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Communication-Centric Capability Interactions in Vehicle Autonomy Interpreted via Deep Fuzzy Layers

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ABSTRACT

Autonomous vehicular communication networks are essential for modern intelligent transportation systems, enabling seamless data exchange among vehicles, roadside units, and centralized control systems. The performance of these networks depends on key parameters such as Random Access Memory (RAM), storage capacity, data transmission rate, and trust factor, which collectively determine the reliability and responsiveness of communication units. In dynamic traffic environments, accurately evaluating these capabilities is critical for ensuring safety, optimizing performance, and improving resource utilization. Traditional evaluation methods rely on manual inspections and threshold-based techniques that assess parameters independently. This approach fails to capture the complex interdependencies among system attributes, making it unsuitable for real-time vehicular scenarios and often leading to inaccurate capability estimation. To address this, machine learning (ML) regression models such as Decision Tree Regressor (DTR), Orthogonal Matching Pursuit Regressor (OMPR), and K-Nearest Neighbors Regressor (KNNR) have been applied. However, these models face challenges in handling nonlinear relationships, noise sensitivity, and generalization across diverse datasets. To overcome these limitations, this study proposes a hybrid Deep Fuzzy Regression (DFR) model that integrates Deep Fuzzy Encoding (DFE) with Random Forest Regressor (RFR) and Linear Regression (LR) in an ensemble framework. The DFE component effectively manages uncertainty and gradual feature variations, while RFR and LR enhance prediction robustness and stability. The system follows a structured pipeline including preprocessing, feature engineering, model training, and evaluation. Experimental results using MAE, MSE, RMSE, and R^2 demonstrate that the proposed model delivers more accurate and consistent predictions, improving communication efficiency and decision-making in autonomous vehicular networks.

Keywords: Autonomous vehicular networks, intelligent transportation systems, machine learning, deep fuzzy encoding, deep fuzzy regression.

1. INTRODUCTION

The rapid evolution of autonomous vehicle technology is significantly transforming modern transportation systems, with large-scale adoption expected in the near future. A fundamental aspect of these systems is reliable communication, where Vehicle-to-Vehicle (V2V) interaction plays a crucial role in enabling coordination, ensuring safety, and supporting real-time responsiveness. The efficiency of autonomous operations largely depends on the performance of communication units embedded within vehicles, as they facilitate key functions such as collision avoidance, traffic flow regulation, and intelligent decision-making. However, traditional approaches for evaluating these communication units are predominantly manual and static, making them unsuitable for highly dynamic vehicular environments. As shown as figure 1 these methods are often time-consuming and fail to capture variations in real-time conditions, resulting in inaccurate performance assessment. As autonomous transportation continues to advance, the need for

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intelligent, data-driven evaluation mechanisms has become increasingly important. At the same time, rising challenges related to traffic congestion and road safety have accelerated the adoption of connected and intelligent vehicle systems [1]. In this context, real-time monitoring of driving behavior has emerged as a critical factor in enhancing vehicle control and traffic management. Analyzing driving patterns provides valuable insights that support advanced control strategies and enable more effective traffic supervision. For autonomous systems to respond efficiently to changing road conditions, accurate recognition of driving behavior in real time is essential.

Driving behavior is typically classified into lateral behaviors, such as lane changes and lane keeping, and longitudinal behaviors, including acceleration, braking, cruising, and stopping. Among these, longitudinal behaviors are particularly important as they provide continuous information about vehicle motion, which is essential for monitoring traffic flow and managing congestion [2]. Additionally, identifying abnormal patterns such as sudden acceleration or harsh braking can support early warning systems and accident prevention strategies, while also contributing to safer driving practices.

