revolutionized the field, the effectiveness of these methods relies heavily on the initial capture of vibration data representative of actual engine states without noise or ambiguity. This design demands careful sensor placement, as locating a sensor too far from a crucial component might result in undetected subtleties. At the same time, the sensor being too close would allow for unwanted background noise. Hence, it is essential for vibration-based diagnosis using neural networks to find the best location for the sensor. This study aims to assess the influence of sensor location on the accuracy of engine misfire detection using vibration data analyzed by neural networks. This paper presents research aimed at identifying areas with the most significant diagnostic accuracy by testing various sensor positions on a four-cylinder engine under different misfire conditions. The results provide information on sensor locations, which can be applied to better practices for any emergent real-time novel diagnostic systems for engine fault detection.

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## 2. LITERATURE REVIEW

### 2.1 Vibration Analysis in Misfire Detection

Vibration analysis for misfire detection has garnered significant attention due to its non-intrusive nature, allowing for direct measurements of engine indicators. Du et al. [9] investigated the use of time-domain vibration signals with probabilistic neural networks for misfire detection, significantly enhancing fault classification accuracy. Similarly, Hashim et al. utilize vibration data to enhance signal clarity in the wavelet packet transform, thereby improving the robustness of a neural network's fault detection in a spark ignition engine. Mofleh et al. [10] demonstrated that vibration signal richness is necessary in certain applications, such as differentiating between various types of misfires. These studies have established vibration analysis as a crucial foundation for engine fault diagnosis by optimizing features extracted from vibration data [11, 12].

### 2.2 Impact of Sensor Placement on Diagnostic Accuracy

Multiple studies have explored optimal sensor locations, emphasizing that sensor placement is crucial to the effectiveness of vibration-based diagnostics. Praznowski et al. [13] investigated the impact of sensor position on misfire identification using multicriteria inference methods to determine the optimal locations. They discovered that the sensors closest to the center of the engine were more efficient in differentiating between misfire patterns, demonstrating how the quality of the vibration signature can directly affect classification output. Research by Syta et al. [14] provided further support for this claim, demonstrating that greater sensitivity to misfire events is achieved through better mixing of ramp data with combustion in a sensor located near combustion events, resulting in higher diagnostic accuracy. Their results supported the hypothesis that the appropriate placement of sensors is necessary for accurately capturing miss batt-induced vibrations, enabling more accurate analysis by neural network models [15, 16]. All of those studies on the effect of sensor placement were from a purely signal analysis perspective, without addressing the use of AI in this domain.

### 2.3 Artificial Neural Networks in Misfire Detection

Neural networks offer a revolution in misfire detection, as systems can now classify vibrations without human intervention [17, 18]. Zheng et al. [19] demonstrated that several key input features, including combustion torque and angular velocity data, are crucial for real-time misfire diagnosis using neural networks. Neural networks using these features were able to differentiate between misfire states with high accuracy, which highlights their ability to adapt to changing environments. Li et al. [20] presented a multi-input transformer-based architecture derived from a deep convolutional neural network (CNN) to process high-noise environments in diesel engines. By combining the input to the neural network, this study achieved better detection rates than previous studies, demonstrating how neural networks can extract features from multidimensional data, such as vibration signals, to provide more reliable diagnostics under challenging conditions [21-23].

### 2.4 Multi-Signal Approaches in Misfire Diagnostics

Vibration data alone provides powerful diagnostic capabilities, but incorporating other data sources, such as acoustic emissions, has further enhanced detection. For instance, Ghazaly et al. [10] combined unsupervised vibration algorithms with acoustic data to provide a more holistic model for misfire detection. Using a neural network to classify misfires, their research showed that the fusion of vibration and acoustic data yielded a more informative dataset, allowing for the classification of misfires with higher accuracy than using vibration data alone. In related work, Zhang et al. [19] examined the effect of training multi-signal convolutional neural networks on diesel engine misfire detection. The results of this study reiterated the necessity of combining different data types, demonstrating that a deep learning CNN trained on both vibration and acoustic signals achieved better performance in detecting misfires than those using only single-source data, in terms of accuracy and robustness.

