ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW

Vol.01 No.02 (2023)

MACHINE LEARNING-BASED ACOUSTIC MONITORING FOR EARLY RECOGNITION OF ENGINE KNOCKING AND VEHICLE FAULT IDENTIFICATION

Fahad Naseer[1], Aziz ur Rehman[2], Usman Hameed[3], Muhammad Hassaan[3]
[1]University of Engineering and Technology, UET Taxila, Pakistan
[2]Sargodha University, Pakistan
[3]Superior University Lahore.

Abstract:
The research paper investigates machine learning as a tool to detect engine knocking in real time to improve the process of recognizing fault in the vehicle in an early stage. The frequency modulation amplitude demodulation (FMAD) engine-sound-data features were extracted and several machine-learning algorithms were assessed through MATLAB. Coarse decision tree algorithm proved to be the most efficient with accuracy in classification standing at 66.01%.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. By comparing the knock index to a statistically defined threshold, we could distinguish between normal and knocking cycles. Our results demonstrated consistency between experimental observations and knock index characteristics. 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, Real-time detection, Engine knocking, Vehicle fault recognition, Frequency modulation amplitude demodulation (FMAD)Engine sound data, Classification accuracy, Knock index, Band-pass filter, Feature extraction.*

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. knocking is a phenomenon of generating unwanted pressure waves that create unpleasant sounds and can damage engine walls during combustion in engines. Knocking is mainly associated with SI engines [1]. It depends on the auto-ignition tendency. The exploring and understanding of various sounds produced by engines [2], to distinguish between normal operating sounds and abnormal engine knocking sounds. The engine can be damaged by knocking[3]. 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[4] have explored various methodologies and techniques[5] to achieve this objective, employing a combination of signal processing, machine learning, and acoustic analysis.

To understand the whole concept of knocking let's look out the combustion process. Knocking is mainly associated with SI engines. It depends on the fuel's auto-ignition quality. A higher auto-ignition temperature results in a lower knocking temperature and a lower knocking tendency. When the piston reaches TDC after compression, the spark plug produces a spark that ignites the compressed mixture, initiating combustion. It ignites only those parts of the mix that spark plug and generates a main flame front which further ignites the whole mixture This will generate a high

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

temperature and pressure force inside the cylinder. These burnt parts of the mix (combustion products) separate the fresh mixture from the spark plug to the other end of the cylinder. As this flame front expands, it compresses the unburned parts of the charge.

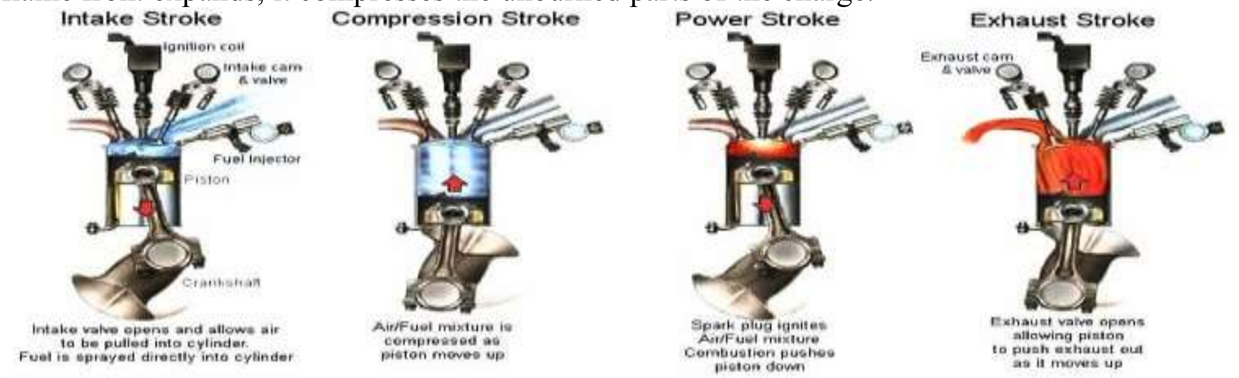


Figure 1.0 Process of combustion is shown in the following figure.

