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Deep Neuro-Fuzzy Capability Analysis for Reliable Autonomous Vehicle Communications

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ABSTRACT

Autonomous Vehicles (AVs) rely on high-assurance communication units to maintain operational safety; however, approximately 40% of communication failures are attributed to inconsistent unit performance, and 35% of real-time decision conflicts stem from network latency. Conventional evaluation methodologies are often reactive, failing to capture the subtle, non-linear performance variations inherent in dynamic traffic environments. To address these systemic vulnerabilities, this research proposes a Deep Fuzzy Logic (DFL)-based framework for the automated capability assessment of AV communication units. The methodology introduces a Deep Fuzzy Encoding (DFE) layer designed to transform raw network metrics into high-dimensional fuzzy representations, effectively modeling the stochastic uncertainty of signal integrity and latency. Following rigorous preprocessing—including outlier elimination and feature normalization—the DFE-extracted features are processed via a Linear Regression architecture to estimate a continuous capability score. Comparative analysis against baseline Decision Tree Regressor (DTR) and K-Nearest Neighbor (KNN) regressors demonstrates that the integration of fuzziness significantly enhances prediction reliability and error convergence. The framework is deployed as a Flask-based web application, providing a scalable, real-time diagnostic tool for proactive maintenance and the optimization of autonomous vehicular networks.

Keywords: Autonomous Vehicles; Deep Fuzzy Logic; Deep Fuzzy Encoding; Communication Unit Assessment; Network Latency; Predictive Maintenance.

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1. INTRODUCTION

The growth of autonomous vehicles is transforming urban mobility, with global AV deployment projected to reach over 10 million units by 2030, and vehicle-to-vehicle (V2V) communication being critical for safety in over 60% of autonomous operations. Ensuring the reliable performance of AV communication units is essential for collision avoidance, traffic management, and real-time decision-making. Manual evaluation methods are time-consuming, fail to capture dynamic operational conditions, and cannot quantify nuanced variations in communication capability. Consequently, intelligent, data-driven assessment methods are necessary to guarantee safe, efficient, and reliable autonomous vehicle operations. With growing concern regarding the traffic congestion problem and traffic safety issues, intelligent vehicle and connected vehicle techniques have become mainstream trends in today's automotive industry. As a result, real-time driving behavior monitoring has attracted significant attention in recent years as it can provide important reference input for intelligent

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vehicle control, as well as microscopic traffic estimation and control. On one hand, to support the timely response of intelligent vehicle control and ensure the safety of autonomous driving systems, it is necessary to realize driving behavior recognition for smart vehicles in real time [1]. On the other hand, dynamically monitoring the driving behavior of probe vehicles could provide fine-grained and efficient traffic information for real-time traffic estimations [2]. When recognizing driving behavior, two types of driving behavior are usually considered: is the first type includes lateral driving behaviors, such as lane changing and lane keeping, and the other includes longitudinal driving behaviors, including acceleration, braking, and stopping or cruising. Monitoring longitudinal driving behaviors can provide real-time data on the movement status of a vehicle, which is very useful for monitoring traffic flow and controlling congestion. In addition, the identification of these longitudinal driving behaviors could help identify undesirable driving behaviors, such as sudden acceleration, sharp braking, etc., so as to achieve early warnings and risk management for traffic accidents. Moreover, such information can be used to evaluate a driver's driving style [3], thus helping the driver to identify and improve bad driving habits and improve driving safety.With the development of the vehicle-infrastructure cooperative system (VICS) [4] in recent years, the OBU (on-board units) has become an essential communication device and is responsible for collecting vehicle-side information and transmitting it to external equipment.

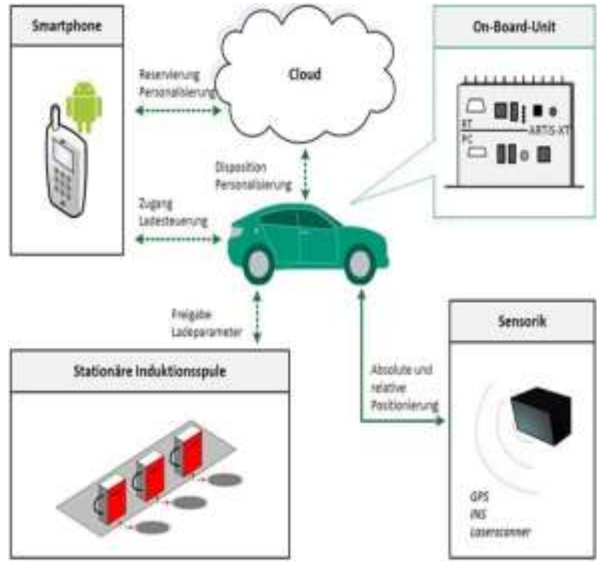

Fig. 1. Functional architecture of vehicle OBU communication system.

