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Exploring the Accuracy of Machine Learning and Deep Learning in Engine Knock Detection

Usman Hameed[1], Dr. Sohail Masood[2], Fawad Nasim[3], Dr. Arfan Jaffar[4]

Abstract
This study explores the use of machine learning for real-time detection of engine knocking, aiming to enhance early vehicle fault recognition. We extracted frequency modulation amplitude demodulation (FMAD) features from engine sound data and evaluated various machine-learning algorithms using MATLAB. The coarse decision tree algorithm emerged as the most effective, achieving a classification accuracy of 66.01%. Subsequently, by using deep learning models, we significantly improved the accuracy: a convolutional neural network (CNN) achieved 45.16%. Accuracy, a deep learning recurrent neural network (RNN) model in LSTM achieved 90% accuracy, and further refinements pushed the accuracy to 93.55%. Additionally, we introduced a knock index to quantify noise levels during each engine cycle. This index, calculated from the integral of the absolute value of the first derivative of a band-pass-filtered vibration signal, provides a visual representation of knock strength. This approach shows promise for early detection of engine knocking, although further refinement of feature extraction methods and algorithm optimization is necessary for practical application. The study highlights the potential of integrating machine learning into real-time vehicle fault detection systems to improve their reliability and effectiveness.
Keywords: Machine Learning, Engine knocking, Frequency modulation amplitude demodulation (FMAD), Deep learning.

1. Introduction

The quantity of heavy components in fuel is increasing as automotive fuels diversify, and engine oil formulations are becoming more complex. These trends result in the formation of larger amounts of carbon deposits as reaction by-products during combustion, potentially worsening the susceptibility of the engine to knock (Aramburu, A., et. Al,). The phenomenon known as "knocking" occurs when unwelcome pressure waves are produced during engine combustion. These waves can damage engine walls and make unpleasant noises. SI (spark plug ignition) engines are typically connected with knocking. It depends on the auto-ignition tendency. The exploring and understanding of various sounds produced by engines, distinguishing between normal operating sounds and abnormal engine knocking sounds. The engine can be damaged by knocking. The real-time detection of engine sound anomalies for early vehicle fault recognition has garnered significant attention due to its potential to enhance vehicle safety, reliability, and performance. Several studies have explored various methodologies and techniques to achieve this objective, employing a combination of signal processing, machine learning, and acoustic analysis.
Let's examine the combustion process to comprehend the knocking notion. SI engines are mostly linked to knocking. It is dependent upon the fuel's auto-ignition quality. There is less down-banging when the auto-ignition temperature increases, causing a lower down-knocking tendency (Hosseini, M). When the piston reaches TDC after compression, the spark plug produces a spark which ignites the compressed mixture and starts the combustion process. It creates a primary flame front that ignites the whole mixture by igniting the sections that spark plug. As a result, the cylinder will experience high temperatures and pressures. The new mixture is separated from the spark plug to the opposite end of the cylinder by these combustion products, or burned portions of the mixture. The portions of the charge that haven't burnt are compressed as this flame front grows.

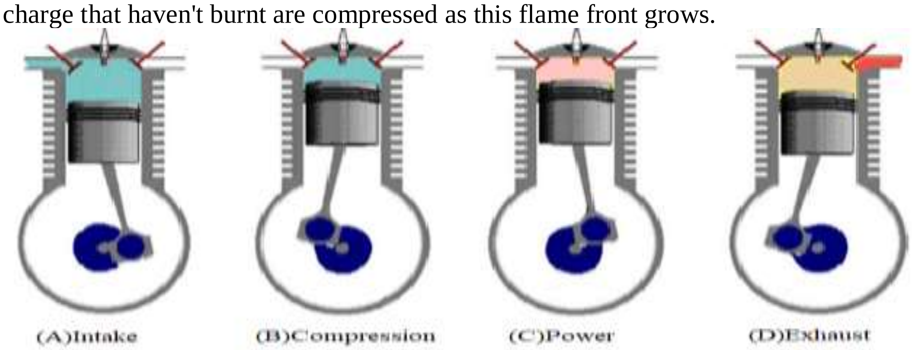

Figure 1: Four-stroke engine combustion process.

