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Cognitively inspired sound-based automobile problem detection: A step toward explainable AI (XAI)

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ABSTRACT

Recently, there have been efforts to create automated systems for diagnosing engine problems using sound detection. However, most of these methods lack robustness and interpretability, functioning as "black boxes" that make it difficult to understand their decision-making processes. The Learning Classifier System (LCS), a machine learning approach that operates using a set of rules, has demonstrated potential for providing robust, interpretable, and generalizable solutions across different domains. This work aims to develop a new LCS-based system for automatically detecting engine problems, with a focus on making its decision-making process understandable, contributing to explainable artificial intelligence. The system's performance is evaluated using features from the time domain, frequency domain, and time-frequency domain. Its robustness is tested with noisy sound data gathered under various normal and abnormal conditions. Experimental results show that this new approach outperforms conventional state-of-the-art methods by 2.6%–6.0%, achieving a maximum performance accuracy of 98.6%.

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1. Introduction

The automobile has undergone a significant transformation from being a luxury item to an indispensable part of our daily lives. It has revolutionized how we travel, making it more convenient and flexible than ever. Reliability is a crucial parameter that determines the overall quality and performance of an automobile (Chen et al., 2021). It refers to the ability of an automobile to perform consistently and dependably over time without frequent breakdowns or unforeseen issues.

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The engine of an automobile is often considered to be the heart of the vehicle, and it plays a pivotal role in its overall performance (Rashidi et al., 2025). Automobile reliability is closely linked to engine potential dangers (Theissler et al., 2021). The engine's sound offers great information about an automobile's condition and performance, providing valuable insights into potential issues within various engine components. It has been observed that when an automobile operates normally, it produces a consistent and regular sound. A sample spectrum of a standard sound signal emitted by a well-functioning engine is shown in Fig. 1. However, if an engine or its component has an underlying problem, the engine sound will undergo noticeable changes, becoming distinct from the normal operating sound.

For instance, when engine oil quality degrades, the piston faces difficulty moving smoothly. Consequently, it generates a harsh sound, a sign of an oil-related issue. The timing chain, another crucial component, controls the valves. If not securely fastened, it can vibrate, leading to an altered sound. A squealing sound often indicates a loose or worn-out serpentine belt that controls all engine accessories, such as the alternator and water pump. A grinding sound in a car could be due to worn-out bearings, clutch, or a bad CV joint. It's serious and requires prompt attention to prevent further damage. A Knocking sound is often described as a pinging or metallic knocking sound while driving. It can be caused by uneven burning of fuel in the cylinders and should be looked at right away. The most common reasons for engine popping are a clogged fuel filter, ignition problems, fouled or dirty spark plugs, damaged plug wires, or a faulty catalytic converter. The sample spectra of such anomalous sound signals are presented in Fig. 2. These abnormal acoustic signals from the engine indicate the presence of various potential faults. A clear distinction can be observed between the normal and anomalous sound spectrums, aiding in identifying potential engine issues. Experienced drivers are adept at recognizing different sounds and their potential implications for the vehicle. They can connect these sounds to possible issues with the car and use this information to determine what needs to be fixed. Finding the patterns from signals and classifying them into meaningful information is called signal processing.

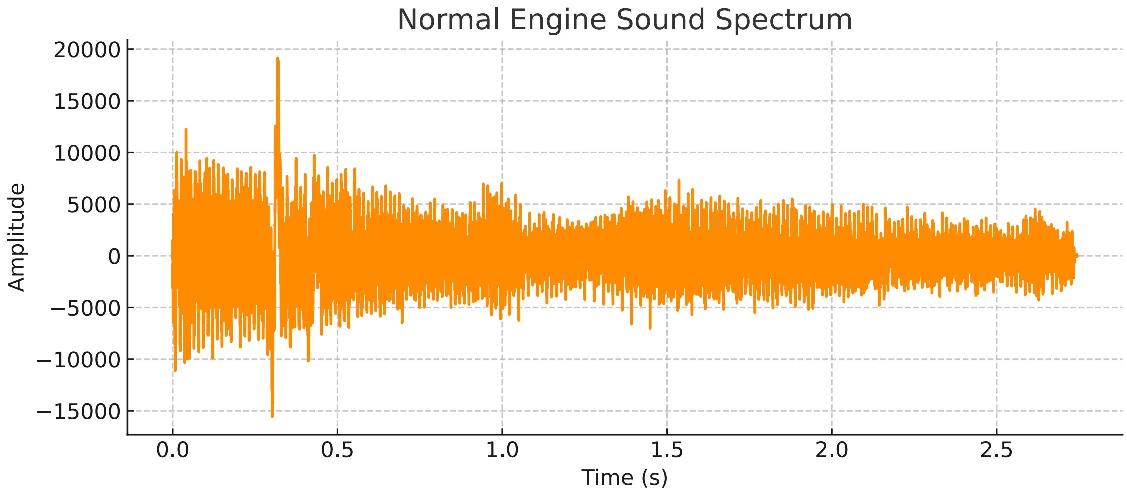


Fig. 1: Normal engine sound spectrum

The remainder of this paper is organized as follows: Section 2 presents the fundamental background information necessary for sound-based engine problem diagnosis. The primary objective of this section is to establish a comprehensive understanding of the key concepts essential to engine acoustic analysis, thereby providing a contextual foundation for the ensuing discussions. Following this, Section 3 outlines the specific objectives and advantages related to the study, providing a clear framework for the subsequent exploration of the subject matter. Section 4 explains the important components and the overall workflow of LCS. Section 5 describes how an LCS-based system can be created to detect vehicle problems. Finally, Section 6 presents a summary of the findings and offers recommendations for future work.

2. Background

Vehicle engine sounds are complex and dynamic signals that reflect the engine's state, performance, and operation. They differ from other machine sounds, which are often stationary or periodic signals with clear features and patterns. Engine sounds are highly non-stationary and non-linear signals that change depending on various factors, such as driving conditions, speed, load, and environment. Mechanical objects always make a unique sound that experts can use to figure out what they are (Marzo et al., 2015). They carry valuable information that can help to accurately determine the spatial location and orientation of their source. Each signal has a certain amount of energy and a specific wavelength. Spectral peaks are the frequencies in a signal that have the highest amplitudes. Originating signals have information about the actual condition of the source. They are distinguished from each other by the attributes they possess. The meaning of sound signals can vary based on these values at different time intervals. Spectral peaks can be used to identify a signal's frequency components and analyze its properties.

There is no single mathematical equation that can accurately model the sound produced by a vehicle engine. However, several mathematical models can simulate the sound of an engine. One such model is the engine order sound model. This model is based on a short-time Fourier transform and synthesis technique, implemented using an active sound generation (ASG) system (Cao et al., 2020). At a certain S_e, the engine order sound can be expressed as,

$$X(S_e) = \sum_{r=1}^{N} A_r \sin\left(r \times \frac{\pi}{60} S_e + \emptyset_r\right) \quad (1)$$

At engine speed S_e, Ar gives the instantaneous amplitude of engine order r or $0.5r$. $\emptyset_r$ gives the instantaneous phase, where N is the total number of possible engine orders. In the temporal domain, the computation of the continuous-time signal of engine order r, denoted as $x_r(t)$, can be determined as follows:

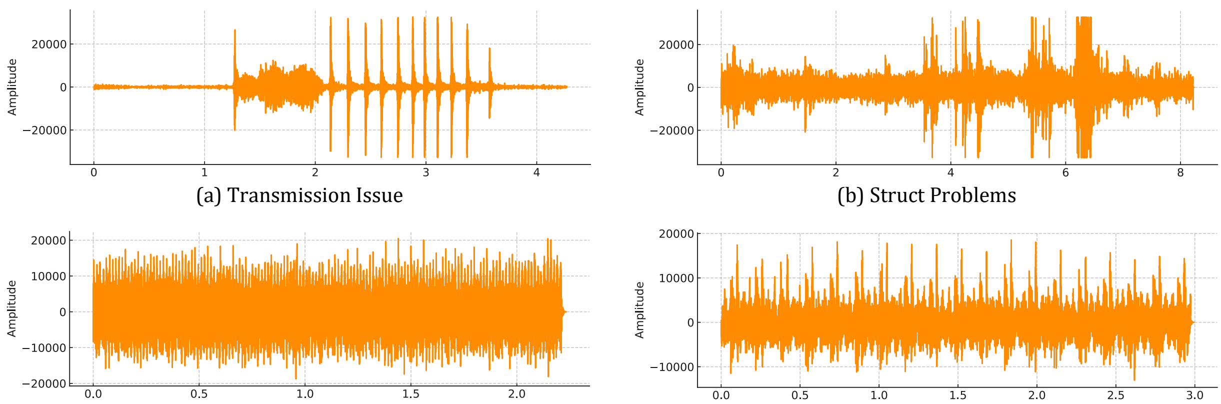
$$x_r(t) = A_r(t) \cdot \sin[2\pi f_r t + \phi_r(t)] \quad (2)$$

where, $A_r(t)$ is the instantaneous amplitude of engine order $0.5r$ at time t; $\emptyset_r(t)$ is the instantaneous phase of engine order $0.5r$ at time t; and f_r is the frequency of engine order $0.5r$. Therefore, the continuous-time signal of engine orders $X_r(t)$ can be expressed by the following equation:

$$\overset{N}{\underset{r=1}{X_r}}(t) = X_{Ar}(t).sin[2\pi f_r t + \emptyset_r(t)] \quad (3)$$

