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Deep Fuzzy Interpretive Modeling for Capability Exploration in Autonomous Vehicle Communication Architectures

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ABSTRACT

Autonomous vehicular communication systems are essential for intelligent transportation, enabling continuous data exchange among vehicles, infrastructure, and centralized networks. These systems rely on key parameters such as Random Access Memory (RAM), storage capacity, transmission rate, and trust factor to ensure efficient and reliable communication. In dynamic environments, accurately evaluating communication unit capability is crucial for maintaining system performance, safety, and optimal resource utilization. Traditional assessment methods depend on manual configuration checks and threshold-based monitoring, treating parameters independently and failing to capture complex interdependencies. This limitation results in unreliable capability estimation in real-time scenarios. To improve automation and prediction accuracy, machine learning models including Decision Tree Regressor (DTR), Orthogonal Matching Pursuit Regressor (OMPR), and K-Nearest Neighbors Regressor (KNNR) are utilized. However, these models struggle with nonlinear relationships, noisy data, and generalization in complex datasets. To address these issues, 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) through an ensemble approach. The DFE component effectively handles uncertainty and gradual feature variations, while the hybrid model enhances robustness and predictive performance. The system follows a structured pipeline including data preprocessing, feature engineering, model training, and evaluation. Performance is measured using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). Results indicate that the proposed DFR model achieves reliable and consistent capability assessment, making it suitable for real-time vehicular communication systems and improving overall efficiency and decision-making.

Key words: Autonomous Vehicular Communication Systems, Intelligent Transportation Systems, Ensemble Learning, Communication Capability Assessment, Real-Time Data Processing.

1. INTRODUCTION

The rapid advancement of autonomous vehicles is reshaping modern transportation systems, with large-scale deployment expected in the coming years. A significant portion of autonomous operations depends on reliable communication mechanisms, particularly Vehicle-to-Vehicle (V2V) communication, which plays a critical role in ensuring safety, coordination, and real-time responsiveness. As shown as figure 1 The effectiveness of these systems largely depends on the performance of communication units embedded within vehicles, as they support functions such as collision avoidance, traffic flow optimization, and intelligent decision-making. Traditional evaluation techniques for communication units are predominantly manual and rely on static assessments, making them unsuitable for dynamic and real-time vehicular environments. These approaches are time-intensive and fail to capture variations in operational conditions, leading to inaccurate estimation of communication capability. As autonomous systems continue to evolve, there is an increasing need for intelligent, data-driven methods that can provide reliable and adaptive performance assessment. In parallel, the growing challenges of traffic congestion and road safety have accelerated the adoption of intelligent and connected vehicle technologies. Real-time monitoring of driving behavior has emerged as a key component in enhancing vehicle control and traffic management. Such monitoring provides valuable insights for intelligent control systems and supports fine-grained traffic analysis. To ensure timely and safe responses in autonomous driving, recognizing driving behavior in real time is essential [1]. Driving behavior is generally categorized into two types: lateral behaviors, which include lane changes and lane keeping, and longitudinal behaviors, such as acceleration, braking, cruising, and stopping. Among these, longitudinal behaviors are particularly important as they provide continuous information about vehicle motion, enabling effective traffic flow monitoring and congestion control. Additionally, identifying irregular patterns such as abrupt acceleration or harsh braking can support early warning systems and accident prevention strategies. These insights also contribute to evaluating driving patterns, thereby promoting safer driving practices [2]. With the evolution of Vehicle Infrastructure Cooperative Systems (VICS), On-Board Units (OBU) have become integral components in connected vehicle environments. These devices are responsible for collecting vehicle-level data and transmitting it to external systems. Modern OBU systems are often equipped with sensors such as Inertial Measurement Units (IMU), enabling continuous monitoring of vehicle dynamics. This capability makes OBU-based systems highly suitable for capturing detailed driving behavior and supporting intelligent transportation applications [3].

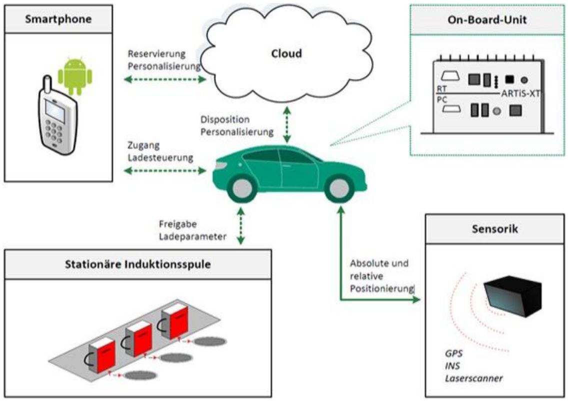


Figure 1: Functional architecture of vehicle on-board unit communication system

Despite these advancements, the potential of OBU-supported systems for dynamic driving behavior analysis remains underexplored [4]. Therefore, this work focuses on leveraging OBU data in combination with machine learning techniques to enable accurate and real-time monitoring of longitudinal driving behavior. This approach aims to enhance traffic management efficiency, improve safety mechanisms, and contribute to the development of more reliable intelligent transportation systems [5].