1.1. Four stages of combustion stroke

1.1.1. Intake Stroke

The air-fuel mixture is drawn in when the intake valve opens and the piston travels from the top dead center (TDC) to the bottom dead center (BDC). Volume (v), Pressure (P), Temperature (T):

$$V - V_{BDC}, P - p_{\alpha tm}, T - T_{\alpha tm} \quad \text{………………..(i)}$$

1.1.2. Compression Stroke

The temperature and pressure of the mixture's unburned portions rise as a result of this pressure. This portion will ignite from the other end and create a new flame front that moves in the reverse direction of the primary flame if its temperature hits the auto-ignition rating (Hosseini, M). The normal condition pressure wave is uniform and used to drive vehicles. But when the flame front compressed the fresh charge the charge auto-ignited, which will create rapid change in the pressure wave (Kalghatgi, G. T., &

[1] Department of Computer Science, Superior University, Lahore, 54000, Pakistan, mscs-s22-006@superior.edu.pk
[2] Professor Department of Computer Science, Superior University, Lahore, 54000, Pakistan, sohailmasood@superior.edu.pk
[3] Department of Computer Science, Superior University, Lahore, 54000, Pakistan, fawad.nasim@superior.edu.pk
[4] Department of Computer Science, Superior University, Lahore, 54000, Pakistan, arfan.jaffar@superior.edu.pk

Bradley, D. 2012). This rapid change in pressure wave high-pressure region wave is created when these two flame fronts clash, damaging the cylinder wall and creating a bad sound. Volume (V), Pressure (ρ), Temperature (T):

$$V = V_{BDC}\left(\frac{V_{BDC}}{V_{TDC}}\right)^{1-\gamma},\ \rho = p_{atm}\left(\frac{V_{BDC}}{V_{TDC}}\right)^{\gamma},\ T = T_{atm}\left(\frac{V_{BDC}}{V_{TDC}}\right)^{\gamma-1} \quad \text{……………..(ii)}$$

Where γ is a combination for a particular heating (usually around 1.4 for air)

1.1.3. Power stroke

The spark plug ignites the compressed mixture, causing a rapid increase in pressure and temperature, pushing the piston from TDC to BDC. Pressure (P), Volume (V), Work Done (W):

$$P=P_{max},\ V=V_{TDC}\left(\frac{V_{BDC}}{V_{TDC}}\right)^{1/Y},\ T=T_{max},\ W=\int_{VTDC}^{VBDC} PdV \quad \text{…………… (iii)}$$

1.1.4. Exhaust Stroke

The exhaust valve opens, and the piston moves from BDC to TDC, expelling the burnt gases. Volume (V), Pressure (P), Temperature (T):

$$V=V_{TDC},\ P=P_{atm},\ T-T_{atm} \quad \text{…………… (iv)}$$

These equations describe the changes in volume, pressure, and temperature during each of the four strokes of an internal combustion engine.

To enhance power density and reduce fuel consumption, high boost with direct injection has become the mainstream technology in SI engines in recent years, and a new knocking mode, called super-knock. It likens the process to unraveling a complex musical composition, where each sound has its significance, and aims to shed light on the differences between what's expected and what's concerning in terms of engine performance (R., Ito, H., & Sunami, K. 2019).

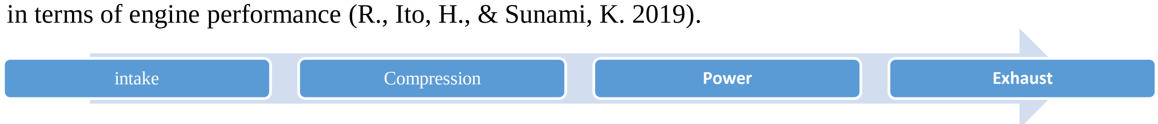

Figure 2:The process starts from intake to exhaust.

2. Literature review

Hosogi et al. (2019) describe how engine block vibrations are analyzed using statistical analytic techniques to identify engine knock in multifuel engines. The technique uses statistical patterns found in vibration data to differentiate between normal combustion and knock conditions. This non-intrusive approach allows for quick adjustments to reduce engine damage and improve multifuel engine performance by utilizing existing sensors.

Hosogi et al. (2019) also review significant studies on engine knock and combustion noise in internal combustion engines. The review covers engine knock sources, consequences, and detection methods, as well as various diagnostic techniques for preventing engine damage. It examines the causes of knocking combustion in spark-ignition engines and potential mitigation techniques, addressing how fuel octane rating, ethanol content, and compression ratio affect engine efficiency and knock tendency. Additionally, it investigates the relationship between knock, combustion phasing, air-fuel ratio, and load.

Tomeh et al. (2024) focus on investigating the relationship between engine knock and exhaust gas temperature for efficient knock detection and subsequent management measures. The study also provides a technique that uses in-cylinder pressure measurements to estimate NOx emissions in diesel engines, offering insights into pollution control by accurately predicting NOx emissions through pressure data. The authors suggest utilizing machine learning techniques to analyze data from cylinder pressure sensors.

