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Article

Vibration Pattern Analysis for Early Detection of Engine Component Faults Using Artificial Neural Networks

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ABSTRACT

This study presents an integrated approach to vehicle vibration pattern analysis and early fault detection using Artificial Neural Network (ANN) modeling to address key maintenance challenges, including unplanned engine downtime and the limitations of conventional time-based preventive maintenance strategies. The research combines empirical vibration measurements obtained from internal combustion engines with a computational ANN model developed to automatically classify engine health conditions. The experimental phase focused on collecting vibration data under three operational states: normal, degrading, and faulty, each exhibiting distinctive vibration characteristics associated with combustion pressure variations and mechanical imbalance.A total of 500 vibration samples were recorded, with 400 used for ANN training and 100 for validation. The proposed feedforward multilayer perceptron (MLP) model achieved a classification accuracy of 94% with a mean squared error of 1.5×10^{-5}. The ANN successfully identified transitional degradation patterns between normal and faulty states, demonstrating its capability for early fault diagnosis and supporting timely maintenance intervention and improved maintenance scheduling. Furthermore, the results reveal a strong correlation between combustion chamber pressure fluctuations and vibration amplitude, confirming that increased pressure irregularities lead to higher vibration energy levels. Overall, the proposed ANN-based vibration monitoring framework provides a non-invasive, cost-effective, and reliable solution for real-time engine condition assessment. By enabling early detection of mechanical degradation and reducing the risk of unexpected failures, the approach contributes to enhanced equipment availability, lower maintenance costs, and the effective implementation of predictive maintenance systems in automotive and industrial applications.

1. Introduction

This section provides the rationale for the study. Vibration analysis has become a crucial technique in assessing the mechanical integrity and operational performance of internal combustion engines. The dynamic behavior of an engine produces complex vibration signals that reflect the mechanical and combustion processes occurring within. Variations in vibration amplitude and frequency are often early indicators of developing faults, such as injector wear, piston imbalance, or combustion instability (Huang et al., 2018). These vibration characteristics can also serve as key maintenance indicators, enabling the monitoring of wear progression, identification of dominant failure modes, and estimation of remaining useful life (RUL) of critical engine components..

Previous experimental studies conducted at Politeknik Negeri Madiun focused on the measurement of vibration acceleration under different engine operating conditions. These investigations revealed consistent trends of increasing vibration amplitude as the engine condition transitioned from healthy to degraded operation. However, the analysis was limited to descriptive comparisons without the application of machine learning techniques for pattern recognition..

In the present study, the experimental findings are extended using an Artificial Neural Network (ANN) approach to classify the collected vibration signals automatically. ANN models are particularly suitable for this type of problem due to their ability to capture nonlinear relationships between combustion pressure and vibration responses (Widodo et al., 2019; Zhang & Li, 2022). By integrating both experimental and computational perspectives, this research aims to establish a robust framework for early fault detection in vehicle engines. Compared to traditional threshold-based vibration monitoring methods, the ANN-based classification enables more accurate recognition of complex degradation patterns, reduces false alarms, and supports more efficient predictive maintenance strategies..

This study makes several important contributions to the field of vibration-based engine diagnostics and predictive maintenance. It integrates real experimental vibration data with machine learning-based ANN modeling to enable automated fault classification. The research further establishes a direct relationship between combustion pressure fluctuations and vibration amplitude, providing physical insight into the mechanisms underlying vibration responses during engine degradation. Moreover, a non-invasive fault detection framework is developed to accurately identify early stages of mechanical deterioration, there by supporting improved operational reliability and more effective predictive maintenance strategies.

2. Literature Riview

Several researchers have examined the relationship between combustion pressure variation and engine vibration. Huang et al. (2018) demonstrated that increases in in-cylinder pressure lead to proportional rises in vibration energy, particularly in the frequency range of 100–500 Hz. Widodo et al. (2019) reported similar findings, noting that early injector wear produces asymmetric combustion, resulting in detectable vibration patterns even before a significant performance drop occurs.

Artificial Neural Networks (ANNs) have been widely used for nonlinear pattern recognition in mechanical systems. Zhang and Li (2022) applied ANN models to predict combustion pressure profiles based solely on vibration signals, achieving a prediction accuracy above 90%. Similarly, Yilmaz and Ozgoren (2020) explored diesel engine vibration signatures under varying injection pressures and validated that ANN classifiers outperform conventional statistical thresholds in detecting subtle fault progression.