OBU is usually embedded with acceleration sensors or IMU sensors, providing the possibility of dynamically monitoring driving behavior with future connected vehicles (CVs). Therefore, monitoring driving behavior with the support of an OBU is a promising means of collecting microscopic traffic information in ITS and could support better traffic management and safety assurance applications. However, few studies have explored the possibility of OBU-supported driving behavior monitoring [5]. Therefore, the present work aims to explore the possibility of applying an OBU for dynamically monitoring longitudinal driving behavior via machine learning approaches.

2. LITERATURE SURVEY

Recent advancements in intelligent transportation systems (ITS) have significantly leveraged machine learning, vehicular communication technologies, and onboard sensing systems to improve driving behavior analysis, road safety, and vehicle-to-everything (V2X) communication frameworks. Wei et al. [6] proposed a machine learning-based approach for monitoring longitudinal driving behavior using an onboard unit (OBU). By collecting velocity, three-axis acceleration, and angular velocity data from mobile vehicle terminals, several machine learning classifiers including support vector machine (SVM), random forest (RF), k-nearest neighbors (KNN), logistic regression (LR), backpropagation neural network (BPNN), decision tree (DT), and Naïve Bayes (NB) were applied. Their results indicated that SVM, RF, and DT provided the most reliable performance in identifying different driving behaviors. Data availability is a critical factor affecting the performance of machine learning models in transportation systems. Krump et al. [7] addressed this issue by investigating the use of synthetic data generated from virtual simulation environments for vehicle detection tasks. Their study compared real and synthetic aerial image datasets and demonstrated that synthetic data can effectively supplement limited real-world datasets, improving training efficiency while maintaining acceptable detection performance.

Vehicular communication systems play an essential role in enabling cooperative intelligent transportation environments. Zadobrischi et al. [8] analyzed communication protocols for vehicle-to-vehicle (V2V) and vehicle-to-road infrastructure (V2R) communications. Through simulation-based evaluations, their study demonstrated that combining communication protocols improves message transmission efficiency and reduces latency, which is critical for road safety applications. Similarly, Sedar et al. [9] developed a standards-compliant onboard unit capable of supporting multiple V2X communication protocols across heterogeneous cloud services. Their real-world deployment experiments validated the interoperability of the system and demonstrated reliable low-latency communication between vehicles and cloud-based services. The evolution of cellular communication technologies also contributes significantly to the development of autonomous and connected vehicles. Kanavos et al. [10] examined the communication requirements of advanced autonomous driving applications and evaluated the capabilities of 4G and 5G networks in supporting these services. Their findings highlight that next-generation cellular networks provide improved latency performance and spectrum efficiency required for real-time vehicular communication systems.

Scalability and reliability of cooperative intelligent transportation systems (C-ITS) have also been widely investigated. Hossan et al. [11] conducted a scalability study comparing two standardized short-range vehicular communication technologies, ITS-G5 and cellular vehicle-to-everything (C-V2X). Their simulation results indicated that ITS-G5 performs better at short communication distances, while C-V2X provides better signal robustness at medium and long distances, making both technologies suitable for different deployment scenarios. Security remains a major challenge in vehicular communication systems. Muslam et al. [12] analyzed existing security protocols used in V2V communication systems and identified several vulnerabilities affecting secure message exchange. Their study proposed enhancements to existing protocols to strengthen the reliability and security of intelligent transportation communication systems. In a broader perspective, Rathore et al. [14] reviewed cybersecurity challenges in in-vehicle communication networks, analyzing different communication architectures, protocols, and security mechanisms including machine learning-based intrusion detection and cryptographic solutions. They also proposed a multi-layer security framework designed to provide protocol-independent protection for in-vehicle communication networks.