Meier et al. (2024) address fuel quality and performance evaluation based on knock characteristics in their discussion of knock measurement techniques. These studies collectively advance the field of engine diagnostics, control, and optimization by covering topics such as fuel evaluation, emissions estimation, and knock detection.

Meng et al. (2024) present a statistical technique for engine knock detection using statistical methods to analyze engine sensor data. The study proposes a real-time engine monitoring and control system that accurately detects knock events using engine pressure data, offering potential applications in improving engine performance and preventing knock-related damage.

Meng et al. (2024) also explore the use of engine block vibrations in spark-ignition (SI) engines as a reliable signal for detecting knock occurrences. The study examines how premature or spontaneous ignition of the air-fuel mixture can lead to uncontrolled combustion, resulting in knock, which can cause engine damage. Detecting knock events is crucial for optimal engine operation and preventing damage.

Mittal (2024) explores the relationship between engine block vibrations and knock incidents. When knock occurs, uneven combustion sends pressure waves through the engine block, causing vibrations. Analyzing these vibrations can help identify the occurrence of knock. The study likely evaluates the effectiveness of engine block vibrations as a knock detection method across various operating conditions, such as load, speed, and fuel types, and discusses how engine management systems can use this technology for real-time knock detection and control.

Suijs et al. (2024) investigate how engine block vibrations can provide valuable information on knock events in spark-ignition engines, offering a potential non-intrusive method for detecting and managing knock. The researchers use accelerometers and other sensors mounted on the engine block to measure vibrations, then apply advanced signal processing techniques to distinguish between vibrations caused by knock and those from normal engine operation.

Suijs et al. (2024) also provide an in-depth examination of artificial intelligence (AI) algorithms for engine performance, control, and diagnostics. The study highlights how AI techniques, such as fuzzy logic, machine learning, and neural networks, can enhance engine efficiency, reliability, and emissions control by diagnosing engine issues, optimizing performance, and adjusting engine settings.

Nasim et al. (2023) present a study on machine learning-based vehicle sound analysis, which shows promise in identifying potential engine issues. The study achieved 97.25% accuracy in detecting normal and abnormal vehicle conditions and 92.74% accuracy in identifying fifteen different engine problems. However, the absence of a publicly available dataset for engine sound analysis hinders further research in this area, and creating such a dataset could significantly advance the field by enabling better model comparison and analysis.

3. Methodology: Machine Learning and Deep Learning Approaches

3.1. Normal engine sounds

An efficient technique for displaying the frequency structure of audio signals across time is a spectrogram. We can learn more about the acoustic properties of 77 WAV audio files with typical noises by examining their spectrograms.

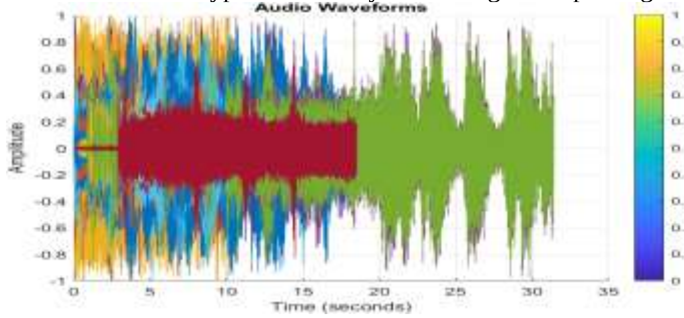

Figure 3: This graph shows audio wave file features in the form of a time-frequency graph.

One may properly evaluate and comprehend the typical sound features by looking at the spectrograms of these audio files. This knowledge can be important for a variety of audio processing and diagnostic applications.

3.2. Abnormal engine sounds

A spectrogram is a vital tool for examining the 76 WAV audio files with typical sounds as it shows the frequency spectrum of audio signals over time visually.

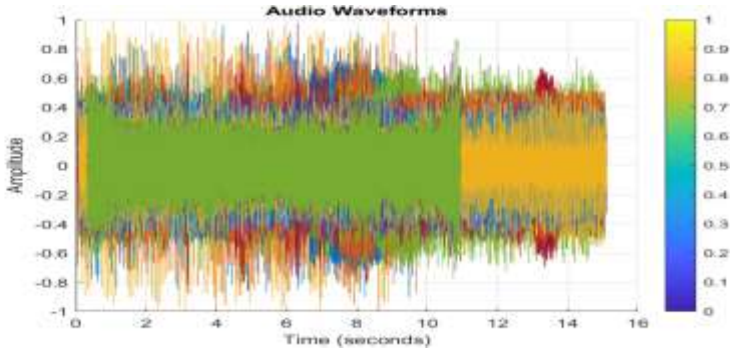

Figure 4: This graph shows waveform abnormal sound features in the form time frequency.

