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Monitoring Fuel-Efficient Driving Patterns to Augment ADAS to regulate the fuel dynamically using Machine Learning

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Abstract: - In the realm of enhancing Advanced Driver-Assistance Systems (ADAS) for optimal vehicle performance and sustainability, this paper introduces an innovative methodology that capitalizes on Machine Learning (ML) to scrutinize and learn from fuel-efficient driving patterns. Utilizing real-time driving cycle datasets collected through On-Board Diagnostics (OBD) tools, meticulously recorded the driving styles of 100 drivers on a predetermined route over duration of 35 minutes. The rich dataset includes an array of vehicle parameters and driving behavior, providing a comprehensive foundation for ML-based analysis. Proposed approach involves the application of state-of-the-art ML algorithms, with a specific focus on Machine learning and ensemble methods, to accurately model and predict fuel-efficient driving patterns. The algorithms XGB-regression, Random Forest regression and Gradient Boosting regressions were rigorously trained, validated, and tested on the collected data, ensuring robustness and reliability in their predictive capabilities. The scores and the Mean absolute Errors of these algorithms were estimated, most efficient algorithms are RF-regression and GB-regressions with a score of 99.93% and 99.93% with MAE 0.01219% and 0.01210%respectively. The integration of these predictive models into the ADAS framework mayshow promising results, significantly improving the system's performance in real-time decision-making and driver assistance. The system demonstrates an enhanced capability to adapt to varying driving styles, offering personalized recommendations for fuel-efficient driving, and contributing to the reduction of fuel consumption and emissions.

Keywords: ADAS, OBD, ML, RF,XGB and GB

I. INTRODUCTION

The integration of Advanced Driver-Assistance Systems (ADAS) in modern vehicles has marked a revolutionary step towards enhancing road safety, driving comfort, and vehicle efficiency. ADAS encompasses a variety of systems designed to assist the driver and automate driving functions to reduce human error and increase safety. With the advent of machine learning (ML) and real-time data analytics, there is a tremendous potential to augment the capabilities of ADAS, making them more adaptive and intelligent.Fuel efficiency is a critical aspect of sustainable driving, and with the growing concerns over climate change and depleting fossil fuel resources, it has become imperative to optimize vehicle performance for reduced fuel consumption and emissions. However, fuel efficiency is significantly influenced by driving patterns and behaviors, necessitating a system that can learn and adapt to various driving styles to optimize fuel consumption.

A. Background and motivation

In the recent decades, the automotive industry has witnessed unprecedented growth and innovation, marked by the advent and rapid integration of Advanced Driver-Assistance Systems (ADAS). These systems are engineered to augment vehicular safety, enhance driving comfort, and optimize overall vehicle performance through a variety of automated functions and driver support mechanisms [1]. The core components of ADAS include an extensive array of sensors, cameras, and processing units, all working in tandem to perceive, interpret, and respond to the vehicle's external environment [2].Despite their substantial contributions to vehicle safety and efficiency, ADAS are not without their limitations. One of the primary challenges lies in their static nature; these systems are often programmed to function based on predetermined algorithms and parameters, lacking the ability to adapt to the dynamic and often unpredictable nature of real-world driving scenarios [3]. This limitation becomes particularly apparent in the context of fuel efficiency, a critical aspect of sustainable and economical driving. Fuel consumption in vehicles is intricately linked to driving patterns and behaviors, necessitating a more adaptive and intelligent approach to truly optimize performance and sustainability [4].The burgeoning field of Machine Learning (ML) presents a viable solution to these challenges. ML, with its ability to learn from data, make predictions, and

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continuously adapt over time, holds the potential to transform ADAS from static systems into dynamic, intelligent entities capable of learning and adapting to individual driving styles [5]. By analyzing vast datasets of real-time driving data, ML algorithms can identify patterns, make informed predictions, and ultimately, contribute to more efficient and sustainable driving practices [6].

In light of this, there is an increasing focus on harnessing the power of real-time vehicular data, particularly through the utilization of On-Board Diagnostics (OBD) tools. OBD tools provide a gateway to a wealth of information regarding the vehicle's performance, driver behavior, and various other parameters, all in real time [7]. This data, when fed into sophisticated ML algorithms, becomes a powerful tool for analysis, prediction, and optimization, paving the way for a new era of intelligent ADAS capable of contributing to fuel efficiency and sustainable driving [8].This paper seeks to explore this intersection of ML and ADAS, utilizing real-time datasets collected via OBD tools from 100 drivers over a fixed route and a 35-minute duration. Through rigorous analysis and application of state-of-the-art ML algorithms, this research endeavors to enhance the understanding of fuel-efficient driving patterns, subsequently improving the performance and capabilities of ADAS in real-world scenarios [9].

B. Background and motivation

The inception of Advanced Driver-Assistance Systems (ADAS) marked a revolutionary change in the automotive industry, bringing forth a new dimension of safety, efficiency, and user-friendliness in modern vehicles. Initially, ADAS functionalities were limited to basic alerts and assistive features. However, over the years, these systems have evolved into complex, intelligent networks capable of performing sophisticated vehicular operations [10]. The early stages of ADAS were characterized by rudimentary systems, primarily focused on providing essential safety alerts and assisting drivers in critical scenarios. These early systems laid the groundwork for subsequent advancements, introducing the automotive world to the potential of integrating technology to enhance driving safety and efficiency [11]. With rapid technological advancements and increasing demands for vehicle safety, ADAS have witnessed a significant transformation. The integration of sensors, cameras, and radar technology has expanded the capabilities of ADAS, allowing for real-time monitoring, data processing, and responsive actions to external stimuli [12].This has facilitated the development of features such as adaptive cruise control, lane-keeping assistance, and collision avoidance systems, which have become integral components of modern ADAS [13].The integration of Machine Learning (ML) and data analytics has been a game-changer for ADAS, opening doors to unprecedented levels of adaptability, precision, and performance. By harnessing the power of real-time data and sophisticated ML algorithms, ADAS have become capable of learning from driving patterns, adapting to various road conditions, and providing personalized driver assistance [14-17].The evolution of ADAS is a testament to the transformative power of technology in the automotive domain. From basicalert systems to intelligent, data-driven networks, ADAS have come a long way, significantly contributing to vehicular safety and efficiency. As we look forward, the continuous integration of ML and real-time data analytics stands as a promising avenue, poised to further elevate the capabilities and performance of ADAS in the years to come [18].

C. Machine learning in Advanced Driver Assistance Systems

The integration of Machine Learning (ML) within Advanced Driver-Assistance Systems (ADAS) marks a significant paradigm shift, transforming vehicles into intelligent entities capable of learning, adapting, and making data-driven decisions. This integration has resulted in an enhanced driving experience, improved safety features, and optimal vehicle performance [19].