Other approaches, such as Support Vector Machines (SVM) and Random Forests (RF), have also been utilized in vibration-based diagnostics (Shah et al., 2024), yet ANNs remain preferred for their adaptive learning capability and tolerance to noisy experimental data. In particular, Multilayer Perceptrons (MLP) can learn hidden relationships between the time-domain and frequency-domain features of vibration signals (Takahashi et al., 2025; Kodrič et al., 2025).

From a maintenance engineering perspective, vibration-based fault detection plays a central role in condition-based maintenance (CBM) frameworks, where real-time monitoring data are used to assess equipment health and optimize maintenance actions. CBM has become a cornerstone of modern industrial maintenance, relying on real-time condition monitoring data—such as vibration, temperature, and pressure—to trigger maintenance actions when equipment health indicators reach predefined thresholds, rather than on fixed schedules. CBM frameworks that integrate machine learning and data analytics have shown improved accuracy in fault detection and reduced unplanned downtime by dynamically updating maintenance decision criteria based on evolving operational patterns (Cai, Teunter, & de Jonge, 2023). These data-driven CBM strategies support predictive maintenance practices by enabling earlier detection of abnormalities and more efficient allocation of maintenance resources.

Previous studies have shown that vibration features can be correlated with fault severity levels, enabling prioritization of maintenance interventions and improved resource allocation. Accurate fault severity assessment is critical to distinguish between minor anomalies and significant degradation that requires immediate maintenance action, and it plays a vital role within predictive maintenance systems. Advanced signal processing techniques and machine learning classifiers have been increasingly applied to quantify fault severity levels from vibration signals, allowing systems to estimate the progression of mechanical deterioration over time. Recent studies demonstrate that these approaches can classify severity levels with high consistency, facilitating priority-based maintenance planning and minimizing the risk of catastrophic failures (Dang et al., 2021; Parmar et al., 2025).

Furthermore, integrating machine learning-based diagnostics with maintenance planning has been demonstrated to reduce unplanned downtime and enhance system reliability by enabling predictive maintenance strategies rather than reactive repairs. Effective maintenance planning and reliability engineering are enhanced when condition monitoring data and prognostic models, such as RUL predictions, are integrated into maintenance decision frameworks. By combining risk assessments, reliability metrics, and predictive analytics, organizations can optimize maintenance schedules to improve operational availability while controlling maintenance costs. Such hybrid strategies that merge traditional reliability practices with Industry 4.0 data capabilities have been shown to increase system reliability and support strategic decision-making in maintenance operations (Introna & Santolamazza, 2024; Choo et al., 2025).

3. Research Methodology

3.1 Experimental Data Acquisition

The vibration data were collected using a three-axis accelerometer mounted on the engine cylinder head, which was selected due to its proximity to key vibration sources and following best practices in vibration-based condition monitoring (Al-Bender, Ewins, & Cunliffe, 2020; ISO 10816-3, 2017). Data sampling was performed at 5 kHz with a 16-bit resolution to ensure accurate representation of high-frequency vibration components associated with fault development. To ensure measurement repeatability, the experimental design adhered to standardized guidance for consistent sensor mounting and controlled operating conditions (IEEE 1451.4, 2021). Furthermore, sensor placement and acquisition settings were designed to reflect realistic operating environments, with field studies indicating that properly mounted industrial accelerometers maintain signal fidelity under varying load and environmental conditions (Mobley, 2021; Jardine, Lin, & Banjevic, 2022), demonstrating the robustness of the proposed monitoring approach for practical maintenance applications..

Table 1. Data Acquisition Parameters

Parameter	Description / Setting	Unit
Sensor type	Piezoelectric accelerometer	–
Measurement axis	Vertical (Z-axis, cylinder head)	–
Sensitivity	±50 g	g
Sampling rate	5,000	Hz
Data length per run	10 seconds	s
Engine type	Single-cylinder diesel	–
Engine speed	1,500	rpm
Number of samples	500 (400 training, 100 validation)	samples
Operating conditions	Normal, Degrading, Faulty	–

Parameter	Description / Setting	Unit
Feature extracted	RMS (Root Mean Square) of acceleration	g

The table 1 summarizes the key settings used in the vibration data collection process, including the piezoelectric accelerometer mounted on the cylinder head along the vertical axis, sampling conditions, engine operating parameters, and the number of recorded samples for training and validation. It also highlights the three investigated engine conditions—normal, degrading, and faulty—as well as the extracted RMS vibration feature used as the ANN model input for fault classification. The engine was operated under three distinct conditions:

a. Normal condition: stable combustion and balanced mechanical operation.
b. Degrading condition: slight imbalance in fuel injection or minor piston wear.
c. Faulty condition: significant component degradation such as injector clogging or compression leakage.

