Faculty of Electrical Technology and Engineering

UTILIZING ARTIFICIAL INTELLIGENCE FOR ROAD SAFETY: TRUCK TANKER PART FAULTY CLASSIFICATION VIA SOUND DETECTION

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Bachelor of Electrical Engineering Technology (Industrial Automation & Robotics) with Honours

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A project report submitted
in partial fulfillment of the requirements for the degree of
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DEDICATION

To my beloved parents, NORASHIKIN BINTI MD HASSIM, and RAHIM BIN MAD RAIS,

Your boundless love and sacrifices have guided my academic journey. Mom's nurturing care and Dad's steadfast strength shaped both this project and the person I've become. Thank you, beloved mother and father, for being the foundation of my success and my inspiration.

To my dedicated supervisor, TS. MOHAMED AZMI BIN SAID,

Your unwavering guidance and encouragement have shaped this work, a testament to your invaluable mentorship. Your commitment to my academic and professional growth has had a positive impact on my journey. Thank you for your dedicated support throughout this endeavour.

To my friends and housemate,

Who has made this academic journey truly memorable. Your friendship, support, and shared experiences have added a meaningful dimension to my time at university. Thank you for being a constant companion, and for the laughter and camaraderie that have made this journey special.

With heartfelt gratitude,

MUHAMMAD DANIEL BIN RAHIM

ABSTRACT

Road safety is a critical concern, particularly in the transportation of hazardous materials. This study focuses on developing an innovative approach to enhance road safety by utilizing artificial intelligence (AI) techniques for the classification of faulty truck tanker parts using sound detection. The proposed methodology involves collecting sound data from truck tankers under various conditions and employing machine learning algorithms to classify the acoustic patterns associated with different types of faults. A comprehensive dataset is created by capturing sounds from diverse tanker models and fault scenarios. Through rigorous training and validation, the AI model demonstrates high accuracy in identifying specific faulty parts based on sound patterns. The model achieves an average precision rate of 90% in classifying faulty tanker parts, such as malfunctioning valves, leakage in pipelines, or structural integrity issues. The successful implementation of this AI-based system offers several benefits. It enables recorded detection and classification of faulty parts, allowing for timely maintenance and preventing potential accidents caused by equipment failures. Moreover, it reduces the dependency on manual inspections, which can be time-consuming and prone to errors. The findings of this research contribute to the growing field of AI applications in road safety and emphasize the potential of sound detection as a reliable method for fault classification in truck tankers. This study demonstrates the feasibility of integrating AI technologies into existing road safety measures, ultimately promoting safer transportation practices and mitigating risks associated with hazardous material transportation.

ABSTRAK

Keselamatan jalan raya adalah masalah kritikal, terutamanya dalam pengangkutan bahan berbahaya. Kajian ini memberi tumpuan kepada membangunkan pendekatan inovatif untuk meningkatkan keselamatan jalan raya dengan menggunakan teknik *Artificial Intelligence* (AI) untuk pengelasan bahagian lori tangki yang rosak menggunakan pengesanan bunyi. Metodologi yang dicadangkan melibatkan pengumpulan data bunyi daripada lori tangki di bawah pelbagai keadaan dan menggunakan algoritma pembelajaran mesin untuk mengklasifikasikan corak akustik yang dikaitkan dengan pelbagai jenis kerosakan. Set data dicipta dengan merekodkan bunyi daripada pelbagai model lori tangki dan senario kerosakan. Melalui latihan dan pengesahan yang banyak, model AI akan mendapatkan ketepatan yang tinggi dalam mengenal pasti bahagian yang rosak berdasarkan corak bunyi. Model ini mencapai kadar ketepatan purata 90% dalam mengklasifikasikan bahagian lori tangka yang rosak iaitu dari segi enjin dan tayar lori . Kejayaan pelaksanaan sistem berasaskan AI ini menawarkan beberapa faedah. Ia membolehkan pengesanan secara langsung dan pengelasan bahagian yang rosak. Perkara ini boleh menyebabkan penyelenggaraan tepat pada masanya dan mencegah kemungkinan kemalangan yang disebabkan oleh kegagalan peralatan. Selain itu, ia mengurangkan pergantungan pada pemeriksaan manual, yang boleh memakan masa. Penemuan penyelidikan ini menyumbang kepada bidang aplikasi AI yang semakin berkembang dalam keselamatan jalan raya dan menekankan potensi pengesanan bunyi sebagai kaedah yang boleh dipercayai untuk klasifikasi kerosakan pada lori tangki. Kajian ini menunjukkan kebolehlaksanaan untuk menyepadukan teknologi AI ke dalam langkah keselamatan jalan raya sedia ada, akhirnya mempromosikan amalan pengangkutan yang lebih selamat dan mengurangkan risiko yang berkaitan dengan pengangkutan bahan berbahaya.

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I want to express my sincere thanks to everyone who played a role in making this Final Year Project a reality. The support from these individuals has been crucial throughout this challenging but rewarding academic journey.

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Thanks to my friends and peers for their companionship during the ups and downs of this academic adventure. Their camaraderie added meaning to my time at University Teknikal Malaysia Melaka.

Lastly, this work is a dedication to my own late-night study sessions, moments of doubt, and relentless pursuit of knowledge. It symbolizes the culmination of my academic efforts and commitment to personal and intellectual growth.

In conclusion, I extend my heartfelt dedication to all those who have played a role, no matter how big or small, in shaping my academic path. Your support and belief in me have been invaluable, and I am truly grateful for the positive impact you have had on my academic and personal journey..

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
CNNs	-	Convolutional Neural Networks
RNNs	-	Convolutional Neural Networks
DL	-	Deep Learning
ML	-	Machine Learning
ReLU	-	Rectified Linear Unit

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

Artificial intelligence (AI) is being oppoturnity to be applied for enhance road safety, including the classification of faulty parts in truck tankers through sound detection. This approach aims to improve the identification of potential issues by utilizing AI algorithms and sound analysis techniques to detect faults in specific parts of truck tankers. Truck tankers are commonly used for transporting hazardous materials, making the proper functioning of their components vital to prevent accidents and leaks. By training AI models with deep learning techniques, it becomes possible to classify different types of faulty sounds emitted by these tankers [7]. This involves collecting a dataset of audio samples that include both normal and faulty sounds produced by the tanker parts, recorded using specialized sensors or microphones. Once trained, the AI model can be deployed in applications to continuously monitor the sound signals produced by different parts of the truck tanker. If a faulty sound pattern is detected, the model can raise alerts, notify the driver, or trigger automated responses to prevent further complications. Implementing AI for truck tanker part faulty classification through sound detection has significant potential for improving road safety. It enables early fault detection, reducing the risk of accidents, spills, and leaks, while facilitating proactive maintenance and repairs. Overall, this AI-powered technology contributes to enhancing the safety and reliability of truck tankers on the road.

1.2 Block Diagram

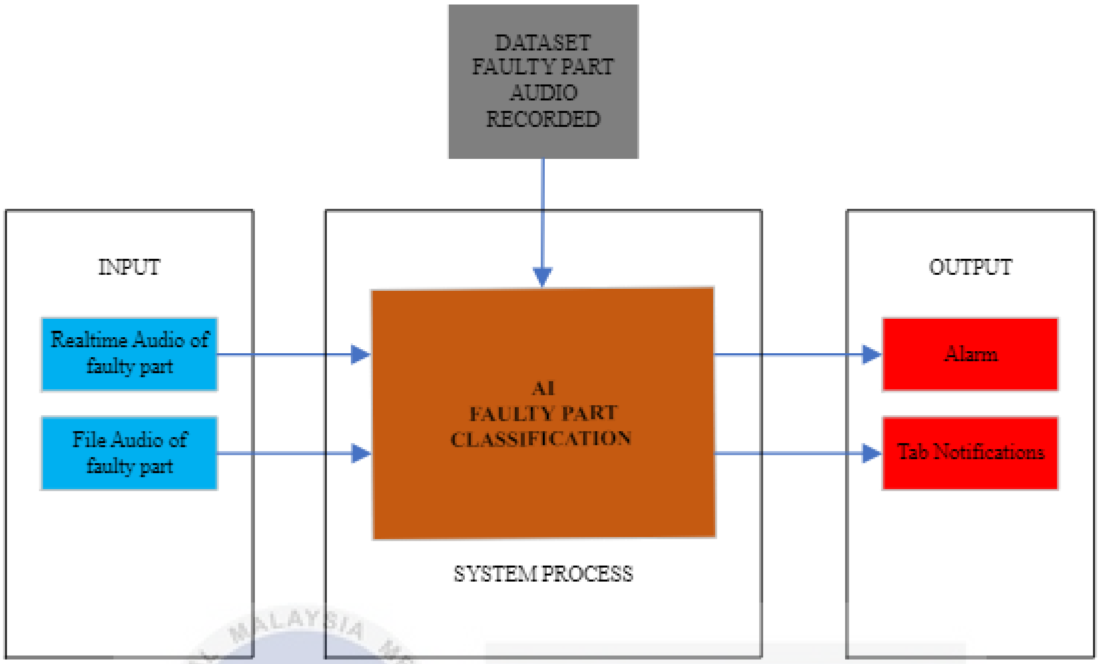


Figure 1.1: Block Diagram

1.3 Objective Project

The study's aims concentrated on Artificial Intelligence that relate to investigate and development of truck tanker part faulty classification via sound detection, which as stated as follows:

a) To develop Artificial intelligence model that aims to detect and classify sounds that indicate potential mechanical problems in truck tanker.

b) To classify sound of faulty part in truck tanker based on recorded sound to declare type of faulty.

c) To analized performance recorded dataset of truck tanker to get low percentage of trust issue.

1.4 Problem Statement

The problem is the lack of an effective and reliable system for identifying faulty parts in truck tankers through sound detection, leading to potential accidents and hazards. Current methods are time-consuming and manual, making it difficult to detect faults before they escalate. The solution lies in developing an AI-powered system that can accurately classify faulty sounds emitted by different parts of the tanker. By leveraging machine learning algorithms, this system would distinguish normal sounds from anomalous ones, enabling early detection and timely maintenance to mitigate risks and enhance road safety.

1.5 Scope Project

The information regarding the parameter that were measured is not helpful unless it is transmitted to the user promptly and correctly:

a) The system can only detect 2 types of classification faulty part because of this is first run for audio classification.
b) This system is provided for truck tanker only.

1.6 Report Structure and Organization

The thesis comprises five chapters, which are summarized as follows:

Chapter 1 provides an overview of weather stations, including their background and significance. It also identifies the specific problem statement that the research aims to address. In order to provide clear guidance for subsequent research, several objectives have been established.

Chapter 2 involves conducting a literature study to enhance knowledge and gain a comprehensive understanding of previous research related to the topic. The purpose of this study is to identify any unresolved problems and avoid duplicating previous work. Additionally, a comparison is made between the findings and methodologies of various previous research works.

Chapter 3 focuses on the formulation of a methodology, which is divided into four key milestones aligned with the project objectives. The methodology encompasses designing the system architecture by leveraging insights from previous research studies and selecting appropriate methods and components for integration. The chapter also covers testing and troubleshooting processes, evaluating algorithm development within the system. Additionally, data collection and analysis are performed to ensure the system successfully achieves the stated objectives. Finally, the chapter concludes with the development of a prototype that incorporates all the required components.