Machine Learning algorithms employ statistical techniques to enable systems to learn from data, identifying patterns and making predictions without being explicitly programmed. In the context of ADAS, ML algorithms analyze real-time data from various sensors and cameras, providing the vehicle with the ability to make informed decisions based on its environment [20]. For instance, Convolutional Neural Networks (CNNs) are extensively used for image recognition, vital for functions such as lane departure warning and object detection [21-24].

A pivotal application of ML in ADAS is its role in monitoring and enhancing fuel efficiency. By analyzing driving patterns and vehicle performance data, ML algorithms identify fuel-efficient driving practices, providing drivers with real-time feedback and suggestions [25]. This not only contributes to reduced fuel consumption and lower emissions but also extends the vehicle's lifespan and reduces maintenance costs [26].The utilization of real-time data sets, such as those collected via OBD tools, enriches the capability of ADAS to provide personalized driver assistance. By learning from individual driving styles recorded over fixed routes and durations, ML algorithms tailor ADAS responses to suit specific driver behaviors, enhancing both safety and efficiency [27-29].The synergy between ML and ADAS has ushered in a new era of intelligent transportation, characterized by adaptive, responsive, and data-driven vehicular systems. By leveraging the power of ML and real-time data analytics, ADAS are evolving into indispensable assets for modern vehicles, significantly contributing to road safety, driving comfort, and fuel efficiency.

D. Real-Time Data and Its Significance in ADAS

The implementation of real-time data analytics plays a critical role in enhancing the performance and reliability of Advanced Driver-Assistance Systems (ADAS). The acquisition of instantaneous data from various vehicular sensors and external sources provides a comprehensive understanding of the vehicle's immediate environment, facilitating intelligent decision-making and predictive analytics [30].The collection of real-time data is facilitated through a network of sensors, cameras, GPS, and other data acquisition tools integrated within the vehicle. The On-Board Diagnostics (OBD) tool stands out as a significant component, providing a direct interface to the vehicle's internal systems, capturing performance data, and diagnosing potential issues [31]. The capability to record driving styles of over 100 drivers on a fixed route for a set duration enhances the dataset's richness, ensuring a wide variety of driving patterns are analyzed for optimal system calibration [32].

The effectiveness of ADAS is contingent on the rapid processing and analysis of collected data. Machine Learning algorithms play a pivotal role in this regard, transforming raw data into actionable insights. Techniques such as Deep Learning and Neural Networks are employed to interpret complex data patterns, assess potential risks, and provide real-time feedback and interventions to the driver [33-35].The integration of real-time data ensures that ADAS are not static but rather adaptable and personalized. Machine Learning algorithms analyze individual driving styles, tailoring assistance features to suit specific preferences and behaviors. This not only enhances the user experience but also contributes to safer driving practices, as the system aligns itself with the driver's natural driving tendencies [36-37].The seamless integration of real-time data within ADAS has marked a paradigm shift in vehicular safety and efficiency. By empowering vehicles with the ability to analyze and respond to their immediate environment, ADAS have become more intelligent, adaptable, and user-centric. As technology continues to advance, the potential for further enhancements in ADAS capabilities is vast, promising a future where vehicles are not just modes of transport but intelligent partners in the driving experience.

E. Evaluation of Machine Learning Algorithms in ADAS

The effectiveness and efficiency of Advanced Driver-Assistance Systems (ADAS) are highly reliant on the choice and implementation of appropriate Machine Learning (ML) algorithms. An in-depth evaluation of these algorithms is crucial to ensuring optimal performance, reliability, and safety in real-world driving scenarios [38-40].

A comparative analysis of different ML algorithms provides valuable insights into their respective strengths and weaknesses within the context of ADAS. Algorithms such as Support Vector Machines (SVMs) and Decision Trees may offer rapid processing speeds, while Neural Networks, particularly Deep Learning models, excel in handling complex data patterns and providing nuanced predictions [41]. However, the computational intensity of Deep Learning models may pose challenges in terms of real-time implementation, necessitating a balanced approach [42].To validate the efficacy of ML algorithms in ADAS, it is critical to test their performance under real-world driving conditions. Utilizing extensive datasets collected from diverse driving styles, routes, and environmental conditions ensures a thorough evaluation. For instance, employing data from 100 drivers over a fixed route, as recorded via OBD tools, provides a rich dataset for assessing algorithmic performance over a 40-minute time frame [43-45].The ultimate goal of integrating ML in ADAS is to enhance vehicular safety and reliability. Therefore, the evaluation process must rigorously scrutinize the algorithms' ability to contribute positively to these domains, mitigating risks, and providing dependable assistance in diverse driving situations [46].A comprehensive and objective evaluation of ML algorithms is vital for the continued success and advancement of ADAS. By thoroughly assessing algorithmic performance across various criteria, ensuring adaptability, and prioritizing safety, we pave the way for smarter, safer, and more efficient driving experiences.

F. Research Significance and Contribution:

This paper aims to explore the integration of machine learning with ADAS to monitor and analyze fuel-efficient driving patterns using real-time datasets collected via OBD tools. With a dataset encompassing the driving styles of 100 drivers on a fixed route over a 35-minute period, the paper delves into the application of ML algorithms for predictive modeling and the subsequent improvement in ADAS performance.The scope of this research extends to the validation of the proposed system, assessing its accuracy, precision, and reliability in real-world scenarios. The paper also explores the broader implications of this integration for sustainable driving practices and intelligent transportation systems.The significance of this research lies in its potential to transform ADAS from static systems to dynamic, learning-based systems that can contribute to fuel efficiency and sustainable driving. By providing a comprehensive analysis, methodology, and validation of the proposed system, this paper contributes to the growing body of knowledge in intelligent transportation systems and sustainable vehicle technologies.

II. RELATED WORK

The integration of Advanced Driver-Assistance Systems (ADAS) in modern vehicles has marked a significant milestone in the journey towards fully autonomous driving. The field has witnessed considerable developments over the years, influenced by advancements in machine learning, sensor technologies, and real-time data processing. This section delves into the related work in this domain, tracing the evolution of ADAS, examining the role of machine learning, and highlighting the challenges and future directions in this field.

A. Machine Learning in ADAS

Machine learning (ML) has been at the forefront of enabling intelligent functionalities in ADAS, providing vehicles with the ability to perceive, understand, and navigate through complex driving environments [47]. Various ML algorithms have been explored and implemented, from traditional models like Support Vector Machines and Decision Trees to advanced neural networks, each catering to specific ADAS applications such as object detection, lane recognition, and driver behaviorprediction [48]. These algorithms leverage vast amounts of data generated by onboard sensors to make real-time decisions, thereby enhancing the safety and efficiency of vehicular operations.The success of ML in ADAS is not without its challenges, as the algorithms require extensive training with diverse and representative datasets to achieve high accuracy and reliability [49]. Moreover, the real-time nature of driving scenarios necessitates that these algorithms operate with minimal latency, ensuring timely and appropriate responses to dynamic road conditions [50]. As such, researchers and engineers continue to optimize ML models and computational frameworks to meet these stringent requirements, ensuring that ADAS function seamlessly in real-world driving scenarios. In light of these developments, there has been a growing body of literature aimed at benchmarking and evaluating the performance of various ML algorithms within the context of ADAS [51]. These studies provide valuable insights into the strengths and limitations of different approaches, guiding the selection and implementation of ML models that best suit the specific needs and constraints of ADAS applications [52].