### 2.5 Cylinder-Specific Analysis in Misfire Detection

Another important feature of misfires is that they can exhibit unique behavior for different cylinders, as each cylinder produces a distinct vibration signature. Researchers [24-26] indicated that adding cylinder-specific information to the neural network could improve misfire diagnosis accuracy, as the vibration patterns of each cylinder are distinct. The targeted nature of this analysis yielded an increased True Positive Rate (TPR) in the case of the cylinders, indicating that since each cylinder fires separately and undergoes distinct combustion patterns, detecting faults for each cylinder individually is critical for optimal fault detection design. Ghazaly et al. [27] investigated these cylinder-specific patterns in more detail by analyzing whether unsupervised vibration algorithms could detect cylinder misfire patterns characteristic of individual cylinders. Specifically, when misfire events are subtle and close to the discriminative threshold, the cylinder-specific data significantly improve the diagnostic performance of the trained models.

## 3. EXPERIMENTAL PROCEDURE

This section outlines the experimental configurations and methods for collecting vibration data from various sensor placements used to diagnose engine misfires. The experiment aims to study the effect of sensor placement on detecting misfire conditions in a four-cylinder engine, providing a basis for evaluating the optimum sensor placement. In the practical experiment, vibration sensors were positioned at four different locations on the engine, as illustrated in Figure

1. It aimed to record vibration signals in five engine conditions: all cylinders functioning normally, and each individual cylinder (Cylinder No. 1 through Cylinder No. 4) experiencing a misfire one at a time. An ignition misfire was induced by disabling the ignition coil of each cylinder. In these trials, the engine's rpm was maintained at a constant value to keep the operating conditions consistent and achieve reliable and comparable data from the misfire tests.

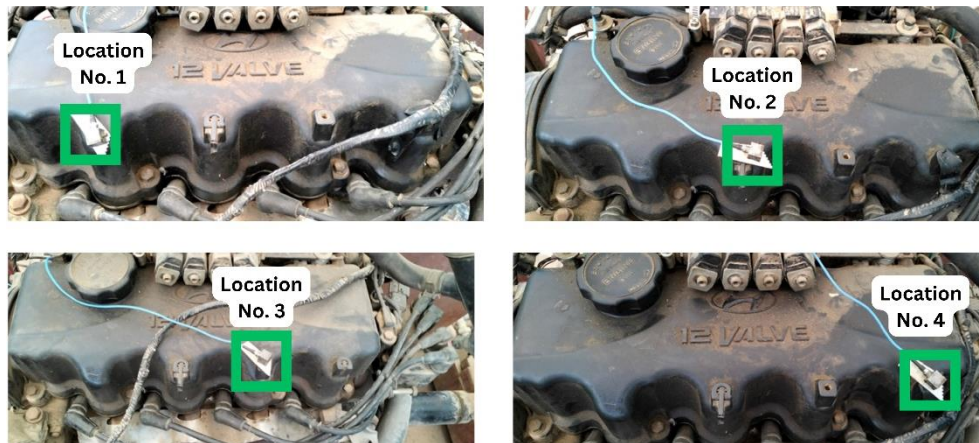


Figure 1. Different locations of accelerometer on the engine

### 3.1 Engine Test Rig Description

The Hyundai G4EH spark ignition engine was utilized as an engine test rig, primarily due to its robust structural and operational properties, which are challenging to undertake using alternative test apparatus. Table 1 presents details of the engine specification. This engine is configured as a four-cylinder, 1341 cm<sup>3</sup>, 9.5:1 compression ratio, among other specifications. Considering its multipoint fuel injection system and other specific parameters, the engine represented a strong candidate for analyzing vibration signals under a controlled ignition fault condition.

Table 1. Specifications of the Hyundai G4EH engine used in the experiment

Engine model	Hyundai (G4EH)
Engine type	Gasoline
Displacement (cm <sup>3</sup> )	1341
Number of cylinders	4
Compression ratio	9.5
Bore (cm)	7.15
Stroke (cm)	8.35
Max. power (kW/rpm)	61.78/5500
Max. torque (Nm/rpm)	116.7/3000
Cycle	Four
Fuel system	Multipoint injection

The setup enabled the study of the overall vibration profile of the engine during changes in misfire, providing vital information for later analysis. All readings were taken at a constant speed of 2500 RPM. Since the primary objective of this research was to investigate the impact of vibration sensor placement on diagnostic accuracy, the engine speed was maintained at a constant level to eliminate any variability caused by changes in speed. This ensured that the evaluation focused solely on how sensor position influences the performance.