The spectrogram shows the normal sound of an engine, with time on the x-axis and frequency on the y-axis. The color scale represents the intensity of the sound, with consistent patterns indicating a stable engine operation

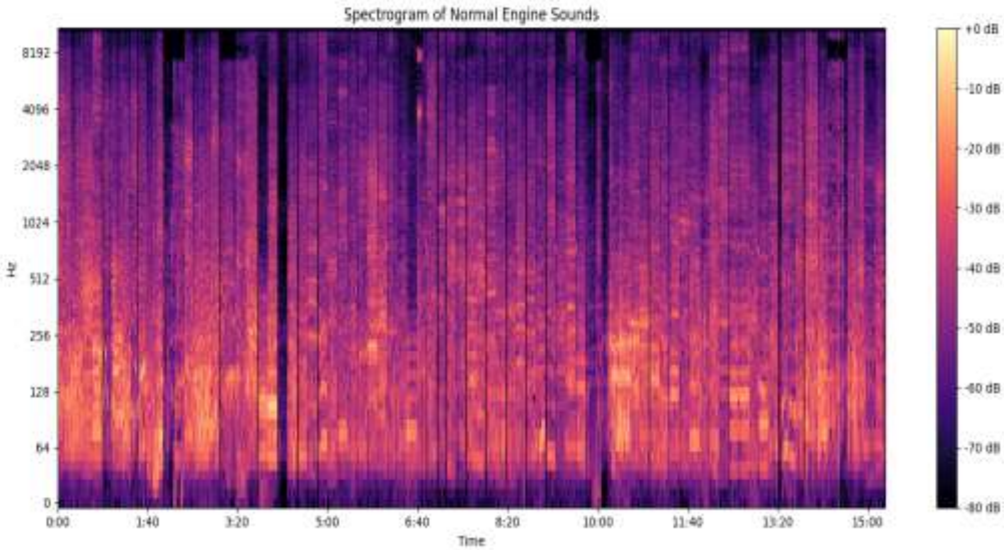

Figure 5: This Spectrogram shows the different sample rates.

The spectrogram shows high-intensity peaks at higher frequencies, indicating irregular, high-frequency bursts typical of the engine.

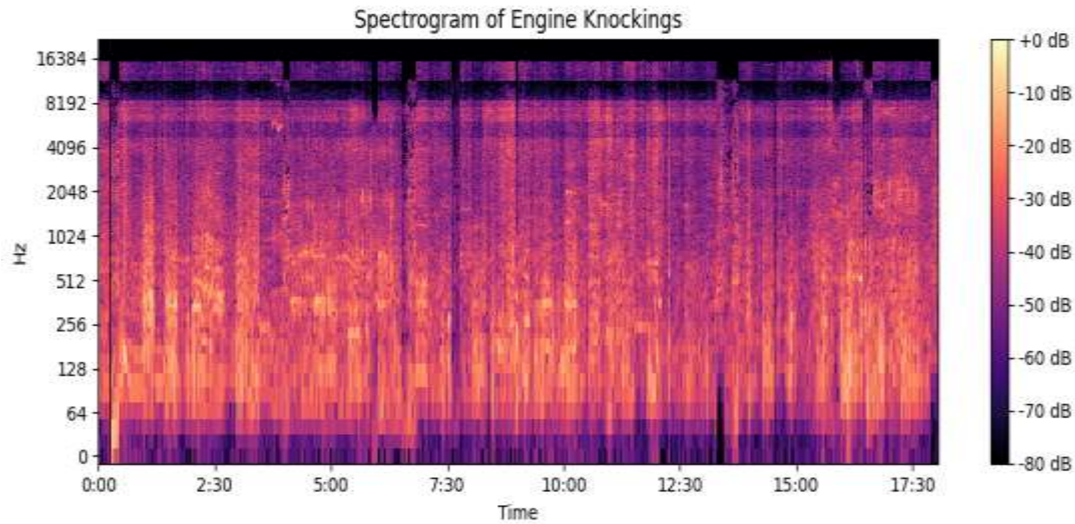

Figure 6: This spectrogram shows the same sample rate.

This graph displays the sound of the engine starting. Higher intensities indicate greater frequency components. The color intensity shows the strength of the frequencies over time.

4. Classification Features Through Machine Learning and deep learning

4.1. FMAD (Frequency-Magnitude Anomaly Detection)

Features are used for analyzing sound signals. They help in identifying abnormal patterns in frequency and magnitude compared to a baseline. These features are crucial for detecting deviations in engine sounds that might indicate faults. By monitoring changes in frequency and intensity over time, FMAD features provide valuable insights for predictive maintenance. Utilizing these features helps in maintaining the reliability and efficiency of machinery.

