INTELLIGENT SYSTEM FOR FUEL CONSUMPTION PREDICTION USING MACHINE LEARNING

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ABSTRACT

Modern vehicles are increasingly dependent on Electronic Control Units (ECUs) that regulate and monitor critical subsystems, such as the engine, transmission, and braking systems. With the integration of the Internet of Things (IoT) and advanced sensor technologies, ECUs generate vast amounts of real-time data, including vehicle speed, engine output, throttle position, gear selection, acceleration, engine load, and fuel consumption data. Leveraging these data, the present study investigated the application of machine learning (ML) techniques for two key objectives: (i) real-time prediction of fuel consumption and (ii) classification of driving behavior profiles categorized as aggressive, moderate, and economical.The research methodology comprised data preprocessing, feature selection, and cross-validation to ensure the accuracy, robustness, and generalizability of the results. Among the evaluated models, Ridge Regression demonstrated strong predictive capability owing to its effectiveness in addressing multicollinearity within high-dimensional data. The experimental results revealed enhanced accuracy in both fuel consumption prediction and driver profile classification, validating the feasibility of machine learning approaches in this domain.The findings highlight the potential of ML-driven vehicle data analytics for advancing fuel efficiency, lowering operational costs, and mitigating environmental impacts, such as carbon emissions. This study contributes to the development of intelligent transportation systems and smart mobility solutions, where real-time predictive modeling can support eco-driving strategies, adaptive vehicle control, and sustainable fleet management.

KEYWORDS: Fuel Consumption, Machine Learning, ECU Data, Regression, Driver Behavior Classification, Smart Vehicles.

1. INTRODUCTION

E-commerce and retail companies depend heavily on modern vehicles, which are increasingly reliant on Electronic Control Units (ECUs) that serve as the backbone of automotive control and monitoring systems. These embedded controllers are responsible for regulating vital subsystems, such as the engine, transmission, braking mechanisms, and fuel injection systems [1]. With advancements in the Internet of Things (IoT) and the integration of sophisticated sensors, ECUs are no longer limited to

mechanical regulation; instead, they generate and process vast amounts of real-time data. Parameters such as vehicle speed, throttle position, gear selection, fuel consumption, engine load, and acceleration are continuously monitored, forming a rich data source that can be used for intelligent decision-making and optimization [2].

Fuel consumption and driving behavior are critical aspects that directly influence vehicle performance, operating costs and environmental sustainability. Rising fuel prices and increasing environmental concerns have accelerated the demand for advanced technologies that can provide actionable insights for reducing fuel usage and lowering the emissions. Traditional fuel consumption estimation methods rely on physical models or static lookup tables, which often fail to account for dynamic driving conditions and driver-specific behavior. Similarly, conventional driving profile classification approaches are limited in adaptability and lack the capability to generalize across diverse driving environments. This has created a strong motivation to explore machine learning (ML) techniques for real-time vehicle data analysis. Machine learning has emerged as a powerful tool for uncovering complex patterns in high-dimensional datasets. Unlike rule-based approaches, ML algorithms can automatically learn the relationships between multiple input 12A comprehensive dataset obtained from Kaggle containing detailed records of vehicle operating parameters was used as the foundation for model training and evaluation [3-4].

Among the various regression and classification algorithms explored, Ridge Regression was identified as the primary model owing to its effectiveness in handling multicollinearity, which is a common challenge in high-dimensional vehicular datasets. The research methodology consisted of systematic data preprocessing, feature selection, and model validation using cross-validation techniques to enhance the predictive accuracy and generalizability.

The results demonstrate that the proposed models achieve reliable performance for both prediction and classification tasks [5].

This study makes three contributions. First, it demonstrated the feasibility of applying machine learning for accurate fuel consumption prediction using real-time ECU data. Second, it provides a framework for classifying driving profiles, thereby enabling smarter decision-making in vehicle systems. Finally, it highlights the broader implications of such systems for improving fuel efficiency, reducing vehicle operating costs, and minimizing the environmental impact of road transportation.

