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INTELLIGENT FUEL CONSUMPTION PREDICTION AND DRIVER BEHAVIOR ANALYSIS USING ECU DATA

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ABSTRACT

With the increasing integration of machine learning (ML) in the automotive industry, real-time fuel consumption prediction and driving profile classification have become essential for improving fuel efficiency, reducing emissions, and optimizing vehicle performance. This research presents a machine learning-based approach that leverages Electronic Control Unit (ECU) data to classify driving behavior and predict fuel consumption with high accuracy. The proposed system applies multiple supervised and unsupervised ML models, including K-Means clustering, Logistic Regression, XGBoost for classification, and Ridge Regression, Support Vector Regression (SVR), and XGBoost for fuel consumption prediction. A rigorous feature selection process is implemented to identify the most relevant variables influencing fuel consumption. The model is trained and tested on real-time ECU data collected from a test vehicle, ensuring reliable and actionable insights. The results demonstrate that the classification models achieve up to 100% accuracy in categorizing driving behavior as fuel-efficient or inefficient. Moreover, the regression models predict fuel consumption with an R^2 value of up to 0.99 and a mean absolute error (MAE) as low as 0.23 L/h, outperforming existing approaches in terms of accuracy and computational efficiency. The real-time data processing capability further enhances its applicability for intelligent transportation systems, eco-driving initiatives, and insurance-based telematics. The study concludes that the proposed ML-based framework provides a robust and efficient method for monitoring and optimizing vehicle fuel consumption, contributing to the development of smart and sustainable automotive solutions.

INTRODUCTION

Background and Motivation

Fuel consumption and driving behavior analysis have become critical research areas in the automotive industry, with direct implications for fuel efficiency, emissions reduction, and vehicle optimization. The increasing global emphasis on reducing greenhouse gas (GHG) emissions and optimizing fuel usage has prompted the development of advanced methodologies for monitoring and analyzing vehicle performance. Traditionally, fuel consumption analysis relied on predefined models and physical testing, which were time-consuming, resource-intensive, and often failed to account for real-world driving conditions. However, with advancements in machine learning (ML) and the increasing availability of real-time data from Electronic Control Units (ECUs), it has become possible to develop intelligent systems that can accurately predict fuel consumption and classify driving behavior based on actual vehicle data. ECU data provide a wealth of information regarding various engine parameters, driving patterns, and environmental conditions that influence fuel efficiency. The ability to leverage this data using ML algorithms enables a deeper understanding of driving profiles and facilitates real-time decision-making for fuel consumption optimization. This research focuses on developing ML-based models for real-time fuel consumption prediction and driving behavior classification, demonstrating how AI-driven solutions can transform the automotive industry by enhancing vehicle performance and driver efficiency.

Problem Statement

The automotive industry faces several challenges in improving fuel efficiency and optimizing driving behavior. Conventional approaches to fuel consumption analysis rely on static models that do not adapt to varying driving conditions, vehicle performance parameters, or individual driving styles. These methods often struggle to provide accurate real-time predictions, leading to inefficiencies in fuel usage and increased environmental impact. Moreover, driver behavior plays a crucial role in fuel consumption, with studies indicating that aggressive driving patterns can increase fuel consumption by up to 30%. Identifying fuel-efficient and inefficient driving profiles is essential for reducing fuel costs and emissions.Existing research has explored ML-based models for fuel consumption prediction and driving profile classification; however, most of these studies either rely on limited datasets, use computationally expensive models, or fail to integrate real-time data processing. There is a need for a comprehensive system that utilizes real-world ECU data to enhance fuel consumption prediction accuracy while maintaining computational efficiency. This research aims to bridge this gap by

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implementing a real-time ML framework capable of classifying driving behavior and predicting fuel consumption with high precision.

Objectives of the Study

This study aims to develop a machine learning-based system that utilizes ECU data to achieve two primary objectives:

1. **Driving Profile Classification** – Categorizing drivers based on their fuel efficiency levels using supervised and unsupervised ML algorithms, such as K-Means clustering, Logistic Regression, and XGBoost.
2. **Fuel Consumption Prediction** – Developing regression models, including Ridge Regression, Support Vector Regression (SVR), and XGBoost, to predict real-time fuel consumption with high accuracy.