To ensure the accuracy of engine order sound, it is important to get a good idea of the frequency of each order at all times and figure out the amplitudes and phases of all the order's parts with the right level of accuracy. The engine order sound model is an important tool for sound experts and engineers involved in designing and developing vehicle sound simulation systems. Another mathematical model that can be used to simulate the sound of an engine is the quasi-steady-state model (Segel and Slemrod, 1989). This model is based on the assumption that the engine is operating at a steady-state condition and that the sound produced by the engine results from the gas pressure fluctuation in the combustion chamber. The quasi-steady-state model can be used to predict the sound pressure level of an engine under different operating conditions. It is important to note that these models are imperfect and might not always accurately simulate an engine's sound. However, they are useful tools for sound experts and engineers designing and developing vehicle sound simulation systems.

In a traditional approach, an expert known as an engine listener carefully listens to the engine's sound to identify abnormal signs or faults in the vehicle. Engine listeners can associate these specific noises with potential problems. Most automakers, such as Ford, have been using professional engine listeners to ensure the quality of their vehicles (Keshun and Huizhong, 2023). These professionals are trained to quickly observe abnormalities in the engine sound patterns and detect associated faults in the vehicle. However, manual inspections are time-consuming, labor-intensive, and susceptible to human error. Conventional methods rely heavily on diagnostic tests, which have inherent limitations. Diagnostic tests often require specialized equipment and expertise, making them costly and inaccessible to many users.



(a) Transmission Issue (b) Struct Problems
(c) Engine sound running without oil (d) Piston slapping sound

Fig. 2: Abnormal engine sound spectrum (all horizontal axes are time (s))

2.1. Machine learning based acoustic analysis systems

Recently, there has been a growing interest in creating acoustic systems that are driven by machine learning to find and classify engine problems. These methods are considered a good alternative to traditional ones (Kumar et al., 2022). Because there are no sound alphabets, traditional sound analysis methods like the Hidden Markov Models (HMM) (Nasim et al., 2023a) cannot be used in these situations. Machine learning (ML) algorithms are powerful tools for analyzing and learning from data, as they can automatically discover patterns (You et al., 2023), make predictions, and improve their performance based on experience. These algorithms can be applied to different kinds of data, including text, audio, images, speech, or numbers. They can solve problems such as classification, regression, clustering, or dimensionality reduction. The utilization of this technology has already demonstrated its ability to enhance physicians' diagnostic accuracy, facilitate the selection of more efficacious treatment options, and even anticipate patient prognoses. Random forest trees, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Dense Neural Networks (DNN) are among the robust algorithms employed for the identification of various diseases based on medical sounds, including heart, lung, and breath sounds. Recognizing this huge potential of ML, researchers have increasingly applied it to engine sound processing for fault detection. They are using ML-based systems to analyze the spectrum of engine sounds to identify vehicle faults. These systems leverage significant advancements in signal processing, machine learning, and AI to automatically analyze the acoustic signatures emitted by various automobile components. These systems can detect abnormal patterns or deviations that indicate potential faults or malfunctions by capturing and analyzing acoustic signals.

A recent study by Ali et al. (2023) introduced a new method called the deformable feature map residual network. This network identifies car engines by adaptively adjusting the pixels in the input feature map and then combining them with the convolutional feature map. They used Mel frequency cepstral coefficients (MFCC) features and reported an accuracy of 84.28% on a car engine sound dataset. Another study by Qureshi et al. (2015) addressed the problem of automatic vehicle and engine identification using audio information. They used spectral features, such as MFCCs, Perceptual Linear Prediction (PLPs), Linear Prediction Cepstral Coefficient (LPCCs) (Ullah et al., 2023), and temporal features (ZCR, STE). They employed SVMs and kNN classifiers and evaluated their performance on a dataset of 100 recordings from 10 different vehicles. Another study by Singh and Krishnan (2023) presented a comprehensive review that covers different artificial intelligence applications, such as assistive technology the feature extraction techniques for EEG signal analysis in various domains, such as time, frequency, decomposition, time-frequency, and spatial. Rehmani et al. (2024) proposed a deep feature selection method for engine fault diagnosis based on a hybrid autoencoder. They used a combination of a convolutional autoencoder and a sparse autoencoder to extract features from engine vibration signals and select the most relevant features based on mutual information. They test their method on a diesel engine test bench and achieve high accuracy and robustness. These studies exemplify the ongoing advancements in leveraging machine learning for engine fault detection. They explore diverse feature extraction techniques, classifier architectures, and sound classification tasks, paving the way for more robust and accurate engine diagnostics in the future. Detecting and classifying vehicle faults based on ML offers several advantages, including real-time monitoring, non-intrusiveness, and cost-effectiveness. ML-based sound detection and classification systems have the potential to revolutionize engine diagnostics.ML can quickly and accurately analyze large amounts of sound data and extract meaningful patterns. Deep learning models can handle noisy and large-scale data in a better way. They can learn complex and high-level features from multidimensional raw audio signals. The advent of deep learning (DL) has revolutionized engine fault detection with its ability to learn complex patterns from diverse data sources (Sahin et al., 2023), including audio signals. They have achieved state-of-the-art performance in various audio classification tasks, such as speech recognition, music genre classification, and environmental sound classification (Zaman et al., 2023). A novel convolutional neural network model was suggested that uses temporal and frequency attention mechanisms to learn time and frequency features from the log-Mel spectrogram more effectively for environmental sound classification (Mu et al., 2021).

2.2. Challenges of ML algorithms

Despite the significant contributions of previous studies, there is a research gap in the sound analysis of automotive engines for problem diagnosis and classification. Firstly, much research has been done on acoustic analysis to identify types of vehicles and engines. These studies have looked at a wide range of topics, such as highlighting the difference between sounds coming from different parts of cars, engines, or machines, sorting noisy or vehicle sounds into different categories, identifying internal vehicle sounds (Anwar et al., 2022), and figuring out what's wrong with machine parts. However, none of these studies have explored using automotive acoustic signals for fault detection and classification, particularly for issues such as timing belts, piston slapping, struts, radiators, etc. Only a few studies have been conducted on detecting automobile engine defects using engine sounds. Current vehicle fault detection techniques do not adequately identify specific engine problems (Nasim et al., 2023b). The major problem with the lack of research work in this area is the unavailability of a well-tested data set that comprises most of the vehicle problems. A few authors, such as Wu et al. (2022), used the Audio Set dataset (Gemmeke et al., 2017) and the VGGSound dataset (Chen et al., 2020) and achieved 84.28% accuracy using a deformable feature map residual network.

Secondly, ML and DL algorithms are highly effective instruments for analyzing and acquiring knowledge from data. However, they face challenges when dealing with real-world data sets. Their vulnerability to missing data, noisy data, outliers, and categorical data is a serious challenge in dealing with new problem sets such as automotive engine sound data. When outliers are present in a dataset, they can skew statistical measures such as the mean and standard deviation, leading to inaccurate model training and prediction results. Outliers may introduce noise or bias into the learning process, causing the model to give excessive importance to these extreme values. Consequently, the model's generalization and predictive performance can be compromised.

Also, data issues can affect machine learning models' quality, reliability, and performance and require appropriate handling methods. ML-based systems lack robustness and transparency, making their results challenging to interpret and trust. DL models work similarly to black boxes. They hide the decision-making processes, and users are left in the dark about how they arrive at their conclusions. Even the most advanced neural networks can exhibit mysterious and obscure characteristics that are difficult to comprehend. This lack of clarity can be a problem in critical situations, like classifying engine sounds, where a correct diagnosis depends on understanding how a model came to its conclusions. We have elaborated on these challenges in Fig. 3.