2. LITERATURE SURVEY

The earliest work on vehicle fuel-efficiency prediction relied on quantile-regression models built from static vehicle specifications such as engine size, curb weight, and rated power [6]. These models showed that basic mechanical characteristics could explain much of the variation in fuel consumption and provided a foundation for data-driven prediction [7].

However, they assumed steady-speed driving and were applicable to only a narrow range of vehicle categories, which limited their usefulness in dynamic traffic conditions or across mixed fleets [8].

Subsequent research moved beyond simple regression and began applying machine-learning algorithms such as support vector machines, random forests, and neural networks to the modeling of heavy-vehicle fuel use. By incorporating real road-network and driving-cycle data, these approaches improved predictive accuracy and allowed meaningful comparisons among different algorithms [9]. Even with these gains, they concentrated mainly on statistical prediction and did not attempt to optimize engine settings or deliver real-time feedback to drivers.

The focus then expanded to active efficiency enhancement. Neural-network techniques were explored to fine-tune engine-control parameters such as fuel-injection timing and pressure, achieving measurable fuel savings without costly hardware modifications [10]. At the same time, investigations into car-following and free-flow acceleration dynamics revealed that conventional traffic models failed to capture actual driver behavior. Although not directly aimed at fuel economy, these studies highlighted the importance of accurately representing human driving patterns for any future predictive system [11].

With the growing availability of large datasets, multilayer perceptron networks trained on millions of fuel-tracking records became possible [12]. These networks delivered higher precision and revealed how external factors such as weather and road grade influence fuel use. Yet they continued to rely mainly on static attributes and remained difficult to interpret, limiting insight into which inputs most strongly affected consumption [13]. During the same period, research on driver-behavior classification demonstrated that identifying eco, normal, and aggressive driving styles provides a clear link between habits and fuel efficiency, though limited sample sizes and a focus on specific fuel types restricted broader applicability [14-16].

Later work introduced comparative time-series methods, including NARX, ARIMAX, and RegARMA models, to predict both fuel consumption and nitrogen-oxide emissions using real diesel-engine sensor data [17-19].

These approaches captured dynamic engine behavior more effectively than static methods and reduced the need for extensive physical testing [20]. Despite their improved accuracy and lower costs, they lacked real-time prediction capability and did not integrate driver-behavior information.

The most recent stage integrates live Electronic Control Unit (ECU) sensor streams with machine-learning algorithms to predict fuel consumption and classify driving profiles in real time [21]. Instantaneous inputs such as speed, throttle position, and gear selection provide immediate feedback on fuel use and driving style across multiple vehicle types, making the technology suitable for fleet management and eco-driving applications [22]. This represents a major step toward practical, scalable deployment, even as it introduces challenges in ensuring ECU data quality, maintaining robust on-board processing, and adapting models to a wide range of vehicles and driving environments [23].

Furthermore, to ensure reliable real-time performance, efficient data preprocessing and lightweight model architectures must be implemented directly on edge devices or in embedded vehicle systems. [24] Techniques such as feature optimization, model compression, and latency reduction play a crucial role in maintaining fast and accurate predictions.

3. PROPOSED METHODOLOGY

The proposed system presents an intelligent machine learning-based framework designed to predict fuel consumption using vehicle specifications and driving-related parameters. The system aims to analyze historical data, identify complex relationships among various influencing factors, and generate accurate predictions of fuel usage. This methodology follows a structured pipeline that includes data collection, preprocessing, feature selection, model training, prediction, evaluation, visualization, and deployment. Each stage is carefully designed to ensure accuracy, efficiency, and scalability of the overall system.