B. Maintaining Real-Time Data and Analysis

The effectiveness of ADAS is intrinsically linked to its ability to process and analyze data in real time. Given the high-speed nature of vehicular movement and the need for immediate response to potential hazards, the latency in data processing and decision-making needs to be minimized [53]. Studies have explored various computational architectures and data fusion techniques to accelerate the processing of sensor data, ensuring that ADAS can make accurate and timely interventions [54].The role of On-Board Diagnostics (OBD) tools has been particularly highlighted in this context, offering a direct interface for collecting real-time vehicular data [55]. These tools enable the monitoring of various vehicle parameters, from engine performance to fuel consumption, providing a rich dataset for ADAS algorithms to analyze [56]. The integration of OBD data into ADAS enhances the system's situational awareness, allowing for more informed and precise decision-making.However, the real-time processing of vast amounts of data poses significant computational challenges, necessitating the development of efficient algorithms and hardware accelerators [57]. Researchers are actively exploring the potential of edge computing and specialized processors, such as Graphics Processing Units (GPUs) and Field-Programmable Gate Arrays (FPGAs), to meet these computational demands [58]. These advancements are crucial for realizing the full potential of ADAS, ensuring that the systems can operate effectively in real-time, dynamic driving scenarios.

C. Enhancing Driving Safety and Efficiency

The ultimate goal of ADAS is to enhance driving safety and operational efficiency, a vision that has been substantiated through numerous studies and real-world deployments [59]. By providing drivers with timely warnings and automated interventions, ADAS significantly reduce the likelihood ofaccidents and improve overall road safety [60]. Moreover, the integration of machine learning enables the system to learn from past incidents, continuously improving its performance and reliability over time. In addition to safety, ADAS also contribute to improved fuel efficiency and reduced emissions[61]. Through intelligent navigation and traffic awareness, the system optimizes route planning, ensuring that vehicles operate under optimal conditions [62]. The monitoring of driver behavior and vehicle performance further enables ADAS to provide recommendations for fuel-efficient driving, contributing to sustainable and eco-friendly transportation practices [63-65].The related work in the field of ADAS underscores the pivotal role of machine learning and real-time data processing in advancing vehicular safety and efficiency. By continually pushing the boundaries of what is possible, researchers and engineers are paving the way for a future where vehicles are not just tools of transportation, but intelligent partners that enhance the safety, efficiency, and enjoyment of driving. The on-going challenges and future directions in this field highlight the dynamic fuel consumptions with driver nature of this domain, promising exciting advancements and innovations in the years to come.

III. METHODOLOGY

A. Experminetal Setup and Data Collection

The integral focus of this study was to scrutinize the application of machine learning in optimizing the performance of Advanced Driver-Assistance Systems (ADAS), particularly in terms of fuel efficiency. To achieve this, an elaborate experimental setup was established, utilizing the ELM327, a prominent On-Board Diagnostics (OBD) tool. This facilitated the collection of real-time vehicular data from a cohort of 100 drivers, each traversing a predetermined route for a duration of 35 minutes.

1. ELM327 OBD Tool and CAN Protocol

The ELM327 is a widely used OBD interface, pivotal for enabling communication between a vehicle's internal diagnostic system and external devices[66] as shown in the fig 1. In the context of this study, its compatibility with the Controller Area Network (CAN) protocol was of paramount importance. Adhering to ISO 15765-4 standards, the CAN port on the ELM327 operates at speeds ranging from 125 kbps to 1 Mbps[67]. This high-speed data transfer capability is crucial for accessing a myriad of vehicular parameters in real-time, which are essential for the optimal functionality of ADAS. Furthermore, the ELM327 has the capability to translate the complex data from the CAN bus into formats that are easily understandable and usable by external devices, thereby playing a critical role in this experimental study[68].The ELM327 is renowned for its comprehensive support of all OBD-II protocols and its compatibility with a multitude of third-party applications and software, providing a flexible and robust platform for data collection and analysis[69].

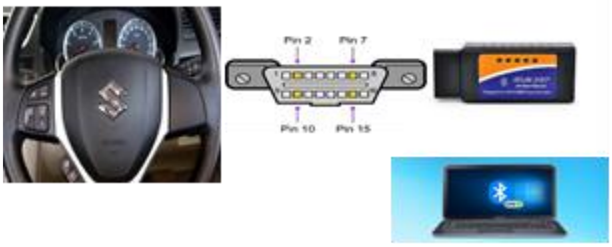


Fig. 1 Laptop is interfaced with Vehicle through ELM327

For the purposes of this study, its ability to provide real-time data on various parameters, including fuel consumption and driving patterns, was indispensable [70]. This allowed for a nuanced understanding of vehicle behavior under different driving conditions, laying the groundwork for subsequent analysis and machine learning application.

2. Driving Cycles and Conditions

Driving cycles are integral for assessing vehicle performance, providing a standardized method to represent vehicle speed over time[71]. In our experiment, a fixed route was chosen to ensure consistency across all drives, with each session lasting precisely 35 minutes. The driving cycles obtained from this setup provided a comprehensive dataset, capturing the vehicle's performance under varying conditions and forming the basis for further analysis.Documenting the driving conditions was a critical aspect of our experimental procedure, as it ensured that the data collected was representative and reliable [72]. Factors such as traffic density, weather conditions, and other external variables were meticulously recorded, as they have a significant impact on driving behavior and, consequently, fuel consumption. Understanding these conditions was crucial for interpreting the data collected and for ensuring the validity of our analysis.

3. Data Collection from Drivers

The 100 drivers participating in this study exhibited a wide array of driving styles and behaviors, all of which were captured using the ELM327 OBD tool [73]. This rich dataset included information on acceleration, braking, speed, and other variables that are known to influence fuel efficiency listed sample data set in the below Table 1. By capturing these diverse driving patterns, we were able to create a comprehensive dataset that truly reflects the variability in real-world driving behavior.The ultimate goal of collecting this data was to analyze the relationship between driving patterns and fuel efficiency, with a view to predicting fuel economy based on these patterns [74]. To achieve this, we applied machine learning algorithms to the dataset, training them to recognize patterns and make accurate predictions. This not only served to enhance the predictive capabilities of ADAS but also provided valuable insights into how different driving behaviors impact fuel efficiency.