This compression increases the temperature and pressure of unburned parts of the mixture. If the temperature of this part reaches its auto-ignition temperature, it will ignite from the other end and a new flame front start moving in the opposite direction of the main flame[6].When both of these flame fronts collide, it will generate a high-pressure wave which produces an unpleasant sound and also damages the cylinder wall.

The normal condition pressure wave is uniformed 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. This rapid change in pressure wave. This rapid change in pressure wave creates unwanted sound until the whole charge of the opposite flame ignites. Piston crowns combustion in various forms, piston ring sticking, cylinder bore scuffing, piston ring-land cracking, cylinder head gasket leakage and cylinder head erosion. In recent years, high boost with direct injection has become the mainstream technology in SI engines to increase power density and decrease fuel consumption, and a novel knocking mode, termed 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. Engine noises are the fundamental notes in the complex orchestra of automobile mechanics they indicate when an engine is operating in harmony or in discord, which indicates an imminent problem.

2. Literature review:

The paper [8] describes how engine block vibrations are analysed using statistical analytic techniques in order to identify engine knock in multifuel engines. The technique uses statistical patterns found in the vibration data to discriminate between normal combustion and knock conditions. This non-intrusive strategy may allow for quick adjustments to reduce engine damage and improve multifuel engine performance by making use of already-installed sensors. This study report compiles and reviews significant studies on engine knock and combustion noise in internal combustion engines.

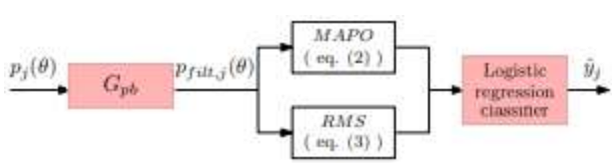


Figure 2 schematic structure of mentioned approach.

The resultant signal, pf ilt,j (θ), is generated by band-pass filtering the recorded pressure traces pj (θ), where θ is the engine crank angle and j is the cycle count. For simplicity's sake, the band-exclusive filter is explained as follows.
The research paper gives a statistical method of detecting engine knock. This application effectively identifies the occurrence of knock using statistical techniques of analyzing engine sensor data. It is meant to provide possible application in real-time engine monitoring and control systems in the context of the intention to enhance engine performance and avoid the harm of knocks. The paper being studied concentrates on the automatic knock detection based on engine pressure data. It suggests that the cases of engine knock can be automatically identified using the pressure data which is provided by the engine sensors. The primary goal of the project is to develop a computerized system to accurately detect the occurrence of knocks as this would optimise the performance of the engine and avoid damage. The piece of study gives an overview of the recent development in the field of spark ignition engine knock detection.
It provides an overview of the latest trends in engine knock detection mechanisms, methods, and technologies.
To measure these vibrations, researchers often use accelerators and other types of sensors attached to the engine block. Thereafter, the vibration data undergoes more sophisticated signal processing techniques to differentiate between vibrations caused by engine knock and engine normal operation.

3. Audio Engine Dataset

3.1 Gathering of data:

We are gathering video footage of several automobile makes and models, together with audio recordings of their engine noises. Market surveys are used to collect this data, which is probably obtained from a variety of sources including manufacturers, workshops, and dealerships. Acquiring audio datasets through direct encounters or field recordings, and making sure the right credit and permission are given when needed. Conducting quality checks to verify the authenticity and fidelity of the collected recordings, addressing any issues or inconsistencies. Labeling the recordings to categorize them into relevant classes, such as normal engine sounds and abnormal noises, to facilitate subsequent analysis.

3.2 Data preparation:

The gathered datasets go through several preparation steps before being analyzed. To do this, the data must be cleaned of any background noise or artifacts that can mask the underlying engine noises. Standardization of formats is also carried out to provide uniformity throughout the dataset. After extracting relevant audio samples, the preprocessing stage produces a revised dataset with 76 examples of aberrant engine knocking noises and 77 examples of regular engine sounds.