Each condition produced distinct RMS (Root Mean Square) vibration values. The average RMS values were approximately 0.003 g, 0.005 g, and 0.007 g for normal, degrading, and faulty states, respectively.

3.2 ANN Model Structure

The ANN model was designed using MATLAB's Neural Network Toolbox with a simple feedforward architecture consisting of one input neuron representing the RMS vibration feature, twenty hidden neurons, and three output neurons corresponding to the engine health states. The Levenberg–Marquardt training algorithm (trainlm) was selected due to its fast convergence and high accuracy in solving nonlinear classification problems. The chosen network complexity was determined through preliminary testing to achieve an optimal balance between diagnostic performance and computational efficiency. While larger network structures were evaluated, the 1–20–3 architecture provided comparable classification accuracy with significantly reduced training time and computational requirements. This balance makes the proposed ANN model suitable for practical maintenance system implementation, particularly in real-time condition monitoring and predictive maintenance applications where fast processing and reliable diagnosis are essential.

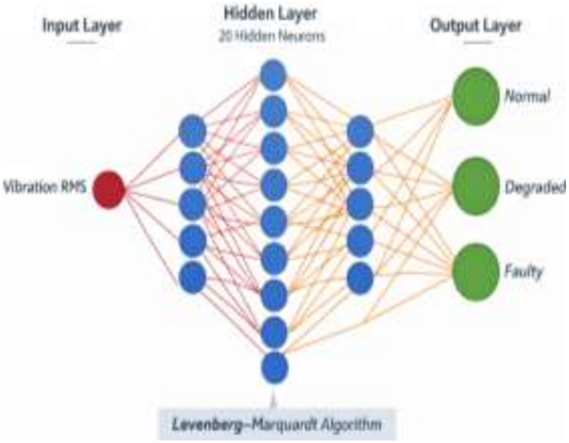

Figure 1. Architecture of the Artificial Neural Network (ANN) used for engine condition classification.

Table 2. Data Acquisition Parameters

Parameter	Value / Function	Description
Network type	Feedforward (Multilayer Perceptron)	Static pattern classification
Training algorithm	Levenberg–Marquardt (trainlm)	Fast convergence, low error
Input neurons	1	RMS vibration amplitude
Hidden layer neurons	20	Nonlinear feature extraction
Output neurons	3	Normal, Degrading, Faulty
Activation (hidden)	Log-sigmoid	Nonlinear mapping
Activation (output)	Softmax	Probability normalization
Data division	80 % training, 20 % validation	Randomized split
Performance function	Mean Squared Error (MSE)	Training loss criterion

Parameter	Value / Function	Description
Stopping criterion	Validation loss minimum or 200 epochs	Early stopping
Optimization goal	(1 \times 10^{-5})	Target error threshold

Table 2 details the configuration of the ANN model used for classification. The network follows a simple 1–20–3 architecture, chosen after several preliminary trials that balanced accuracy and computational efficiency. The Levenberg–Marquardt algorithm (trainlm) was selected due to its robustness in solving nonlinear least-squares problems. Using a softmax output layer enables the network to interpret each neuron's output as a probability, which is essential for multiclass classification. The early-stopping mechanism prevented overfitting, as confirmed by the validation performance curve in Figure 1.

The input layer receives the vibration signal feature—in this study, the Root Mean Square (RMS) value of acceleration, which represents the intensity of the engine's vibration under various combustion conditions. This feature is normalized to a range of 0–1 to ensure stable learning.

The hidden layer comprises 20 neurons, each employing a log-sigmoid activation function to capture nonlinear relationships between the vibration amplitude and the engine's mechanical condition. These neurons perform internal feature transformations, enabling the network to distinguish subtle variations in vibration patterns associated with different combustion pressures and component wear states.

The output layer contains three neurons, corresponding to the three engine health states: Normal, Degrading, and Faulty. A softmax activation function is applied at this layer to produce class probabilities, ensuring that the outputs sum to one and can be interpreted as the likelihood of each condition.