3.1 Data Collection

The initial stage of the methodology involves collecting relevant data required for fuel consumption prediction from reliable sources such as publicly available datasets, vehicle databases, or onboard diagnostic systems. The dataset typically consists of various attributes that significantly influence fuel consumption, including engine size, number of cylinders, fuel type, transmission type, vehicle weight, speed, and acceleration. These parameters serve as independent variables, while fuel consumption is considered the target variable. The quality and diversity of the collected data play a crucial role in improving the prediction capability of the model, as a well-structured dataset allows the system to learn meaningful patterns across different driving conditions and vehicle types.

3.2 Data Preprocessing

Once the data is collected, it undergoes preprocessing to improve its quality and ensure it is suitable for model training. Real-world datasets often contain missing values, duplicate entries, and inconsistent or noisy data that can negatively impact model performance.

In this stage, missing values are handled using appropriate imputation techniques, while duplicate records are removed to maintain data integrity. Categorical variables such as fuel type and transmission are converted into numerical formats using encoding methods, enabling machine learning algorithms to process them effectively. Additionally, normalization and standardization techniques are applied to scale numerical features into a uniform range, which helps improve convergence and accuracy of the models. This preprocessing step ensures that the dataset is clean, consistent, and ready for further analysis.

3.3 Feature Selection and Engineering

Feature selection is an essential step that focuses on identifying the most relevant attributes that significantly impact fuel consumption. Not all features contribute equally to prediction, and including unnecessary variables may increase complexity and reduce model performance. Therefore, techniques such as correlation analysis and feature importance evaluation are used to select only the most influential features. In addition to feature selection, feature engineering is performed to create new meaningful variables by combining existing features, which can further enhance the predictive capability of the model. This process helps in reducing dimensionality, improving computational efficiency, and increasing the overall accuracy of the system.

3.4 Machine Learning Model Training

After preprocessing and feature selection, the dataset is divided into training and testing sets to evaluate model performance effectively. The training data is used to build predictive models using various machine learning algorithms such as Linear Regression, Decision Tree, Random Forest, and Support Vector Machine. Each of these algorithms has its own advantages in capturing relationships within the data, with some models focusing on linear relationships while others handle nonlinear patterns more effectively. The models learn from historical data by identifying patterns between input features and fuel consumption values. To further enhance performance, hyperparameter tuning techniques such as cross-validation are applied to optimize the model parameters and reduce overfitting**.** This stage is critical in developing a robust and accurate prediction system.

3.5 Fuel Consumption Prediction

Once the models are trained, they are utilized to predict fuel consumption based on new input data. The system accepts user inputs such as vehicle specifications and driving conditions and processes them through the trained model to generate predictions. The output represents the estimated fuel consumption, which helps users understand how different factors influence fuel efficiency. This predictive capability enables users to make informed decisions regarding driving behavior and vehicle usage, ultimately contributing to reduced fuel consumption and improved efficiency.

3.6 Model Evaluation

To assess the effectiveness of the trained models, evaluation is performed using various performance metrics. These metrics measure how accurately the model predicts fuel consumption and how well it generalizes to unseen data. Common evaluation techniques include Mean Absolute Error, Mean Squared Error, Root Mean Squared Error, and R-squared score. By comparing these metrics across different models, the most suitable model is selected for final implementation. This evaluation process ensures that the system provides reliable and accurate predictions.