The specific objectives of the research include:

- **Feature Selection:** Identifying the most relevant ECU parameters that influence fuel consumption.
- **Model Development and Evaluation:** Implementing ML models and comparing their performance based on accuracy, precision, recall, mean squared error (MSE), and R^2 score.
- **Real-Time Data Processing:** Ensuring that the models operate efficiently with real-time data, enabling dynamic feedback to drivers and fleet managers.
- **Comparative Analysis:** Evaluating the proposed approach against existing methods in terms of computational efficiency, prediction accuracy, and practical applicability.

Contributions of the Study

This research makes several key contributions to the field of machine learning-based automotive analytics:

1. **Real-Time Data Utilization** – Unlike many previous studies that rely on offline datasets, this work integrates real-time ECU data for fuel consumption prediction and driving behavior classification.
2. **Feature Selection and Optimization** – The study employs advanced feature selection techniques to identify the most significant variables affecting fuel consumption, ensuring that the models are both accurate and computationally efficient.
3. **Performance Benchmarking** – The proposed models are compared against existing state-of-the-art methods to highlight improvements in prediction accuracy and classification precision.
4. **Scalability and Practical Application** – The ML framework developed in this research can be adapted for various applications, including fleet management, eco-driving programs, and automotive insurance risk assessment.

Methodology Overview

The research methodology follows a systematic approach, beginning with data collection from a vehicle's ECU, followed by preprocessing and feature selection. The selected features are then used to train and evaluate different ML models for driving profile classification and fuel consumption prediction. The methodology consists of the following key steps:

1. **Data Collection** – Real-time data is acquired from an ECU connected to a test vehicle. The dataset includes parameters such as engine speed, throttle position, vehicle speed, fuel injection rate, and ambient conditions.
2. **Feature Selection** – A combination of statistical techniques and machine learning-based methods is used to determine the most relevant features for classification and regression tasks.
3. **Model Development** – Three ML models (K-Means, Logistic Regression, and XGBoost) are trained for driving profile classification, while three regression models (Ridge Regression, SVR, and XGBoost) are developed for fuel consumption prediction.
4. **Model Evaluation** – Performance metrics such as accuracy, precision, recall, MSE, MAE, and R^2 score are used to evaluate the effectiveness of the models.
5. **Real-Time Implementation** – The models are deployed on a cloud-based system that processes ECU data in real time, enabling instant feedback for drivers and fleet operators.

Challenges and Limitations

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Despite the promising results, the study acknowledges several challenges and limitations:

- **Data Variability:** Real-world driving conditions introduce variability in ECU data, making it challenging to develop a universal model applicable to all vehicles.

- **Computational Constraints:** While the models are optimized for real-time analysis, processing large volumes of ECU data may require high-performance computing resources.

- **Driver Behavior Complexity:** Human driving behavior is influenced by multiple factors, including road conditions, traffic, and psychological aspects, which may not be fully captured in ECU data.

LITERATURE SURVEY

Introduction

Machine learning (ML) has significantly impacted the automotive industry, particularly in fuel consumption prediction and driving profile classification. Traditional methods relied on deterministic models and statistical approaches, which lacked adaptability to real-world driving conditions. The advancement of ML has enabled the use of real-time data from Electronic Control Units (ECUs) to develop predictive models that offer improved accuracy and efficiency. This section reviews previous research on fuel consumption prediction and driving behavior classification, highlighting key methodologies, findings, and gaps that this study aims to address.

Machine Learning in Automotive Applications

ML techniques have been widely adopted in various automotive applications, such as predictive maintenance, fuel efficiency optimization, and driving behavior analysis. Industry 4.0 technologies have facilitated the integration of AI with vehicle systems, enabling real-time data processing for enhanced decision-making. Studies such as Ahmed et al. (2022) emphasize the role of ML in vehicle automation and efficiency improvements, showcasing its potential to reduce costs and enhance fuel economy. However, a major challenge remains in selecting the most relevant features and optimizing computational efficiency for real-time applications.

Driving Profile Classification

Impact of Driving Behavior on Fuel Consumption

Driving behavior is one of the primary factors influencing fuel consumption. Studies indicate that aggressive driving, frequent acceleration and braking, and high-speed driving significantly increase fuel consumption. Liimatainen (2011) demonstrated that providing drivers with real-time feedback on fuel usage led to a reduction of 2–10% in fuel consumption. Similarly, Toledo and Shiftan (2016) found that monitoring driver behavior and providing targeted feedback can improve fuel efficiency and reduce emissions.