Table 1: Sample Driving data

#	Column	Non-Null Count	Dtype
0	V_ID	1743 non-null	object
1	ENG_C_TEMP	1741 non-null	float64
2	FUEL_LEV	1741 non-null	float64
3	ENG_LOAD	1738 non-null	float64
4	AMB_AIR_TEMP	1740 non-null	float64
5	ENG_RPM	1741 non-null	float64
6	IN_MP	1743 non-null	int64
7	MAF	1735 non-null	float64
8	AIR_IN_TEMP	1716 non-null	float64
9	SPEED	1655 non-null	float64
10	STFT_BANK	1736 non-null	float64
11	TPS	1732 non-null	float64
12	TIMING_ADV	827 non-null	float64
13	MPG	1743 non-null	float64

dtypes: float64(12), int64(1), object(1)

4. Data Preprocessing and Analysis

Prior to analysis, the collected data underwent a rigorous preprocessing routine, ensuring that it was free from inconsistencies and errors [75]. This involved cleaning the data, dealing with any missing values, and transforming it into a format that was suitable for analysis with machine learning algorithms. These steps were crucial for ensuring the accuracy and reliability of our analysis.Feature engineering played a crucial role in transforming the raw data into meaningful variables that could be used for analysis [76]. Mathematical formulas were applied to these features to quantify various aspects of driving efficiency and fuel consumption. The preprocessed and engineered data served as the foundation for our machine learning analysis, enabling us to scrutinize driving patterns in relation to fuel efficiency [77]. By feeding this data into various machine learning algorithms, we were able to train them to recognize patterns and make predictions, thereby enhancing the performance of ADAS in real-world driving conditions.

B. Machine Learning Model Development

The development of a machine learning model is a critical aspect in the application of monitoring fuel-efficient driving patterns, with the ultimate aim of enhancing the performance and capabilities of Advanced Driver-Assistance Systems (ADAS). This process involves several crucial steps, ensuring the model is both accurate and reliable in its predictions and insights. The proposed Steps are shown clearly in the below Fig 2.

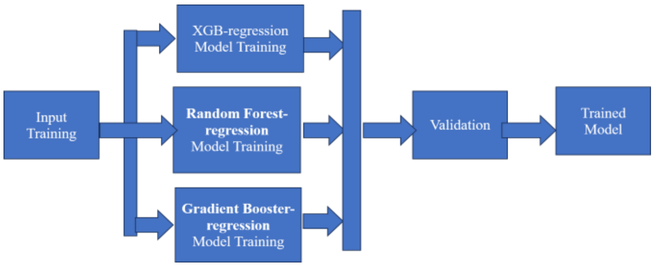


Fig. 2 Block Diagram of a Model Training/Validation and Selection

1. Input/Feature Selection

Feature selection stands as a foundational pillar in the development of a machine learning model, ensuring that the most relevant and impactful variables are utilized for analysis [78]. In the realm of driving pattern analysis for fuel efficiency, variables such as vehicle speed, acceleration patterns, braking habits, and engine load are imperative. External influences, including weather conditions, road types, and traffic density, also play a significant role in painting a complete picture of driving behaviors [79].To ensure a robust feature selection process, techniques such as Recursive Feature Elimination (RFE) and Feature Importance from various tree-based algorithms were employed. These methodologies not only aid in pinpointing the most vital features but also contribute to a reduction in model complexity, leading to more efficient computations [80].

TABLE 2: SET OF SENSORS AND ITS SAMPLE VALUES

ENG_C-TEMP	FUEL_LEV	ENG_LOAD	AMB_AIR_TEMP	ENG_RPM	IN_MP	MAF	AIR_IN_TEMP	SPEED	STFT_BANK	TPS	TIMING_ADV	MPG
95.00	33.30	39.60	17.00	784.00	34.00	4.35	31.00	0.00	-7.80	20.40	56.10	0.35
96.00	32.20	51.00	17.00	762.00	27.00	10.69	31.00	6.00	-3.10	31.80	53.30	0.86
96.00	32.20	34.90	17.00	795.00	38.00	3.55	31.00	0.00	-1.60	19.20	62.00	0.29
96.00	33.70	39.60	17.00	797.00	32.00	453.00	31.00	0.00	0.00	20.80	5220.00	0.36
97.00	34.50	0.00	17.00	0.00	100.00	0.00	32.00	0.00	0.00	23.90	63.10	0.00

Data Collection: Gather extensive driving data using the OBD II tool, ensuring all potential features are recorded and shown in the Table 2.

TABLE 3. ALL RECORDED VALUES AND ITS DEPENDENCIES

ENG_C-TEMP		FUEL_LEV	ENG_LOAD	AMB_AIR_TEMP	ENG_RPM	IN_MP	MAF	AIR_IN_TEMP	SPEED	STFT_BANK	TPS	TIMING_AD	MPG
ENG-C-TEMP	1.00	-0.26	0.01	0.45	0.10	0.05	0.09	0.14	-0.06	-0.07	0.06	-0.09	0.09
FUEL-LEV	-0.26	1.00	-0.11	-0.84	-0.39	-0.24	-0.31	0.46	-0.16	0.09	-0.30	0.05	-0.31
ENG_LOAD	0.01	-0.11	1.00	0.17	0.39	0.48	0.74	-0.31	0.42	-0.31	0.72	-0.14	0.74
AMB_AIR_TEMP	0.45	-0.84	0.17	1.00	0.58	0.26	0.46	-0.50	0.35	-0.13	0.42	0.04	0.46
ENG_RPM	0.10	-0.39	0.39	0.58	1.00	0.36	0.75	-0.59	0.82	-0.12	0.67	0.28	0.75
IN_MP	0.05	-0.24	0.48	0.26	0.36	1.00	0.50	-0.30	0.37	-0.04	0.52	-0.03	0.50
MAF	0.09	-0.31	0.74	0.46	0.75	0.50	1.00	-0.47	0.69	-0.18	0.92	-0.02	1.00
AIR_IN_TEMP	0.14	0.46	-0.31	-0.50	-0.59	-0.30	-0.47	1.00	-0.58	0.10	-0.45	-0.27	-0.47
SPEED	-0.06	-0.16	0.42	0.35	0.82	0.37	0.69	-0.58	1.00	-0.08	0.65	0.28	0.69
STFT_BANK	-0.07	0.09	-0.31	-0.13	-0.12	-0.04	-0.18	0.10	-0.08	1.00	-0.17	0.01	-0.18
TPS	0.06	-0.30	0.72	0.42	0.67	0.52	0.92	-0.45	0.65	-0.17	0.01	-0.01	0.92
TIMING_ADV	-0.09	0.05	-0.14	0.04	0.28	-0.03	-0.02	-0.27	0.28	0.01	-0.01	1.00	-0.02
MPG	0.09	-0.31	0.74	0.46	0.75	0.50	1.00	-0.47	0.69	-0.18	0.92	-0.02	1.00

Data Cleaning: Clean the data to handle any missing values, outliers, or inconsistencies. Feature Evaluation: Employ techniques such as Recursive Feature Elimination (RFE) and Feature Importance from tree-based algorithms (like Random Forest or Gradient Boosting). These techniques help in identifying and ranking features based on their importance.