Technological cooperation between communication systems, infrastructure, and vehicles is another important factor in enhancing road safety. Arena and Pau [13] investigated emerging intelligent road infrastructure systems and communication protocols that support cooperative vehicular environments. Their analysis demonstrated that integrating advanced communication technologies significantly improves traffic management and road safety outcomes. Finally, Alabdouli et al. [15] examined road guidance systems (RGS) and their integration with V2X communication technologies. Their study evaluated various communication architectures and proposed a framework for integrating RGS with next-generation V2X systems, highlighting the importance of robust communication infrastructure for future intelligent transportation applications.

2.1 Research Gap and Motivation

Several studies have explored intelligent transportation systems using machine learning, vehicular communication protocols, and onboard sensing technologies. For example, machine learning algorithms have been used to analyze driving behavior using onboard sensor data [6], while synthetic data generation techniques have been proposed to improve model training when real-world datasets are limited [7]. In addition, vehicular communication frameworks such as V2V, V2R, and V2X have been widely studied to enhance cooperative vehicle communication and road safety [8], [9]. Research has also investigated advanced communication infrastructures including 4G, 5G, ITS-G5, and C-V2X to improve latency and communication reliability for autonomous driving applications [10], [11].

However, most existing studies primarily focus on communication efficiency, protocol interoperability, or driving behavior analysis rather than evaluating the capability and reliability of vehicular communication units themselves. Furthermore, current security and communication frameworks mainly address protocol-level protection and network performance but lack intelligent mechanisms for predicting communication performance degradation under uncertain network conditions [12], [14]. Traditional machine learning methods also struggle to capture the non-linear and uncertain characteristics of real-time vehicular communication environments.

Motivated by these limitations, this research proposes a Deep Fuzzy Logic (DFL)-based framework for automated capability assessment of autonomous vehicle communication units. By incorporating fuzzy representations of network metrics and integrating them with machine learning regression, the proposed approach aims to model uncertainty in communication performance and provide a reliable diagnostic mechanism for improving the safety and efficiency of autonomous vehicular networks.

3. PROPOSED METHODOLOGY

This research is a web-based machine learning system built using Flask that performs predictive analysis for estimating the Eligible score of entities (e.g., vehicles, nodes, or other units) using multiple regression models. The systemin Fig. 2 is designed to handle dataset uploads, preprocessing, EDA, model training, and both single and batch predictions**.** It integrates a proposed DFE Regressor as the main predictive model, along with several conventional regression models for comparison. The workflow begins with the dataset upload interface, where users can upload CSV files. Uploaded datasets are processed through the MLProcessor class, which performs data cleaning, encoding of categorical features, and splitting into training and testing sets. The system supports automatic labels encoding for categorical data, filling missing values, and ensures the dataset is ready for regression tasks. Once the dataset is processed, the system provides an EDA module that generates histograms, boxplots, scatter plots, and correlation heatmaps to visualize relationships among features such as RAM, Storage, Trust factor, and Transmission Rate with respect to the target variable Eligible. This helps users understand the distribution and influence of different features before model training. The proposed DFE Regressor improves prediction accuracy by encoding input features into multiple fuzzy membership values, capturing nonlinear relationships and uncertainties in the data. Its hybrid architecture combines the robustness of Random Forest with the linearity and interpretability of Linear Regression, making it suitable for real-time capability assessment in autonomous systems.

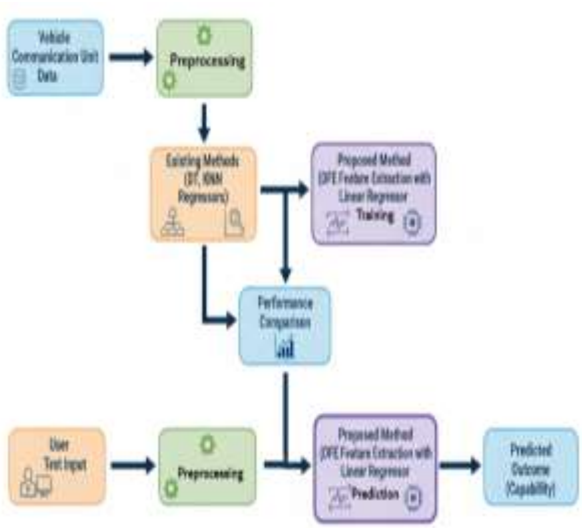

Fig. 2. System architecture for assessing autonomous vehicle communication units.