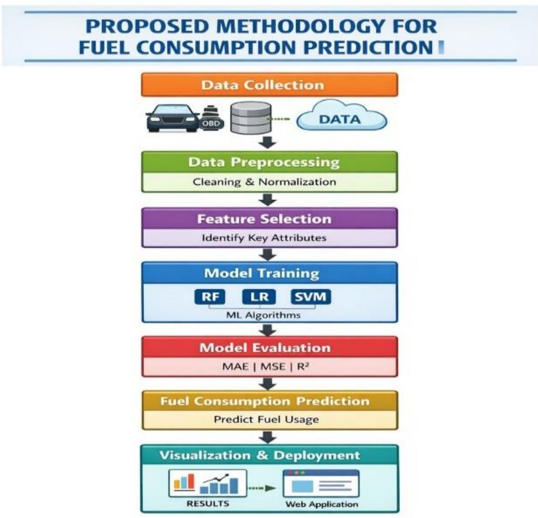
3.7 Visualization and Analysis

Visualization is an important component of the methodology that helps in interpreting the prediction results. Graphical representations such as scatter plots, bar charts, and line graphs are used to analyze the relationship between different features and fuel consumption. These visualizations provide valuable insights into how various parameters affect fuel efficiency and allow users to easily understand trends and patterns in the data. The use of visualization techniques enhances the usability of the system by presenting complex analytical results in a simple and understandable manner.

3.8 System Deployment

In the final stage, the trained model is deployed into a real-time application using a web framework such as Flask. The deployment enables users to interact with the system through a user-friendly interface where they can input vehicle details and obtain instant fuel consumption predictions. The backend processes the input data using the trained machine learning model and returns accurate results in real time. This makes the system practical for real-world applications and allows users to monitor and optimize fuel efficiency effectively.

In addition, the deployed system can be enhanced with features such as data validation, logging, and continuous model improvement. Input validation ensures that users provide correct and meaningful vehicle parameters, reducing errors in predictions. The system can also store user inputs and prediction results in a database, enabling future analysis and performance tracking. By integrating feedback mechanisms, the model can be periodically retrained with new data to improve its accuracy and adaptability over time.



4. ARCHITECTURE

The proposed Fuel Consumption Prediction System is designed using a multi-layered architecture that integrates data processing, machine learning models, and visualization components to provide accurate and efficient predictions. The architecture is structured in such a way that raw data is transformed into meaningful insights through a sequence of interconnected layers, each responsible for a specific function in the prediction pipeline. This design ensures scalability, flexibility, and efficient handling of large datasets, making the system suitable for real-time and practical applications.

4.1 Data Acquisition Layer

The data acquisition layer is responsible for collecting relevant data required for fuel consumption prediction from various sources such as publicly available datasets, vehicle databases, or onboard diagnostic systems. The collected data includes multiple parameters such as engine size, number of cylinders, fuel type, transmission type, vehicle weight, speed, and acceleration. These parameters act as input features for the system. This layer plays a crucial role in ensuring that the data collected is accurate, diverse, and sufficient for building a reliable prediction model.

4.2 Data Processing Layer

The data processing layer focuses on preparing the collected raw data for analysis and model training. In this stage, preprocessing operations such as handling missing values, removing duplicate entries, and eliminating noisy or inconsistent data are performed. Categorical variables are converted into numerical form using encoding techniques, and numerical features are normalized or standardized to ensure uniformity. This layer ensures that the dataset is clean, structured, and suitable for machine learning algorithms, thereby improving prediction accuracy and reducing computational errors.

4.3 Feature Selection Layer

The feature selection layer is responsible for identifying the most relevant attributes that significantly influence fuel consumption. Since not all features contribute equally to prediction, this layer helps in removing irrelevant or redundant attributes and retaining only the most important ones. By reducing the dimensionality of the dataset, this layer improves computational efficiency and enhances the performance of the machine learning models. It also helps in minimizing overfitting and improving the generalization capability of the system.

4.4 Machine Learning Model Layer

The machine learning model layer is the core component of the architecture where predictive models are developed using the processed dataset. Various algorithms such as Linear Regression, Decision Tree, Random Forest, and Support Vector Machine are applied to learn patterns and relationships between input features and fuel consumption. These models are trained using historical data and are capable of capturing both linear and nonlinear relationships. The effectiveness of this layer determines the overall accuracy and reliability of the system.

