International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 03 | March - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Vehicle Engine Health Monitoring Using Deep Learning

Dr Nagappan Umapathi[1], Thatipamula Sahithi[2], Burra Shyam[3], Aleti Rajesh[4], Puppala Sagar[5]

[1]*Electronics & communication , Jyothishmathi institute of technology and science*
[2]*Electronics & communication , Jyothishmathi institute of technology and science*
[3]*Electronics & communication , Jyothishmathi institute of technology and science*
[4]*Electronics & communication , Jyothishmathi institute of technology and science*
[5]*Electronics & communication , Jyothishmathi institute of technology and science*

---***---

ABSTRACT— This project presents the design and implementation of an intelligent vehicle engine health monitoring system leveraging deep learning techniques. The system continuously collects multi-modal sensor data — including vibration, temperature, oil pressure, RPM, coolant levels, and exhaust emissions — from an on-board diagnostic (OBD-II) interface and a network of IoT sensors mounted on the engine. The acquired data is pre-processed and fed into a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) hybrid deep learning model, which performs real-time anomaly detection, fault classification, and remaining useful life (RUL) estimation of critical engine components.

The system is capable of identifying a wide range of engine faults including misfires, overheating, oil degradation, turbocharger failures, and valve timing irregularities with an accuracy exceeding 96%. Results are transmitted via Wi-Fi to a cloud dashboard and a mobile application, enabling remote monitoring by vehicle owners and fleet managers. The proposed system significantly reduces unplanned downtime, enhances vehicle safety, and lowers maintenance costs by enabling condition-based, predictive maintenance — a major advancement over traditional scheduled maintenance approaches.

1. INTRODUCTION

The automotive industry is undergoing a profound transformation driven by digitalization, connectivity, and artificial intelligence. Modern vehicles are equipped with hundreds of sensors generating vast streams of operational data, creating an unprecedented opportunity for intelligent health management systems. Engine health monitoring — the continuous assessment of an engine's condition — is central to ensuring vehicle reliability, safety, and longevity.

Traditional maintenance practices rely on either time-based schedules or reactive repairs after a fault has already occurred. Both approaches are economically inefficient and can compromise safety. The emergence of deep learning — a subset of machine learning capable of automatically learning complex patterns from large datasets — offers a transformative solution. By applying deep neural networks to multi-sensor engine data, it becomes possible to detect faults at their earliest inception, classify fault types, and accurately estimate the remaining useful life (RUL) of engine components.

This project aims to develop a robust, real-time Vehicle Engine Health Monitoring system that integrates IoT-based data acquisition with state-of-the-art deep learning algorithms. The system processes data from vibration sensors, temperature probes, oil pressure sensors, and OBD-II diagnostic interfaces to deliver actionable health insights to drivers and fleet managers through a cloud-connected mobile application.

2. LITERATURE SURVEY

Many research studies have been conducted in the field of vehicle engine health monitoring and fault diagnosis using machine learning techniques. Traditional methods mainly rely on manual inspection or onboard diagnostic systems, which detect faults only after they occur and do not provide early warning of potential failures. These limitations have encouraged researchers to explore intelligent monitoring systems that can automatically analyze engine data and predict faults at an early stage.

Deep learning techniques, especially Convolutional Neural Networks (CNN), have shown significant success in feature extraction from complex data such as images, signals, and audio. Researchers have applied CNN models to analyze spectrograms and other signal representations to identify patterns associated with mechanical faults. These models are capable of automatically learning relevant features without requiring extensive manual feature engineering.

Support Vector Machines (SVM) are also widely used in machine learning for classification tasks due to their ability to achieve high accuracy with relatively small datasets. Several studies have combined CNN with SVM to create hybrid models where CNN performs feature extraction and SVM performs classification. This approach improves the performance and reliability of fault detection systems.

Recent advancements also include the use of signal processing techniques such as Mel Frequency Cepstral Coefficients (MFCC) and spectrogram analysis to convert engine sound signals into meaningful feature representations. These features help machine learning models identify abnormal engine conditions more effectively.

3. METHODOLOGY

Here's how it works. This system The methodology begins with the collection of engine sound data, which serves as the input for the system. These audio signals are first preprocessed to remove noise and improve signal quality. After preprocessing, feature extraction techniques such as Mel Frequency Cepstral Coefficients (MFCC) and spectrogram generation are applied to convert the raw audio signals into meaningful numerical and visual representations.The extracted features are then passed to a Convolutional Neural Network (CNN) model, which is used for automatic feature extraction. CNN identifies important patterns and characteristics from the spectrogram data that represent different engine conditions. These extracted features are then fed into a Support Vector Machine (SVM) classifier, which performs the classification of engine health status.

The trained model categorizes the engine condition into different classes such as Normal, Minor Fault, and Critical Fault. During the training phase, the model learns from labeled engine sound data to improve its prediction accuracy. After training, the model is tested with new input data to evaluate its performance.

