DESIGN AND DEVELOPMENT OF REMOTE ASSERT MONITORING SYSTEM FOR USING ON-BOARD DIAGNOSTICS-II

Thesis Submitted for the Award of the Degree of

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in

Electronics and Communication Engineering

By

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DECLARATION

I Raman Kumar declare that the thesis entitled, “Design and development of Remote assert monitoring system for using On-board diagnostics-II “under the guidance of Dr.Anuj Jain, Professor, School of Electronics and Electrical Engineering, Lovely Professional University, Punjab, India. No part of this thesis has formed the basis for the award of a degree or fellowship previously.

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CERTIFICATE

The thesis entitled "Design and Development of Remote Assert Monitoring System for Using On-board Diagnostics-II", being submitted by Raman Kumar (Reg No-41800181), S/O Sh. Kartar Chand to the Lovely Professional University, Phagwara for the award of the degree of Doctor of Philosophy is a bonafide research work carried out by him. He has worked under our supervision and has fulfilled the requirements for the submission of this thesis, which has attained the standard required for a Ph.D. degree from the University. The content of the thesis, in full or parts has not been submitted to any other Institute or University for the award of any other degree or diploma.

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Abstract

The transportation industry is leveraging the Internet of Things (IoT) and machine learning technologies to enhance performance and reduce costs. automobiles after 1995, the electronic control unit (ECU) underwent a substantial change that went beyond its initial function of improving engine performance and reducing pollution. It has developed into a crucial component of contemporary automotive technology, handling numerous functions that collectively influence how we drive today. The ECU was first designed to optimize fuel efficiency and lower hazardous emissions, but it now plays an important part in keeping us safe while driving. It is responsible for things like anti-lock brakes (ABS), airbags that inflate properly, functioning seatbelts, electronic stability control (ESC), and traction control systems. Together, these safety features increase driving security, underlining the crucial function of the ECU in modern automobiles. The ECU now plays a part in automotive security by controlling who can enter and preventing unauthorized individuals from starting the vehicle. This includes high-tech devices like special keys that unlock and start cars using radio waves (RF) and radio-frequency identification (RFID). The ECU links to a connection called On-Board Diagnostics (OBD), which enables drivers and mechanics to access crucial information about the health of the vehicle and address any issues, to assist customers in understanding how their automobiles are doing. The On-Board Diagnostics (OBD)-II is a vital part of the engine control system in modern vehicles. It provides a standardized method for monitoring and diagnosing engine performance, emissions, and other related systems. The OBD-II layer consists of an electronic interface called the OBD port that is typically located under the dashboard of a vehicle. This port is used for extracting data from the Engine Control Unit (ECU) of the engine, which is responsible for controlling and regulating various aspects of the engine's performance. To use the OBD-II protocol for data acquisition, a study of the protocols and frame structure was conducted, and then the data was stored in the

local storage before being forwarded to a remote server. Real-time data associated with the vehicle action, including critical performance data such as speed, RPM of engine, paddle position, determined engine load, and 46 other parameters, can be acquired through the OBD interface. Additionally, an engine oil quality sensor has been developed based on optical and inductive properties to collect another crucial parameter related to engine operation. This sensor can provide information about the quality of the engine oil, which can affect engine performance and longevity. By using the OBD-II protocol to acquire real-time data from the engine, Remote Asset Monitoring System (RAMS) can monitor and analyze vehicle performance in real-time. This information can be used to diagnose engine problems and recommend corrective actions, such as adjusting driving habits or scheduling maintenance. RAMS is a hardware and software-based solution that uses OBD-II to monitor engine operations in real-time, and it is designed to be compatible with most engines. The communication layer is responsible for transmitting data between the OBD-II protocol and the data processing layer, which uses embedded systems and IoT-based methods to analyze and process the data efficiently. The user interface layer provides a user-friendly interface that enables easy access to the data. RAMS can categorize driver behavior into ten classes, including fuel consumption, steering stability, velocity stability, and braking patterns, using machine learning techniques including Support Vector Machines (SVM), AdaBoost, and Random Forest. RAMS is a multi-layered design that allows for effective data processing while cutting down on the price of transmission. In order to categorize driver behavior, it gathers crucial vehicle performance data, including an additional characteristic pertaining to engine function. RAMS is a useful tool for examining driving behavior and recommending improvements for safe and effective driving. Important driving events including forceful braking at high speeds, rapid acceleration, deceleration, and uneven turning are all included in RAMS. Line plots and correlation matrices are two visualization techniques that are used to compare drivers' performance. The method considers the time-series values of the sensor data, and supervised learning methods are used to compare all driver classifications. The SVM, AdaBoost, and Random Forest algorithms are used to categorize driver behavior. Which gave an accuracy of 99%, 99%, and 100% respectively. vehicles must have the OBD-II layer, the network layer, and RAMS. RAMS, a user-friendly hardware and software solution that can provide feedback to help drivers improve their driving, is compatible with the majority of engines. It is an effective means to study driving behavior and recommend corrective actions for effective and safe driving. The work presented shows how cutting-edge machine-learning algorithms can be successfully applied to produce remarkable levels of accuracy. The result has significant effects because the work that has been presented has a wide range of practical applications in many different fields. In particular, when rented assets are used by people who are not the original owners, the future scope of this endeavor shows significant potential. This idea correlates with how ride-sharing services like OLA and Uber can use the proposed method, and it has the potential to apply to a wide range of applications and sectors.

ACKNOWLEDGEMENT

Firstly, I would like to express my sincere gratitude to my supervisor Dr. Anuj Jain for the continuous support of my Ph.D. study and related research, for his patience, motivation, and immense knowledge, and without whom I would have no content for my thesis. His guidance helped me in all the time of research and writing of this thesis. The meetings and conversations with my supervisor were vital in inspiring me to think outside the box, from multiple perspectives to form a comprehensive and objective critique. I could not have imagined having a better supervisor, advisor and mentor for my Ph.D. study.

Last, but not least, I would like to thank my family: my parents and my brothers and sister for supporting me spiritually throughout writing this thesis and my life in general.

Raman Kumar

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List of Abbreviations

RAMS - Remote Asset Monitoring System

ECM - Engine Control Module

ECU - Engine Control Unit

SVM - Support Vector Machine

OBD - On-Board Diagnostics

RF - Radio Frequency

IoT - Internet of Things

WSN - Wireless Sensor Network

GPS - Global Positioning System

GSM - Global System for Mobile Communications

IDE - Integrated Development Environment

LTE - Long-Term Evolution

CPU - Central Processing Unit

RFID - Radio-Frequency Identification

WiFi - Wireless Fidelity

IR – Infrared

List of Appendices **(Pages)**

CHAPTER 1
INTRODUCTION

The Remote Asset Monitoring System (RAMS) is a cutting-edge requirement in industries like transportation, logistics, and construction. These systems enable real-time monitoring of assets such as vehicles, machinery, and equipment, offering companies the ability to optimize operations, cut costs, and enhance safety. With RAMS, companies can keep track of their assets' performance and status, no matter where they are located. The data collected can be analyzed to improve asset utilization, predict maintenance needs, and enhance fleet management. In the automotive industry, remote monitoring of internal combustion (IC) engines is increasingly essential. Onboard diagnostics (OBD) play a vital role in this context. OBD-II, a standard protocol, retrieves diagnostic information from a vehicle's engine control unit (ECU). By using an OBD-II adapter like ELM327, engine data can be easily extracted and sent to a remote server for further analysis. The collected information is stored in a cloud-based database and examined using machine learning algorithms to detect any irregular behavior or potential faults in the engine. This real-time monitoring and analysis enable prompt intervention and preventive maintenance, ensuring efficient engine performance. While the OBD scanner is valuable for accessing a vast majority of engine-related parameters, it unfortunately cannot measure engine oil quality. To address this limitation, the development of a new sensor is necessary. This sensor should easily integrate into the onboard system, allowing it to measure oil quality accurately. This integration would enable real-time monitoring of engine oil quality, enabling timely intervention and preventive maintenance to safeguard the engine's durability and optimal performance. Remote asset monitoring systems are crucial not only for IC engine-based assets but also for electric vehicles. With the advent of new technology and increasing demand for sustainability, electric vehicles have become a popular choice for businesses and individuals alike. However, they also require constant monitoring and maintenance to ensure optimal performance and longevity. Remote asset monitoring systems can be used to track and analyze data from electric vehicles, such as battery charge levels, power consumption, and driving patterns. This data can be used to predict maintenance needs, optimize energy usage, and improve overall efficiency. As such, remote asset monitoring systems are not just a futuristic requirement for IC engine-based assets, but also for the rapidly growing market of electric vehicles.

1.1. Thesis contribution: Problem identification

Assets such as IC engines must be monitored for their proper operation for several reasons:

Performance: Making sure internal combustion (IC) engines operate at their best is essential to achieve maximum efficiency and power output. By keeping an eye on engine parameters like fuel consumption, power output, and emissions, we can ensure that the engine is performing at its peak.

Safety: Safety is a top priority, and a malfunctioning IC engine can be dangerous for both the operator and those around them. That's why it's important to monitor engine parameters such as oil pressure, coolant temperature, and exhaust gas temperature to spot potential problems before they lead to accidents.

Maintenance: Taking good care of our assets is key to their longevity and cost-effectiveness. Regularly monitoring their parameters helps us catch potential issues early on, allowing for preventative maintenance. This approach not only extends the engine's lifespan but also helps to reduce overall maintenance costs.

Compliance: Different regions have regulations in place regarding IC engine emissions. Monitoring emissions is crucial to ensure that we comply with these regulations and do our part in reducing environmental impact.

Cost: Keeping an eye on engine performance can save us a lot of money in the long run. By detecting and addressing issues early, we can avoid major damages or breakdowns that would lead to expensive repairs and costly downtime for businesses or individuals.

1.2. Motivation

The development of Remote Asset Monitoring Systems based on IoT and machine learning is a rapidly growing and fascinating field, presenting ample opportunities for research and advancement. With IoT devices becoming more prevalent and the growing demand for predictive maintenance, remote asset monitoring systems have become crucial for various industries. Creating an efficient and effective system to monitor remote assets can lead to time and cost savings, improved productivity, and reduced downtime for businesses. The integration of machine learning in these systems opens up new avenues for predictive maintenance and has the potential to revolutionize how we approach asset monitoring. Machine learning algorithms can analyze data in real-time, detecting patterns and anomalies, thereby identifying and addressing potential problems before they escalate. This technological advancement can contribute to the creation of more efficient and sustainable asset monitoring systems, benefiting businesses and society as a whole. Engaging in research in this field not only adds to academic knowledge but also offers practical applications in multiple industries, making it a thrilling and rewarding opportunity [40].

1.3. Research issues and objectives

The primary objective of this research is to create a reliable and real-time remote asset monitoring system that provides asset owners with insights into the use of their assets and enables them to assign work to drivers and operators based on performance reports generated by the system. To accomplish this goal, the researcher must complete several tasks.

First, they must determine or install sensors that provide reliable and real-time data on engine operation, while keeping the system's cost and complexity to a minimum. Additionally, the researcher must identify the essential parameters related to engine operation that need to be analyzed, while ignoring the other parameters.

Secondly, they must design a system that can communicate with existing asset systems without difficulty and complexity, which involves studying protocols. If any of the essential parameters are not available, the researcher must develop new sensors.

Thirdly, they must create hardware and software that are compatible with this purpose. To implement machine learning, a suitable amount of data must be collected.

After gathering data, suitable algorithms must be chosen for performing classification based on ML. Lastly, scores must be assigned based on data analysis, and the model must be validated with the algorithms implemented. The goal of this research is to create a system that is both efficient and cost-effective, allowing businesses to maximize productivity and reduce downtime.

The investigator has completed the following objectives by considering all points discussed above

1. Study and Analysis of OBD-II protocols and their frame structure to extract useful information
2. Development of low-cost, reliable, and less complex lubricating oil quality sensors.
3. Extract data engine data with the help of an IoT-based device and perform an analysis of the operating habits of the driver/operator with the data collected.
4. Comparative analysis of operating habits of driver/operator with data collected.

1.4. Research methodology

1. The initial goal of studying and analyzing OBD-II protocols and their frame structure to extract valuable information was achieved by conducting research on various sources, including research papers, articles, patents, and product catalogs. This research enabled the identification of appropriate hardware and software platforms to accomplish the objective. Additionally, the structure of OBD data frames was analyzed thoroughly to ensure that the extracted information was reliable and accurate. Through this comprehensive analysis, a deep understanding of the protocols and their structures was gained, which laid the foundation for achieving subsequent objectives.
2. The goal of developing a low-cost, reliable, and less complex lubricating oil quality sensor was achieved by studying various methods utilized in the automotive industry. Based on this research, a low-cost, reliable, and less complex lubricating oil quality sensor was developed. This research involved the use of two different sensors based on the optical and inductive properties of oil, resulting in the creation of two types of sensors. These sensors are capable of accurately measuring the quality of lubricating oil in a cost-effective and efficient manner. This achievement represents a

significant advancement in the field of automotive technology, making it easier for engineers and manufacturers to optimize vehicle performance and efficiency.

3. Open-source software and hardware platforms such as Arduino, GitHub, ELM327, and Bluetooth built-in libraries have played a significant role in the successful extraction of valuable data from car ECU. These platforms provide the necessary tools and resources to access and analyze the data from the ECU, making it easier for researchers and developers to gain insights and make improvements. With the help of these platforms, extracting useful data from the ECU has become more efficient and effective, leading to a better understanding and optimization of car performance. Thus, these open platforms have played a crucial role in advancing the field of car technology.

4. A model was created based on driving or operating events, assigning scores and classifying them into different categories using machine learning methods such as SVM, AdaBoost, and Random Forest. The proposed method was tested, and the results were excellent, verifying the effectiveness of the approach. This model can be used to classify and analyze driving behavior and patterns, enabling the identification of potential risks and improvements in vehicle operation. By using advanced machine learning techniques, such as those employed in this study, more accurate and reliable assessments of driving behavior can be made, leading to enhanced safety and efficiency on the road. This has been explained in Fig. 1.1

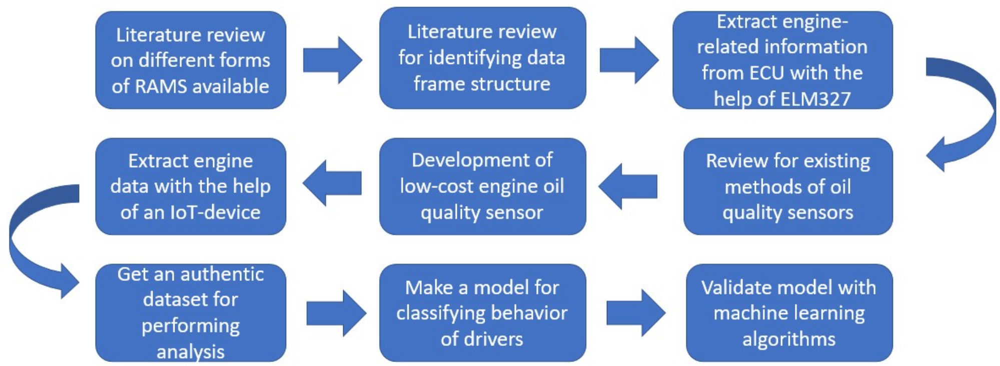


Fig. 1.1. Research methodology

1.5. Thesis contribution

This thesis makes several significant contributions by addressing various questions and objectives within the realm of Remote asset monitoring systems (RAMS). The following paragraphs will summarize each of the contributions.

Firstly, the thesis begins with a comprehensive literature review of RAMS, providing an in-depth understanding of the concepts, methodologies, and best practices in this field. This review serves as a foundation for the subsequent investigations and analyses.

Secondly, the study delves into the examination of On-Board Diagnostics (OBD) protocols and the structure of data frames. By exploring these protocols and their data frames, the thesis aims to enhance the understanding of the communication between vehicle components and diagnostic tools.

The third contribution entails the development of a sensor capable of determining engine oil quality using two different methods. This innovative sensor aims to provide accurate and reliable measurements, enabling efficient monitoring of the engine's oil condition and facilitating timely maintenance actions.

The fourth aspect of the thesis focuses on extracting information from the Engine Control Unit (ECU) utilizing the ELM327 interface and open-source libraries. This investigation aims to harness the power of the ECU data for further analysis and decision-making processes.

The fifth contribution involves the analysis of driving data. By collecting and analyzing data related to driving patterns, the thesis aims to gain insights into vehicle behavior and performance, ultimately contributing to improved safety and efficiency.

Finally, leveraging machine learning techniques, the thesis tackles the assignment and classification of drivers based on their behavior. By utilizing advanced algorithms, the aim is to identify patterns and characteristics in driving data that can help distinguish between different driver profiles.

In summary, this thesis encompasses a wide range of contributions, including an extensive literature review of RAMS, a study of OBD protocols and data frames, the development of an innovative sensor for determining engine oil quality, information extraction from the ECU, analysis of driving data, and driver classification using machine learning. These findings collectively contribute to the advancement of knowledge and understanding in the field of automotive engineering, with potential implications for safety, reliability, and maintenance practices.

1.6. Thesis organization

Overall, the thesis encompasses the introduction and motivation of Remote asset monitoring systems (RAMS), a literature review to identify research gaps, an overview of the proposed method and sensors, experimentation and analysis using real-world data, and a conclusion with limitations and future scope. This comprehensive approach contributes to the advancement of remote asset monitoring systems, addressing challenges and providing potential solutions for improved reliability and maintenance practices. As mentioned in Fig. 1.2.

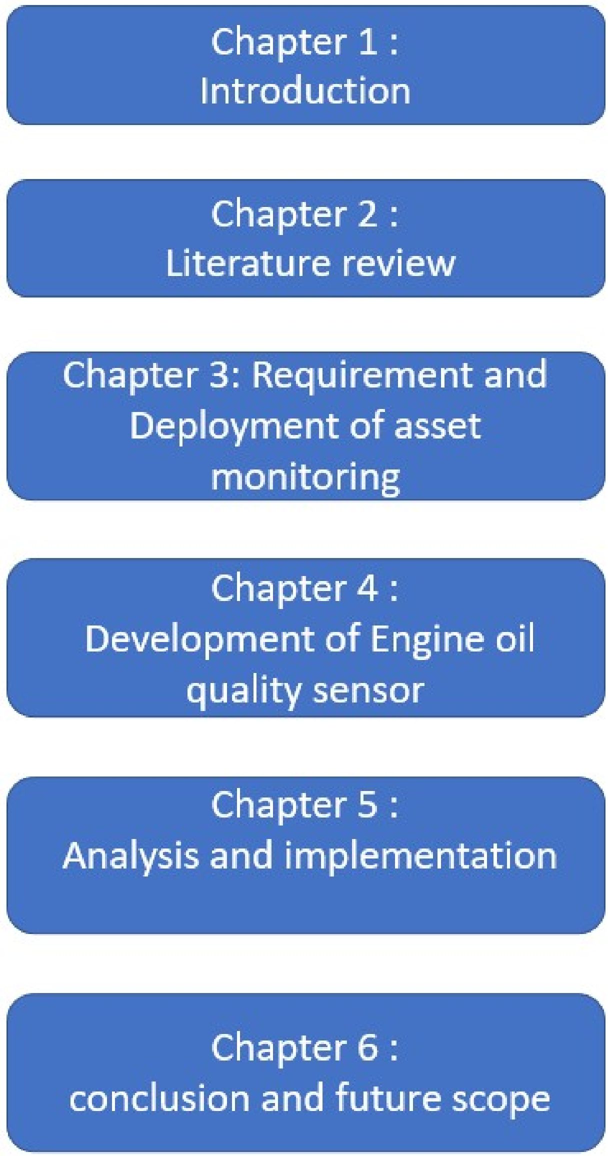


Fig. 1.2. Chapter Organization

Chapter 1: Introduction - Remote Asset Monitoring System and Its Requirements. The first chapter of the thesis introduces the remote asset monitoring system (RAMS) concept and provides an overview of its requirements. The motivation behind this research is explained, highlighting the need for efficient monitoring and management of remote assets. The thesis's contribution is also stated, emphasizing the goal of addressing the identified challenges and gaps in the field of RAMS.

Chapter 2: Literature Review

This chapter conducts a comprehensive literature review, examining various research articles, papers, and patents related to RAMS. This review aims to identify existing knowledge and practices in the field and determine the research gap that the thesis aims to address. The review also serves as a foundation for developing the proposed method.

Chapter 3: Requirement and Deployment of Asset Monitoring System

Overall, this chapter provides a comprehensive overview of the proposed method for the RAMS system. It discusses the integration of the ELM, Bluetooth module, and NodeMCU-based system, along with the requirements for an engine oil quality sensor. Chapter 3 provides an overview of the proposed method for RAMS. The chapter discusses how the proposed method can offer improved reliability and reduced complexity compared to existing approaches. It outlines the tools, hardware, software, and techniques employed in the proposed method. The chapter emphasizes the advantages and unique features of the proposed approach and highlights its potential applications in real-world scenarios.

Chapter 4: Development of Engine Oil Quality Sensor

This chapter focuses on the development of specific sensors for the RAMS. It details the design and implementation of an engine oil quality sensor based on the optical and inductive properties of the oil. The chapter explains how the sensor can accurately assess the quality of engine oil, enabling proactive maintenance actions and preventing potential failures.

Chapter 5: Analysis and Implementation

Describes the experimentation and analysis carried out to validate the proposed method. The thesis presents the experimental setup using a Suzuki Alto800 car and acknowledges the use of a dataset from another vehicle with permission from the author. Additionally, it highlights the importance of employing machine learning techniques for data analysis and presents specific algorithms used in the analysis process. Driving behavior analysis is performed using Python libraries, and algorithms such as AdaBoost, Support Vector Machines (SVM), and Random Forest are implemented for classification and prediction tasks.

Chapter 6: Conclusion and future scope

The final chapter concludes the thesis by summarizing the findings and conclusions derived from the research. The limitations of the proposed method are acknowledged, and future scope for improvement and further research is outlined. This chapter provides a concise overview of the thesis's accomplishments and highlights its contribution to the field of RAMS.

CHAPTER 2

LITERATURE REVIEW

Literature review delved into related methods for remotely accessing engine data, performing analysis on remote data, studying engine parameters, and exploring various sensors and their available data. By surveying reputable journals and studying national/international patents, the review aimed to identify existing knowledge, highlight research gaps, and provide a foundation for the proposed research in the thesis. Some of the key findings were presented in a tabular format within the chapter to facilitate a comprehensive understanding of the research landscape. A comprehensive literature review was conducted to explore related methods for remotely accessing engine data, performing analysis on remote data, studying engine parameters, and examining various sensors and their available data. The review encompassed reputable journals and national/international patents to identify existing research and potential research gaps in the field. Several key findings from the literature review were summarized in a tabular format within the chapter. The literature review focused on studies that investigated remote access to engine data, highlighting different approaches and technologies used for data retrieval from engines. This included techniques such as the utilization of OBD protocols, CAN bus systems, and wireless communication modules [6]. The review also explored research on data analysis methods for extracting meaningful insights from remote engine data, encompassing various statistical and machine learning techniques. Furthermore, the literature review examined the study of engine parameters and the sensors used to collect data related to these parameters. Different types of sensors, such as temperature sensors, pressure sensors, and vibration sensors, were reviewed to understand their capabilities and limitations in capturing engine performance information [4]. Additionally, the review encompassed studies that focused on analyzing sensor data to identify patterns, anomalies, and potential faults within the engine system. Analyzing patents helped identify novel approaches and potential research gaps that could be addressed in the thesis.

2.1. Development of Engine Oil Quality Sensor:

The first type of study focuses on the development of an engine oil quality sensor [39]. This sensor is designed to provide information about the engine oil being used and its remaining lifespan. This type of sensor is crucial as it addresses a common issue where drivers or operators may overlook the importance of monitoring the condition of engine oil. Additionally, such problems are often not reported by the Engine Control Unit (ECU). The study likely involves research and development of a sensor system that can accurately measure and analyze the quality of engine oil, potentially using various parameters such as viscosity, contamination levels, and chemical composition. The goal is to create a reliable sensor that can alert the driver or operator about the need for oil change or maintenance based on the oil's condition.

2.2. Development of Driver/Operator Behavior Classification:

The second type of study focuses on classifying driver/operator behavior. It involves studying communication protocols, analyzing data frames, and gathering vital parameters related to the engine[8]. The purpose is to develop a system or algorithm that can classify and differentiate various driver or operator behaviors based on the collected data. This classification may involve identifying aggressive driving, erratic behavior, fuel-efficient driving, or other patterns that can impact vehicle performance, safety, and fuel efficiency. To accomplish this, the study likely involves reviewing existing literature and previous work in the field, as well as implementing machine learning algorithms to analyze and classify the collected data. The ultimate aim is to develop a system that can provide insights into driver/operator behavior and potentially assist in improving overall vehicle operation and performance.

2.3. Review of methods for driver/operator behavior classification

Bartosz Jachimczyk et al. 2018 [1] Eight indicators related to vehicle speed, acceleration, jerk, engine rotational speed, and driving time are used in the study to suggest an objective assessment method. The safety, economy, and comfort driving style parameters are all estimated using these metrics. The solution is implemented using an embedded system built on the idea of the Internet of Things, which collects data from the OBD-II port for vehicle diagnostics as well as an additional accelerometer sensor and GPS module (see Fig. 2.1a). The suggested driving skills evaluation approach has proven to be capable of quantitatively differentiating between various driving styles through experimental validation on a group of drivers. The collected results demonstrate the system's ability to enhance driving behavior through study and testing on lengthy routes. A spider diagram technique also offers a thorough and understandable visualization platform for multidimensional comparisons and overall evaluations. This study makes a significant contribution to the field of objective driving style assessment and provides insightful tips for improving skill evaluation in fields where precise and accurate assessments are crucial. The results given here create prospects for improving performance and safety in numerous fields where driving competency plays a critical role. They also pave the way for further developments in objective skill assessment approaches.

Research findings- To propose an objective assessment method for studying vehicle dynamics, several additional sensors, such as GPS, RTC (Real-Time Clock), and accelerometers, have been integrated. This augmentation has enhanced the system's capabilities but also introduced complexity and installation-related overhead. These sensors now provide data on vehicle speed, acceleration, jerk, engine rotational speed, and driving time, contributing to a more comprehensive analysis.

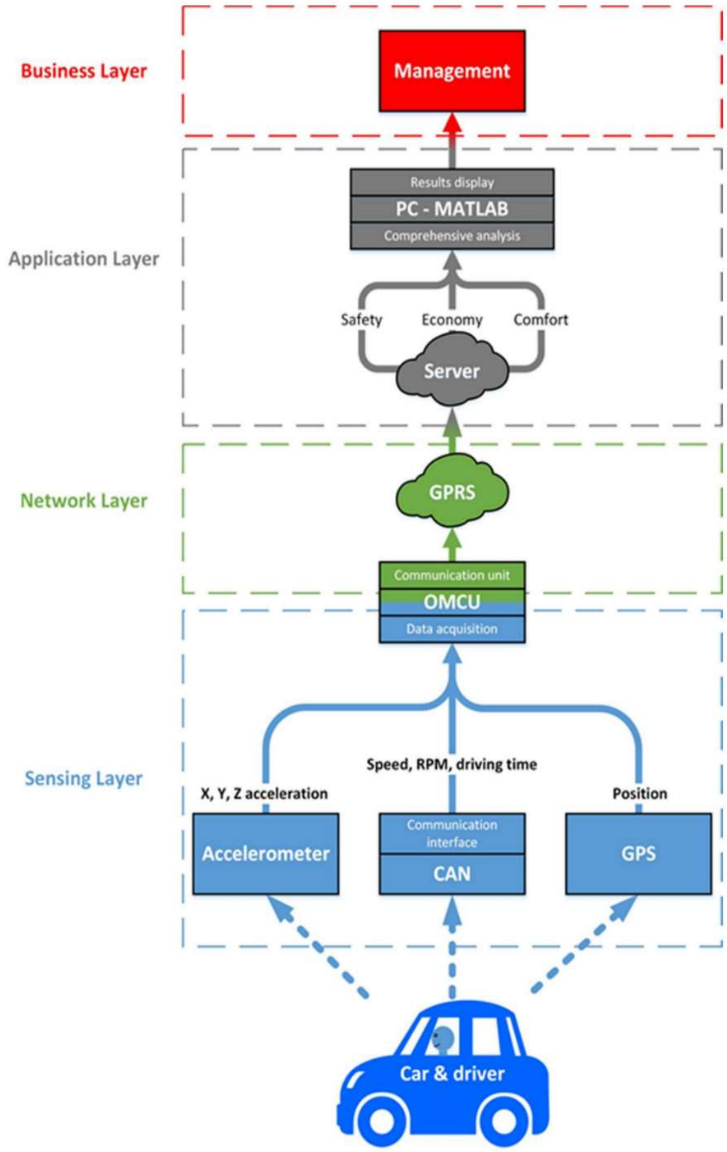


Fig. 2.1a. Overall architecture [1]

Aiswarya Kolisetty et. al. (2019) [2] in this paper a system where a vehicle comprising of a vehicle computing system (VCS) along with various modules such as adaptive cruise control, lane departure warning, navigation, and alert mechanisms is been proposed. The VCS communicates with an activity-tracking device worn by the driver, which records biometric characteristics and exchanges data with the VCS. Using the data from the activity tracking device, the VCS generates at least one output signal. For example, the adaptive cruise control module can adjust the distance between vehicles based on this signal. Similarly, the navigation system can suggest a parking spot based on the difference between step goals and the current steps recorded by the activity tracking device.