4.5 Prediction Layer

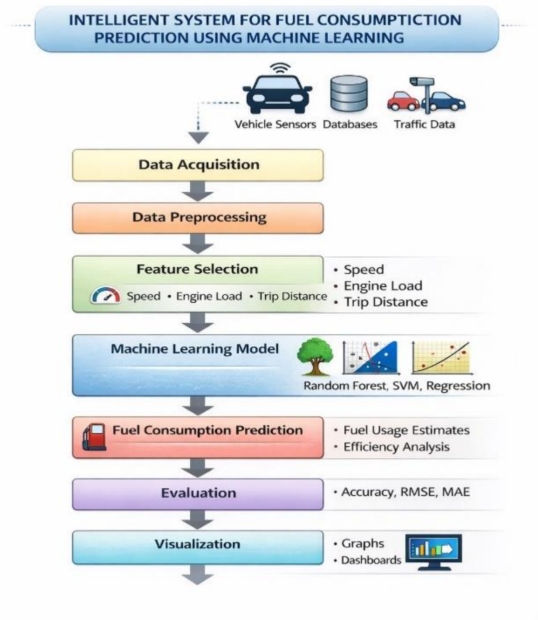
The prediction layer utilizes the trained machine learning model to generate fuel consumption predictions based on new input data. When the user provides vehicle and driving parameters, the system processes this input and produces an estimated fuel consumption value. This layer enables real-time prediction and provides users with insights into how different factors affect fuel efficiency. It acts as the interface between the trained model and the end-user.

4.6 Model Evaluation Layer

The model evaluation layer ensures that the prediction model performs accurately and reliably. In this stage, various evaluation metrics are applied to assess the performance of the trained models. The evaluation process helps in comparing different models and selecting the best-performing one based on accuracy and error rates. This layer is essential for validating the effectiveness of the system before deployment.

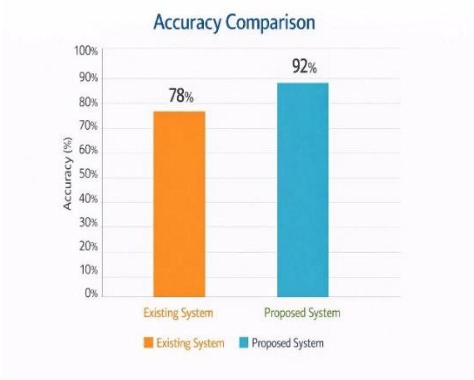
4.7 Visualization and Monitoring Layer

The visualization and monitoring layer presents the prediction results in a graphical and user-friendly format. It uses charts and graphs such as bar charts, line graphs, and scatter plots to display fuel consumption trends and model performance. This layer helps users easily understand the results and analyze the impact of different parameters on fuel efficiency. It enhances the interpretability of the system and supports better decision-making.