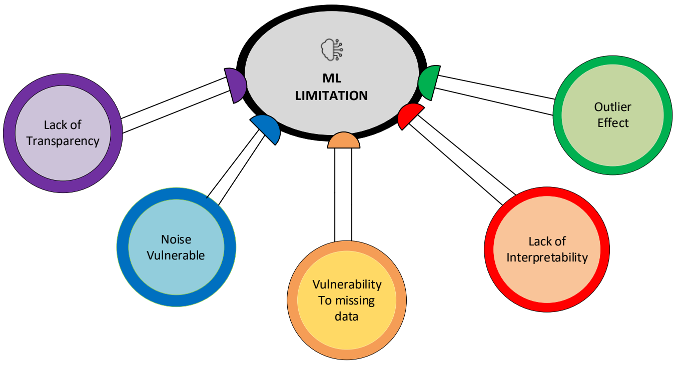


Fig. 3: Machine learning gaps

Explainability is crucial in vehicle engine fault diagnosis, as it can help the mechanics and the users understand the causes and solutions to the problems. To address these challenges, researchers are exploring novel approaches like explainable Machine Learning that promise to unlock the inner workings of DL models and make them more accessible and understandable to users.

3. Objectives and advantages

The proposed system will be able to explain its decision-making process clearly and understandably. This is an essential feature of explainable AI, which aims to make artificial intelligence more transparent and accountable. The system can increase its users' and stakeholders' trust and confidence by providing interpretable explanations. The proposed solution is to design a Learning Classifier System-based system that can effectively learn the underlying engine sound patterns and provide efficient and reliable detection of vehicle problems. The primary objective of this study is to create an LCS-based system for automatically detecting vehicle problems. The system will be able to receive a sound signal, identify underlying patterns, and predict the engine problem. To attain this goal, the subsequent objectives have been established:

1. Create a novel LCS-based system to receive an input sound signal and predict associated engine problems.
2. Develop techniques for analyzing and identifying underlying patterns in a sound signal.
3. Compare existing Machine learning approaches for engine fault detection, outlining their strengths and limitations.

Learning Classifier System (LCS) has emerged as a powerful explainable approach for sound analysis. It learns from experience and improves its performance over time. Unlike traditional ML algorithms, it effectively handles datasets in a more explainable manner. It provides interpretability by generating human-readable rules, allowing domain experts to understand and validate the system's decision-making process. LCS excels in dynamic and changing environments, as its evolutionary nature allows it to adapt and evolve continuously. This adaptability has been leveraged in applications such as autonomous robots and adaptive control systems. It identifies patterns that traditional machine-learning methods may miss. This algorithm can handle noisy data, which can be a problem for traditional machine-learning methods. It can handle large and complex data sets with many attributes, common in new datasets. It can incorporate domain knowledge. This is a significant advantage because it can improve the algorithm's performance by incorporating the expertise of the problem domain. These systems have already demonstrated explainability in speech recognition, music classification, environmental noise monitoring, and biomedical signal processing (Carter et al., 2023; Zinemanas et al., 2021; Ahmed et al., 2024; Dissanayake et al., 2020).

Various types of LCS, such as Michigan and Pittsburgh, have been applied in sound analysis tasks. For example, Ndou et al. (2021) used LCS to select the optimal frequency bands and time frames from the spectrogram that are most relevant for the classification task. These studies highlight the potential of LCS in engine fault detection and diagnosis, showcasing the effectiveness of rule-based systems in handling complex engine data. The conceptual Taxonomy of XAI Methods has been summarized in Table 1. Multiple explainable methods have different types of explainability at different levels of explainability and in different types of applications. We have listed them all in Table 2.

4. Learning classifier system (LCS)

The first LCS, "Cognitive System One" or CS-1, was developed by Holland and Reitman. LCSs are a class of machine learning algorithms that combine reinforcement learning, evolutionary computation, and rule-based representation to learn from data and adapt to changing environments. LCS learns from the input and generates rules that map the acoustic features to the corresponding phonetic symbols. LCSs use genetic algorithms to generate new rules and explore unique niches in the problem space. The LCS develops a set of classifier rules during training that cooperate to solve the current problem, with each rule's fitness being based on how much it contributes to the solution. In the learning process, LCSs improve the fitness of good rules and produce new, fitter rules.

4.1. LCS framework

The algorithm generates a set of guidelines that specify how to categorize data according to particular characteristics or traits. If-then sentences that connect input data to output predictions are used to express these principles. For instance, "if the input data has attributes A, B, and C, then predict output Y."

Next, the system predicts fresh, unseen data using these criteria. The algorithm modifies the rules to increase accuracy if the predictions are inaccurate. Reinforcement learning is used in this process of changing the rules. These rules are generated via a genetic algorithm. Natural selection is possible because of the genetic algorithm. Thus, regulations that have been refined through time are more precise and beneficial.

Table 1: Conceptual taxonomy of XAI methods

Dimension	Categories
Interpretability techniques	Feature importance: Quantifying the influence of individual features on model predictions (e.g., LIME, SHAP). Attention mechanisms: Visualizing which parts of an input (e.g., pixels in an image) contribute most to the prediction. Model distillation: Training a simpler model to mimic the behavior of a complex model, thereby making its reasoning more accessible. Counterfactual Explanations: Simulating how changing an input would affect the prediction, providing insight into model decision boundaries. Rule-based Explanations: Extracting interpretable rules from the model, similar to decision trees.
Explainability level	Local: Explaining individual predictions or instances (e.g., why this image was classified as a cat?). Global: Explaining the overall behavior of the model (e.g., what are the most important features across the entire dataset?). Model-agnostic: Can be applied to any model, regardless of its internal structure (e.g., LIME). Model-specific: Tailored to specific model architectures or types (e.g., attention mechanisms in deep learning).
Application domain	Audio anomaly Detection: Explaining why a sound clip is classified as anomalous. Image classification: Explaining why an image is classified as a specific category. Natural language processing: Explaining the sentiment or intent behind a piece of text. Risk Assessment: Understanding how a model assigns risk scores to individuals. Healthcare diagnostics: Making AI-based medical diagnoses more transparent and trustworthy.

Table 2: XAI methods and properties of complex and dynamic data

XAI method	Interpretability technique	Explainability level	Application domain
LIME	Feature importance	Local, model-agnostic	Image classification, text classification
SHAP	Feature importance	Local, global, model-agnostic	Image classification, tabular data
Grad-CAM	Saliency maps	Local, model-specific	Image classification
BERT-ATTACK	Attention mechanisms	Local, model-specific	Natural language processing
TCAV	Model distillation	Global, model-specific	Image classification
CEM	Counterfactuals	Local, model-agnostic	Image classification, tabular data
ProtoDash	Prototypes	Local, global, model-agnostic	Image classification, audio anomaly detection
Med-explain	Feature importance, counterfactuals	Local, model-agnostic	Healthcare

An LCS consists of several components, which are described according to the order in which they appear in the LCS framework:

- Setting: An environment that offers input data representing the issue domain is present in an LCS. The instances or observations that make up this input data each have their characteristics, features, and intended results or labels. The surroundings create the conditions necessary for the LCS to process the input data, learn from it, and make judgments.
- Match set: Every population classifier that satisfies the current input requirements for the dataset is assembled into a Match Set by the LCS. The requirements of these classifiers match or overlap with the characteristics of the input instance.
- Prediction: The Match Set's classifiers provide predictions or take actions depending on the condition.
- Rule discovery: If the Match Set is not empty, but none of its classifiers provide accurate predictions, the LCS employs a rule discovery process. Rule discovery involves creating new classifiers with conditions derived from the input instance and desired outcome. These new classifiers aim to learn from the misclassifications and improve the system's performance.
- Subsumption: The LCS checks for subsumption, determining if any existing classifier in the population can subsume the newly generated classifier. Subsumption occurs when an existing classifier can cover the same input conditions as the new classifier and provide more accurate predictions or actions.
- Parameter updating: LCS updates the parameters of the classifiers in the Match Set and newly generated classifiers based on reinforcement learning. The fitness values associated with the classifiers are adjusted to reflect their performance and contribution to successful predictions or actions.
- Rule compaction: LCS performs rule compaction to eliminate redundant or less effective classifiers. Rule compaction ensures that the population

remains concise and efficient, focusing on the most relevant and accurate classifiers.

Overall, an LCS combines the power of genetic algorithms, which simulate the process of natural selection, with reinforcement learning to develop a framework that, through interactions with its surroundings, may learn and become more adept at making decisions. The LCS can tackle complicated issues and respond to changing situations by iteratively evaluating, selecting, reproducing, and altering the classifiers. Typically, an LCS is used to specify the problem and generate a population of classifiers. Conditions that describe input patterns or situations and associated actions that indicate the desired response or decision make up each classifier. Next, the performance of the classifier population on the provided challenge is assessed. The action or prediction made by the classifier(s) that were chosen in the Match Set based on their greatest fitness values is normally the LCS's output. This result signifies the choice made. This feedback is then used to adjust the parameters or weights of the classifiers, enabling them to make better decisions in similar situations in the future. The learning process in an LCS occurs iteratively over multiple generations. During each iteration, the population of classifiers goes through evaluation, selection, reproduction, and reinforcement learning. The classifiers that perform well on the problem are selected to reproduce, passing on their knowledge and characteristics to the next generation. Through this process, the LCS adapts and improves its performance over time. The learning in LCS continues until a stopping criterion is met. This criterion can be defined as reaching a desired level of performance or a maximum number of iterations. Once the stopping criterion is satisfied, the LCS can be trained and is ready to make decisions or solve problems in the given domain. Thus, it makes a promising alternative for larger, higher-dimensional classification problems. This interpretability is a great advantage of this method. There are a variety of Learning classifier systems as shown in Fig. 4. Each system has its strengths and weaknesses. In the next section, we will present a short review of different variants to give readers a deep understanding of these systems.

