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Research Paper

Developing Car Engine Noise Recognition Using Artificial Intelligence and Machine-Learning Applications

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Abstract
In the era of Industrial Revolution 4.0 (IR4.0), technology continues to advance at an unprecedented pace. One prominent innovation in this realm is the Internet of Things (IoT), which has significantly improved the operational efficiency of car engines while simultaneously reducing maintenance costs. However, to fully harness the benefits of this progress, car owners need to possess a fundamental understanding of identifying and addressing engine faults. Addressing this need, this study focuses on the development of a sophisticated system that utilizes Artificial Intelligence (AI) and Machine Learning (ML) applications to identify and diagnose car engine noise. By employing various machine-learning algorithms and analyzing the distinct characteristics of car air conditioning belting noise, the system aims to provide an efficient and reliable solution. To accomplish this, the study utilizes a Personal Audio Classifier (PAC) framework, which effectively manages and categorizes the collected samples in the machine learning process. The preliminary results demonstrate accuracies ranging from 70% to 80%, indicating the system's potential for successful identification and classification of car engine noise. With the advent of IR4.0 and the integration of IoT, this research contributes to the ongoing evolution of automotive technology by providing car owners with an accessible and effective tool to identify and address faulty car engines. By leveraging the power of AI and ML, this system holds the promise of optimizing car engine maintenance, reducing costs, and enhancing overall performance.

Keywords: Artificial intelligence; Engine noise detection; Machine-learning application

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I. Introduction

Similar to artificial intelligence (AI) techniques like machine learning and deep learning, smart automation has emerged as a transformative approach that minimizes human involvement in machine operations. By employing embedded data-driven methodologies, intelligent smart automation systems can accurately forecast operational requirements with high precision [1]. This results in error-free operations and improved operational efficiency [2][3].

When a car engine experiences faults, it produces a distinct and significant sound spectrum [4][5][6][7]. Therefore, it is essential for automobile owners to be vigilant about their vehicle's engine health, particularly if the vehicle is older than ten years. However, many car owners lack the technical knowledge necessary to identify engine problems, such as differentiating between the various sounds produced during engine operation [8].

Similarly, the mechanical processes involved in propelling trains generate diverse engine noises, including exhaust noise, fan rotation, and vibrations from the cooling and transmission systems. These noises are commonly referred to as motor noise, power-unit noise, or traction noise [9]. Before the advent of electric trains, engine noise typically dominated the acoustic environment, especially at speeds below 60 kilometers per hour. Predominant frequency bands are established in areas with high noise levels [10]. Most of the sound energy below 20 Hz is primarily caused by road-induced vibrations transmitted through the wheel and suspension system, while acceptable noise within the audible range (30-300 Hz) mainly arises from body resonance resulting from various motor harmonics [11].

The vibrations in non-electric trains are generated by the combustion process in each cylinder and the associated pressure waves in the intake and exhaust systems. The intake and exhaust systems are positioned at the engine's rotational speed, with the pitch changing as the RPM increases or decreases [12]. Calculating the dominant frequency at any given RPM is a straightforward process [13]. The overall timbre of the engine is influenced by numerous variables, including additional structural and piping vibrations occurring at the firing rate. Most performance-oriented automobiles exhibit aggressive exhaust notes, with frequencies 2.5 to 3.5 times higher than the firing frequency, providing a desired sensation, particularly in sports vehicles. Typically, modifications are made at the exhaust port, and the relative volume of different frequency ranges determines the distinct characteristics of each engine's sound. These variations generate the engine's unique chord structure based on the root note. However, it remains unclear which supplementary frequencies are produced by the sound, vibration, and rigidity engineering (NVH) and which frequencies are suppressed. An exhaust system cancels out some unwanted frequencies that may otherwise resonate in the cabin at a given load and RPM. Each engine sound is the result of a symphony of factors, including bushings, pipe lengths, numerous metal sheet pieces with varying thicknesses, and other design elements like exhaust arrangement, isolation, and body shell [14].