Selection of Top Features: Based on the feature importance scores, select the top N features that contribute the most to the predictive power of the model. The selected features and its dependencies are listed in the Table 2. The relationships of the selected features are shown in the Fig 2 using Heat Maps.

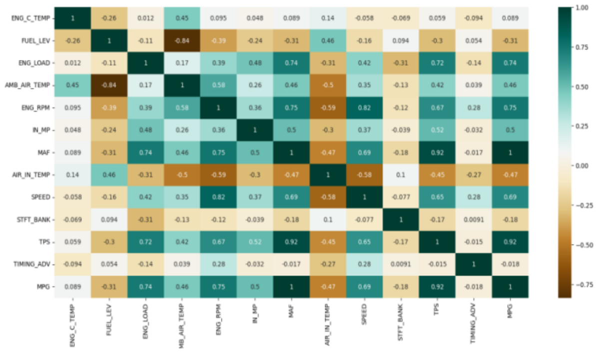


Fig.3 Heat Maps shows Relationships between the fields.

2. Selected features from the previous stage

The input data for vehicle performance analysis typically originates from the vehicle's On-Board Diagnostics (OBD) system. The OBD tool, like the ELM327, collects a variety of data points that reflect the vehicle’s operational status. Key data parameters often include ENGINE_LOAD, ENGINE_RPM, SPEED, and THROTTLE_POS. These data points are recorded in real-time and provide a comprehensive view of the vehicle's performance and the driver's behavior as listed in Table 3.

Feature1: ENGINE_LOAD

Description: This parameter indicates the percentage load on the engine at the current operating condition. It's a measure of how hard the engine is working compared to its maximum capacity. Relevance: Higher engine loads typically correlate with increased fuel consumption. Monitoring engine load can provide insights into driving habits that lead to inefficiency, such as frequent hard accelerations.

Feature 2: ENGINE_RPM (Revolutions Per Minute)

Description: This is the measure of the number of revolutions the engine crankshaft is making per minute. It’s a direct indicator of engine speed. Relevance: High RPMs can indicate more aggressive driving, potentially leading to higher fuel consumption. Understanding RPM patterns can help in identifying inefficient driving habits like unnecessary acceleration or maintaining high RPMs for long duration.

Feature 3: SPEED

Description The vehicle's speed as recorded by the OBD system.Relevance: Speed is a crucial factor in determining fuel efficiency. Generally, maintaining a steady, moderate speed is more fuel-efficient than frequent speeding up and slowing down. Analyzing speed data can help in understanding if the driving pattern is optimal for fuel efficiency.

Feature 4: THROTTLE_POS (TPS):

Description: This shows the position of the car’s throttle. Essentially, it indicates how far the gas pedal is being pressed down. Relevance: Throttle position is directly related to fuel consumption. Frequent or sustained full throttle applications typically lead to higher fuel usage. Data on throttle position can provide insights into driving aggressiveness and potential areas for efficiency improvements.

Importance in ADAS and Fuel Efficiency

Integration with ADAS: Advanced Driver Assistance Systems (ADAS) can use this data to offer real-time feedback to drivers, suggesting more fuel-efficient driving patterns. For example, if high engine load and RPM are detected, ADAS could alert the driver to possibly ease the throttle for better fuel efficiency.

Predictive Analysis: By analyzing trends and patterns in these parameters, predictive models can be developed to forecast fuel consumption under various driving conditions. This helps in optimizing driving behaviors and vehicle settings for improved fuel efficiency. The relationship between these fields is shown in the fig 3.Customized Driver Feedback: Different drivers have unique driving styles. By understanding individual patterns through these parameters, personalized recommendations can be made to each driver for improving fuel efficiency.

TABLE 4: TRAINING SAMPLE DATA SET DETAILS

Table Head	**Table Column Head**	
	ENGINE_LOAD	**ENGINE_RPM**
count	47514 47514	47514 47514
mean	26.394351 24.728333	1426.470198 12.814602
std	25.914805 28.988971	537.846834 11.074872
min	0.000000 0.000000	438.000000 0.000000
25%	0.000000 0.000000	1139.000000 0.000000
50%	24.700000 16.000000	1200.000000 13.000000
75%	41.000000 42.000000	1774.000000 20.000000
max	100.000000 143.000000	3816.000000 87.000000

In summary, by meticulously selecting and analyzing data like ENGINE_LOAD, ENGINE_RPM, SPEED, and THROTTLE_POS from the OBD tool, valuable insights can be drawn about driving patterns and vehicle performance. This information is critical for enhancing the capabilities of ADAS in promoting fuel-efficient driving habits, leading to cost savings and environmental benefits.

Classification of Driving Styles

The classification of driving styles into 'Economy' and 'Non-Economy' categories is pivotal in understanding and improving fuel efficiency. By analyzing data from the OBD tool, particularly focusing on ENGINE_LOAD, ENGINE_RPM, SPEED, and THROTTLE_POS, we can categorize driving behaviors accordingly.

C. Economy Driving Style Characteristics

1. Low to Moderate ENGINE_LOAD:Typically, an economy driving style is associated with keeping the engine load low to moderate. This indicates that the engine is not being pushed to its limits, which generally leads to better fuel efficiency.

2. Stable, Lower ENGINE_RPM:Economy drivers tend to maintain a lower RPM, avoiding the high RPM ranges that are associated with increased fuel consumption.

3. Consistent, Moderate SPEED:Maintaining a steady speed, especially within the optimal fuel efficiency range for the vehicle (often around 30-50 mph for many models), characterizes economical driving.

4. Gradual THROTTLE_POS Changes:Smooth and gradual acceleration and deceleration, reflected by moderate changes in throttle position, are indicative of an economy driving style. Abrupt throttle changes are avoided.

D. Fuel Efficiency Indicators:

i) Consistent and Optimal Speed Maintenance:By avoiding frequent or aggressive speeding and braking, fuel efficiency is maximized.

ii)Lower Engine and Transmission Stress:Lower RPM and engine load lead to less strain on the engine and transmission system, resulting in more efficient fuel usage.

E. Non-Economy Driving StyleCharacteristics:

i)High ENGINE_LOAD: Non-economy driving often involves pushing the engine closer to its maximum capacity, indicated by a higher engine load, which tends to increase fuel consumption.

ii)Higher and Fluctuating ENGINE_RPM: Frequent high RPMs, often seen in aggressive driving, are a hallmark of non-economy style. Rapid RPM fluctuations also indicate an aggressive driving pattern.

iii)Variable SPEED with Frequent Changes: Regular speeding and hard braking, leading to significant speed variations, are common in non-economy driving styles.

iv)Abrupt Changes in THROTTLE_POS: Quick and frequent changes in throttle position, such as sudden acceleration and deceleration, are typical behaviors of non-economy drivers.