4. RESULTS DESCRIPTION

Fig. 3 shows the user interface of the Vehicle Eligibility Prediction System, designed to help users upload a dataset containing vehicle capability data (e.g., RAM, storage, trust factor, transmission rate, and eligibility). The interface allows users to select and upload a CSV file, after which they can train machine learning models using algorithms like Decision Tree Regressor, Orthogonal Matching Pursuit, and DFE + Linear Regressor. The system also provides options to evaluate model performance by comparing metrics like accuracy and mean squared error, and to make predictions for new vehicles to determine their eligibility score. The layout is intuitive, with distinct sections for dataset upload, model training, performance evaluation, and prediction, ensuring easy and efficient user experience.

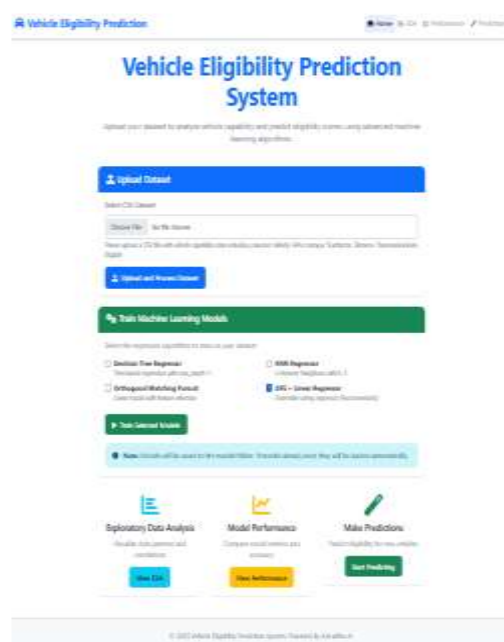

Fig. 3. Web interface of vehicle eligibility prediction system application.

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Fig. 4 displays the web interface of vehicle eligibility prediction system. In this section, users can select one or more regression algorithms to train on the uploaded dataset. The available models include Decision Tree Regressor, Orthogonal Matching Pursuit, K-Nearest Neighbors (KNN) Regressor, and DFE + Linear Regressor (Ensemble voting regressor), with specific parameters indicated for each model, such as max_depth=1 for the Decision Tree and k=5 for KNN. Once the models are selected, users can click on the "Train Selected Models" button to begin the training process. This part of the interface is designed to be user-friendly, allowing users to easily choose the models they want to use for their analysis.

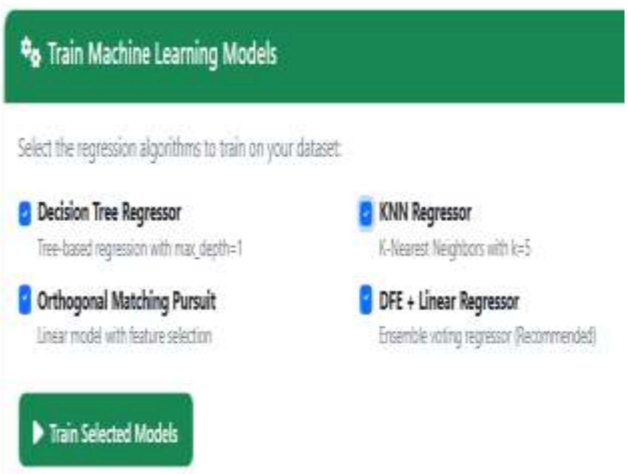

Fig. 4. User Interface for Training Machine Learning Models.

Fig. 5. Performance Metrics Comparison Interface after Training the models.

Fig 5 illustrates the Performance Metrics Comparison Interface displayed after training machine learning models in the Vehicle Eligibility Prediction System. It shows the comparison of four regression models (Decision Tree Regressor, Orthogonal Matching Pursuit Regressor, KNN Regressor, and DFE + Linear Regressor) based on various performance metrics, including MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and R^2 Score. Each model is evaluated, and the performance is rated as Fair or Excellent based on the results. The interface also provides explanations of the metrics, helping users understand the significance of each one. This visualization assists users in selecting the best-performing model based on the comparison of these key metrics.