Research Findings:- The VCS (Vehicle Control System) establishes communication with an activity-tracking device worn by the driver, capturing biometric data and facilitating data exchange with the VCS. The VCS processes the information from the activity tracking device to generate output signals. For instance, in the case of a cruise control system, it utilizes these signals. It's important to note that the proposed method relies exclusively on additional sensors and does not rely on pre-existing vehicle sensors. Furthermore, these signals are exclusively linked to the driver's biometric data.

Ashwin Srinivasan et al. (2018) [3] in this paper author explain that IoT has diverse applications, including improving vehicle quality and safety in the automobile industry. To address rising accidents and declining car performance, we propose a real-time monitoring system using Raspberry Pi with ML algorithms (KNN and Naïve Bayesian). This system predicts vehicle conditions and lifespans, such as the engine and coolant. For user-friendly interaction, we suggest two data handling methods: 1) Bluetooth Low Energy for cloud database transmission, and 2) 4G Dongle for direct cloud and mobile app data transfer. BLE's low power consumption and scalability make it an ideal choice, supporting multiple sensors. Proposed prototype integrates OBD-II in a Ford car, extracting speed, air pressure, temperature, CO2 emissions, GPS coordinates, and fuel level data. Raspberry Pi executes the ML algorithm, providing real-time results and live condition predictions to the mobile app.

Research Findings:- In this research, the Raspberry Pi serves as a GPU for executing machine learning algorithms. These algorithms are employed to predict the condition and estimate the lifespan of various vehicle components, such as the engine and coolant system. The research also involves delivering real-time results and ongoing vehicle condition predictions to a mobile application. However, it's important to note that this method relies primarily on input data from just two major sensors, specifically those measuring engine coolant and tire pressure. This limited sensor input may not be sufficient for comprehensive condition monitoring.

Ryan Ahmed et al. (2014) [4]In this paper, the authors present a technique for detecting and classifying engine faults using vibration data in the crank angle domain.

They use artificial neural networks (ANNs) to detect these faults in a four-stroke gasoline engine. They compare their method, called SVSF-ANN, with other techniques like the backpropagation (BP) method, Levenberg-Marquardt (LM) method, quasi-Newton (QN) method, extended Kalman filter (EKF), and smooth variable structure filter (SVSF). SVSF-ANN is a new method designed to train ANNs efficiently. They assess its accuracy in engine fault detection and classification and find it effective in identifying various levels of engine issues, such as defective lash adjusters, piston chirps (PC), and chain tensioner (CT) problems. This customizable diagnostic system can be used in dealerships or assembly plants to significantly reduce warranty costs for manufacturers.

Research Findings:- The core focus of this research revolves around the detection of engine faults, and various methodologies have been developed to serve this purpose effectively. It is imperative to underscore that this system is not intended for utilization by asset owners for addressing emergency maintenance needs. Additionally, it's worth noting that the applicability of this research may have limitations when applied to remote assets.

Channakeshava Gowda et al. (2015) [5] This research work addresses the current scenario where many public and commercial transportation organizations utilize vehicle tracking systems for real-time monitoring. However, certain organizations, such as cab service providers, public vehicles, and school buses, lack such security systems. The goal of this project is to provide a comprehensive system with real-time online monitoring, efficient vehicle tracking, a dedicated remote server for fleet data storage, and improved security features. An embedded microprocessor with a Linux operating system is used to implement the Real-Time Vehicle Fleet Management and Security System project. It has a GSM-GPRS modem for communication, a GPS receiver for tracking the location of the car, and a number of security features like a physical panic button, a biometric sensor, a camera, and speakers. A dedicated server is employed for data acquisition, while a user-friendly graphical user interface (GUI) renderer is designed to visualize and display real-time data dynamically.

Research Findings:- In this research project, a GSM-GPRS modem serves as the communication tool, and for enhanced security measures, a physical panic button, a biometric sensor, a camera, and speakers have been incorporated. Additionally, a dedicated server is utilized for data acquisition, and a user interface is designed with a GUI renderer. This GUI renderer is responsible for dynamically plotting and displaying real-time data. It's important to note that the majority of the collected parameters are operator-centric and may not provide sufficient data for asset monitoring purposes.

Hwa-seon Kim et al. (2015) [6] This research paper highlights the increasing interest in vehicle diagnostics by both the industry and researchers in recent years. The diverse and heterogeneous nature of vehicle diagnostics employment has been a significant factor driving this interest. The paper introduces a technique for analyzing vehicle diagnostics attained from a vehicle connected to OBDII (On-Board Diagnostics II) and processing the diagnostics data using Raspberry Pi. This application also allows users to send commands to their vehicles. The choice of Raspberry Pi for this purpose is justified by its multitasking capabilities. Although the focus is currently on delivering vehicle diagnostic data to the user's smartphone, Raspberry Pi proves to be a suitable platform. In future research related to OBD-II scanners, the paper recommends the use of scanners with Bluetooth instead of Wi-Fi, citing advantages such as energy efficiency, ease of use, and stability.

Research findings- In this system, a message is sent to the Electronic Control Unit (ECU) instructing it to transmit data via a smartphone. The ECU transmits 31 pieces of engine condition information simultaneously and also sends the trouble diagnostic code. This diagnostic system allows for real-time communication through modules, enabling users to check engine condition information at any given moment. However, it's important to note that this system primarily relies on fault codes generated by the ECU, and it serves as an informative system, offering valuable diagnostic insights.

Beek s.h. et al. (2014) [7] In this research work, the conventional method of obtaining the current driving condition of a vehicle via On-Board Diagnosis-II (OBD-II) data is discussed. Recently, there has been a trend of using OBD-II data from the vehicle network for accessibility devices related to real-time vehicle regulation and driving info. However, a problem arises when these devices receive vehicle data from the OBD-II network, as each device receives its own information separately using its specific vehicle network. This poses an inconvenience to the driver, who needs to change the product and OBD-II connector whenever they switch devices.

Consequently, the driver ends up spending unnecessary money on new products and connectors to accommodate OBD-II usage. To address this drawback, this paper presents the implementation of an integrated OBD-II connector that utilizes Wi-Fi, WCDMA and Bluetooth modules. By integrating these modules into the OBD-II connector, the aforementioned disadvantage can be overcome. This integrated connector enables seamless connectivity and compatibility with various devices, eliminating the need for the driver to purchase new products or change the OBD-II connector when switching devices.

Research findings - In this paper, the researchers addressed the need for adaptability in OBD connectivity. Specifically, when a driver switches from a data scanner utilizing OBD-II to OBD-I, there's a requirement to modify the OBD-II connector accordingly. To tackle this issue, the researchers implemented an integrated OBD-II connector equipped with Bluetooth, Wi-Fi, and WCDMA modules. This integration effectively resolves the mentioned disadvantage, offering a versatile solution for OBD connectivity. The primary aim of this research is to enhance flexibility in OBD connectivity options.

Maurizio et. al. (2011) [8] The objective of this paper is to demonstrate how both traditional and innovative procedures and algorithms can enhance knowledge in fleet route planning and management across different transportation modes. In order to achieve effective and sustainable transportation for both passengers and cargo, it will be extremely difficult to keep up with the creation of new transport and logistics services. As a result, efficient resource management is essential. Due to the interdisciplinary character of transport and logistics services, it is necessary to collaborate with numerous scientific fields and international cross-cultural application initiatives. The creation of new fleet management models that incorporate data mining, forecasting, simulation, and decision heuristic models is a current academic trend. To support decision-making, these models are included into comprehensive decision-support systems. Parallel and distributed computing techniques can be used to increase the computational effectiveness of fleet management solution methodologies. Additionally, the incorporation of algorithms and meta-heuristics approaches into cooperative search methods, along with the development of cooperation mechanisms based on mathematical ideologies, such as decomposition methods. Integrating operations research methods and artificial intelligence procedures also presents fruitful research directions. By exploring these methodologies and algorithms, this paper contributes to the advancement of fleet planning and management, addressing the challenges posed by new transport and logistics services while striving for efficient resource utilization and sustainable mobility.

Research findings- In this research study, we have employed algorithms and meta-heuristic approaches to enhance cooperative search methodologies. Additionally, we have devised cooperation mechanisms rooted in mathematical principles, particularly through decomposition methods. Our proposed methodology demonstrates its effectiveness in optimizing fleet route planning with remarkable efficiency. It is noteworthy that the implementation of this approach can yield substantial positive impacts on remote assets.

J. V. Moniaga et. al. (2011) [9] This paper focuses on the utilization of OBD-II (On-Board Diagnostics II) and Raspberry Pi technology for diagnosing the condition of vehicles. Transportation accidents continue to be a significant challenge in many countries, and internal system problems of vehicles are among the factors contributing to such accidents. To address this issue, OBD-II technology has been developed to diagnose the condition of vehicles. The OBD-II scanner is connected to the vehicle's OBD-II port, also known as the Data Link Connector (DLC). The scanner then sends the diagnostics data to Raspberry Pi for processing. In comparison to other microcontrollers like Arduino, Raspberry Pi is chosen for its ability to handle real-time diagnostics, process data, and send commands to automobiles simultaneously. This is advantageous over Arduino, which requires one process to finish before starting another. The outcome of this application is to enable vehicle owners to diagnose their own vehicles. If any irregularities or issues are detected, the application notifies the user, allowing them to identify and address the problem before using the vehicle safely. By leveraging OBD-II and Raspberry Pi technology, this application enhances the safety and maintenance of vehicles, potentially reducing transportation accidents caused by internal system problems.

Research findings - This paper emphasizes the application of OBD-II technology in conjunction with Raspberry Pi for assessing vehicle conditions. Internal faults within vehicles can sometimes lead to accidents. To mitigate this concern, OBD-II technology has been harnessed to diagnose vehicle conditions. This approach can also be integrated into remote asset management systems.

Nikolaos Peppes et al. (2021) [10] Various well-known machine ML algorithms were tested and evaluated in this work with the intention of creating a thorough proof-of-concept procedure for examining driver behavior utilizing a large amount of vehicle data. We used and evaluated a variety of deep learning and machine learning methods to manage the big and frequent data packets of vehicular information. The outcomes showed that applying both machine learning and deep learning techniques to the dataset resulted in good results. The benefit comes from the fact that deep learning and machine learning calculations can both be performed on the same hardware. For this purpose, it is suggested to consider a cloud-based framework with flexible and scalable competencies (see Fig. 2.1). In the future, research efforts should be directed towards exploring novel and advanced approaches while also investigating any potential disadvantages, dangers, and threats associated with the advancement of transportation systems. Furthermore, researchers should focus on enhancing the figuring efficiency and trustworthiness of dynamic AI systems and implementing robust network security measures. These endeavors will support the development of more sophisticated and dependable driver behavior analysis systems.

Research findings - In this study, machine learning (ML) algorithms were systematically tested and assessed with the aim of analyzing driver behavior by leveraging extensive vehicle data. To handle the substantial and frequent data streams of vehicular information, a diverse range of deep learning and machine learning techniques were employed and evaluated. The findings indicated that the application of both machine learning and deep learning methods to the dataset yielded favorable results. As a result, the proposed method can be effectively employed for the analysis of driver behavior across various scenarios.

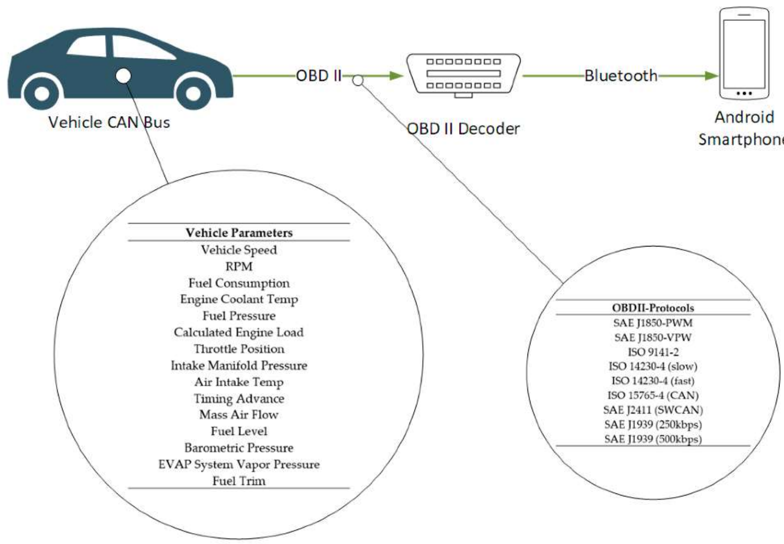


Fig 2.1. Cloud-based architecture [10]

Lisheng Jin et al. (2021) [23] The study focused on how various aspects, such as driving knowledge, mindset, and boldness, significantly impact driving behavior, even though their direct effects are stimulating for evaluation. To address this issue, the researchers employed survey techniques, which are commonly used in such cases. This work presents the findings from 59 driving behavior investigations. The study aimed to understand the association between driving behaviors and their underlying reasons, taking into account driving data, instructions, and the factors influencing the direction and intensity of these behaviors. By merging different variables, the researchers gained insights into real-world driving experiences, thoughts, and behaviors. The study's outcomes have valuable applications in understanding and investigating driving behavior. They provide both theoretical support and practical implications for enhancing road traffic wellbeing and reducing the risks drivers pose to other road users. Moreover, the findings can be useful in driver education and preparation, contributing to overall road safety improvement.

Research findings- The researchers in this study utilized survey techniques, a common approach for investigations of this nature. The study encompasses the results of 59 driving behavior inquiries. Its primary objective was to gain insights into the correlation between driving behaviors and the factors that underlie them. This investigation considered a range of variables, including driving data, instructions, and the elements that influence the nature and extent of these behaviors. It is worth noting that the proposed method introduced in this study can effectively explore the factors influencing driver behavior. This understanding can have a direct impact on enhancing asset performance.

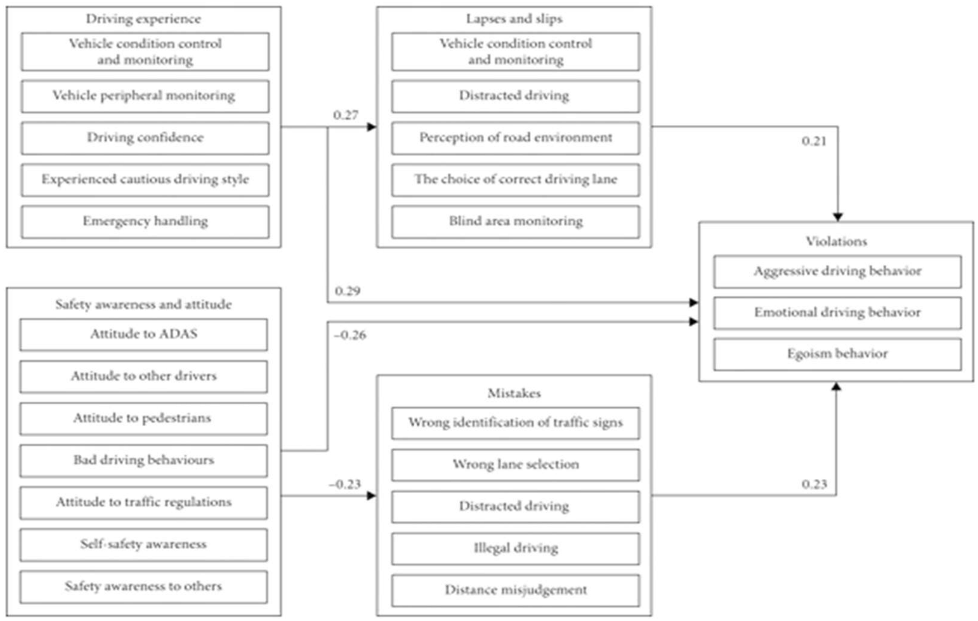


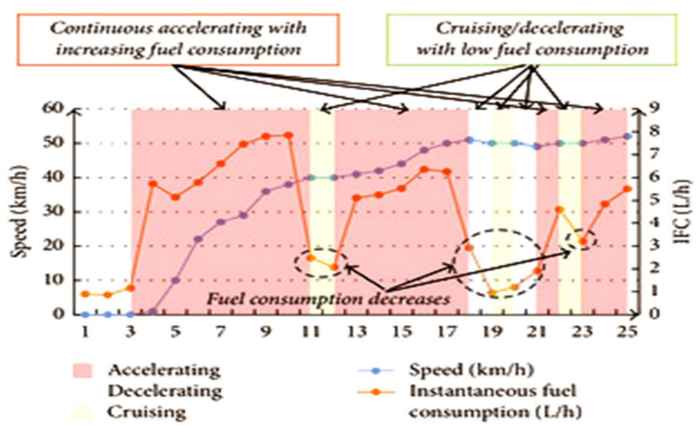
Fig. 2.2. Driving behavior and influencing factors [23]

Chen Chen et. al. (2018) [24] This study focuses on vehicle operating and fuel usage data to develop a model for assessing a driver's eco-driving behavior. The research begins by examining the effects of three important vehicle operational parameters: vehicle speed, style of driving, and fuel usage. Additionally, Fig. 2.3 predicts a relationship between nine driving incidents and fuel usage. Principal Component Analysis (PCA) and multiple linear regression (MLR) are used to build the eco-driving evaluation model. The study provides nine unique eco-driving tips as a result. The model offers an easy and quantitative method for determining how a driver's behavior affects fuel consumption. It also offers useful driving advice based on actual driving situations. The results of this study have implications for improving eco-driving assistance technology. The model's simplicity and accuracy pave the way for advancements in eco-driving practices in the field of transportation.

Research findings - This study centers around the analysis of vehicle operating data and fuel consumption patterns to construct a model for evaluating a driver's eco-driving behavior. The research commences by investigating the impacts of three critical vehicle operational variables: vehicle speed, driving habits, and fuel consumption. The primary emphasis of this work lies in enhancing fuel efficiency, which can be regarded as a significant factor influencing asset management.

Time (yyyymmddhhmmss)	Vehicle ID	Speed (km/h)	Instantaneous fuel consumption (L/h)
20140815124154	11BP8350	0	0.903221
20140815124155	11BP8350	0	0.866404
20140815124156	11BP8350	0	1.157593
20140815124157	11BP8350	1	5.73186
20140815124158	11BP8350	10	5.15094
20140815124159	11BP8350	22	5.79366
20140815124200	11BP8350	27	6.60942
20140815124201	11BP8350	29	7.46226
20140815124202	11BP8350	36	7.80216
20140815124203	11BP8350	38	7.8516
20140815124204	11BP8350	40	2.475
20140815124205	11BP8350	40	2.078204
20140815124206	11BP8350	41	5.12004
20140815124207	11BP8350	42	5.24982
20140815124208	11BP8350	44	5.5341
20140815124209	11BP8350	48	6.36222
20140815124210	11BP8350	50	6.26334
20140815124211	11BP8350	51	2.91996
20140815124212	11BP8350	50	0.961562
20140815124213	11BP8350	50	1.198728
20140815124214	11BP8350	49	1.908836
20140815124215	11BP8350	50	4.61328
20140815124216	11BP8350	50	3.202268
20140815124217	11BP8350	51	4.84812
20140815124218	11BP8350	52	5.50938

Raw data



Line chart of raw data

Fig. 2.3. Relationship between vehicle instantaneous fuel consumption and acceleration [24]

Rana Massoud et al. (2019) [25] With the goal of motivating users and enhancing driving behavior, a system for promoting more fuel-efficient driving has been devised. Fleet managers, insurance providers, and driving schools might find use for this game-based approach to driving categorization. The game gives the player or driver-specific suggestions when it notices unfriendly driving practices. They can then adjust their driving style to cut down on fuel use and emissions. This feedback is based on information gathered from a number of sources, including paddle position, engine RPM, vehicle speed, and vehicle jolt (i.e., the rate at which speed changes over time). Findings objective is to assess a driver's level of hostility, which is known to correlate with increased fuel usage. After each drive, the game assigns the driver a score ranging from 100 to 0, classifying their natural driving style into 3 classes: "Fuel Saver," "Average," and "Indiscreet." The game emulates real-life driving style and can suggestively impact driving effectiveness. This game can provide justification for the properties of driving habits and other factors that impact fuel productivity. A higher score shows that the driver is harmless and more careful when using the acceleration pedal related to other drivers of similar vehicle types.

Research findings- The proposed approach employs a simulation-based game wherein players or drivers receive personalized recommendations when the system detects unfavorable driving behaviors. This allows them to modify their driving techniques to reduce fuel consumption and emissions. The feedback provided is generated from a diverse set of data sources, including paddle position, engine RPM, vehicle speed, and vehicle jolts. This comprehensive data analysis enables the profiling of drivers based on their driving habits, offering valuable insights for further assessment.

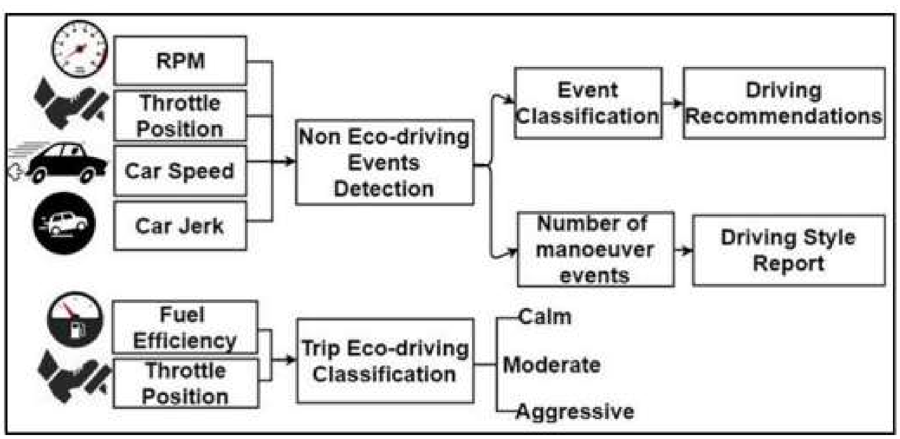


Fig. 2.4. Driving profiling methodology [25]

Ward Ahmed Al-Hussein et al. (2021) [26] This work focuses on the field of sensor-built driving behavior investigation. It deliberates the enthusiasms that attract scientists to this area, common difficulties, and challenges, and offers recommendations. Moreover, the proposed work provides research guidelines constructed on the authors' understanding of the existing literature, suggesting paths for future developments. These guidelines include the development of an effective Driving Assistance System (DAS) (Fig. 2.5), a method to profile drivers according to their behavior modes, and the proposal of a deep learning-based algorithm to classify drivers based on their defined profiles. The results of the study are made available for other professionals to use in their future work. Additionally, the paper compares driving behaviors across different demographics, such as sex (male and female) drivers, age group (young and older drivers), driving on working days versus weekends, and during traffic limitations. This research work also presents the performance of a deep learning-based algorithm for classifying drivers based on their behavior. Overall, the paper sheds light on sensor-based driving behavior analysis, providing insights and suggestions for further research and advancements in this field.

Research findings- The proposed work provides a set of guidelines pertaining to driver classification. These guidelines encompass the creation of an efficient Driving Assistance System (DAS), a methodology for categorizing drivers based on their behavioral modes, and the introduction of a deep learning-based algorithm for classifying drivers according to these defined profiles. The study's findings are shared openly, facilitating their utilization by fellow professionals in their future endeavors.

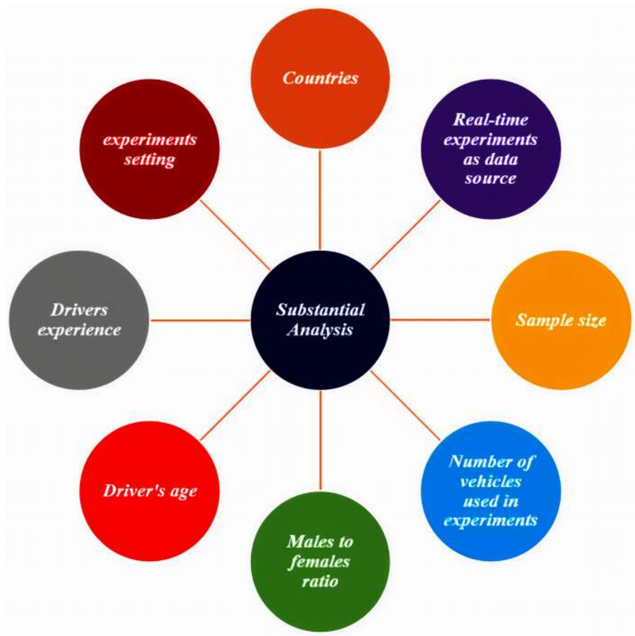


Fig. 2.5. Elements for substantial analysis [26]

Shi-Huang Chen et al. (2015) [27] This study introduces a method for examining driving behavior using AdaBoost algorithms and onboard diagnostic (OBD) data from automobiles. The method uses the OBD port to gather important vehicle information like speed, RPM, throttle position, and engine load. Then, it makes significant use of AdaBoost algorithms to research how drivers act. The proposed driving behavior analysis technique, according to test results, had a typical accuracy rate of 99.8% in a variety of driving environments. Surprisingly, the AdaBoost algorithm-based proposed solution achieved 99.9% accuracy in just 15 iterations. These results imply that the method can be successfully implemented in a useful driver aid system.

Research findings - The method leverages the OBD port to collect crucial vehicle data such as speed, RPM, throttle position, and engine load. Subsequently, it extensively utilizes AdaBoost algorithms to analyze driver behavior. It's worth noting that the proposed method does not rely on derived parameters to aggregate behavioral data, nor does it employ driving scores or rankings in its approach.

Ashanira MatDeris et al. (2011) [28] This paper discusses various modeling techniques used in machining research. In recent years, there has been a focus on using computational methods like Support Vector Machine (SVM), Artificial Neural Network (ANN), Genetic Algorithm (GA), Artificial Bee Colony (ACO), and Particle

Swarm Optimization (PSO) to model machining processes. This paper specifically looks at SVM, which is considered a popular method for modeling both traditional and modern machining operations. SVM is a powerful mathematical tool that is commonly used for tasks like classifying data, making predictions, and estimating functions, and it has found extensive use in modeling machining operations. SVM uses different types of mathematical functions, known as kernel functions, to train its parameters, including linear, polynomial, radial basis function (RBF), sigmoid, and Gaussian kernel functions.

Research findings - In this research work, the process of machining involves modeling and optimization, which are inherently challenging and require appropriate methodologies to meet the criteria for producing high-quality products while minimizing cost estimation. The study employs a range of computational techniques, including Support Vector Machine (SVM), Artificial Neural Network (ANN), Genetic Algorithm (GA), Artificial Bee Colony (ACO), and Particle Swarm Optimization (PSO). This paper offers a comprehensive review of the application of SVM and other algorithms, serving as a valuable resource for gaining a concise understanding of their practical applications in machining processes.

Charlyn Nayve Villavicencio et al. 2021 [29] SVM, which stands for Support Vector Machine, is a tool used in studies about diseases in our bodies. Right now, there's a huge sickness spreading all over the world called COVID-19. It's a sickness that spreads when sick people release tiny drops into the air. To stop more people from getting sick and keep them safe, we need to quickly check who might have this sickness. At first, there weren't many tests for COVID-19, and the ones in labs took a long time. So, researchers developed a computer algorithm using AI and SVM to find if someone has COVID-19. They used a special program and adjusted some settings to make the guesses better. After checking many times, they saw that the program was right about 98.02% of the time when it used the best settings. This is good news and can help us find and treat sick people better.

Research findings- In this study, scientists devised a computer algorithm harnessing AI and SVM technology to determine the presence of COVID-19 in individuals. They fine-tuned the algorithm by customizing certain parameters to enhance its accuracy. After conducting numerous tests, it was observed that the program achieved an impressive accuracy rate of approximately 98.02% when operating with its optimal settings. This research holds potential for application in the proposed study, offering a valuable tool for detecting COVID cases through computer algorithms.

Ji Young Woo et al. (2016) [31] This research addresses the persistent issue of auto theft, which continues to rise despite the implementation of numerous anti-theft technologies. The security vulnerabilities of cars, particularly with the increasing adoption of computerized electronic devices, pose a significant threat by allowing perpetrators to bypass anti-theft systems. Specifically, keyless car theft attacks are expected to proliferate as these technologies become more prevalent. To effectively combat auto theft, we propose a novel driver verification method that leverages driving pattern analysis using sensor measurements from the vehicle. This approach incorporates previously overlooked mechanical features of automotive parts, which can be distinguished based on drivers' driving behaviors. By including these features in the model, increased its accuracy and applicability compared to previous studies. To optimize the detection performance and reduce feature processing time, employed feature selection techniques to identify the most significant features. Additionally, enriched the feature set by deriving statistical features such as mean, median, and standard deviation. This strategy mitigates the impact of feature value fluctuations per driver and ultimately generates a more reliable model for auto-theft detection. Also, investigating the effect of the sliding window size on performance enables the author to identify the point at which the detection becomes reliable and promptly inform vehicle owners of potential theft events. By conducting real driving experiments, to validate the effectiveness of the proposed model and demonstrate its valuable contribution to the field of driver identification. research offers a comprehensive approach to address the increasing challenge of auto theft. By analyzing driving patterns and incorporating mechanical features, we provide a reliable and efficient method for auto-theft detection. We believe that continued research and development in this area will be essential to stay ahead of evolving auto-theft techniques and safeguard vehicle owners from potential theft incidents.