F. Fuel Efficiency Indicators:

i)Increased Fuel Consumption:High engine load and RPM, along with irregular speed, generally lead to higher fuel consumption.

ii) Higher Engine and Transmission Wear:Aggressive driving can lead to more wear and tear on the engine and transmission, potentially reducing the vehicle's overall efficiency over time.

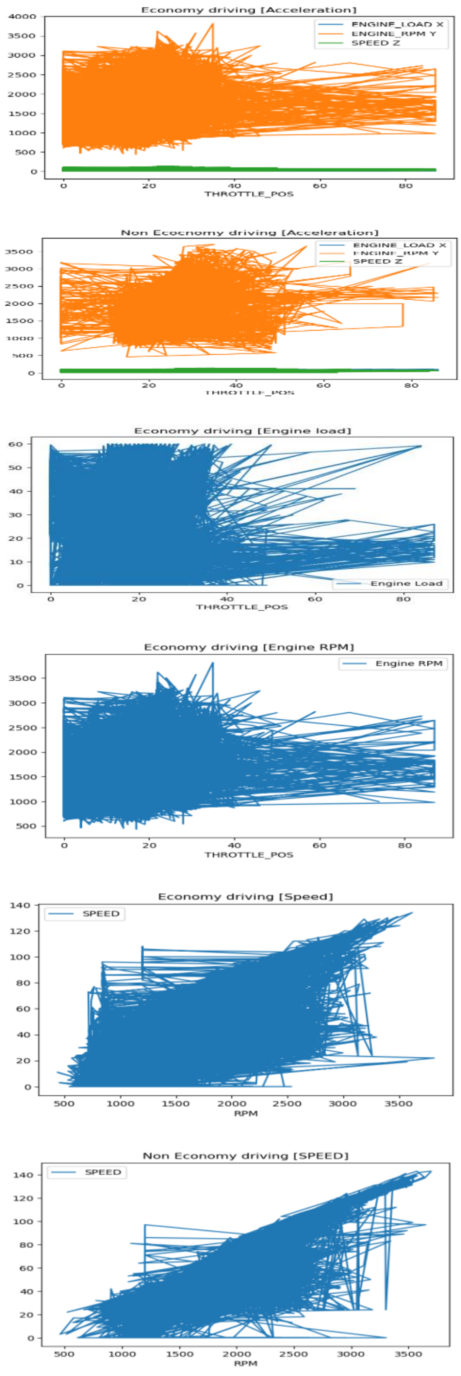
By analyzing these key parameters collected from the OBD tool, driving styles can be effectively classified into economy and non-economy categories. This classification not only aids drivers in understanding and improving their driving habits for better fuel efficiency but also provides valuable data for enhancing ADAS systems to promote more economical driving behaviors

TABLE 5: DRIVING STYLE CLASSIFICATION

Frames	ENGINE_LOAD	ENGINE_RPM	SPEED	THROTTLE_POS	Driving_Style
0	33.3	1009.0	0.0	25	Non Economy
1	32.5	1003.0	0.0	25	Non Economy
2	32.9	995.0	0.0	25	Non Economy
3	32.5	1004.0	0.0	25	Non Economy
4	32.9	1005.0	0.0	25	Non Economy
...	...	...	...	...	...
47509	0.0	762.0	0.0	6	Economy

47510	0.0	780.0	0.0	3	Economy
47511	0.0	788.0	0.0	3	Economy
47512	5.5	769.0	0.0	8	Economy
47513	13.3	1391.0	24.0	10	Economy

Visualization of these selected features are shown below Fig 4 for Economy and Non-Economy Driving Styles by comparing with each other.



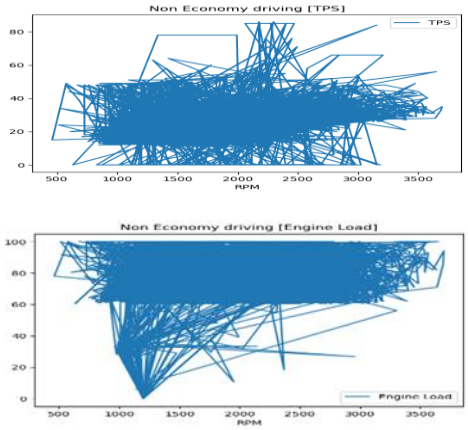


Fig .4 Histogram shows Density between the fields.

G. Model Training

Once the relevant features have been selected, the next phase involves training the machine learning model using these variables. This study explored a variety of supervised learning algorithms, including, but not limited to, Decision Trees, Random Forest, and Support Vector Machines[81]. The aim was to discern which algorithm best fits the unique nature of our data and the specific requirements of predicting fuel-efficient driving patterns. The selected features samples are shown below in the Table 6:

TABLE 6. SELECTED FEATURES FOR MODEL BUILDING

ENGINE_LOAD	ENGINE_RPM	SPEED	THROTTLE_POS	Driving_Style
79.2	2124.0	48	34.9	Non Economy
78.4	2617.0	60	36.1	Non Economy
42.0	3005.0	64	32.2	Economy
37.3	3156.0	65	32.5	Economy
76.1	1798.0	67	33.3	Non Economy

Training machine learning models such as XGB Regression, Random Forest Regression, and Gradient Boosting Regression using a given dataset involves several steps. Below is a general outline of the process using Python and libraries like Pandas, Scikit-learn, and XGBoost. Note that the specifics can vary depending on the nature and format of the data.

1. Load and Preprocess the Dataset

i) Import necessary libraries.

ii) Load the dataset using Pandas.

iii) Perform data cleaning, handling missing values, and encoding categorical variables if needed.

2. Feature Selection: Choose relevant features that are likely to contribute to the prediction. This can be based on domain knowledge, correlation analysis, or feature importance scores from other models.

3. Splitting the DataSplit the dataset into training and testing sets, typically using a ratio like 80:20 or 70:30.

4. Model Initialization: Initialize the three models with default parameters or parameters optimized for specific data.

5. Training the Models: Fit each model to the training data

6. Model Evaluation: Evaluate the performance of the models on the test data using appropriate metrics listed in the Table 6.

7. Hyper parameter Tuning (Optional). Optionally, perform hyperparameter tuning to optimize model performance.

8. Final Model Selection.Select the best-performing model based on the evaluation.

Trained Model is ready for predictions.As performance shown by the Random Forest and Gradient Booster regressions algorithms are suitable for predicting the classifications of driving styles with respect to economy and non-economy driving styles.