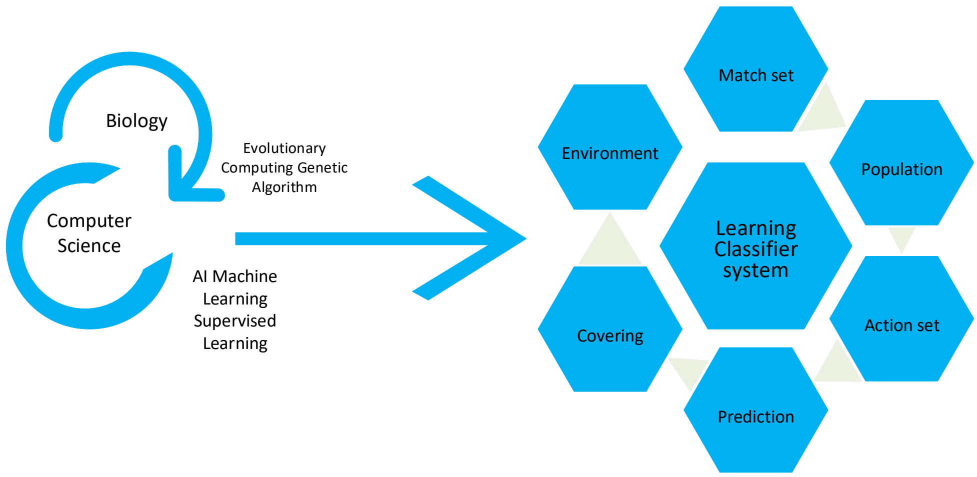


Fig. 4: Learning classifier system framework

4.2. Variants of LCS

There are many variants of LCS. We will briefly analyze them and discuss their strength and weaknesses to choose the best fit for our problem. Genetic Algorithm Classifier System (GACS) (Dee Miller et al., 2015) is a type of LCS that uses genetic algorithms to evolve a population of rules that can classify data and adapt to changing environments. GACS has been applied to domains such as pattern recognition, data mining, optimization, and control. However, GACS also faces challenges such as scalability, interpretability, generalization, and robustness. Rule-based classifier System (RBCS) is a machine learning algorithm that uses IF-THEN rules to classify data into different classes. RBCS can be interpretable, flexible, and modular, and can handle both discrete and continuous attributes. However, RBCS also faces some challenges, such as rule extraction, rule pruning, rule ordering, and rule evaluation. Reinforcement Learning Classifier System (RLCS) (Schönberner and Tomforde, 2022) is a type of LCS that uses reinforcement learning to learn a population of rules that can interact with an unknown environment and maximize a reward signal. RLCS can handle sequential decision-making problems, partial observability, and delayed feedback.

However, RLCS also faces some challenges, such as exploration-exploitation trade-offs, function approximation, credit assignment, and policy evaluation. Bayesian Classifier System (BCS) (van de Schoot et al., 2021) is a type of LCS that uses Bayesian inference to learn a population of rules that can classify data and update their probabilities based on evidence. BCS can handle uncertainty, noise, and missing data and can provide interpretable and probabilistic rules. However, BCS also faces challenges, such as computational complexity, prior specification, rule extraction, and rule pruning. Table 3 highlights some recent studies and their explainability models.

Table 3: XAI techniques and their approach

Reference	Input data	Model architecture	Explanation technique
Mishra et al. (2017)	Spectrogram	A decision tree and a random forest	Local interpretable model-agnostic explanations (LIME)
Zinemanas et al. (2021)	Spectrogram of environmental sounds	An encoder, a decoder, and a classifier. The encoder and decoder are CNNs that learn a latent representation of the input spectrogram. The classifier is a linear model that predicts the class label based on the similarity between the latent representation and a set of learned prototypes, which are representative examples of each class	Prototype matching in latent space
Dissanayake et al. (2020)	Spectrograms	CNN based on the VGG16 architecture, with some modifications. The CNN had 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. The CNN was pretrained on the ImageNet dataset and fine-tuned on the spectrogram features.	Saliency maps and Grad-CAM
Wang et al. (2023)	The heart sound recordings were converted into six types of time-frequency representations: STFT, LMT, Hilbert-Huang transform (HHT), wavelet transform (WT), Mel transform (MT), and Stockwell transform (ST)	CNN based on the ResNet-50	Layer-wise relevance propagation (LRP)
Carter et al. (2023)	Spectrograms of the cardiac signals	CNN and an LSTM network	Saliency maps and Shapley values
Becker et al. (2024)	Waveform or spectrogram of spoken digits	CNN or RNN	LRP

5. Methodology

The dataset contains a diverse range of both normal and faulty engine sounds, collected from different car models that presented a variety of problem scenarios, including timing belt issues, piston slapping, strut malfunctions, radiator problems, and more, as shown in Table 4.

Table 4: Abnormal sounds data set

ID	Problem type	Count
1	Exhaust prob	40
2	Hole in muffler	37
3	Failing water pump	28
4	Valves tapping	28
5	Transmission slipping	28
6	Vacuum hose leak	28
7	Brake pad	25
8	Struts	20
9	Unworn serpentine belt	19
10	Radiator boiling	18
11	Engine running without oil	18
12	Piston slapping	18
13	Loose heat shield	17
14	Engine seized	14
15	Car stopping metal to metal	13

The data was collected under different speeds, loads, temperatures, and environmental conditions. Although there are various car models and manufacturers, they all have the same basic structure, which implies that they produce similar types of sounds for specific problems. To categorize the audio samples based on their types, experienced car mechanics provided valuable insights, aiding in the labelling process.

There are 351 abnormal files in the dataset, as listed in Table 5. The recorded sound had an audio sample rate of 48kHZ with 2(stereo) channels and a bit rate of 260kbps with varying length. We used these sounds to train a learning model for detecting vehicle abnormalities. The dataset contains 214 normal sounds from vehicles without faults. We used these sounds to develop a model to detect normal vehicle sounds. The dataset was partitioned into training and testing sets to facilitate model evaluation and performance assessment. The novel approach classifies the sounds made by various engines as normal and abnormal. We followed the formal ML pipeline for both phases, which includes preprocessing, feature extraction, and classification. Fig. 5 shows a technology roadmap to briefly summarize the main experimental schemes and detection methods.

Table 5: Total dataset

Total abnormal files	351
Total normal files	214
Total files	555

5.1. Feature extraction

Feature extraction is the technique of pulling attributes from an audio signal to generate a signal representation that is simpler to process and analyze. In pattern recognition, features play a vital role. Multiple methods exist to extract features from the sound data using different parameters over different domains. But for information extraction, the most popular types of sound features are time domain, frequency domain, and time-frequency features. A lot of different statistical functions are used in time-domain feature extraction. These include mean energy, zero-crossing value, spectral entropy, variance value, arithmetic mean, Petrosian fractal dimension, median, and more (Table 6).

These functions help us understand and analyze signals based on their time-related attributes. The time-domain features only show how the signal changes over time. On the other hand, the frequency-domain features show how the signal changes over the frequency band. Rényi entropy, Median Frequency, Yule-Walker Spectral Estimation, Covariance Spectral Estimation features, etc., are used in this domain. The median calculation is derived from the data shown in Table 7. An autoregressive (AR) method is used to model the spectra of data with higher power spectral density at certain frequencies. It is possible to solve a linear system with the Yule-Walker autoregressive (AR) approach and find the AR parameters, which give you the Yule-Walker estimates.