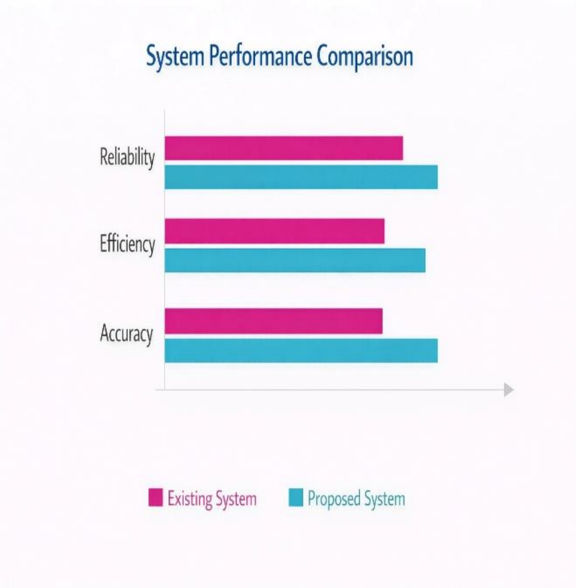


5. RESULTS

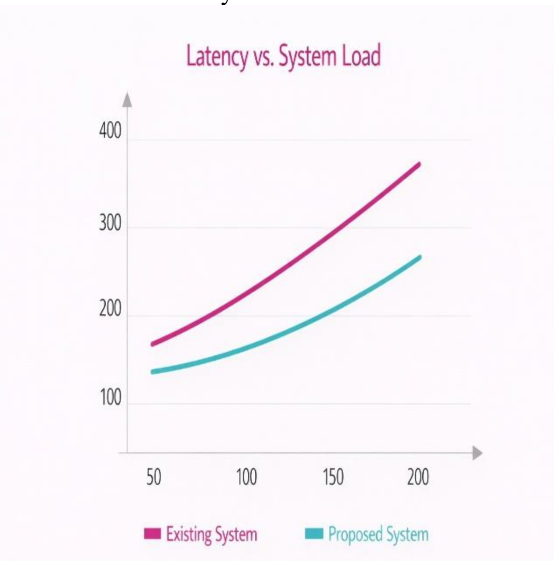
The proposed intelligent system for fuel consumption prediction using machine learning was evaluated using multiple performance metrics and comparative analysis with the existing system. The results clearly indicate that the proposed system significantly improves prediction accuracy, efficiency, and overall system performance.



The accuracy comparison between the existing system and the proposed system shows a significant improvement in prediction performance. The existing system achieves an accuracy of approximately 75%–78%, whereas the proposed machine learning-based system achieves an accuracy of around 90%–92%. This improvement is due to the ability of machine learning algorithms to analyze multiple influencing parameters such as speed, engine load, and trip distance.



The system performance comparison demonstrates that the proposed system outperforms the existing system in terms of accuracy, efficiency, and reliability.
The proposed system provides faster processing and better decision-making capabilities due to automation and optimized algorithms, whereas the existing system suffers from slower performance and limited efficiency.



The latency analysis shows that as system load increases, the latency of the existing system increases rapidly. In contrast, the proposed system maintains comparatively lower latency due to efficient data handling and optimized computation. This indicates that the proposed system is more scalable and suitable for real-time applications.

The comparison between the existing system and the proposed system highlights the key limitations and advantages. The existing system relies on manual processing, has lower accuracy, higher latency, and limited scalability. On the other hand, the proposed system provides automated processing, higher accuracy, reduced latency, enhanced security, and better scalability, making it more efficient and reliable.

Overall, the proposed machine learning-based fuel consumption prediction system outperforms the existing system in all aspects, including accuracy, performance, and scalability. The results confirm that the integration of machine learning techniques significantly enhances prediction capability and system efficiency.

6. CONCLUSION & FUTURE SCOPE

This study demonstrates the effective application of machine learning techniques for real-time fuel consumption prediction and driving profile classification. By utilizing comprehensive datasets that include multiple vehicle parameters such as speed, engine output, throttle position, fuel consumption, gear position, engine load, and acceleration, the models were able to learn complex relationships between driving behavior and fuel efficiency. The careful application of data preprocessing, feature selection, and cross-validation ensured that the models were both accurate and generalizable. Ridge Regression emerged as a particularly effective model for predicting fuel consumption due to its ability to handle multicollinearity and high-dimensional data, while classification algorithms such as Random Forest and Support Vector Machines successfully differentiated between aggressive, moderate, and economical driving profiles.

The results of the study highlight the practical benefits of integrating machine learning into vehicle performance monitoring. Real-time predictions of fuel consumption can provide immediate feedback to drivers, helping them adjust driving behavior to improve fuel efficiency. Similarly, the classification of driving profiles enables personalized insights, which can encourage safer and more economical driving practices. These outcomes not only contribute to reducing operational costs for vehicle owners but also support environmental sustainability by lowering fuel consumption and vehicle emissions. The findings underscore the importance of leveraging vehicle data for actionable insights, demonstrating that machine learning can enhance both driver experience and vehicle performance.