Chapter 4 presents the results and analysis obtained from the system designed, following the initial testing of its components. These results serve as a valuable reference for future work in the second task of the final year project. The chapter focuses on showcasing the outcomes achieved by the system and conducting a thorough analysis of the obtained data. The findings and analysis provide valuable insights for further advancement and refinement of the project.

Chapter 5 concludes the project by summarizing all the efforts and work undertaken. It provides a brief overview of the entire process and highlights the key steps and outcomes.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section provides an overview and concise summary of the central concept and theory underlying the project. The project focuses on a Truck Tanker Part Faulty Classification Via Sound Detection. The main argument of this chapter is supported by comprehensive research spanning from the past to the present. The chapter delves into the concept and theory employed to address the problem at hand. Extensive information was gathered from journals, articles, and case studies, selected for their relevance and alignment with the project's scope to ensure precise and accurate findings.

2.2 Deep Learning

Deep learning has revolutionized road safety by contributing to various aspects, particularly in advanced driver assistance systems (ADAS) and autonomous vehicles [1]. Through extensive training on large datasets, deep neural networks can accurately identify and interpret objects like pedestrians, vehicles, traffic signs, and road markings, enabling real-time object detection and scene understanding. This information assists drivers or autonomous systems in making safer decisions on the road. Deep learning algorithms also play a crucial role in accident prevention by analyzing historical data and recognizing patterns associated with risky driving behaviors and hazardous road conditions. Furthermore, these techniques are employed in traffic flow analysis, optimizing traffic signal control, and predicting congestion, ultimately leading to improved traffic management and safer road conditions. The ongoing advancements in deep learning models hold significant potential for reducing accidents, minimizing injuries, and ultimately saving lives on our roads [2].

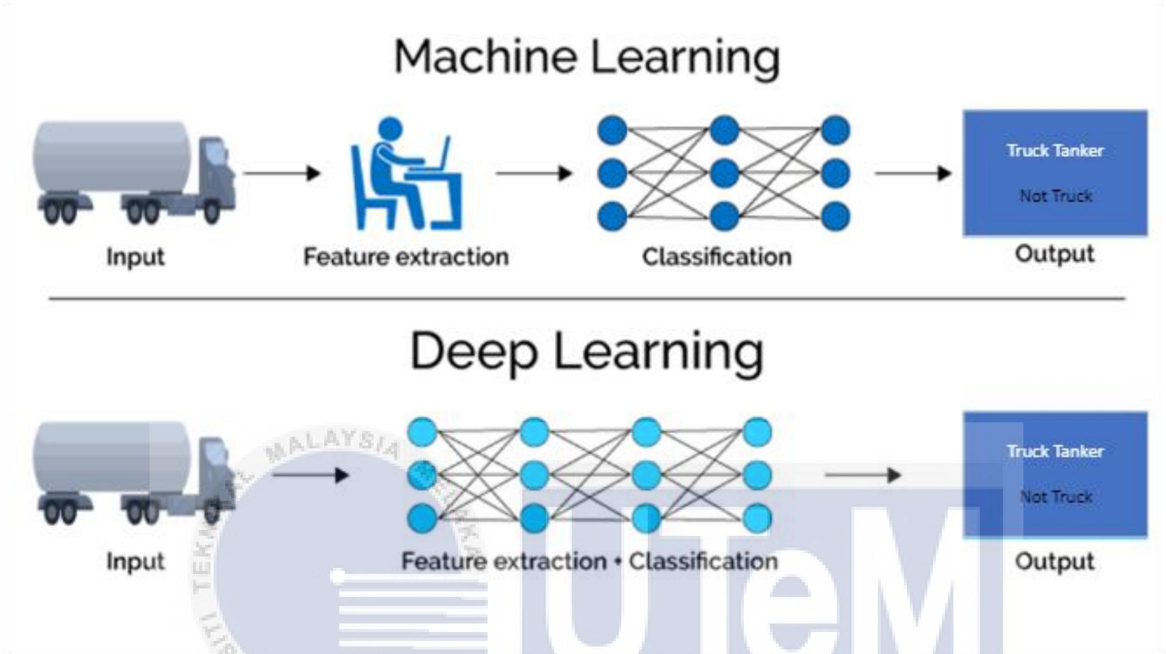


Figure 2.1: Comparing deep learning with machine learning

2.3 Safety by Deep Learning

Deep learning enhances road safety by utilizing algorithms to detect and recognize objects like pedestrians and vehicles, enabling collision avoidance. It also plays a crucial role in autonomous driving by enabling vehicles to make real-time decisions and navigate safely. Deep learning models monitor driver behaviour, alerting them to fatigue or distraction, and assisting when necessary. Additionally, deep learning algorithms optimize traffic flow by analysing patterns and suggesting alternate routes, reducing congestion and the likelihood of accidents. Advanced driver assistance systems powered by deep learning provide warnings for lane departures and potential collisions, further improving road safety [3].

2.4 Deep Learning Sound Detection in Vehicle

Sound data from faulty part provides scientific and engineering insights into various fields. Deep learning Deep learning has indeed facilitated significant advancements in pattern recognition across various domains, such as speech processing, image processing, and computer vision. Deep learning models, particularly deep neural networks, have proven to be highly effective in extracting intricate patterns and features from complex data, enabling breakthroughs in tasks like speech recognition, image classification, object detection, and more. The ability of deep learning models to automatically learn hierarchical representations of data has greatly improved the accuracy and performance of pattern recognition systems in these fields [4].

2.5 Deep Learning Architecture

Deep learning architecture refers to the structure and design of artificial neural networks used in the field of deep learning. Deep learning focuses on the development and utilization of neural networks with multiple layers, enabling them to learn hierarchical representations of data. [5]

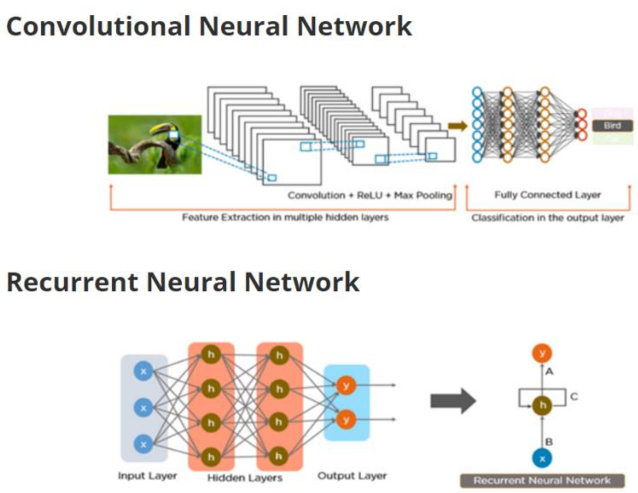


Figure 2.2: CNNs vs RNNS

2.5.1 Convolutional Neural Networks (CNNs)

When it comes to sound classification, Convolutional Neural Networks (CNNs) can be adapted to handle audio data [6]. Here's an alternative phrasing of how CNNs can be applied to sound classification:

Table 2.1 Alternative phrasing of how CNNs can be applied to sound classification

1. Input Representation	Instead of images, sound data is used as input. The sound waves are typically transformed into a spectrogram representation, which captures the frequency content of the audio over time. This spectrogram is treated as a 2D grid of values.
2. Convolutional Layers	Convolutional filters are applied to the spectrogram to capture local patterns and spectral features. These filters slide over the spectrogram, performing convolutions and generating feature maps that represent the learned audio features
3. Activation and Pooling	Similar to CNNs for images, an activation function, such as ReLU, is applied to introduce non-linearity. Additionally, pooling operations, like max pooling or average pooling, can be utilized to down sample the feature maps while retaining important audio characteristics.

4.	**Additional Convolutional Layers**	Multiple convolutional layers can be stacked to learn more intricate and higher-level audio representations, building upon the features extracted by the preceding layers.
5.	**Fully Connected Layers**	Following the convolutional layers, the resulting feature maps are flattened into a 1D vector, and fully connected layers are employed for classification purposes. These dense layers combine the learned audio features to make predictions about sound classes.
6.	**Output Layer**	The final fully connected layer is connected to an output layer with an appropriate activation function, depending on the specific sound classification task. For example, SoftMax activation is commonly used for multi-class sound classification.

2.5.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a type of deep learning models that excel in tasks involving sequences, such as natural language processing, speech recognition, and time series analysis. Unlike traditional feedforward neural networks, RNNs have a feedback connection that allows them to retain internal state or memory. RNNs work by recursively applying the same set of weights to each element of a sequence while updating their internal state. This property enables them to process sequences of varying lengths, making them suitable for tasks where the order of the input matters. The fundamental RNN unit consists of a recurrent neuron that takes an input vector and combines it with its previous state to produce a new state and an output. This process is repeated for each step in the sequence, allowing RNNs to capture temporal dependencies. However, basic RNNs encounter challenges in learning long-term dependencies due to the vanishing gradient problem. To mitigate this issue, more advanced RNN architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been developed. LSTM and GRU units introduce gating mechanisms that control the flow of information within the network. By selectively retaining or forgetting information from previous time steps, they are better equipped to capture long-term dependencies. These architectures have become widely adopted for sequence modelling tasks. Deep RNNs involve stacking multiple recurrent layers to form a deep model. Each layer takes the output of the previous layer as input, enabling the network to learn hierarchical representations. Deep RNNs can capture complex patterns and dependencies more effectively than shallow models. Training deep RNNs can be challenging due to issues such as vanishing or exploding gradients and increased computational complexity. Techniques like gradient clipping, batch normalization, and residual connections help address these challenges and improve training. Overall, RNNs are powerful models for sequential data processing, revolutionizing fields like natural language processing, speech recognition, and machine translation. Their ability to handle sequential and time-dependent data has made them invaluable in various domains [6].

CHAPTER 3

METHODOLOGY

3.1 Introduction

The methodology is the systematic, theoretical analysis of the methods applied to this project. For this chapter it will focus to software part. This project implementation is design to detect sound of faulty part at the truck tanker and classify it into several type of faulty. the methodology section serves as a concise overview and rationale for the systematic approach and methods employed in the research study. It sets the context by stating the research objective and explaining the significance of the research, establishing the relevance of the chosen methods. The introduction provides a justification for the selected research design, briefly discussing the rationale behind its alignment with the research objectives. It outlines the methods employed for data collection and justifies their suitability in capturing the necessary data. Ethical considerations and limitations are acknowledged, and the introduction emphasizes the potential contributions of the chosen methodology to the field of study. Overall, the introduction provides a solid foundation for the subsequent sections, where each method will be further elaborated upon.