### 3.2 Vibration Data Acquisition

An accelerometer sensor designed to record vibration to acquire vibration data was placed vertically (Z-axis Vibration) at each of the four spots on the engine. The accelerometer was connected via a four-channel PCB amplifier (Figures 2(a) and (b)) to obtain sufficient amplification to record the signals accurately. The vibration data were subsequently channeled to a multi-channel signal acquisition system, having an analog-to-digital (A/D) converter for converting analog signals to digital signals, facilitating further analysis.

Each misfire condition was sampled according to a standardized method. Across the five engine states, 120 readings per engine state and sensor location were obtained (24 per engine state and sensor location). There was a six-second duration for each reading and a time interval of 0.001 seconds, resulting in detailed vibration information critical in identifying misfire patterns for each cylinder. While temperature and electromagnetic interference from ignition coils are known factors that may influence accelerometer readings, no significant distortion or anomaly was observed during data acquisition. A vibration sensor designed to operate efficiently within a temperature range suitable for the engine

environment was used. In addition, the duration of each reading was relatively short (6 seconds), which reduces the possibility of thermal drift in the signal. No abnormal distortions or peaks indicating electromagnetic noise were observed. Based on the above, the recorded vibration signals can be considered to accurately represent the mechanical behavior of the engine under various misfire conditions, without distortion caused by the mentioned environmental factors.

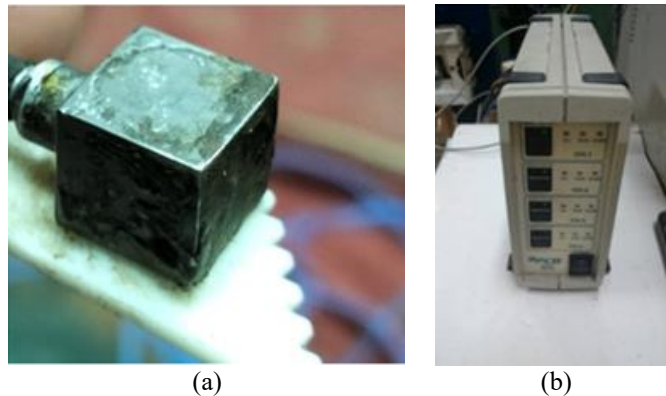


Figure 2. Data Acquisition Instruments: (a) Accelerometer, (b) PCB 4-channel amplifier

#### 4. METHODOLOGY

This study examines the impact of sensor placements on the accuracy of engine misfire detection using artificial neural networks. This method first prepares vibration data from each sensor location before selecting key features and then builds neural network models to study classification precision as a function of sensor location.

##### 4.1 Data Preparation and Pre-Processing

The initial step involved preparing the vibration data collected from accelerometer sensors positioned in four different locations on the engine. MATLAB was used to perform preliminary data processing, which included essential signal refinement procedures to improve data quality. The signals were analyzed in both the time and frequency domains to extract detailed characteristics. Each signal provided a basis for calculating a set of statistical features, allowing for a comprehensive representation of the vibration patterns. From each signal, a total of 20 statistical features were derived, with 10 features originating from the time domain and 10 from the frequency domain. The features calculated included the mean, median, standard deviation, range, skewness, kurtosis, maximum, minimum, energy, and crest factor. These features collectively provided a multifaceted view of the vibration data, capturing key attributes relevant to diagnosing misfire conditions.

The feature extraction and selection steps outlined above are summarized in a flowchart, as shown in Figure 3, which illustrates the full methodology from data acquisition to model evaluation. Figure 4 shows samples of vibration signals in both the time and frequency domains from different sensor locations under the condition of cylinder (A) misignition (under the same operating conditions).

