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Original Research

Convolutional transformer approach for engine spark plug fault diagnosis using acoustic signal

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ABSTRACT

Detecting and rectifying spark plug faults are pivotal in preventing engine-related issues that can have substantial operational and financial consequences. To improve the accuracy and robustness of spark plug fault diagnosis, this research introduces a novel Convolutional Transformer approach that leverages the strengths of Convolutional Neural Networks and Transformers, which effectively capture both local and extended temporal dependencies within spark plug acoustic signals. The results of this groundbreaking approach, as presented in accompanying tables and figures, demonstrate its superior performance, achieving an impressive 97.1% accuracy in a challenging 4-class classification scenario using solely acoustic signals. This achievement signifies a significant advancement in spark plug fault detection, potentially ushering in more reliable and precise diagnostic methods, ultimately contributing to the prevention of costly engine breakdowns and the extension of engine lifespan. Deep learning techniques such as Convolutional Transformers offer a promising way to improve the reliability and performance of internal combustion engines as the automotive industry continues to evolve, highlighting the importance of this research for future automotive developments.

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1- Introduction

The proper functioning of spark plugs in spark ignition engines is paramount for maintaining engine efficiency and overall performance [1]. Spark plug faults, such as fouling or improper gaps, can significantly impact engine operation, leading to issues like misfires, knocking, hard starts, and reduced gas mileage. Furthermore, the widening of the spark plug gap can result in the deterioration of engine performance [2], causing misfires and knocking due to pre-ignition between the spark plug electrodes [3]. In essence, spark plug faults represent a crucial aspect of diagnosing engine problems, and addressing them promptly is essential to prevent costly breakdowns [4].

Various diagnostic techniques have been explored in the quest for reliable methods to detect spark plug faults. Researchers have extensively investigated using vibration and acoustic signals to monitor engine conditions and identify spark plug issues. Vibration analysis has been a key component of fault recognition, with studies converting analog vibration signals into digital data for in-depth analysis [4]. The use of fuzzy and probabilistic methods, such as the Fuzzy and Probabilistic Simultaneous-Fault Diagnosis (FPSD), has further expanded the toolbox for engine fault diagnosis [5].

As the volume of data generated by these monitoring techniques can be substantial, feature extraction and selection are essential. Extracting relevant information from the acoustic and vibration signals is critical to reducing computational complexity and improving classifier performance [6]. When correctly chosen, these features can diagnose faults in various mechanical components across different systems [7].

The success of a diagnostic method hinges on the classification algorithm used. Several approaches have been explored, such as Dempster-Shafer evidence theory, which leverages evidence fusion techniques to improve fault detection [8]. Furthermore, the Least Square Support Vector Machine (LS-SVM) has shown its efficiency in fault diagnosis [9]. Artificial Neural Networks (ANNs) have been used in pattern recognition, fault detection, and data classification [10]. Vibration and acoustics are essential techniques in engine condition monitoring. They are reliable and effective for analyzing engine behavior, as failures often impact engine sound and vibration patterns. Much literature has focused on using acoustics and vibrations for fault diagnosis and engine condition monitoring [3].

While machine learning and deep learning have applications in various systems, including internal combustion engines, Convolutional Neural Networks (CNNs) and Transformers have not been extensively studied for spark plug fault diagnosis. Machine learning approaches, such as random forests, Support Vector Machines, and K-means, have been used in prior research for signal-based fault detection [11]. However, the potential of deep learning models, particularly the combination of CNNs and Transformers, presents an exciting avenue for improving the accuracy of spark plug fault diagnosis within internal combustion engines.

This paper proposes a novel Convolutional Transformer approach for spark plug fault diagnosis using acoustic signals. Drawing inspiration from recent advancements in deep learning and feature-learning techniques, we aim to harness the power of CNNs for effective feature extraction from acoustic signals and exploit Transformers to model temporal relationships within the data. By combining these state-of-the-art techniques, we seek to enhance the accuracy and robustness of spark plug fault diagnosis, ultimately contributing to the prevention of engine breakdowns and the extension of engine lifespan.

2- Dataset

This study investigated the XU7 four-cylinder spark-ignition (SI) engine featuring both functional and defective spark plugs. The specifications of the engine are illustrated in Table 1. Acoustic signals were recorded under various engine conditions to assess their differences. Under normal operating conditions, all four cylinders had properly functioning spark plugs with a 0.9 mm gap. To create an abnormal condition mimicking engine wear, a spark plug with a 1.4 mm gap, known as a wide spark plug gap, was introduced. A healthy and faulty spark plug is shown in Figure 1.