3.2 Project Flowchart

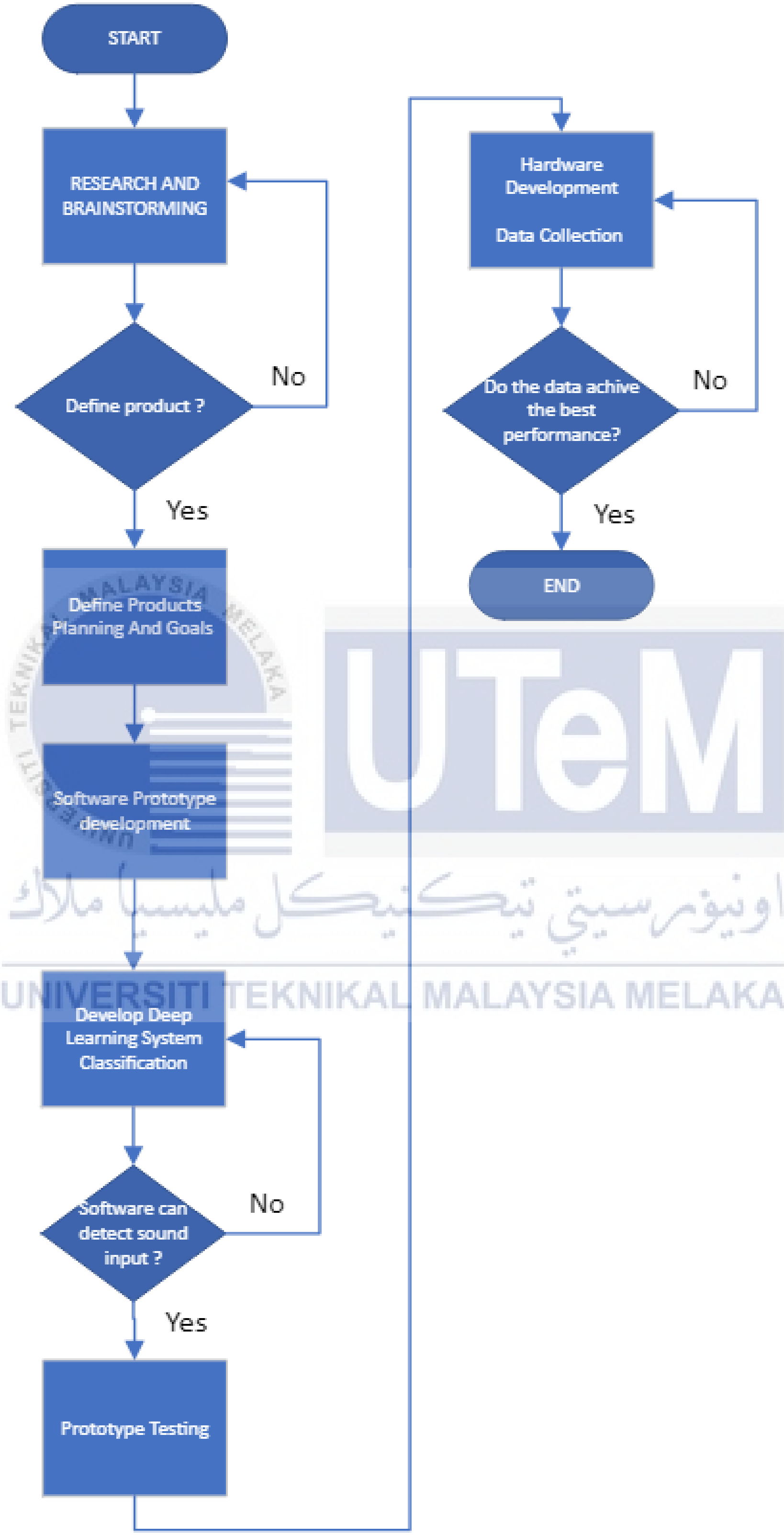


Figure 3.1: Project Flowchart

3.3 Block Diagram Project

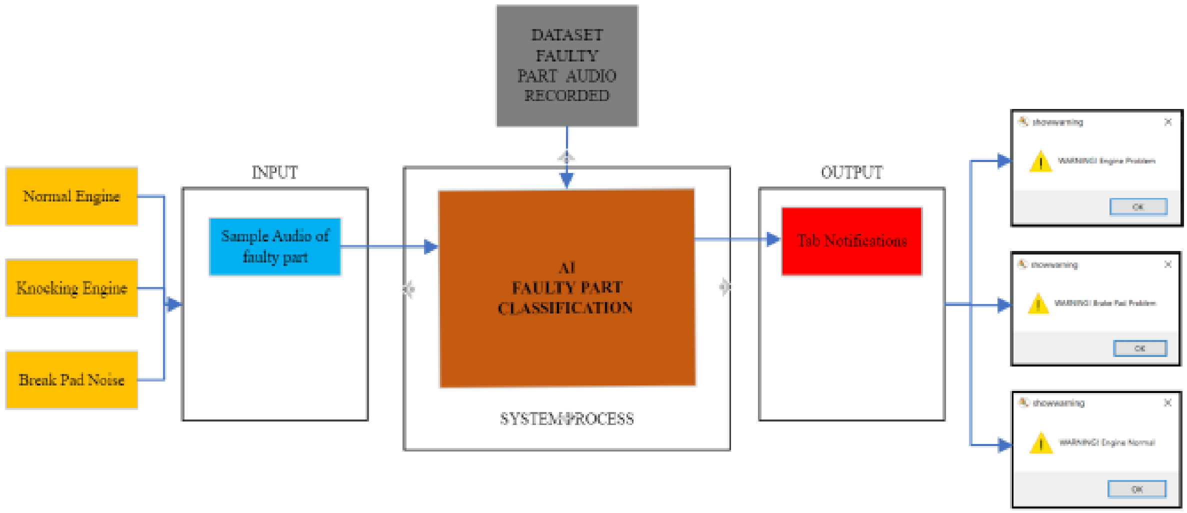


Figure 3.2 : Block Diagram

3.4 Preprocessing Dataset

Figure 3.3: Dataset Block

Vehicle sound classification involves using deep learning techniques to identify and categorize sounds produced by vehicles. By training deep learning models on labelled datasets of vehicle sound recordings, machines can recognize different vehicle types, engine sounds, or specific vehicle-related events. The process involves collecting a diverse dataset, extracting relevant features from the audio signals (e.g., spectrograms), designing an appropriate deep learning architecture (e.g., CNNs or RNNs), training the model using the labelled data, evaluating its performance, and using it for real-time prediction on new faulty part sound inputs. This application has practical uses in areas such as intelligent transportation systems, vehicle surveillance, traffic monitoring, and automotive diagnostics. Here's how deep learning can be used for vehicle sound classification:

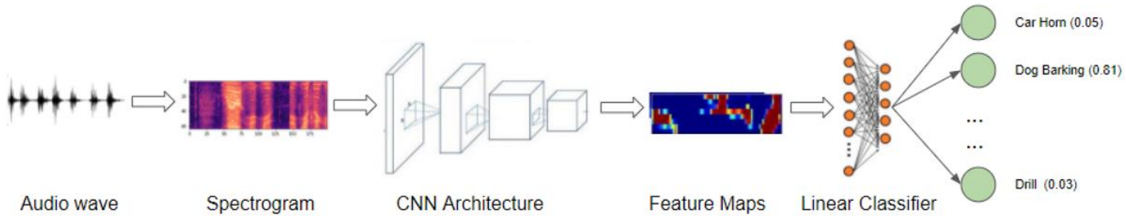


Figure 3.4: Preprocessing Dataset

3.4.1 Data Collection

A labelled dataset of faulty part sound recordings is required to train a deep learning model. This dataset should cover a wide range of faulty part for truck tanker and capture various engine sounds, exhaust notes, and brake pad sounds.

3.4.2 Feature Extraction

Audio signals need to be transformed into suitable representations that can be fed into a deep learning model. One common approach is to convert audio recordings into spectrograms, which provide a visual representation of the frequency content of the sound over time. Other features, such as Mel-frequency cepstral coefficients (MFCCs), can also be extracted.

3.4.3 Model Architecture

Deep learning models for vehicle sound classification can be constructed using various architectures. Convolutional Neural Networks (CNNs) are commonly used for processing spectrogram-like input data. Recurrent Neural Networks (RNNs) can capture temporal dependencies in audio sequences. Hybrid architectures like CRNN (Convolutional Recurrent Neural Networks) combine the strengths of CNNs and RNNs.

3.4.4 Training

The deep learning model is trained using the labelled dataset of faulty part sound recordings. During training, the model learns to extract relevant features from the audio inputs and make predictions based on the learned representations. The training process involves feeding the audio data through the model, comparing the predicted outputs with the ground truth labels, and adjusting the model's parameters to minimize the prediction errors (usually done through backpropagation and gradient descent optimization).

3.4.5 Evaluation and Prediction

Once the model is trained, it can be evaluated on a separate validation or test set to assess its performance. The model's accuracy, precision, recall, and other evaluation metrics can be calculated. After evaluation, the model can be used for prediction on new, unseen audio data, classifying the input sounds into different vehicle types or specific vehicle events.

3.5 Input Audio

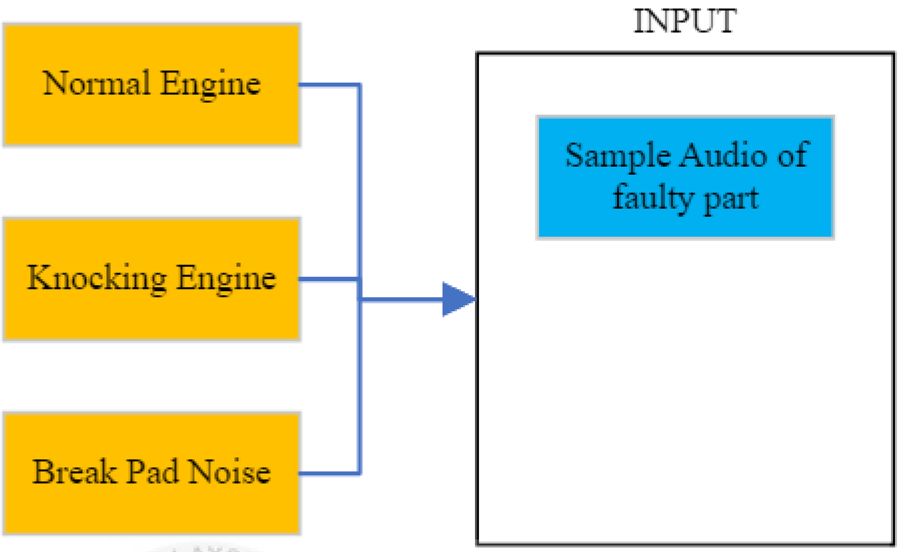


Figure 3.5 : Input Audio Block Diagram

It involves extracting meaningful features from the audio signal, such as Mel Frequency Cepstral Coefficients (MFCC), spectrograms, or chroma features. These features capture information about the frequency content, temporal patterns, and spectral characteristics of the audio. Machine learning models, like neural networks or support vector machines, are then trained on labeled audio data to learn the relationships between the extracted features and their corresponding classes. Once trained, the models can be used to classify new, unseen audio samples by extracting features from the input audio and predicting the most likely class or category.