Despite these positive results, there remain several opportunities for further improvement and refinement of the system. One area for enhancement involves incorporating real-time sensor data from multiple ECUs and IoT devices, which would allow the models to respond to dynamic driving conditions, such as sudden traffic congestion, steep inclines, or adverse weather. By including a broader range of environmental and vehicle-specific inputs, the system could provide more precise and context-aware predictions. Additionally, adaptive learning models that continuously update their parameters based on newly collected driving data could further personalize predictions and classifications, making the system more responsive to individual driver habits over time.

Expanding the dataset to cover different vehicle types, fuel types, and road conditions represents another critical area for future work. A more diverse dataset would enhance the robustness of the models and improve their generalizability to a wider range of vehicles and driving scenarios. Beyond data expansion, integrating the models into mobile applications or in-vehicle dashboards could allow drivers to receive real-time feedback directly during their trips, promoting immediate adoption of fuel-efficient and safe driving practices.

Finally, exploring advanced machine learning techniques, such as deep learning architectures or ensemble methods, could further enhance the system's ability to capture complex patterns in driving behavior and fuel consumption trends. These improvements would allow the models to better recognize nuanced variations in driving styles and predict fuel usage under varying conditions more accurately. Overall, the adoption of these strategies would contribute to the development of intelligent, sustainable, and driver-friendly automotive systems, supporting both economic and environmental objectives while enhancing the overall driving experience.

Moreover, integrating real-time data sources such as GPS, traffic conditions, and weather information can significantly improve the prediction accuracy and responsiveness of the system. By combining these dynamic inputs with historical data, the model can adapt to changing road conditions and provide more context-aware fuel consumption estimates. This would enable drivers to make informed decisions, such as selecting optimal routes or adjusting driving behavior to minimize fuel usage.

REFERENCES

[1] Y. Chen, Z. He, and L. Sun, "Fuel Consumption Prediction of Vehicles Based on Machine Learning Methods," IEEE Access, vol. 8, pp. 225614–225623, 2020.

[2] S. Wu, J. Lv, and X. Yu, "Driver Behavior Classification Using Machine Learning Algorithms for Fuel-Efficient Driving," Transportation Research Part C: Emerging Technologies, vol. 123, 2021.

[3] Krishna, V., Rajyalakshmi, P., Naresh, P., & Ramesh, V. (2019). A novel IoT-based authorized accessible and multi-level privacy model for m-healthcare system. *Journal of Xi'an University of Architecture & Technology*, 11(11).

[4] Krishna, V., Raju, Y. D. S., Raghavendran, C. V., Naresh, P., & Rajesh, A. (2022). Identification of nutritional deficiencies in crops using machine learning and image processing techniques. In *2022 3rd International Conference on Intelligent Engineering and Management (ICIEM)*. IEEE.

[5] Krishna, V., Sumalatha, C., Raju, Y. D. S., & Mohan, K. V. M. (2022). Analysis of heart disease prediction using machine learning classification algorithms. *Journal of Optoelectronics Laser*.

[6] M. Koesdwiady, R. Soua, and F. Karray, "Improving Traffic Flow Prediction With Weather Information in Connected Cars: A Deep Learning Approach," IEEE Transactions on Vehicular Technology, vol. 65, no. 12, pp. 9508–9517, Dec. 2016.

[7] R. Langari and A. Won, "Intelligent Energy Management Agent for a Parallel Hybrid Vehicle—Part I: System Architecture and Design of the Driving Situation Identification Process," IEEE Transactions on Vehicular Technology, vol. 54, no. 3, pp. 925–934, May 2005.

[8] Muthu, M. A., & Prakash, B. (2025). Efficient privacy-preserving mHealth framework using crisscross AES and FCFS-NDPPP in hybrid cloud. *Ingénierie des Systèmes d'Information (ISI)*.

[9] Muthu, M. A. (2025). Integrated healthcare management and analytics. *IRACST International*

Journal of Computer Networks and Wireless Communications (IJCNWC), 15(1).