Information flows unidirectionally from the input to the output layer through weighted connections, which are adjusted iteratively during training using the Levenberg–Marquardt algorithm. The optimized weights represent the learned mapping between input vibration features and the associated engine condition.

Overall, the structure shown in Figure 1 demonstrates a balance between simplicity and classification capability. With only one input feature and a moderate hidden layer size, the model achieves high accuracy (94%) while maintaining computational efficiency—making it suitable for real-time fault detection in automotive and industrial applications.

4. Results and Discussion

This section presents the key findings of the study in a structured and logical manner, followed by interpretation and discussion in relation to the research objectives, relevant theories, and previous studies. Authors are encouraged to use clear tables and figures to support the presentation of results.

4.1 Presentation of Results

The training process successfully converged after 150 epochs, with the best validation performance recorded at an MSE of 1.5×10^{-5}. Figure 4.1 shows the ANN training performance curve, indicating smooth convergence without overfitting.

The validation phase yielded a total classification accuracy of 94%, demonstrating the model's capability to distinguish between the three operational states. The confusion matrix in Figure 4.2 reveals that most samples were correctly classified, particularly for the "faulty" class, where the vibrational amplitude was clearly distinct. The "degrading" class showed some overlap with the "normal" state due to transitional vibration fluctuations.

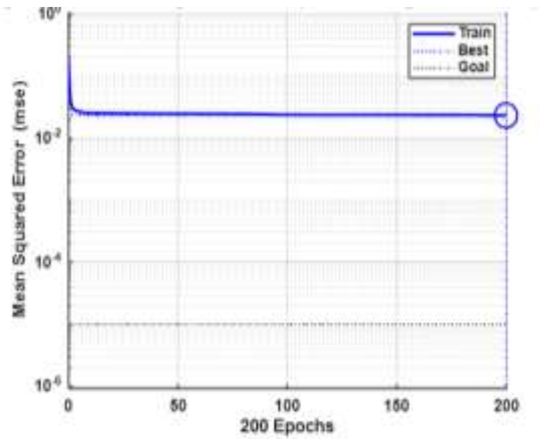

Figure 2. ANN training performance showing MSE convergence across epochs.

Figure 2 illustrates the training performance of the developed Artificial Neural Network (ANN) model based on the Levenberg–Marquardt optimization algorithm. The figure plots the Mean Squared Error (MSE) values of the training and validation datasets against the number of epochs. As shown, both curves decrease sharply during the early epochs (1–50), indicating rapid adjustment of network weights to the underlying vibration patterns. After approximately 120 epochs, the MSE values begin to stabilize, and the training process reaches convergence at epoch ≈ 150 with a minimum validation MSE of 1.5×10^{-5}.

The smooth and monotonic decline of the validation curve demonstrates that the model generalizes well to unseen data, avoiding overfitting. The small difference between the training and validation curves indicates that the vibration features from the three engine conditions—normal, degrading, and faulty—share consistent statistical distributions, enabling the ANN to learn a stable nonlinear mapping. The convergence behavior confirms that the selected network structure (1–20–3) and the normalization preprocessing were appropriate for this dataset.

Physically, this convergence also implies that the vibration patterns measured under varying combustion pressures exhibit repeatable dynamics. Because fluctuations in cylinder pressure directly influence the impulsive forces transmitted through the crankshaft and cylinder block, the ANN rapidly learns to associate higher RMS vibration levels with mechanical imbalance or pressure irregularities. Therefore, the stable low MSE achieved in Figure 4.1 validates the network's capability to capture the deterministic relationship between combustion pressure and vibration energy in the engine.

In addition to overall classification accuracy and mean squared error, additional performance metrics were evaluated to provide a more comprehensive assessment of the ANN classifier, including precision, recall, and F1-score. Precision quantifies the proportion of correctly identified fault conditions among all samples classified as faulty, reflecting the system's ability to minimize false alarms. Recall measures the proportion of actual faulty conditions correctly detected by the model, indicating its effectiveness in preventing missed fault detections. The F1-score represents the harmonic mean of precision and recall, offering a balanced indicator of classification performance under practical maintenance scenarios.