Research findings- In proposed method, we introduce an innovative driver verification approach that harnesses driving pattern analysis through sensor data collected from the vehicle. This method incorporates mechanical attributes of automotive components that have previously been overlooked, enabling the distinction of drivers based on their unique driving behaviors. We have conducted real-world driving experiments to validate the effectiveness of our proposed model and showcase its valuable contribution to the field of driver identification. The primary objective of this research is to develop an anti-theft method aimed at enhancing vehicle security.

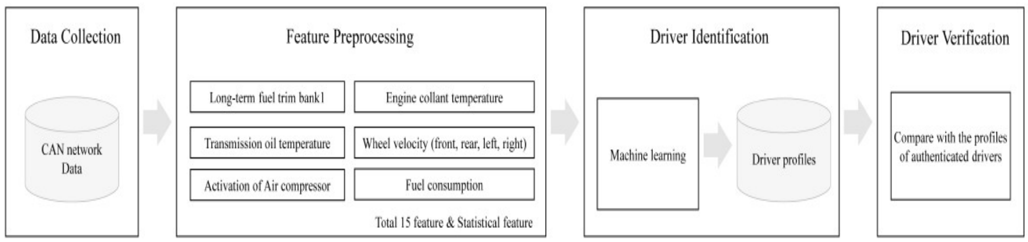


Fig. 2.6. Driver verification model [32]

Table 2.1. Patent documents for oil quality sensors

Patent no.	**Description**	**Identified Gap**
US4782332A Lubricant oil monitoring system, sensor for monitoring lubricant oil quality and method of manufacturing sensor for monitoring lubricant oil quality	This invention is about a sensor designed to be used directly in an electrical circuit. The special feature of this sensor is that it corrodes when the oil it's exposed to deteriorates. As a result of this corrosion, the sensor's electrical current changes due to an increase in resistance. The sensor is made of a ceramic tube, and it has two layers – the first one is nickel that's deposited through an electroless process, and the second one is lead that's plated electrolytically. Leads are	In the example, the sensor corrodes related to oil degradation and delivers a changing electrical current due to increased resistance brought on by said corrosion, illustrating how the invention pertains to an improved sensor for use in-situ in an electrical circuit. Improved lubricants or the presence of antioxidants in different environments can reduce output.

	attached to both ends of the tube to make it usable. When this sensor is placed in oil, it will corrode and change its resistance, allowing it to measure the quality of the oil as it deteriorates. [11].	
WO2012074109A1 Lubricating oil degradation sensor	A lubricating oil degradation sensor capable of enabling the immediate identification of the type of impurity in a machine lubricating oil is provided. The lubricating oil degradation sensor installed in a machine is a sensor for detecting degradation in lubricating oil comprises a white LED that emits a white light, an RGB sensor that detects the color of received light, a gap-forming member that has an oil gap for the lubricating oil to penetrate [12].	Illustrates a sensor that detects the deterioration of the lubricant of the machine, and includes a white light emitting element that emits white light, and a color of the received light. The lubricating oil deterioration sensor of the present invention identifies the type of contaminant in the lubricating oil of the machine. This makes a limitation in that sensor can be used for a particular set of color and needs calibration with the change in the oil's color.
US20080174323A1 Corrosion sensor to monitor and control the acidity of the lube oil and	The invention is about a corrosion sensor that has a corrodible component. This element corrodes in a lubricant or hydraulic oil. The main	Illustrates corrosion sensors having a corrodible component that is corrodible in a lubricant or hydraulic

hydraulic oil	purpose of this sensor is to monitor the degradation of the lubricant or hydraulic oil. [13].	oil. The presence of anti-oxidants in varying environments or improved lubricants can hamper output.
US7612874B2 Method and apparatus for monitoring oil deterioration in real time	The technique and apparatus for real-time monitoring of oil deterioration are described. The method involves shining light into the oil and measuring its intensities at red, green, and blue wavelengths after transitory through a certain thickness of the oil. By using these measured intensities, the ratio between the red wavelength range and the green wavelength range is calculated. This process is repeated to continuously monitor any changes in the ratio value during the use of the oil [14].	Measurement of oil quality with the use of a color sensor for measurement of quality of oil. As degradation of oil turns oil less transparent because of the presence of carbon and other contamination. There for color of the oil need not to detected as done in the disclosed document. The present embodiment does not use any temperature compensation making it less complicated.
	The invention is about a monitoring system used to inspect a fluid inside a reservoir. The system works by inserting a sample of the fluid into a take-off of the reservoir. The monitoring system	The disclosed method suggests an optical transmitter and detector for measurement require a modification in the system in order to implant the sensing unit inside engine. Present

WO2019002651A1 System and method for monitoring the state of a fluid	includes a measuring area where the fluid sample can flow through. There are light emitting and light detector systems located on the same side of the monitoring system, with an optical window between them and the measuring area. On the other side of the monitoring system, there is a rear optical element. The lighting system emits light towards the measuring area, and the light detector system detects the light reflected by the fluid or transmitted through the fluid and reflected by the rear optical element. The monitoring system also has an electronic subsystem with processing means that control the activation and deactivation of the lighting system and process the signals obtained from the light detector system. This system can effectively monitor the fluid in the reservoir. The invention also includes the monitoring method [15].	embodiments do not require such modification as it can be installed in return pipe of existing engine. Secondly the disclosed document does not measure oil temperature which is desired for exact measurement of oil quality. Present embodiment collects data about received light intensity and compensate temperature also for exact measurement of oil quality
	The invention offers different	disclosed invention requires

US10151687B2 Systems, apparatuses, and methods for fluid analysis and monitoring	systems, apparatuses, and methods for analyzing fluids. One of the embodiments includes a removable and replaceable sampling system connected to a logical system. This sampling arrangement allows the fluid to flow through it, and it collects real-time data from the fluid. The collected data is then sent to the logical system for processing. The system consists of a command-and-control system, which receives and stores the real-time data in a database. It then compares this data with existing data for the fluid in the database to identify any specific conditions existing in the fluid. This invention allows for effective and efficient fluid analysis [16].	routing of the oil under test utilizing a spectral scanner/spectrometer/custom electro-optical system to instantaneously and continuously scan and inform a user of the molecular makeup and condition of any fluid. Making the system complex and less practical, especially for engines.

Table 2.2. Comparison of various kinds of sensing techniques.

S. no.	Reference	Technique(s)	Advantage	Disadvantage
1	Dipstick with automatic warning light US5299456 A[17]	The quantity of engine oil was tested using a floatable conducting ball and a tube containing copper electrodes in which contact is made and broken by the floating conductive ball.[17]	The simplest system for detecting the level of engine oil. No modifications in the engine are required. No requirement for microprocessors or complex electronic circuits.	Quality of oil not reported Requires regularly maintained components Only two options to display
2	An acoustic automotive engine oil quality sensor [18]	Acoustic waves are generated with a piezoelectric resonator present in oil. Contamination of oil changes the visco-elastic characteristics of the oil, which produces a change in the characteristics of the shear waves, and hence piezoelectric resonator (resonance frequency).	An accurate method of testing oil quality. Oil quality can be displayed in percentage etc. The circuit is away from the machine so less affected by temperature	Shear waves are affected by temperature. The sensor itself requires a complex circuit. Not easy to install on board.
3	A remote acoustic engine oil quality	A piezoelectric probe having shear mode and an onboard VCO-based electronic measurement	Resonance frequency measurement may have noise but the inductive property	The circuit required is complex and requires

	sensor [19]	system. Capable of identifying different grades and relating oil conditions resulting from engine operation and contamination due to dilution with water, coolant, gasoline, etc	was used in it. hence low noise Can differentiate between new and used oils	isolation A dedicated section for oil quality measurement hard to make on board
4	Electrical measurement of oil quality [20]	The sensor is based on the capacitive measurement relative to the permittivity of the oil, having an oscillator circuit and the sensor is one of the components of the unit for measurement The oscillator circuit comprises an LC oscillator Which provides an output signal, whose amplitude is dependent upon the looseness of the oil.	The direct relation of lessens of oil with permittivity. The system does not require a dedicated microprocessor etc.	Based on the oscillator circuit so requires stabilization. Temperature drift may produce large variations in signals.
5	A Novel Approach to On-Line Oil Quality Sensing Through	A polished and grooved optical fiber was used which was immersed into the oil whose characteristics need to be determined.	The method uses the optical property for measurement. Optical property and temperature both are measured	Optical fiber requires complicated coupling and the range of sensors may

	Side-Polished Optical Fiber [21]	Thermocouple was used to find temperature. The viscosity of oil can change the optical properties of wavelengths traveling via optical fiber.	simultaneously.	vary. The sensor must have a thermocouple in the oil bath making it more complicated and larger in size.
6	A Novel Method for online monitoring Engine Oil [49]	In this optical fiber was used as a medium for sensing oil quality. A laser diode was used for the purpose of light which would pass through optical fiber and the refractive index of fiber was varied as the lubricating properties	Contactless type of sensor requires low maintenance. More accurate due to the presence of a spectroscope. Do not require a temperature sensor	Spectroscope is a costly and complex hard-to-make onboard sensor. No temperature compensation was provided. Optical fiber construction is guided

2.4. Conclusion

In conclusion, the study ideas take a thorough and diverse approach to vehicle dynamics and diagnostics, utilizing machine learning techniques with the help of Raspberry Pi ,Arduino and sensors for sophisticated vehicle monitoring. In addition to recording vital parameters like vehicle speed, acceleration, and driving duration, the system connects with an activity-tracking device for driver behaviour by including sensors like GPS, RTC, and accelerometers. Because of its capacity to multitask, the Raspberry Pi and other microcontroller-based subsystems can interpret OBD-II vehicle diagnostic data, forecast engine and other component lifespans, and send real-time results to mobile applications. This configuration, which line up adaptability and versatility, optimizes connectivity across various OBD protocols by integrating an OBD-II connector with Bluetooth, Wi-Fi, and WCDMA modules. Whereas AdaBoost techniques enable driver behavior assessment without depending on derived parameters or driving scores, machine learning and meta-heuristic algorithms make it easier to analyze driver behavior, fuel economy, and eco-driving. Additionally, the study presents a novel driver verification model for anti-theft protection that is based on the assessment of distinct driving behaviors and mechanical characteristics. Future research in vehicle diagnostics and security systems, the results of real-world testing show how the system may enhance fleet path planning, remote asset management, and driver classification.

While in detection of oil quality by resolving the shortcomings of a few approaches, the study work described here has enhanced the sensor design for oil degradation detection. The sensor uses a white light emitter to identify contaminants by color analysis and measures variations and one method use electrical current caused by corrosion-induced resistance to detect lubricant deterioration. However, the sensor's susceptibility to better lubricants or antioxidants and its requirement for calibration with changes in oil color limit its use. This embodiment is more practical since it can be inserted in the return pipe without changing the system, unlike other designs that need to be modified for in-engine installation. Additionally, unlike earlier techniques, the sensor adjusts for temperature, increasing the precision of oil quality readings without the need for sophisticated equipment like spectral scanners. The reduced design in this study avoids the complex circuitry and on-board installation issues that were present in prior methods, but it is still vulnerable to temperature-induced signal fluctuations. Ultimately, a sensor is needed to provide a more practical and efficient way to check oil quality in real time across a range of settings.

CHAPTER 3

REQUIREMENT AND DEPLOYMENT OF ASSET MONITORING

The internal combustion (IC) engine, a highly intricate power-producing machine, is widely used in the automotive industry. Component failures in automobiles are a common occurrence, impacting the lives of individuals at some point. Many automotive vehicles endure demanding conditions, often operating without any form of in-depth inspection throughout their lifespan. In cases where vehicle parts are damaged, they are frequently replaced without further monitoring [2]. This lack of oversight increases the risk of sudden component failures, potentially leading to accidents and loss of life [32]. Unfortunately, vehicle owners generally show limited interest in periodic maintenance and monitoring of their vehicles [5]. Consequently, unexpected component failures may arise. Certain parts within a vehicle are commonly referred to as the "heart" of the vehicle. If these crucial components become damaged, accidents become more likely. These safety-critical items, if found to have in-service failures within a specific batch, often result in recalls of all affected vehicles. This leads to significant costs and negative publicity. Therefore, in automotive failure analysis, it becomes vital to determine the source of a failure and assess its likelihood of occurring in other vehicles. Failures in automotive components can arise from various factors, including mechanical stresses, thermal stresses, wear mechanisms, temperature degradation, oxidation mechanisms [11], and more.

In the context of automotive vehicles, engine component damages have traditionally been attributed to wear and lubrication sources. However, it is important to note that some damages, where wear and lubrication mechanisms are identified as the main cause, may have originated from a fatigue crack at the root cause. Based on an analysis of automotive component failures investigated, it has been observed that the failure rate is typically dependent on time. As a system progresses through its expected life cycle, the failure rate changes over time. For instance, an older automobile may have a significantly higher failure rate in its 5^{th} year of service compared to its 1^{st} year. In the initial stages of service, one does not typically anticipate the need to replace an exhaust pipe, perform extensive brake repairs, or encounter major transmission issues. Figure 3.1 illustrates the distribution of component failures, revealing that engine failures are the most common, accounting for 41% of the total. Additionally, Figure 3.2 showcases the distribution of failure causes, indicating that abuse is the most common cause, accounting for 29% of the total failures.

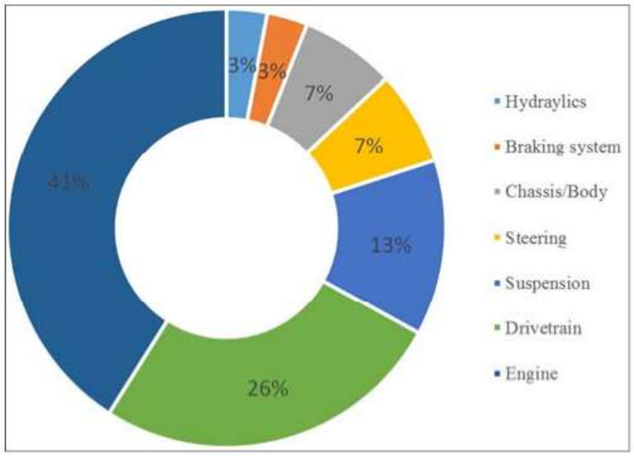


Fig. 3.1. Component failures [32]

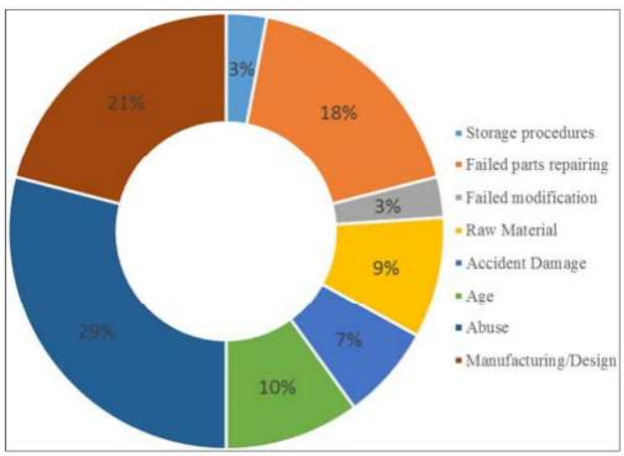


Fig. 3.2. Cause of failure [32]

A significant proportion of the total failures, amounting to 29%, is attributed to operator negligence, highlighting the direct or indirect role of users in engine failures. Another notable factor contributing to failures is the use of repaired parts, accounting for 18% of the failures. Additionally, modifications made by operators or drivers account for 3% of the failures. These three reasons for engine failures are directly linked to user actions, emphasizing the importance of user awareness and knowledge to prevent such incidents. There is a clear need for an asset monitoring system to handle these issues and reduce the risks connected with user-related errors. With the help of such a system, owners and operators would be able to proactively anticipate possible problems and take preventative action by receiving continuous monitoring and real-time input on the state of crucial components. Owners can learn important information about the condition of the engine and other relevant parts of their car by putting in place an asset monitoring system. A variety of technologies and sensors can be incorporated into an asset monitoring system to track important characteristics like fluid levels, temperature, vibration, and oil pressure. These sensors can deliver information that makes it possible to identify anomalous circumstances, excessive wear etc. By receiving timely alerts and warnings, owners can take prompt action, such as scheduling maintenance or repairs, before a minor issue escalates into a major failure. Furthermore, an asset monitoring system can facilitate the collection and analysis of data from a fleet of vehicles, allowing owners to identify common failure patterns, assess the performance of specific components or models, and make informed decisions concerning maintenance and component replacement. This data-driven approach can minimize downtime, and ultimately enhance the reliability and longevity of automotive engines.

Educating vehicle owners and operators about the importance of regular maintenance, obedience for service intervals, and the potential implications of neglecting these aspects is critical. Although the asset monitoring system, awareness campaigns and training programs can help users understand their role in preventing engine failures and reinforce the significance of responsible vehicle operation. The significant percentage of engine failures attributed to operator negligence, use of repaired parts, and modifications highlights the need for user awareness and a robust asset monitoring system. By implementing such a system, owners can actively monitor their vehicle’s health, detect potential issues early on, and ensure timely maintenance, ultimately reducing the occurrence of engine failures and enhancing the safety and reliability of automotive [2-6].

There are several types of engine monitoring systems [1-5], [8-9] available that offer various levels of monitoring and functionality. Here are some commonly used types:

3.1.1. On-Board Diagnostics (OBD) Systems: OBD systems are standard in most modern vehicles. They monitor the vehicle's engine and emissions, providing diagnostic trouble codes (DTCs) when a fault is detected helpful for technicians. OBD systems primarily focus on emissions-related issues but can also provide basic engine performance data [9].

3.1.2. Engine Control Units (ECUs): Electronic control modules that manage and monitor various aspects of the engine's operation. They collect data from sensors throughout the engine and make adjustments to optimize performance. ECUs can provide real-time engine parameters, and diagnostic information, and even enable tuning and customization options.

3.1.3. Condition Monitoring Systems: These systems continuously monitor engine parameters, such as temperature, pressure, vibration, and fluid levels. They use sensors and computer algorithms to detect abnormalities or potential failures. Condition monitoring systems are commonly used in industrial and heavy machinery applications to ensure the longevity and reliability of engines.

3.1.4. Performance Monitoring Systems: These systems focus on monitoring and optimizing engine performance. They provide data on fuel efficiency, power output, air-fuel ratios, and other performance-related metrics called MAP. Performance monitoring systems [41] are often used in high-performance and racing applications to fine-tune engine parameters.

3.1.5. Remote Telemetry Systems: These systems enable remote monitoring and data collection from engines located in different locations [40]. They use wireless communication technologies (IoT and WSN) to transmit engine data to a central monitoring station. Remote telemetry systems are particularly useful in fleet management and remote equipment monitoring scenarios.

3.1.6. Predictive Maintenance Systems: These systems utilize advanced analytics and machine learning algorithms to predict engine catastrophes or maintenance requirements based on historical data and real-time monitoring. They can identify patterns and variances to provide proactive maintenance recommendations, helping to avoid unexpected breakdowns and minimize downtime. Pint to be noted that the availability and functionality of these systems depended on the specific vehicle or engine type. Additionally, advancements in technology continue to introduce new and more sophisticated engine monitoring systems to enhance engine performance, consistency, and safety.

3.1.7. Proposed method

A hardware and software was developed employing the following steps:-

- OBD scanner (ELM327)was connected to car OBD port
- using blue tooth module connectivity was established with the scanner
- data from vehicle ECU was request using suitable subroutines
- data was stored and forwarded to thingspeak IoT
- visualizations were used for making graph with the help of MATLAB visualization program

The approach for obtaining data from the OBD-II port includes two major components that is hardware (see Fig. 3.3.) and firmware.

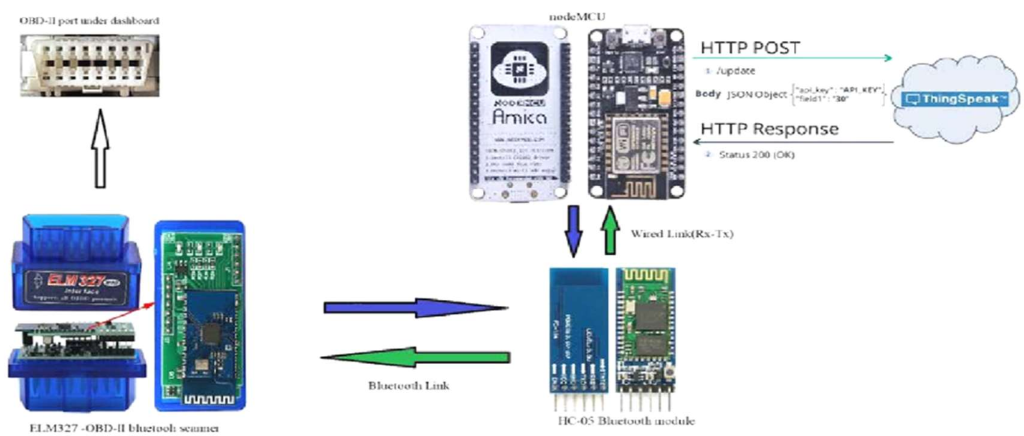


Fig. 3.3. Hardware architecture of the proposed system

The system is made up of the ELM327, a multi-protocol communication device based on Bluetooth [30] that is compatible with the following OBD-II protocols: -

VPW (10.4 kbit/s) SAE J1850

250 kbit/s SAE J1939

500 kbit/s SAE J1939

500 kbit/s SAE J1939

(41.6 kbit/s) PWM CAN protocol SAE J1850 (11 bit ID, 500 kbit/s) ISO 15765-4

10.4 kbit/s, ISO 14230-4 KWP (5 baud initialization)

Rapid initialization, 10.4 kbit/s, ISO 14230-4

CAN (29 bit ID, 500 kbit/s) ISO 15765-4

CAN (11 bit ID, 250 kbit/s) ISO 15765-4

ISO 9141-2 (10.4 kbit/s, 5 baud initialization)

The gadget is attached to the car's OBD port, as seen in Fig.3.6. The Tx and Rx pins of the HC-05 are connected to the Rx and Tx pins of the microcontroller board (nodeMCU), respectively, to enable communication with Bluetooth modules built into microcontroller-based boards. as mentioned in Fig. 3.3 this experimental setup was developed with the following components

nodeMCU 550/-

Bluetooth module HC-05 250/-

OBD scanner ELM327 750/-

Wires and jumpers etc. 500/- having approximate cost 2050/-(INR)

3.2.1. Engine Control Module/Unit (ECM/ECU)

In today's automotive world, the internal combustion engine has undergone significant advancements with the incorporation of an engine control unit (Fig.3.3). This electronic equipment plays a pivotal role in overseeing and managing abundant engine jobs. The level of complexity exhibited by ECUs can vary, with basic units focusing on regulating fuel volume injection or spark timing, while more sophisticated ones take control of a wide range of engine operations. By harnessing information from an array of sensors purposefully positioned throughout the engine, the ECU effectively administrates these functions with precision. An average ECU incorporates a processor that, despite being smaller than a typical desktop computer's processor, beats it in terms of efficiency. Moreover, the program executed by the ECU processor is highly optimized, allowing it to operate flawlessly. While desktop code typically demands many gigabytes of memory, ECU code requires only about a few megabyte of storage space. The mutual relationship between the ECU and the internal combustion engine has led to a new age of automotive control. Through its intelligent management of engine processes, the ECU ensures enhanced performance, fuel efficiency, and adherence to emission norms. With ongoing advancements in automotive technology, ECUs continue to evolve, pushing the boundaries of engine optimization and opening the way for greener and more efficient vehicles [33]. The engine control unit plays a crucial role in processing real-time information from peripheral sensors distributed throughout the vehicle. Equipped with a microprocessor, the ECU efficiently handles this data and generates real-time feedback. The ECU's hardware consists of a circuit board made up of electronic components mounted on a printed circuit board (Fig.3.4). At the heart of this circuit board is a microcontroller chip, serving as the central processing unit of the ECU. The software component of the ECU is stored within the CPU and other additional electronic components. Typically, the storage format takes the shape of EEPROM or flash memory, allowing for reprogramming possibilities. Installing modified software are common methods for reprogramming the ECU. To establish communication with various devices both inside and outside the engine, the ECU relies on the functionalities of the Controller Area Network or associated protocols, an automotive network. Through this , the ECU establishes connections with devices such as automatic transmissions, traction control systems, and other electronically controlled functions, depending on the vehicle's design. The communication protocol typically adheres to the OBD (On-Board Diagnostics) standard.

Fig. 3.4. A car's ECU/ECM [33]

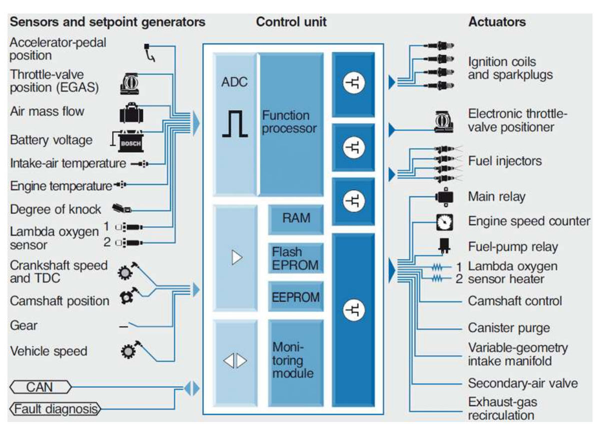


Fig.3.5. Blocks of ECU/ECM [33]

The Engine Control Unit (ECU) or Engine Control Module (ECM) is responsible for managing various aspects of an engine's operation. It gathers data from different sensors and uses that information to control fuel injection, ignition timing, and other engine functions. There are several engine-related parameters recorded by the ECU/ECM. Here are some of the key parameters:

3.2.1.1. RPM (Revolutions Per Minute): It measures the engine speed in revolutions per minute. The ECU uses this parameter to determine the appropriate fuel injection time.

3.2.1.2. Engine Load: It indicates the load on the engine and is usually expressed as a percentage. The load is calculated based on factors like throttle position, intake manifold pressure, and mass airflow. The ECU adjusts fuel injection and ignition timing based on the engine load.

3.2.1.3. Coolant Temperature: This parameter measures the temperature of the engine coolant. It helps the ECU determine when to activate the cooling fan, adjust fueling during warm-up, and prevent overheating.

3.2.1.4. Intake Air Temperature: It measures the temperature of the incoming air to the engine. The ECU uses this information to adjust the air-fuel mixture for optimal combustion.

3.2.1.5. Throttle Position: It indicates the position of the throttle paddle, which controls the airflow into the engine. The ECU uses this parameter to determine the desired air-fuel mixture and engine load.

3.2.1.6. Oxygen (O2) Sensors: These sensors monitor the level of oxygen in the exhaust gases. The ECU uses this feedback to adjust the fuel-air mixture in real time, ensuring efficient combustion for reducing emissions.

3.2.1.7. Mass Airflow (MAF) Sensor: It measures the amount of air entering the engine. The ECU uses this data along with other inputs to determine the appropriate fuel-air ratio and ignition timing.

3.2.1.8. Ignition Timing: This denotes to the exact moment when the spark plug fires to ignite the air-fuel mixture. The ECU controls the ignition timing based on inputs like RPM, engine load, and other parameters for optimal performance and efficiency.

3.2.1.9. Fuel Pressure: It measures the pressure of the fuel delivered to the fuel rail. The ECU monitors this parameter to ensure the fuel system is functioning properly and adjusts fueling accordingly.

3.2.1.10. Knock Sensor: It detects engine knock or detonation, which is an unwanted disorder that can cause engine damage. The ECU uses this information to adjust the ignition timing and avoid knocking.

3.2.1.11. Fuel Trim: Fuel trim refers to the adjustment made by the ECU to maintain the proper air-fuel ratio. They are of two types: short-term fuel trim (STFT) and long-term fuel trim (LTFT). STFT is the immediate adjustment made by the ECU based on real-time sensor data, while LTFT is a long-term adjustment based on average conditions over time.

3.2.1.12. Engine Timing Advance: This parameter refers to the alteration of the spark ignition timing in relation to the current piston angle. The ECU determines the ideal timing advance based on inputs like RPM, engine load, and sensor data to optimize power and fuel efficiency.

3.2.1.13. Engine Misfire Detection: The ECU monitors individual cylinders for misfires, which occur when combustion does not happen appropriately. Misfire detection helps diagnose potential issues with spark plugs, fuel injectors, or ignition components, allowing the ECU to take corrective action.

3.2.1.14. Throttle Response: Throttle response denotes to the speed at which the engine responds to changes in throttle input. The ECU uses various parameters to optimize throttle response for smooth acceleration and driving comfort.

3.2.1.15. EGR (Exhaust Gas Recirculation) Valve Position: The EGR valve controls the recirculation of a portion of exhaust gases back into the engine intake. The ECU monitors the EGR valve position to regulate the quantity of exhaust gas recirculation for emissions control and engine efficiency.