4.2. Scatter plotting Model

Scatter plots are a popular tool for visualizing this kind of data because they may draw attention to anomalies and trends. The scatter figure used in this investigation compares two types of audio signals: red dots indicate banging noises, while blue dots reflect good engine sounds.

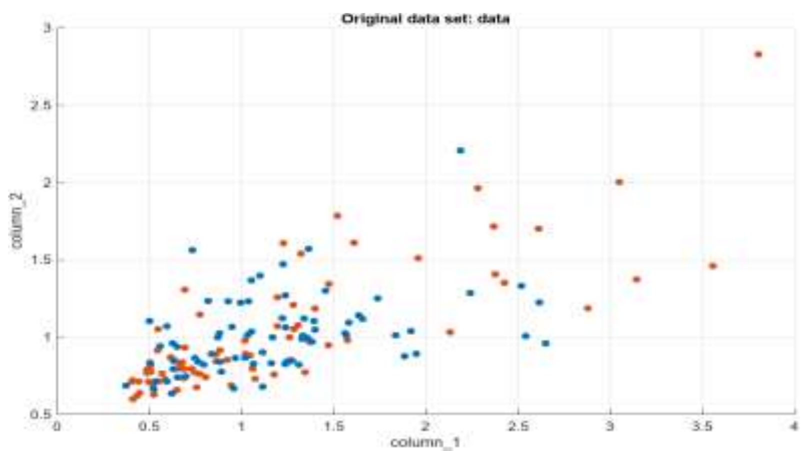

Figure 6 This graph shows red and blue dots of engine sounds.

4.3. Data Distribution and Patterns

4.3.1. Good Sounds (Blue Dots)

The blue dots are primarily grouped, indicating a consistent set of auditory characteristics characteristic of a well-running engine. This cluster most likely represents typical operating noises that are contained within reasonable ranges.

4.3.2. Scarlet Dots for Knocking Sounds

The red dots are more evenly spaced, signifying variations in the auditory characteristics linked to engine knocking. This dispersion implies that banging noises might differ greatly, either as a result of various underlying causes or differing degrees of severity.

4.3.3. Inspection Model of Confusion Index

An essential instrument for assessing classification models is the confusion matrix. It makes it possible to analyze the model's performance in great detail, showing both its strong and weak points. Through the use of measures like accuracy, recall, and F1 score, practitioners may acquire a thorough grasp of their models.

4.4. The following is the confusion array

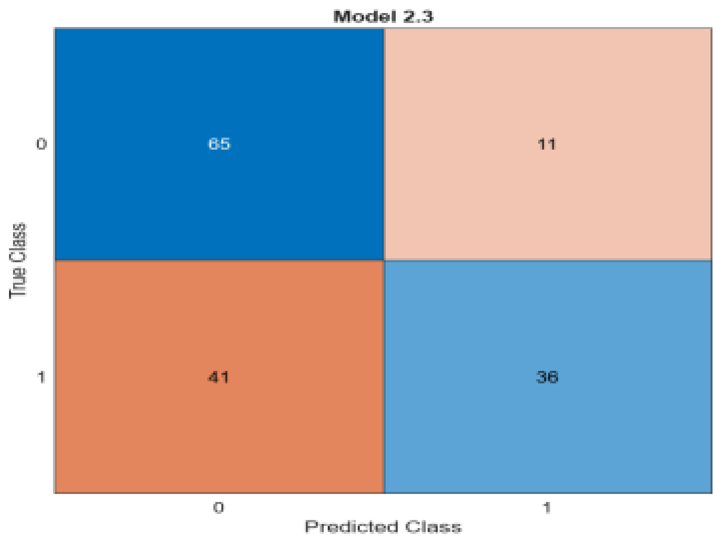

Figure 7: This graph shows data about normal and abnormal classification data.

True Negatives (TN): 65
False Positives (FP): 11
False Negatives (FN):41
True Positives (TP): 36

Calculation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Evaluate the following values:

$$\frac{36 + 65}{36 + 65 + 41 + 11}$$

After calculating values:

The estimated accuracy of the model, derived from the input confusion matrix, is around 0.6601, or 66.01%.

Summary:
True Positives (TP): 36
False Positives (FP): 11
True Negatives (TN): 65
False Negatives (FN): 41

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{36+65}{36+65+11+41} = \frac{101}{153} \approx 0.6601$$

The model identified around 66.01% of them correctly.