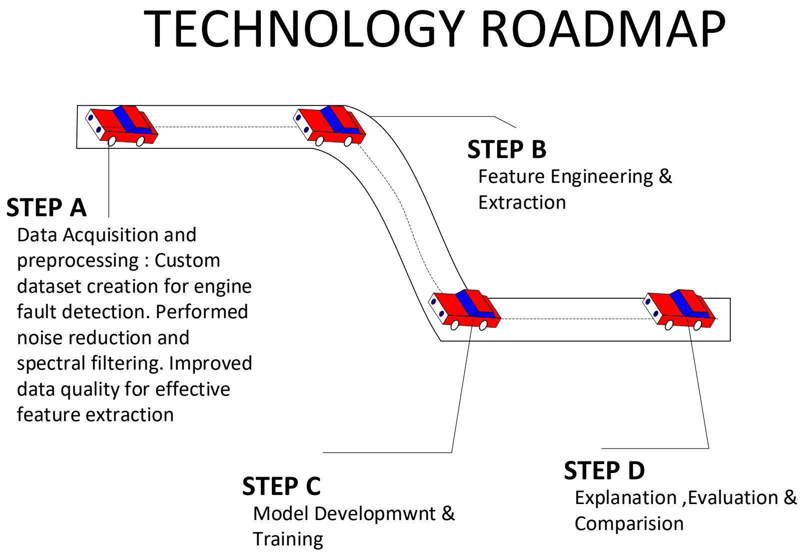


Fig. 5: Technology roadmap

Table 6: Temporal features and their mathematical definitions

Temporal features	Formula
Mean energy	$\frac{1}{N}\sum_{i=1}^{N} x_i^2$
Zero-crossing value	$\frac{1}{2N}\sum_{i=1}^{N-1} \lvert sgn(x_i) + sgn(x_{i+1})\rvert$
Spectral entropy	$-\sum_{i=1}^{N} p_{i\,log_2(p_i)}$
Variance value	$\frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2$
Arithmetic mean	$\frac{1}{N}\sum_{i=1}^{N} x_i$
Petrosian fractal dimension	$\frac{log_{10}(N)}{log_{10}(N) - log_{10}(N/\delta)}$
Median	$med(x)$

Table 7: Frequency domain features table

Frequency domain	Features formula
Power spectral density	$S_{xx}(f) = \lim_{T\to\infty}\frac{1}{T}E\,[\lvert X_T(f)\rvert\text{^}2]$
Spectral entropy	$H(f) = -\int_{-\infty}^{\infty} p(f)\log_2 p(f)df$
Spectral flatness	$\frac{\exp(\frac{1}{N}\sum_{n-0}^{N-1} \log_2(\lvert X(n)\rvert)}{\frac{1}{N}\sum_{n-0}^{N-1}(\lvert X(n)\rvert)\rvert)}$
Spectral centroid	$\frac{\sum_{n-0}^{N-1} f(n)\lvert X(n)\rvert\text{^}2}{\frac{1}{N}\sum_{n-0}^{N-1}(\lvert X(n)\rvert\text{^}2)}$
Spectral spread	$\sqrt{\frac{\sum_{n-0}^{N-1} f(n)\lvert X(n)\rvert\text{^}2}{\frac{1}{N}\sum_{n-0}^{N-1}(\lvert X(n)\rvert)}}$
Spectral skewness	$\frac{\sum_{n=0}^{N-1}(f(n)-\mu)\text{^}3\lvert X(n)\rvert\text{^}2}{\varpi\text{^}3}$
Spectral kurtosis	$\frac{\sum_{n=0}^{N-1}(f(n)-\mu)\text{^}4\lvert X(n)\rvert\text{^}2}{\varpi\text{^}4}$
Renyi entropy	$H(f) = \frac{1}{1-\alpha}\log_2(p(f)\text{^}\alpha\, df)$
Median frequency	$\int_{med} = \frac{\sum_{n=0}^{N-1}\lvert X(n)\rvert}{2}$
Yule-Walker spectral estimation	$S_{yy}(f) = \frac{\varpi_v^2}{\lvert 1+\sum_{k=1}^{p} a_k e^{-j2\pi kfT}\rvert\text{^}2}$
Covariance spectral estimation	$S_{yy}(f) = \frac{1}{T}\mathbb{E}[Y_T(f)Y_T^*(f)]$

The signal energy is distributed over different frequency components in the frequency domain. The discrete Fourier transform (DFT) is a mathematical tool that performs this transformation, and it can be expressed by Eq. 4. Using FFT enables the implementation of the DFT with substantially reduced computing complexity.

$$F(\varpi) = \sum_{x=1}^{x} f(x).e^{\frac{j2\pi\omega}{x}}, \varpi = 1, 2, \ldots\ldots, n \quad (4)$$

DFT computed using Eq. 5 captures the spectrum components present in the data. However, it is incapable of detecting temporal fluctuations across different frequencies. The time-frequency analysis is conducted by using the STFT with a Hamming window and a 50% overlap, as seen in Eq:5

$$(\mathrm{t}, \varpi) = \sum_{x=1}^{x} f(\mathrm{t}+x).\mathrm{w}(\mathrm{x}).e^{\frac{j2\pi\omega}{x}}, \varpi = 1, 2, \ldots\ldots, n \quad (5)$$

The Power Spectral Density (PSD) is a mathematical representation that illustrates power distribution across different signal frequencies within the frequency domain. The data demonstrates significant fluctuations across many frequency bands, presenting potential value for subsequent investigation. The signal was partitioned into overlapping windows, and each window's PSD was computed. This Short-Time Power Spectral Density (ST-PSD) offers substantial insights into various signal components. Features are retrieved from the signal to have a comprehensive understanding of it.

Let $I(x)$ represent the input signal, and $a(x)$ denote the autocorrelation of the input signal.

$$a(x) = I(x) * I(-x) \quad (6)$$

PSD of a signal is defined as the result of the Fourier transform of the autocorrelation function of the signal and is typically represented as:

$$P(\omega) = F(a(x)) = F\{I(x)\}F\{I(-x)\} = F(\omega)F^{*}(\omega) \quad (7)$$

Eq. 6 demonstrates that the PSD of a signal may be computed by multiplying the Fourier transform of that signal with the Fourier transform of its complex conjugate. The short-time power spectral density, represented as $P(t,\omega)$, may be obtained by squaring the Fourier transform $F(t,\omega)$.

As a feature vector, the element-wise mean of the PSD of each window is used as shown in Fig. 6. The length of this feature vector will be the same as the size of the window that was used. These are the possible ways to write the signal's feature vector based on its short-time $PSD(t,\omega)$:

$$FE(\varpi) = \frac{1}{T}\sum_{t}^{T} PSD\ (t, w) \quad (8)$$

Many sound processing tasks, like speech recognition, music analysis, and finding acoustic events, use time-frequency features that can be extracted using STFT or CWT. These features give us useful information about how sound signals change over time, which lets us analyze their temporal and spectral properties more accurately and completely. Time-frequency analysis is a crucial technique in sound processing that simultaneously allows the examination of temporal and spectral information. It breaks down a signal into individual frequencies and amplitudes over time. This lets us find transient events, harmonic components, and changes in spectral characteristics. The Short-Time Fourier Transform (STFT), which Gabor proposed in 1946, is one widely used method for extracting time-frequency features. These features are widely regarded as the most accurate and exact representation of signals seen in real-world scenarios. The STFT divides the signal into short, overlapping windows and performs the Fourier Transform on each window to obtain a time-frequency representation. This provides insights into the signal's frequency content at different time points. The spectrogram, which displays the magnitude or power spectrum over time, is a common visualization of the STFT.

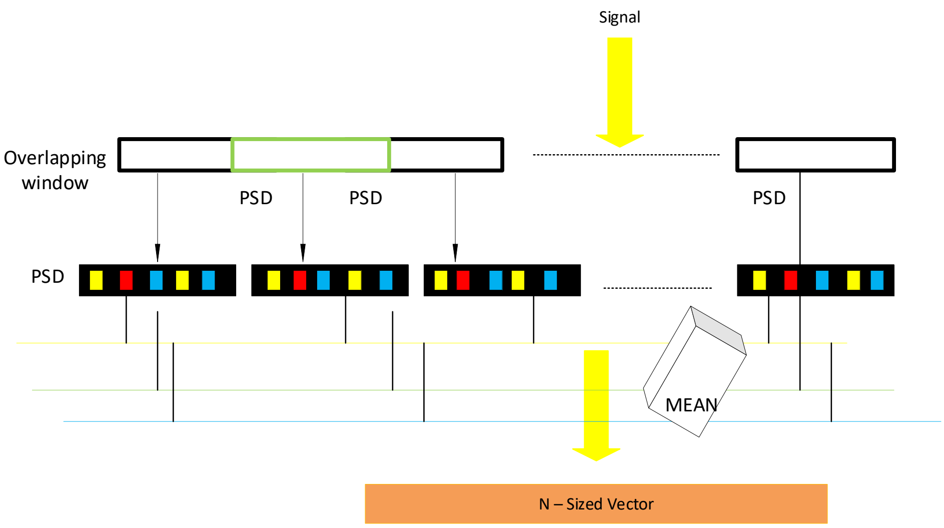


Fig. 6: STFT feature extraction

5.2. Detection of normal/abnormal engine sound using ML classifiers

We have separated the train and test data into separate directories. 173 of the 341 abnormal files were used for training, and 168 were used for assessment. Out of the 214 normal files, 108 are used for training, and 106 are used to test our system. We used advanced ML algorithms, such as random forests and trees, to divide sounds into standard and anomalous groups. A decision tree-based model is trained to classify normal and anomalous vehicle sounds. In the Time domain, '1' and '2' are designated for the target classes. We used '1' for normal car conditions and '2' for abnormal conditions. Our model has a correlation coefficient of 89.98% and 93.98% on the random and random forest trees, with an absolute error of 4.74% and 7.93%, respectively, as shown in Fig. 7.