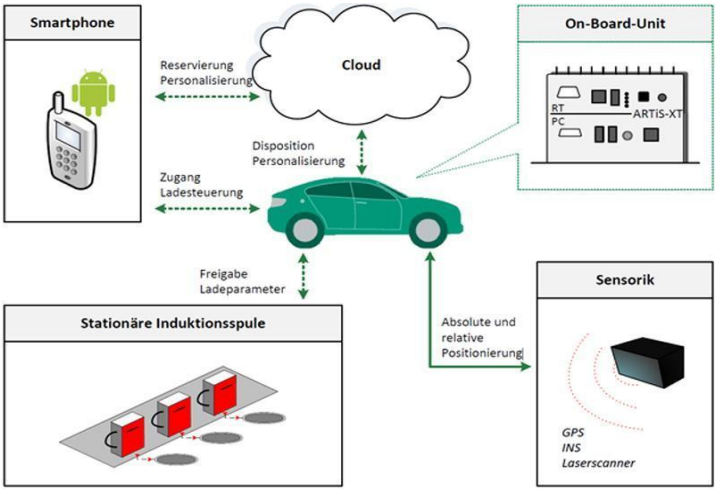


Figure 1: Functional Architecture of Vehicle On-Board Unit Communication System

With the advancement of Vehicle Infrastructure Cooperative Systems (VICS), On-Board Units (OBU) have become essential components in connected vehicle environments [3]. These units are responsible for collecting vehicle-level data and transmitting it to external systems for further processing. Modern OBUs are commonly equipped with sensors such as Inertial Measurement Units (IMU), which enable continuous monitoring of vehicle dynamics [4]. This capability makes OBU-based systems highly effective for capturing detailed driving behavior and supporting intelligent transportation applications. Despite these advancements, the full potential of OBU-enabled systems for dynamic and real-time driving behavior analysis remains insufficiently explored [5]. This highlights the need for more effective approaches to leverage available data for improving traffic management, enhancing safety measures, and supporting the ongoing development of intelligent transportation systems.

2. LITERATURE SURVEY

Wei et al. [6] proposed the monitoring of longitudinal driving behavior using a machine learning approach with the support of an on-board unit (OBU). Specifically, based on velocity, three-axis acceleration and

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three-axis angular velocity data were collected by a mobile vehicle terminal OBU; through the process of data preprocessing and feature extraction, seven machine learning algorithms, including support vector machine (SVM), random forest (RF), k-nearest neighbor algorithm (KNN), logistic regression (LR), BP neural network (BPNN), decision tree (DT), and the Naive Bayes (NB), were applied to implement the classification and monitoring of the longitudinal driving behavior of probe vehicles. The results showed that the three classifiers SVM, RF and DT achieved good performances in identifying different longitudinal driving behaviors.

Krump et al. [7] evaluated the performance of deep learning-based algorithms was significantly influenced by the quantity and quality of the available training and test datasets. Since data acquisition was complex and expensive, especially in the field of airborne sensor data evaluation, the use of virtual simulation environments for generating synthetic data were increasingly sought. In this article, the complete process chain was evaluated regarding the use of synthetic data based on vehicle detection. Among other things, content-equivalent real and synthetic aerial images were used in the process. This included, in the first step, the learning of models with different training data configurations and the evaluation of the resulting detection performance. Subsequently, a statistical evaluation procedure based on a classification chain with image descriptors as features was used to identify important influencing factors in this respect. Zadobrischi et al. [8] offered an opportunity to use common communication adaptable protocols, depending on the context of the situation, coding techniques, scenarios, analysis of transfer rates, and reception of messages according to the type of protocol used. Communications between the road infrastructure and users through a relative communication protocol were highlighted and simulated in this manuscript. The results obtained by the proposed and simulated scenarios demonstrated that it was complementary and that the common node of V2V/V2R (R2V) communication protocols substantially improved the process of transmitting messages in low-latency conditions and was ideal for the development of road safety systems.