3.3 Conversion of video datasets in audio:

After collecting different video dataset from different places. We split video in useful frames where we think we get frequent sound from samples. We split into different time frames each video data set less then from 60 seconds. Further we convert these videos dataset samples in wav format. This can simplify processing tasks and reduce computational resources required for analysis, as video data often contains additional visual information that may not be relevant to audio analysis tasks. Moreover, WAV format preserves high-quality audio data, ensuring fidelity during conversion and subsequent analysis.

3.4 Sound signal processing techniques:

Sound signal techniques are used for Filtering stands as a cornerstone, enabling the selective adjustment of frequency components through low-pass, high-pass, band-pass, and notch filters, sculpting the spectral profile of sound. Equalization, another pivotal technique, allows for nuanced tonal shaping by rebalancing frequency distributions using parametric, graphic, or shelving EQs. Compression, meanwhile, plays a vital role in dynamic range management, delicately attenuating loud sections while amplifying softer passages to ensure a consistent audio experience. Adaptive filtering and spectral subtraction are two methods used in noise reduction techniques that carefully identify and remove undesirable noise while maintaining signal integrity. By separately changing both pitch and temporal length, time stretching and pitch-shifting techniques expand the range of possible outcomes and encourage creative audio manipulation. Stereo panning and reverberation are examples of spatial processing techniques that give soundscapes more depth and dimension, improving immersion. Sampling and quantization are essential to digital audio processing because they transform analog signals into discrete digital representations of different resolutions. Important characteristics like pitch and spectral content are extracted for further examination using feature extraction techniques, which are invaluable in domains like as voice recognitionSynthesis methods, from granular to additive, provide a variety of soundscapes and provide imaginative pathways for sound investigation. Last but not least, spectral processing and analysis methods that make use of spectrograms and Fourier transforms provide insights into the features of frequency and amplitude, making jobs like pitch identification and sound source separation easier.When combined, these methods create a powerful toolset for constructing, enhancing, and comprehending audio signals, stimulating innovation in all sound-related businesses[10].

4. Feature extraction of datasets

Using this procedure, the energy in various frequency bands inside each audio signal frame is calculated.It provides information about the distribution of energy across different frequency ranges. fMAD (Frequency Mean Absolute Deviation). This method calculates the mean absolute deviation of the frequency components within each frame. It is used to characterize the variation or dispersion of frequencies within the frame. Spectrogram Analysis. MATLAB's spectrogram function computes the spectrogram of an audio signal of two vectors which represents the magnitude of the Short-Time Fourier Transform over time. Spectrogram analysis provides insight into the frequency content and temporal dynamics of the signal and can be used for feature extraction.

4.1 Normal sounds of engine data :

The 2D line graph used to display multiple lines representing different data series over time, with the X-axis typically representing time and the Y-axis representing the amplitude or frequency of the sound signals. This is a common way to visualize time-series data, especially for analyzing patterns like engine normal sound.

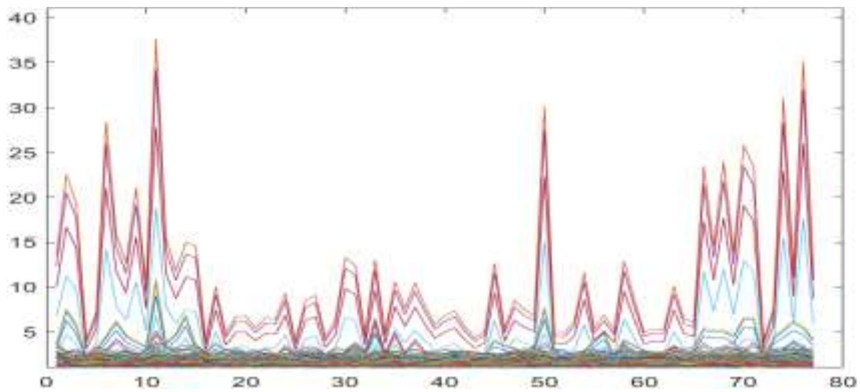


Figure 3 shows the normal sounds of engine data from the fmad feature extraction.

Based on the FMAD graph analysis, none of the engines in this dataset appear to show signs of engine knocking. The graph's regularity, consistency in amplitude, and balanced frequency spectrum suggest that these engines, whether manual or automatic, are operating normally without the irregularities typical of knocking sounds.