To address the challenge of identifying car engine noise, this study presents a system that utilizes AI and machine learning applications. Machine learning algorithms were employed to analyze the function of car air conditioning belting noise as a representative sample. This research aims to develop an effective approach for accurately identifying and categorizing car engine noise, thereby assisting car owners in recognizing and addressing potential engine issues.

II. Methodology

This study employed a noise recognition system to enable end users to identify the noise produced by a car engine. The system utilized the smartphone's microphone to capture and acquire noise samples, which were then processed using the integrated machine-learning application. The collected data were uploaded to a dedicated database for further analysis, and the results were displayed on the front end of the mobile application for user interaction. The display provided information on various engine noise symptoms stored in the database.

The software implementation of the system utilized the web application MIT App Inventor, which is an integrated development environment initially developed by Google and currently maintained by the Massachusetts Institute of Technology (MIT). This web application enabled the creation of the mobile application software (app) specifically for the Android operating systems [15]. MIT App Inventor is an open-source software, and its source code is licensed under the Creative Commons Attribution-Share Alike 3.0. It offers a graphical user interface (GUI) similar to Scratch and Star Logo, allowing users to easily drag and drop visual objects to build applications for Android devices.

2.1 Layout of the Final System Application

The back-end of the system application was developed using MIT App Inventor, which facilitated the integration of interactive AI modules. This programming tool enabled the definition and troubleshooting of system modules using error codes, significantly reducing the time required to identify engine problems. Figure 1 presents the completed back-end code, demonstrating the implementation of the system's functionality

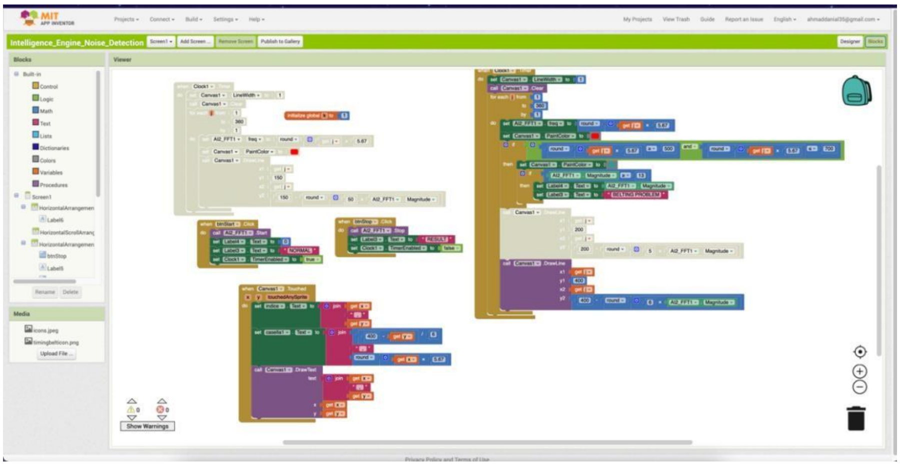
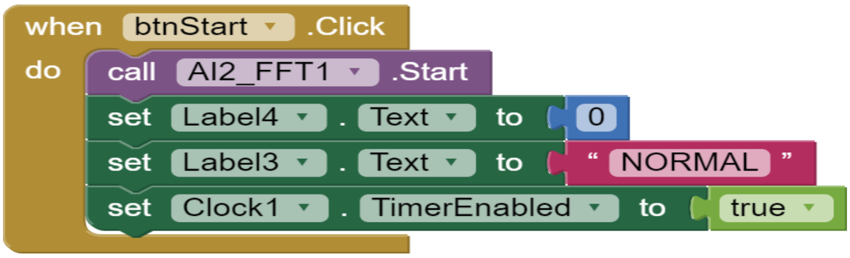