3.2.1.16. Fuel Injector Pulse Width: It measures the ON duration or width of the fuel injector pulse, which determines the amount of fuel injected into the engine. The ECU regulates the injector pulse width based on engine load, RPM, and other parameters to sustain the desired air-fuel ratio.

3.2.1.17. Camshaft Position: The ECU monitors the position of the camshafts to ensure proper synchronization with the crankshaft and to control valve timing.

3.2.1.18. Knock Retard: If the knock sensor detects engine knock, the ECU responds by retarding the ignition timing by a few degrees to prevent further knocking. Knock retard is the amount of ignition timing adjustment made by the ECU to prevent knocking.

3.2.1.19. Battery Voltage: The ECU measures the battery voltage to ensure that it remains within the appropriate range. It uses this parameter to control charging system operation and RPM to detect potential electrical system faults.

3.3. OBD-II

OBD-II stands for On-Board Diagnostics-II. It is a standardized system used in vehicles to monitor and diagnose the performance of various components and systems. OBD2 was introduced to provide a consistent and universal way for mechanics and technicians to access and interpret diagnostic information from vehicles. The OBD2 system consists of two main components i.e. OBD2 port and the OBD2 diagnostic tool. The OBD2 port is a connector located in the vehicle's cabin, usually under the dashboard. It provides access to the vehicle's diagnostic system. The OBD2 diagnostic tool, such as a scan tool (called ODB scanner), is a device used to communicate with the vehicle's OBD2 system. OBD2 has become a usual requirement for vehicles vended in many countries, since 1996. It has greatly improved the capability to diagnose and repair vehicle issues, standardizing the diagnostic process across different makes and models. In Addition, OBD2 has played a critical role in emissions control and monitoring and helped to reduce harmful pollutants emitted by vehicles and improve overall air quality. Following are main functions:

Read and Clear Diagnostic Trouble Codes (DTCs): OBD2 allows users to recover diagnostic trouble codes, which are alphanumeric codes that indicate specific faults or malfunctions within the vehicle's systems. These codes provide valuable information to diagnose and troubleshoot problems. Once the issues are resolved, the codes can be cleared using the OBD2 tool.

Monitor Emissions Control Systems: OBD2 continuously monitors various emissions control systems, such as the performance of catalytic converter, oxygen sensors etc., and ensures they are functioning appropriately. If a fault is detected, the OBD2 system generates a diagnostic trouble code and illuminates the "Check Engine" light on the dashboard.

Retrieve Live Data: OBD2 allows users to access real-time data from various sensors and components in the vehicle. This includes parameters such as engine RPM, coolant temperature, vehicle speed, throttle position, and many others. Live data stream provides valuable perceptions into the performance of the vehicle and can help in diagnosing faults.

Readiness Monitors: This has a readiness monitors system that check if the vehicle's emissions control systems are ready for an emissions test. its readiness status indicates whether the vehicle has completed the necessary self-diagnostic tests. This helps ensure that vehicles are properly equipped before emissions tests.

Vehicle Information: The security feature of OBD2 provides access to specific information about the vehicle, including VIN (Vehicle Identification Number), RFID and other manufacturer-specific data. This information can be useful for vehicle history, software updates, and identifying specific vehicle arrangements.

3.3.1 OBD-II scanners

DTC scanners or OBD-II scanners (see Fig.3.6) are used to retrieve and interpret diagnostic trouble codes generated by a vehicle's onboard computer system. They are an essential tool for diagnosing and troubleshooting automotive issues. DTC stands for "Diagnostic Trouble Code," and DTC scanners, also known as OBD-II (On-Board Diagnostics) scanners, are tools used to read and interpret the diagnostic codes produced by a vehicle's onboard computer system. Modern vehicles are equipped with an onboard computer, known as the Engine Control Unit, which monitors various sensors and systems within the vehicle. When a problem is detected, such as an engine misfire or an emissions issue, the ECU generates a corresponding DTC. These codes provide valued information about the specific problem, allowing technicians to diagnose and repair the issue more efficiently. DTC scanners are used by automotive technicians, mechanics, and car enthusiasts to retrieve and interpret these codes. The scanners typically connect to the vehicle's OBD-II port, which is usually located under the dashboard or near the driver's side footwell. Once connected, the scanner can communicate with the ECU, retrieve the DTCs, and provide information about the specific problem areas. These scanners come in various forms, ranging from basic code readers that only retrieve and display the codes to more advanced models that offer additional features like live data streaming, freeze frame data, and the ability to reset or clear the codes. mostly used scanners are ELM327 and STM1110

3.3.1.1. ELM327

ELM327 is an extensively used embedded system based OBD-II interface designed to connect a vehicle's OBD-II (see Fig.3.6.) port to external devices, such as laptops, smartphones, or tablets. It enables communication between the vehicle's onboard computer system (ECU) and the external device, allowing users to read and read diagnostic information.

Fig.3.6. (a)OBD connector pinout, (b)OBD scanner

ELM327 is primarily used as a bridge between the OBD-II port and an external device to access and analyze diagnostic data from the vehicle's ECU [34]. It is compatible with most vehicles manufactured from 1996 onwards, as these vehicles are equipped with the standardized OBD-II port. It supports the OBD-II protocols, such as ISO 9141-2, ISO 14230-4 (KWP2000), ISO 15765-4 (CAN), and more. The ELM327 provides the ability to retrieve diagnostic trouble codes (DTCs), view sensor data, monitor real-time parameters (e.g., engine RPM, vehicle speed, coolant temperature), and perform certain actions like clearing DTCs or resetting the ECU.

ELM327 interfaces with the vehicle's OBD-II port via a physical connector, typically a 16-pin DLC (Data Link Connector). The other end of the ELM327 device connects to the external device, such as a laptop or smartphone, using serial port, Bluetooth, or Wi-Fi connectivity. To utilize the ELM327, you need compatible application software installed on the device. Various third-party software options are available for different platforms, including Windows, Android, and iOS. These applications communicate with the ELM327, send commands, and receive data from the vehicle's ECU. Its purpose may depend on the software used and the vehicle's ECU capabilities. It provides access to standardized OBD-II parameters but may not support advanced manufacturer-specific functions and programming.

3.3.1.2. STN1110

STN1110 is specifically designed for use in automotive applications and is compliant with the OBD-II standards [34]. It provides the necessary functionality to interface with a vehicle's OBD-II system and communicate with the onboard ECU. It supports various OBD protocols, including ISO 9141-2, ISO 14230-4 (KWP2000), ISO 15765-4 (CAN), and more, allowing for communication with the vehicle's ECU. STN1110 offers capabilities for reading and clearing diagnostic trouble codes (DTCs), retrieving sensor data, monitoring real-time parameters, and performing other diagnostic tasks. It provides the necessary interfaces to connect to the vehicle's OBD-II port, such as UART (Universal Asynchronous Receiver-Transmitter) or CAN (Controller Area Network), enabling communication with the ECU. STN1110 may include additional integrated peripherals such as timers, ADCs (Analog-to-Digital Converters), GPIOs (General Purpose Input/Output), and other features to facilitate the development of OBD-related applications.

3.3.2. Data Link Connector

Data link connector cited is a 16-pin female type connector as exposed in Fig. 3.6.

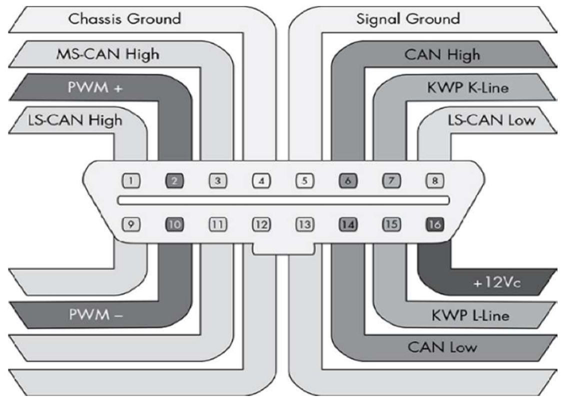


Fig. 3.7. (DLC)Data link connector [30].

For most of the vehicles, this connector can be located near the ashtray, under the dash, under the driver's or passenger's seat, or in a location that is simple to access from the driver or codriver seat without the requirement of special tools.

3.3.2.1. Date frame structure

The user must write 2 bytes onto the bus of serial data in order to interconnect with ECU [30]. The reply 4-bit data frame is received with the first byte being the mode byte and the next being the PID (parameter identification). typical data frame modes (see Table 3.1, Fig. 3.6A).

Table 3.1. Standard modes of the data frame

Mode Byte	Description
0x01	Current vehicle data
0x02	Vehicle data during freeze frame
0x03	Diagnostic trouble codes (DTCs)
0x04	Clear MIL (malfunction indicator lamp) and diagnostic trouble codes
0x05	Test results for oxygen sensor monitoring
0x06	Test results for other component monitoring
0x07	Pending DTCs
0x08	Control operation of on-board system
0x09	Vehicle metadata
0x0A	Permanent DTCs

3.3.2.2. Standard PID of the data frame

PID [30] byte along with the requested data example mentioned in Table 3.2.

Table 3.2. PID and request data example

PID Byte	Full Request	Description
0x00	0x0100	PIDs in range 0x01 – 0x20 supported
0x0C	0x010C	Engine RPM
0x0D	0x010D	Vehicle Speed
0x04	0x0104	Engine Load
0x0F	0x010F	Intake air temperature
0x10	0x0110	Mass air flow rate
0x1F	0x011F	Engine run time (in seconds)
0x20	0x0120	PIDs in range 0x21 - 0x40 supported

3.3.2.3. Response Data format

ECU's respond [30] with a frame which contains a mode specific header and 4 bytes of response data, as revealed in Table 3.3.

Table. 3.3. Response bytes formats.

Header	Response Payload (32 bits/4 bytes)			
Width depends on configuration	Byte A	Byte B	Byte C	Byte D

3.3.2.4. Example of the read operation

For example, if we require engine load data from the ECU, we must send hex data code 0x0104 to the ECU. This request has two bytes(Fig.3.8):

The first byte of 0x01 is the diagnostic service ID.

0x04 the second byte represents the ID of the demanded engine related parameter (LOAD in this case).

ECU answered with 4100C8. a data byte consists of 3 bytes:

The first 0x41 is a positive acknowledgment (40 + 01), while the second 0x04 is an acknowledgment of the parameter ID to be read.

The third 0xC8 represents the actual response parameter (LOAD).

To visualize, we must translate the value in hexadecimal for LOAD to a physical value.

For each PID, we first convert it to decimals as defined by ISO and SAE standards.

The conversion for the calculated engine load is LOAD% = 200/255 DECIMAL

e.g.: 78.431% (according to data received).

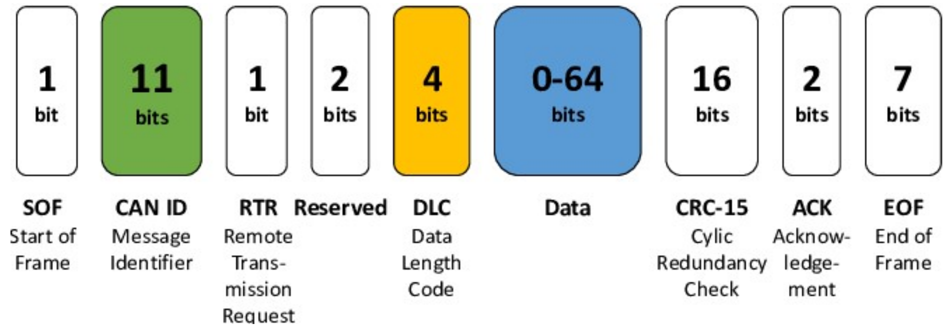


Fig. 3.8. OBD Data frame

3.3.2.5. Firmware

Firmware [30] comprises subprograms and header files for ELM327 Bluetooth activation and protocol findings. PIDs are well-defined in the program and supplied to the ELM327 in AT command approach. If the connection is successful, the main program sends the necessary request for the anticipated sensor data. Debug information about the proposed system is sent to the computer's serial port, which is optional (it may or may not be connected); data collected through the nodeMCU is uploaded to the thing-speak server and visualized using visualization techniques.

3.4. Experimentation

3.4.1 NodeMCU

The ESP8266 Wi-Fi chip is at the heart of NodeMCU, an open-source development board. It is a popular choice for Internet of Things (IoT) projects since it combines the microcontroller unit (MCU) with integrated Wi-Fi capabilities. The NodeMCU platform is simple to use for developing Wi-Fi-enabled applications, and it supports the Lua scripting language, which facilitates programming and rapid prototyping.

3.4.2. NodeMCU Pin Description:

GPIO Pins: The NodeMCU includes (Fig. no. 3.9) a number of General-Purpose Input/Output (GPIO) pins that can be used for digital input or output. The board normally includes ten GPIO pins, labelled D0 through D9, which can be configured as input or output pins.

Analogue Input Pins: The NodeMCU has a single analogue input pin (A0) for reading analogue voltage data from sensors or other devices. For analog-to-digital conversion, this pin can provide a 10-bit resolution.

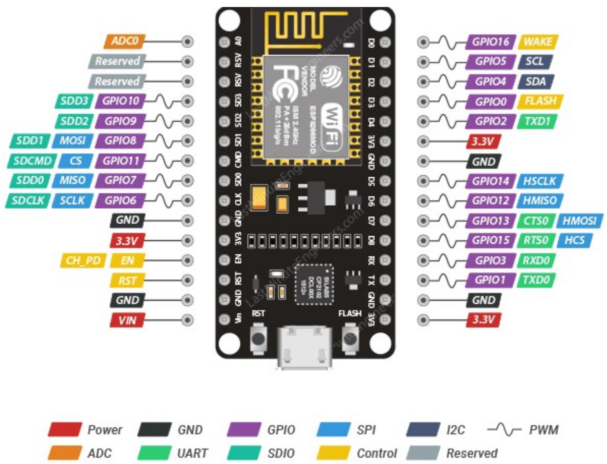


Fig. 3.9. Pinout of nodeMCU

Power Pins: The NodeMCU board has several power pins for powering the board and associated devices. These pins are as follows:

Vin: This is the power supply pin for the board. It is capable of accepting voltages ranging from 4V to 9V.

3V3: This pin provides a 3.3V regulated output that can be used to power external components.

GND: These are the board's ground connectors.

Pins for Serial Communication: The NodeMCU has two serial communication pins:

TX: Serial communication transmit pin. It transmits data from the NodeMCU board.

RX: Serial communication receive pin. It receives data and sends it to the NodeMCU board.

3.4.3. HC-05 Bluetooth module

The HC-05 Bluetooth module is a commonly used Bluetooth transceiver module that allow radio link communication between devices. It is based on the Bluetooth 2.0 specification and offers a simple and cost-effective solution for adding Bluetooth functionality to various applications.

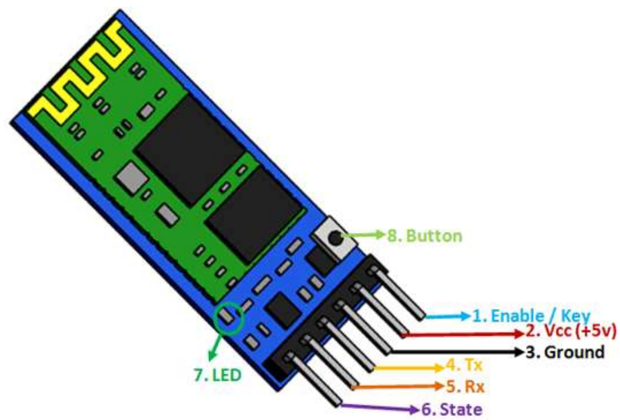


Fig. 3.10. Bluetooth module HC-05 pinout

Features of the HC-05 Bluetooth Module:

Bluetooth Version: The HC-05 module is Bluetooth 2.0 compliant and supports the Serial Port Profile (SPP). With this profile, the module can function as a transparent serial communication link between devices.

Serial Communication Interface: For serial communication, the HC-05 module has a UART (Universal Asynchronous Receiver/Transmitter) interface. To make a wireless serial connection, it can be readily connected to a microcontroller or other devices through the TX (transmit) and RX (receive) pins.

Master/Slave Mode: The module may function in both master and slave mode. In slave mode, it can create a wireless serial connection with a master device (such as a smartphone or desktop). The module may dynamically search for and connect to additional Bluetooth devices when in master mode.

Configuration Modes: The HC-05 module supports two different configuration modes: AT command mode and Transparent mode.

AT Command Mode: The module accepts AT commands received across the UART port in this mode. These instructions allow users to change the device name, pairing code, baud rate, and other module characteristics. In transparent mode, the module acts as a simple wireless serial connection, with data received on one device wirelessly sent and received on the other. This performs it via AT commands during data transmission.

The HC-05 module has a normal range of roughly 10 meters, which can vary depending on variables. It uses a 3.3V power source and is hence compatible with the majority of microcontrollers and development boards.

Pinout: The HC-05 module typically has six pins: VCC (power supply), GND (ground), TXD (transmit data), RXD (receive data), EN (enable), and STATE (status indication).

3.4.4. Bluetooth ELM327

The Bluetooth ELM327 is a variant of the ELM327 chip that integrates Bluetooth connectivity. It is specifically designed to wirelessly communicate with a host device, such as a smartphone, tablet, or computer, via Bluetooth, providing a convenient and wireless solution for vehicle diagnostics.

Features of Bluetooth ELM327:

OBD-II Compatibility: Similar to the standard ELM327 chip, the Bluetooth ELM327 is compatible with the OBD-II protocol. It allows for communication with vehicles that comply with the OBD-II standards, providing access to various engine and vehicle parameters.

Bluetooth Connectivity: The Bluetooth ELM327 module integrates Bluetooth technology, allowing wireless communication between the vehicle's onboard computer and a Bluetooth-enabled host device. It eliminates the need for physical networks such as USB cables or serial networks, if Wi-Fi or Bluetooth is used for greater flexibility and convenience.

Diagnostic Commands: The Bluetooth ELM327 module supports the same set of OBD-II commands as the standard ELM327 chip. These commands allow users to retrieve diagnostic trouble codes (DTCs), monitor sensor data in real time, access vehicle information, and perform various diagnostic functions.

Compatibility with OBD-II Protocols: The Bluetooth ELM327 module, like the conventional ELM327 chip, is compatible with several OBD-II protocols, including ISO 9141-2, ISO 14230-4 (KWP2000), and ISO 15765-4 (CAN). This provides interoperability with a wide range of automobiles, regardless of OBD-II protocol capability.

Compatibility with Third-Party Software: The Bluetooth ELM327 module is compatible with a wide range of third-party software applications designed for OBD-

II diagnostics. These applications offer a simple interface for interfacing with the Bluetooth ELM327 device, allowing users to remotely read and understand car data. A multi-protocol OBD scanner (ELM327), a Bluetooth module (HC-05), and a microcontroller-based board (ESP8266) were all used during the experimentation. In this study, OBD-II platform-compatible hardware and basic software were used to capture important parameters related to car on-road operation. Experiments employing parameters that the driver can see (such as the coolant temperature, speed, RPM, and throttle position sensor) provided more evidence for this. During this experiment, these parameters were recovered and examined. The OBD scanner's latency was over 15 seconds that is why there weren't as many parameters sought. The results were what was predicted. Additionally, more than 50 parameters could be gathered from the ECU and used for numerous applications, including driver or operator behavior, pertinent recommendations or endorsements for the driver or operator, information regarding preventive and scheduled maintenance, warnings, and data that the insurance company could use when disbursing claims. The test was conducted on a Suzuki Alto800 automobile that had a computer and Wi-Fi hotspot on board, and was driven for about 30 minutes in mixed traffic with the ELM327 linked to an OBD port. Bluetooth communication was used to establish the connection to ELM327 (see Fig.3.11), and data samples were collected having the following parameters: -

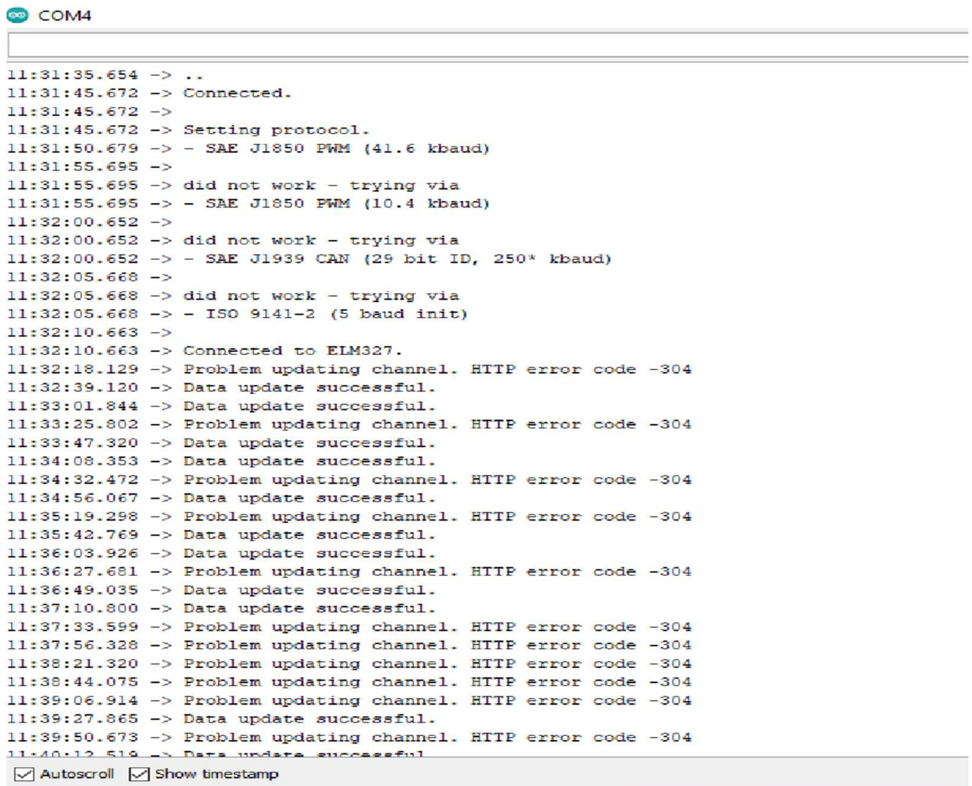
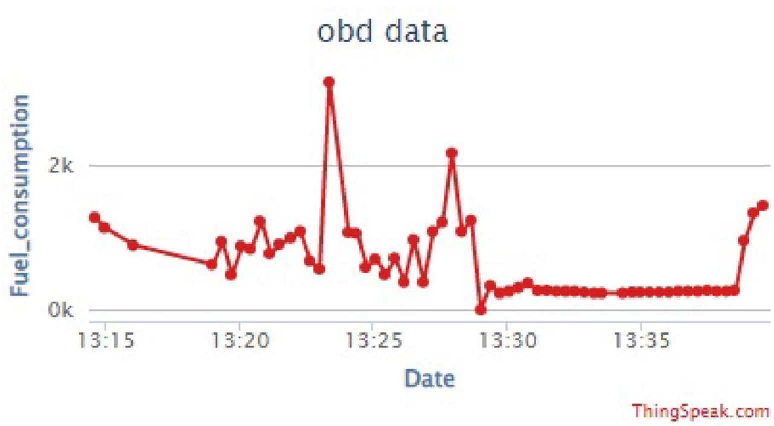


Fig. 3.11. Debug information from the serial monitor.

3.4.5. Fuel consumption

The vehicle ECU's data of the instant fuel consumption CC for 300 samples is shown



in Fig. 3.12.

Fig. 3.12. Fuel consumption in CC.

3.4.6. Absolute throttle position

The percentage output of the throttle position sensor as reported by the vehicle ECU for 300 samples recorded is displayed in Fig. 3.13.

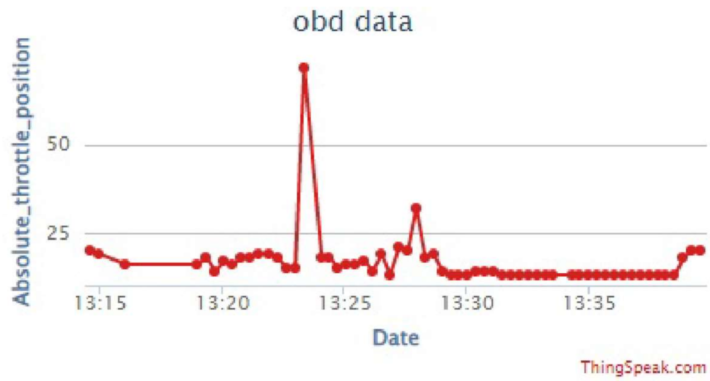


Fig. 3.13. Throttle position sensor's output

3.4.7. Engine speed

Engine speed in RPM as recorded by the vehicle ECU for 300 samples is shown in

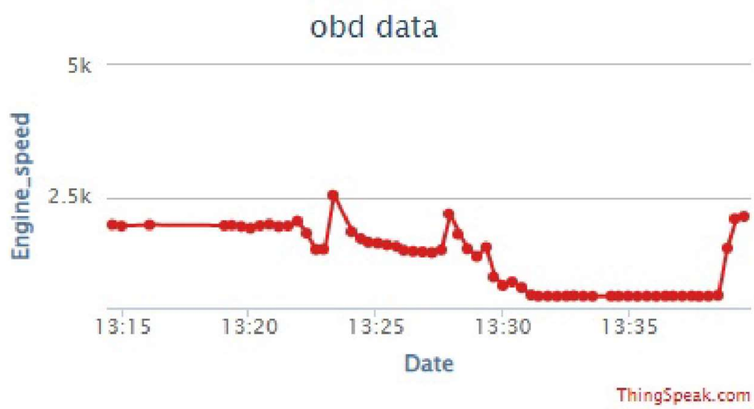


Fig. 3.14.

Fig.3.14. Engine speed in RPM.

3.4.8. Engine coolant temperature

In Fig. 3.15 output of the engine coolant temperature sensor, expressed in degrees Celsius, as reported by the vehicle's electronic control unit for 300 samples.

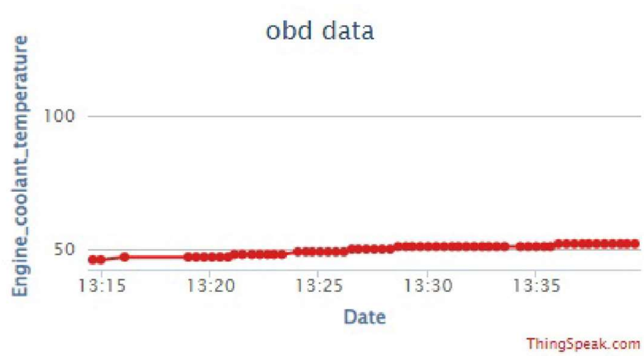


Fig. 3.15. Engine coolant temperature sensor's output in ^{o}C.

3.4.9. Vehicle speed

The car ECU recorded the output of the vehicle speed sensor in kilometers per hour for 300 samples obtained. The information was subsequently recorded to the flash memory of the nodeMCU, where it may be later imported into a CSV file for examination. 300 sampled values for Absolute throttle position, Engine speed, and Vehicle speed were plotted in the Thingspeak.com IoT server using MATLAB visualization [30] to achieve remote data visualization, as shown in Fig. 3.16. A serial monitor from Arduino was used to gather debug information, as shown in the screenshot in Fig.3.10.

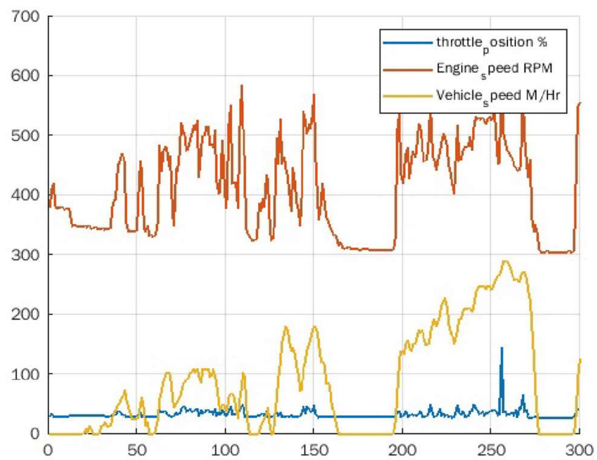


Fig. 3.16. Visualization of Absolute throttle position, Engine speed, and Vehicle speed.

3.5. Conclusion

Using a multi-protocol OBD scanner, a Bluetooth module, and a nodeMCU, the experiment was successfully carried out. Hardware and software compatible with the OBD-II vehicle platform were used to gather important parameters related to road vehicle operation. Experiments on parameters that the driver could see on the dashboard, such as vehicle speed, engine RPM, coolant temperature, and throttle position signal, further supported this. Because only a few parameters were requested from the scanner, the OBD scanner's latency was nearly real-time, and the outcomes were as anticipated. Additionally, the ECU has over 50 metrics that may be gathered for a variety of uses, including driver and operator behavior, pertinent suggestions or recommendations for the driver and operator, and information and warnings pertaining to scheduled and preventive maintenance.