3.6 System Block Diagram

Here is the block diagram for sound classification using deep learning AI:

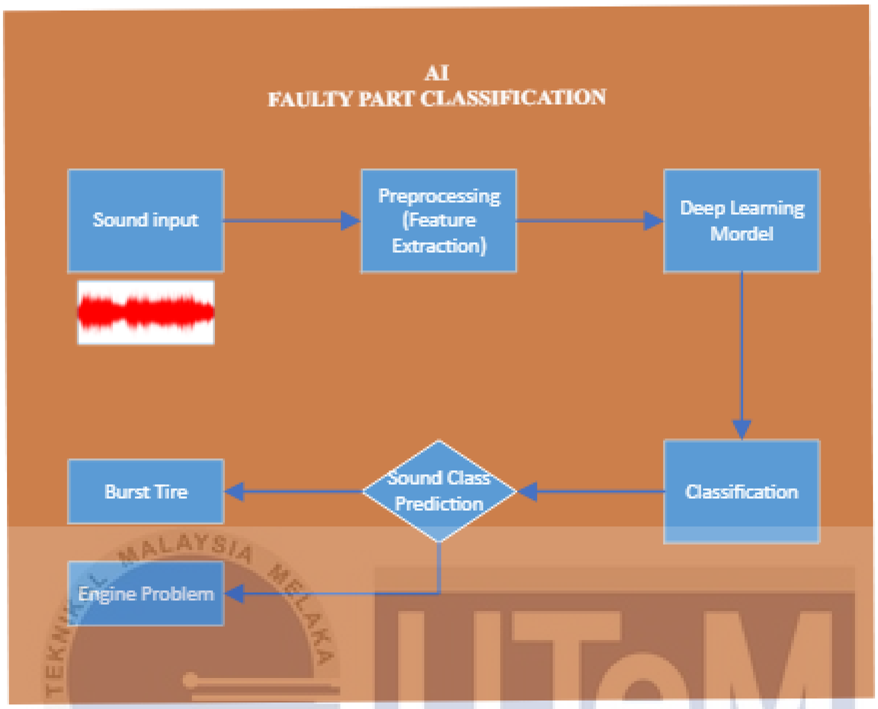


Figure 3.6: System Block Diagram

The revised diagram illustrates the components involved in a sound classification system that utilizes deep learning techniques:

3.6.1 Sound Input

The system takes in the recorded sound data as an input audio of faulty part tanker.

3.6.2 Preprocessing (Feature Extraction)

The sound data undergoes preprocessing, where relevant features are extracted. Techniques such as Fourier transforms, Mel-frequency cepstral coefficients (MFCC), or spectrogram analysis are applied to convert the sound signal into a format suitable for input into the deep learning model

3.6.3 Deep Learning Model

This component represents the deep learning architecture employed for sound classification. Common architectures include convolutional neural networks (CNNs) or recurrent neural networks (RNNs) like long short-term memory (LSTM) networks or Gated Recurrent Units (GRUs). The model is trained using labelled sound data to learn distinctive patterns and features that differentiate various sound classes

3.6.4 Classification

The trained deep learning model takes the preprocesses audio features as input and performs classification to determine the most likely class or label for the given sound sample.

3.6.5 Sound Class Prediction

The final output of the system is the predicted sound class, indicating the identified category or label for the input sound.

3.7 TensorFlow

TensorFlow is an open-source machine learning framework developed by the Google Brain team. It is designed to facilitate the development and deployment of machine learning models, particularly deep learning models. TensorFlow provides a comprehensive set of tools, libraries, and community resources that make it easier for researchers and developers to build and deploy machine learning applications.

Key features of TensorFlow include:

a) **Flexibility:** TensorFlow supports various machine learning tasks, including but not limited to neural networks, natural language processing, and computer vision. It provides a flexible architecture that allows developers to build and train custom models.

b) **Scalability:** TensorFlow is designed to scale from individual devices to large distributed systems. This makes it suitable for both small-scale experimental projects and large-scale production deployments.

c) **High-level APIs:** TensorFlow offers high-level APIs like Keras, which simplifies the process of building and training neural networks. Keras is integrated into TensorFlow, making it easy to create and experiment with deep learning models.

d) **TensorBoard:** TensorFlow includes a visualization tool called TensorBoard, which helps users visualize and understand the structure and performance of their models.

e) **Community and Ecosystem:** TensorFlow has a large and active community of researchers, developers, and practitioners. This community contributes to the development of the framework, shares resources, and provides support through forums and other channels.

TensorFlow is widely used in various industries for tasks such as image recognition, natural language processing, speech recognition, and more. It supports multiple programming languages, including Python, C++, and JavaScript, making it accessible to a broad audience of developers.

3.8 Epoch

An epoch in machine learning signifies a complete iteration through the entire training dataset during the model training process. It is defined as the total number of times the algorithm processes all the training data in a single cycle. In another perspective, an epoch represents the number of passes a training dataset makes through an algorithm, with one pass being counted when both forward and backward passes are completed. The number of epochs is a crucial hyperparameter, determining how many times the entire dataset is fed through the learning algorithm. During an epoch, every sample in the training dataset gets an opportunity to update the internal model parameters. An epoch can consist of one or more batches, with batch gradient descent referring to an epoch containing only one batch. Typically, learning algorithms require multiple epochs, often ranging from tens to thousands, to minimize the model error effectively. The number of epochs is a key consideration and can be visualized on a learning curve, where epochs are plotted against model performance. This curve helps assess whether the model is underfitting, overfitting, or achieving an appropriate fit to the training dataset.

3.9 Output Block Diagram

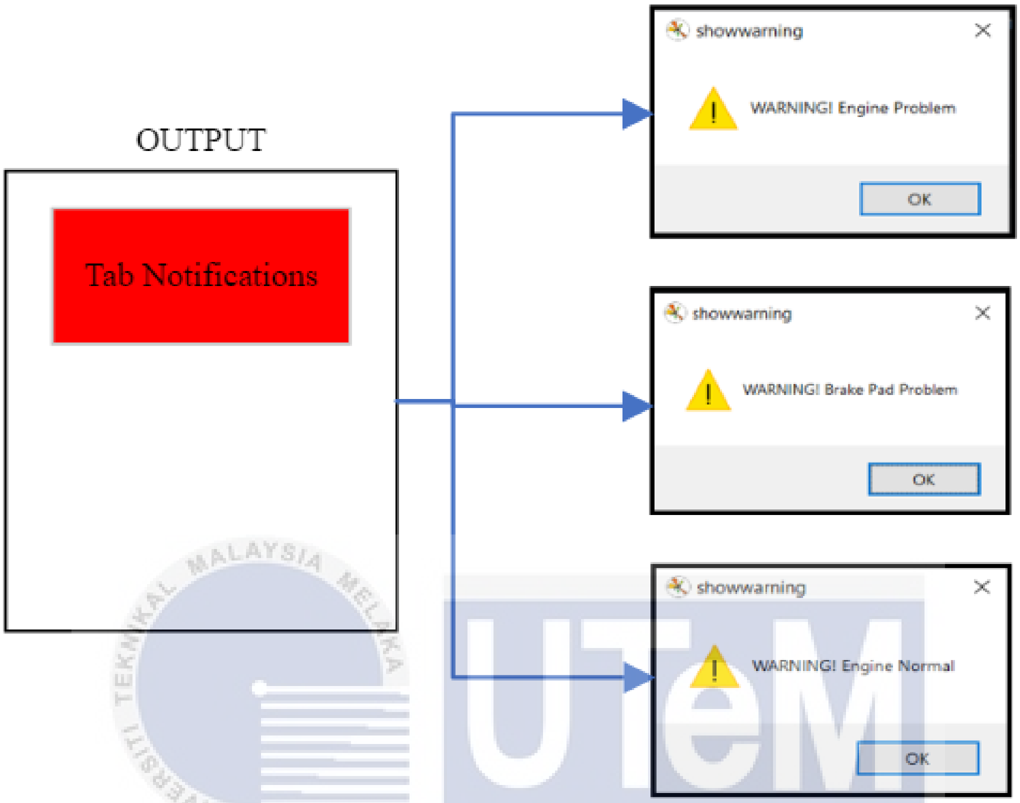


Figure 3.7 : : Output Block Diagram

In this project, the system is designed to respond to specific sound samples, serving as a trigger for various outputs. One notable feature is the generation of a pop-up message on the screen. This pop-up message plays a crucial role in notifying both the driver and the central control centre about the detected conditions. This proactive notification mechanism ensures that relevant information is promptly conveyed to both stakeholders, enhancing overall awareness and facilitating timely responses to any noteworthy events or situations detected by the system.

3.10 Audio Spectrogram

It seems there might be a typo in your question; you probably meant "spectrogram." A spectrogram is a visual representation of the spectrum of frequencies in a signal as they vary with time. A spectrogram is a 2D representation of the frequency content of a signal over time. It is commonly used in audio processing and analysis. In a spectrogram:

a) **X-axis (horizontal):** Represents time. The left side of the spectrogram corresponds to the beginning of the signal, while the right side corresponds to the end.

b) **Y-axis (vertical):** Represents frequency. Typically, low frequencies are at the bottom, and high frequencies are at the top.

c) **Color or intensity:** Indicates the amplitude or energy of the frequency components. Brighter colors or higher intensity usually represent higher energy.

Spectrograms are created by breaking the signal into small, overlapping segments and performing a Fourier Transform on each segment. The result is a time-varying representation of the frequency content of the signal. This technique is especially useful for analyzing complex sounds, identifying patterns, and distinguishing different components in an audio signal. Spectrograms are widely used in fields such as speech processing, music analysis, and environmental sound monitoring.