Sedar et al. [9] presented the development of a standards-compliant experimental vehicular on-board unit (OBU) that supported the integration of multiple V2X protocols from different vendors to communicate with heterogeneous cloud-based services that were offered by several original equipment manufacturers (OEMs). They experimentally demonstrated the functionalities of the OBU in a real-world deployment of a cooperative collision avoidance service infrastructure that was based on edge and cloud servers. In addition, they measured end-to-end application-level latencies of multi-protocol supported V2X information flows to show the effectiveness of interoperability in V2X communications between different vehicle OEMs. Kanavos et al. [10] provided a comprehensive analysis of these use cases and a harmonized view of the requirements for the latest and most advanced autonomous driving applications. It also investigated the extent of support that 4G and 5G networks could offer to these use cases in terms of delay and spectrum needs. The paper identified open issues and discussed trends and potential solutions.

Hossan et al. [11] presented a comprehensive scalability study of C-ITSs to support a deployment of Day 1 advisory services on the busiest Irish motorway. Specifically, the performance of the two standardized C-ITS short-range communication technologies, namely ITS-G5 and C-V2X, were quantified. Both technologies were evaluated while considering different market penetration rates (MPRs), real-world vehicle densities during daily time periods, and data traffic demands linked to real world C-ITS services. The simulation results showed that ITS-G5 performed slightly better at shorter distances, and C-V2X performed marginally better at medium and longer distances, benefiting from technology that supported

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better signal quality and communication robustness. Muslam et al. [12] aimed to provide a comprehensive understanding of the strengths and weaknesses of the current V2V communication security protocols. Furthermore, based on the findings, this paper proposed improvements and recommendations to enhance the security measures of the V2V communication protocol. Ultimately, this research contributed to the development of more secure and reliable V2V communication systems, propelling the advancement of intelligent transportation technology.

Arena et al. [13] examined and assessed the most relevant systems, applications, and communication protocols that would distinguish the future road infrastructures used by vehicles. The results of the investigation revealed the real benefits that technological cooperation could involve in road safety.

Rathore et al. [14] explored the literature on cyber security for in-vehicle communication focusing on technical architecture, methodologies, challenges, and possible solutions. In-vehicle communication network architecture was presented considering key components, interfaces, and related technologies. The protocols for in-vehicle communication had been classified based on their characteristics, and usage type. Security solutions for in-vehicle communication had been critically reviewed considering machine learning, cryptography, and port-centric techniques. A multi-layer secure framework was also developed as a protocol and use case-independent in-vehicle communication solution. Finally, open challenges and future dimensions of research for in-vehicle communication cyber security were highlighted as observations and recommendations. Alabdouli et al. [15] aimed to evaluate the RGS architectures proposed to date in the literature, providing comparisons and classifications based on their structures and requirements for communication systems. Moreover, it explored existing, next generation, as well as prospective choices for V2X communication technologies, evaluating how well they contributed to the development of RGS applications by integrating them with potential communication systems. Specifically, this study assessed the suitability of communication technologies in meeting the requirements of RGS applications. In conclusion, it suggested a framework for integrating RGS and V2X systems and offered directions for future research in this area.

3. PROPOSED SYSTEM

The system architecture is designed as an integrated pipeline that connects a Flask-based web interface with a backend ML processing module for intelligent capability prediction. Users initiate the workflow by uploading datasets and interacting with functionalities such as EDA, model training, and prediction through predefined routes. The uploaded data is systematically processed through data handling stages, including preprocessing, encoding, and dataset splitting to ensure quality input for model learning. Within the ML processor, detailed EDA is performed to analyze feature distributions and relationships, enabling better understanding of the dataset.