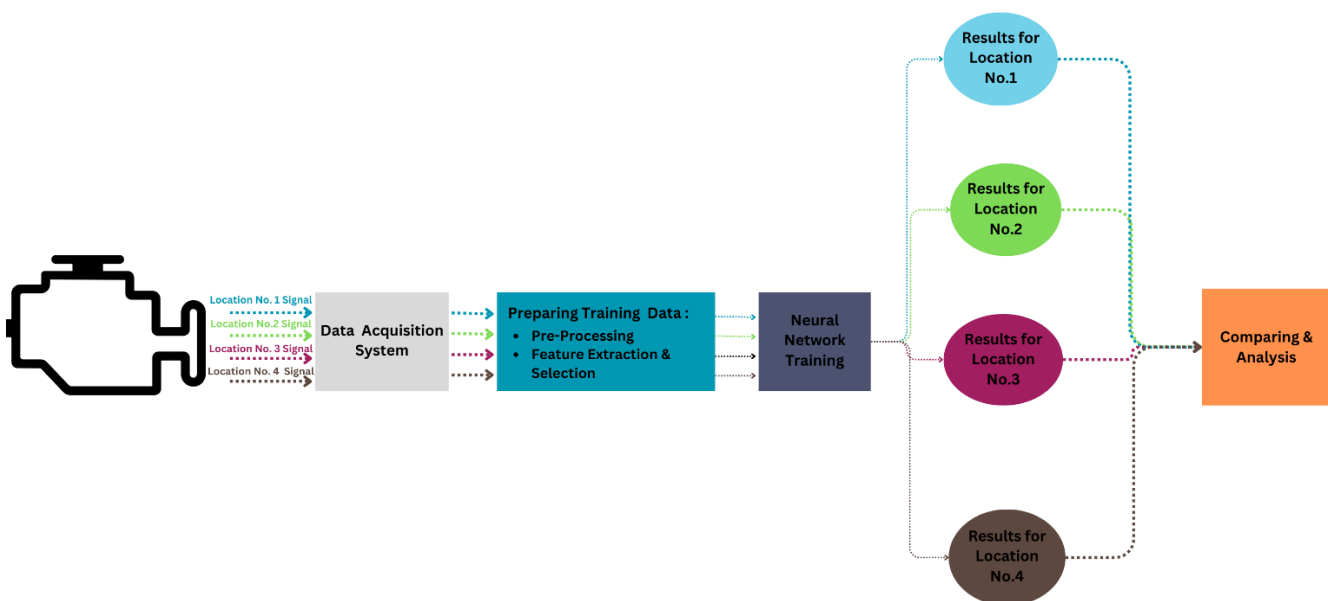


Figure 3. Flowchart of methodology for misfire detection

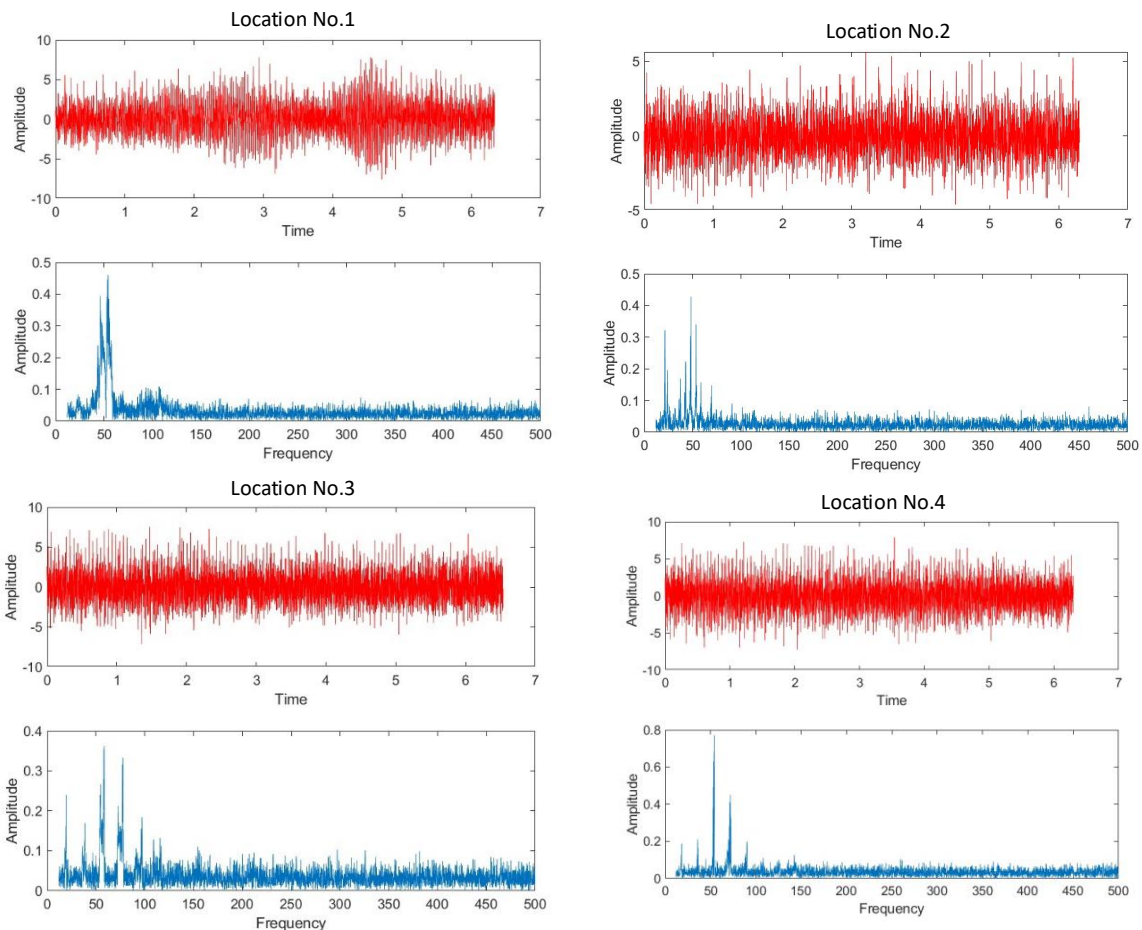


Figure 4. Samples of vibration signals in each time domain and frequency domain from different locations of the sensor at condition of cylinder (A) misignition

### 4.2 Feature Selection

This optimization was performed to enhance classification accuracy and reduce time complexity by eliminating irrelevant features after feature extraction. A different statistical feature selection method was used for each sensor location to optimize features specifically for their respective vibration interactions. At Location No. 1, the Minimum Redundancy Maximum Relevance (MRMR) method was employed to reduce the pool of 20 features to the 12 most methodologically relevant and least redundant.

Table 2. A summary of features selected by selection algorithms with different signal locations

Base signal location	No. of features selected /No. of total features	Algorithm used	Features/domain
Location No.1	12/20	MRMR	[skewness/time, minimum/frequency, crest_factor/frequency, max/time, std/frequency, energy/time, mean/frequency, range/frequency, range/time, crest_factor/time, skewness/frequency, std/time]
Location No.2	12/20	Kruskal Wallis	[Skewness/time, kurtosis/time, max/time, range/time, Median/frequency, std/time, energy/time, mean/time, mean/frequency, skewness/frequency, Kurtosis/frequency, energy/frequency]
Location No.3	12/20	Chi2	[skewness/time, std/time, kurtosis/time, crest_factor/time, mean/time, energy/time, Median/frequency, std/frequency, Median/time, mean/frequency, energy/frequency, range/frequency]
Location No.4	20/20	-	All Features in each time and frequency domains (No Algorithms Used)