ML-Based Driving Profile Classification

Several ML algorithms have been applied to classify driving behavior based on fuel efficiency. Ping et al. (2019) used Support Vector Machines (SVM) and Artificial Neural Networks (ANNs) to classify driving styles, achieving an accuracy of 80–83%. However, their approach incorporated visual information, which added computational complexity. Peppes et al. (2021) applied K-Means clustering and supervised learning models such as Logistic Regression and Random Forest for eco-friendly driving classification. Their results showed that deep learning models provided marginal improvements over traditional ML models but at a significantly higher computational cost.

Zheng et al. (2022) explored real-time driving behavior classification using short-time window observations, achieving classification accuracies between 70–90% using clustering methods. While effective, their study did not integrate real-time data processing or ECU parameters, limiting its practical applicability.

In contrast, this research builds upon these approaches by implementing a real-time ML framework that classifies driving behavior directly from ECU data, ensuring greater accuracy and efficiency in real-world applications.

Fuel Consumption Prediction Models

Traditional Methods for Fuel Consumption Estimation

Conventional approaches to fuel consumption modeling relied on physical and polynomial models, often requiring extensive testing and calibration. Rios-Torres et al. (2019) developed personalized driving cycles for predicting fuel consumption in hybrid and conventional vehicles, showing that customized models improved accuracy. However, their method was computationally expensive and lacked adaptability to varying driving conditions.

Pavlovic et al. (2020) examined the discrepancies between laboratory-based fuel consumption tests and real-world conditions, finding that predictive models often fail to capture the dynamic nature of driving behavior. These findings emphasize the need for ML-based approaches that can adapt to real-time driving conditions and improve prediction accuracy.

ML-Based Fuel Consumption Prediction

Machine learning has emerged as a promising solution for fuel consumption prediction. Multiple regression models have been explored, including Ridge Regression, Support Vector Regression (SVR), and XGBoost.

Hamed et al. (2021) applied SVR using Onboard Diagnostic (OBD) data and reported an R^2 score of 0.96, highlighting the model's potential for high-accuracy predictions. Liu and Jin (2023) implemented a transient fuel consumption model using SVR with Gaussian Mixture Models (GMM), achieving a Root Mean Squared Error (RMSE) of 0.2137, a Mean Absolute Error (MAE) of 0.1526, and a Mean Absolute Percentage Error (MAPE) of 13.69%. These results demonstrate the effectiveness of SVR in modeling fuel consumption.

Yao et al. (2020) used smartphone and OBD data to develop fuel consumption prediction models based on Random Forest (RF), Support Vector Machines (SVM), and Back Propagation (BP) Neural Networks. Their study reported R^2 scores ranging from 0.5 to 0.6, with RF performing the best. However, the reliance on smartphone data introduced inconsistencies due to varying sensor quality and sampling rates.

Kanarachos et al. (2019) explored deep learning-based fuel consumption estimation using Nonlinear Autoregressive Exogenous (NARX) Recurrent Neural Networks (RNNs), achieving an accuracy of 96%. While promising, the computational cost of deep learning models remains a significant limitation for real-time applications. This research addresses these challenges by implementing efficient ML models that balance computational performance and predictive accuracy.

Real-Time Data Processing and Model Deployment

Cloud-Based Fuel Consumption Prediction

The integration of cloud computing with ML models has enabled real-time data processing for automotive applications. Ma et al. (2023) proposed a distributed meta-learning approach for adaptive powertrain fuel consumption modeling, demonstrating that cloud-based ML models can process large-scale ECU data more efficiently than onboard vehicle computers.

Cloud-based deployment allows real-time feedback and analysis, making it suitable for fleet management, telematics-based insurance, and intelligent transportation systems. However, bandwidth limitations and latency concerns must be addressed to ensure seamless integration.

Feature Selection and Optimization in ML Models

Feature selection plays a crucial role in ML model performance. Feature selection techniques such as Recursive Feature Elimination (RFE), SelectKBest, and Sequential Feature Selector have been widely used to enhance model accuracy. Zebari et al. (2020) highlighted the importance of dimensionality reduction in improving ML model performance and reducing computational complexity.