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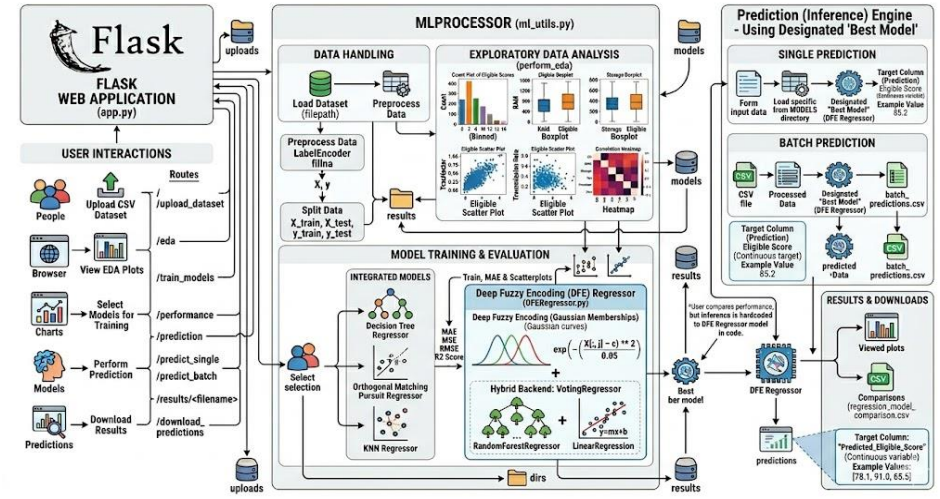


Figure 2: Proposed System Architecture

The processed data is then passed into multiple regression models, including DTR, OMPR, and KNNR, which are trained and evaluated using standard performance metrics. In addition to these baseline models, a hybrid DFR model is implemented by integrating DFE with RFR and LR to improve robustness and handle uncertainty in feature values. All models are compared based on MAE, MSE, RMSE, and R^2 scores, and the best-performing model is selected automatically. This selected model is then deployed within the prediction engine, which supports both single input and batch predictions. The system generates outputs in the form of predicted values, visual plots, and downloadable reports. The architecture ensures a seamless flow from data input to result generation, enabling efficient, accurate, and scalable prediction as depicted in Figure 2.

Step 1: User Interaction and Dataset Upload: The process begins with a Flask web application that provides an interactive interface for users. Users can upload datasets, view EDA plots, train models, and perform predictions through dedicated routes. This layer ensures accessibility and smooth communication between the user and backend components.

Step 2: Data Handling and Preprocessing: Once the dataset is uploaded, it undergoes preprocessing steps such as handling missing values, label encoding, and separating features and target variables. The cleaned dataset is then divided into training and testing sets. This step ensures that the data is properly structured and suitable for effective model training.

Step 3: Exploratory Data Analysis (EDA): EDA is conducted to understand the statistical properties and relationships within the dataset. Visualizations like scatter plots, box plots, and heatmaps are generated to identify correlations, trends, and outliers. These insights assist in improving model performance and guiding feature understanding.

Step 4: Model Training and Evaluation: The processed data is used to train multiple regression models, including DTR, OMPR, and KNNR. Each model learns the relationship between input features and the target variable. Their performance is evaluated using MAE, MSE, RMSE, and R^2 metrics, enabling a comparative analysis of prediction accuracy and generalization.

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Step 5: Hybrid DFR Model Construction: A hybrid DFR model is developed by combining DFE with RFR and LR using an ensemble approach. The DFE component transforms input features into fuzzy representations to handle uncertainty and gradual transitions. The integration of RFR and LR enhances prediction stability and captures both nonlinear and linear relationships effectively.

Step 6: Prediction Engine and Result Generation: After evaluation, the best-performing model among DTR, OMPR, KNNR, and DFR is selected and deployed in the prediction engine. The system supports both single prediction (manual input) and batch prediction (CSV input). Final outputs include predicted values, visual performance plots, and downloadable result files, ensuring usability and transparency.