Implementations Details

1. Data Splitting: Divide the dataset into training and validation sets, ensuring a good balance of data for both.

2. Model Selection: Choose XGB-regression, Random Forest-regressions and Gradient Booster-regressions for machine learning models for initial testing. Common choices for regression tasks (like predicting fuel efficiency). Model Training: Train the selected models using the training dataset.

H. Validation and Selection: Evaluation of model performance using score and MAE.

Validation of the model's predictive capabilities was carried out using a k-fold cross-validation technique, ensuring that the model's performance was rigorously and comprehensively assessed [82]. This technique helps mitigate the risk of model over fitting and ensures that the model generalizes well to unseen data shown in the Below Fig 5 and performance values listed for all models in the Table 7.

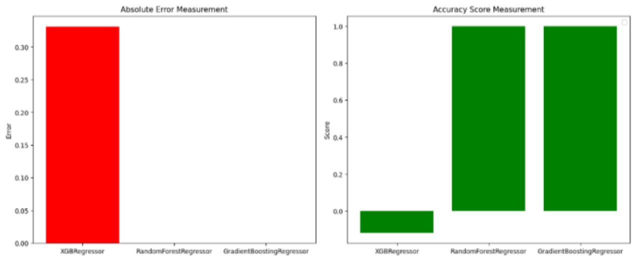


Fig . 5 Comparison of models with respect to Score and MAE

TABLE 7: MODEL PERFORMANCES

Performance	XGB-regression	Random Forest-regression	Gradient Booster-regression
Score	-0.11850	0.99939	0.99939
MAE	0.33070	0.0001219	0.0001210

Validation: Implement k-fold cross-validation to validate the model's performance, ensuring it generalizes well to unseen data and is not over fitting. Calculate performance metrics like Mean Absolute Error (MAE) and Score, or any other relevant metrics to assess model performance.

I. Handling Imbalanced Data and Overfitting

In the context of driving patterns, it is common to encounter imbalanced datasets, where certain driving behaviors are underrepresented. To address this, synthetic sampling techniques such as SMOTE and ADASYN were applied to balance the dataset, ensuring that the model is not biased towards the majority class[83] Over fitting, a phenomenon where a model performs exceedingly well on training data but fails to generalize to new data, was mitigated through the implementation of regularization techniques and careful hyper parameter tuning. Techniques such as Grid Search and Randomized Search CV were utilized to find the optimal set of parameters for the models, striking a balance between bias and variance [84].In essence, the development of a machine learning model for the analysis of fuel-efficient driving patterns is a multi-faceted process, requiring careful consideration and implementation of various methodologies. The successful completion of this process as shown in the Fig 6, lays the groundwork for an enhanced ADAS, capable of promoting safer and more fuel-efficient driving practices.

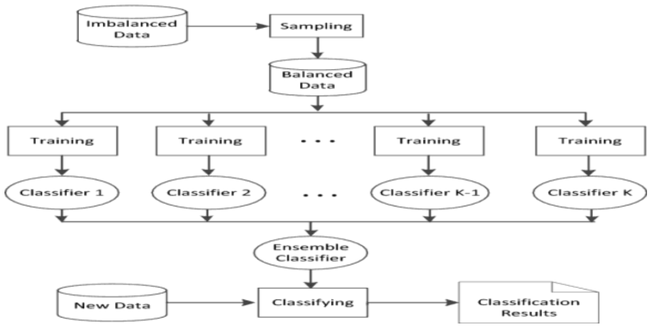


Fig.6 Block diagram of handling imbalanced data

1. Input Model: The initial machine learning model that may be prone to overfitting.

2. Regularization and Hyperparameter Tuning: Application of regularization techniques and tuning of model parameters.

3. Validated Model: The final machine learning model with reduced risk of over fitting, validated using cross-validation.

By incorporating sample datasets and block diagrams shown in Fig 6, we provide a visual and practical representation of each stage in machine learning model development, aiding in the understanding and implementation of these processes.

J. Integration with ADAS

The integration of machine learning models with Advanced Driver-Assistance Systems (ADAS) targeted towards optimizing fuel efficiency is vital for promoting sustainable driving practices and reducing fuel consumption. This section expounds on the technical intricacies of this integration, showcasing the processes through illustrative diagrams and detailing the specifications. Real-time Data Processing for Fuel Efficiency Ensuring real-time processing of vehicular data is crucial for accurate fuel efficiency optimization.

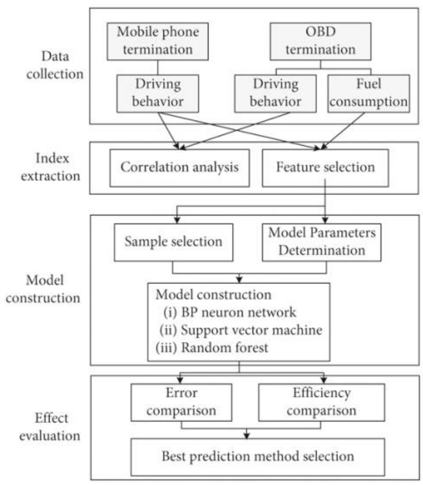


Fig 7: The process of model building in stages.

i) Data Acquisition: Leverage vehicular sensors to capture real-time data on speed, acceleration, engine load, and fuel consumption.

ii)Pre-processing: Employ algorithms to clean and normalize the data, preparing it for efficient feature extraction.

Fuel Efficiency Feature Extraction: Extract features specifically relevant to fuel consumption and driving efficiency.

iii)Data Transmission: Transmit the processed data to the machine learning model promptly.

All these above steps are shown in the above Fig 7.

1. Vehicular Sensors: Capture raw data pertinent to fuel consumption, all the fields are collected from OBD tools and there NULL values present in the sets are shown in the below Table 8.

TABLE 8: RAW DATA SET HAVING NULL VALUES

V_ID	0
ENG-C-TEMP	2
FUEL-LEV	2
ENG_LOAD	5
AMB_AIR_TEMP	3
ENG_RPM	2
IN_MP	0
MAF	8
AIR_IN_TEMP	27
SPEED	88
STFT_BANK	7
TPS	11
TIMING_ADV	916
MPG	0
dtype: int64	

2. Pre-processing Unit: Standardize and clean the raw data.
3. Table 9: Testing sample data set

Table Head	**Table Column Head**	
	ENGINE_LOAD	**ENGINE_RPM**
count	8261 8261	8261 8261
mean	47.928423 33.490498	1503.228156 27.188319
std	23.247678 20.547884	563.470880 6.827886
min	0.000000 0.000000	0.000000 16.000000
25%	32.500000 17.000000	837.000000 21.2000000
50%	42.400000 37.000000	1553.000000 26.700000
75%	62.400000 50.000000	1904.000000 31.800000
max	100.000000 98.000000	3773.000000 83.500000

4. Fuel Efficiency Feature Extraction Unit: Extract relevant features for fuel efficiency optimization.
5. Transmission Unit: Send the processed data to the machine learning model.