This research adopts an advanced feature selection process to identify the most relevant ECU parameters affecting fuel consumption, ensuring optimal model performance while maintaining computational efficiency.

Comparative Analysis and Research Gaps

Table 1 summarizes key related works in driving profile classification and fuel consumption prediction, comparing their methodologies, results, and limitations.

Study	Approach	Model Used	Accuracy / R^2	Key Findings
Peppes et al. (2021)	Driving Profile Classification	K-Means, Logistic Regression	90-100%	High accuracy but computationally expensive models
Zheng et al. (2022)	Real-Time Driving Behavior	Clustering	70-90%	Lacked ECU data integration
Hamed et al. (2021)	Fuel Consumption Prediction	SVR	R^2 = 0.96	High accuracy with OBD data
Yao et al. (2020)	Fuel Prediction	RF, SVM, BP Neural Network	R^2 = 0.5-0.6	Smartphone data introduced inconsistencies
Kanarachos et al. (2019)	Fuel Estimation	NARX RNN	96% Accuracy	High computational cost
This Study	Fuel Prediction &	XGBoost, SVR,	R^2 = 0.99,	Real-time ECU data processing

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Study	Approach	Model Used	Accuracy / R^2	Key Findings
	Driving Profile Classification	Ridge Regression	Accuracy = 100%	with high efficiency

Conclusion

The literature review highlights the growing application of ML in fuel consumption prediction and driving behavior classification. While previous studies have demonstrated the effectiveness of ML models, many lack real-time processing capabilities, rely on simulated or offline datasets, or employ computationally expensive approaches. This research aims to address these gaps by developing an optimized, real-time ML framework that leverages ECU data to achieve high-accuracy fuel consumption prediction and driving behavior classification with minimal computational overhead.

EXISTING SYSTEM

Overview of Traditional Fuel Consumption Prediction and Driving Behavior Analysis

Traditional methods for fuel consumption prediction and driving behavior analysis primarily rely on deterministic models, statistical approaches, and physical simulations. These techniques involve empirical formulas, fuel consumption maps, and pre-defined driving cycles to estimate fuel usage. However, they fail to capture the real-time variations introduced by dynamic driving conditions, road traffic, environmental factors, and individual driving behaviors.

Deterministic and Empirical Models

Deterministic models use predefined mathematical equations based on engine parameters such as fuel injection rates, throttle position, and air-to-fuel ratios. These models assume a fixed relationship between vehicle parameters and fuel consumption, limiting their adaptability to real-world driving conditions. For instance, the **Vehicle Specific Power (VSP) model** estimates fuel consumption based on instantaneous power demand but lacks the ability to adapt to varying driver behaviors and road conditions.

Empirical models, such as those based on polynomial regression and curve fitting, attempt to create fuel consumption estimation equations using large datasets collected from controlled experiments. While these models offer improved accuracy over purely deterministic approaches, they still require extensive calibration and fail to generalize across different vehicle types and driving environments.

Physical and Simulation-Based Approaches

Physical simulation models, such as the **Autonomie** and **ADVISOR** software, simulate vehicle performance under controlled conditions using detailed vehicle parameters. These simulations rely on laboratory-based testing, such as **chassis dynamometers** and **portable emissions measurement systems (PEMS)**, to gather fuel consumption data. However, these approaches are expensive, time-consuming, and not suitable for real-time applications.

Onboard Diagnostic (OBD) and Data-Driven Approaches

With advancements in vehicle electronics, Onboard Diagnostic (OBD) systems have been increasingly used to monitor fuel consumption in real-time. OBD-based approaches leverage sensors embedded in the engine control system to record data such as **engine speed, mass air flow, and fuel injector pulse width**. While OBD systems provide better insights into fuel usage, they are often limited by **low sampling rates, lack of advanced predictive capabilities, and dependency on manufacturer-specific parameters**.

Machine Learning in Existing Approaches

Recent research has explored ML models for fuel consumption prediction and driving behavior classification. However, many of these studies have limitations, such as:

- **Use of Static or Simulated Data**: Many studies rely on datasets that do not reflect real-world conditions.
- **Computational Complexity**: Deep learning models, such as Neural Networks, require significant computational power, making real-time implementation challenging.
- **Limited Feature Selection**: Some approaches fail to identify the most influential ECU parameters, leading to suboptimal prediction accuracy.
- **Lack of Real-Time Implementation**: Most existing ML-based studies focus on offline training and do not integrate real-time feedback mechanisms.