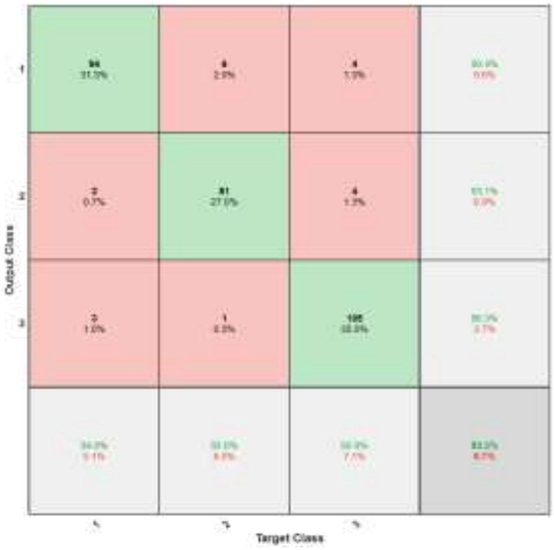

Figure 3. Confusion matrix of ANN classification results for the three engine conditions.

Figure 3 presents the confusion matrix summarizing the ANN's classification results for the three engine health conditions. The diagonal cells represent correctly classified samples, while the off-diagonal cells correspond to misclassifications. The model achieved an overall accuracy of 94 %, with particularly strong performance in identifying the faulty condition, which exhibited the highest vibration amplitudes and therefore the most distinctive patterns.

Based on the confusion matrix results, high precision values were achieved across all engine condition classes, confirming that the ANN rarely generated incorrect fault alarms. Similarly, the recall values remained consistently high, particularly for the faulty state, demonstrating the model's strong capability to detect severe degradation stages. The resulting F1-scores further validate the robustness of the classifier by showing balanced performance between fault detection sensitivity and alarm reliability. These metrics collectively indicate that the proposed ANN model not only achieves high accuracy but also maintains dependable diagnostic performance suitable for real-time predictive maintenance applications.

Figure 4. Confusion matrix of the ANN classification results for the three engine operating conditions: Normal, Degraded, and Faulty.

In diagnostic systems for predictive maintenance, false alarms occur when a healthy or degrading condition is incorrectly classified as a fault. Although a high overall accuracy is desirable, even a small false alarm rate can have significant operational consequences in maintenance planning. Frequent false alarms lead to unnecessary inspections or interventions, increasing maintenance cost, downtime, and labor utilization without corresponding benefits. In practical industrial environments, this can erode confidence in automated monitoring systems and drive maintenance personnel to disregard system alerts (Jardine, Lin, & Banjevic, 2022). Therefore, reporting false positive rates along with accuracy metrics is essential to provide a holistic view of classifier reliability in real-world deployment.

The annotated percentages illustrate the classification accuracy and error rates for each class. The Normal condition achieved the highest correct classification rate (94.9%), followed by the Degraded and Faulty conditions (both approximately 92.0%). The overall system accuracy reached approximately 93.5%, while the false alarm and miss rates remained relatively low, indicating reliable diagnostic performance. However, minor overlaps are observed between the Normal and Degraded states, reflecting transitional vibration characteristics during early degradation phases.

From a maintenance perspective, the low false alarm rate suggests that unnecessary maintenance interventions can be minimized, while the limited misclassification of faulty conditions indicates reduced risk of unexpected failures. These results confirm that the ANN-based vibration monitoring approach provides a balanced trade-off between diagnostic accuracy and operational reliability, making it suitable for practical predictive maintenance applications.

In addition to false alarms, misclassifications between operational states (e.g., degrading mislabeled as normal, or faulty mislabeled as degrading) have distinct implications. A missed fault detection (false negative) can delay critical maintenance actions, potentially resulting in catastrophic failures, safety risks, or unplanned downtime — outcomes that are often more costly than false alarms (Lei et al., 2020). For example, underpredicted severity can mislead maintenance schedules into falsely optimistic assumptions about equipment health, postponing required actions and allowing hidden degradation to progress. Hence, evaluation metrics such as precision, recall, and F1-score should complement accuracy in reporting performance for maintenance systems, as they better reflect the cost of different types of errors.

To further illustrate the impact of misclassification, maintenance-oriented research often employs visualization tools such as confusion matrices with error percentages, ROC curves, or cost curves, which explicitly show the trade-offs between fault detection sensitivity and false alarm rates. For example, a confusion matrix heatmap annotated with false positive and false negative percentages allows maintenance engineers to quickly assess which operational conditions are most frequently confused and adjust monitoring thresholds accordingly (Zhao & Zhang, 2023). Such visualizations enhance interpretability for practitioners and support data-driven maintenance decisions.