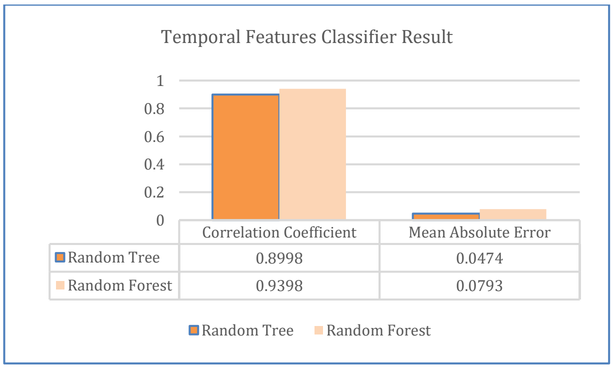


Fig. 7: Temporal features classifier result

The correlation coefficient is a way to measure how two factors are related. It goes from -1, which means there is no correlation, to +1, which is a perfect connection. When the correlation coefficient is 0, there is no link between the two factors. When the correlation value is low, the data points tend to group instead of falling in a straight line.

There are 104 attributes in the frequency domain. Our model exhibits a correlation coefficient of 97.25 % and 93.2 %, with a 3.2% and 4.5% mean absolute error on the random tree and random forest tree, respectively, as shown in Fig. 8.

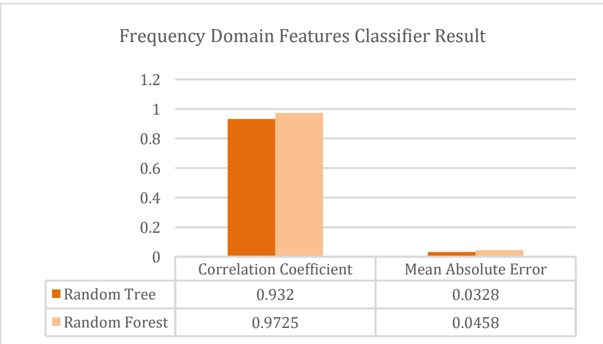


Fig. 8: Frequency domain features classifier result

The time-frequency domain features are obtained by transforming the sound signals from the time domain to the frequency domain using a spectrogram or wavelet transform, which can capture more information and patterns of the sound signals. Features for the time-frequency domain can be recorded with the help of the time-frequency transformation, as discussed in the Feature Extraction section. The training set built by this technique contains 258 attributes each. Within this dataset, there exist two distinct classes that serve as targets. These classes correspond to normal car conditions, denoted by the numerical value '1', and abnormal car conditions, denoted by the numerical value '2'. The model exhibits correlation coefficients of 88% and 96% with mean absolute errors of 5% when applied to the random tree and random forest tree, respectively, as shown in Fig. 9.

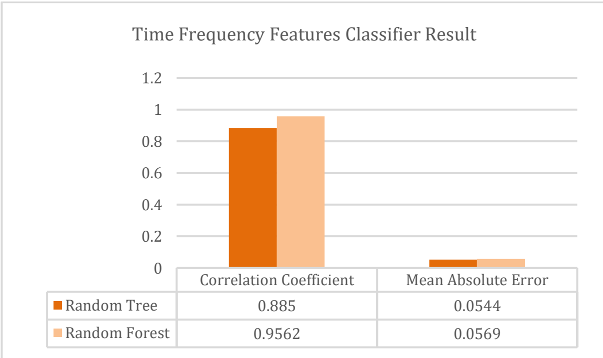


Fig. 9: Time-frequency domain features classifier result

These values are comparatively lower than the performance of the frequency domain features. Fig. 10 shows the result of the comparisons.

5.3. Rule-based machine learning

Rule-based machine learning is an explainable approach that refers to a category of machine learning that can recognize, develop, and acquire rules to address a specific issue or a specific component of a problem. These rules collectively provide knowledge of the environment in a *piece-wise* manner. Evolutionary Rule-based Machine Learning (ERBML) combines the strengths of open-ended genetic search with powerful machine learning techniques. It is gaining popularity due to its ability to solve complex problems.

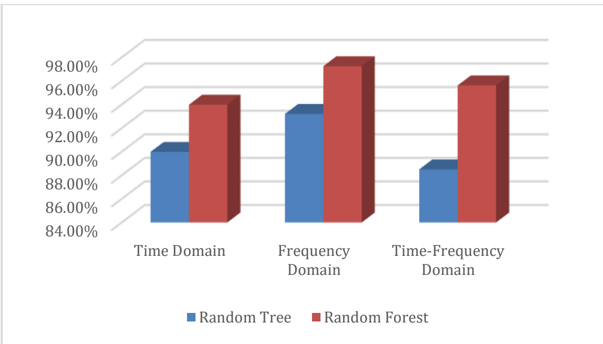


Fig. 10: Traditional ML classifier comparison

LCS is a cutting-edge ERBML technique that embeds evolution with rule-based machine learning to provide efficient solutions for complex problems (Hussain et al., 2023; Burhan et al., 2023). LCS can provide unique advantages, such as transparency and interpretability, which are highly valuable in domains where explainability is crucial. LCSs have the inherent ability to split the problem space into niches and learn rules to solve the whole problem piece-wise. The learned rules are humanly interpretable, a step towards explainable AI (Khaliq et al., 2022). The LCS we used is ExSTra CS (Bilal et al., 2022), which is an extension of LCS that uses supervised learning and can handle numerical and categorical data. ExSTra CS generated a set of rules that human experts can easily interpret and analyze. The algorithm starts with the Initialization of the population of classifiers from the Dataset. For each classifier in the population:

- Calculate the fitness based on the extracted features
- Select the best classifiers based on their fitness
- Generate new classifiers by applying genetic operators such as mutation and crossover to the best classifiers
- Evaluate the performance of the new classifiers using a validation dataset
- Replace the worst classifiers in the population with the new classifiers

This pseudocode outlines the basic steps in building an ExSTraCS for acoustic-based engine fault detection, as shown in Fig. 11. The algorithm uses a population of classifiers that are trained and evaluated on acoustic data from the engine. Rules are usually stored using the ternary notation {0,1,#}. Fig. 12 shows a rule cluster having 16 attributes. The fitness of each classifier is calculated based on the extracted features, and the best classifiers are selected for reproduction. New classifiers are generated by applying genetic operators such as mutation and crossover to the best classifiers, and the worst classifiers are replaced with the new classifiers. This process is repeated until the performance of the classifiers is satisfactory. We observed that random forest, a tree-based ensemble method, achieved high performance on the time-frequency domain features of problematic engine sound. Random forest correctly classified 92.7% of the instances on a test set. However, LCS outperformed random forest with an accuracy of 98.6%, which is a remarkable improvement, as shown in Fig. 13.

5.4. Result comparison

In previous studies regarding vehicle diagnostics, the authors focused mostly on the vehicles' critical condition. As shown in Table 8, the authors focused on a very limited number of problems. The authors applied different techniques, like Artificial Neural Networks and MFCC SVM. In one study, Artificial Neural Networks were applied to the data, and the accuracy of the results went up to 67% for some problems.

For some problems, the accuracy was only 56%. A study was also conducted on bike data, focusing on four problems. In 3rd top study, the authors focused on the three problems and achieved a maximum accuracy of 96%.

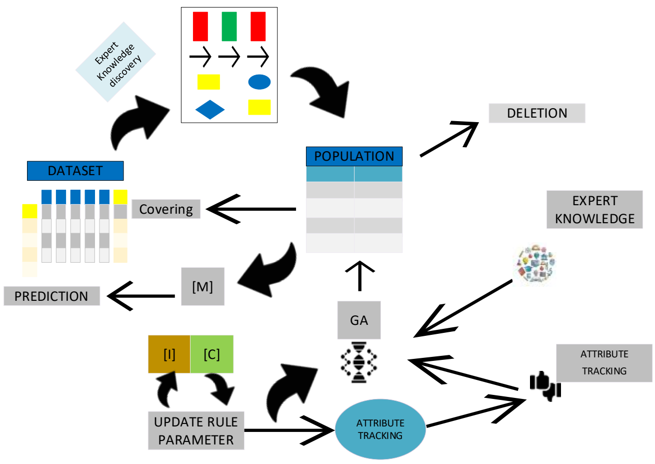


Fig. 11: ExSTra CS architecture diagram

Table 8: Audio analysis comparison

Reference	Problems	Technique	Results
Navea and Sybingco (2013)	Vehicle drive belt analyzer, engine start analyzer, tune-up analyzer	ANN	56% for the vehicle drive belt analyzer and engine start analyzer. 67% for tune-up analyzer
Dandare and Dudul (2014)	Air filter fault, Insufficient fuel supply, and insufficient lubricant fault	ANN, SVM	96%
Kemalkar and Bairagi (2016)	Bike oil fault, chain fault, crank fault, and valve fault	MFCC	56% to as high as more than 75% for some faults
Mishra et al. (2017)	Music content analysis	SoundLIME	Accuracy of 85%
Zinemanas et al. (2021)	Sound classification	TCN	Accuracy of 93%,94.6% and 97 % in different data sets
Wang et al. (2023)	Heart sound classification	CNN	Accuracy of 65.2%
Carter et al. (2023)	Heart conditions with spectrogram	CNN and LSTM	Mean accuracy of 86.7%
Yong et al. (2023)	Vehicle interior sound quality	XGBoost	94.3%
Our study	Normal/abnormal condition of the car has fifteen different problems	LCS	98.6%