In summary, the provided graph does not indicate any engine knocking. All the engines from different models with either manual or automatic transmissions appear to have normal engine sound profiles.

4.2 Abnormal sounds of engine knocking data:

The graph appears to be a 2D line graph. It displays multiple lines representing different data series over time, with the X-axis typically representing time and the Y-axis representing the amplitude or frequency of the sound signals. This is a common way to visualize time-series data, especially for analyzing patterns like engine knocking.

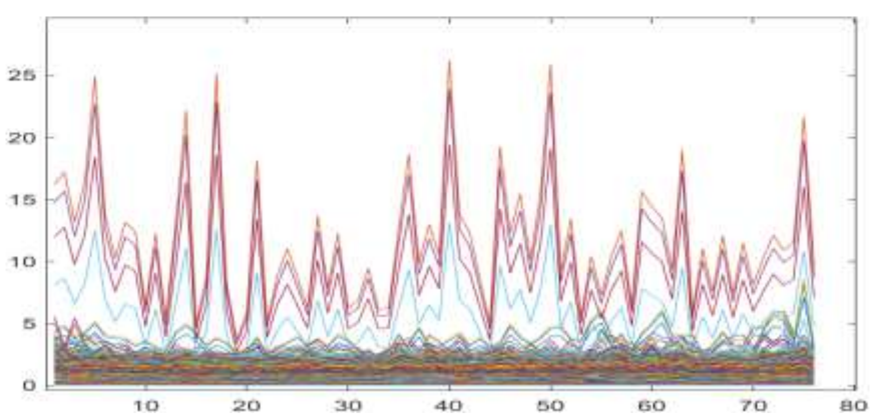


Figure 4 shows abnormal sounds of engine knocking data

The graph indicates that manual and automatic transmission engines are experiencing knocking. Higher volume and more erratic peak patterns are more common in manual transmission engines, which suggests more severe banging. The moderate amplitude peaks in automatic transmission engines indicate that the smoother gear changes may result in less severe banging. This assessment sheds light on the frequency and intensity of knocking noises in various transmission scenarios.

Extreme Frequency Curves (Above 20 units): More severe banging is heard in engines with manual transmissions when inappropriate gear changes occur.
Medium Frequency Peaks (about 10–20 units): Mostly automatic transmission engines are banging, but it's not as bad because of better gear changes.

4.3 Selecting features :
Requires considerable thought and trial and error since it is dependent on the particular requirements of the application as well as the characteristics of the audio data being studied. Efficient feature selection plays a pivotal role in enhancing the precision, resilience, and computational effectiveness of audio processing systems, hence propelling progress across several fields such as multimedia analysis, human-computer interaction, and acoustic scene

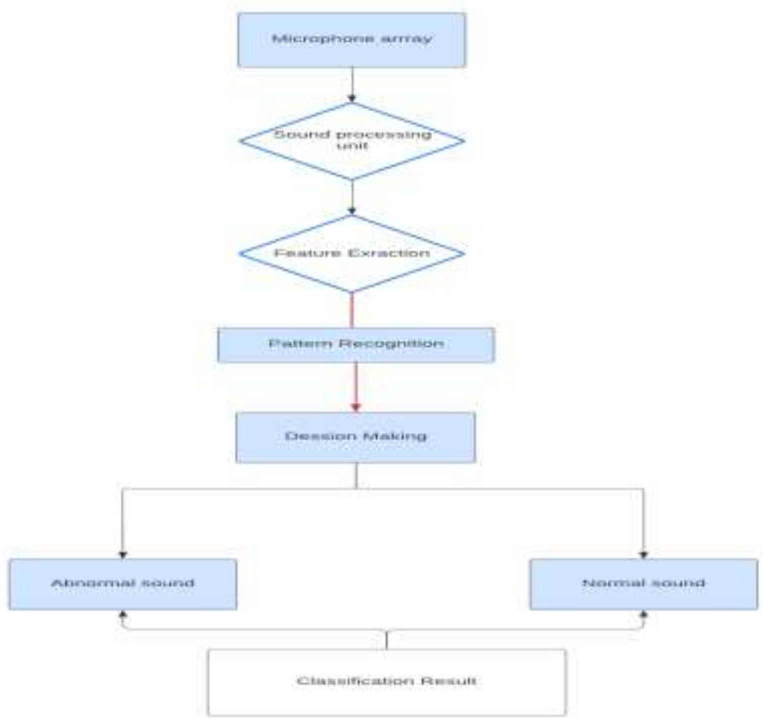


Figure 5 represents the whole feature extraction methodology.