4. RESULTS ANALYSIS

The results of the proposed system demonstrate that the Hybrid Deep Fuzzy Regression (DFR) model provides more accurate and consistent predictions of the Eligible Score compared to traditional regression models. By effectively combining fuzzy logic with ensemble learning, the model successfully captures both nonlinear relationships and uncertainty present in OBU communication parameters. Evaluation metrics such as MAE, MSE, RMSE, and R^2 indicate improved performance and better generalization on unseen data. The system also enables clear visualization of prediction accuracy through comparative plots, enhancing interpretability. The results validate that the proposed approach significantly improves capability assessment and supports efficient decision-making in autonomous vehicular communication systems.

Figure 3: Exploratory data analysis of Vehicular OBU Capability (VOCC) data. countplot of Eligible score (toprow-left). Boxplot of Eligible score by RAM Ranges(toprow - middle). Boxplot of Eligible score by Storage Ranges (toprow-right). Scatterplot of Eligible Score vs Trustfactor(bottom row - left). Scatter plot of Eligible Score vs Transmission Rate (bottom row - middle). Correlation heatmap (bottom row - right).

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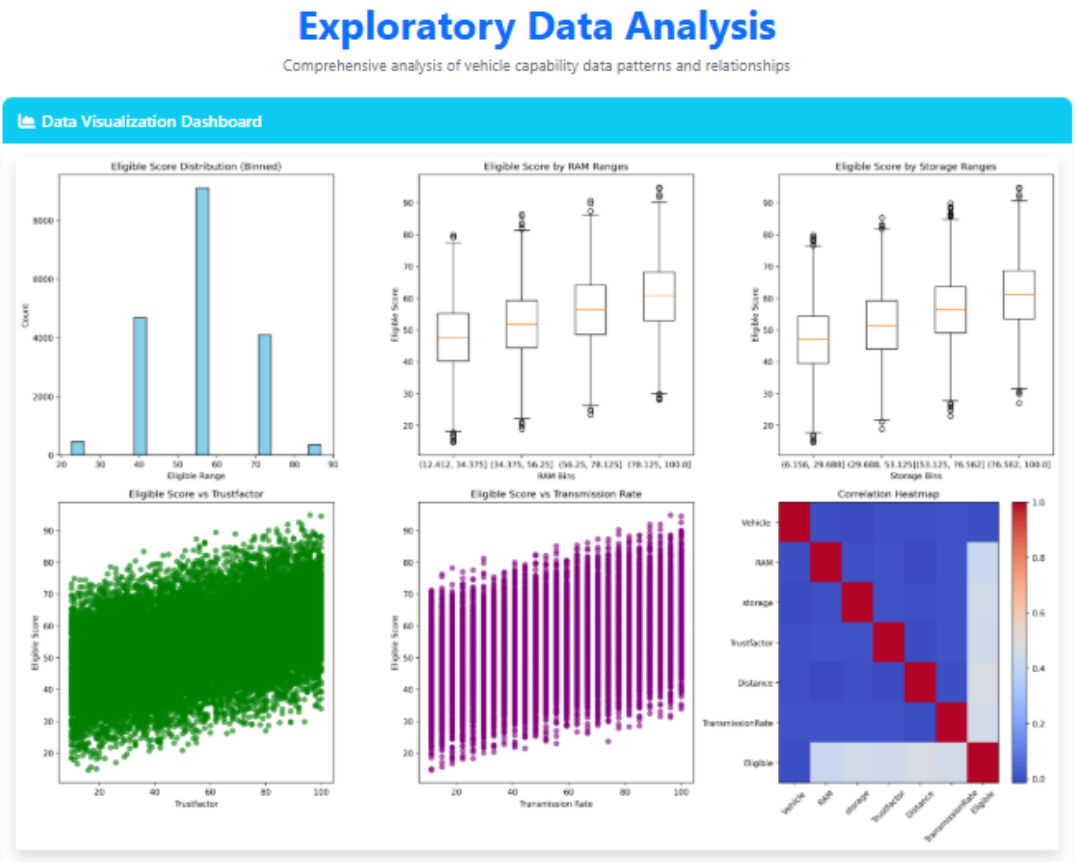


Figure 3: EDA for Vehicle Communications

Figure 3.1 - Eligible Score Distribution (Binned) (top row - left):

- This countplot displays the distribution of the Eligible score across binned ranges. The plot shows a significant concentration of vehicles in the higher Eligible score range (around 60-70), indicated by a tall green bar. Other bins (e.g., 40-50, 50-60) have moderate counts (orange and red bars), while the lower ranges (below 40) have minimal representation (blue and purple bars), suggesting most vehicles have above-average eligibility.