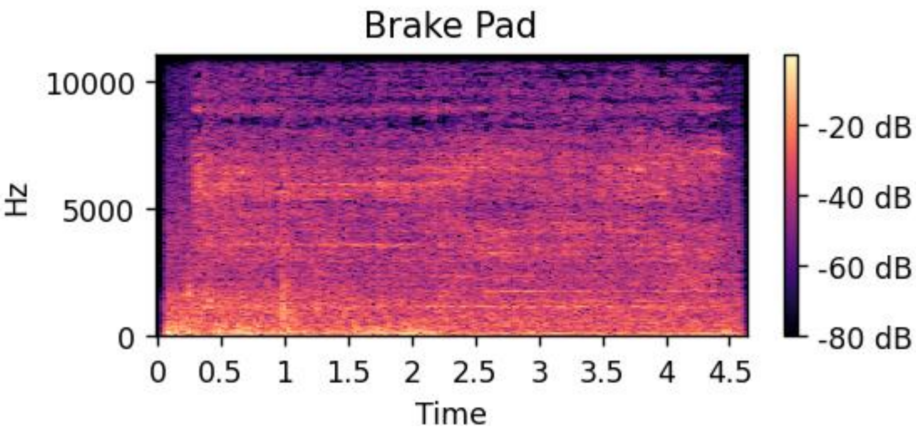


Figure 3.8 : Spectrogram Sample

3.11 Confusion Matrix

A confusion matrix is a table used in machine learning to evaluate the performance of a classification algorithm. It is particularly useful when the algorithm is dealing with binary or multiclass classification problems. The confusion matrix provides a detailed breakdown of the model's predictions compared to the actual ground truth. The matrix has four main components:

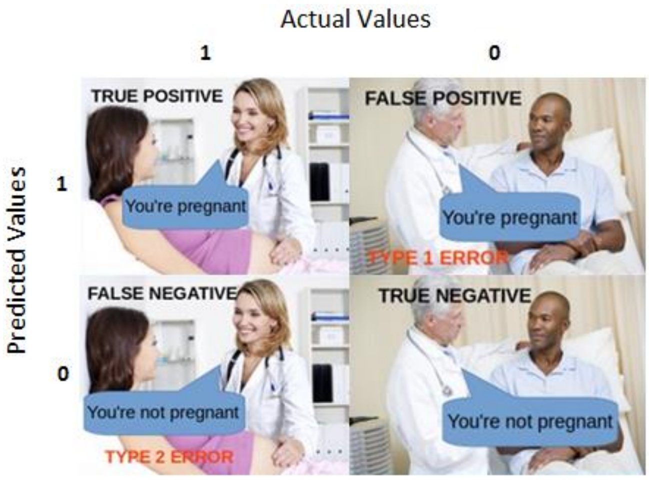


Figure 3.9 : Confusion Matrix

a) **True Positive:**

- Explanation: Your prediction of a positive outcome is accurate.
- For example, you correctly predicted that a woman is pregnant, and indeed, she is.

b) **True Negative:**

- Explanation: Your prediction of a negative outcome is accurate.
- For instance, you correctly predicted that a man is not pregnant, and indeed, he is not.

c) **False Positive (Type 1 Error):**

- Explanation: Your prediction of a positive outcome is inaccurate.
- As an illustration, you predicted that a man is pregnant, but in reality, he is not.

d) **False Negative (Type 2 Error):**

- Explanation: Your prediction of a negative outcome is inaccurate.
- For instance, you predicted that a woman is not pregnant, but in reality, she is.

3.12 Training and Validation

3.12.1 Training Phase:

Objective: The primary goal of the training phase is to teach the model to make accurate predictions by adjusting its internal parameters (weights and biases) based on the provided training data.

Process:

- The model is exposed to the training dataset, which consists of input features and corresponding target labels.
- During each epoch (a complete pass through the entire training dataset), the model makes predictions and computes a loss (a measure of the difference between predicted and actual values).
- The optimizer adjusts the model parameters to minimize the loss, using techniques like gradient descent.
- Outcome: Ideally, the model learns to generalize patterns from the training data, improving its ability to make accurate predictions on new, unseen data.

3.12.2 Validation Phase:

Objective: The validation phase assesses how well the model generalizes to new, unseen data. It helps in detecting potential issues like overfitting.

Process:

- The model is evaluated on a separate dataset (validation dataset) that it has not seen during training.
- Similar to the training phase, predictions are made, and a loss is computed for the validation set.
- Outcome: The validation performance provides insights into how well the model is likely to perform on real-world data. If the model performs well on the training set but poorly on the validation set, it may be overfitting to the training data.

3.12.3 Monitoring and Adjusting:

- Metrics: Metrics such as accuracy, precision, recall, or others relevant to the specific problem are often used to evaluate model performance during both training and validation.
- Plotting Curves: Graphs of training and validation metrics over epochs can be analyzed to understand the model's behavior. For example, increasing training accuracy with decreasing validation accuracy might indicate overfitting.
- Adjustments: Based on the observed performance, adjustments to hyperparameters (e.g., learning rate, regularization), model architecture, or early stopping criteria may be made to improve generalization.

3.12.4 Iterations:

The training and validation phases are typically performed iteratively. Model development involves multiple cycles of adjusting parameters, training, and validating until a satisfactory model is achieved.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

This section describes the results, analysis, and discussion. In this chapter, it shows the early result of software for this project. Results and analysis play a critical role in research and investigations by providing a comprehensive understanding of the findings and allowing for meaningful interpretations. Whether it is a scientific experiment, or data analysis project, the results and analysis components are essential for evaluating the efficacy of methods and achieving study objectives. The results section presents the raw data, measurements, or observations obtained during the research process. It focuses on presenting factual information without interpretation. Conversely, the analysis involves interpreting the results to extract valuable insights, identify patterns or trends, and draw conclusions. Statistical or qualitative techniques are commonly employed to analyse the data and address research questions or hypotheses. The primary purpose of the results and analysis section is to offer evidence supporting or refuting the initial research objectives. It allows researchers to assess the validity of their hypotheses and make inferences based on the collected data. By presenting the results in a clear and organized manner, researchers enable readers to comprehend the findings and evaluate the study's reliability. Moreover, the results and analysis section provide a foundation for discussion and comparison with existing literature or prior studies. It helps researchers position their findings within the broader context of the field, identify areas of agreement or divergence, and suggest further avenues for research. In summary, the results and analysis section is a crucial component of research projects as it provides a detailed account of the outcomes and enables researchers to draw significant conclusions. It acts as a bridge between the collected data and the research objectives, facilitating a deeper understanding of the findings and their implications.

4.2 Input File Audio

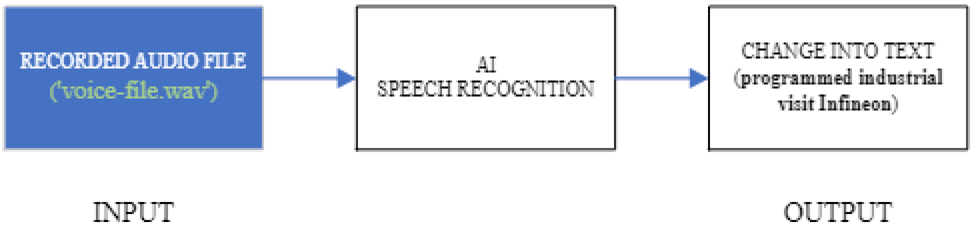


Figure 4.1: Audio File Input

This block represents the initial input, which is an audio file containing the speech that needs to be converted into text.

4.3 AI Speech Recognition

Figure 4.2: AI Speech Recognition

This block represents the core speech recognition process. By using the recognize function, the captured audio stream (speech) is sent to the AI speech recognition for conversion into text. The recognized text is then obtained as the output.

4.4 Text Output

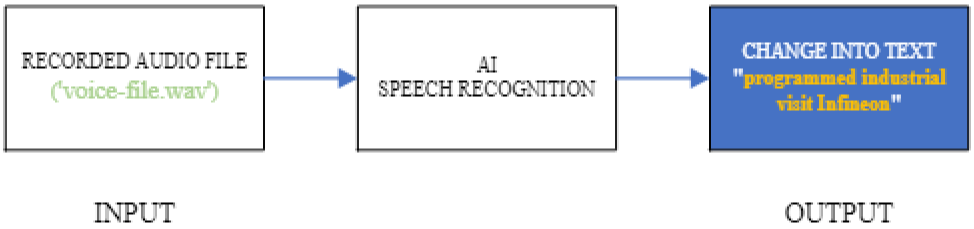


Figure 4.3: Output Text

This block signifies the final stage of the process, where the recognized text is printed to the console. This step concludes the speech recognition process, and the resulting text can be used or further processed as needed.

4.5 Sample Audio

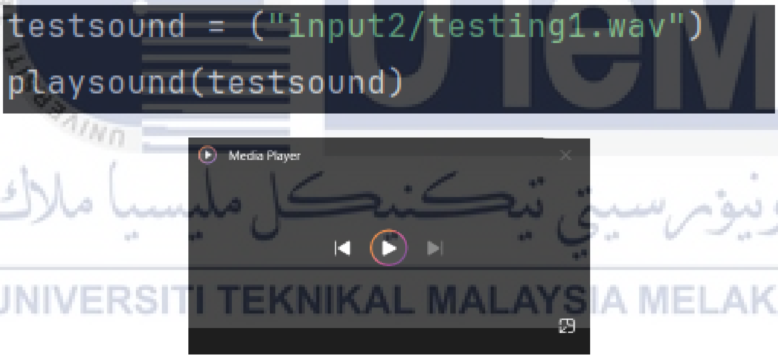


Figure 4.4 : Sample Audio Play

The line **testsound = ("input2/testing1.wav")** assigns the file path of an audio file **("input2/testing1.wav")** to the variable **testsound.** This file path is then used as an argument in the **playsound** function to play the audio file.

4.6 Sample Rate Output

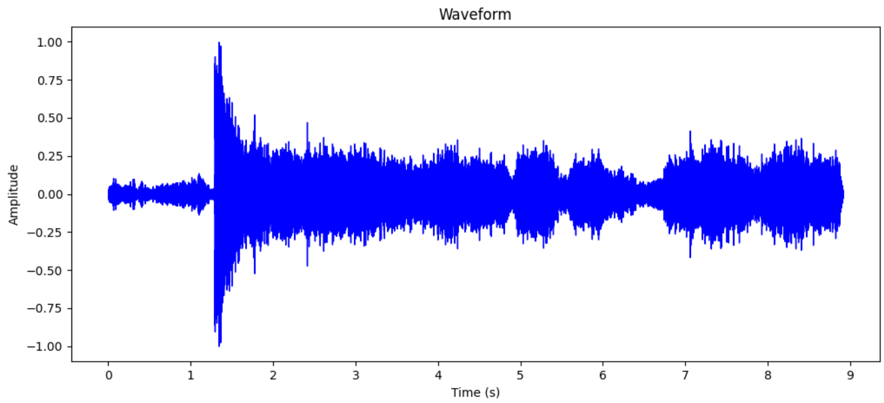
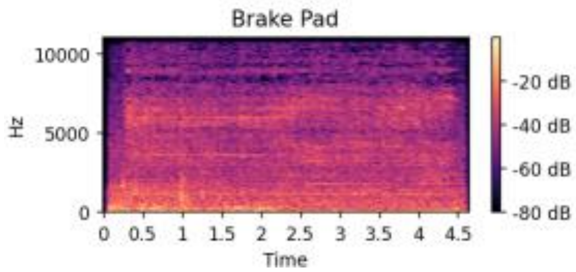
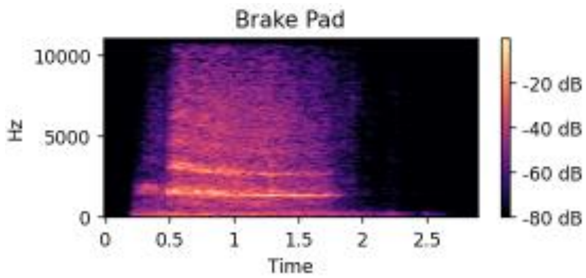