A_0	A_1	A_2	A_3	R_0	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_10	R_11	R_12	R_13	R_14	R_15	Class
1	1	0	1	0	#	1	#	#	#	0	0	#	#	1	1	1	0	0	1	0
1	0	1	0	1	#	1	#	#	#	1	1	#	#	0	#	0	0	0	0	0
1	0	1	0	1	#	1	#	#	#	1	1	#	#	0	1	1	0	0	0	0
1	1	#	#	#	#	0	#	#	#	#	1	#	#	#	#	0	0	#	0	0
1	1	#	#	#	#	0	#	#	#	#	1	#	#	#	#	#	0	0	0	0
0	0	1	0	#	#	0	#	#	#	#	0	#	#	#	#	1	#	1	0	0
#	1	0	#	#	#	0	#	#	#	#	1	#	#	#	#	0	0	#	0	0

Fig. 12: Rules cluster

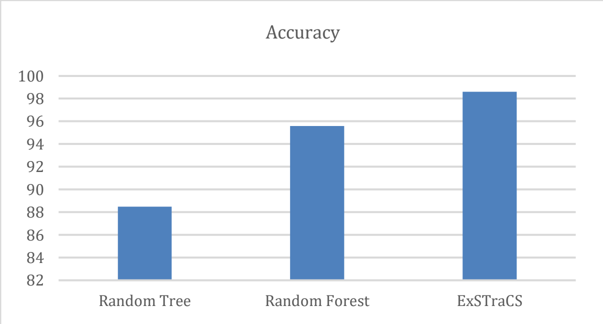


Fig. 13: Performance comparison with conventional ML classifiers

The problems targeted in this study are different We did extensive research on the issue of vehicles by addressing more issues that were not previously examined in other studies. Moreover, previous studies focused on a single type of car, but we focused on the different types of cars in our study. We obtained 98% accuracy in detecting the normal and abnormal conditions of the vehicle.

6. Conclusion

The analysis of vehicle engine sounds for diagnosing potential issues is an emerging area of research with limited existing literature. Engine sounds can be represented using spectrograms, which display frequency, amplitude, and time. While various sound analysis techniques have been developed for fields such as machine fault detection, healthcare, music, and speech recognition, these methods are not well-suited to vehicle engine sounds, which have unique characteristics. Traditional approaches may fail to capture the specific features and variations in engine noise that are critical for accurate diagnosis.

Different engine problems produce distinct acoustic patterns in their spectrograms, particularly in terms of resonance frequencies. This study shows that these unique sound features can be used to identify different engine faults. Accurate sound-based diagnosis is both important and challenging, with valuable applications in vehicle maintenance and performance improvement. Early detection of engine issues can lead to better performance and the development of quieter engines.

The goal of this research is to automatically detect various engine problems by analyzing engine sounds. ML algorithms have shown strong performance in pattern recognition tasks across many domains. However, ML models often operate as black boxes, offering limited transparency and interpretability. In contrast, rule-based systems, such as LCSs, can generate understandable rules after training, providing insights into their decision-making processes. However, LCS suffers from some constraints. Scalability of rules, generalization, computational complexity, and interpretability are these issues. Scalability of rules refers to the number of rules required to handle every scenario. The ability of the rules to handle novel or unobserved instances is known as rule generalization. The amount of time and resources required to run the LCS algorithm is known as computational complexity. Interpretability is the degree to which the rules produced by the LCS algorithm are simple to comprehend. To overcome these obstacles, researchers have suggested several tactics, including the use of ensemble learning to enhance rule generalization and feature selection techniques to lower rule complexity. To minimize dimensionality and noise, feature selection approaches identify the most pertinent characteristics of the data. Several models are combined in ensemble learning to increase diversity and overall performance. To handle large-scale sound datasets, the computational complexity still presents a hurdle that calls for optimization techniques. In addition, a lot of the rules generated by LCS may be hard for domain specialists to understand.

Acoustic-based engine diagnosis of a vehicle is a growing research field with many practical applications in different domains. In addition to saving both time and cash on manual inspections, this task can enhance vehicle performance and safety. Because there isn't a standardized dataset for engine problems, generating more exact rules would be possible with more diversified and reliable data. But doing so would also make the system's computations more difficult. Subsequent investigations ought to concentrate on merging LCS with deep learning methodologies, including convolutional neural networks, to improve feature extraction and classification precision.

List of abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
AR	Autoregressive
ASG	Active sound generation
BCS	Bayesian classifier system
CNN	Convolutional neural network
CWT	Continuous wavelet transform
DFT	Discrete Fourier transform
DL	Deep learning
DNN	Dense neural network
EEG	Electroencephalogram
ERBML	Evolutionary rule-based machine learning
ExSTra CS	Extended supervised tracking and classifier system
FFT	Fast Fourier transform
GACS	Genetic algorithm classifier system

HHT	Hilbert-Huang transform
HMM	Hidden Markov models
kNN	k-nearest neighbors
LCS	Learning classifier system
LIME	Local interpretable model agnostic explanations
LPCCs	Linear prediction cepstral coefficients
LRP	Layer-wise relevance propagation
LSTM	Long short-term memory
MFCC	Mel frequency cepstral coefficients
ML	Machine learning
MT	Mel transform
PLP	Perceptual linear prediction
PSD	Power spectral density
RBCS	Rule-based classifier system
RLCS	Reinforcement learning classifier system
SHAP	SHapley additive explanations
ST	Stockwell transform
STE	Short-time energy
STFT	Short-time Fourier transform
SVM	Support vector machine
TCN	Temporal convolutional network
TCAV	Testing with concept activation vectors
WT	Wavelet transform
XAI	Explainable artificial intelligence
ZCR	Zero crossing rate

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Ahmed A, Qureshi KN, Anwar M, Masud F, Imtiaz J, and Jeon G (2024). Link-based penalized trust management scheme for preemptive measures to secure the edge-based Internet of Things networks. Wireless Networks, 30: 4237-4259. https://doi.org/10.1007/s11276-022-02948-4

Ali G, Anwar M, Nauman M, Faheem M, and Rashid J (2023). Lyme rashes disease classification using deep feature fusion technique. Skin Research and Technology, 29: e13519. https://doi.org/10.1111/srt.13519

Anwar M, Masud F, Butt RA, Idrus SM, Ahmad MN, and Bajuri MY (2022). Traffic priority-aware medical data dissemination scheme for IoT based WBASN healthcare applications. Computers, Materials and Continua, 71: 4443-4456. https://doi.org/10.32604/cmc.2022.022826

Becker S, Vielhaben J, Ackermann M, Müller KR, Lapuschkin S, and Samek W (2024). AudioMNIST: Exploring explainable artificial intelligence for audio analysis on a simple benchmark. Journal of the Franklin Institute, 361(1): 418-428. https://doi.org/10.1016/j.jfranklin.2023.11.038

Bilal M, Ali G, Iqbal MW, Anwar M, Malik MSA, and Kadir RA (2022). Auto-Prep: Efficient and automated data preprocessing pipeline. IEEE Access, 10: 107764-107784. https://doi.org/10.1109/ACCESS.2022.3198662

Burhan M, Alam H, Arsalan A, Rehman RA, Anwar M, Faheem M, and Ashraf MW (2023). A comprehensive survey on the cooperation of fog computing paradigm-based IoT applications: Layered architecture, real-time security issues, and solutions. IEEE Access, 11: 73303-73329. https://doi.org/10.1109/ACCESS.2023.3294479

Cao Y, Hou H, Liu Y, Tang L, and Li Y (2020). Engine order sound simulation by active sound generation for electric vehicles. SAE International Journal of Vehicle Dynamics Stability and NVH, 4(2): 151-164. https://doi.org/10.4271/10-04-02-0011

Carter TS, Yang GH, Loke G, and Yan W (2023). Deciphering simultaneous heart conditions with spectrogram and explainable-AI approach. Biomedical Signal Processing and Control, 85: 104990. https://doi.org/10.1016/j.bspc.2023.104990

Chen C, Liu Y, Sun X, Di Cairano-Gilfedder C, and Titmus S (2021). An integrated deep learning-based approach for automobile maintenance prediction with GIS data. Reliability Engineering and System Safety, 216: 107919. https://doi.org/10.1016/j.ress.2021.107919

Chen H, Xie W, Vedaldi A, and Zisserman A (2020). Vggsound: A large-scale audio-visual dataset. In the IEEE International Conference on Acoustics Speech and Signal Processing, IEEE, Barcelona, Spain: 721-725. https://doi.org/10.1109/ICASSP40776.2020.9053174

Dandare SN and Dudul SV (2014). Multiple fault detection in an automobile engine using single sensor system. International Journal of Computer Science and Mobile Computing, 3(5): 635-647.