At Location No. 2, a Kruskal-Wallis statistical test was performed, and the 12 top features exhibiting the most differential across the dataset were identified. Location No. 3 used the Chi-square (Chi2) test, a widely-used feature selection method,

and consistently reported 12 features with the highest contribution to fill according to classification performance. On the other hand, for Location No. 4, all 20 features were retained because this location relied more on the total features to identify its specific vibration mode. These optimized feature subsets allowed efficient model training while retaining crucial diagnostic information. Table 2 presents a summary of features selected by different selection algorithms at various signal locations.

### 4.3 Neural Network Model Development

After feature selection, the vibration dataset was split into training and testing sets, with 70% of the dataset allocated for model training and 30% for model testing. The resubstitution scheme validated model consistency. Each neural network model was customized using sensor data from a specific location, with settings and configurations optimized using MATLAB's Classification Learner tool. The main parameters tuned for each model were the number of layers, the size of the layers, the activation function, and the iteration limit, as shown in Table 3. These parameters were adjusted to achieve the best diagnostic accuracy for each sensor location. The four models were then trained and tested on the selected training and testing data to determine their general accuracy rates and identify which classes were strong or weak. The model's performance was evaluated using a confusion matrix for each sensor site, which calculated the true positive rates and false negative rates for each classification. This evaluation allowed us to better understand the impact of sensor placement on diagnostic characteristics, which serves as the basis for comparisons in the following sections.