Table 1 The specifications of the engine [12]

Engine type	4-cylinder inline
Firing order	1-3-4-2
Engine capacity (cc)	1761
Number of valves	8
Compression ratio	9.25:1
Fuel system	Multi-point injection
Maximum power (hp/r/min)	97/6000
Maximum torque (N.m/r/min)	148/3500

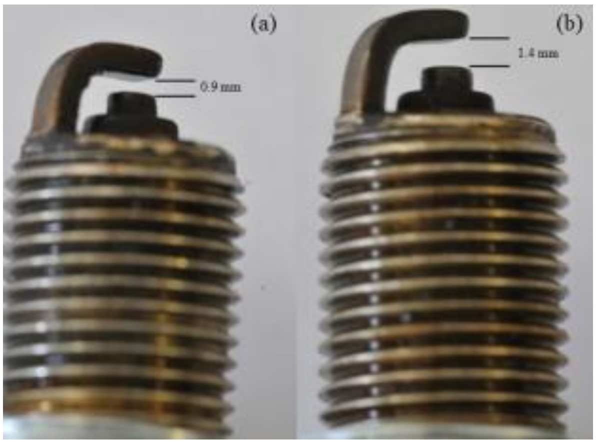

Figure 1 a) healthy, gap = 0.9 mm and b) faulty spark plug, gap = 1.4 mm [13]

The three specific abnormal conditions examined were as follows:

1. A faulty spark plug was placed in the first cylinder.
2. A faulty spark plug was placed in the second cylinder.
3. A faulty spark plug was placed in the third cylinder.

These conditions are detailed in Table 1. The engine operated at an idle speed of 867 rpm without any external load, chosen to create a scenario where defects were less likely to appear, making fault detection more challenging.

Acoustic signals were recorded using a B&K microphone (type 4188) placed on top of the engine. Data acquisition involved a Brüel & Kjær (B & K) NEXUS conditioning amplifier (type 2692) with high bandwidth and a 17-channel data acquisition system. Two channels were dedicated to capturing acoustic and crank position signals. Signals were sampled at 32,768 Hz for 5 seconds, and each engine condition underwent four sampling repetitions.

Each original signal, with a length of 163,840, was segmented into 140 sample signals, generating 700 acoustic samples for each engine condition. A "sample signal" represented a segment spanning two complete revolutions of the crankshaft, during which four combustions occurred, with each spark plug firing once within the duration of the sample signal [13].

Figure 2 shows samples of waveforms for each normal class and three fault classes.

3- Methodology

Figure 3 illustrates a convolutional transformer model designed for spark plug fault classification. This efficient approach seamlessly integrates the merits of CNNs and the transformer model. Commencing with the acoustic signal, this technique employs CNNs to extract pertinent features. The transformer subsequently processes the resultant features to model temporal relationships. These transformed features are then directed into the classifier for fault diagnosis. This method strives to leverage local and extended temporal dependencies in spark plug acoustic signals, ultimately enhancing the efficiency of fault diagnosis in internal combustion engines. This approach optimally diagnoses spark plug faults by merging the feature extraction capabilities of CNNs with the temporal transformer's ability to capture long-term temporal dependencies and patterns. CNNs excel at extracting local acoustic signal features, while the temporal transformer adeptly captures extended temporal dependencies, ensuring precise fault assessments [14].