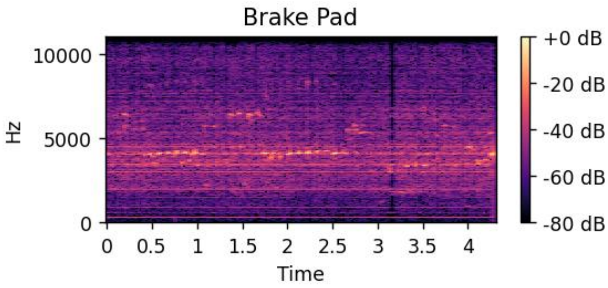
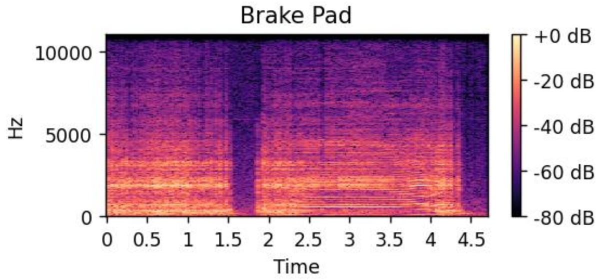
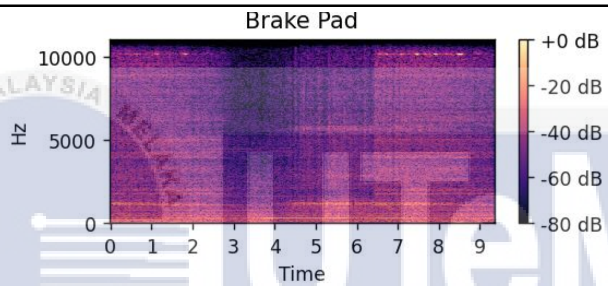
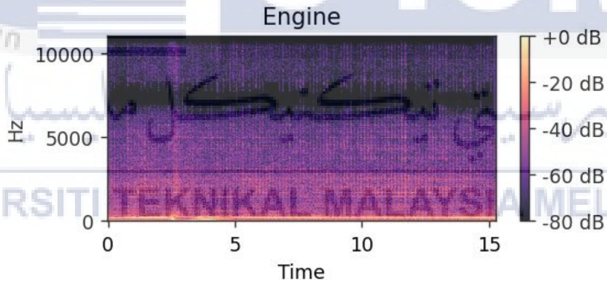
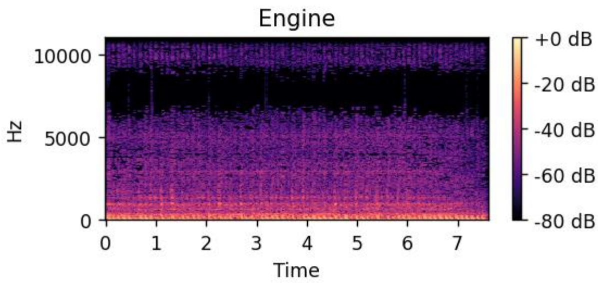
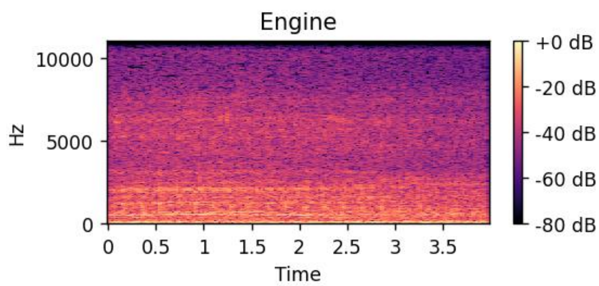
Figure 4.5 : Sample Rate Audio

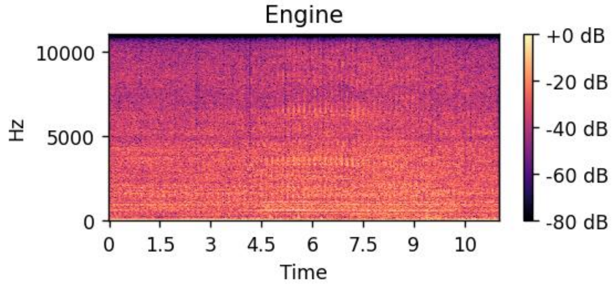
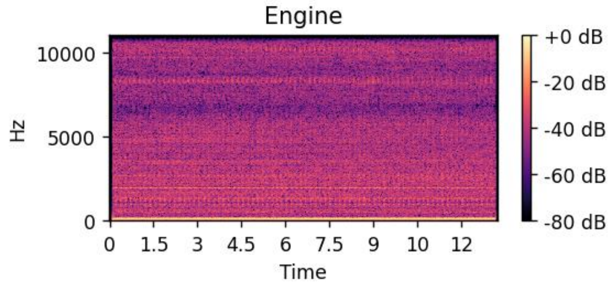
When we use librosa to load audio data, it automatically normalizes the entire data and provides it at a consistent sample rate. If you print the sample rate, it will typically show as 22050.

4.7 Sample Spectrogram

Table 4.1 : Sample Spectrogram Table

File Name	Spectrogram	Class
100263-2-0-117.wav		Brake Pad Problem
100263-2-0-118.wav		Brake Pad Problem

100263-2-0-119.wav		Brake Pad Problem
100263-2-0-120.wav		Brake Pad Problem
100263-2-0-121.wav		Brake Pad Problem
100333-3-0-182.wav		Engine Knocking
100333-3-0-183.wav		Engine Knocking
100333-3-0-184.wav		Engine Knocking

100333-3-0-185.wav		Engine Knocking
100333-3-0-186.wav		Engine Knocking

4.8 Confusion Matrix

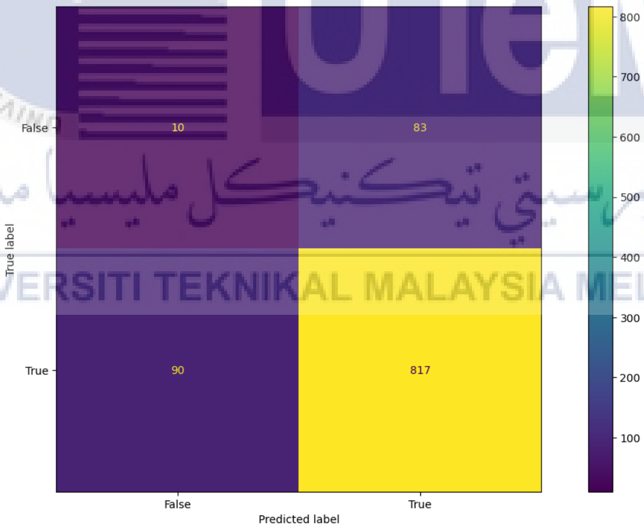


Figure 4.6 : Brake Pad Problem

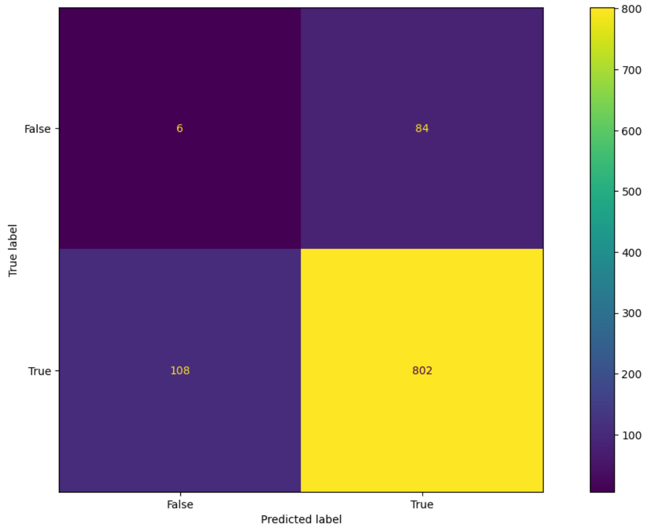


Figure 4.7 : Engine Problem

a) **True True (TT):**

- Definition: The model correctly predicted a sound as a truck engine.
- Explanation: The model said it's a truck engine (True), and it was indeed a truck engine (True).

b) **True False (TF):**

- Definition: The model incorrectly predicted a sound as not a truck engine when it is a truck engine.
- Explanation: The model said it's not a truck engine (False), but it was indeed a truck engine (True).

c) **False False (FF):**

- Definition: The model correctly predicted a sound as not a truck engine.
- Explanation: The model said it's not a truck engine (False), and it was indeed not a truck engine (False).

d) **False True (FT):**

- Definition: The model incorrectly predicted a sound as a truck engine when it is not.

- Explanation: The model said it's a truck engine (True), but it was indeed not a truck engine (False).