Table 3. Optimized hyperparameters for each type of base signal

Base signal location	No. of Layers	1st layer size	2nd layer size	3rd layer size	Activation Function	Iteration Limit
Location No.1	3	30	10	40	None	2000
Location No.2	3	20	10	10	Sigmoid	1000
Location No.3	3	40	30	10	Sigmoid	1000
Location No.4	2	10	30	-	Sigmoid	1000

## 5. RESULTS

The findings from this study indicate the impact of sensor placement on the performance of neural network models in detecting engine misfires at a high degree of fidelity. From the accuracy and classification analysis for each model, considering different sensor positions, it is possible to conclude the optimal placement for accurate identification.

### 5.1 Model Accuracy and Evaluation

Several validation and testing metrics were calculated for the neural network models created at each sensor location to measure the accuracy and content of each model by sensor placement. Table 4 displays the validation accuracy, which indicates how well the model performs on the training data, and the test accuracy, which measures how the model performs on new data that it has never seen before.

Table 4. Average accuracy of neural network models by sensor location

Model according to location	Accuracy (Validation)	Accuracy (Test)
Location No.1	92.85 %	61.11 %
Location No.2	100.00 %	82.36 %
Location No.3	100.00 %	77.77 %
Location No.4	100.00 %	66.67 %

From the accuracy results, the best test accuracy (82.36%) is achieved by the model of Location No. 2. The second-best accuracy (77.77%) belongs to the model of Location No. 3. We gain lower test accuracies (61.11% and 66.67%) for models that are trained on data from Location No.1 and Location No.4, respectively. The results highlight the necessity of sensor placement, with the No. 2 location being the best site for misfire detection. This consolidation suggests that vibration data from here has more diagnostic information, helping the neural network better classify the type of vibration data.

### 5.2 Confusion Matrix Analysis

For an additional evaluation of each model in classifying engine states, confusion matrices were created for each sensor location, summarized in Table 5. The subsequent confusion matrices summarize true positive, true negative, false positive, and false negative predictions across both models, along with the TPR and false negative rate (FNR) metrics. It brings more insight into how well each model is able to catch correct normal and misfire events for different cylinders.

Table 5. Confusion matrices for each model, including TPR and FNR metrics

Model according to location	Test Confusion Matrix	Test Confusion Matrix With TPR & FNR																																																												
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The confusion matrix for Location No. 2 indicates the better predictive power of the model with maximum TPR and minimum FNR for all running states of the engine. Location No. 2 will therefore produce reliable diagnostic results,

making it more suitable for misfire detection. In contrast, models derived from data pertaining to Location No. 1 and Location No. 4 exhibited higher frequencies of prediction misclassifications compared to other misfire conditions, which explains their lower overall accuracy scores. The diagnostic reliability across different sensor locations illustrates the dependence of performance on placement, reinforcing the identification of Location No. 2 as the optimal position for accurate diagnostics.

## 6. DISCUSSION

Data from this study demonstrate that the careful selection and placement of sensor locations are critical for reliable diagnostics of automotive engine misfire detection using vibration data. The performance of metrics against the neural network — using data acquired from four different sensor positions/points — gives insight into how closely the quality of signals captured by the vibration sensor differs from the performance metric of diagnostic results. A comparative review of all sensor sites follows, discussing aspects that might lead to differences in classification accuracy and recommendations for optimal sensor positioning to enhance diagnostic ability.

### 6.1 Comparison of Sensor Locations

Across sensor locations, Location No. 2 consistently performed the best in validation and test results. The better performance at Location No. 2 indicates that this point provides the most sensitive vibration signal profile concerning changes in engine condition, most likely because it is closer to the middle of the engine and the engine's main components. On the contrary, the accuracy levels of target locations No. 1 and No. 4 are lower than those of the above target locations, suggesting that these positions possibly receive more subtle vibration patterns, especially when differentiating the misfire states. The significance of Location No. 2 substantiates the notion that the proximity of the sensor to the middle of the engine, where the vibration variation is larger, assists the model in separating the classes of misfire events more appropriately. Figure 5 gives a summary of the comparison of results at sensor locations. So, we can say that the sensor produces signals that are more sensitive to the change occurring in the engine if it is placed in the middle of the engine. Therefore, we find that the results of the correct prediction in the event that the sensor is located on the outer edges of the engine are the least possible.