Limitations of the Existing System

From the analysis of traditional approaches and existing ML-based methods, the following key limitations can be identified:

1. **Inability to Adapt to Real-Time Driving Conditions** – Many models are built on static datasets and fail to adapt to real-time ECU data.
2. **High Computational Costs** – Advanced deep learning models require significant computational resources, making real-time deployment infeasible.
3. **Limited Generalizability** – Many models are designed for specific vehicle types and may not generalize well to other vehicles.
4. **Lack of Integration with Cloud-Based Systems** – Most existing systems do not incorporate cloud computing for efficient data processing and remote monitoring.

Due to these limitations, there is a need for a **real-time, efficient, and adaptable ML-based framework** that leverages actual ECU

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data for fuel consumption prediction and driving behavior classification.

PROPOSED SYSTEM

Overview of the Proposed Machine Learning-Based Framework

To address the limitations of traditional and existing ML-based fuel consumption prediction methods, this research proposes a **real-time, ECU-integrated machine learning framework**. The system applies supervised and unsupervised ML techniques to classify driving behavior and predict fuel consumption with high accuracy and computational efficiency.

The proposed framework consists of the following key components:

1. **Real-Time ECU Data Acquisition** – Data is collected directly from the vehicle's ECU, ensuring high-frequency sampling and real-time insights.
2. **Feature Selection and Optimization** – A rigorous feature selection process identifies the most relevant parameters affecting fuel consumption.
3. **Driving Profile Classification** – ML models classify drivers as fuel-efficient or inefficient based on their driving behavior.
4. **Fuel Consumption Prediction** – Regression models predict fuel consumption based on real-time vehicle and environmental conditions.
5. **Cloud-Based Processing and Feedback System** – The models are deployed on a cloud server, providing instant feedback to drivers and fleet managers.

Methodology of the Proposed System

The proposed system follows a structured methodology that includes data acquisition, feature selection, ML model development, and real-time deployment.

Data Acquisition from ECU

- Real-time data is extracted from the vehicle's ECU using a Controller Area Network (CAN) interface.
- The dataset includes **engine speed, throttle position, fuel injection rates, vehicle speed, ambient temperature, and gear position**.
- The collected data is transmitted to a cloud server for processing and model inference.

Feature Selection Process

To ensure optimal model performance, feature selection techniques such as:

- **SelectKBest**
- **Recursive Feature Elimination (RFE)**
- **Principal Component Analysis (PCA)**

are applied to determine the most influential variables. The selected features enable the ML models to achieve high accuracy while maintaining computational efficiency.

Machine Learning Models for Classification and Prediction

The system applies the following ML algorithms for classification and regression:

1. **Driving Profile Classification:**
   - **K-Means Clustering** – Unsupervised method to group driving styles.
   - **Logistic Regression** – A lightweight classifier for binary classification.
   - **XGBoost** – A powerful boosting algorithm for improved accuracy.
2. **Fuel Consumption Prediction:**
   - **Ridge Regression** – Regularized regression model for stable predictions.
   - **Support Vector Regression (SVR)** – Non-linear regression for complex patterns.
   - **XGBoost Regressor** – Optimized tree-based ensemble model for high accuracy.

Real-Time Cloud-Based Implementation

- The ML models are deployed on a cloud server for real-time inference.
- The system provides **instant feedback** on fuel efficiency and driving behavior.
- Data visualization is enabled through a web-based dashboard for monitoring and analysis.

Advantages of the Proposed System

The proposed framework offers several advantages over existing systems:

1. **Real-Time Data Processing** – The use of cloud computing enables real-time analysis and feedback.
2. **High Prediction Accuracy** – The combination of optimized feature selection and ML models improves classification and regression accuracy.
3. **Computational Efficiency** – Lightweight models like Logistic Regression and Ridge Regression ensure that the system remains efficient.

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4. **Scalability and Adaptability** – The system can be adapted for different vehicle types and applications, such as fleet management and insurance telematics.

5. **Enhanced Fuel Optimization** – By providing real-time insights, the system allows drivers to modify their behavior to reduce fuel consumption.

Conclusion

The proposed system overcomes the limitations of traditional and existing ML-based models by leveraging real-time ECU data and computationally efficient ML techniques. By integrating driving profile classification with fuel consumption prediction, the system provides **accurate, scalable, and real-time insights for vehicle optimization and sustainability**.