Fig. 1. The back-end development of the MIT Inventor

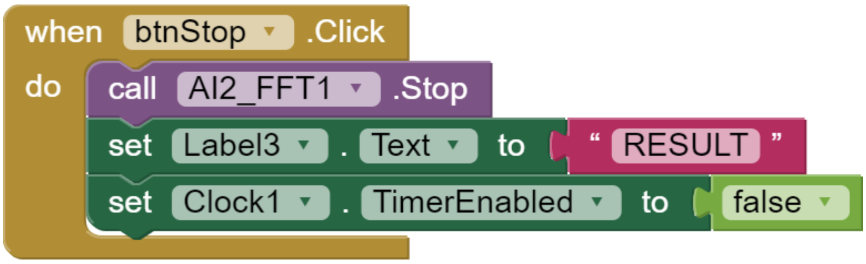
2.2 The Back-End System, Start Button, Stop Button, and Troubleshooting Component

The back-end system served as a foundation for integrating all the collected data, including data samples and machine-learning algorithms, with the functionality of the buttons and components present in the front-end user interfaces (UIs). Within the front-end layout, pressing the start button (Figure 2) triggered the activation of the Fast Fourier Transform (FFT) algorithm, while simultaneously initiating the timer to record noise samples captured by the smartphone's microphone. Conversely, pressing the stop button (Figure 3) halted the operation of the FFT algorithm and the timer. The recorded noise samples were then compared with the sound samples stored in the system and subsequently displayed on the front-end layout for user interaction and analysis. The back-end system furnished a platform for connecting all the collected data, such as data samples and machine-learning algorithms, to the functionality of the buttons and components at the front-end for the interaction with User Interfaces (UIs). Pressing the start button at the front-end layout would initiate the Fast Fourier Transformer (FFT), switching on the timer to record noise samples from the phone microphone (Figure 2).



```
when btnStart .Click
do  call AI2_FFT1 .Start
    set Label4 . Text to 0
    set Label3 . Text to " NORMAL "
    set Clock1 . TimerEnabled to true
```

Fig. 2. The initiation of the "Start" button



```
when btnStop .Click
do  call AI2_FFT1 .Stop
    set Label3 . Text to " RESULT "
    set Clock1 . TimerEnabled to false
```

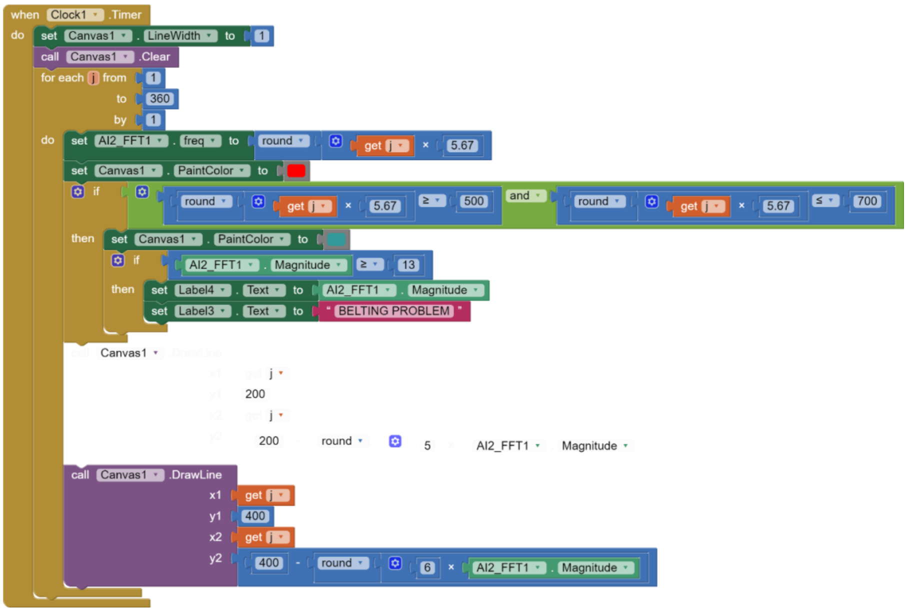
Fig. 3. The algorithm of the "Stop" button

On the other hand, pressing the stop button (Figure 3) would stop the operation of FFT and the timer. Recorded samples were compared with the sound sample in the sound samples stored in the system and subsequently displayed on the front-end layout for user interaction and analysis.