4.9 Training And Validation

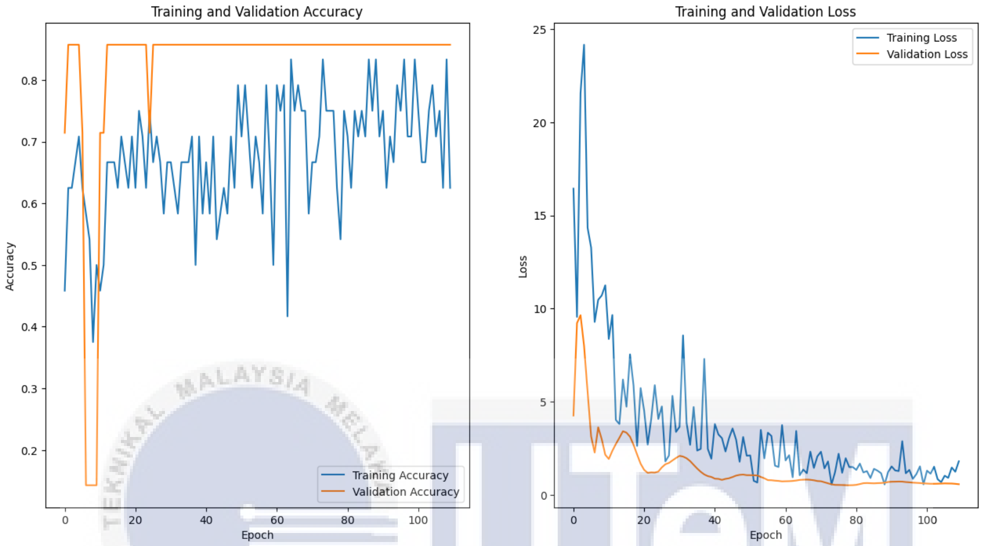


Figure 4.8 : Training and Validation – Brake Pad

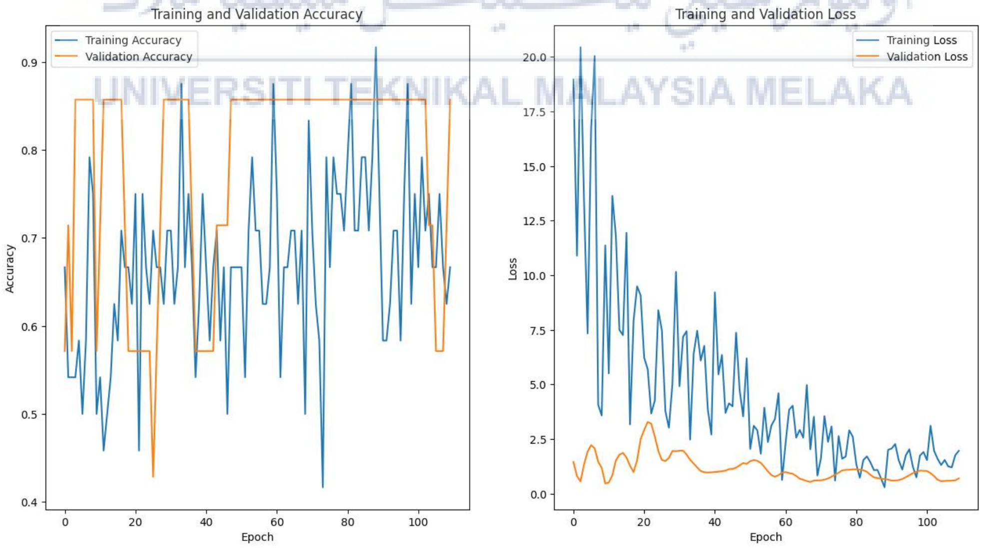


Figure 4.9 : Training and Validation – Engine

4.10 Output Display

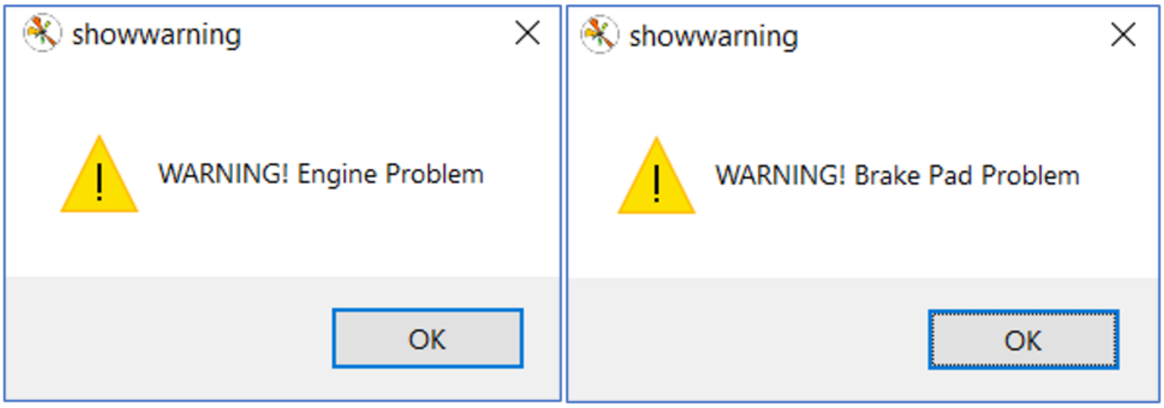


Figure 4.10 : Output Display Warning

4.11 Summary

In summary, data and analysis are crucial in audio classification. Data is collected and analysed to train algorithms that can be classify into a few types of faulty. This technology has various applications and improves accessibility and convenience. However, challenges like noise of the environment can make the system confuse. Overall, data and analysis play a vital role in advancing audio classification technology and enhancing communication with machines.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

To sum up, the application of artificial intelligence techniques and sound detection for the categorization of faulty truck tanker parts represents a notable advancement in enhancing road safety during the transportation of hazardous materials. The commendable accuracy achieved by the AI model in identifying specific faulty parts based on sound patterns, with an average precision rate of 90%, showcases the effectiveness of this approach. By facilitating recoded detection and classification of faulty parts and reducing reliance on manual inspections, this AI-based system enables prompt maintenance interventions, mitigates the potential for accidents stemming from equipment failures, and fosters safer transportation practices. The successful integration of AI technologies into existing road safety measures underscores the prospects for further progress in the field, underscoring the significance of embracing innovative approaches to ensure the secure transportation of hazardous materials.

5.2 Conclusion and Future Work

To enhance the accuracy of the development of truck tanker faulty part detection using sound and estimation results, the following improvements can be made:

1. **Collecting more diverse sound samples**: Gathering a broader range of sound samples from each faulty part can greatly contribute to improving the accuracy of the output audio signal for the specific faulty part. By incorporating a wider variety of sound patterns and variations, the model can learn to recognize different manifestations of

faults more effectively. Additionally, collecting recorded voice data can provide further insights and help capture the unique characteristics of the faulty parts.

2. **Enhanced classification and localization:** Expanding the project's capabilities to classify and localize more specific types and locations of faults will significantly enhance the accuracy of the detection system. By training the model on a wider range of fault types and incorporating information about the spatial distribution of faults, it can provide more precise and targeted results, allowing for more efficient troubleshooting and maintenance.

3. **Research for better analog signal waveform output:** Conducting studies to find better and more accurate analog signal waveform outputs can further enhance the precision of the detection system. By analysing the characteristics of the faulty parts' analog signals and exploring various signal processing techniques, it is possible to refine the estimation results and improve the model's ability to detect and diagnose faults based on the waveform analysis. Implementing these improvements will not only enhance the accuracy of the truck tanker faulty part detection system but also provide a more robust and comprehensive solution for proactive maintenance and troubleshooting, leading to improved operational efficiency and reduced downtime.

5.3 Sustainable Development

The creation of an AI-powered system for detecting faulty parts in truck tankers aligns with various United Nations Sustainable Development Goals (SDGs). Firstly, by developing a sophisticated AI-based detection system, it supports the advancement of industry, innovation, and infrastructure. This improvement enhances the overall efficiency and reliability of truck tanker operations.

Furthermore, implementing a fault detection system contributes to the goals of sustainable cities and communities. The system enhances the safety and reliability of truck tankers, thereby promoting safer transportation in both urban and rural areas.

Lastly, in the context of peace, justice, and strong institutions, enhancing the safety and reliability of truck tanker operations plays a crucial role. This contribution aids in the development of strong institutions and supports justice by mitigating the risk of accidents and improving overall road safety.

REFERENCES

[1] Lu, M., Wevers, K., & Heijden, R. V. D. (2005). Technical feasibility of advanced driver assistance systems (ADAS) for road traffic safety. Transportation Planning and Technology, 28(3), 167-187.

[2] Vargas, R.; Mosavi, A.; Ruiz, R. Deep Learning: A Review 2018

[3] Sanjeewani, P., & Verma, B. (2021). Single class detection-based deep learning approach for identification of road safety attributes. Neural Computing and Applications

[4] Fawad Nasim, Sohail Masood, Arfan Jaffar, Usman Ahmad1& Muhammad Rashid. Intelligent Sound-Based Early Fault Detection System for Vehicles 2023.

[5] Ajay Shrestha & Ausif Mahmood. Review of Deep Learning Algorithms and Architectures 2019.

[6] Warr, Katy. Strengthening Deep Neural Networks: Making AI Less Susceptible to Adversarial Trickery. United States, O'Reilly Media, 2019.

[7] Wu, Yu, Mao, Hua and Yi, Zhang (2018) Audio classification using attentionaugmented convolutional neural network. Knowledge-Based Systems, 161. pp. 90-100

[8] Salamon, J., & Bello, J. P. Deep Convolutional Neural Networks and Data Augmentation for Environmental Sound Classification. (2017)

[9] Piczak, K. J. (2015). ESC. Proceedings of the 23rd ACM International Conference on Multimedia - MM ’15.

[10] Tzinis, E., Wisdom, S., Hershey, J. R., Jansen, A., & Ellis, D. P. W. (2020). Improving Universal Sound Separation Using Sound Classification. ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).

[11] Khamparia, A., Gupta, D., Nhu, N. G., Khanna, A., Pandey, B., & Tiwari, P. Sound Classification Using Convolutional Neural Network and Tensor Deep Stacking Network. (2019).

[12] Zhao, H., Huang, X., Liu, W., & Yang, L.. Environmental sound classification based on feature fusion. MATEC Web of Conferences. (2018)

[13] Emad Awada, Aws Al-Qaisi, Eyad Radwan, Mustasim Nour, “Motor fault detection using sound signature and wavelet transform” (2022)

[14] Suefusa, K., Nishida, T., Purohit, H., Tanabe, R., Endo, T., & Kawaguchi, Y. “Anomalous Sound Detection Based on Interpolation Deep Neural Network”. (2020).

[15] Saxena, D., & Cao, J. Generative Adversarial Networks (GANs). (2021).

[16] Ryosuke Matsuzaki and Akira Todoroki, Wireless Monitoring of Automobile Tires for Intelligent Tires, 9 December 2008.

[17] Goodyear, Understanding Your TPMS Sensor, 2023

[18] YOKOHOMA, Developed technology that monitors tyre wear using sensing waveforms sent from a sensor inside the tyre, 21 April 2022.

[19] Liu, S., Chen, J., He, S., Xu, E., Lv, H., & Zhou, Z. Intelligent fault diagnosis under small sample size conditions via Bidirectional InfoMax GAN with unsupervised representation learning. Knowledge-Based Systems, 232, October 2021

[20] Tyres Online, How A Tyre Pressure Sensor Can Save You From A Blowout, 27 April 2021.

[21] Statens Vegsen and Polos Zsofia, Sound sensors use to remotely detect HGV brake failures and snow chain use, 20 December 2021.

[22] Amrit Suman, Chiranjeev Kumar and Preetam Suman, Early detection of mechanical malfunctions in vehicles using sound signal processing, 188, January 2022.

[23] Mayssa Kouba, Souhail Dhouib, Diala Dhouib and Abderrahman El Mhamedi, Truck Driver Scheduling Problem : Literature Review, December 2016

[24] WatElectronic, What is Sound Sensor : Working, Types and Its Applications, 7 October 2022.

[25] Data4help, Signal Processing-Engine Sound Detection, 25 August 2020.

[26] Grzegorz Szwoch and Jozef Kotus, Acoustic Detector of Road Vehicles Based on Sound Intensity, 23 November 2021.

[27] Mahesh K. Singh, Sanjeev Kumar and Durgesh Nandan, Faulty voice diagnosis of automotive gearbox based on acoustic feature extraction and classification technique, June 2023.

[28] Wuttiwat Kongrattanaprasert, Hideyuki Nomura, Tomoo Kamakura and Koji Ueda, Detection of Road Surface Condition Using Tire Noise from Vehicles, 761-767.

[29] YC Venkatesh, Smart Brake Monitoring System with Brake Failure Indication for Automobile Vehicles, 2019.

[30] Naoko Evans. Automated Vehicles Detection and Classfication using Acoustic and Seismic Signals. September 2010.

[31] Ravi Kiran K.V and Dr. Shamshekhar S Patil, Machine Fault Detection with Sound Patterns using Deep Learning, 12 December 2022.