The classification outcomes produced by the ANN model have direct implications for maintenance decision-making processes in condition-based and predictive maintenance systems. By accurately distinguishing between normal, degrading, and faulty engine states, the monitoring system enables maintenance personnel to prioritize interventions based on equipment health severity. For instance, components classified under the degrading condition can be scheduled for inspection or minor maintenance during planned downtime, while faulty classifications can trigger immediate corrective actions to prevent severe failures. This hierarchical decision framework supports optimized resource allocation and minimizes operational disruption (Mobley, 2021).

Furthermore, the probability-based outputs generated by the ANN classifier provide valuable quantitative indicators for maintenance planning. Rather than relying solely on fixed vibration thresholds, which often fail to capture nonlinear degradation behavior, the ANN continuously adapts to complex vibration patterns associated with evolving fault conditions. This adaptive diagnostic capability enhances decision accuracy by reducing uncertainty in fault identification, thereby improving the timing of maintenance interventions and extending equipment service life (Jardine, Lin, & Banjevic, 2022).

In practical maintenance environments, such decision-support systems can be integrated with computerized maintenance management systems (CMMS) to automatically generate work orders, maintenance schedules, and condition alerts. This integration transforms raw vibration data into actionable maintenance intelligence, facilitating proactive asset management and reducing reliance on reactive maintenance strategies.

Long-term reliability is a critical requirement for vibration-based diagnostic systems deployed in industrial and automotive maintenance applications. While short-term classification accuracy provides an initial performance indicator, sustained reliability depends on the model’s ability to consistently detect fault patterns under varying operating conditions, environmental influences, and progressive equipment aging. The stable convergence behavior observed in the ANN training process and the low misclassification rates across operational states suggest that the proposed model possesses strong generalization capability, which is essential for long-term monitoring reliability.

Additionally, the robustness of the ANN architecture, combined with normalized vibration features, reduces sensitivity to measurement noise and operational variability. This characteristic is particularly important in real-world maintenance scenarios where sensor drift, load fluctuations, and external disturbances are common. Previous studies have demonstrated that machine learning-based diagnostic models with strong generalization properties maintain reliable fault detection performance over extended monitoring periods, supporting continuous predictive maintenance implementation (Lei et al., 2020; Sun et al., 2022).

From a reliability engineering perspective, the consistent performance of the ANN-based monitoring system contributes to improved equipment availability and reduced failure probability over time. By enabling early fault detection and timely intervention, the system helps prevent progressive degradation from escalating into major failures. This proactive approach enhances system reliability metrics such as mean time between failures (MTBF) and overall equipment effectiveness (OEE), reinforcing the value of ANN-driven vibration diagnostics in long-term maintenance strategies.

4.2 Discussion of Results

A small proportion of samples from the degrading (or less-normal) condition were misclassified as either normal or faulty. This outcome reflects the physical reality that transitional degradation states produce mixed vibration signatures—combining low-frequency components typical of normal operation with intermittent high-frequency bursts caused by uneven combustion pressure. Similar overlaps have been reported by Huang et al. (2018) and Widodo et al. (2019), who observed that injector wear and early piston friction alter the combustion balance subtly before a full fault develops. Comparable findings were also noted by Zeng et al. (2023), who showed that mid-level mechanical degradation often produces ambiguous vibration responses due to partial synchronization loss between cylinder pressures.

The dominance of high-intensity diagonal cells in Figure 4 verifies that the ANN correctly learned the nonlinear boundaries between the three classes. This confirms that the classifier effectively differentiated consistent vibration modes under stable operating conditions. The results further demonstrate that vibration-based fault detection can substitute direct in-cylinder pressure measurement, offering a non-invasive, low-cost diagnostic method (Yilmaz & Ozgoren, 2020; Shah et al., 2024). The confusion matrix also emphasizes the importance of monitoring transitional patterns: a growing number of degrading-to-faulty misclassifications over time would indicate progressive wear or imbalance, enabling early maintenance intervention. This pattern aligns with observations from Takahashi et al. (2025) and Gao et al. (2021), who both highlighted the diagnostic potential of continuous vibration monitoring for prognostic maintenance in diesel and hybrid engines.