Fig. 6 illustrates the scatter plots of actual versus predicted values for the four regression models (a) Decision Tree, (b) Orthogonal Matching Pursuit (OMP), (c) K-Nearest Neighbors (KNN), and (d) proposed DFE with Linear Regression (DFE + LR) provide insight into their predictive performance. The Decision Tree model shows a clustering of predictions into distinct horizontal bands, indicating limited variability and potential overfitting or underfitting. The OMP model exhibits a more scattered distribution around the diagonal line, suggesting moderate predictive accuracy with some spread, reflecting its ability to handle sparse data. The KNN model displays a dense, evenly distributed scatter along the diagonal, indicating a strong correlation between actual and predicted values, though with some noise. The proposed DFE with LR model demonstrates the tightest alignment with the diagonal line, suggesting superior predictive accuracy and consistency, likely due to the

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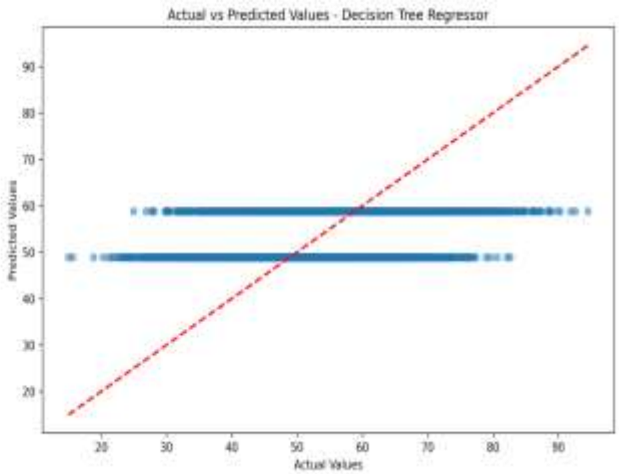
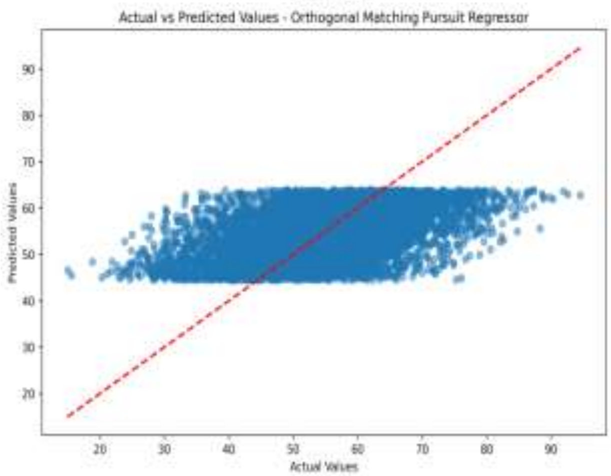
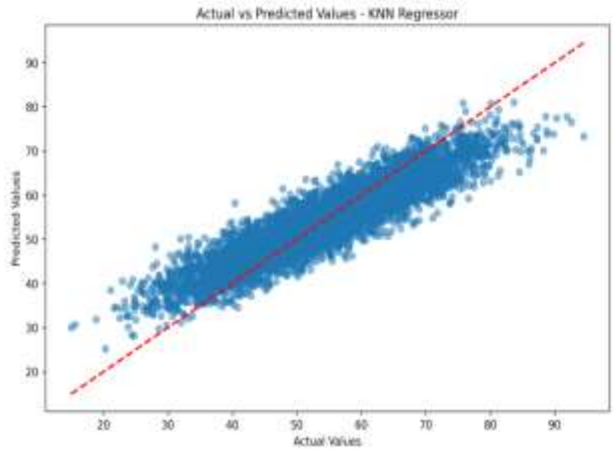
combination of Deep Fuzzy Encoding and Linear Regression's interpretability.

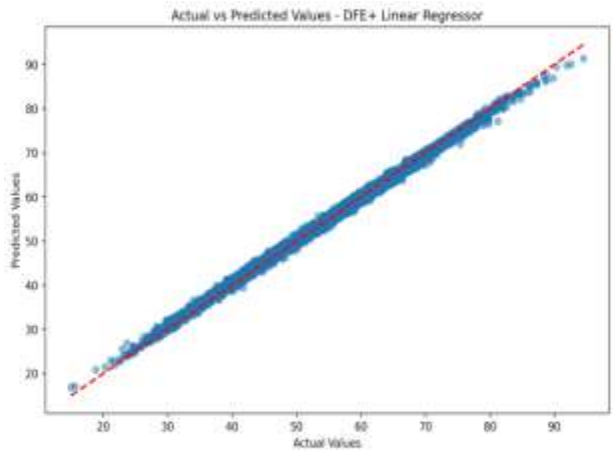




(a)

(b)





(c)

(d)

Fig. 6. Scatter plot of actual vs predictions obtained using (a) DTR model.