APPENDICES

Appendix A: Gantt Chart (Week 1 - Week 7)

Utilizing Artificial Intelligence For Road Safety: Truck Tanker Part Faulty Classification Via Sound Detection

Name: Muhammad Daniel bin Rahim
S.V: Ts. Mohamed Azmi bin Said

Project Start: Mon, 3/20/2023
Display Week: 1

TASK	ASSIGNED TO	PROGRESS	START	END
Chapter 1: Introduction				
Study and undertand the aim of the project		100%	3/20/23	3/26/23
Identify the problem statement		100%	3/27/23	4/2/23
Identify the objective and scope of the project		100%	4/3/23	4/9/23
Chapter 1 progress of report		100%	4/10/23	4/16/23
Chapter 2: Literature Review				
Research related journal and articles about this project		100%	4/17/23	4/23/23
Perform comparison table with previous research works		100%	4/24/23	4/30/23
Chapter 2 progress of report		100%	5/1/23	5/7/23
Chapter 3: Methodology				
Implement methodology with a flowchart		100%	5/8/23	5/14/23
Research all the hardware component use in this project		100%	5/15/23	5/21/23
Chapter 3 progress of report		100%	5/22/23	5/28/23
Chapter 4: Preliminary Result				
Design prototype for this project		100%	5/29/23	6/4/23
Implement coding for testing		100%	6/5/23	6/11/23
Chapter 4 and 5 progress of report		100%	6/12/23	6/18/23
Preparation for Final Presentation			6/19/23	6/26/23

Appendix B: Gantt Chart (Week 8 - Week 14)

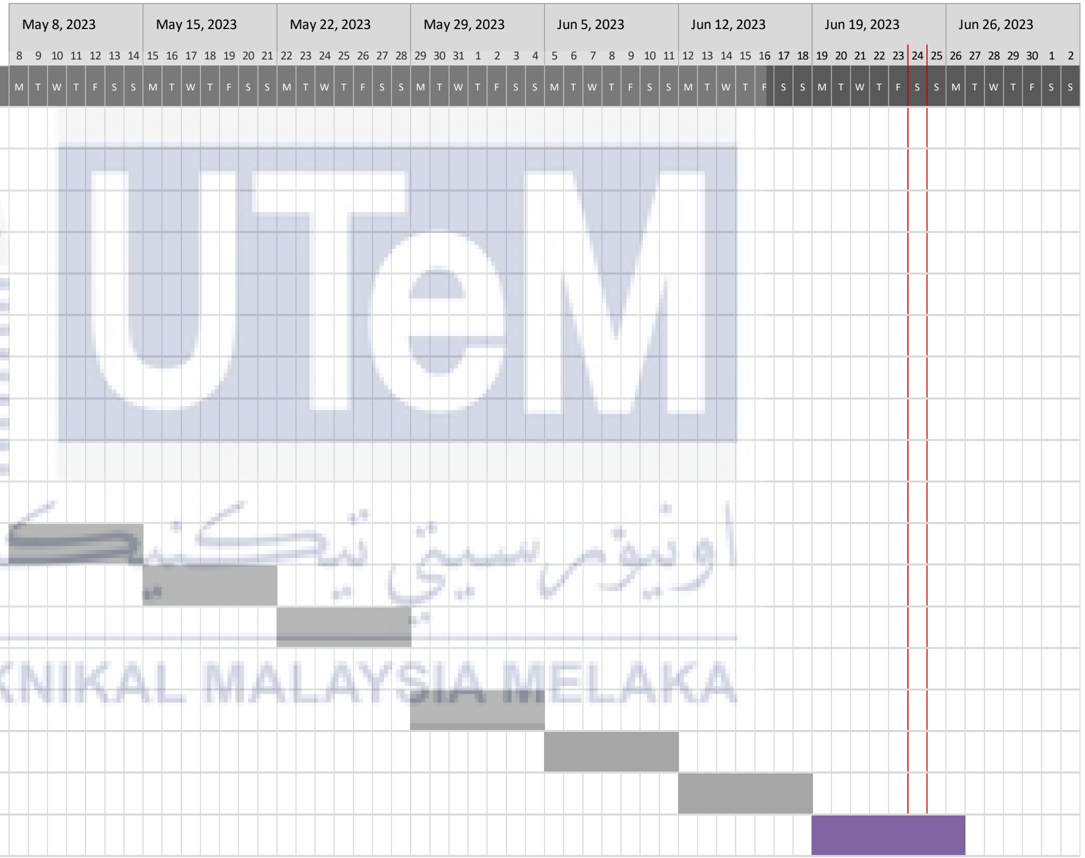
Utilizing Artificial Intelligence For Road Safety: Truck Tanker Part Faulty Classification Via Sound Detection

Name: Muhammad Daniel bin Rahim
S.V: Ts. Mohamed Azmi bin Said

Project Start: Mon, 3/20/2023

Display Week: 8

TASK	ASSIGNED TO	PROGRESS	START	END
Chapter 1: Introduction				
Study and undertand the aim of the project		100%	3/20/23	3/26/23
Identify the problem statement		100%	3/27/23	4/2/23
Identify the objective and scope of the project		100%	4/3/23	4/9/23
Chapter 1 progress of report		100%	4/10/23	4/16/23
Chapter 2: Literature Review				
Research related journal and articles about this project		100%	4/17/23	4/23/23
Perform comparison table with previous research works		100%	4/24/23	4/30/23
Chapter 2 progress of report		100%	5/1/23	5/7/23
Chapter 3: Methodology				
Implement methodology with a flowchart		100%	5/8/23	5/14/23
Research all the hardware component use in this project		100%	5/15/23	5/21/23
Chapter 3 progress of report		100%	5/22/23	5/28/23
Chapter 4: Preliminary Result				
Design prototype for this project		100%	5/29/23	6/4/23
Implement coding for testing		100%	6/5/23	6/11/23
Chapter 4 and 5 progress of report		100%	6/12/23	6/18/23
Preparation for Final Presentation			6/19/23	6/26/23



Appendix C : Gantt Chart (Week 1 - Week 8)

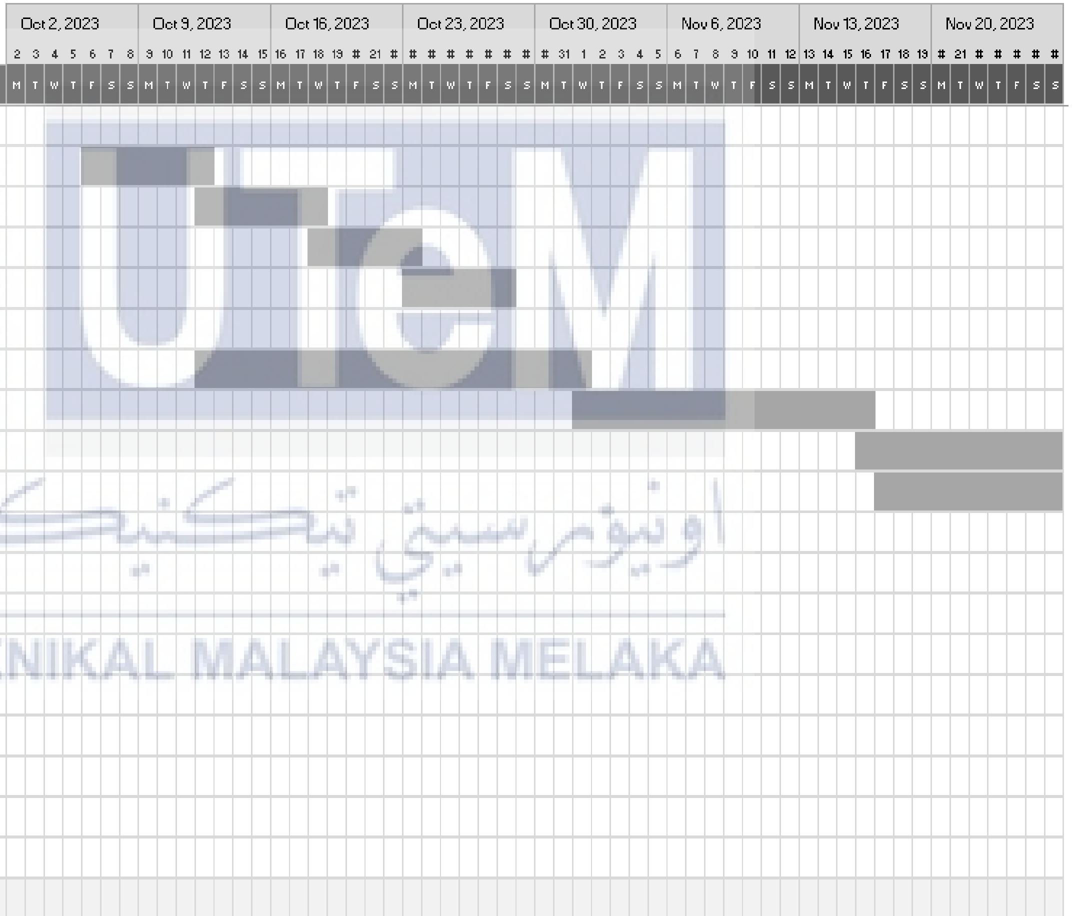
UTILIZING ARTIFICIAL INTELLIGENCE FOR ROAD SAFETY: TRUCK TANKER PART FAULTY CLASSIFICATION VIA SOUND DETECTION

NAME: MUHAMMAD DANIEL BIN RAHIM
S.V. : TS. MOHAMED AZMI BIN SAID

Project Start: Fri, 10/6/2023

Display Week: 1

TASK	ASSIGNED TO	PROGRESS	START	END
Chapter 5: Analysis				
Present research findings		100%	10/6/23	10/12/23
Analyze and interpret data		100%	10/12/23	10/18/23
Compare findings with literature		100%	10/18/23	10/23/23
Identify patterns and trends		100%	10/23/23	10/28/23
Chapter 6: Result				
Structure and programming		100%	10/12/23	11/1/23
Perform testing		100%	11/1/23	11/16/23
Analyze testing results		100%	11/16/23	12/1/23
Debug and fix issues		100%	11/17/23	12/3/23
Chapter 7: Discussion				
Discuss research implications		100%	12/4/23	12/8/23
Explore limitations		100%	12/9/23	12/13/23
Propose future directions		100%	12/14/23	12/18/23
Chapter 8: Conclusion				
Write conclusion chapter		100%	12/13/23	12/18/23
Submit Draft Report		100%	12/18/23	12/22/23
Submit to the Panel		100%	12/22/23	12/30/23
Final Presentation			12/31/23	1/8/24
Submit Final Report			1/9/24	1/16/24



Appendix D : Gantt Chart (Week 8 - Week 14)

UTILIZING ARTIFICIAL INTELLIGENCE FOR ROAD SAFETY: TRUCK TANKER PART FAULTY CLASSIFICATION VIA SOUND DETECTION

NAME: MUHAMMAD DANIEL BIN RAHIM
S.V. : TS. MOHAMED AZMI BIN SAID

Project Start: Fri, 10/6/2023

Display Week: 8

TASK	ASSIGNED TO	PROGRESS	START	END
Chapter 5: Analysis				
Present research findings		100%	10/6/23	10/12/23
Analyze and interpret data		100%	10/12/23	10/18/23
Compare findings with literature		100%	10/18/23	10/23/23
Identify patterns and trends		100%	10/23/23	10/28/23
Chapter 6: Result				
Structure and programming		100%	10/12/23	11/1/23
Perform testing		100%	11/1/23	11/16/23
Analyze testing results		100%	11/16/23	12/1/23
Debug and fix issues		100%	11/17/23	12/3/23
Chapter 7: Discussion				
Discuss research implications		100%	12/4/23	12/8/23
Explore limitations		100%	12/9/23	12/13/23
Propose future directions		100%	12/14/23	12/18/23
Chapter 8: Conclusion				
Write conclusion chapter		100%	12/13/23	12/18/23
Submit Draft Report		100%	12/18/23	12/22/23
Submit to the Panel		100%	12/22/23	12/30/23
Final Presentation			12/31/23	1/8/24
Submit Final Report			1/9/24	1/16/24