4.5. Validation ROC Curve Model

Plotting the True Positive Rate (TPR) vs the False Positive Rate (FPR) at different threshold values is known as the ROC curve. The capacity of the model to discriminate between classes is shown by the Area Under the Curve (AUC). The AUC in this instance is around 0.6345 for both models.

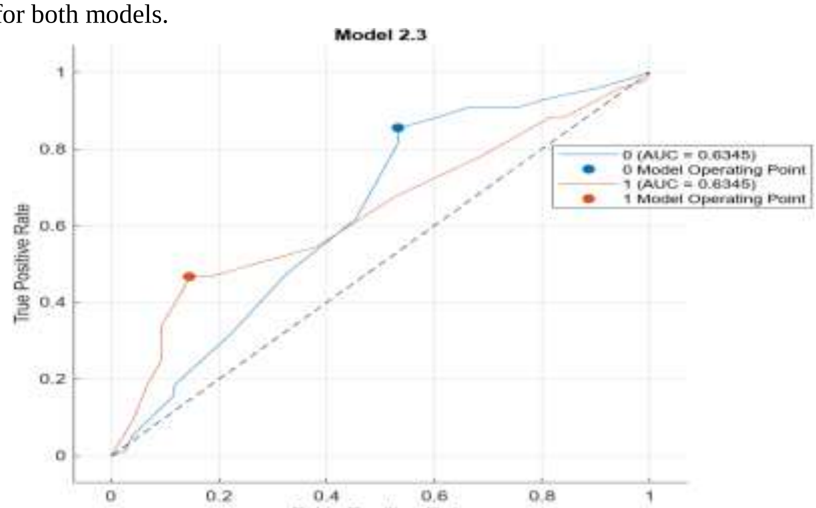

Figure 8: This model shows the two lines of red and blue data.

5. Classification through deep learning model CNN (convolutional neural network) RNN (Recurrent Neural Network) or LSTM (Long Short-Term Memory) network

The deep learning model likely used in this scenario for classifying engine sounds could be a Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) or an LSTM (Long Short-Term Memory) network as these models are well-suited for processing audio data.

5.1. CNN model performance

CNNs are effective in capturing spatial hierarchies in audio spectrograms, which are visual representations of the sound frequencies over time. RNNs or their variants (such as Long Short-Term Memory Networks, LSTMs) are effective in capturing temporal dependencies and patterns in sequential data, such as audio signals. Without specific details on the model architecture, it's challenging to determine the exact model used. However, the deep learning model involved here would likely utilize one of these architectures or a combination of both (e.g., a CNN followed by an RNN) to leverage both spatial and temporal features for accurate classification of engine sounds. The accuracy of the CNN model is 45.16%.

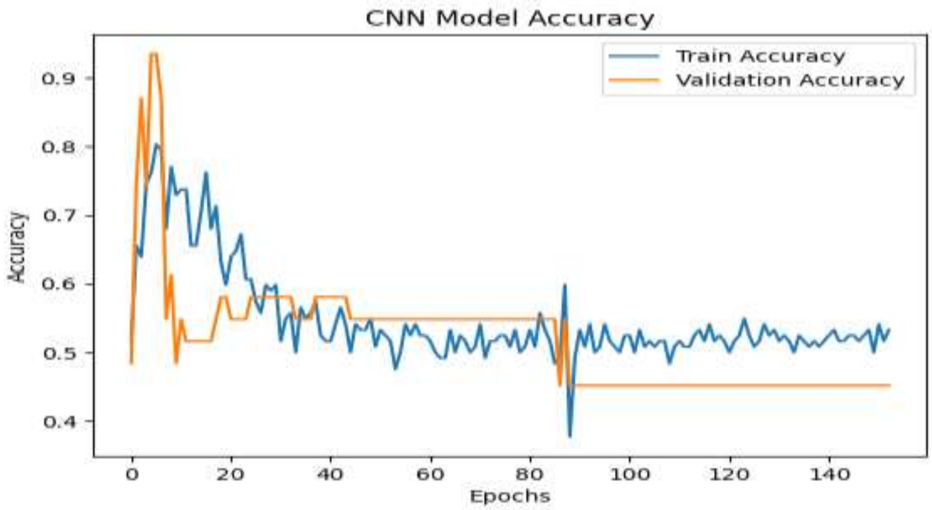

Figure 9: This model shows the low accuracy of the CNN model.