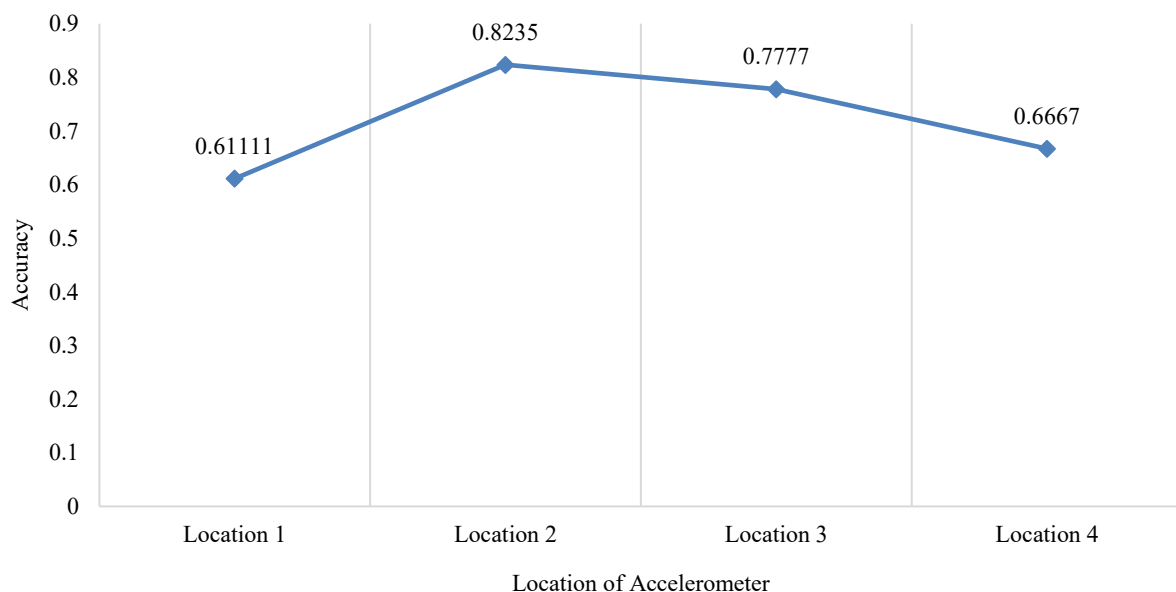


Figure 5. Comparison of network results across sensor locations

### 6.2 Per-Cylinder Diagnostic Performance

Results also indicate that diagnostic accuracy differed across individual cylinders, as the individual combustions and subsequently firing impacts each cylinder may vary in vibratory characteristics. However, the model achieved the highest TPR across all sensor orientations for Cylinder No. 3, suggesting that these misfire signatures may be more easily detected since they are associated with distinct vibrations for that cylinder. On the other hand, Cylinder No. 1 showed the weakest TPR, meaning that the misfire signal could be less pronounced or masked by background vibrations, which would complicate the process of accurate detection. Such findings clearly highlight that diagnostic models must incorporate cylinder-specific parameters, as some cylinders, by nature, always appear to have a more readily noticeable detectable contribution when a misfire does occur. The difference in TPR between the cylinders is depicted in Figure 6. Therefore, the unique combustion characteristics of each individual cylinder may increase or decrease the correct classification percentage. The more unique the cylinder's combustion behavior, the greater the percentage of its individual classification is expected to be correct, and vice versa.