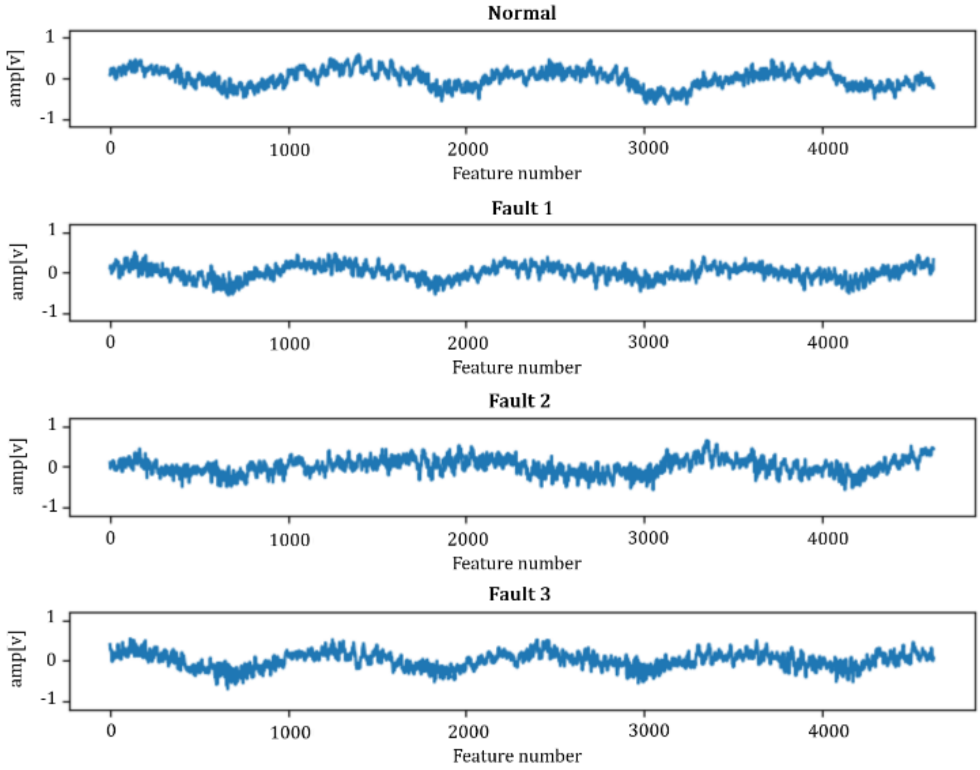

Figure 2 Sample waveforms for each class

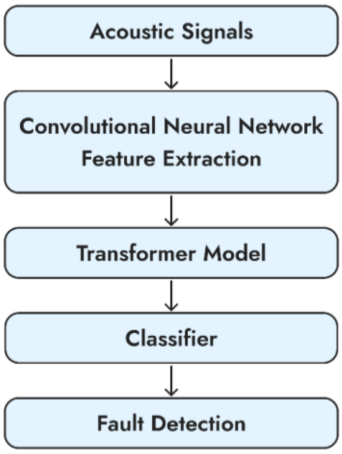

Figure 3 Convolutional-transformer model architecture

Convolutional Neural Networks (CNNs) are intricate neural networks featuring layers like input, convolution, pooling, fully connected, and output. They specialize in feature learning, progressively extracting meaningful features through convolutional, activation, and pooling processes applied to input data. This enables the network to identify unique data characteristics. Convolution layers apply filters to raw input data, creating invariant local features. Simultaneously, pooling layers extract essential information from the convolved data [14]. In mathematical terms, the convolution operation is represented as follows:

$$h_j = \left(\sum\nolimits_i X_i * W_{ij} + b_j\right) \tag{1}$$

h_j denotes the j-th output feature map in the current convolutional layer while X_i signifies the i-th feature map from the previous layer. The convolution operator $(*)$ connects them through W_{ij}, the convolution kernel mapping from c input features to the current layer's j-th output feature. b_j represents the bias for the j-th feature kernel and f is the activation function, typically ReLU, expressed as:

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \tag{2}$$

The pooling layer reduces output dimensionality through non-linear down-sampling techniques, such as maximum pooling, average pooling, and random pooling. Maximum pooling is commonly applied and can be mathematically expressed as follows:

$$X_j = f\left(\alpha_j down(X_i) + b_j\right) \tag{3}$$

Where X_j represents the j-th output from the current pooling layer, the constant α_j is used to control the level of data adjustment by the pooling layer. The $down(X_i)$ function describes the down-sampling applied to the i-th output from the preceding layer. b_j denotes the bias linked to the j-th feature kernel in the current pooling layer. Finally, f represents the activation function. The structure of the suggested CNN feature extractor is illustrated in Figure 4.