Meanwhile, the troubleshooting component was developed to obtain samples from the phone microphones for analysis. By default, this component would provide a graph with coordinate points for the magnitudes and frequencies of x on the front-end layout.

2.3 Component Integration

Integrating various components (Figure 4) was crucial for the back-end system to run smoothly and perform as planned. When reaching an interval of 200 ms, three events would happen. They included receiving and graphing the magnitude spectrum on each running frequency (0 - 20 kHz), making the belting audio sound available within the standard audio range of 5 - 7 kHz, and automatically triggering and setting the result on label 3 to Belting Problem when the magnitude was higher than the standard range.



```
when Clock1 .Timer
do  set Canvas1 . LineWidth to 1
    call Canvas1 .Clear
    for each j from 1
                 to 360
                 by 1
    do  set AI2_FFT1 . freq to round ( get j × 5.67 )
        set Canvas1 . PaintColor to
        if ( round ( get j × 5.67 ) ≥ 500 ) and ( round ( get j × 5.67 ) ≤ 700 )
        then set Canvas1 . PaintColor to
             if AI2_FFT1 . Magnitude ≥ 13
             then set Label4 . Text to AI2_FFT1 . Magnitude
                  set Label3 . Text to " BELTING PROBLEM "
        Canvas1
                  j
                  200
                  j
                  200   round   5   AI2_FFT1   Magnitude
        call Canvas1 .DrawLine
                  x1 get j
                  y1 400
                  x2 get j
                  y2 400 - round ( 6 × AI2_FFT1 . Magnitude )
```

Fig. 4. Component integration

2.4 The Front-End Design Application

The application's UI was the point for users to interact with the system. The front-end design for this program was created using MIT Inventor apps coupled with the back-end to allow easy access for the developer to modify or improve the system. Figure 5 shows the finalised design of the application's front end

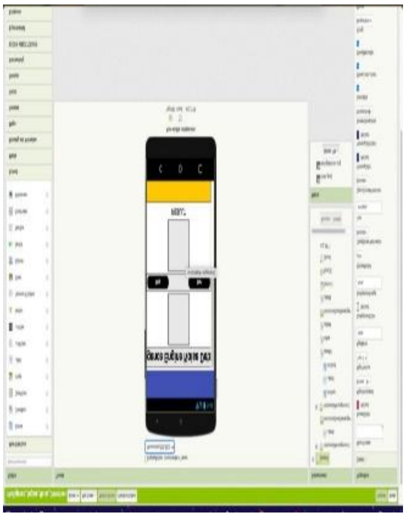


Fig. 5. The front-end design of the MIT Inventor apps

III. Results

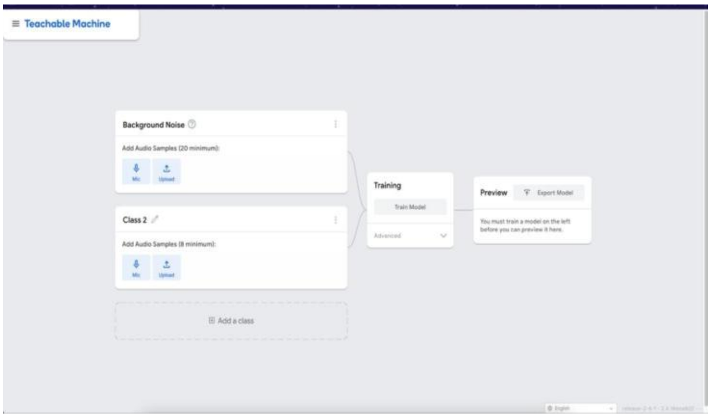
3.1 Data Sampling Analysis

The data sampling and analysis phase involved the utilization of Google's Teachable Machine to facilitate the collection and processing of data. This platform was employed to train the system in recognizing and distinguishing various data inputs associated with the intended actions of the software. Figure 6 depicts the interface of Google's Teachable Machine, which was used for this purpose.