First, we extract audio waveform data from a WAV file. After that, this data is transformed into an analytically-ready numerical representation. During this conversion process, abnormal engine sounds are assigned the numeric value 0, while normal engine sounds are assigned the value 1. This numeric representation allows us to analyze the waveform data effectively.

ISSN E: 3006-1466
ISSN P: 3006-1458
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW

4.4 Handling Sound Techniques

It is used to characterize the variation or dispersion of frequencies within the frame. Spectrogram Analysis: MATLAB's spectrogram function computes the spectrogram of an audio signal, which represents the magnitude of the Short-Time Fourier Transform over time. Spectrogram analysis provides insight into the frequency content and temporal dynamics of the signal and can be used for feature extraction. The timing chain's main job is to turn on the valves. It vibrates and modifies sound if it is not securely fastened. Crank defects may lead to the destruction of the oil ring, first ring, or second ring. Because of valve opening and closing, a significant rise in peak combustion chamber pressure can alter engine sound. A machine produces sound signals and vibrations while it operates. To learn more about the condition of the machine, these may be assessed. Every signal has a wavelength and contains some energy.

4.4.1 wavelet transform:

Wavelet transform is a mathematical tool used for signal processing, including sound analysis. It decomposes a signal into different frequency components, allowing the analysis of both frequency and time characteristics simultaneously. Unlike Fourier transform, which analyzes the frequency content of a signal over its entire duration, wavelet transform provides localized frequency information, making it suitable for analyzing signals with non-stationary characteristics, such as sound.

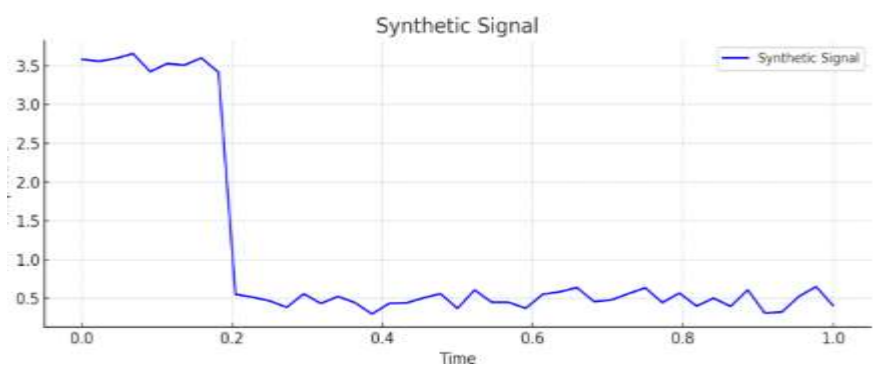


Figure 6

Mathematically, the continuous wavelet transform (CWT) of a signal $f(t)$ with respect to a mother wavelet function $\psi(t$ is given by the following equation:

$$CWT_f(a,b) = \int_{\infty}^{\infty} f(t).\frac{1}{\sqrt{|a|}}\psi * \left(\frac{t-b}{a}\right) dt$$

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.01 No.02 (2023)

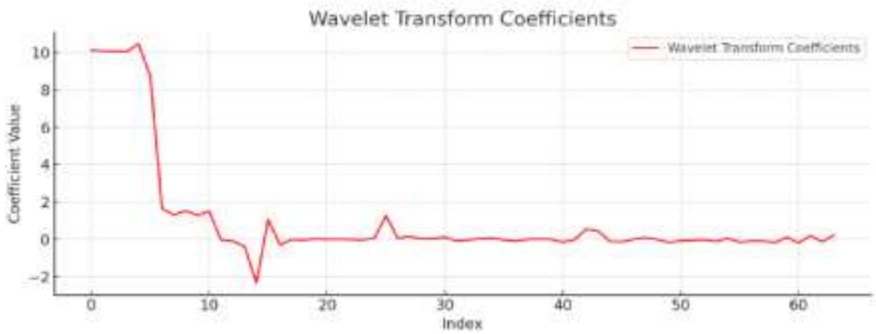


Figure 7

Where:

- The scale parameter, denoted by a a, determines the wavelet function's width.
- The translation parameter, denoted by b, governs the wavelet function's location along the time axis.
- ψ∗ represents the mother wavelet function $\psi(t)$'s complex conjugate.
  Using scaled and translated copies of the mother wavelet $\psi(t)$,

This equation calculates the inner product of the signal $f(t)$ at various scales and places.

Detailed Analysis
Peaks and Spikes: Prominent peaks at specific intervals (e.g., 10, 30, 50, and 70 seconds) indicate possible knocking events. Additional investigation is required in these dramatic amplitude increases.
Data Consistency: The graph's several lines of consistent data demonstrate how reliable the measurements are. This consistency aids in verifying that the anomalies found are indeed knocking occurrences rather than sensor mistakes.
Engine Health Monitoring: By employing these kinds of graphs for continuous monitoring, preventative maintenance can be made to make sure that any indications of banging are dealt with before they cause serious engine damage.

ISSN E: 3006-1466
ISSN P: 3006-1458
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW

Vol.01 No.02 (2023)

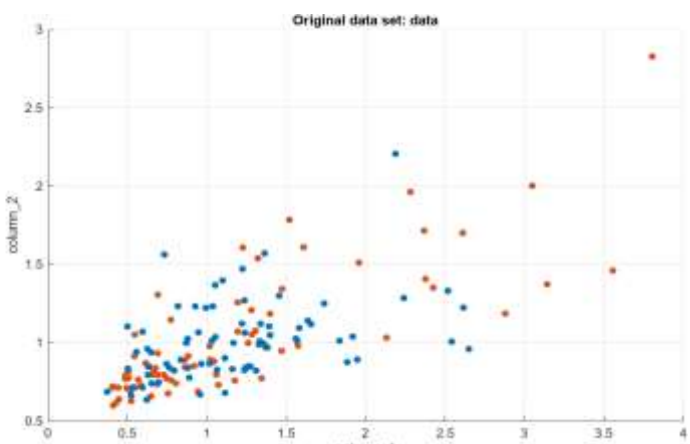
Temperature (°C)	Knocking Intensity	Potential Damage	Description
80 - 90	Low	Minimal	Slight knocking; usually manageable with minor adjustments in tuning.
90 - 100	Moderate	Moderate	Noticeable knocking; may require tuning and monitoring to prevent further issues.
100 - 110	High	Significant	High knocking; increased risk of damage to pistons, valves, and bearings.
110 - 120	Very High	Severe	Severe knocking; potential for serious engine damage including piston failure.
120+	Critical	Critical (Engine Failure)	Critical knocking; imminent engine failure, immediate shutdown required.

5. Classification Features Through Machine Learning

Coarse tree: 66.01 percent accuracy

6.1 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.



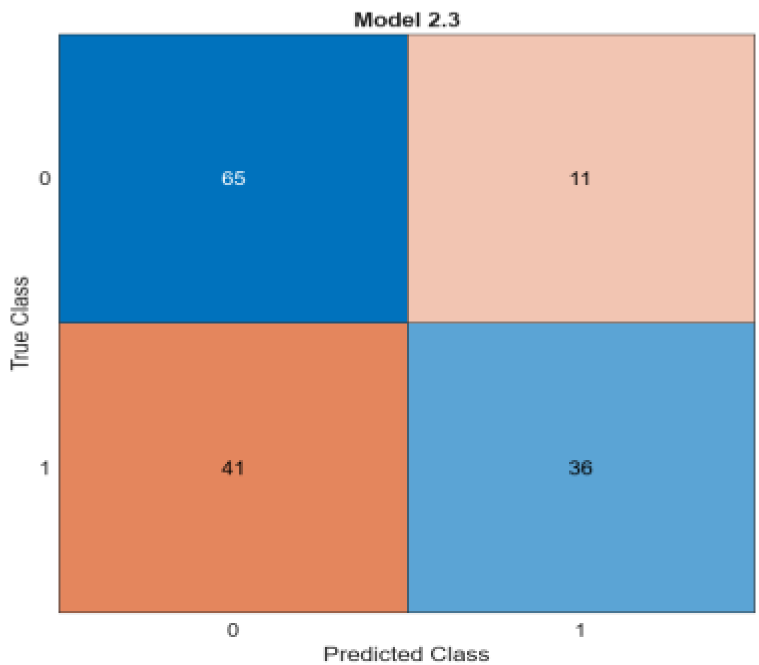
Data Distribution and Patterns:

Good Sounds (Blue Dots): The blue dots are primarily grouped together, 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.

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.

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 as accuracy, recall, and F1 score, practitioners may acquire a thorough grasp of their model's

6.2 The following is the confusion array:



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

Calculation:

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

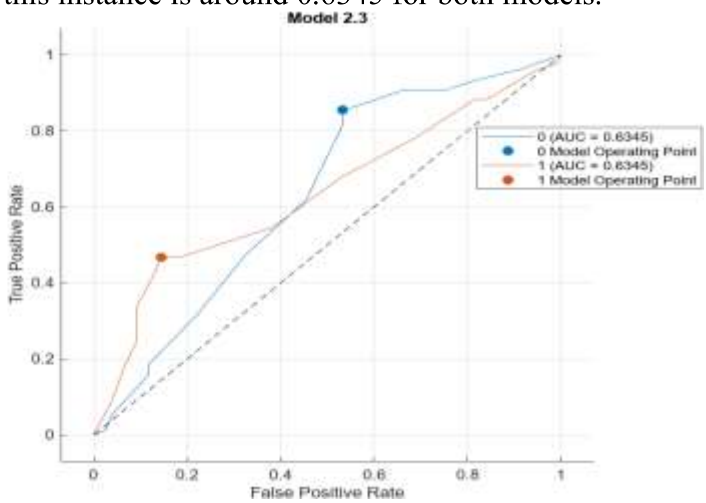
$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{36+65}{36+65+11+41} = \frac{101}{153} \approx 0.6601$$

ISSN E: 3006-1466
ISSN P: 3006-1458
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW

The model identified around 66.01% of them correctly.

6.3 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.



6. **Results and discussion:** This setup involves training and validating machine learning models on a binary classification task using a dataset with 153 observations and 200 predictors. The use of 5-fold cross-validation ensures that the model's performance metrics are reliable and not biased by the specific data partitioning. This setup is typical in high-dimensional data scenarios where robust validation techniques are critical for accurate model assessment.

Session: untitled

Training Data: data Observations: 153 Predictors: 200 Response Name: column_201 Response Classes: 2

Validation: 5-fold cross-validation

The accuracy rates vary across models, with decision trees (Model 2.3) achieving the highest accuracy of 66.01%. Among KNN models, Model 2.7 has the best accuracy at 64.00%. Efficient Logistic and Efficient Linear SVM models exhibit moderate accuracy at 54.90% and 52.29%, respectively.

Model Number	Model Type	Accuracy (Validation)	Total Cost (Validation)	Error Rate (Validation)	Training Time (sec)	PCA
1	Tree	57.52 %	65	42.48 %	8.1172	95% explained variance
2.1	Tree	57.52 %	65	42.48 %	2.7561	95% explained variance
2.2	Tree	59.48 %	62	40.52 %	1.8665	95% explained variance
2.3	Tree	66.01 %	52	33.99 %	0.91229	95% explained variance
2.4	KNN	54.90 %	69	45.10 %	2.0099	95% explained variance
2.5	KNN	62.75 %	57	37.25 %	0.93686	95% explained variance
2.6	KNN	42.48 %	88	57.52 %	1.0311	95% explained variance
2.7	KNN	64.05 %	55	35.95 %	1.2327	95% explained variance
2.8	KNN	62.09 %	58	37.91 %	1.0361	95% explained variance
2.9	KNN	58.17 %	64	41.83 %	0.9177	95% explained variance
2.10	Efficient Logistic ...	54.90 %	69	45.10 %	2.4579	95% explained variance
2.11	Efficient Linear SVM	52.29 %	73	47.71 %	1.0827	95% explained variance