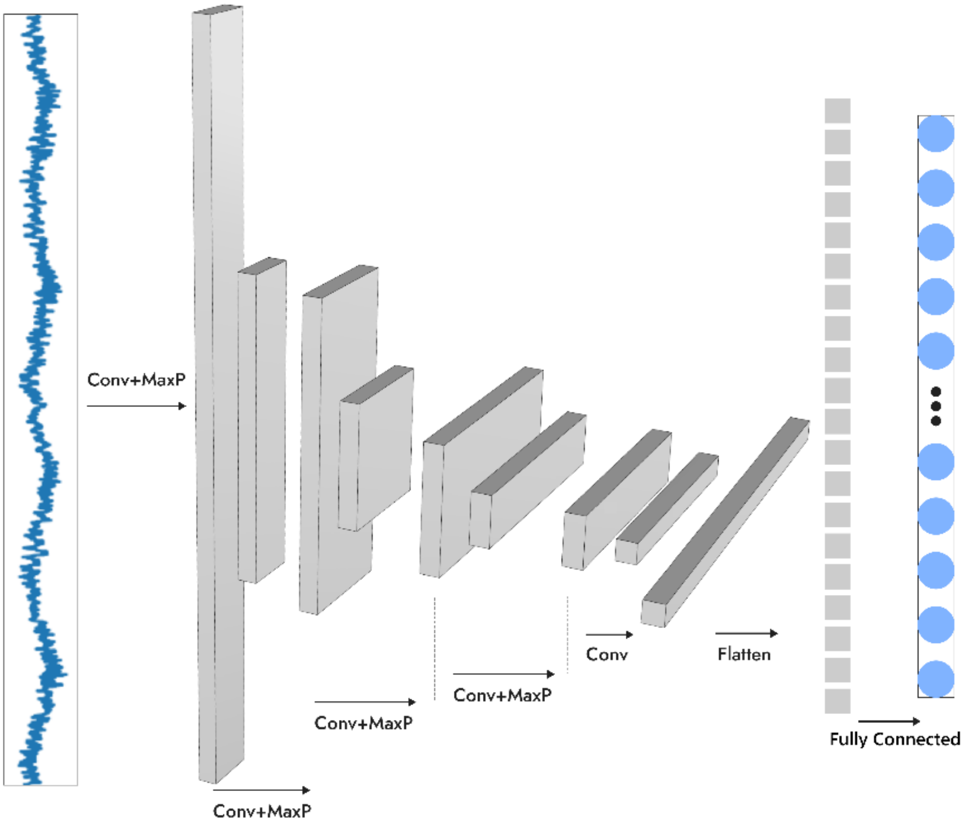

Figure 4 Proposed CNN feature extractor architecture

The transformer design combines stacked encoder and decoder modules [15]. Figure 5 depicts this structure: the encoder (left side) transforms input data into feature vectors using multi-head attention and a fully connected layer. The decoder uses the encoder's output and previous predictions on the right, employing masked multi-head attention, multi-head cross-attention, and a fully connected layer.

We utilized a temporal transformer encoder of multiple layers with two sub-layers: multi-head self-attention and a position-wise fully connected feedforward network [16]. Residual connections are applied to address the vanishing gradient problem, along with layer normalization. The sub-layer output can be represented as:

$$LayerNorm[x + Sublayer(x)] \tag{4}$$

Where Sublayer(x) denotes the sub-layers function. All model sub-layers, including the embedding layers, generate outputs of dimensionality d_{model} for seamless integration of residual connections.

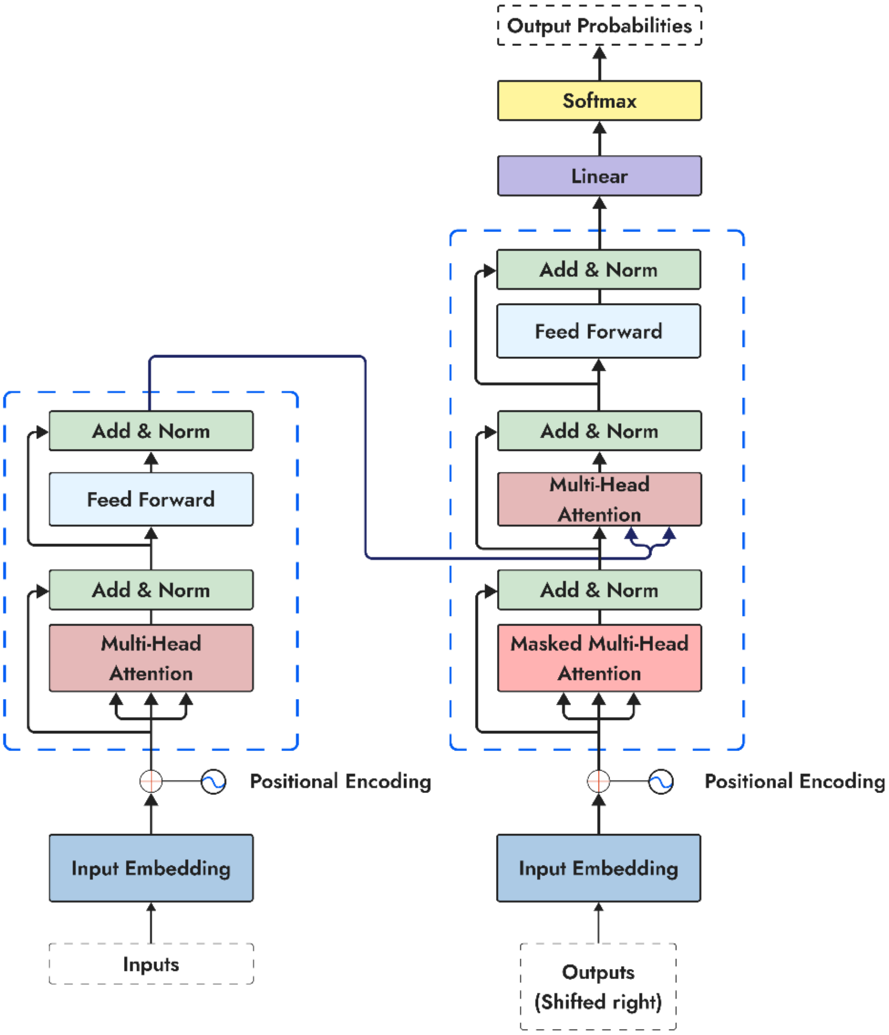

Figure 5 The overall architecture of the transformer

Machine learning's attention mechanism allows a model to focus on particular parts of the input sequence, which are inputted as a set of key-value pairs and a query vector. The query vector represents the model's current focus, whereas the key-value pairs correspond to different parts of the input sequence. The attention function calculates a weighted summation of the value vectors, where the compatibility between the query vector and the key vectors determines the weights. This allows the model to emphasize the most relevant parts of the input sequence based on the query. The query vector comes from the model's encoder, and the key-value pairs contain information about different segments of the input sequence. The keys assess compatibility, and the weights assigned to the value vectors influence the output. The output is a weighted sum of the value vectors, with weights calculated by a compatibility function measuring the similarity between the query vector and the key vectors.