Once the data samples were collected, they were subjected to analysis using a machine-learning technique known as Convolutional Neural Networks (CNN). CNNs are widely used for image and pattern recognition tasks, making them well-suited for analyzing and classifying complex data inputs. The collected noise samples were transformed into spectrograms, which are visual representations of the frequency content of the sound signals. These spectrograms were then used as input data for the CNN algorithm.

The CNN algorithm was trained on the collected data samples, enabling it to learn and identify distinct patterns and characteristics associated with different engine noise types. The training process involved iteratively adjusting the weights and biases of the neural network to minimize the error between the predicted outputs and the actual labeled noise samples. This iterative training process continued until the CNN achieved a satisfactory level of accuracy in classifying the engine noise samples.

The trained CNN model was subsequently tested on a separate set of validation data to evaluate its performance and generalization ability. The accuracy of the model was assessed by comparing the predicted noise classifications with the ground truth labels assigned to the validation samples. Through this data sampling analysis, the system was trained to accurately recognize and differentiate various engine noise patterns, thereby enabling it to effectively identify and categorize engine issues based on the recorded noise samples.



You must train a model on the left before you can preview it here.

Fig. 6. Google's teachable machine interfaces

3.2 Data Sampling for the Air-Conditioning Belting

In this study, a total of 100 data samples were collected from diverse car manufacturers and models to evaluate the system's performance in detecting the status of the air conditioning belting. These samples encompassed both non-problematic states and faulty conditions. The results of the analysis revealed that the system achieved a commendable accuracy of 86% in identifying the typical non-problematic state of the air conditioning belting (Figure 7). This indicates that the system was able to accurately classify the noise patterns associated with a well-functioning air conditioning belting in the majority of cases.

Furthermore, the system demonstrated remarkable performance in detecting faulty air conditioning belting, achieving an impressive accuracy of 95% (Figure 8). This suggests that the system excelled in identifying and distinguishing abnormal noise patterns associated with malfunctioning air conditioning belting. These results underscore the effectiveness and reliability of the developed system in recognizing both normal and faulty states of the air conditioning belting. The high accuracy rates obtained for both non-problematic and faulty conditions demonstrate the system's capability to assist car owners in promptly identifying potential issues with their vehicles' air conditioning systems based on the analysis of engine noise.

These findings validate the successful application of the machine-learning algorithms employed in this study, enabling accurate identification and classification of car engine noise related to the air conditioning belting

Fig. 7. The data sample for the standard air conditioning

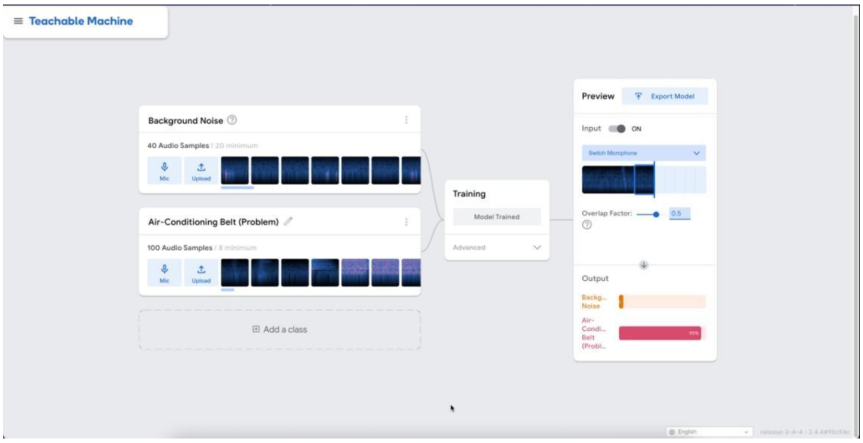


Fig. 8. Data sampling for the faulty air conditioning

3.3 Project Validation

Validation is a crucial procedure aimed at demonstrating the system's ability to meet the specified requirements. In this study, the data validation process involved a combination of design validation and rigorous testing to ensure the effectiveness and reliability of the software noise detection system.