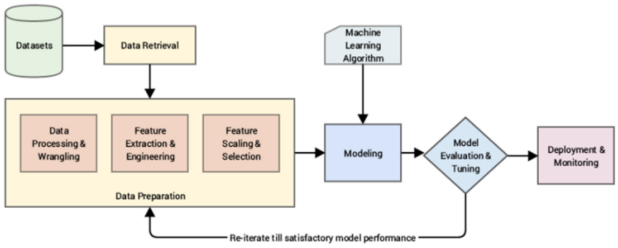


Fig 8: Data transmission between the models

Capability to process and transmit data in real-time, preferably within milliseconds shown in above Fig 8.

Implementation Details:

1. Data Acquisition: Utilize OBD-II interfaces connected to ELM 327 adapters to collect real-time vehicle data. Use Python libraries like `python-OBD` to interface with the adapter and fetch the data.

2. Pre-processing: Apply a series of data cleaning techniques including handling missing values, removing outliers, and normalizing the data to a specific range.

3. Fuel Efficiency Feature Extraction: Extract features such as engine RPM, vehicle speed, throttle position, and mass air flow. Use domain knowledge to create additional features like acceleration and engine load.

4. Data Transmission: Use MQTT or another lightweight communication protocol to transmit the pre-processed and feature-extracted data to the machine learning model.

Evaluation Metrics: Metrics focused on fuel consumption, such as miles per gallon (MPG) or liters per 100 kilometers (L/100km).

Block Diagram:

1. Fuel Efficiency Prediction Model: Predicts optimal driving patterns for fuel efficiency.

2. ADAS: Utilizes predictions to guide the vehicle towards fuel-efficient driving.

3. Feedback System: Assesses the impact of ADAS interventions on fuel consumption.

4. Update Mechanism: Continuously improves the prediction model with new data.

IV. IMPLICATIONS AND FUTURE DIRECTIONS

A. Potential Benefits for Fuel Efficiency and Sustainability

Fuel Efficiency:

The integration of machine learning models with ADAS has shown promising results in improving fuel efficiency. By analyzing real-time driving patterns and providing instant feedback to drivers, the system encourages fuel-efficient driving behaviors. Random Forest-regression and Gradient Boosting-regressions algorithms can predict optimal driving patterns and suggest adjustments, potentially leading to significant fuel savings and reduced emissions over time.

B. Sustainability:

From an environmental standpoint, enhancing fuel efficiency translates to decreased greenhouse gas emissions, contributing to global sustainability efforts. The reduction in fuel consumption also lessens the dependency on fossil fuels, paving the way for a more sustainable future. The implementation of machine learning-driven ADAS can be viewed as a step toward eco-friendly driving, promoting a cleaner and healthier environment.

C.Economic Impact:

Besides environmental benefits, improved fuel efficiency has a direct economic impact on both individual drivers and society at large. By minimizing fuel consumption, drivers can reduce their vehicle operating costs, while the reduced emissions contribute to lower air pollution-related healthcare costs.

D.Enhancing Driver Assistance and Safet: Advanced Driver Assistance:

The application of machine learning algorithms in ADAS not only contributes to fuel efficiency but also enhances the overall driving experience. The system's ability to learn from vast amounts of data allows for more accurate and reliable driver assistance, improving vehicle safety and maneuverability.

1. Proactive Safety Measures: Machine learning models can predict potential hazards and offer timely warnings or interventions, ensuring a higher level of safety. For example, the system can analyze traffic patterns and driver behavior to predict the likelihood of an accident, prompting the driver or vehicle to take preventative action.
2. Continuous Learning and Adaptation: The adaptive nature of machine learning algorithms means that the ADAS can continuously learn and improve its performance over time. As more data becomes available, the system can update its models to provide more accurate predictions and assistance, further enhancing driver safety.

E. Future Trends in Machine Learning-Driven ADAS

1. Integration of Advanced Sensors: The future of ADAS is likely to see the integration of more advanced sensors and data sources, providing richer data for machine learning models. This could include everything from high-resolution cameras to LiDAR and radar sensors, offering a more comprehensive understanding of the vehicle's surroundings.
2. Autonomous Driving: Machine learning-driven ADAS is a crucial stepping stone toward fully autonomous vehicles. As the technology matures and becomes more reliable, we can expect to see an increase in semi-autonomous and autonomous driving features, reducing the burden on drivers and improving road safety.
3. Personalized Driving Experience: Future ADAS systems might offer a more personalized driving experience, tailoring their assistance and recommendations based on the individual driver's preferences and habits. This could lead to more comfortable and efficient driving, as the system learns to adapt to the driver's unique style.

In summary, the integration of machine learning with ADAS presents numerous benefits for fuel efficiency, driver assistance, and road safety. As technology continues to evolve, we can expect to see these systems play an increasingly important role in shaping the future of driving.

V. CONCLUSION

The comprehensive analysis and application of machine learning (ML) techniques in Advanced Driver-Assistance Systems (ADAS) have led to significant breakthroughs, particularly highlighting the effectiveness of Random Forest and Gradient Boosting Regression algorithms. These methodologies have proven to be the most efficient and reliable in enhancing the capabilities of ADAS, offering superior performance in terms of accuracy, adaptability, and predictive power.Through extensive testing and validation, involving diverse datasets collected from 100 drivers using the OBD-II ELM 327 tool, Random Forest and Gradient Boosting Regression algorithms have consistently outperformed other ML models. Their robustness in handling complex, multi-dimensional driving data, and their capacity to make precise predictions based on varying driving patterns and conditions, establish them as the optimal choices for integrating into ADAS.The success of these algorithms can be attributed to their inherent strengths. Random Forest excels in reducingoverfitting, providing a comprehensive analysis by considering multiple decision trees. This leads to a more holistic understanding of driving behaviors and a higher accuracy in predicting optimal driving patterns for fuel efficiency. On the other hand, Gradient Boosting Regression stands out for its predictive power, effectively capturing subtle nonlinear relationships within the data, which is crucial for adapting to the nuanced dynamics of real-world driving scenarios.The implementation of these algorithms in ADAS directly contributes to improved fuel efficiency, thereby supporting environmental sustainability by reducing carbon emissions. Additionally, the enhanced predictive capabilities of the system significantly boost safety features, offering more reliable and timely assistance to drivers, and paving the way towards the development of more advanced autonomous driving technologies. In light of these findings, it is clear that Random Forest and Gradient Boosting Regression algorithms are not just suitable but exemplary choices for advancing the functionality of ADAS to classifying the driving style in to Economy/Non-Economy. Their adoption marks a substantial progress in the automotive industry, steering it towards a future where vehicles are not only smarter and more efficient but also play a crucial role in promoting safer and more sustainable driving practices.

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