CHAPTER 4

DEVELOPMENT OF SENSOR FOR ENGINE OIL QUALITY MEASUREMENT

On-board diagnostics (OBD) systems can extract the majority of engine-related parameters. However, engine oil quality and the useful remaining life of engine oil are not often evaluated directly via OBD. Instead, they are frequently evaluated manually or by adhering to manufacturer-recommended maintenance schedules. While visual inspection is a widely used method [17], it has limits and the risk of being neglected or incorrectly appraised. This can result in insufficient lubrication and have an impact on the engine's performance and longevity. Regular oil changes are essential for the smooth running and lifetime of an internal combustion engine. Lubrication oil is a crucial component in these engines since it fulfills various functions. It not only lubricates the engine's moving parts, decreasing friction and wear, but it also plays an important function in dispersing heat created during operation. Neglecting oil quality can lead to substantial maintenance concerns, emphasizing the significance of detecting oil quality. Several approaches [11-20] for assessing oil quality have been proposed, including the use of onboard sensors and laboratory testing [21-22]. A unique and low cost measuring idea is provided in this paper, providing a simple and cost-effective method for assessing the physical and chemical properties of engine oil. The proposed equipment uses an optical and inductive method, allowing for the assessment of oil conditions with a simple and inexpensive setup Furthermore, interoperability with existing engines is considered to assure simple integration into present systems. As engine oil is exposed to high temperatures and used, it oxidizes, resulting in an increase in metal particle concentration. It is critical to detect such changes in oil quality in order to minimize potential engine damage [39]. Engine operators can recognize when it is required to change the oil to ensure optimal engine performance and avoid potential concerns by periodically evaluating the oil's physical and chemical qualities.

Engine oil numbers and their significance, such as 15W-40. Engine oil's numbers signify its viscosity rating, which is a measure of the oil's resistance to flow. The rating is divided into two parts: the viscosity rating at low temperatures and the viscosity rating at high temperatures. Viscosity Rating ("W") for Cold Temperatures:

The first number, followed by the letter "W," denotes the winter viscosity grade of the oil. It relates to how quickly oil flows at low temperatures, especially when cold weather begins. In cooler circumstances, lower numbers indicate better flow. The "15W" signifies the winter viscosity rating in the example of 15W-40. This means that the oil has been engineered to flow more easily at low temperatures, making it ideal for use in engines. Viscosity rating at higher temperatures (2^{nd} number), The second number represents the oil's viscosity rating at higher temperatures, typically at normal operating conditions. It displays the thickness of the oil or its resistance to flow when the engine is running and producing heat. Higher numbers imply a heavier oil that protects against high temperatures and heavy loads. The "40" in 15W-40 signifies the viscosity rating at higher temperatures. This implies that when the engine is running at normal temperatures, the oil retains its thickness and flow properties properly. To summarize, the viscosity grade of 15W-40 oil implies that it is suited for cold weather starting (15W) and provides adequate viscosity and protection at typical operating temperatures (40). This oil is designed to flow smoothly in cold situations while still providing adequate lubrication and protection at normal engine operating temperatures. There are two methods proposed here for determining engine oil quality.

4.1. Oil Quality Based on Optical Properties of Oil

As we all know, lubricating oil in an engine is extremely critical, as is its quality [22]. Almost all engine-related variables in a modern engine are measured using sensors in the engine, hence an engine oil quality sensor is also required [26]. Many oil quality sensors have already been suggested, but the majority of them are sophisticated and difficult to integrate into an engine, or they are much more expensive and cannot be offered on board with the engine. Several methods for measuring oil quantity and quality have been studied. The quantity of engine oil is detected using a floatable conducting ball and a tube with copper electrodes in [17], but the quality is not given. Regular maintenance of components is required for this method. In [12], a capacitive sensor based on the permittivity of the oil is utilized in conjunction with an oscillator circuit. However, the oscillator circuit's stability is critical, because temperature drift can cause large signal differences. Another method suggested in [14] is to use viscosity and corrosivity sensor equipment with electrodes exposed to the oil and coupled to an oscillator that provides data on both the viscosity and corrosivity of oil. [15] proposes a wireless oil filter sensing system that uses acoustic wave sensing devices and antennas to detect and communicate data on oil quality. These previous references present a variety of ways for measuring and assessing oil, each with its own set of advantages and disadvantages. The method and apparatus disclosed are based on the simple phenomenon that the color of oil darkens when carbon content, soot, oxidized oil, and moisture increase, resulting in a decline in quality. This is accomplished by the use of a simple optical principle that includes a light receiver and transmitter, and the channel in between them is lubricating oil whose quality is to be determined. A photodiode or phototransistor is utilized as the sensor here, while a light-emitting diode is employed as the transmitter. The channel (optical property of lubricating oil) determines the amount of light traveling through a photodiode. The channel determines the intensity of the light received, which with the help of voltage dividers circuit may be easily translated into voltage, which shows the quality of the oil. Many variables are measured in any internal combustion engine for proper operation. These variables include engine temperature, intake manifold pressure, engine RPM, load, throttle position sensor, and many more. These variables are required for proper operation, and efficiency, and to avoid any engine failure. Lubricating fluid plays an important function in engine operation. If we do not change the engine oil or lubricating oil in an engine, we risk: -

- Premature wear in moving parts such as pistons, rings, and cylinders.
- Early failure of turbo and its parts.
- Overheating of engine components.

Oil quality assessment is critical in many industries, including automotive, manufacturing, and food processing. This research study describes a method for determining oil quality based on the amount of light transmitted through the oil, which can serve as an indicator of its color and general quality. The proposed method makes use of a microcontroller or development board, such as Arduino, to simplify analog-to-digital conversion within a single chip. As a fundamental component, a phototransistor is used, which operates on the concept that current flows through the base area when light falls on the junction, acting as a virtual base terminal. The phototransistor, typically configured in a common emitter arrangement, exhibits typical characteristics due to its larger base and collector areas compared to conventional transistors. To activate the transistor, an appropriate base supply is required depending on the specific type of transistor used. The resulting output of the phototransistor shows a change in current, which directly corresponds to the incident light. However, since microcontrollers cannot directly detect current changes, a voltage divider circuit comprising 4.7k thermistors is used to convert the current change into a voltage change, as depicted in Figure 4.5. This transformed voltage input is then fed into the analog input channel of the microcontroller, enabling its conversion into a digital value. The acquired digital value, ranging from 0 to 5V, serves as an indicator of oil quality, with higher values indicating a lower amount of incident light and thus a darker color, signifying degraded oil quality resulting from aging or excessive usage. The proposed method with reference to the accompanying Fig.4.1-4.2. It should be noted that the method is not limited to the specific embodiments presented herein but aims to provide a thorough and comprehensive understanding of the method's scope for those skilled in the art. Technical and scientific terms used in this context have the same meaning as commonly understood by individuals with ordinary skills in the relevant field.

Fig. 4.1. Color relation of the sample left used and right unused engine oil

The simplified structures represented in Fig.4.1 represent selected elements and functional entities, which may differ in execution from what is shown. The connections shown are logical, while the physical connections may differ. Those knowledgeable in the art will recognize that the structure may comprise other functions and structures not expressly shown. Fig. 4.1 displays horizontally oriented glass containers containing lubricating oil, including a sample used for 5000 km in a diesel engine and an unused sample, to differentiate the colors based on the age of the oil. The deeper color noticed in used oil implies lesser quality, which serves as the foundation for the described innovation for determining oil quality based on color.

Fig. 4.2. Four samples of engine oil.

Fig. 4.2 illustrates four transparent test tubes representing different oil compositions. Fig.4.3 illustrates the various phenomena experienced by light passing through lubricating oil, including absorption, Raman scattering, transmittance, fluorescence, diffuse refractance, and reflectance, which collectively contribute to measuring oil quality.

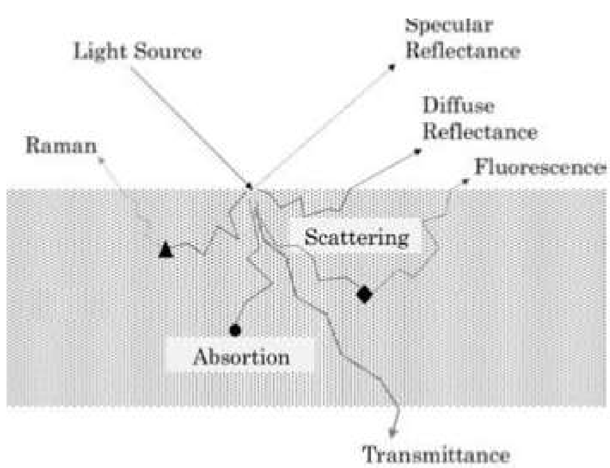


Fig. 4.3. Interaction of light with the medium as oil

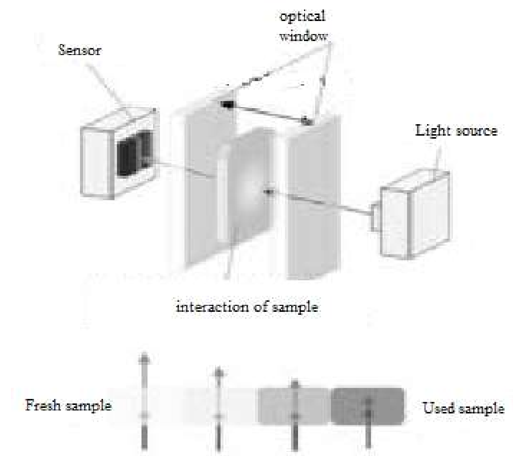


Fig.4.4. Proposed method and arrangement

Fig. 4.4 shows the preferred arrangement of the device, utilizing a light source and a cavity where the lubricating oil acts as the medium for light to be b transmitted. Fig. 4.5 and 4.6 represent the actual experimental setups, showcasing the proposed design and the components used, such as photodiodes, LEDs, thermistor bridge circuits for temperature compensation, stable power supplies, and digital multimeters.

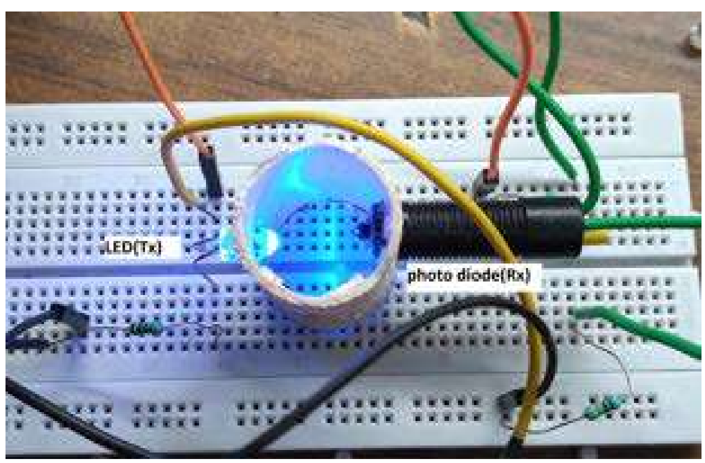


Fig. 4.5. Actual experimental setup

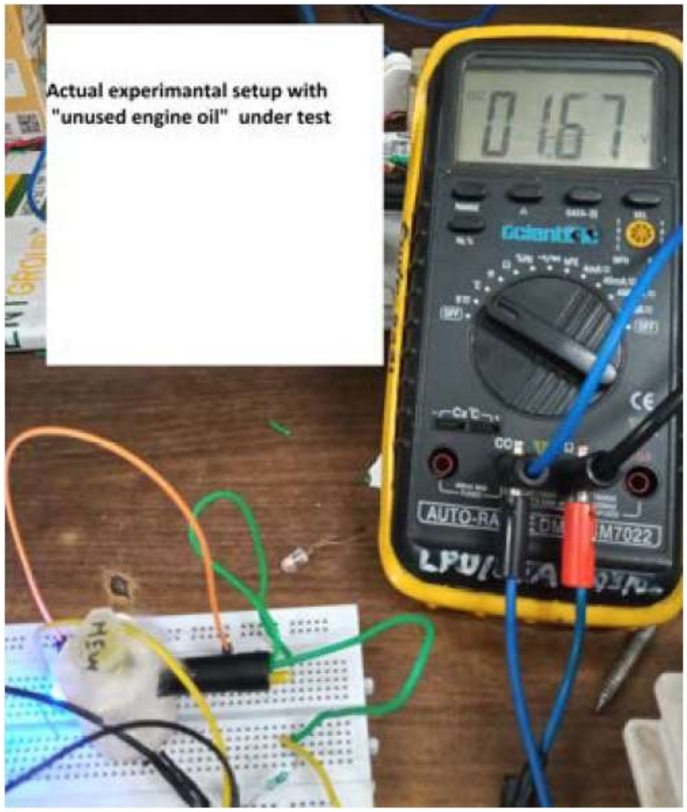


Fig. 4.6. Actual experimental setups with a sample under test

Fig. 4.7 presents the circuit diagram of the proposed method, featuring a microcontroller board, a phototransistor aligned in front of the LED transmitter, and connections for analog reading. The program written enables the microcontroller to read analog values and display them on a device such as a serial monitor.

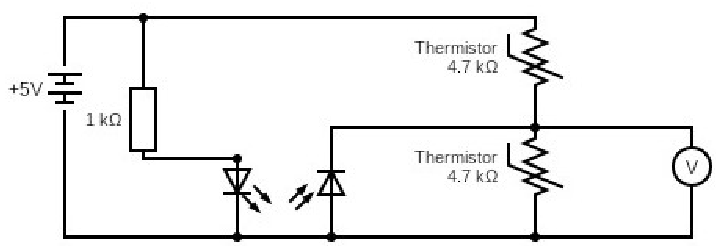


Fig. 4.7. Circuit diagram

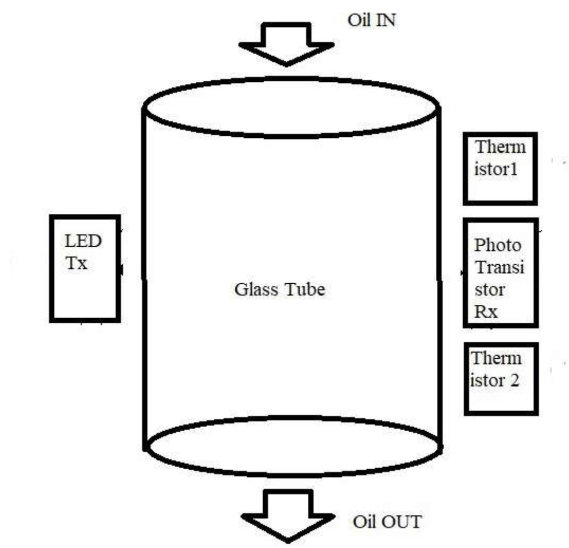


Fig. 4.8. Arrangement of the sensor

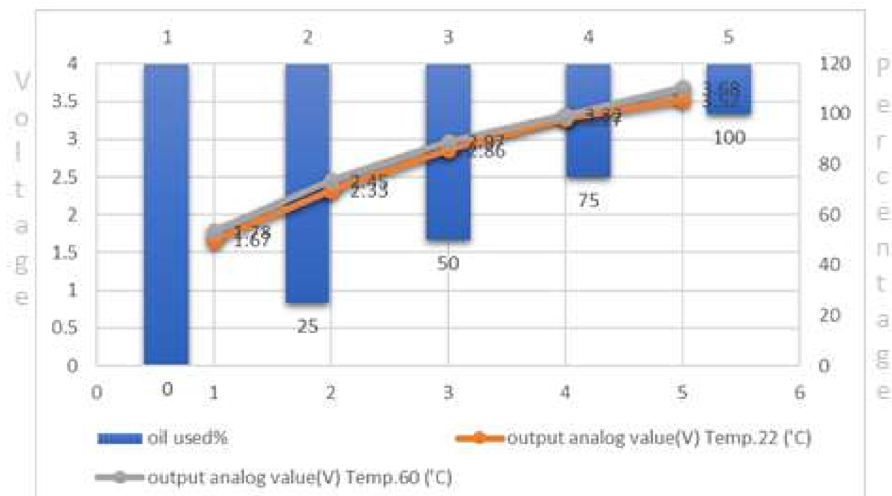


Fig. 4.9. Experimental results for different types of engine oils

4.1.1. Conclusion

The research work proposes a simple, cost-effective, and advantageous approach for checking the quality of engine oil. One of its key advantages is its low cost of implementation, as it does not impose large investments. Furthermore, the approach is simple to implement into current engines without requiring major alterations. Traditionally, operators and engineers use a dipstick to visually evaluate the oil color and carbon content to decide if an oil change is essential. Proposed methodology offers a feasible alternative by allowing them to evaluate the oil's quality based on observed findings. Individuals may make useful findings regarding oil changes by integrating this technique, which optimizes engine performance and lifetime. The research does, however, notify two shortcomings of the proposed method. To begin, it states that the approach suffers from output drift induced by temperature changes. Although temperature correction was included in the procedure, this issue may still have an impact on the accuracy and dependability of the results. Future work to solve this issue could include further analysis and improvement in temperature-compensating methods. Second, the study found that there was very little difference in output voltage between degraded and undegraded oil samples. This suggests that the method is not highly sensitive to detecting changes in oil quality. This limitation can also be a potential area for future research, aiming to enhance the method's ability to differentiate between degraded and undegraded oil more effectively. Finally, the provided method provides a practical and cost-effective alternative for assessing engine oil quality. It is simple to integrate into existing engines and gives useful information to operators and engineers for making refined decisions about oil changes. While the approach has significant drawbacks, such as output drift and low sensitivity. Having drawbacks kept in mind they can be significantly reduced by calibration method in which we need to add 100% new engine oil from a sealed container and set the output calibration value of the voltage at 0v so that any small change in the quality of the engine can be easily detected.

4.2. Engine Oil Quality Sensor Based on Inductive Properties of Oil

Addressing the limitations of the previous optical engine oil quality sensor, a novel method has been developed to overcome these drawbacks. This innovative approach utilizes inductive properties of oil that offer improved accuracy, reliability, and real-time monitoring of engine oil quality. Onboard sensors and laboratory testing have been proposed as ways for monitoring oil quality. The authors of this work present a simple and cost-effective measurement concept for assessing the physical and chemical properties of engine oil. The methodology employs an inductive process a simple configuration. To facilitate continuous integration, the suggested method's compatibility with existing engines is also taken into account.

As the engine oil is used and subjected to high temperatures, it oxidizes, resulting in an increase in the number of metal particles. This change in concentration modifies the oil's inductive properties, which can be detected as an electric signal. The suggested sensor is based on the discovery that when oil is used as a coupling medium between a transformer's primary and secondary windings, the transformer responds with a change in output voltage. This sensor provides a reliable technique for monitoring changes in engine oil quality, allowing operators to take appropriate action before engine failure occurs. Overall, the described method is a practical and cost-effective way to estimate engine oil quality. By monitoring the inductive characteristics of the oil, this sensor provides a means to detect changes in its physical and chemical properties.

4.2.1. Methodology

Many parameters are there in order to measure lubricating oils quality a few of them are given below: -

1. The Acid Number (AN), a metric used to assess oil quality, is mostly taken into account when the quality of the oil is deteriorating. A technique for calculating the acid number is ASTM D664 (American Society for Testing and Materials).
2. Residual antioxidant additives are measured using the Remaining Useful Life Evaluation Procedure (RULER). The slowing of the oil's breakdown process as a result of these additives indicates the number of additives still present.
3. **Viscosity, is another crucial criterion to measure for oil estimation because lubricating oils require a particular viscosity for proper operation.**
4. Technicians usually employ ASTM D500, another method that visually evaluates the color of oil, to assess contamination [35]. The proposed method uses a very simple approach to find out oil quality, working depends on a low-frequency

transformer step-up transformer whose number of turns is fixed and the geometry (area) of primary and secondary coils are fixed core of the transformer whose data is mentioned in table 1, is kept vacant so that it can be replaced with oil under test. Primary voltage is kept at 6v-50Hz on the secondary side of the transformer RC network is connected so as to have a stable output signal. When the core was replaced by a sample of oil which was kept in a transparent tube output variation in the voltage was perceived. In order to verify the results four different samples were taken for testing purposes. Results were in the form of output voltage variations, direct in relation to the quality or concentration of engine oil.

4.2.2. Implementation

In order to understand the working of the proposed sensor working of the transformer should be studied. Fig. 4.10 shows the equivalent circuit of the transformer, where L1 and L2 are the self-inductances of the N1 and N2 windings, individually. the two windings are twisted on the same core. The coupling constant k is differed by changing the mode of the windings. Fig. 4.11 shows the low and mid frequency model of the transformer. The Parts r1 and r2 address the winding dc opposition of the essential and optional windings, individually. The inductances Ll1 and Ll2 address the leakage inductance of the first and second windings, individually.

$$n = N_1/N_2 \tag{4.1}$$

where N1 is the number of turns of the primary winding and N2 is the number of turns of the secondary winding. mean path by flux lines length of the N1 and N2 windings is reliant upon the coefficient of coupling between loops as N1 and N2 are fixed. In this way, the common coupling between the N1 to N2 windings as well as the other coil is not the same. Mutual inductance between the primary and secondary is given by

$$M = \sqrt{L_1 L_2} \tag{4.2}$$

where k addresses the coupling coefficient between the N1 and N2 windings. The coupling coefficient relies upon the distance of partition between the two windings which is kept fixed in the proposed strategy but the medium between loops is changed here. The self-inductance of the primary winding N_1 is

$$L1 = \mu N_1^2 A_o / l_o \tag{4.3}$$

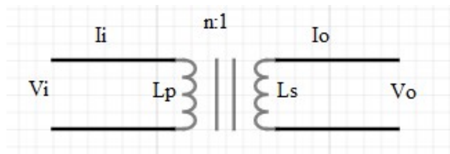


Fig. 4.10. Two winding transformers

where A_o addresses the cross-sectional region of the normal transition in the core, l_o is the mean path length of magnetic flux linking connecting the primary and secondary windings, and $\mu = \mu_0 \mu_r$ is the permeability of the core. Similarly, the self-inductance of the secondary winding is given by

$$L2 = \mu N_2^2 A_o / l_o \tag{4.4}$$

From Fig. 4.10, inductances L1 and L2 make a transformer and give the expected turns proportion, while the magnetic energy is stored inside the charging inductance and both leakage inductances. The turns ratio and the self-inductance.

$$n = \sqrt{N_1 / N_2} \tag{4.5}$$

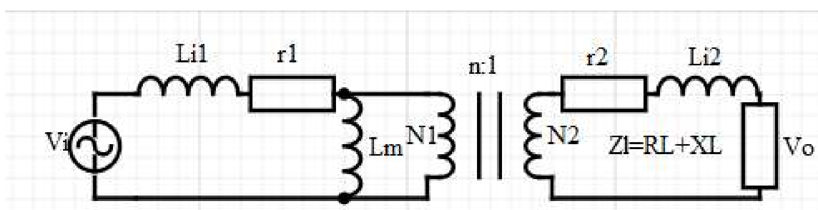


Fig. 4.11. Equivalent circuit two-winding transformer.

In transformers with loosely coupled windings, the leakage magnetic flux is critical and relies upon the coupling between the two windings and is displayed as leakage inductances. The magnetizing inductance is expressed as

$$L_m = kL_1 = K \, \mu N_1^2 A_o / l_o \tag{4.6}$$

In transformers with loosely coupled windings, the leakage transition is huge and relies upon the coupling between the two windings and is demonstrated as leakage inductances.

4.2.3. Proposed setup

The proposed setup consists of a transformer with a vacant core as mentioned in Fig.4.12. The primary winding consists of three wires yellow in color and secondary winding red in color, core is made up of plastic where a test sample can be inserted. Transformer data is mentioned in Table 4.1.

Table 4.1. Transformer Data

Transformer and Ampere rating	**Primary turns and wire gauge**	**Secondary turns and wire gauge**	**Core area**	**Bobbin size**
6-0-6 240v and 500mA	2943T - 43SWG	170T - 24SWG	0.75”	1”

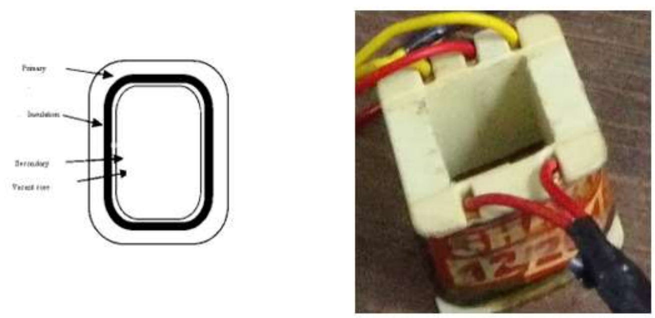


Fig. 4.12. Transformer with vacant core (left) and actual transformer (right)

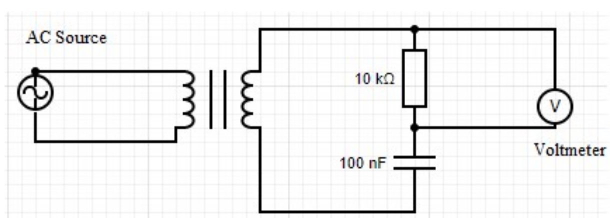


Fig. 4.13. Circuit diagram for the proposed method.

For the proposed method unused oil(15W-40) from a sealed container was taken and used engine oil from a diesel engine having 5000km driven was taken mentioned in Fig. 4.1. From this sample of oil four samples were made with different concentrations as mentioned in Fig. 4.2. percentage of concentrations of used and unused oil is mentioned in table 4.2.

Table 4.2. The concentration of used and unused oil in samples

Sample number	Used %	Unused %
1	100	0
2	25	75
3	50	50
4	0	100

4.2.4. Experimentation

The experiment was performed on the samples as mentioned in Table 4.2. at room temperature 20'C input voltage was 6 volts AC at 50Hz with the help of a step-down transformer. The input voltage was given to the proposed transformer without a core having a turn ratio 170 – 2943 RC series circuit having C= 100nF and R=10k ohms was used with a high accuracy digital voltmeter, output result was as expected i.e. induced voltage of the transformer increased with increase in the concentration of used oil also above setup can detect the absence of sample inside the core of transformer which can be verified from the output voltage (4.1 -4.6) of the proposed system as mentioned in table 4.1 and Figures 4.12 and 4.13.