Figure 6 provides a visual depiction of the schematic representation of multi-head attention, showcasing the concurrent operation of numerous parallel attention layers.

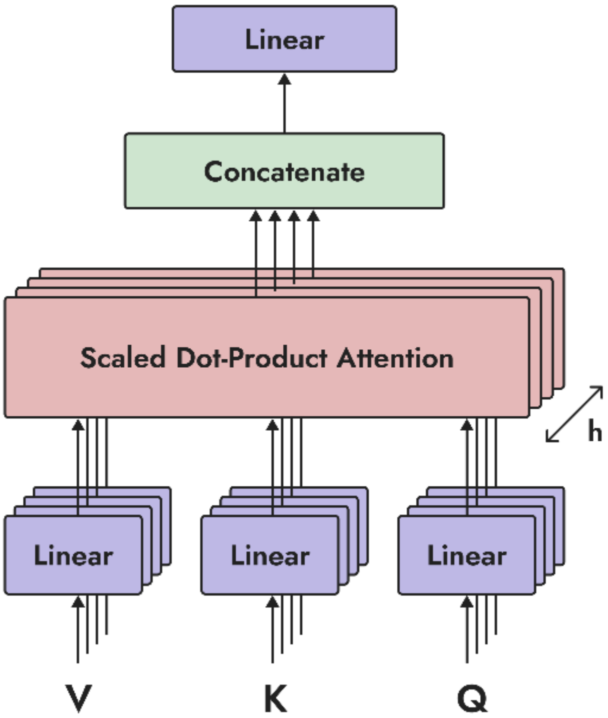

Figure 6 Multi-head attention schematic

Scaled dot-product attention is the primary approach for calculating attention interactions, known as self-attention computation [15]. This method involves organizing queries into a Q matrix keys into a K matrix, both with dimension $\mathrm{d_k}$, and values into a V matrix with dimension $\mathrm{d_v}$. The output matrix is determined as follows:

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_K}}\right)\mathrm{V} \tag{5}$$

Multi-head attention uses linear projections for transforming queries, keys, and values into $\mathrm{d_k}$ and $\mathrm{d_v}$ dimensions, each learned separately. The attention function is performed on these versions simultaneously, producing $\mathrm{d_v}$ -dimensional output values. This enables the model to consider information from various representation subspaces and positions simultaneously. Mathematically, this can be represented as follows:

$$MultiHead(Q,K,V) = Count(head_1, head_2, \dots, head_h)W^O \tag{6}$$

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{7}$$

where linear projection matrices $\mathrm{W_i^Q} \in \mathbb{R}^{\mathrm{d_{model}} \times \mathrm{d_k}}$, $\mathrm{W_i^K} \in \mathbb{R}^{\mathrm{d_{model}} \times \mathrm{d_k}}$, $\mathrm{W_i^V} \in \mathbb{R}^{\mathrm{d_{model}} \times \mathrm{d_v}}$, and $\mathrm{W^O} \in \mathbb{R}^{\mathrm{d_v} \times \mathrm{d_{model}}}$.

The temporal transformer encoder module in Figure 7 processes CNN-extracted features. Self-attention records interactions in the feature sequence, allowing the model to discover long-term dependencies within acoustic signals. This comprehensive understanding makes it easier to identify temporal patterns. The features are integrated with the input features utilizing residual connections and layer normalization. A feedforward network strengthens non-linear interactions and extracts discriminative high-level information for classification.