5.2. RNN model's performance

The graph illustrates the accuracy of an RNN model on both the training and validation datasets across 153 epochs. The y-axis represents accuracy, while the x-axis represents the number of epochs. From the beginning of the training process, the training accuracy (depicted in blue) increases sharply, indicating that the model is rapidly learning from the training data. This steep rise continues until around the 5th epoch, after which the training accuracy exceeds 95% and gradually approaches 100%, eventually plateauing. The validation accuracy (depicted in orange) follows a similar trend but with a few key differences. Initially, the validation accuracy also rises quickly, achieving over 90% by the 2nd epoch. However, unlike the training accuracy, the validation accuracy levels off sooner and maintains a consistent value just below 95% for the remainder of the training process. The RNN model accuracy is 87.10%.

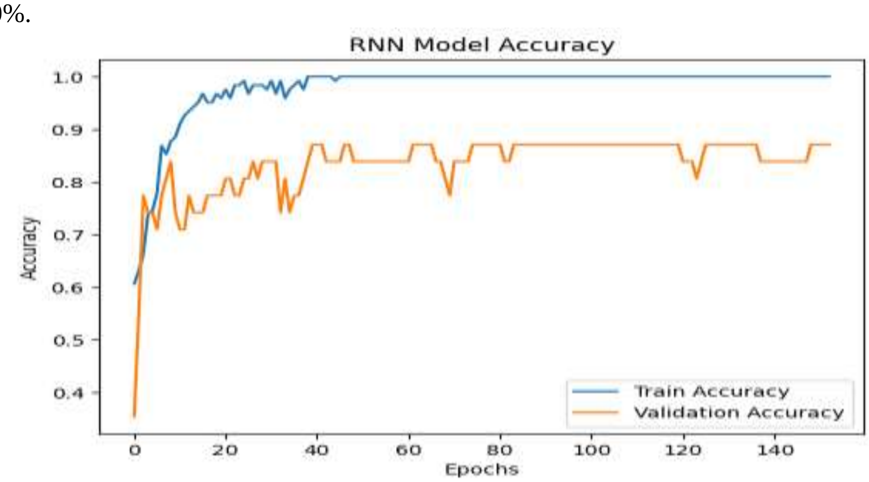

Figure 10: Two lines show accuracy for the RNN model.

5.3. LSTM model's performance

The graph depicts the accuracy of an LSTM model on both the training and validation datasets across 153 epochs. The y-axis represents accuracy, while the x-axis represents the number of epochs. In the early stages of training, the training accuracy (depicted in blue) and the validation accuracy (depicted in orange) both increase rapidly. Initially, the validation accuracy fluctuates more than the training accuracy, with significant variations, but it remains generally high. By around the 20th epoch, both the training and validation accuracies stabilize, hovering around 95% to 100%. The training accuracy shows slight variations but maintains a high level, indicating the model's strong performance on the training data. The validation accuracy, despite some oscillations, also reaches near-perfect accuracy, indicating that the model generalizes well to unseen data. The accuracy of the LSTM model is 93.55%.

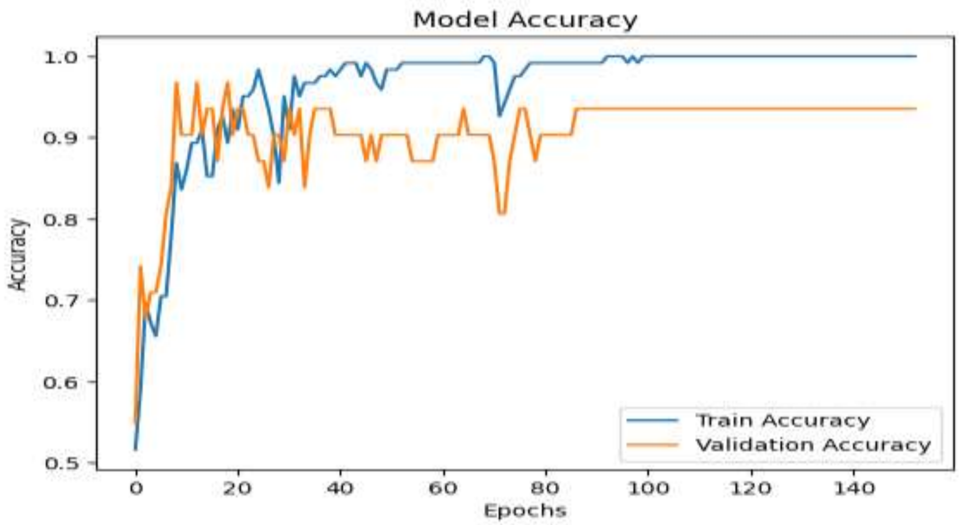

Figure 11: Two lines show the accuracy of the LSTM model.

6. Results and discussion

This study investigates binary classification on a high-dimensional dataset with 153 observations and 200 features. To ensure robust model evaluation and mitigate bias from data partitioning, 5-fold cross-validation is employed. This technique is particularly crucial for high-dimensional data, where strong validation techniques are essential for accurate assessment.