(b) OMP model. (c) KNN model. (d) Proposed DFE + LR model.

Fig. 7. Interface for model recommendations.

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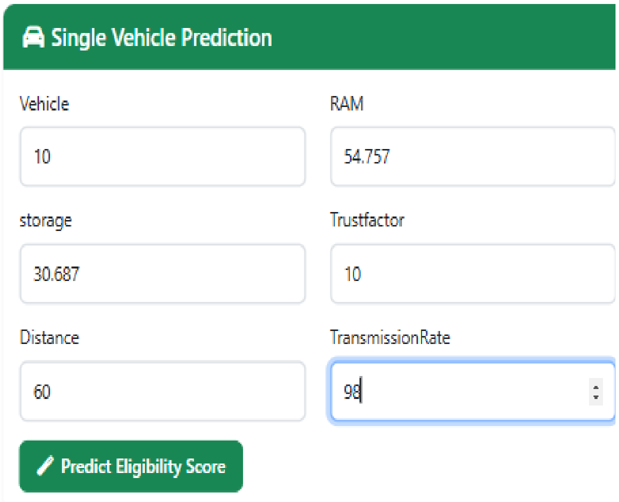

Fig. 8. Single vehicle prediction interface for single input analysis.

Fig. 7 shows the Model Recommendations Interface within the Vehicle Eligibility Prediction System. After evaluating multiple machine learning models, the system highlights the DFE + Linear Regressor as the best-performing model, based on its R^2 score of 0.9961 and MAE of 0.0006. The recommendation section provides a brief explanation, indicating that this model delivers the highest performance for vehicle eligibility prediction and will be used automatically for predictions on the prediction page. This guidance helps users understand which model to rely on for optimal prediction accuracy.

Fig. 8 illustrates the Single Vehicle Prediction Interface in the Vehicle Eligibility Prediction System, designed for users to predict the eligibility score of a single vehicle. Users input specific values for vehicle attributes, such as Vehicle ID, RAM, storage, trust factor, distance, and transmission rate. After entering the data, users can click on the "Predict Eligibility Score" button to receive the eligibility score prediction for that vehicle. This interface provides an easy and interactive way to analyze individual vehicles' eligibility scores based on the features.

Fig. 9. Prediction result of the test data.

Fig. 9 displays the Prediction Result for a single vehicle input in the Vehicle Eligibility Prediction System. After entering the vehicle's attributes and clicking "Predict Eligibility Score", the system provides the Predicted Eligibility Score, which in this case is 50.383037. This score reflects the vehicle's eligibility based on the machine learning model's analysis of the input data. The result is displayed in a clear and prominent manner, ensuring that users can easily interpret the output for further decision-making or analysis.

5. CONCLUSION

The research presented a comprehensive study on predicting vehicular performance using machine learning regression models, focusing on onboard unit capability datasets. Multiple models such as DTR, OMP, KNN, and a DFE + LR were trained and evaluated based on critical metrics such as MAE, MSE, RMSE, and R^2 Score. The comparative analysis revealed that traditional models like DTR and OMP struggled to achieve high accuracy, with R^2 Scores of 0.1590 and 0.2094, respectively, indicating limited generalization. The KNN model showed substantial improvement (R^2 = 0.8033), demonstrating its effectiveness in capturing local data structures. However, the most significant advancement came from the hybrid model, which combined the ensemble power of DFE with the linear interpretability of Linear

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Regression. It achieved an exceptional R^2 Score of 0.9961, MAE of 0.0006, and MSE of 0.0001, highlighting its robustness, low bias-variance tradeoff, and high generalization capability across test data. These results validate the superiority of hybrid modeling for high-resolution vehicular prediction tasks, enabling more informed and accurate decision-making for intelligent transportation systems. In addition to performance gains, the model's design allows for easy integration into GUI-based applications, improving user accessibility and real-time deployment feasibility. The modular architecture and preprocessing pipeline also ensure scalability to diverse vehicular datasets in future scenarios.

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