- Best Overall Accuracy and Lowest Error: Model 2.3 (Tree)
- Best KNN Model: Model 2.7
- Fastest Training: Model 2.8 (KNN)

Moderate Performance: Efficient Logistic and Efficient Linear SVM

while decision trees (specifically Model 2.3) demonstrate the best overall performance in terms of accuracy and error rate, KNN models, particularly Model 2.7, also show strong performance with the added benefit of shorter training times. Efficient Logistic and Efficient Linear SVM models provide decent performance but lag in comparison to the best Tree and KNN models.

8 Conclusion:

This study 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

Featured Work:

In this work, we presented a unique method for detecting engine knocking in real time by utilizing knock index computation and machine learning. We were able to accurately categorize engine knocking noises and measure the severity of the knock throughout a series of engine cycles by utilizing machine learning algorithms and cutting-edge signal processing techniques. Our research highlights machine learning's potential for early car defect detection. However, for practical implementation, more accuracy improvements are required. In order to improve the efficacy and dependability of real-time car problem detection systems, future research might concentrate on improving feature extraction techniques and optimizing algorithms.

References :

[1]. T. K. R. I. H. a. S. K. Hosogi, ""Research of Knocking Deterioration due to Accumulated Carbon Deposits on Piston Surfaces,"," SAE Technical, no. Paper 2019-01-1141, 2019.

[2]. Nasim, F., Masood, S., Jaffar, A., Ahmad, U., Rashid, M. (2023). Intelligent Sound-Based Early Fault Detection System for Vehicles. *Computer Systems Science and Engineering*, *46(3)*, 3175–3190. https://doi.org/10.32604/csse.2023.034550

[3]. Kalghatgi, Gautam T., and Derek Bradley. "Pre-ignition and 'super-knock'in turbo-charged spark-ignition engines." *International Journal of Engine Research* 13, no. 4 (2012): 399-414.

[4]. Arif, Aftab, Fadia Shah, Muhammad Ismaeel Khan, Ali Raza A. Khan, Aftab Hussain Tabasam, and Abdul Latif. "Anomaly detection in IoHT using deep learning: Enhancing wearable medical device security." *Migration Letters* 20, no. S12 (2023): 1992-2006.

[5]. Akbar, Zeeshan, Ahmed Hassaan, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, and Sikander Niaz. "Leveraging Data and Artificial Intelligence for Sustained Competitive Advantage in Firms and Organizations." *Journal of Innovative Computing and Emerging Technologies* 3, no. 1 (2023).

[6]. Wang, Zhi, Hui Liu, Tao Song, Yunliang Qi, Xin He, Shijin Shuai, and JianXin Wang. "Relationship between super-knock and pre-ignition." *International Journal of Engine Research* 16, no. 2 (2015): 166-180.

[7]. Hassaan, Ahmed, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, Zeeshan Akbar, and Sikander Niaz. "ETHICAL ANALYTICS & DIGITAL TRANSFORMATION IN THE AGE OF AI: EMBEDDING PRIVACY, FAIRNESS, AND TRANSPARENCY TO DRIVE INNOVATION AND STAKEHOLDER TRUST." *Contemporary Journal of Social Science Review* 1, no. 04 (2023): 1-18.

[8]. Ismail, Muammar Mukhsin, Mas Fawzi, Juntakan Taweekun, and Theerayut Leevijit. "Engine knock detection for a multifuel engine using engine block vibration with statistical approach." *MethodsX* 8 (2021): 101583.

[9]. Khan, Muhammad Ismaeel, Hassan Tahir, Aftab Arif, Md Ismail Jobiullah, Ali Raza A. Khan, Sakera Begum, and Ihtasham Hafeez. "Enhancing IoT Security: A Lightweight Cloning Approach for RFID/NFC Access Control Systems." *Cuestiones de Fisioterapia* 52, no. 2 (2023): 231-248.