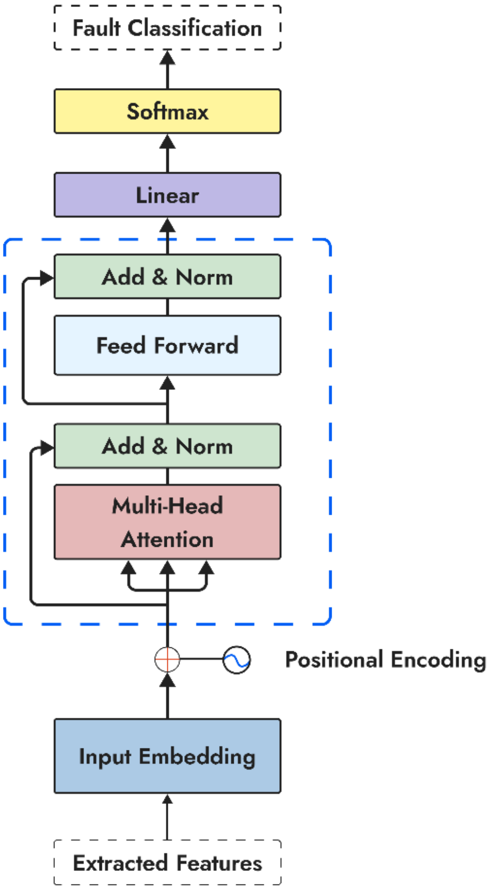

Figure 7 Architecture of the temporal transformer encoder

Ultimately, the algorithm transforms the input sequence and uses it for classification. This transformation is normalized to increase its discriminative ability and diminish the effects of scale and distribution. A classification layer is then applied to the transformed representation, mapping it to a vector of class scores. The class scores are turned into a probability distribution using a Softmax layer, ensuring that the probabilities collectively equal one. As a result, anticipated class labels can be construed probabilistically. The temporal encoder uses self-attention, feedforward networks, classification, and Softmax layers to discover the temporal dynamics and complex patterns in CNN-based acoustic signal characteristics.

4- Results and Discussion

Our initial step involved utilizing a CNN to extract essential features from the collected signals. This network utilized 1D convolution operations with a ReLU activation function and max-pooling using a kernel size 3. A visual representation of the feature extraction network structure can be observed in Figure 4, and the implementation parameters are detailed in Table 2.

Following feature extraction, our approach for fault detection in spark plug utilizes a transformer-based architecture with self-attention mechanisms for capturing temporal dependencies. This architecture includes a self-attention layer, layer normalization, and removal regularization. A feedforward network further processes the features, and a final layer maps them to output classes, with a Softmax layer generating class probabilities. Model parameters were carefully chosen through iterative experiments, ensuring efficiency and effectiveness. Table 3 details the selected parameters for our method's time transformer encoder component.

Table 2 CNN feature extraction parameters

Conv 1D		Maxpoolig 1D	
Filters	4, 8, 16, 16, 32	Pool size	3
Kernel sizes	33, 17, 9, 5, 3	Padding	Same
Strides	1	Fully connected neurons	256
Activation	ReLU		
Padding	Same		

Table 3 Transformer parameters

Parameter	Value	Training Option	Value
Hidden size	128	Loss function	Cross Entropy Loss
Number of layers	6	Optimizer	Adam
Number of heads	8	Number of epochs	250
Activation function	ReLU		

To ensure a comprehensive evaluation, a 10-fold cross-validation technique was utilized. This method partitions the data into ten subsets, allowing each part to serve as the test data once, providing a comprehensive assessment of our model's performance.

Additionally, we implemented a convolutional neural network (CNN) for comparative purposes. This CNN shares a similar architecture with our feature extraction network, differing only in the presence of a fully connected layer comprising 100 neurons, followed by a final layer with 4 neurons using Softmax activation for classification.

In Tables 4 and 5, our approach's effectiveness becomes evident as the conventional transformer model achieved an accuracy of 0.97, surpassing the convolutional network's 0.91 accuracy. This stark contrast underscores the pivotal role of our transformer architecture in harnessing CNN-extracted features for spark plug air gap fault detection.

Table 4 Convolutional transformer classification scores

Number	Precision	Recall score	F1- score
Normal	0.98	0.99	0.98
Fault 1	0.97	0.95	0.96
Fault 2	0.96	0.97	0.97
Fault 3	0.97	0.96	0.97
Accuracy		0.971	

Table 5 Convolutional neural network scores

Number	Precision	Recall score	F1- score
Normal	0.94	0.96	0.95
Fault 1	0.88	0.88	0.88
Fault 2	0.93	0.85	0.89
Fault 3	0.87	0.92	0.89
Accuracy		0.91	

Figure 8 and Figure 9 present the confusion matrices for both models, vividly illustrating their actual label versus predicted class relationships. These visualizations underscore the strength of our conventional transformer model in precise class predictions.