Figure 3.2 - Eligible Score by RAM Ranges (top row - middle):

- This boxplot illustrates the distribution of Eligible scores across different RAM ranges. Each box represents a RAM range (e.g., 0-32, 32-64, 64-96), with medians marked by lines inside the boxes. The green box (higher RAM range) shows a higher median Eligible score compared to the orange and blue boxes (lower RAM ranges), indicating a positive relationship between RAM and eligibility, with some variability (whiskers and outliers).

Figure 3.3 - Eligible Score by Storage Ranges (top row - right):

- This boxplot shows the distribution of Eligible scores across different Storage ranges. Similar to the RAM boxplot, higher storage ranges (green box) have a higher median Eligible score, while

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lower ranges (blue and orange boxes) show lower medians. The spread of data (whiskers) suggests variability, with potential outliers affecting the upper bounds of eligibility.

Figure 3.4 - Eligible Score vs Trustfactor (bottom row - left):

- This scatterplot depicts the relationship between Eligible score and Trustfactor. A dense green cluster indicates that most vehicles have Trustfactor values between 20 and 80, with Eligible scores generally ranging from 40 to 70. The spread suggests a weak positive correlation, with higher Trustfactor values occasionally corresponding to higher Eligible scores.

Figure 3.5 - Eligible Score vs Transmission Rate (bottom row - middle):

- This scatterplot explores the relationship between Eligible score and TransmissionRate. The purple vertical bands indicate TransmissionRate values clustered around 40, 70, and 100, with Eligible scores varying widely (40-70). The plot suggests no strong linear correlation, but higher TransmissionRate values (e.g., 100) may slightly elevate Eligible scores.

Figure 3.6 - Correlation Heatmap (bottom row - right):

- This heatmap displays the correlation coefficients between variables in the dataset. Strong positive correlations (e.g., RAM and Eligible at 1.00, Storage and Eligible at 0.95) are shown in dark red, indicating a near-perfect relationship. Weaker correlations (e.g., Distance and Eligible at 0.47) appear in lighter shades. The diagonal (1.00) reflects perfect self-correlation, while negative or negligible correlations (e.g., Vehicle with others) are in blue.

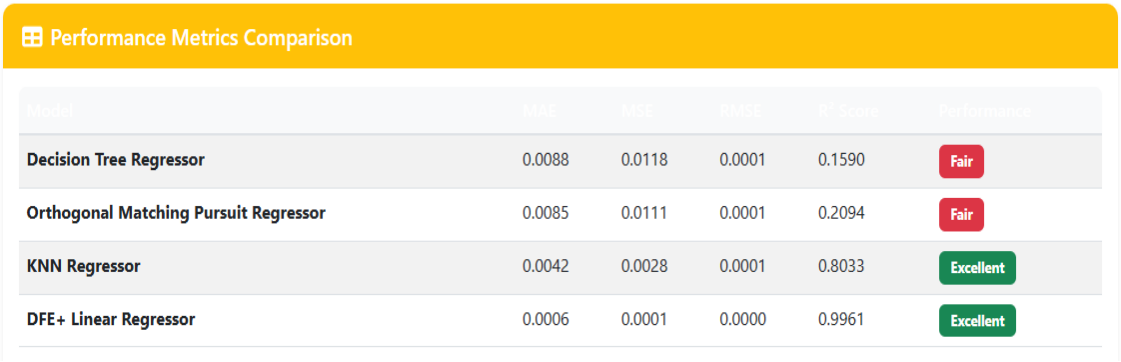


Figure 4: Performance Metrics Comparison Interface after Training the models.