Table 4.3. Concentration of used and unused oil in samples

Sample number	Unused %	Used %	Output voltage
Vacant	NA	NA	1.545
1	100	0	1.550
2	50	50	1.553
3	25	75	1.556
4	0	100	1.569

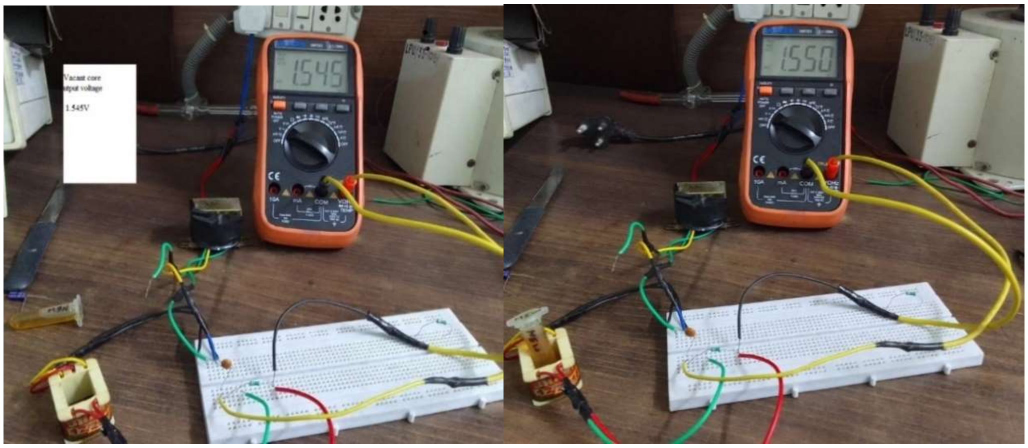


Fig. 4.14. Experimental setup without sample(left) with 100% unused sample(right)

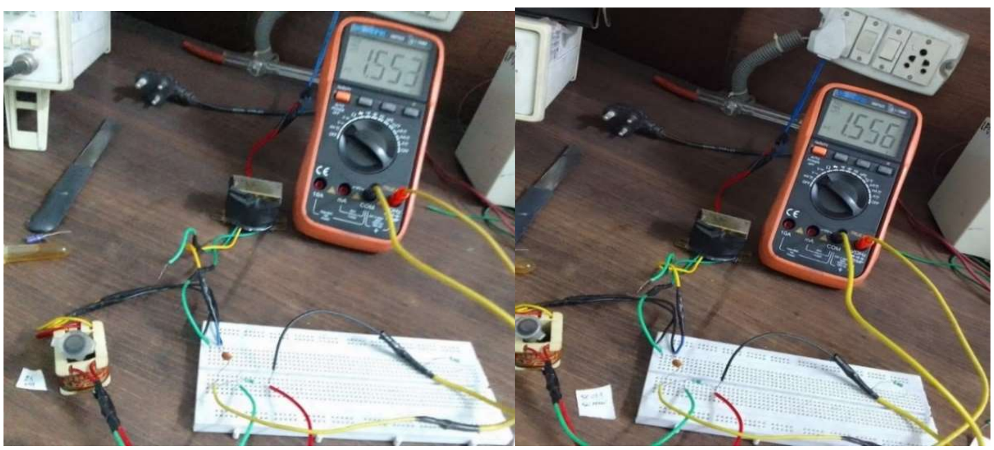


Fig. 4.15. Experimental setup 25% unused sample(left) with 50% unused sample(right)

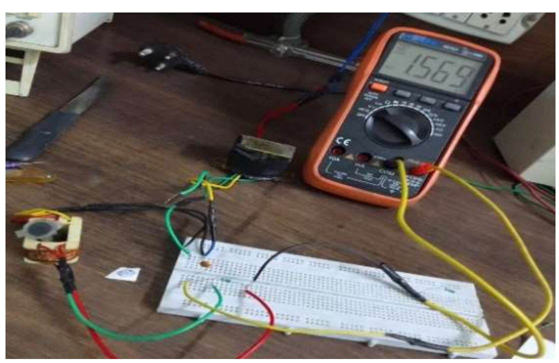


Fig. 4.16. Experimental setup 100% used sample

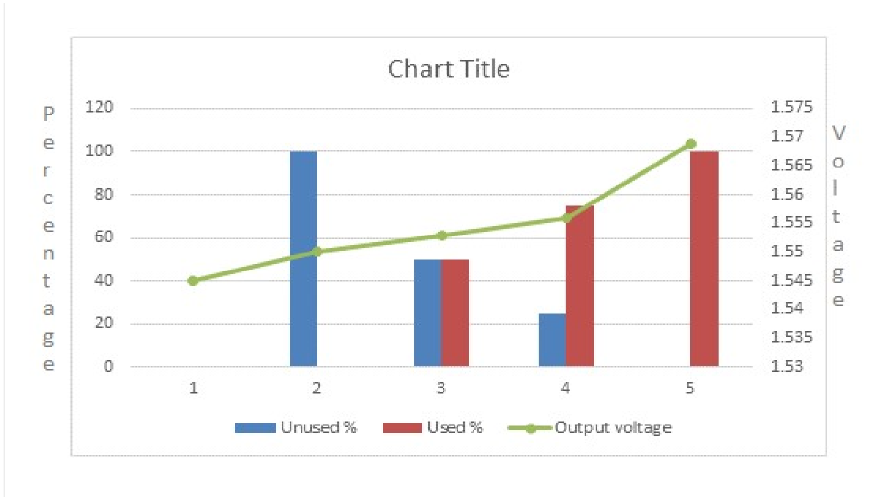


Fig. 4.17. Output voltage vs oil percentage

4.2.5. Conclusion

The proposed method for assessing engine oil quality relies on the changing inductive properties of the oil as it becomes contaminated by various substances such as metal shavings, soot, carbon, and oxidation. By monitoring these changes, the method provides a means to determine the condition of the engine oil. What sets this method apart is its simplicity and ease of installation, as it can be implemented in existing engines without any modifications. Additionally, its contactless nature ensures that the engine remains unaffected, even in harsh operating conditions. The sensor can be conveniently attached to any tube or pipe through which the engine oil flows, enabling continuous monitoring. One of the key advantages of this method is its superior design simplicity and cost-effectiveness compared to other state-of-the-art techniques. It offers the flexibility to calibrate and adapt to different types of engine oils, making it suitable for a wide range of applications. Moreover, it can be implemented on engines that undergo movement or vibrations without requiring any additional complex hardware or setups. This simplicity and affordability make it an attractive alternative for oil quality assessment. Continuous monitoring without the need for manual intervention is another significant advantage of this method. It provides real-time information about the oil's condition, enabling proactive maintenance and reducing overall maintenance costs. By ensuring that the engine oil remains in optimal condition, the method improves engine efficiency and extends the engine's operational life. However, it is important to acknowledge the limitations of this oil quality detection method. One such limitation is its relatively low sensitivity to changes in oil concentration. This means that relying solely on the method's readings may not provide accurate decision-making when it comes to determining the need for an oil change. Therefore, additional factors and indicators should be considered to make informed decisions regarding oil change intervals. In conclusion, the proposed method for engine oil quality assessment based on inductive properties offers numerous advantages, including its simplicity, low cost, adaptability, and non-intrusive nature. Continuous monitoring without manual intervention reduces maintenance costs, improves engine efficiency, and extends engine lifespan. However, its low sensitivity to changes in oil concentration necessitates the consideration of other factors when making decisions about oil changes.

Table 4.4. Comparison of two proposed methods

S.no.	**Sensor optical based**	**Sensor-based on inductive properties**	**Remarks**
1	Temperature dependence of output signal	Almost independent of temperature	A compensation network was provided in an optical-based sensor with the help of thermistors. Not required in the inductive sensor.
2	Can work on existing 12v or 5v supply	Requires AC supply for its operation	Inductive based sensor can require additional inverter circuit for its operation
3	Affected by contamination of oil lines	Not affected by contamination as the sensor is based on inductive properties	
4	Small in size ~ 50x24mm(approx.)	Larger in size as it may require additional circuits i.e. Invertor ~ 63x100mm(approx.)	The inductor-based sensor is larger due to the inherent property of inductor.

Table 4.5. Validation of output from proposed sensors

Degradation percentage	Optics based sensor	Inductance based sensor	KV value
0	3.52	1.550	14.3534
25	3.27	1.551	26.9881
50	2.86	1.553	39.3229
75	2.33	1.556	51.6576
100	1.67	1.569	62.3230

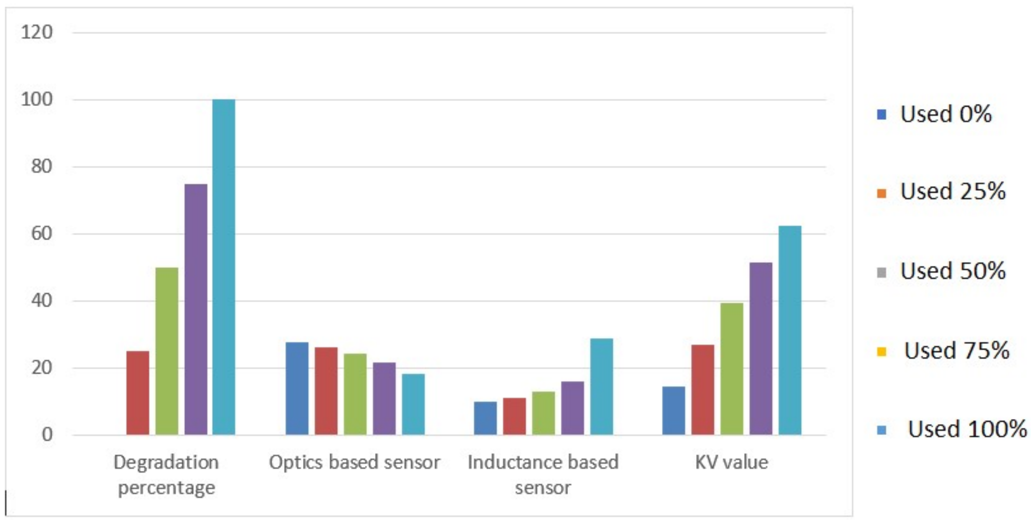


Fig. 4.18. Comparison to proposed sensor output with standard values

The proposed sensors, one using optical technology and the other based on inductance, are used to measure the Kinematic Viscosity of engine oil. They provide output readings that can be compared with the standard value of fresh engine oil. This comparison allows us to determine the percentage of degradation or deterioration of the engine oil. The results of these comparisons are presented in Table 4.5, which shows the different levels of deterioration for the engine oil samples measured by the optical and inductance sensors. Each row in the table represents a specific level of degradation expressed as a percentage [43]. To visually represent the data, Figure 4.18 illustrates a graph or chart that showcases the percentage of degradation of engine oil measured by the two sensors over time or different oil samples. The figure helps us visualize how the Kinematic Viscosity of the engine oil changes with usage or under different conditions, providing valuable insights for maintenance and monitoring purposes.

CHAPTER 5

ANALYSIS AND IMPLEMENTATION OF RAMS

After successfully implementing and experimenting with the extraction of engine operation data from the Engine Control Unit (ECU) using an On-Board Diagnostics (OBD) compatible setup consisting of ELM327[3][5][7], HC-05, and NodeMCU-based hardware and software, the extracted information was uploaded to the Thingspeak IoT server, as described in Chapter 3. However, in order to proceed with the research, a dataset was required that was uniform and obtained from at least 10 different drivers or operators, following the same route and preferably using the same vehicle. There were two options to acquire such a dataset. The first option was to conduct the experimentation on one's own car, which would involve a significant amount of time and attention to collect the required data and create the dataset for the desired system. This option required extensive effort and resources. The second option involved requesting a valid dataset from someone who was already working in a similar research area. Fortunately, a suitable dataset was discovered, and a formal request [31] was made to utilize it for this research work. The details of this dataset and the person providing it are acknowledged in Appendix A. By obtaining a dataset from a reliable source, the research team could save valuable time and resources that would have been required to collect the data themselves. This approach allowed them to focus on the analysis and interpretation of the dataset, as well as the development and evaluation of the required system.

5.1. About Dataset

A driving dataset with the following details was requested: -
Driving time: about 23 hours
Driving length: about 46km (round-trip)
Driving path: between Korea University and SANGAM World Cup Stadium
Number of Drivers: 10
File name: Driving Data (KIA SOUL)_(150728-160714)_(10 Drivers_A-J)
File size:16.9Mb
Rows: 94381
Columns:54 The collected dataset was in the CSV file format[31].

Table 5.1. Engine parameters along with their units

S. No.	Parameter Name	Explanation	Units
1	Fuel_consumption	The rate at which fuel is consumed by the engine or vehicle	Liters per hour
2	Accelerator_Pedal_value	Position or degree to which the accelerator pedal is pressed	Percentage
3	Throttle_position_signal	Indicates the position of the throttle valve	Percentage
4	Short_Term_Fuel_ Trim_Bank1	Short-term adjustment made to the fuel mixture (bank 1)	Percentage
5	Intake_air_pressure	Pressure of the air entering the engine's intake system	Kilopascal (kPa)
6	Filtered_Accelerator _Pedal_value	Accelerator pedal value that has been filtered or processed	Percentage
7	Absolute_throttle_position	Absolute position of the throttle valve	Percentage
8	Engine_soaking_time	Duration of time required for the engine to reach optimal temperature	Seconds
9	Inhibition_of_engine_ fuel_cut_off	Indicates whether there are any inhibitions on cutting off the engine's fuel supply	Binary (0/1)
10	Engine_in_fuel_cut_off	Indicates whether the engine is currently in a fuel cut-off state	Binary (0/1)
11	Fuel_Pressure	Pressure of the fuel within the engine's fuel system	Kilopascal (kPa)
12	Long_Term_Fuel_ Trim_Bank1	Long-term adjustment made to the fuel mixture (bank 1)	Percentage
13	Engine_speed	Rotational speed of the engine, typically measured in RPM	Revolutions Per Minute (RPM)
14	Engine_torque_after _correction	Engine torque value after applying corrections or adjustments	Newton meters (Nm)
15	Torque_of_friction	Amount of frictional torque present in the engine	Newton meters (Nm)
16	Flywheel_torque_ (after_torque_interventions)	Torque applied to the flywheel after torque interventions	Newton meters
17	Current_spark_timing	Current timing or synchronization of the spark ignition	Degrees

S. No.	Parameter Name	Explanation	Units
18	Engine_coolant_ temperature	Temperature of the engine coolant	Degrees Celsius (°C)
19	Engine_Idle_ Target_Speed	Desired or targeted engine idle speed	Revolutions Per Minute (RPM)
20	Engine_torque	Torque produced by the engine	Newton meters
21	Calculated_LOAD_value	Calculated value representing the engine load	Percentage
22	Minimum_indicated_engine_torque	The minimum value of the indicated engine torque	Newton meters
23	Maximum_indicated _engine_torque	The maximum value of the indicated engine torque	Newton meters
24	Flywheel_torque	Torque applied to the flywheel of the engine	Newton meters
25	Torque_scaling_factor (standardization)	A scaling factor used to standardize or normalize torque values	Unitless
26	Standard_Torque_Ratio	A standardized ratio or relationship between torque values	Unitless
27	Requested_spark_retard _angle_from_TCU	The requested angle by which the spark ignition timing should be retarded, as determined by the TCU (Transmission Control Unit)	Degrees
28	TCU_requests_engine_ torque_limit_(ETL)	The torque limit requested by the TCU (Transmission Control Unit) for the engine (ETL: Engine Torque Limit)	Newton meters
29	TCU_requested_engine_ RPM_increase	The requested increase in engine RPM (Revolutions Per Minute) by the TCU	RPM
30	Target_engine_speed_ used_in_lock-up_module	The target engine speed used in a lock-up module, typically associated with automatic transmissions	Revolutions Per Minute
31	Glow_plug_control_ request	A request for controlling the glow plugs in a diesel engine	Binary (0/1)
32	Activation_of_Air _compressor	Indicates the activation or operation of an air compressor	Binary (0/1)
33	Torque_converter_speed	The speed of a torque converter, commonly used in automatic transmissions	RPM
34	Current_Gear	The currently engaged gear in a vehicle's transmission system	Numeric value

S. No.	Parameter Name	Explanation	Units
35	Wheel_velocity_front _left-hand	The velocity or speed of the front left-hand wheel	Kilometers per hour (km/h)
36	Wheel_velocity_rear _right-hand	The velocity or speed of the rear right-hand wheel	Kilometers per hour (km/h)
37	Wheel_velocity_front _right-hand	The velocity or speed of the front right-hand wheel	Kilometers per hour (km/h)
38	Wheel_velocity_rear _left-hand	The velocity or speed of the rear left-hand wheel	Kilometers per hour (km/h)
39	Torque_converter_turbine _speed_-_Unfiltered	The unfiltered speed of a turbine within a torque converter	RPM
40	Clutch_operation_ acknowledge	Indicates the acknowledgment or confirmation of clutch operation	Binary (0/1)
41	Converter_clutch	Indicates the operation or status of a converter clutch in an automatic transmission	Binary (0/1)
42	Gear_Selection	Represents the selected gear in a vehicle's transmission system	Numeric value
43	Vehicle_speed	The speed of the vehicle	Kilometers per hour (km/h)

A few columns are not mentioned in this table e.g., path order, class, etc. as they only represent the driver's name here (A to J) while path order is in case a different path was followed by the concerned driver. To perform data analysis, we required live vehicle data [1-2]. Only relevant parameters were selected from the complete dataset. The reordered parameters span various engine facets. Start with fuel management, fuel consumption and trim are covered. Factors like intake air pressure and accelerator pedal follow, responsiveness. Throttle position, soaking time, and brakes, Fuel pressure, long-term trim, engine speed, and torque are detailed. Friction and flywheel torque join spark timing. Engine coolant and idle speed lead to modulation via pedals and throttle. Load, scaling, and ignition angles follow. Transmission interactions involve RPM and speed targets. Converter, gear, and dynamics are presented. Wheel velocities and clutch follow, concluding with gear, pressure, and steering insights., as well as a "Class" column. The dataset was further cleaned using Python (NumPy and Pandas) for null values [8][10]. Along with the above-mentioned parameters few derived parameters are calculated and based on which classification was done as stated below.

5.2. Derived Parameters

5.2.1. Average fuel (AVG_FUEL)

The average fuel consumption directly correlates with the driver's behavior and lowers the driving score. The average of all immediate fuel consumption readings is used to calculate the average fuel consumption for a certain driver using Equation 5.1.

$$A=\frac{1}{n}\sum_{i=1}^{n} ai \tag{5.1}$$

5.2.2. Idle Engine (IDLE_ENGINE)

The fact that the offered engine is idle. Fuel is spent if a vehicle is left running for an extended period of time while the engine is idle, which lowers the driving score
(i.e., RPM > 100 && gear position == 0). (This engine's idle speed ranged from 680 to 750 RPM).

5.2.3. Brakes at high speed (HIGH_SPEED_BRAKING)

A high-speed braking incident occurs when the brake is applied at a vehicle speed of greater than 55km/h. Brakes applied at high speeds have a negative impact on driving scores and are only somewhat effective.

5.2.4. Revving Engine (REVV_ENGINE)

Fuel gets wasted when the engine is ramped up again, with no useful work being done. This is viewed as a detriment in our suggested method for determining the driving score. When the engine is revving while the automobile is motionless or in neutral, it means the accelerator pedal is depressed. The following was decided: -
Current gear == 0 && !IDLE_ENGINE = TRUE.

5.2.5. Deviation in steering (DEV_STR)

Driving straight rather than zigzagging is seen as desirable driving behavior in the proposed model. The phrase "steering position deviation" describes how much variation there was in the driver's steering movement. Utilizing the formula in 5.2, where μ = Mean, σ = Standard deviation, N= Total number of data values and x_i =Each value.

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum(\mathbf{xi} - \mu)}{\mathbf{N}}}$$

(5.2)

5.2.6. Vehicle Speed Deviation (VS_DEV)

In the suggested model, a constant vehicle speed is preferred over fast acceleration and deacceleration. Vehicle speed deviation denotes the amount of variation in vehicle speed for a specific driver. Equation (5.2) mentions the formula.

5.2.7. Average Speed (AVG_SPEED)

In the proposed strategy, a good average speed is judged to be between 50 and 70 km/h. The vehicle's average speed is derived using data from the vehicle speed sensor. Equation (5.1) mentions the formula utilized.

5.2.8. Average Gear (AVG_GEAR)

Gear shifting should be situational, so as not to impose undue strain on the engine and gearbox. The average gear utilized by the driver is estimated using the formula in Equation 1. Its value ranges from 0 to 6th gear.

5.2.9. Idle instance(IDLE_INSTANCE)

In our concept, idle instances should be as little as feasible because they have a negative impact on driving scores. The number of times the vehicle was left idling while in condition.

IF IDLE_ENGINE==!FALSE increment IDLE_INSTANCE

5.2.10. High-speed braking instances (HB_INSTANCES)

High-speed braking should be avoided as much as possible because it lowers the driving score. The following are the high-speed braking events.

IF HIGH_SPEED_BRAKING == !FALSE increment HB_INSTANCES.

5.2.11. Revving Instances (REV_INSTANCES)

In our concept, a skilled driver should not rev the engine excessively; these occasions also have a negative impact on the score. The following is how revving engine instances are computed.

IF REVV_ENGINE == !FALSE increment REV_INSTANCES.

In the comprehensive analysis of driving parameters, various factors were considered, such as AVG_FUEL, IDLE_ENGINE, HIGH_SPEED_BRAKING, REVV_ENGINE, DEV_STR, VS_DEV, AVG_SPEED, AVG_GEAR, IDLE_INSTANCE, HB_INSTANCES, and REV_INSTANCES. The impact of these parameters on the driving score, whether positive or negative, was explicitly outlined in the provided Table 5.2. Additionally, the influence of each parameter on the driving score was quantified, with a scale of 1x denoting low influence, 2x indicating medium influence, and 3x signifying high influence [25]. This detailed examination facilitates understanding of how each parameter contributes to the overall driving performance assessment, enabling users to make informed decisions based on these insights.

5.3. Fitting derived parameters to create a classification model

Driving scores [36] are assigned for driver classification based on the derived factors listed in Table 5.2, as well as the effect and impact on driving score. Drivers were classified into ten classes using the driving score, as shown in Table 5.3.

Table 5.2. Assignment of driving scores [25]

Name of Derived Parameter	**Its effect on the driving score**	**Its influence on the driving score**
"AVG_FUEL"	-VE	3x
"IDLE_ENGINE"	-VE	1x
"HIGH_SPEED_BRAKING"	-VE	2x
"REVV_ENGINE"	-VE	1x
"DEV_STR"	-VE	2x
"VS_DEV"	-VE	2x
"AVG_SPEED"	+VE	2x
"AVG_GEAR"	+VE	3x
"IDLE_INSTANCE"	-VE	1x
"HB_INSTANCES"	-VE	2x
"REV_INSTANCES"	-VE	1x

Table 5.3. Ten driver classes based on driving data

Driver rank based on score	**Assigned class**
1	EXCELLENT
2	EXTREMELY GOOD
3	VERY GOOD
4	GOOD
5	ABOVE AVERAGE
6	AVERAGE
7	BELOW AVERAGE
8	BAD
9	POOR
10	POOREST

A correlation matrix, as shown in Figure 5.1, was created to examine the relationship between the individual parameters listed in Table 5.1. The goal of this correlation matrix was to help finding the interdependence of numerous driving data factors. The correlations between different parameters can be determined by inspecting the matrix. For example, with a correlation coefficient of 0.72, it demonstrates that fuel usage has a substantial positive association with engine speed. This correlation matrix is useful because it provides insights into derived factors that may be used to award scores to drivers and then categorize them. Using the identified correlations, it is feasible to determine the impact of one parameter on another and form conclusions about their relationship. In this case, the correlation value between fuel consumption and engine speed indicates a significant relationship between these two variables, suggesting that engine speed influences fuel consumption. Ultimately, the correlation matrix aids in the assessment and classification of drivers by allowing the identification of crucial driving parameters and their respective correlations. By using this information, it becomes feasible to develop a scoring system that evaluates drivers based on their performance across these correlated factors.

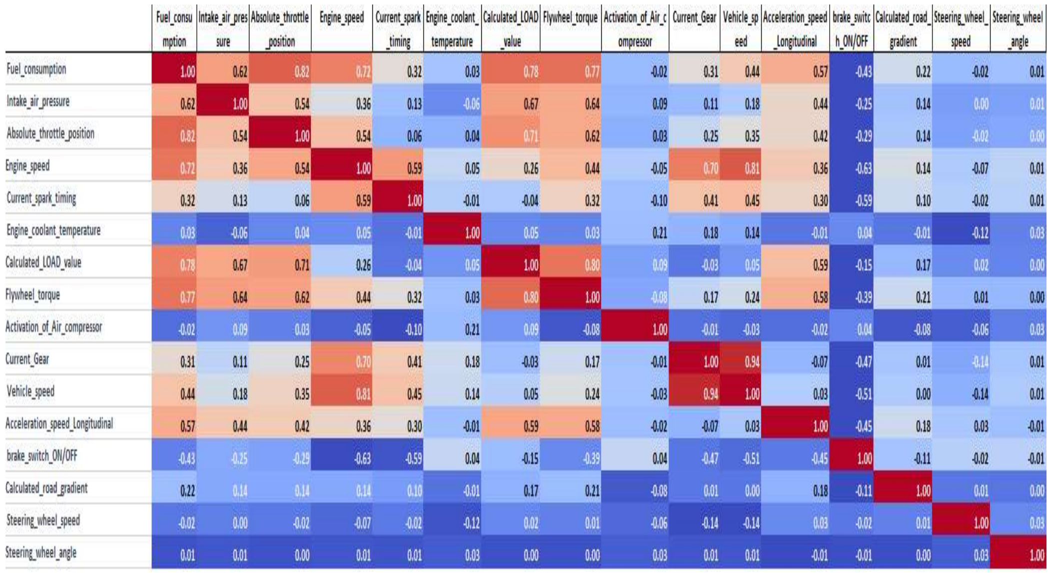


Fig. 5.1. Correlation matrix for parameters extracted

5.4. Features for Classification of Dataset

The feature classification, denoted in Figure 5.2, offers a visual illustration of the derived parameters across various driver classes. It is evident from the representation that driver class A exhibits the highest fuel consumption, while driver class B demonstrates the highest number of idle instances. The visualization of these parameters, along with others, provides a clear overview of the data, enabling the development of a driver classification model. By examining the feature classification, patterns, and trends among the different driver classes become apparent. These patterns can provide useful information for developing a robust model that appropriately categorizes drivers based on their attributes. The graphical representation provides a thorough knowledge of the links between the derived parameters and the driver classes with which they are related. Analyzing feature categorization assists in the development of a structured framework for driver classification. It is possible to set particular criteria or rules for assigning drivers to different classes by utilizing the distinct parameter values and their visual representation. For example, in the categorization model, drivers with higher fuel consumption or Driver B with more idle instances are compared individually in Fig. 5.3 to 5.9.