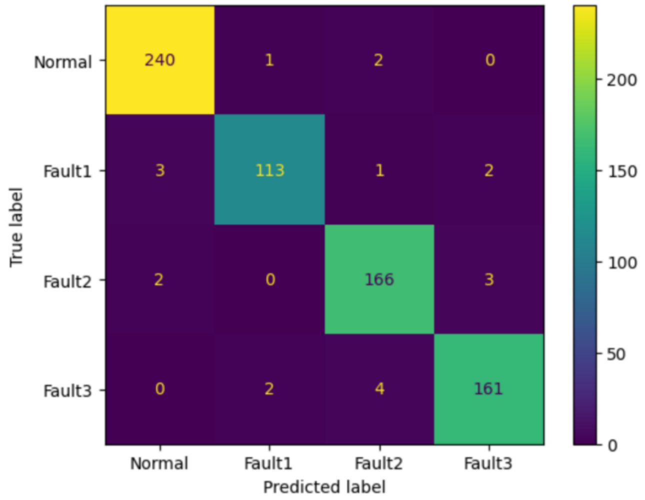

Figure 8 Convolutional transformer classification confusion matrices

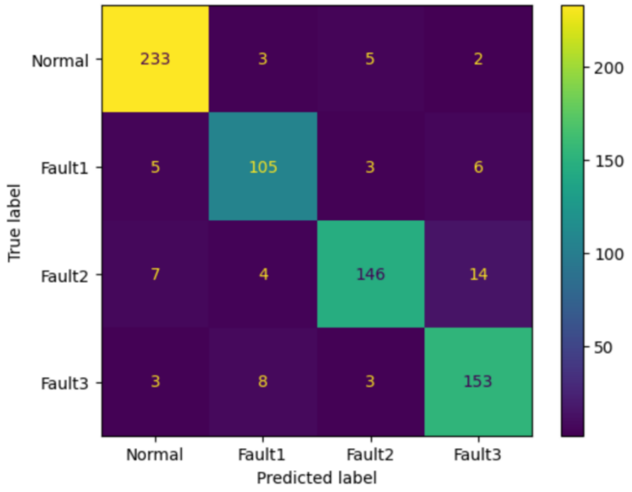

Figure 9 CNN classification confusion matrices

Table 6 Spark plug fault detection score comparison

Reference	Data	Method	Testing Accuracy (%)
[17]	Acoustic, 3 class	ANN	4000 rpm: 80 3000 rpm: 73.3
[13]	Acoustic, 2 class	ANN	67.46
[13]	Acoustic, 2 class	LS-SVM	65.08
[13]	Acoustic & Vibration, 2 class	D–S Theory	98.56
Our work	Acoustic, 4 class	CNN	91
Our work	Acoustic, 4 class	CNN-Transformer	97.1

Table 6 reveals a distinctive facet of our research. Unlike previous studies that primarily focused on binary classification for spark plug fault detection, we ventured into a more challenging domain of 4-class classification, broadening the scope of this critical field.

Prior research, with its best performance achieved through the D-S Theory, was confined to a binary classification framework using both vibration and acoustic data. However, our work introduces a groundbreaking achievement: we attained an impressive accuracy of 97.1% in a 4-class classification scenario using only acoustic signals. This accomplishment showcases the effectiveness of our approach in addressing the complexities of real-world spark plug fault detection, pioneering new horizons in the realm of spark plug fault detection.

5- Conclusions

In conclusion, this study underscores the importance of utilizing efficient methodologies for feature extraction and fault detection in spark plugs within spark ignition engines, thereby ensuring optimal engine efficiency and overall performance. Rapid and accurate identification of spark plug faults is crucial to mitigate potential engine-related issues that could have operational and financial consequences. This research presents a significant breakthrough in spark plug fault detection using acoustic signals by leveraging a Convolutional Transformer approach. By harnessing the combined strengths of Convolutional Neural Networks and Transformers, this methodology effectively captures both local and extended temporal dependencies within spark plug acoustic signals. The remarkable results, as demonstrated in the accompanying Tables and Figures, highlight the superiority of this proposed model, achieving an outstanding accuracy of 97.1% in a challenging 4-class classification scenario using only acoustic signals. This achievement represents a substantial advancement in spark plug fault detection, offering the potential to streamline diagnostic methods while eliminating the need for multiple sensors. Ultimately, it prevents costly engine breakdowns and extends the lifespan of internal combustion engines. As the automotive industry continues to evolve, applying deep learning techniques such as Convolutional Transformers holds immense promise in enhancing the reliability and performance of internal combustion engines.

References

[1] Javan S, Hosseini S, Alaviyoun S, Ommi F. Effect of electrode erosion on the required ignition voltage of spark plug in CNG spark ignition engine. The Journal of Engine Research, 2022;26(26):31-9.

[2] Moosavian S, Najafi G, Ghobadian B, Jafari S, Sakhaei B, Khazaee M. Fault diagnosis in engine spark plug by vibration analysis using neural network. The Journal of Engine Research, 2022;28(28):21-9. [In Persian]

[3] Azrin AA, Yusri IM, Sudhakar K, Mohd W, A Zainal, Majeed A. An overview of the spark plug engine profile in a spark ignition engine. IOP Conf Ser: Mater Sci Eng. 2021 Mar 1;1092(1):012030. doi: 10.1088/1757-899x/1092/1/012030

[4] Han J, Yamashita H, Hayashi N. Numerical study on the spark ignition characteristics of hydrogen-air mixture using detailed chemical kinetics. International Journal of Hydrogen Energy. 2011 Jul;36(15):9286–97. doi: 10.1016/j.ijhydene.2011.04.190

[5] Vong CM, Wong PK, Wong KI. Simultaneous-fault detection based on qualitative symptom descriptions for automotive engine diagnosis. Applied Soft Computing. 2014 Sep 1;22:238–48. doi: 10.1016/j.asoc.2014.05.014

[6] Shen Z, Chen X, Zhang X, He Z. A novel intelligent gear fault diagnosis model based on EMD and multi-class TSVM. Measurement. 2012 Jan;45(1):30–40. doi: 10.1016/j.measurement.2011.10.008