Figure 4: Performance Metrics Comparison Interface after Training the Models. This figure 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 based on various performance metrics, including MAE, MSE, RMSE, 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.

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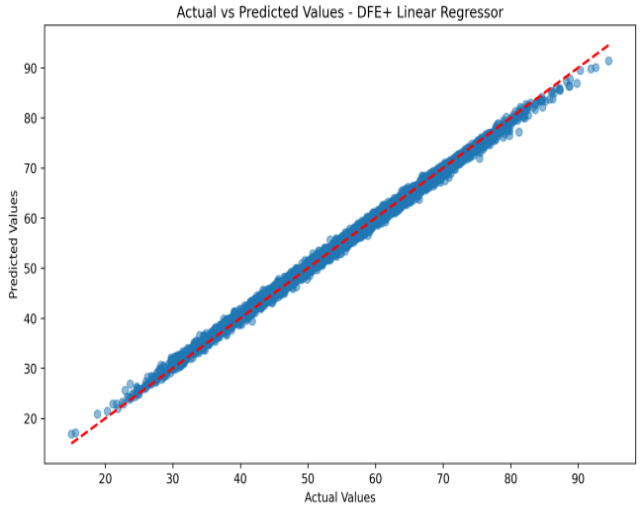


Figure 5: Scatter plot of actual vs predictions obtained using Proposed DFR model.

The figure 5 illustrates the relationship between actual values and predicted values generated by the proposed DFR model. The data points are closely aligned along a straight diagonal trend, indicating a strong correlation between predicted and actual outcomes. This alignment suggests that the model is highly accurate in estimating the Eligible Score across different input ranges. The minimal deviation of points from the diagonal line reflects low prediction error and high consistency. The plot confirms that the proposed model achieves reliable and precise prediction performance.

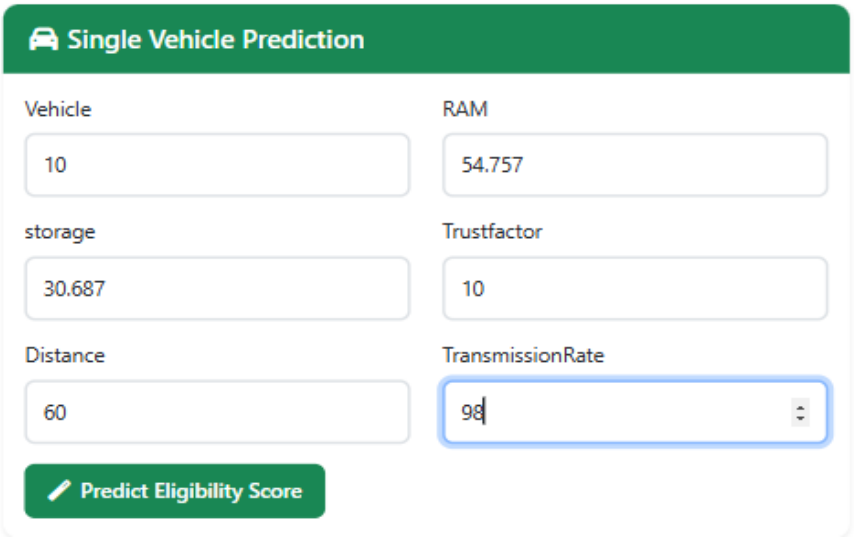


Figure 6: Single Vehicle Prediction Interface for Single Input Analysis.

Figure 6: Single Vehicle Prediction Interface for Single Input Analysis. This figure 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

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provides an easy and interactive way to analyze individual vehicles' eligibility scores based on the input features.