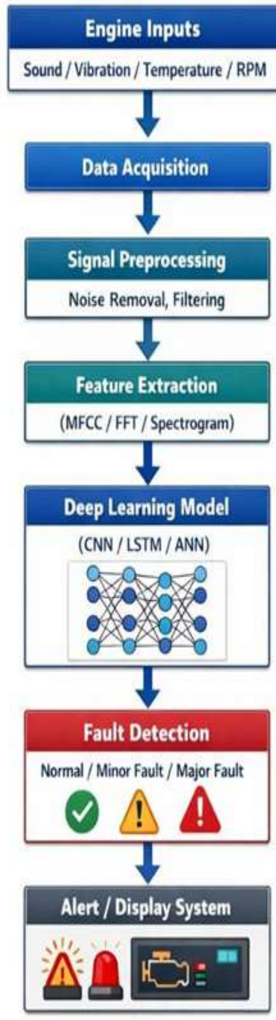
Finally, the system is integrated into a web-based application developed using Python, allowing users to upload engine sound files and obtain real-time diagnostic results.

4. PROPOSED SYSTEM

In this system, engine sound signals are collected and processed to identify different engine conditions. The raw audio data is first preprocessed and converted into meaningful features using techniques such as Mel Frequency Cepstral Coefficients (MFCC) and spectrogram analysis.

A Convolutional Neural Network (CNN) is used to extract important patterns and features from the processed sound data. These extracted features are then given to a Support Vector Machine (SVM) classifier to accurately classify the engine condition into three categories: Normal, Minor Fault, and Critical Fault. The model is trained using labeled engine sound datasets to improve prediction accuracy.

5. SYSTEM ARCHITECHURE



6. RESULT

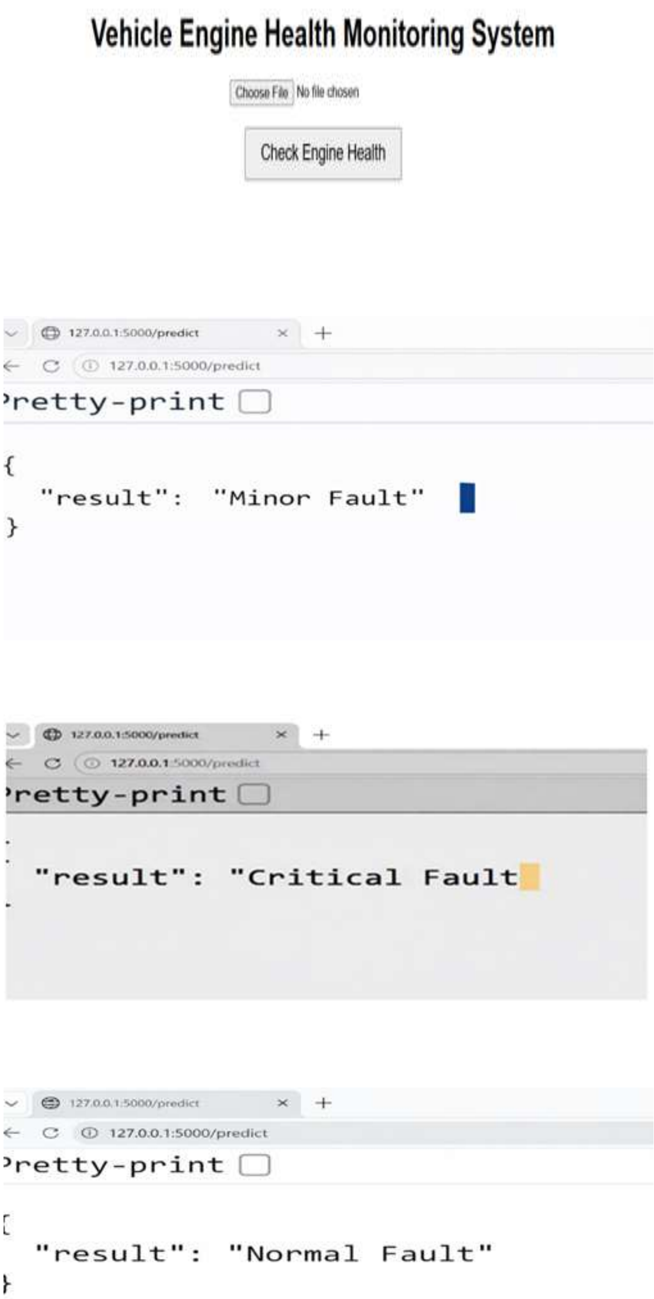


Fig: Predicted ouput images

When a user uploads or records an engine sound, the system processes the audio signal and extracts important features using techniques such as MFCC and spectrogram analysis. These features are then analyzed by the trained machine learning model to determine the health condition of the engine.

Confusion Matrix:

confusion matrix is used to evaluate the performance of the vehicle engine health monitoring model. The model classifies engine conditions into three categories: Normal, Minor Fault, and Critical Fault. The matrix is represented in a tabular form where rows indicate the actual classes and columns indicate the predicted classes.