[7] Khazaee M, Ahmadi H, Omid M, Banakar A, Moosavian A. Feature-level fusion based on wavelet transform and artificial neural network for fault diagnosis of planetary gearbox using acoustic and vibration signals. Insight-Non-Destructive Testing and Condition Monitoring. 2013 Jun 1;55(6):323–30. doi: 10.1784/insi.2012.55.6.323

[8] Basir O, Yuan X. Engine fault diagnosis based on multi-sensor information fusion using Dempster–Shafer evidence theory. Information Fusion. 2007 Oct;8(4):379–86. doi: 10.1016/j.inffus.2005.07.003

[9] Xiao R, Hu Q, Li J. Leak detection of gas pipelines using acoustic signals based on wavelet transform and Support Vector Machine. Measurement. 2019 Nov;146:479–89. doi: 10.1016/j.measurement.2019.06.050

[10] Zarei J, Tajeddini MA, Karimi HR. Vibration analysis for bearing fault detection and classification using an intelligent filter. Mechatronics. 2014 Mar;24(2):151–7. doi: 10.1016/j.mechatronics.2014.01.003

[11] Huangfu Y, Seddik E, Habibi S, Wassyng A, Tjong J. Fault Detection and Diagnosis of Engine Spark Plugs Using Deep Learning Techniques. SAE International Journal of Engines. 2021 Nov 10;15(4):515–25. doi: 10.4271/03-15-04-0027

[12] Moosavian A, Khazaee M, Najafi G, Khazaee M, Sakhaei B, Jafari SM. Wavelet denoising using different mother wavelets for fault diagnosis of engine spark plug. Proceedings of the Institution of Mechanical Engineers Part E, Journal of Process Mechanical Engineering. 2015 Jul 21;231(3):359–70. doi: 10.1177/0954408915595952

[13] Moosavian A, Khazaee M, Najafi G, Kettner M, Mamat R. Spark plug fault recognition based on sensor fusion and classifier combination using Dempster–Shafer evidence theory. Applied Acoustics. 2015 Jun;93:120–9. doi: 10.1016/j.apacoust.2015.01.008

[14] Wu H, Triebe MJ, Sutherland JW. A transformer-based approach for novel fault detection and fault classification/diagnosis in manufacturing: A rotary system application. Journal of Manufacturing Systems. 2023 Apr;67:439–52. doi: 10.1016/j.jmsy.2023.02.018

[15] Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention Is All You Need [Internet]. arXiv.org. 2017.

[16] Ahmed H, Nandi AK. Convolutional-Transformer Model with Long-Range Temporal Dependencies for Bearing Fault Diagnosis Using Vibration Signals. Machines. 2023 Jul 17;11(7):746–6. doi: 10.3390/machines11070746

[17] Mofleh A, Shmroukh A, Ghazaly N. Fault detection and classification of spark ignition engine based on acoustic signals and artificial neural network. Int J Mech Prod Eng Res Dev. 2020 Jul 30;10:5571–8.

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یادگیری ماشین

چکیده

تشخیص و اصلاح عیوب شمع‌ها در جلوگیری از مسائل موتور که می‌تواند منجر به عواقب عملیاتی و مالی قابل توجهی شود، بسیار مهم است. برای افزایش دقت و استحکام تشخیص عیب شمع، این تحقیق یک رویکرد ترنسفورمر پیچشی را معرفی می‌کند که از نقاط قوت شبکه‌های عصبی و ترنسفورمرها استفاده می‌کند تا به طور مؤثر وابستگی‌های زمانی محلی و طولانی را در علامت‌های صوتی شمع‌ها ثبت کند. نتایج این رویکرد پیشگامانه، همانطور که در جداول و شکل‌های همراه ارائه شده است، عملکرد برتر آن را نشان می‌دهد و به دقت چشمگیر ۹۷٫۱٪ در مسئله چالش‌برانگیز طبقه‌بندی ۴ کلاس صرفاً با استفاده از علامت‌های صوتی دست یافته است. این دستاورد نشان‌دهنده پیشرفت قابل توجهی در حوزهٔ تشخیص عیب شمع است، با ظرفیت راه‌اندازی روش‌های تشخیصی مطمئن‌تر و دقیق‌تر، که در نهایت به جلوگیری از خرابی‌های پرهزینهٔ موتور و افزایش طول عمر موتور کمک می‌کند. همانطور که صنعت خودرو به تکامل خود ادامه می‌دهد، پذیرش روش‌های یادگیری عمیق مانند مبدل‌های ضرب پیچشی یک راه امیدوارکننده برای افزایش قابلیت اطمینان و عملکرد موتورهای احتراق داخلی ارائه می‌دهد و اهمیت این تحقیق را در زمینهٔ پیشرفت‌های آینده خودرو برجسته می‌کند.

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