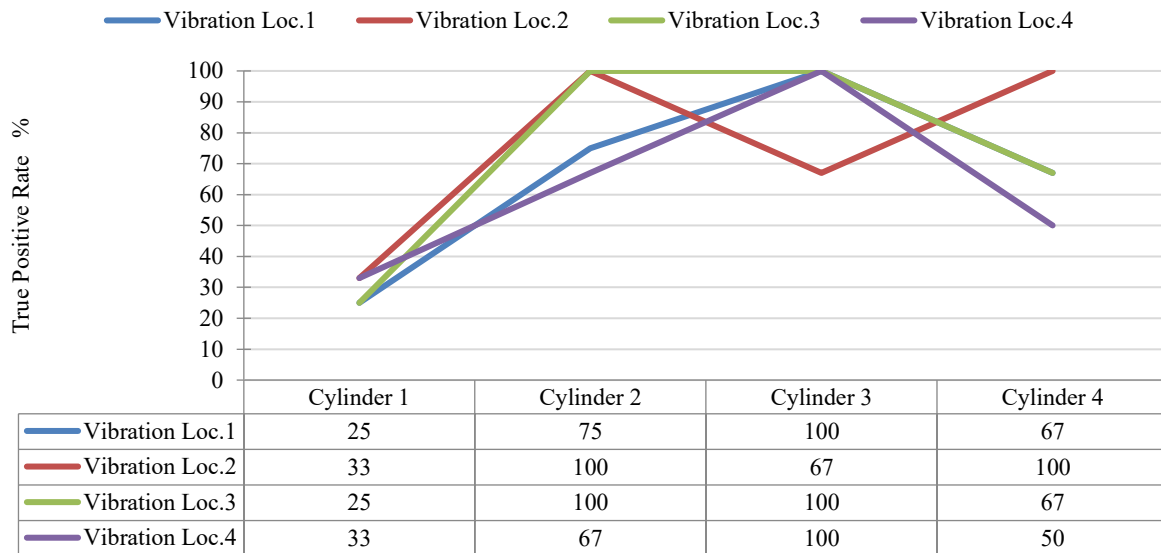


Figure 6. TPR for each cylinder across sensor locations

### 6.3 Implications for Engine Diagnostics

The results improve the standards of how vibration-based monitoring systems should be designed and implemented for diagnostic purposes in automobile engines. Location No. 2 provides the highest accuracy, which is preferred; thus, Location No. 2 is the best location for misfire detection as it gives the best input data for the neural network. This understanding can be used to devise necessary guidelines for the placement of sensors in automotive diagnostics that require monitoring of systems for real-time detection and early fault prediction of engine failures. Second, awareness of these cylinder-specific differences in diagnostic performance can inform more targeted model training improvements, which, in turn, may improve the model’s ability to detect small misfire events across all cylinders.

## 7. CONCLUSIONS

This study highlights the important role of sensor locations on the performance of vibration-based misfire detection systems in automotive engines. By analyzing neural network models trained over data from four different sensor locations, we found significant differences in the accuracy of diagnoses, as well as excellent performance produced by specific placement positions. In particular, the sensor located near the central components of the engine had the highest diagnostic accuracy of up to 82.36% in the tested memory. With this ideal positioning, the ANN can identify misfires even more accurately, which is crucial in vehicles due to the added complexity, as some misfires may be subtle or intermittent, making it mostly difficult to be picked up from the environment. Results also reveal that diagnostic accuracy varies across individual cylinders, as the unique combustion and firing characteristics of each cylinder influence its vibratory signature. For instance, the model demonstrated the highest TPR for Cylinder No. 3 across all sensor locations, likely due to its distinct misfire signatures. Conversely, Cylinder No. 1 exhibited the weakest TPR, suggesting that its misfire signals may be masked by background vibrations, complicating accurate detection. These findings highlight the need to incorporate cylinder-specific parameters into diagnostic models, as certain cylinders inherently present more detectable misfire signatures.

Moreover, the results emphasize the benefits of vibration analysis as a cost-effective and straightforward non-destructive diagnostic method, particularly when applied with advanced machine learning methods. Through the placement of sensors, systems of diagnosis can provide robust and real-time performance and make a missed detection less likely, leading to greater reliability for the engine as a whole. This provides valuable information for the design of future diagnostic systems, especially where strict fault detection is needed. The findings presented here will act as a basis for subsequent work combining multi-signal data and machine learning, for further refinement of this automotive diagnostic technology to directly translate into improved performance, safety, and reduced environmental impact. Future work will focus on expanding the sample size and incorporating a wider range of operating cycles and conditions, in order to enhance the generalizability of the findings and improve the statistical robustness of the sensor placement evaluation. Also, the set of performance evaluation metrics will be expanded beyond the TPR, which was primarily used in this study due to its direct alignment with the objective of detecting misfire events. As the dataset is expanded and more diverse operating conditions are included, additional performance indicators such as Precision, Recall, and F1-Score will be incorporated to enable a more comprehensive and balanced assessment of the diagnostic model. Through this, a deeper understanding of the model’s behavior under various misfire scenarios will be achieved, and the robustness of the evaluation will be enhanced.

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## CONFLICT OF INTEREST

The authors declare no conflicts of interest.

## AUTHORS CONTRIBUTION

Mohamed H. Abdelati (Conceptualization; Methodology; Writing - original draft; Supervision)

Al-Hussein Matar (Data curation; Formal analysis; Writing - review & editing)

M. Mourad (Investigation; Validation; Visualization)

M. Rabie (Software; Resources; Writing - review & editing)

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