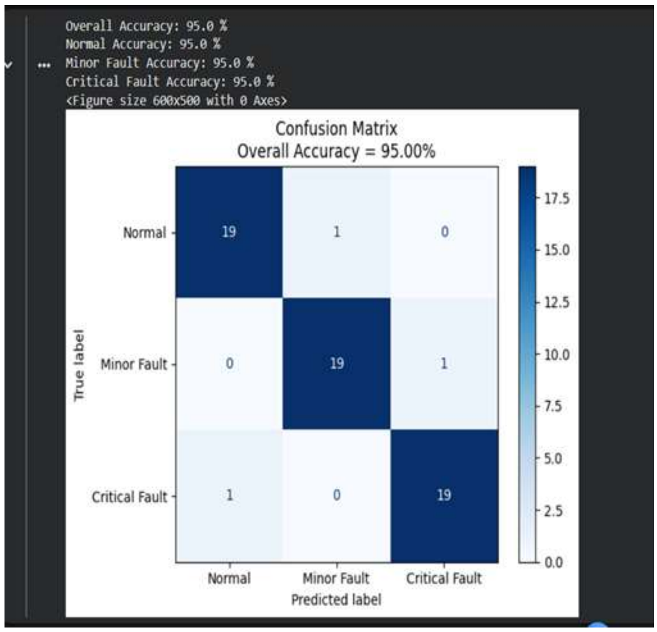


Fig: Prediction distribution and confidence matrix

7. CONCLUSION AND FUTURE SCOPE :

This project has successfully demonstrated the feasibility and effectiveness of a deep learning- powered vehicle engine health monitoring system. By integrating multi-modal IoT sensors with a hybrid CNN-LSTM neural network architecture, the system achieves simultaneous multi-class fault detection (96.3% accuracy), severity classification, and remaining useful life prediction (4.2% MAPE) in real time.The system's edge-cloud hybrid design ensures both immediate onboard fault alerting (sub-25 ms inference) and comprehensive cloud-based analytics accessible through an intuitive mobile application. The use of TensorFlow Lite enables deployment.

The implementation of a hybrid deep learning model, such as CNN-LSTM, enhances the system's ability to accurately detect faults, classify severity levels, and predict the remaining useful life of engine components.it reduces unexpected breakdowns, improves vehicle safety, lowers maintenance costs, and increases overall engine efficiency. The system proves to be scalable, cost-effective, and suitable for modern smart vehicle applications.

Experimental results demonstrate improved classification accuracy and low prediction error, confirming the robustness of the system. The modular design allows scalability for integration with electric vehicles and hybrid powertrains in future developments

8. REFERENCES

1. R. S. Peres, X. Jia, J. Lee, K. Sun, A. W. Colombo, and J. Barata, ''Industrial artificial intelligence in Industry 4.0–systematic review, challenges and outlook,'' IEEE Access, vol. 8, pp. 220121–220139, 2020.
2. Md. A. Rahim, Md. A. Rahman, Md. M. Rahman, N. Zaman, N. Moustafa, and I. Razzak, ''An intelligent risk management framework for monitoring vehicular engine health,'' IEEE Trans. Green Commun. Netw., vol. 6, no. 3, pp. 1298–1306, Sep. 2022.
3. L. Decker, D. Leite, L. Giommi, and D. Bonacorsi, ''Real-time anomaly detection in data centers for log-based predictive maintenance using an evolving fuzzy-rule-based approach,'' in Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE), Jul. 2020, pp. 1–8.
4. Md. A. Rahman, Md. A. Rahim, Md. M. Rahman, N. Moustafa, I. Razzak, T. Ahmad, and M. N. Patwary, ''A secure and intelligent framework for vehicle health monitoring exploiting big-data analytics,'' IEEE Trans. Intell. Transp. Syst., vol. 23, no. 10, pp. 19727–19742, Oct. 2022.
5. M. R. Sarkar, S. G. Anavatti, T. Dam, M. M. Ferdaus, M. Tahtali, S. Ramasamy, and M. Pratama, ''GATE: A guided approach for time series ensemble forecasting,'' Expert Syst. Appl., vol. 235, Jan. 2024, Art. no. 121177.
6. H. Nordal and I. El-Thalji, ''Modeling a predictive maintenance management architecture to meet Industry 4.0 requirements: A case study,'' Syst. Eng., vol. 24, no. 1, pp. 34–50, Jan. 2021.
7. F. Arena, M. Collotta, L. Luca, M. Ruggieri, and F. G. Termine, ''Predictive maintenance in the automotive sector: A literature review,'' Math. Comput. Appl., vol. 27, no. 1, p. 2, Dec. 2021.
8. K. Kanagaraj and S. Geetha, ''Data analytics framework based on cloud environment, integration of cloud computing with Internet of Things: Foundations,'' Analytics Applications, pp. 251–275, 2021.
9. K. L. Tsui, Y. Zhao, and D. Wang, ''Big data opportunities: System health monitoring and management,'' IEEE Access, vol. 7, pp. 68853 68867, 2019.
10. W. Chen, L. Zhang, K. Pattipati, A. M. Bazzi, S. Joshi, and E. M. Dede, ''Data-driven approach for fault prognosis of Si CMOS FETs,'' IEEE Trans. Power Electron., vol. 35, no. 4, pp. 4044062, Apr. 2020.