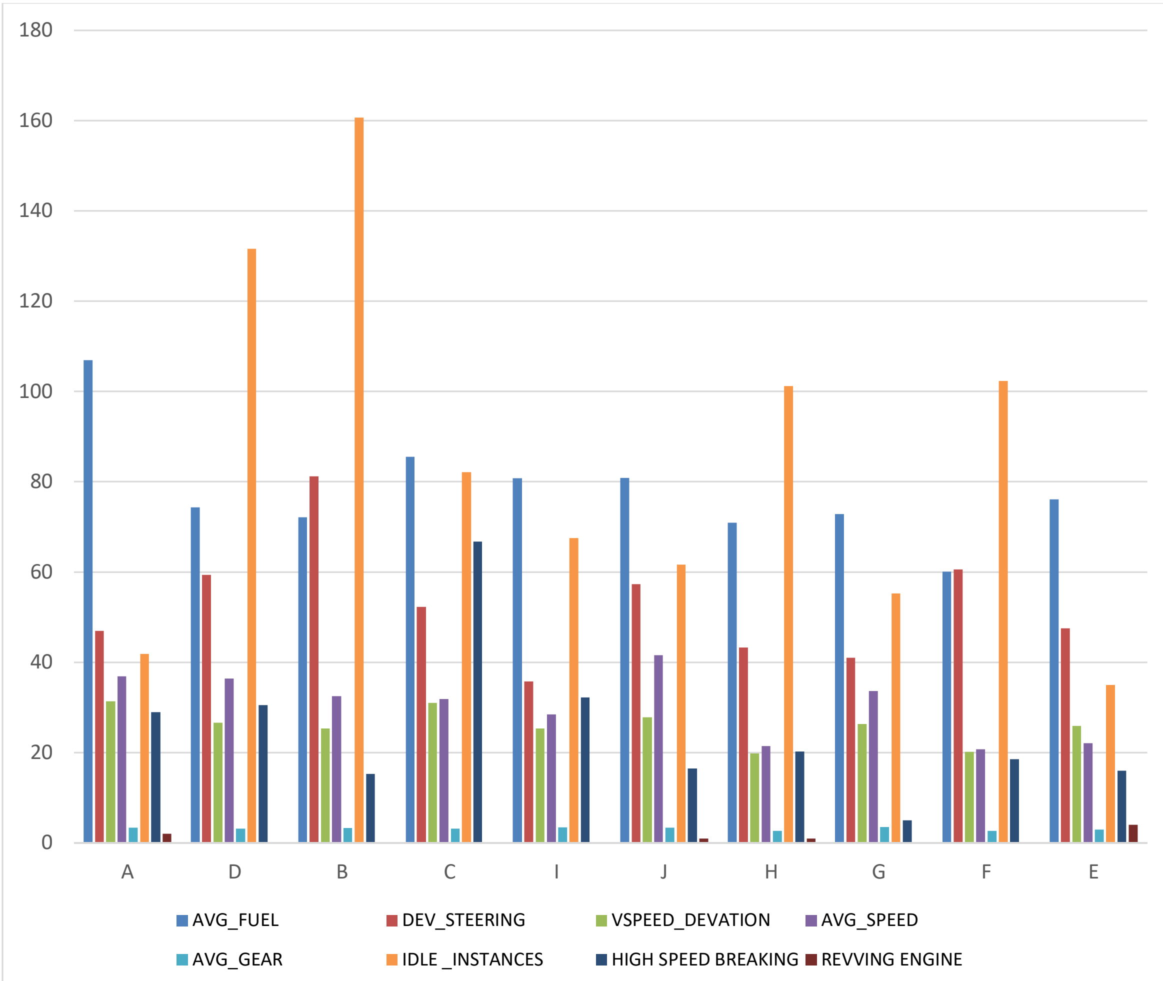


Fig. 5.2. Features of entrust for classification and analysis

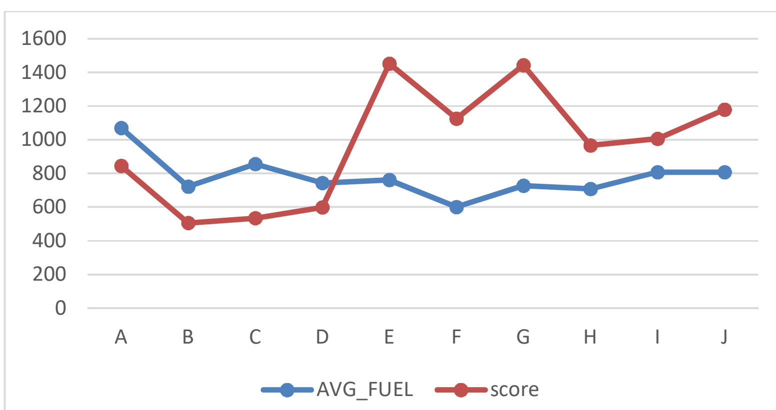


Fig. 5.3. Comparison of average fuel consumption with assigned score

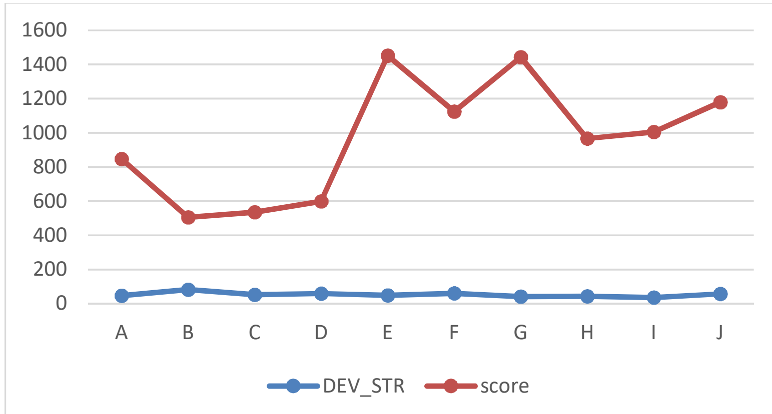


Fig. 5.4. Comparison of deviation in steering with the assigned score

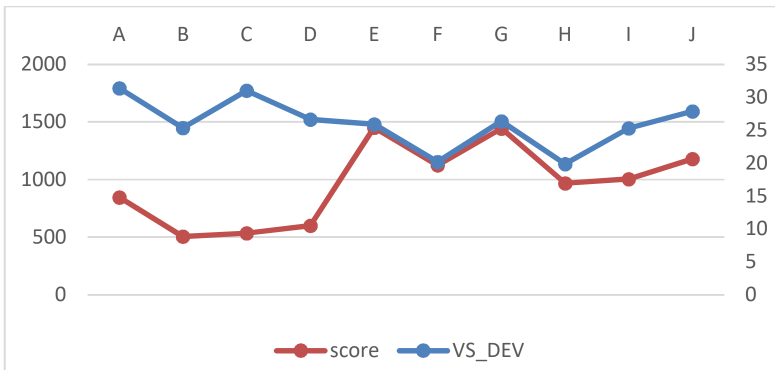


Fig. 5.5. Comparison of deviation vehicle speed with the assigned score

Fig. 5.6. Comparison of average speed with the assigned score

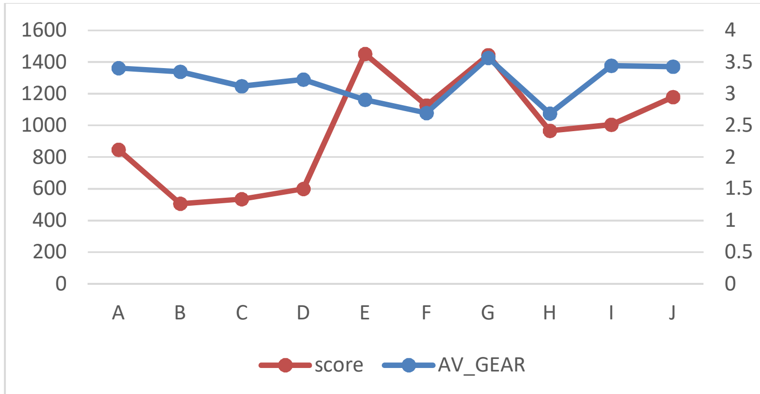


Fig. 5.7. Comparison of average gear with the assigned score

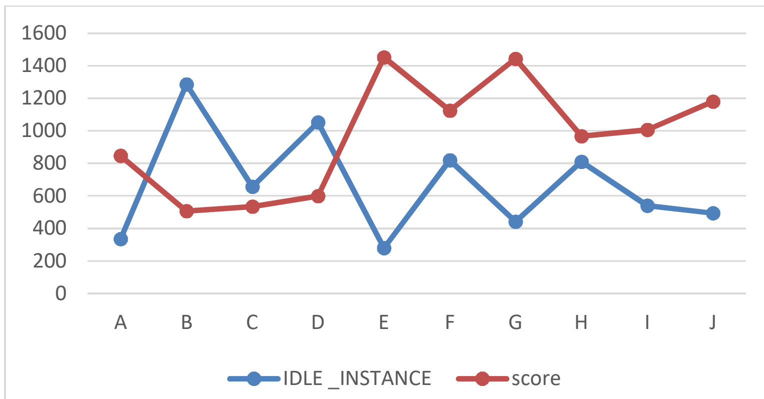


Fig. 5.8. Comparison of idle instances with the assigned score

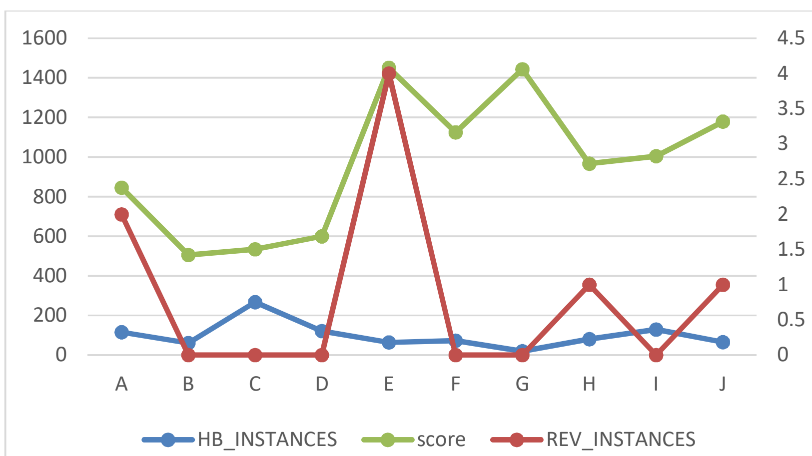


Fig. 5.9. Comparison of high-speed braking instances, revving engine with the assigned score

In Fig. 5.3, it's evident that the average fuel consumption varies significantly among drivers, with Driver A having the highest consumption and 'B' having the lowest. This trend continues in Fig. 5.4, where the deviation in steering is most noticeable in

Driver E and Driver G, resulting in lower assigned ranks. Fig. 5.5 illustrates that the deviation in vehicle speed is also highest for Driver E and Driver G. Furthermore, in Fig. 5.6, the average speed is notably elevated for Driver E and Driver G, directly influencing their driving scores. Moving to Fig. 5.7, it's clear that higher gears are associated with higher scores. Fig. 5.8 reveals that idle instances are minimum for Driver E. F, in Fig. 5.9, instances of high-speed braking are more widespread in Driver C, while Driver E tends to rev the engine more frequently, both factors influencing their assigned scores.

5.5. Implementation of the proposed method

The proposed method was implemented by fitting the model to a dataset extracted from a CSV file. To evaluate the performance and validity of the model, several classification algorithms were employed, and the results were analyzed. The dataset was divided into a training set and a test set, with a ratio of 70:30, respectively. This division ensured that the model was trained on a significant portion of the data while retaining a separate portion for testing. The implementation process followed the guidelines depicted in Figure 5.3, which outlined the step-by-step procedure for executing the proposed method. Each step, from data extraction to model evaluation, was carefully followed to ensure accurate and reliable results. The dataset, sourced from the CSV file, provided the necessary input for the model. By fitting the proposed model to this dataset, it was possible to capture the underlying patterns and relationships within the data, enabling subsequent classification tasks. To validate the model, various classification algorithms were utilized, considering their suitability for the specific problem at hand. The results obtained from these algorithms were examined and analyzed to assess the model's performance in accurately classifying the data. The training-test ratio of 70:30 ensured that a significant portion of the data was used for training the model, while the remaining portion served as an independent test set to evaluate the model’s classification capabilities.

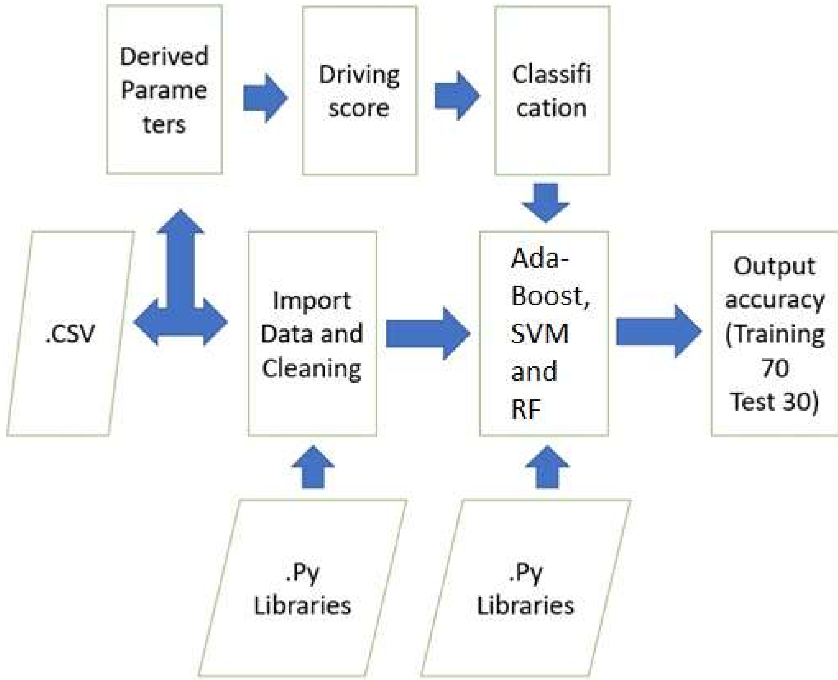
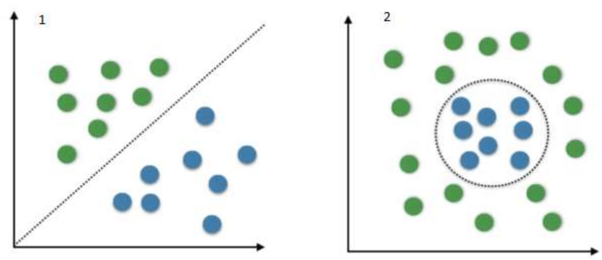


Fig. 5.10. Implementation technique

5.5.1. Support vector machine

A well-known method for training computers to learn from examples is called SVM. You can use it to find solutions to issues involving classification and prediction [28-29]. SVM is efficient at managing data that is multidimensional and dynamic. Because it only uses some of the training examples, it is also memory efficient. When you have data that can be divided by a straight line, SVM performs well. In machine learning, it is mostly employed to group items into several categories. The goal of SVM is to locate the ideal border or line in the data so that we can quickly classify fresh data into the appropriate groups. Imagine it as the act of distinguishing one item from another this line is clearer. In this best-case scenario, a hyperplane is more defined. SVM's vectors and spots aid in the establishment of the hyperplane. These extreme points are denoted as support vectors, and the SVM technique is named after them.



a b

Fig. 5.11. (a) linear data, (b) non-linear data [29]

For any type of data, binary classifiers can be created. Each classifier will produce one of two results: either the data point fits into that class OR it does not. For instance, we can develop a binary classifier for each fruit in a group of fruits in order to conduct multi-class categorization. We'll use a binary classifier to determine whether or not something falls under the "Orange" category. The output of the SVM is the classifier with the highest score. For data that can be linearly separated without any alterations, as illustrated in Fig. 5.4b, complex (not separable linearly) SVM performs well. If a set of data can be seen on a graph, it is thought to be linearly separable. if it can be displayed on a graph and divided into classes by a straight line. Fig. 5.4a. We use kernelized SVM to separate data that cannot be separated linearly. Take into account a set of data that can be divided non-linearly along a single axis.

This data is linearly separable and modifiable in two dimensions. To achieve this, each 1-D data point is converted into a corresponding 2-D pair. As a result, we can easily make linearly separable data in any dimension by relocating it to a higher dimension. This significant change has far-reaching implications. A kernel is nothing more than a comparison of how similar two data points.

5.5.2. Implementation of SVM using scikit-learn

Ten drivers travelled the same 34-kilometer mixed traffic course, and the ECU of their cars recorded the data that was used in this study. The car's 50 different measurements, all of which are available in the time-based domain at a sampling rate of one per second, are included in the dataset. Python's read_csv function is used to import the data from a CSV file. Importing libraries for implementation was accomplished using the following methods: -

"import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns"

5.5.2.1. Training the algorithm

Datasets for training and testing are provided. We will train our SVM using the Scikit-Learn SVM, which offers built-in classes for several types of SVM algorithms. Because we will be performing a classification of time-based data, we will make use of Scikit-Learn SVM package's Support Vector Classifier (SVC) class, which only takes kernel-based input. For a straight (linear) SVM that only classifies input data that can be separated linearly, set the kernel type parameter to "linear". It should be noted that this parameter setting only works for data that can be separated linearly. The subsequent process was applied: -

"from sklearn.model_selection import train_test_split

training_set, test_set = train_test_split(data, test_size = 0.3, random_state = 1)

from sklearn.svm import SVC

classifier = SVC(kernel='linear', random_state = 1)

classifier.fit(X_train,Y_train)"

The accuracy of the model was calculated as follows: -

"from sklearn.metrics import confusion_matrix

cm = confusion_matrix(Y_test,Y_pred)

accuracy = float(cm.diagonal().sum())/len(Y_test)

print("\nAccuracy Of SVM For The Given Dataset : ", accuracy)"

5.5.3. AdaBoost

AdaBoost is one of the most promising, quick, and simple machine learning algorithms available. since it does not require any prior knowledge about the weak learner and can be used alone or in conjunction with additional algorithms to identify weak hypotheses. The AdaBoost method creates a cluster of weak learners by saving a set of weights across training data and modifying them after each cycle of weak learning. Training samples are weighted more strongly than categorically correct training samples based on the categorizations that the weak learner is currently using. This is how the algorithm functions. [27][37]:

Initialize the weight vector, w, for the first round. The weights are initially set to 1/N, where N is the number of labeled examples. For each round, do the following:

a. Normalize the weight vector, w, to obtain a probability distribution, p.

b. Train a weak learner (decision tree) using the distribution, p, and get a hypothesis, h, with prediction values for each example.

Calculate the error term, ε, which represents the weighted misclassification rate of the hypothesis, h.

Calculate the coefficient, β, by dividing ε by (1 - ε). This coefficient represents the importance assigned to the hypothesis based on its performance.

Update the weight vector, w, by multiplying the individual weight by β. This increases the weight of incorrectly predicted samples, forcing the subsequent weak learners to focus on them. Samples that were predicted correctly receive a higher weight. Repeat steps 2-5 for a total of T rounds.

The final hypothesis is obtained by combining the predictions of all T weak learners. For classification problems, this is typically done through a weighted majority vote, where the weight of each weak learner is determined by its coefficient, β. For regression problems, a weighted median is often used instead.

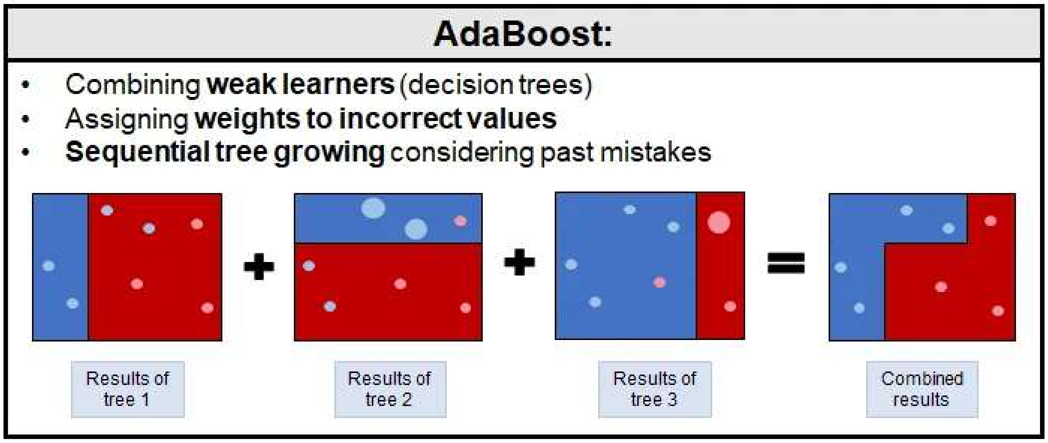


Fig. 5.12. AdaBoost simplified [*37*]

5.5.3.1. Implementation of AdaBoost

The dataset utilized for this is derived from the car's ECU [30] for a group of ten divers on the same 34-kilometer trip with mixed traffic. 52 different parameters that were gathered about the car are listed in the dataset title. At a sampling rate of one sample per second, all data is available in the sequential time domain. The CSV file containing the dataset can be imported into Python by using the read_csv method. The following techniques were used to import libraries for implementation: -

"import pandas as pd

import numpy as np

import matplotlib. pyplot as plt

import seaborn as sns

from sklearn.preprocessing import LabelEncoder

le=LabelEncoder()

y=le.fit_transform(y)"

5.4.3.2. Training the algorithm

Data sets for training and testing have been created. We can train our classifier using this data. In the context of machine learning, there are two types of learners: those who learn the connections effectively and produce reliable predictions, and those who are lazy and produce predictions that are only slightly more reliable than chance or assumption. Strong learners fall into the first type, whereas those who are weak or passive fall into the second. The main goal of boosting is to strengthen weak learners by increasing their success or performance. Essentially, boosting is the process of developing a strong classifier or regressor from a series of weak classifiers by learning from their inaccurate predictions. The following method were used: -

```
"# Import train_test_split function
from sklearn.model_selection import train_test_split
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
# Import train_test_split function
from sklearn.model_selection import train_test_split
# Import the AdaBoost classifier
from sklearn.ensemble import AdaBoostClassifier
# Create an adaboost classifer object
abc = AdaBoostClassifier(n_estimators=50, learning_rate=2, random_state=1)
# Train Adaboost Classifer
model1 = abc.fit(X_train, y_train)
#Predict the response for the test dataset
#import scikit-learn metrics module for accuracy calculation
from sklearn.metrics import accuracy_score
# calculate and print model accuracy
print("AdaBoost Classifier Model Accuracy:", accuracy_score(y_test, y_pred))"
```

5.5.4. Random Forest Classifier

A machine learning approach that can solve classification and regression issues. To increase classification accuracy and prevent overfitting, a Random Forest classifier creates several decision trees that are trained on various regions of the same training set. By choosing the qualities at random, Random Forest generates K trees with different attributes without trimming each time. In contrast to Random Forest, which examines the test data on each created tree, the most common output is then assigned to that instance.

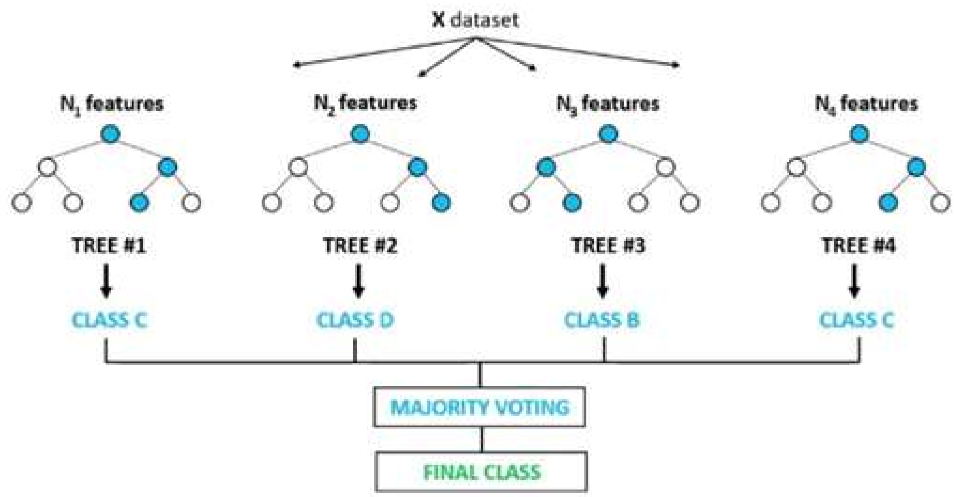


Fig. 5.13. Random forest simplified [38]

Decision Tree (see Fig. 5.6) tests the test data on a single created tree after allocating the most common output to that instance [38]. A random forest with more trees will be more robust. The described algorithm is AdaBoost, an ensemble learning method. It employs weak learners in the form of progressively developing decision trees, with a focus on correcting misclassified samples by assigning them greater weights. AdaBoost is a powerful ensemble learning technique that integrates many decision trees to generate a strong predictive model. This is achieved by repeatedly teaching weak learners and altering their weights based on prediction accuracy. The ultimate forecast is formed by averaging all of the weak learners' weighted votes or ratings. The random forest algorithm includes the following steps:

Random Sampling: The algorithm starts by randomly choosing a subset of samples from the provided dataset. This random sampling is done with replacement, meaning that a sample can be chosen multiple times or not.

Decision Tree Creation: For each of the selected samples, a decision tree is constructed. These decision trees are built using a subset of features from the dataset. Each tree learns from different combinations of features, providing variation in the group.

Prediction Generation: Once the decision trees are created, they are used to make predictions on the corresponding samples. Each decision tree independently produces a prediction based on the features and labels it has learned.

Voting: The predictions obtained from the decision trees are subjected to a voting process. For classification problems, most frequently occurring prediction is determined among the individual tree predictions.

Final Prediction: The prediction that received the highest number of vote or had the highest average is selected as the final prediction of the random forest algorithm. This prediction represents the collective decision made by the ensemble of decision trees. By combining the predictions from multiple decision trees through random sampling and voting, the random forest algorithm improves prediction accuracy and generalization ability.

5.5.4.1. Implementation of Random Forest Classifier

```
“from sklearn.ensemble import RandomForestClassifier
X = data
from sklearn.model_selection import train_test_split
X= data.drop(columns=’behaviour’, axis=1)
y= data[‘behaviour’]
X_train, X_test, y_train, y_test= train_test_split(X,y,test_size= 0.3)
from sklearn.ensemble import RandomForestClassifier
rf= RandomForestClassifier()
rf.fit(X_train,y_train)
predictions= rf.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
print(“\nAccuracy For The Given Dataset : “)
print(rf.score(X_train, y_train))”
```

5.6. Experimentation

The driving behavior analysis involved the development of a comprehensive model that incorporated several derived parameters, as outlined in Table 5.2, which directly or indirectly influenced the behavior of drivers. These parameters played a crucial role in assigning different classes to the drivers, as specified in Table 5.3. To ensure the validity of these class assignments, various machine-learning algorithms were employed. In order to handle the complex nature of the dataset, which comprised multiple dimensions, linearity, and time-dependent information, the Support Vector Machine (SVM) algorithm with a linear kernel was chosen. SVM, renowned for its memory efficiency, utilizes a subset of training points known as support vectors, enabling effective classification. The simplicity and reasonable performance of SVM made it a suitable choice for this task. Another algorithm used in the analysis was AdaBoost, which offered the advantage of not requiring prior knowledge about weak learners. AdaBoost could be effectively executed both independently and in combination with other algorithms to identify weak hypotheses, providing flexibility and robustness in the classification process. To address challenges related to missing data and overfitting, the random forest classifier was implemented. This algorithm effectively handled missing data and mitigated overfitting issues by randomly selecting subsets of features at each splitting point of the decision trees within the random forest. This approach enhanced the accuracy and reliability of the classification results. The dataset underwent pre-processing using the SVM, AdaBoost, and Random Forest algorithms, which led to the derivation of meaningful characteristics, as presented in Table 5.2. The classification assignments were then determined and documented in Table 5.3. Subsequently, the model was fitted by means of these algorithms, and the accuracy of the driving behavior analysis was assessed using both training and test data. The SVM and AdaBoost algorithms achieved a remarkable accuracy rate of 99%, indicating their effectiveness in accurately classifying driver behavior. Furthermore, the Random Forest algorithm demonstrated an exceptional overall accuracy of 100%, underscoring its proficiency in predicting driver behavior with utmost precision.

5.7. Results and Conclusion

In current research work a comprehensive classification model for analysing and categorizing driver's driving behaviors using OBD data. The utilisation of SVM, ADAboost, and Random Forest algorithms resulted in impressive accuracy rates, highlighting the model's effectiveness. The primary objective of this research was to develop a robust classification model for analysing and categorizing driver's driving behaviors using data obtained from the OBD system of vehicles. The study involved recording and analyzing over 50 vehicle-related operating parameters, along with the calculation of eleven additional driving metrics or behavior-related events. These derived parameters played a crucial role in accurately constructing a behavior classification model. By considering various combinations of these parameters, the model aimed to provide a systematic and logical approach to assess the direct and indirect impacts of a driver's actions on their behavior. To validate and improve the classification model, three popular machine learning algorithms were employed: SVM, ADAboost, and Random Forest. These algorithms are widely recognized for their effectiveness in classification tasks. The SVM algorithm was chosen for its ability to handle multidimensional and time-dependent data efficiently. By utilizing a subset of training points known as support vectors, SVM maximizes the separation between different classes, making it well-suited for this task. ADAboost, on the other hand, is an ensemble learning algorithm that combines weak learners to create a strong classifier. It was selected for its versatility and robustness in handling various types of data and learning scenarios. The Random Forest algorithm was chosen due to its ability to handle missing data and mitigate the overfitting problem often associated with decision trees. By randomly selecting subsets of features at each node's splitting point, Random Forest ensures the diversity and independence of the individual trees within the ensemble, resulting in highly accurate predictions. The classification model created through this research yielded ten distinct classes of driving behaviors.The accuracy rates achieved by the model were remarkable, with SVM, ADAboost, and Random Forest demonstrating accuracy rates of 99%, 99%, and 100%, respectively. The implications of this research are significant. The behavior classification model developed can have practical applications for various stakeholders, including traffic police, insurance companies, and remote claims processing. The model's accuracy and reliability make it a valuable tool for assessing driving behaviors, enabling informed decision-making in areas such as risk assessment, driver profiling, and driver assistance systems. It's important to note that while the research utilized modern tools and algorithms, there is potential for applying other advanced software tools and procedures in line with evolving technological advancements and requirements. In conclusion, the presented methodology is not only useful for internal combustion engine-based vehicles but can be extended to hybrid and electric vehicles. This adaptability ensures the model's relevance in the context of the ongoing transition towards greener transportation solutions. However, the potential impact of data acquisition and storage delays on behavior classification accuracy should be considered as a limitation of real-time data acquisition, another challenge as short road trips or variations in vehicles and routes may impose limits on accuracy and uniformity in while performing classification of driving behaviors.

Table 5.4. Comparison of the performance of various ML algorithms

Title of Work	**Performance with**			
	KNN	**Random forest**	**SVM**	**Ada-Boost**
Proposed system in this thesis	**NA**	**1.00**	**.999**	**.999**
Know your master: Driver profiling-based anti-theft method [31]	.957	.996	NA	NA
Driving Behavior Analysis Based on Vehicle OBD Information and AdaBoost Algorithms[44]	NA	NA	NA	.998
Identification and Classification of Driving Behaviour at Signalized Intersections Using Support Vector Machine [45]	NA	NA	.970	NA
Machine Learning Framework for Road Safety of Smart Public Transportation [46]	.776	.946	.779	.837
Identification and Analysis of Driver Postures for In-Vehicle Driving Activities and Secondary Tasks Recognition [47]	.623	.736	.747	NA
A Review of the Driving Behavior Recognition Methods Based on Vehicle Multi-sensor Information [48]	.900	.750	.800	NA
Driving Behaviour Analysis Using Machine and Deep Learning Methods for Continuous Streams of Vehicular Data [10]	NA	1.00	.998	NA

Table 5.4 compares the performance of various machine learning algorithms, including K-Nearest Neighbors (KNN), Random Forest, SVM, and AdaBoost, for determining driver behavior based on vehicle data. The accuracy scores for each algorithm are provided in the table5.4, allowing to understand how effectively each method performs in driver behavior analysis. The proposed method achieved high accuracy scores for Random Forest, SVM, and AdaBoost, but the KNN results are not performed. Other existing methods also achieved varying levels of accuracy across different algorithms, indicating the importance of selecting the most suitable algorithm for specific driver behavior analysis tasks.

In conclusion, this research has successfully developed a behavior classification model that accurately categorizes driver-driving behaviors based on vehicle data. The model's high accuracy rates, achieved through the implementation of SVM, AdaBoost, and Random Forest algorithms, make it a valued tool with practical applications for traffic management, insurance, and driver assistance systems. The adaptability of the methodology to different vehicle types ensures its relevance in reference to EV and other greener transportation solutions. However, considering potential data acquisition and storage delays remains crucial for maintaining accuracy. Overall, this research represents a significant step forward in understanding and analyzing driver behavior, contributing to safer and more efficient transportation systems.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE OF WORK

In conclusion, research bears considerable accountability in improving the reliability and emergency maintenance of remote assets. By focusing on a specific subject and employing a multidomain research approach, the researcher has developed a sophisticated system design that addresses the issue of negligence by operators or drivers. This research provides asset owners with crucial information about their assets and offers a comprehensive framework for monitoring and classifying their performance. While the proposed system cannot completely eliminate asset failures, it significantly enhances their performance, reducing the likelihood of untimely incidents. The research findings and contributions serve as a valuable resource for asset owners and stakeholders interested in enhancing the reliability and maintenance of remote assets.

Research plays a significant role in improving the reliability and emergency maintenance of remote assets. In line with this responsibility, the researcher has chosen a specific subject for investigation with the aim of developing novel and sophisticated achievable system designs that can effectively address the issue of negligence by operators or drivers. The thesis seeks to provide asset owners with valuable information about their assets, encompassing a wide range from small engines in cars to jet engines and heavy machinery powered by internal combustion engines. Failure of operational assets can occur due to various reasons, and while some of these failures can be avoided with the proposed system, others may remain unavoidable. To address this challenge, the researchers utilized real-time data from diverse scientific sources and adopted multiple approaches to develop a comprehensive and multidomain research outline. This involved the integration of know-how from fields such as engine electronics, mechanical engineering, the Internet of Things (IoT), and machine learning. The resulting system offers considerable benefits to asset operators (especially for costly rented assets), asset owners, law enforcement agencies, insurance companies, and other stakeholders. The research explains the necessary procedures involved in developing a remote asset monitoring system, providing a detailed insight into the methodologies employed. It is important to note that while the proposed system does not guarantee the prevention of asset failures, it significantly improves their performance, thereby reducing the likelihood of untimely incidents. A notable contribution of the research is the presentation of a new sensor specifically designed to determine engine oil quality, which plays a critical role in evaluating remote assets. Research work has successfully demonstrated various techniques for designing low-cost and efficient sensors that can be flawlessly integrated into the proposed system, enhancing its overall effectiveness. The research findings and contributions are presented comprehensively in the subsequent section, highlighting the significant developments and insights gained from the study. These insights prove precious for asset owners and stakeholders seeking to optimize the reliability and maintenance of their remote assets.