Initially, a machine learning model achieved an accuracy of 66.01%. Subsequently, deep learning models were explored to potentially improve performance. Among those tested, The Long Short-Term Memory (LSTM) model achieved the highest test accuracy, reaching 96.0%. This represents a significant improvement compared to the initial machine learning model.

6.1. F1 Score Bar

The bar graph shows that the LSTM model has the highest F1 score, at 0.93. The RNN model is in second place, with an F1 score of 0.87. The Machine Learning model has a score of 0.66, and the CNN model has 0.45, with the lowest F1 Score.

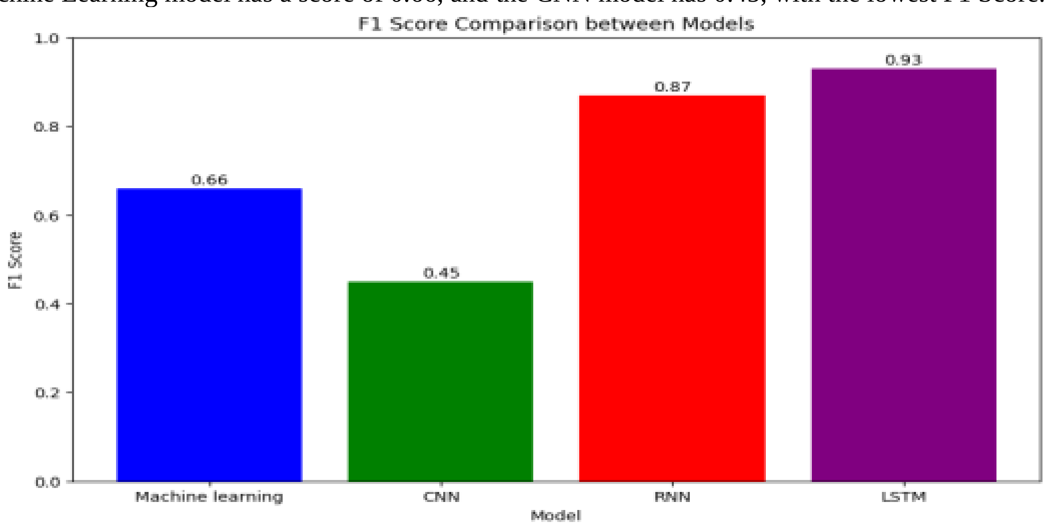

Figure 12: F1Score bar between machine learning, CNN, RNN, and LTSM Models.

6.2. Machine Learning Deep Learning Model Performance

A deep learning model was then implemented, achieving an accuracy on the extracted features. F1 Score bar Shown in figure 12 The Long Short-Term Memory (LSTM) model exhibited strong performance on both the training and validation datasets. Validation accuracy plateaued after a few epochs, indicating effective initial learning and good generalization to unseen data. Interestingly, the model achieved high accuracy on both datasets early in training. Validation accuracy even reached 100%, suggesting exceptional generalization and performance on unseen data.

7. Conclusion

The study "Real-Time Detection of Engine Sounds Knocking for Early Vehicle Fault Recognition" demonstrates the effectiveness of machine learning in classifying engine knocking sounds as normal or abnormal. By extracting FMAD features from engine sound data and testing various machine learning algorithms, we achieved a classification accuracy of 66.01%, with the coarse decision tree algorithm performing the best. Additionally, we introduced a knock index to measure noise levels during engine cycles, providing a visual representation of knock strength. By comparing this index to a statistically defined knock threshold, we can determine whether each cycle is normal or knocking. This method enables the detection of knock combustion in each cycle, even in engines where knock events are random, facilitating exploration into the underlying causes of knock occurrences. Furthermore, we applied deep learning models to improve classification accuracy. Using a CNN model, we achieved an accuracy of 45.16%. With an RNN model, the accuracy increased to 87.10%. And with an LSTM model, we attained an accuracy of 93.55%. These results highlight the potential of deep learning techniques in enhancing the detection and classification of engine knocking sounds, providing a more reliable and accurate tool for early vehicle fault recognition.

8. Featured Work

This work presented a unique method for detecting engine knocking in real-time by utilizing knock index computation and machine learning, including deep learning. We accurately categorized engine knocking noises and measured the severity of the knock throughout a series of engine cycles by employing machine learning algorithms and advanced signal processing techniques. Our research highlights the potential of machine learning for early car defect detection. However, further improvements in accuracy are needed for practical implementation. Future research could focus on enhancing feature extraction techniques and optimizing algorithms to improve the efficacy and reliability of real-time vehicle problem detection systems.

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