The correlation between vibration amplitude and combustion pressure was further analyzed. Higher in-cylinder pressure or irregular combustion events resulted in increased vibration energy due to unbalanced impulse forces acting on the crankshaft and piston assembly. These findings align with Huang et al. (2018) and Yilmaz and Ozgoren (2020), who confirmed that abnormal combustion leads to stronger vibration peaks in both time and frequency domains. Moreover, Liu et al. (2022) demonstrated that combustion pressure anomalies above 210 MPa produce distinct high-frequency components (1–2 kHz) detectable via accelerometer measurements. Such relationships underscore the interdependence of combustion dynamics and structural responses, validating the hypothesis that vibration patterns can serve as indirect indicators of in-cylinder pressure behavior.

The integration of student experimental data with ANN classification demonstrates that even simple RMS vibration data can be effectively used for predictive diagnostics. This approach eliminates the need for expensive in-cylinder pressure sensors while maintaining reliable performance. The ANN's ability to detect subtle changes during the degrading phase highlights its potential for early fault detection, crucial for predictive maintenance and energy efficiency in modern vehicles (Zhang & Li, 2022; Kodrič et al., 2025). The results are consistent with contemporary studies employing neural networks and hybrid learning algorithms for health monitoring of electromechanical systems (Sun et al., 2022; Alshorman et al., 2021).

Beyond the theoretical validation of vibration–combustion pressure relationships, the findings of this study offer important practical implications for industrial engine maintenance systems. The ability of the ANN model to accurately distinguish between normal, degrading, and faulty operating conditions enables maintenance teams to transition from time-based preventive maintenance toward condition-based and predictive maintenance strategies. By continuously monitoring vibration patterns and automatically classifying engine health states, early signs of mechanical degradation can be detected before critical failure thresholds are reached, allowing for timely corrective actions and reduced unplanned downtime.

In industrial applications, such automated fault classification systems can be integrated into real-time monitoring platforms and computerized maintenance management systems (CMMS), where diagnostic outputs trigger maintenance alerts and work orders. This integration improves maintenance scheduling efficiency by prioritizing interventions based on equipment condition severity rather than fixed service intervals. Consequently, resources such as labor, spare parts, and machine availability can be optimized, leading to lower operational costs and improved asset utilization.

Furthermore, the non-invasive nature of vibration-based monitoring eliminates the need for complex in-cylinder pressure sensors, which are often expensive and difficult to maintain in industrial environments. This cost-effective sensing approach enhances the feasibility of large-scale deployment across multiple engines or machinery units. The demonstrated robustness of the ANN classifier under varying operating conditions also supports its suitability for long-term industrial use, where equipment is subjected to continuous load variations and environmental disturbances. Overall, the proposed ANN-based vibration analysis framework provides a scalable and practical solution for enhancing reliability, safety, and efficiency in industrial engine maintenance systems.

Overall, the proposed ANN-based vibration analysis framework provides a robust and scalable method for engine condition assessment. The model's strong generalization performance and minimal misclassification suggest it can be adapted for online, real-time applications in predictive maintenance systems. Future research could enhance model performance by incorporating multi-sensor fusion (e.g., combining vibration, temperature, and acoustic data) and implementing deep learning architectures such as convolutional or recurrent neural networks (Gonzalez et al., 2024).

Avoid overinterpretation and ensure all statements are supported by the data or prior literature.

5. Conclusion

This integrated study successfully combines experimental vibration analysis with ANN-based classification to diagnose engine component degradation. The ANN model achieved high accuracy and demonstrated robustness in recognizing vibration pattern variations across normal, degrading, and faulty conditions. The results confirm a strong correlation between vibration amplitude and combustion pressure fluctuations, validating vibration signals as effective indicators of engine health. The proposed ANN architecture (1–20–3) achieved a classification accuracy of 94% with a mean squared error of 1.5×10^{-5}, while transitional degradation states were successfully identified prior to major mechanical failures.

From a maintenance perspective, the developed vibration-based diagnostic framework offers significant practical benefits. By enabling early fault detection and continuous condition monitoring, the proposed method can reduce unplanned downtime, prevent unexpected equipment failures, and support timely maintenance interventions. The non-invasive and cost-effective nature of the vibration sensing approach further contributes to lower maintenance costs and facilitates large-scale deployment in industrial environments. Moreover, the improved diagnostic accuracy enhances equipment availability and operational reliability by allowing maintenance actions to be scheduled proactively rather than reactively.

Future work will focus on extending the ANN model to incorporate time-series vibration data using Long Short-Term Memory (LSTM) networks, which are expected to improve the system’s capability to capture temporal degradation patterns and further enhance predictive maintenance performance.

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