IMPLEMENTATION

The **Intelligent Fuel Consumption Prediction and Driver Behavior Analysis System** uses data from the **Electronic Control Unit (ECU)** of a vehicle to analyze fuel usage and driving patterns using machine learning techniques. The system is divided into several functional modules that work together to collect, process, and analyze vehicle data.

ECU Data Acquisition Module

This module collects real-time vehicle data from the **Electronic Control Unit (ECU)** using vehicle communication protocols such as **OBD-II or CAN bus**.

Collected parameters include:

- Engine speed (RPM)
- Vehicle speed
- Throttle position
- Fuel injection rate
- Engine load
- Air intake and temperature data

The collected data is transmitted to the processing unit for further analysis.

Data Preprocessing Module

The raw ECU data may contain noise, missing values, or inconsistent measurements. This module prepares the data before feeding it into the machine learning model.

Functions of this module:

- Data cleaning and filtering
- Handling missing values
- Normalization and scaling
- Data formatting and structuring

This improves the **quality and reliability of the dataset** used for prediction.

Feature Extraction Module

This module extracts important features from the processed ECU data that influence fuel consumption and driving behavior.

Example features:

- Average vehicle speed
- Acceleration patterns
- Engine load variations
- Idle time
- Fuel injection duration

These features help the machine learning model understand the relationship between **vehicle operation and fuel consumption**.

Machine Learning Model Module

This is the core module responsible for predicting fuel consumption and classifying driver behavior.

Possible algorithms used:

- Random Forest
- Support Vector Machine (SVM)
- Artificial Neural Networks (ANN)
- Gradient Boosting

The model learns patterns from historical ECU data to predict **future fuel consumption and driving profiles**.

Fuel Consumption Prediction Module

This module estimates the **real-time fuel consumption** of the vehicle based on ECU parameters.

Functions:

- Predict fuel usage under different driving conditions

- Provide fuel efficiency estimates
- Help drivers optimize driving style for better fuel economy.

Driver Behavior Classification Module

This module analyzes driving patterns and categorizes driver behavior.

Examples of driving profiles:

- Aggressive driving
- Normal driving
- Eco-friendly driving

This classification helps identify behaviors that **increase fuel consumption or vehicle wear**.

Visualization and Monitoring Module

This module provides a **dashboard or user interface** to display analysis results.

Displays:

- Real-time fuel consumption
- Driver behavior category
- Vehicle performance metrics
- Fuel efficiency statistics

The information can be shown on **mobile applications, vehicle displays, or monitoring systems**.

CONCLUSION

Implementing Industry 4.0 technologies such as IoT and AI can enhance automation and efficiency in automobile manufacturing processes. This can lead to improved production quality, reduced lead times, and increased flexibility in responding to market demands. The presented work analyzed two scenarios related to fuel consumption. First, we compared three ML models to classify the driving profile concerning fuel consumption, and, second, compared three ML regression models to predict the fuel consumption, proving its validity on both subjects with results that indicate a correct categorization of the driver in economic or non-economic and an accurate prediction of consumption. The evaluation of the models (training and testing phases) was carried out using real data collected from a vehicle ECU. The models were integrated into a cloud server, which allows for data processing at runtime (while the car is running), making it possible to monitor the results using web tools or local software applications. In this way, drivers and stakeholders can monitor vehicle data while driving, making the work applicable in various sectors such as industry, security, tracking, transport, and automotive in general. In the classifiers, we could obtain values up to 100% of accuracy, precision, and recall, with an average of around 97% in models like XGBoost, as well as similar results with Logistic Regression. This shows an improvement to other works, where lesser scoring was obtained, despite using more complex and expensive models or not real collected data. Furthermore, in the regressors our models were able to show R 2 scores up to 0.99, an MAE of 0.23 (l/h), besides an average MSE of 0.49 (l/h)2 , reaching down to 0.28 (l/h)R 2 in some tests. These results, compared to similar works, also show advancements in reaching good scores with similar or even less expensive models, besides the use of real data collected for the training and tests. Due to the multidisciplinarity of the automotive industry and the demand for more data, we expect vehicle ECUs and other automotive components to generate more information, creating the opportunity for more complex data-based analyses with ML.

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