Design validation involved a comprehensive evaluation of the system's architecture, algorithms, and data processing techniques against the intended objectives and requirements. This validation step ensured that the system was designed in a manner that facilitated accurate noise detection and classification.

To further validate the system's performance, rigorous testing was conducted. The software noise detection system underwent extensive testing to verify its functionality, robustness, and accuracy. Various test scenarios were employed to assess the system's ability to accurately identify and differentiate between different engine noise patterns, specifically focusing on the detection of air conditioning belting issues that can be seen in Figure 9 and Figure 10.

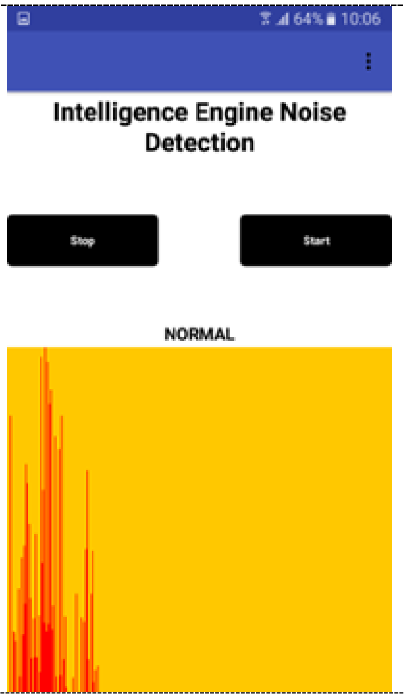


Fig. 9. Engine noise was detected in normal conditions

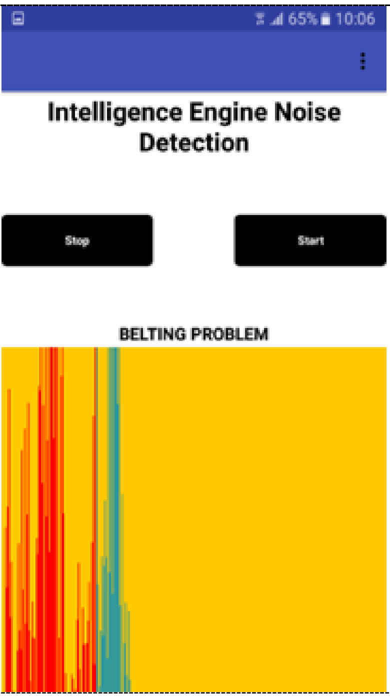


Fig. 10. Faulty air conditioning belting

IV. Conclusions

In this study, a sound spectrum identification system utilizing detection mechanisms and machine-learning applications was developed to analyze car engine noise. The system demonstrated an impressive accuracy rate of 90% in detecting the typical (non-problematic) car engine noise. Despite encountering several challenges during the initial development and implementation stages, all the project objectives were successfully achieved.

The significance of this research extends beyond the automotive industry. The methodology and findings have the potential to be applied in various other industries, contributing to the improvement of community activities in our daily lives. The ability to accurately identify and differentiate between different engine noise patterns using machine-learning techniques opens doors for advancements in noise analysis and troubleshooting across multiple sectors.

The high accuracy rate achieved by the system in detecting non-problematic car engine noise is a testament to its reliability and effectiveness. Car owners can leverage this technology to gain valuable insights into the health and performance of their vehicles' engines, enabling them to take proactive measures and address potential issues promptly. This can lead to enhanced vehicle maintenance, reduced downtime, and improved overall safety and efficiency on the roads.

Furthermore, the successful development and implementation of this system highlight the potential of combining detection mechanisms and machine-learning applications in solving complex real-world challenges. The study serves as a valuable contribution to the field of automotive diagnostics and showcases the power of data-driven methodologies in improving decision-making processes and operational efficiency.

In conclusion, this research successfully developed a sound spectrum identification system for car engines using machine-learning applications. With a remarkable accuracy rate of 90% in detecting non-problematic engine noise, the study has fulfilled its objectives despite initial setbacks. The potential applications of this research extend beyond the automotive industry, offering opportunities for advancements in various sectors and positively impacting our daily lives.

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