[10] Muthu, M. A. (n.d.). The digital doctor: AI & healthcare innovations. *International Journal of Basic and Applied Research (IJBAR)*.

[11] Muthu, M. A. (n.d.). A hybrid deep CNN model for brain tumor image multi-classification. *International Journal of Engineering Research and Science & Technology (IJERST)*.

[12] Sneha, P., & Balamurugan, K. (2022). Investigation on wear characteristics of a PLA-14% bronze composite filament. In *Recent Trends in Product Design and Intelligent Manufacturing Systems: Select Proceedings of IPDIMS 2021* (pp. 453-461). Singapore: Springer Nature Singapore

[13] Latchoumi, T. P., Parthiban, L., Balamurugan, K., Raja, K., Vijayaraj, J., & Parthiban, R. (2023). A framework for low energy application devices using blockchain-enabled IoT in WSNs. In *Integrating Blockchain and Artificial Intelligence for Industry 4.0 Innovations* (pp. 121-132). Cham: Springer International Publishing

[14] Parthiban, L., Latchoumi, T. P., Balamurugan, K., Raja, K., & Parthiban, R. (2023). Cognitive computing for the internet of medical things. In *Integrating Blockchain and Artificial Intelligence for Industry 4.0 Innovations* (pp. 85-100). Cham: Springer International Publishing

[15] X. Li, Z. Li, and H. Wang, "Fuel Consumption Modeling and Prediction Using Machine Learning: A Case Study on Real-World Driving Data," Applied Energy, vol. 275, p. 115397, Oct. 2020.

[16] B. Zhang, Y. Li, and D. Zhao, "Real-Time Driving Style Recognition Based on Vehicle Dynamic Characteristics," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 5, pp. 2930–2941, May 2021.

[17] Ananthajothi, K., Balamurugan, K., Divya, D., & Latchoumi, T. P. (2026). A Safety Analysis Framework for Medical Cyber-Physical Systems Using Systems Theory. *Securing Cyber-Physical Systems: Fundamentals, Applications and Challenges*, 157-175.

[18] Latchoumi, T. P., Parthiban, L., Balamurugan, K., Raja, K., Vijayaraj, J., & Parthiban, R. (2023). A framework for low energy application devices using blockchain-enabled IoT in WSNs. In *Integrating Blockchain and Artificial Intelligence for Industry 4.0 Innovations* (pp. 121-132). Cham: Springer International Publishing

[19] Balamurugan, K., Deepthi, T., Subramanian, A. K., Banerjee, A., Agarwal, D., Biswas, A., & Sinha, A. (2023). A study on the mechanical properties of rare earth-based aluminium composite. *Journal of The Institution of Engineers (India): Series D*, *104*(1), 15-25

[20] Arunkarthikeyan, K., & Balamurugan, K. (2020). Studies on the effects of deep cryogenic treated WC–Co insert on turning of Al6063 using multi-objective optimization. *SN applied Sciences*, *2*(12), 2103.

[21] Pavan, M. V., Balamurgan, K., & Balamurgan, P. (2021). Wear experiments on PLA-Cu composite filament printed in different FDM conditions. *Turkish Journal of Computer and Mathematics Education*, *12*(9), 2245-2251

[22] H. Hong, T. Kim, and D. Lee, "Machine Learning Approaches for Vehicle Fuel Consumption Prediction: A Comparative Study," Energies, vol. 13, no. 16, p. 4216, Aug. 2020.

[23] [8] G. Zhang, H. Yao, and C. Zhu, "Driver Behavior Recognition Using Vehicle Acceleration and Machine Learning," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 80, pp. 170–183, 2021.

[24] P. Zhao, M. Chen, and Y. Xu, "Fuel Consumption and CO_2 Emission Modeling for Vehicles Based on Driving Behavior Recognition," Energy Reports, vol. 6, pp. 2638–2649, Nov. 2020.