Dee Miller L, Soh LK, and Scott S (2015). Genetic algorithm classifier system for semi-supervised learning. Computational Intelligence, 31: 201-232. https://doi.org/10.1111/coin.12018

Dissanayake T, Fernando T, Denman S, Sridharan S, Ghaemmaghami H, and Fookes C (2020). A robust interpretable deep learning classifier for heart anomaly detection without segmentation. IEEE Journal of Biomedical and Health Informatics, 25: 2162-2171. https://doi.org/10.1109/JBHI.2020.3027910

Gemmeke JF, Ellis DP, Freedman D, Jansen A, Lawrence W, Moore RC, Plakal M, and Ritter M (2017). Audio Set: An ontology and human-labeled dataset for audio events. In the IEEE International Conference on Acoustics Speech and Signal Processing, IEEE, New Orleans, USA: 776-780. https://doi.org/10.1109/ICASSP.2017.7952261

Hussain M, Bilal A, Faheem M, Anwar M, and Zia MS (2023). A conditioned reflex action embedded associative context learning-based energy efficient paradigm in smart city milieu. IET Wireless Sensor Systems, 13: 151-162. https://doi.org/10.1049/wss2.12064

Kemalkar AK and Bairagi VK (2016). Engine fault diagnosis using sound analysis. In the International Conference on Automatic Control and Dynamic Optimization Techniques (ICACDOT), IEEE, Pune, India: 943-946. https://doi.org/10.1109/ICACDOT.2016.7877726

Keshun Y and Huizhong L (2023). Feature detection of mineral zoning in spiral slope flow under complex conditions based on improved YOLOv5 algorithm. Physica Scripta, 99: 016001. https://doi.org/10.1088/1402-4896/ad0f7d

Khaliq A, Kashif SAR, Ahmad F, Anwar M, Shaheen Q, Akhtar R, Shah MA, and Abdelmaboud A (2022). Indirect vector control of linear induction motors using space vector pulse width modulation. Computers, Materials and Continua, 74: 6263-6287. https://doi.org/10.32604/cmc.2023.033027

Kumar J, Sharma S, and Bharti AK (2022). Fault detection and classification in automobile engine based on its audio signature using support vector machine. In: Kumar A and

Mozar S (Eds.), ICCCE 2021: Proceedings of the 4th International Conference on Communications and Cyber Physical Engineering: 103-114. Springer Nature, Singapore, Singapore. https://doi.org/10.1007/978-981-16-7985-8_11

Marzo A, Seah SA, Drinkwater BW, Sahoo DR, Long B, and Subramanian S (2015). Holographic acoustic elements for manipulation of levitated objects. Nature Communications, 6: 8661. https://doi.org/10.1038/ncomms9661

Mishra S, Sturm BL, and Dixon S (2017). Local interpretable model-agnostic explanations for music content analysis. In the Proceedings of the 18th ISMIR Conference, Suzhou, China: 537-543.

Mu W, Yin B, Huang X, Xu J, and Du Z (2021). Environmental sound classification using temporal-frequency attention based convolutional neural network. Scientific Reports, 11: 21552. https://doi.org/10.1038/s41598-021-01045-4

Nasim F, Masood S, Jaffar A, Ahmad U, and Rashid M (2023b). Intelligent sound-based early fault detection system for vehicles. Computer Systems Science and Engineering, 46: 3175-3190. https://doi.org/10.32604/csse.2023.034550

Nasim F, Yousaf MA, Masood S, Jaffar A, and Rashid M (2023a). Data-driven probabilistic system for batsman performance prediction in a cricket match. Intelligent Automation and Soft Computing, 36: 2865-2877. https://doi.org/10.32604/iasc.2023.034258

Navea RF and Sybingco E (2013). Design and implementation of an acoustic-based car engine fault diagnostic system in the Android platform. In the Proceedings of the International Research Conference in Higher Education, Manila, Philippines.

Ndou N, Ajoodha R, and Jadhav A (2021). Music genre classification: A review of deep-learning and traditional machine-learning approaches. In the IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), IEEE, Toronto, Canada: 1-6. https://doi.org/10.1109/IEMTRONICS52119.2021.9422487

Qureshi KN, Abdullah AH, Mirza A, and Anwar RW (2015). Geographical forwarding methods in vehicular ad hoc networks. International Journal of Electrical and Computer Engineering, 5: 1407-1416. https://doi.org/10.11591/ijece.v5i6.pp1407-1416

Rashidi SF, Olfati M, Mirjalili S, Platoš J, and Snášel V (2025). A comprehensive DEA-based framework for evaluating sustainability and efficiency of vehicle types: Integrating undesirable inputs and social-environmental indicators. Cleaner Engineering and Technology, 27: 100989. https://doi.org/10.1016/j.clet.2025.100989

Rehmani F, Shaheen Q, Anwar M, Faheem M, and Bhatti SS (2024). Depression detection with machine learning of structural and non-structural dual languages. Healthcare Technology Letters, 11: 218-226. https://doi.org/10.1049/htl2.12088

Sahin SE, Gulhan G, Barua PD, Tuncer T, Dogan S, Faust O, and Acharya UR (2023). PrismPatNet: Novel prism pattern network for accurate fault classification using engine sound signals. Expert Systems, 40: e13312. https://doi.org/10.1111/exsy.13312

Schönberner C and Tomforde S (2022). Deep reinforcement learning with a classifier system–first steps. In: Schulz M, Trinitis C, Papadopoulou N, and Pionteck T (Eds.), International conference on architecture of computing systems: 256-270. Springer International Publishing, Cham, Switzerland. https://doi.org/10.1007/978-3-031-21867-5_17

Segel LA and Slemrod M (1989). The quasi-steady-state assumption: A case study in perturbation. SIAM Review, 31: 446-477. https://doi.org/10.1137/1031091

Singh AK and Krishnan S (2023). Trends in EEG signal feature extraction applications. Frontiers in Artificial Intelligence, 5: 1072801. https://doi.org/10.3389/frai.2022.1072801

Theissler A, Pérez-Velázquez J, Kettelgerdes M, and Elger G (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. Reliability Engineering and System Safety, 215: 107864. https://doi.org/10.1016/j.ress.2021.107864

Ullah KA, Rehman F, Anwar M, Faheem M, and Riaz N (2023). Machine learning-based prediction of osteoporosis in postmenopausal women with clinical examined features: A quantitative clinical study. Health Science Reports, 6: e1656. https://doi.org/10.1002/hsr2.1656

van de Schoot R, Depaoli S, King R, Kramer B, Märtens K, Tadesse MG, Vannucci M, Gelman A, Veen D, Willemsen J, and Yau C (2021). Bayesian statistics and modelling. Nature Reviews Methods Primers, 1: 1. https://doi.org/10.1038/s43586-020-00001-2

Wang Z, Qian K, Liu H, Hu B, Schuller BW, and Yamamoto Y (2023). Exploring interpretable representations for heart sound abnormality detection. Biomedical Signal Processing and Control, 82: 104569. https://doi.org/10.1016/j.bspc.2023.104569

Wu Z, Wan Z, Ge D, and Pan L (2022). Car engine sounds recognition based on deformable feature map residual network. Scientific Reports, 12: 2744. https://doi.org/10.1038/s41598-022-06818-z

Yong ZH, Fei-Tan PE, E-Chuan YA, Ke-Lin RE, and Jian RK (2023). Prediction and analysis of vehicle interior sound quality based on XGBoost algorithm. Noise and Vibration Control, 43(3): 161-166.

You K, Qiu G, and Gu Y (2023). An efficient lightweight neural network using BiLSTM-SCN-CBAM with PCA-ICEEMDAN for diagnosing rolling bearing faults. Measurement Science and Technology, 34: 094001. https://doi.org/10.1088/1361-6501/acd5ef

Zaman K, Sah M, Direkoglu C, and Unoki M (2023). A survey of audio classification using deep learning. IEEE Access, 11: 106620-106649. https://doi.org/10.1109/ACCESS.2023.3318015

Zinemanas P, Rocamora M, Miron M, Font F, and Serra X (2021). An interpretable deep learning model for automatic sound classification. Electronics, 10(7): 850. https://doi.org/10.3390/electronics10070850