6.1. Major Research Contributions

The research involves a methodology for the development of a remote asset monitoring system. With the following outcomes:-

- State of the art methods for determining oil quality were explored while identifying research gap two methods for determining engine oil quality was introduced to facilitate a high level of monitoring of oil as this is very critical component in any asset.
- The study involves a comparative analysis of various methods available for engine operating parameters, data extraction and storage on the cloud after identifying research gap a low-cost technique was developed which is compatible with most of the engines, equipment’s and machinery
- The research proposes a low cost method capable of extracting sensor data. An in-depth analysis of the OBD data frame structure and engine data is presented. The report provides an inclusive outline for the intelligent implementation of IoT and machine learning as an autonomous system.
- Method presented here requires minimal or no modification in the engine, equipment or machinery ,instead it relies on existing sensors already installed by manufacturer.
- From above mentioned technique for gathering real-time data of engine operation implementation of modern machine learning techniques was done on the collected data, and ultimately the classification of the operator or driver behavior.

- Proposed method may be used by asset owners, law enforcement, rented equipment’s and insurance companies to track maintenance, condition and claim settlement process.

Additionally, and presents a complete illustration of the proposed system, as represented in Figure 6.1. The methodology for developing the remote asset monitoring system involves several key steps. Firstly, it involves capturing engine operating parameters, as crucial indicators of the asset's performance. This data is then extracted and stored securely on the cloud, ensuring accessibility and reliability for subsequent analysis. Next, machine learning algorithms are employed to analyze the collected data and extract meaningful understandings. These algorithms utilize machine learning techniques to identify patterns and trends, enabling the classification of operator or driver behavior. By detecting abnormal behavior or deviations from expected norms, potential issues or risks can be promptly identified. To facilitate unified data transmission and real-time monitoring, a transmitting device is proposed. This device is capable of efficiently sensing and relaying the data to a centralized system for further analysis. The integration of IoT technology ensures the connectivity and interoperability of the monitoring system. The research also investigates into the detailed structure of OBD data frames and the specific engine data to be monitored. Understanding the configuration and organization of the data is crucial for effective implementation and accurate analysis. The research provides insights into the key parameters and metrics to be considered, allowing for a comprehensive monitoring approach. The proposed system illustration, as depicted in Figure 6.1, visually represents the different components and their interactions within the remote asset monitoring system. It highlights the integration of IoT, machine learning, and data transmission to create an intelligent and independent system.

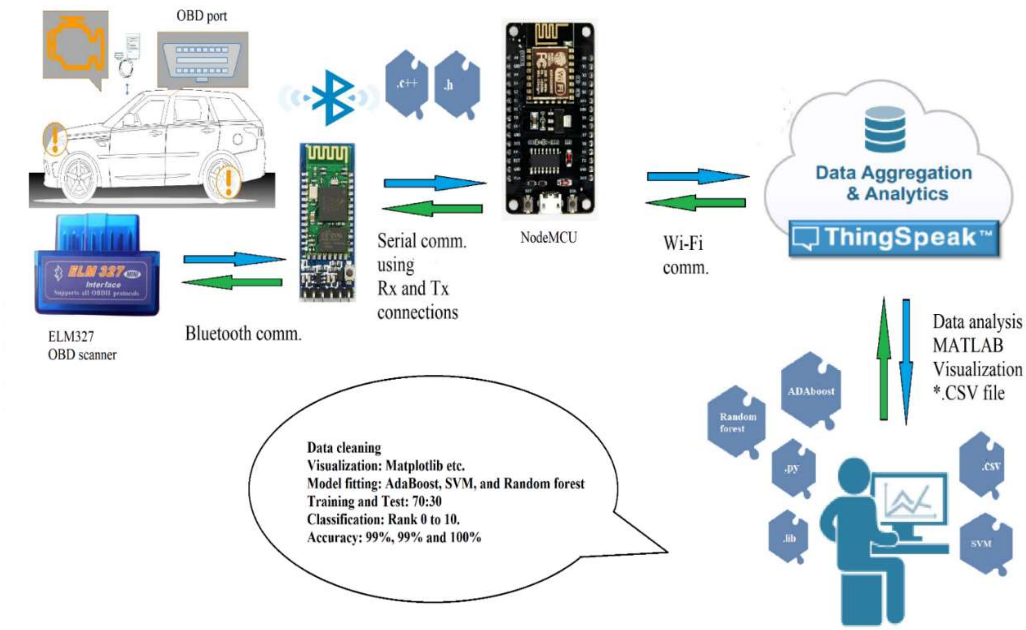


Fig. 6.1. The proposed system illustration

6.2. Deployment

Determining the right deployment location for a device is vital for the Remote Asset Monitoring System (RAMS), taking into account factors such as the type of asset, reliability, and cost. The primary objective is to develop a cost-effective, minimally modified, and highly reliable mechatronics, IoT, and machine learning-based system that benefits. The deployment strategy focuses on the cost of assets and maintenance expenses. This method accommodates various types of assets, whether movable or fixed. The researcher successfully created a system that utilizes current sensors to predict operator or driver behavior and the likelihood of downtime. The deployment requires an asset with an onboard computer; and, it relies on a good internet connection. The deployment process can be completed quickly, although the installation of an oil quality sensor may take some additional time. By utilizing this system, authorities can take appropriate measures for insurance renewal, manual maintenance expenses, if necessary, enforce fines and penalties to ensure effective monitoring and enhance operator, driver, and public safety.

6.3. Significance of the presented thesis Work for the society

The presented thesis work holds significance for society as follows:

- The research work focuses on using machine learning (ML) and embedded processors to monitor and alert the status of assets. This proactive approach allows for sensible maintenance, reducing emergency situations and elongating the useful life of assets. This has direct benefits for various sectors such as transportation, manufacturing, and infrastructure.
- The proposed system emphasizes a low-cost deployment approach that requires minimal or no modification to the existing infrastructure. By leveraging existing systems and incorporating only one sensor, the research ensures cost-effectiveness and practicality in implementation. This makes it reachable to a wide range of asset owners, including those who may have limited resources or rely on rented assets.
- The research particularly addresses the needs of susceptible assets that are rented or used by multiple operators. By providing a comprehensive monitoring system, both the asset owners and the operators can get an advantage. Asset owners can safeguard the optimal performance and longevity of their assets, while operators can avoid unexpected failures or accidents, leading to increased safety and efficiency.
- The proposed system explores two different types of engine oil quality sensors, optical and inductive methods, along with all onboard sensors from ECU simultaneously. This comprehensive approach allows for better monitoring and detection of possible faults related to oil quality also.
- The proposed system is based on a multiprotocol connection, which automatically detects the protocol during system set-up. This adaptability enables seamless integration with different types of assets and systems, making it adaptable to various industrial applications.
- The present invention safeguards a transparent monitoring system that cannot be altered by operators or end-users. This transparency helps to maintain the integrity of data collected and alerts created, enabling accurate decision-making and preventing any potential mismanagement.
- The system exhibits a reliable and robust architecture where the failure of one subsystem does not affect the functioning of other systems. This fault-tolerant design ensures continuous monitoring and alerts, even in the event of subsystem failures, thereby enhancing the overall robustness and dependability of the system.

6.4. Limitations and future scope

The presented work successfully developed a remote asset monitoring system for IC engine-based assets, specifically those that are not operated or driven by the owner. However, the research identified several limitations that need to be addressed for future improvement and development of the system.

- Firstly, the proposed system is not appropriate for assets that are operated for short periods or driven for small distances. To overcome this limitation, the researcher is exploring and developing machine learning algorithms that can effectively train on small data-sets while maintaining accuracy. By achieving this, the system will be able to perform well even with limited data inputs, thereby expanding its applicability to assets with shorter operating times.
- Secondly, the proposed system currently relies on data stored in files due to network delays. To enhance real-time monitoring capabilities, the researcher is working on exploring even faster and more efficient communication protocols. By improving data transmission speed, the system will be able to provide real-time monitoring and analysis, enabling timely decision-making and proactive asset management.
- Another limitation identified is the difficulty in behavior classification when routes or vehicles change. To address this, future research could focus on developing more robust algorithms capable of adapting to different routes and vehicle types. This may involve integrating additional sensors and improving existing machine-learning models to handle variations in behavior patterns. By enhancing the system's adaptability, it can effectively monitor assets with various usage scenarios.

Furthermore, the proposed optical-based oil quality sensor requires calibration separately at the time the engine oil change, while the inductive-based sensor has low sensitivity. To overcome these challenges, future research could concentrate on improving the oil quality sensor's sensitivity and reducing the need for frequent calibration. This could involve exploring alternative sensor technologies, optimizing sensor design, or developing advanced calibration techniques. Enhancing the accuracy and convenience of oil quality monitoring will contribute to better asset maintenance and extend their operational lifespan.

- Furthermore, the limitations of engine oil quality sensor(s) I also acknowledged here as optical-based sensor requires calibration as engine oils used to have different colors and the proposed sensor is also based on the optical principle so every time replacement of oil we should consider calibration by making the output of the sensor as 0v so that smallest change in the output about oil quality can be detected. the second proposed method of engine oil sensor is inductance based whose limitation is the change in output voltage is very small which can be considered as a limitation and further can be overcome by the use of bridge based circuit and frequency adjustment as the proposed method uses AC signal.

6.5. List of Publications

S. No	Name of the Journal/ Conference	Journal Indexing	Title of the Paper	Published Date	Volume & Issue Number	ISSN/ISBN Number
1	Journal of Emerging Technologies and Innovative Research	UGC	Reading DTC using OBD2	Jan-2019	VOL. 6 ISSUE 1	ISSN-2349-5162.
2	International Conference on Sustainable Energy Sources, Technologies, and Systems 2023	Conference	Method For Determining Engine Oil Quality Based on Inductive Properties of Used Engine Oil	2nd- Aug-2023	1st	NA
3	THINK INDIA JOURNAL	UGC	A technology review for lubricating oil sensors in reference to lubricating properties of engine oil	Sep-2019	Vol-22-Issue-17	ISSN: 0971-1260
4	Indian patent office	IPR	Simple low-cost engine oil quality sensor for internal combustion engine	10-Nov-2022	Application number 202211070256	Application number 202211070256
5	CCICT 2022 – INDIA	Scopus	Monitoring and Remote Data Logging of Engine Operation via On Board Diagnostic Port	9-Jul-2022	5th	DOI: 10.1109/CCICT53244.2021
6	The Journal of Supercomputing	SCI	Driving Behavior Analysis and Classification by Vehicle OBD Data Using Machine Learning	19-May-2023	79	https://doi.org/10.1007/s11227-023-05364-3

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SAFETY DATA SHEET

Leypower Diesel Engine Oil 15W-40

02334/15W-40/1

1. IDENTIFICATION OF THE SUBSTANCE/MIXTURE AND OF THE COMPANY/UNDERTAKING

Product identifier : Leypower Diesel Engine Oil 15W-40

Viscosity Grade : SAE 15W-40

Product code Gulf Oil International : 02334/15W-40/1

Relevant identified uses of the substance or mixture and uses advised against : Engine oil (lubricant).
This oil should not be used for any other purpose than the intended use as an engine oil without expert advice.

Details of the supplier of the safety data sheet : Gulf Oil Lubricants India Ltd., IN Centre, 49/50, MIDC, 12th Road, Andheri (East),

Mumbai -400 093

Emergency telephone number : +91 22 66487777

2. HAZARDS IDENTIFICATION

Classification of the substance or mixture : Not classified as dangerous under EC criteria.

Most important adverse physico-chemical effects : Combustible liquid

Most important adverse human health effects : Sensitising substances; allergic reactions possible

Most important adverse environmental effects : No specific risk for the environment.

Label elements:

- safety advices : Do not empty into drains; dispose of this material and its container in a safe way.

Other hazards : During use in engines, contamination of oil with low levels of cancer-causing combustion products occurs. Used motor oils have been shown to cause skin cancer in mice following repeated application and continuous exposure. Brief or intermittent skin contact with used motor oil is not expected to have serious effects in humans if the oil is thoroughly removed by washing with soap and water. Avoid prolonged contact with used motor oil. Overexposure to oil mist may cause respiratory irritations. Oil mist deposited on surfaces may cause slip hazard.

3. COMPOSITION/INFORMATION ON INGREDIENTS

Chemical characterization : Mixture of highly refined mineral oils and additives.(PCA-content < 3% - IP 346)

Composition of the mixture:

Substance name	Contents	CAS No	EC No	Annex No	Ref REACH	Classification
Phosphorodithioic acid, O,O-di-C1-14- : alkyl esters, zinc salts	0.79 - 1.47 %	68649-42-3	272-028-3	-----	01-2119493626-26	Xi; R38-41 N; R51-53
Calcium branched chain alkyl phenate	1.08 - 2.08 %	90480-91-4	291-829-9	-----	-----	R53
Polyolefine polyamine succinimide, Polyol :	0.93 - 1.74 %	-----	-----	-----	POLYMER	R53
Zinc dialkyl dithiophosphate :	0.72 - 1.34 %	68649-42-3	272-028-3	-----	-----	Xi; R36/38-41 N; R51-53
Polyolefin polyamine succinimide, borated :	0.57 - 1.07 %	-----	-----	-----	POLYMER	R53
Calcium long chain alkaryl sulphonate	0.36 - 0.66 %	-----	-----	-----	-----	R53

SECTION 3. COMPOSITION/INFORMATION ON INGREDIENTS (continued)

Substance name		Contents	CAS No	EC No	Annex No	Ref REACH	Classification
Alkaryl amine	:	0.14 - 0.26 %	-----	-----	-----	-----	N; R51-53

4. FIRST AID MEASURES

Description of first aid measures:

- **after inhalation** : Assure fresh air breathing. If you feel unwell, seek medical advice.
- **after contact with skin** : Remove contaminated clothing and shoes. Wash skin thoroughly with mild soap and water. Never use kerosine or gasoline for cleaning the skin.
- **after contact with the eyes** : Rinse immediately with plenty of water. Seek medical attention if irritation develops.
- **after ingestion** : Do not induce vomiting.
Seek medical attention immediately.

Most important symptoms and effects, both acute and delayed : Symptoms of overexposure to vapours include drowsiness, weakness, headache, dizziness, nausea, vomiting, dimming of vision.

Indication of any immediate medical attention and special treatment needed : The ingestion of lubricating oils is an unlikely event. No specific therapy is indicated in view of the very low toxicity of the base oil(s) and other components. Treat with supportive measures as appropriate to the patient's condition.

5. FIRE-FIGHTING MEASURES

Suitable extinguishing media : Water fog. Carbon dioxide. Foam. Dry chemical product

Extinguishing media which shall not be used for safety reasons : Do not use a heavy water stream.

Special hazards arising from the substance or mixture : Under fire conditions, hazardous fumes will be present.

Advice for firefighters : Wear self-contained breathing apparatus, rubber boots and thick rubber gloves.
Do not enter fire area without proper protective equipment, including respiratory protection.
Use water spray or fog for cooling exposed containers.
Avoid fire-fighting water to enter environment.

6. ACCIDENTAL RELEASE MEASURES

Personal precautions, protective equipment and emergency procedures:

- **for non-emergency personnel** : Evacuate unnecessary personnel.
- **for emergency responders** : Equip cleanup crew with proper protection. Wear suitable protective clothing, gloves and eye or face protection. Remove ignition sources.

Environmental precautions : Contain any spills with dikes or absorbents to prevent migration and entry into sewers or streams. Avoid release to the environment. Notify authorities if liquid enters sewers or public waters.

Methods and material for containment and cleaning up : Clean up any spills as soon as possible, using an absorbent material to collect it. Use suitable disposal containers.

Reference to other sections : See Heading 8 &

7. HANDLING AND STORAGE

Precautions for safe handling : Keep away from sources of ignition. No naked lights. No smoking. Use only in well ventilated areas. Avoid release to the environment. Do no eat, drink or smoke when using this product. Wash hands and other exposed areas with soap and water before leaving work.

Conditions for safe storage, including any incompatibilities : Store this product in a dry location where it can be protected from the elements. Store in tightly closed, properly ventilated containers away from heat, sparks, open flame, strong oxidizers, radiations, and other initiators.
Keep at temperature not exceeding 50℃.

Specific end use(s) : Use only as engine oil.

8. EXPOSURE CONTROLS/PERSONAL PROTECTION

Control parameters:

Occupational exposure limit values:

- Australia : National exposure standards for atmosperic contaminants in the occupational environment; Time-Weighted Average (normal eight-hour working day, for a five-day working week): 5 mg/m³ for oil mist, refined mineral. (National Occupational Health & Safety Commission [NOHSC: 1003(1995)]

- Canada : The American Conference of Governmental Industrial Hygienists (ACGIH) has assigned mineral oil mist a threshold limit value (TLV) of 5 mg/m(3) as a Time Weighted Average (TWA) for a normal 8-hour workday and a 40-hour workweek and a short-term exposure limit (STEL) of 10 mg/m(3) for periods not to exceed 15 minutes. Exposures at the STEL concentration should not be repeated more than four times a day and should be separated by intervals of at least 60 minutes.
[ACGIH 1994, p. 28]

- EU : Occupational Exposure Standard (OES) of 5 mg/m³,
8-hour time-weighted average reference period for oil mist.

- USA : The American Conference of Governmental Industrial Hygienists (ACGIH) has assigned mineral oil mist a threshold limit value (TLV) of 5 mg/m(3) as a Time Weighted Average (TWA) for a normal 8-hour workday and a 40-hour workweek and a short-term exposure limit (STEL) of 10 mg/m(3) for periods not to exceed 15 minutes. Exposures at the STEL concentration should not be repeated more than four times a day and should be separated by intervals of at least 60 minutes.
[ACGIH 1994, p. 28]

Occupational Exposure Limits

Biological limit values : No data

Exposure controls:

Appropriate engineering controls : Provide adequate ventilation to minimize dust and/or vapour concentrations.

Individual protection measures, such as personal protective equipment:

- eye / face protection : Chemical goggles or safety glasses (EN 166)

- skin protection : Wear suitable protective clothing.

- hand protection : Wear suitable gloves resistant to chemical penetration. (EN 374)

- respiratory protection : The use of Filtertype A (EN 141) is recommended If exceeding the Occupational Exposure Limit.

- others : Do not wear leather soled shoes.

Environmental exposure controls : Avoid release to the environment.

9. PHYSICAL AND CHEMICAL PROPERTIES

Information on basic physical and chemical properties:

- physical state	:	Oily liquid.
- colour	:	Yellow-brown.
- odour	:	Light odour of petroleum.
- flash point	:	230℃
- density @ 15℃	:	894.8 kg/m³
- solubility in water	:	Insoluble.
- viscosity @ 100℃	:	14.3 cSt
- pour point	:	-27℃
Other information	:	See Product Data Sheet for detailed information

10. STABILITY AND REACTIVITY

Reactivity	:	No data available.
Chemical stability	:	Stable under normal conditions.
Possibility of hazardous reactions	:	None under normal conditions.
Conditions to avoid	:	Extremely high or low temperatures
Incompatible materials	:	Strong oxidizing agents.
Hazardous decomposition products	:	None under normal conditions.

11. TOXICOLOGICAL INFORMATION

Information on toxicological effects:

- acute toxicity	:	No specific toxicity data on this product available.
- irritation	:	Not expected to be an irritant to eyes or skin. Inhalation of fumes or vapours may cause respiratory irritation.
- corrosivity	:	No adverse health effects were noted.
- sensitisation	:	Repeated exposure may cause sensitization due to an allergic reaction of the skin.
- repeated dose toxicity	:	No data available.
- carcinogenicity	:	This product contains mineral oils which are considered to be severely refined and not considered to be carcinogenic under IARC. All of the oils in this product have been demonstrated to contain less than 3% extractables by the IP 346 test.
- mutagenicity	:	Not expected to be mutagenetic.
- reproductive toxicity	:	Not expected to be toxic.

Information on likely routes of exposure:

- after ingestion	:	Ingestion may cause nausea, vomiting and diarrhoea.
- after inhalation	:	Inhalation of vapours may cause respiratory irritation.
- after skincontact	:	Prolonged or repeated skin contact with the material will remove natural oils and could lead to a dermatitis.
- after eyecontact	:	Slight eye irritant upon direct contact.
Symptoms related to the physical, chemical and toxicological characteristics	:	No adverse health effects were noted.
Delayed and immediate effects as well as chronic effects from short and long-term exposure	:	No adverse health effects were noted

SECTION 11. TOXICOLOGICAL INFORMATION (continued)

Other toxicological information : No data

12. ECOLOGICAL INFORMATION

Toxicity : No specific ecotoxicity data on this product available.

Persistence and degradability : Major components are inherently biodegradable.

Bioaccumulative potential : Not determined.

Mobility in soil : It is to be expected small mobility in soil. Some or a few components may get into the soil and may cause pollution of ground water. Product spreads on the water surface.

Results of PBT and vPvB assessment : Not applicable.

Other adverse effects : May contaminate water supplies.

13. DISPOSAL CONSIDERATIONS

Waste treatment methods : Dispose in a safe manner in accordance with local/national regulations. See Directive 2001/118/EC

Waste Code European Waste List : 13 02 05 - mineral-based non-chlorinated engine, gear and lubricating oils.
15 01 10 - packaging containing residues of or contaminated by dangerous substances.

14. TRANSPORT INFORMATION

Not regulated.

15. REGULATORY INFORMATION

Safety, health and environmental regulations/legislation specific for the substance or mixture:

- Australian Inventory of Chemical Substances (AICS) : All components are in compliance with chemical notification requirements in Australia.

- Canadian Environmental Protection Act (CEPA) : All components are in compliance with the Canadian Environmental Protection Act (CEPA) and are present on the Domestic Substances List (DSL).

- European Inventory of Existing Commercial Chemical Substances (EINECS) : All components listed.

- USA Toxic Substances Control Act (TSCA) : All components of this material are on the US TSCA Inventory or are exempt

- Water Hazard Classification (Germany): : Water Hazard Class: 1 - low hazard to waters

Chemical safety assessment : Not

16. OTHER INFORMATION

Revision Indicators	:	None.
Key to abbreviations and acronyms used in the safety data sheet	:	ACGIH = American Conference of Industrial Hygienists CLP = Classification and Labelling of Substances and Preparations EC = European Commission. EN = European Norm IARC= International Agency for Research on Cancer IP = Institute of Petroleum. ISO = International Organization for Standardization NLGI = National Lubricating Grease Institute PCA = Polycyclic Aromatics TLV = Threshold Limit Value. TWA = Time Weighted Average VG = Viscosity Grade
Key literature references and sources for data	:	Concawe Report 01/53, Concawe Report 01/54, Concawe Report 05/87. Regulations (EC) No 1907/2006, 1272/2008 & 453/2010 of the European Parliament and of the Council.
List of relevant R-phrases	:	R36/38 : Irritating to eyes and skin. R38: Irritating to skin. R41: Risk of serious damage to eyes. R51/53: Toxic to aquatic organisms, may cause long-term adverse effects in the aquatic environment. R53 : May cause long-term adverse effects in the aquatic environment.
Training advice	:	See information supplied by the manufacturer.

The contents and format of this SDS are in accordance with COMMISSION REGULATION (EU) No 453/2010 of 20 May 2010 amending Regulation (EC) No 1907/2006 of the European Parliament and of the Council on the Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH).

End of document

Gmail

Raman Kumar <ramankanythia@gmail.com>

[HCRLab] The dataset you requested for: 8) Driving Dataset

1 message

ocslab@hksecurity.net <ocslab@hksecurity.net> Fri, Aug 26, 2022 at 10:41 AM
Reply-To: ocslab
To: ramankanythia@gmail.com

Dear, raman kumar

Thank you for your interest in our HCR Lab DataSet. Please click on the link below to download Dataset.

※ Download links are as follows:

▶ Driving time : about 23 hours
ㄴDriving length : about 46km (round-trip)
ㄴDriving path : between Korea University and
ㄴSANGAM World Cup Stadium
# of Driver : 10

https://drive.google.com/a/hksecurity.net/file/d/0Bx1Nsg-bc9ovcmJJczkydkRHYk0/view?usp=sharing

★ If you have found our dataset helpful in your research, please consider citing our paper:
Byung Il Kwak, Jiyoung Woo and Huy Kang Kim, "Know Your Master: Driver Profiling-based Anti-theft Method", PST (Privacy, Security and Trust) 2016

★ You can get download link for the full paper and citation from the link below

For more information(including links for the full paper and citation), please visit:
https://sites.google.com/a/hksecurity.net/ocslab/Datasets/driving-dataset

Thank you.

In [122]:
```
from sklearn.preprocessing import LabelEncoder

le=LabelEncoder()

y=le.fit_transform(y)
```

In [123]:
```
# Import train_test_split function
from sklearn.model_selection import train_test_split

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

In [124]:
```
# Import the AdaBoost classifier
from sklearn.ensemble import AdaBoostClassifier


# Create adaboost classifer object
abc = AdaBoostClassifier(n_estimators=50, learning_rate=2, random_state=1)

# Train Adaboost Classifer
model1 = abc.fit(X_train, y_train)


#Predict the response for test dataset
y_pred = model1.predict(X_test)
```

In [125]:
```
#import scikit-learn metrics module for accuracy calculation
from sklearn.metrics import accuracy_score

# calculate and print model accuracy
print("AdaBoost Classifier Model Accuracy:", accuracy_score(y_test, y_pred))
```

```
AdaBoost Classifier Model Accuracy: 0.9995441075906086
```

In [13]:
```python
from sklearn.model_selection import train_test_split
training_set, test_set = train_test_split(data, test_size = 0.3, random_state = 1)

#Classifying the predictors and target

X_train = training_set.iloc[:,0:19].values
Y_train = training_set.iloc[:,20].values
X_test = test_set.iloc[:,0:19].values
Y_test = test_set.iloc[:,20].values

#Initializing Support Vector Machine and fitting the training data

from sklearn.svm import SVC
classifier = SVC(kernel='linear', random_state = 1)
classifier.fit(X_train,Y_train)

#Predicting the classes for test set

Y_pred = classifier.predict(X_test)

#Attaching the predictions to test set for comparing

test_set["Predictions"] = Y_pred
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test,Y_pred)
accuracy = float(cm.diagonal().sum())/len(Y_test)
print("\nAccuracy Of SVM For The Given Dataset : ", accuracy)
```

```
Accuracy Of SVM For The Given Dataset :  0.9999240179317681
```

In [20]:

```
from sklearn.ensemble import RandomForestClassifier
X = data
from sklearn.model_selection import train_test_split
X= data.drop(columns='behaviour', axis=1)
y= data['behaviour']
X_train, X_test, y_train, y_test= train_test_split(X,y,test_size= 0.3)

from sklearn.ensemble import RandomForestClassifier
rf= RandomForestClassifier()
rf.fit(X_train,y_train)
predictions= rf.predict(X_test)
from sklearn.metrics import classification_report, confusion_matrix
#print(confusion_matrix(y_test,predictions))
#print('\n')
#print(classification_report(y_test,predictions))
print("\nAccuracy For The Given Dataset : ")
print(rf.score(X_train, y_train))
```

```
Accuracy For The Given Dataset :
1.0
```

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Report of Analysis

Job Reference: N	**Job Created**: 9-Mar-2023
**Job Location : ** Punjab	**Job Description:** CB

Client :Raman Kumar
Contact :09988900339
Address :Jalandhar

Sample summary

Sample Number	Date completed	Description
2023-MMBI-001052-001	11- Mar-2023	15W-40 SEMI-SYNTHETIC, CAR DIESEL 5000KMS

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Description	Method	Test	Result	Units
15W40 SEMI-SYNTHETIC, CAR DIESEL 5000KMS				
	ASTMD2896	Base Number	14.89	mg KOH/g
	ASTMD445	Kinematic viscosity at 100^{o}c	62.323	mm^2/s
	ASTMD95	Water Content	<0.06	Vol%
	Sootometer	Soot Content	0.4	%

Remarks: Analysis results are normal; oil is NOT suitable for service. However, the trend needs to be monitored. Please refer to OEM specifications for the Base number.

Note: This report relates specifically to sample(s) that were drawn and/or provided by the client or nominated third party solely for testing. The reported result(s) provides no warranty or verification on the sample(s) representing any specific goods and/or shipment and only relates to the sample(s) as received and tested. This report was solely prepared for the client named on this report. Intertek disclaims any and all liability or damage or injury which result in the use of the information contained herein and accepts no responsibility for any loss, damage, or liability suffered by a third party as a result of any reliance upon or use of report

Signed ____**Date** ______________________________

Authorized signatory
Kavish Vibhute, Laboratory Supervisor

11-Mar-2023