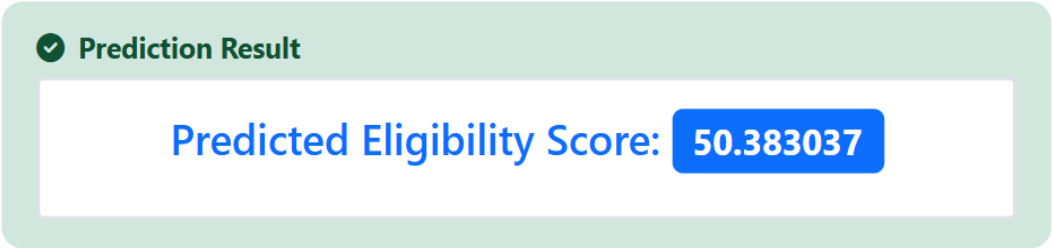


Figure 7: Prediction Result of the Test Data.

Figure 7: Prediction Result of the Test Data. This figure 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.

Table 1: Performance evaluation obtained using existing Decision Tree, OMP, KNN, and proposed DFE +LR regression models.

Model	MAE	MSE	RMSE	R2Score
DTR	0.0088	0.0118	0.0001	0.1590
OMPR	0.0085	0.0111	0.0001	0.2094
KNN Regressor	0.0042	0.0028	0.0001	0.8033
DFR	0.0006	0.0001	0.0000	0.9961

Table 1 represents an introduction to the performance metrics of four regression models evaluated through Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R2 Score.

- **Decision Tree Regressor**: This model has an MAE of 0.0088, MSE of 0.0118, RMSE of 0.0001, and an R2 Score of 0.1590. The relatively high MAE and MSE, combined with a low R2 Score, suggest that the model struggles to accurately predict values, likely due to overfitting or limited ability to capture complex patterns.
- **Orthogonal Matching Pursuit Regressor**: This model shows a slightly better performance with an MAE of 0.0085, MSE of 0.0111, RMSE of 0.0001, and an R2 Score of 0.2094. The marginal improvement over the Decision Tree Regressor indicates a better fit for sparse data, though the R2 Score remains low, reflecting moderate predictive accuracy.

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- **KNN Regressor**: This model performs significantly better, with an MAE of 0.0042, MSE of 0.0028, RMSE of 0.0001, and an R2 Score of 0.8033. The lower errors and higher R2 Score suggest a strong correlation between actual and predicted values, indicating good predictive performance with some noise.
- **DFE + Linear Regressor**: The hybrid model excels with an MAE of 0.0006, MSE of 0.0001, RMSE of 0.0000, and an impressive R2 Score of 0.9961. These metrics indicate exceptional predictive accuracy and consistency, likely benefiting from the combined strengths Deep Fuzzy Encoding and Linear Regression's interpretability.

5. CONCLUSION

This study presents an ML-based framework designed to estimate the capability of vehicular communication units by leveraging regression techniques trained on OBU datasets. Multiple models, including DTR, OMPR, KNNR, and a hybrid DFR model that combines DFE with LR, are developed and assessed using performance metrics such as MAE, MSE, RMSE, and R^2 score. The evaluation results reveal that traditional models like DTR and OMPR exhibit limited predictive strength, with R^2 scores of 0.1590 and 0.2094, indicating poor generalization across the dataset. In contrast, KNNR demonstrates a significant improvement, achieving an R^2 value of 0.8033, reflecting its capability to effectively capture localized data patterns. Among all approaches, the DFR model delivers the highest performance, attaining an R^2 score of 0.9961 along with minimal error values (MAE = 0.0006 and MSE = 0.0001), highlighting its superior prediction accuracy. These findings indicate that integrating fuzzy-based feature transformation with regression techniques substantially improves the modeling of complex and uncertain relationships present in vehicular communication data. Additionally, the system is implemented with a modular design and a web-based interface, ensuring scalability and enabling efficient real-time capability evaluation within intelligent transportation systems.

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