2. RELATED WORK

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 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 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 proposed system presents a complete machine learning-based framework for evaluating communication unit capability in autonomous vehicular environments. It integrates data ingestion, preprocessing, model training, evaluation, and prediction within a unified Flask-based web application. The architecture begins with secure user authentication, followed by dataset upload and structured preprocessing to transform raw inputs into model-ready features. Multiple regression models including DTR, OMPR, KNNR, and the proposed DFR are trained and evaluated to determine the most effective predictor. The DFR model leverages DFE along with RF and LR to enhance prediction robustness. The system further generates performance insights through visualization and metric evaluation, enabling comparative analysis across models. Finally, the trained model is deployed for both single and batch predictions through an interactive user interface, ensuring real-time usability and scalability as illustrated in Figure 2.

Step 1. User Authentication & Access Control: The system begins with a secure authentication mechanism implemented using a Flask-based web interface. Users are categorized into admin and general users, where admins have privileges to upload datasets, perform EDA, and train models, while users are limited to prediction functionalities. This role-based access ensures system security and controlled operation. Session management is handled to maintain login states and restrict unauthorized access.

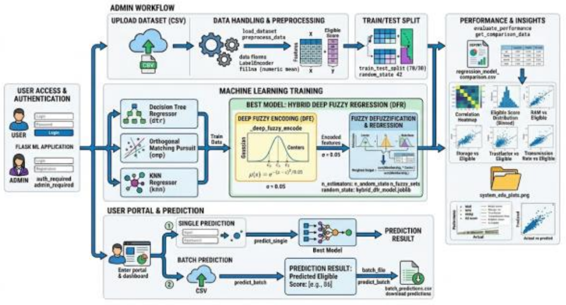


Figure 2: Proposed system architecture

Step 2. Dataset Upload & Preprocessing: The admin uploads the dataset in CSV format, which is then processed to remove irrelevant columns and handle missing values. Categorical features are converted into numerical form using Label Encoding, ensuring compatibility with machine learning models. The dataset is then split into feature variables and the target variable (Eligible score), followed by train-test splitting to prepare data for model training.

Step 3. Machine Learning Model Training: The processed dataset is used to train multiple regression models including DTR, OMPR, and KNNR as baseline approaches. In addition, the proposed DFR model is trained by integrating DFE with RF and LR using an ensemble strategy. This step focuses on learning the relationship between communication parameters and capability scores. Each model is trained using the same dataset to ensure fair comparison.

Step 4. Performance Evaluation & Visualization: After training, all models are evaluated using regression metrics such as MAE, MSE, RMSE, and R² score. The system generates visual insights including scatter plots for actual vs predicted values and correlation heatmaps. A comparison table is also created to analyze the performance of each model. These insights help in identifying the most effective model for deployment.

Step 5. Model Selection & Deployment: Based on the evaluation results, the best-performing model (DFR) is selected and saved for further use. The trained model is stored using joblib, allowing it to be reused without retraining. This ensures efficiency and reduces computational overhead during prediction. The deployment phase makes the model accessible through the web interface.

Step 6. Prediction (Single & Batch): The system supports both single and batch prediction modes through the user portal. In single prediction, users input feature values manually to obtain an immediate prediction. In batch prediction, users upload a CSV file, and the system processes all entries to generate predictions. The results are displayed on the interface and can also be downloaded as a CSV file for further analysis.

4. RESULTS ANALYSIS

The results demonstrate the effectiveness of the proposed Deep Fuzzy Regression (DFR) model in accurately predicting vehicular communication capability. Comparative analysis with baseline models such as Decision Tree Regressor (DTR), Orthogonal Matching Pursuit Regressor (OMPR), and K-Nearest Neighbors Regressor (KNNR) shows that DFR significantly outperforms them across all evaluation metrics. The model achieves minimal error values in terms of MAE, MSE, and RMSE, along with a high R² score, indicating strong predictive accuracy and consistency. Visualizations such as scatter plots and correlation heatmaps further validate the model's ability to capture complex relationships among features. The integration of Deep Fuzzy Encoding enhances handling of uncertainty and nonlinear patterns in the dataset.

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).

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).

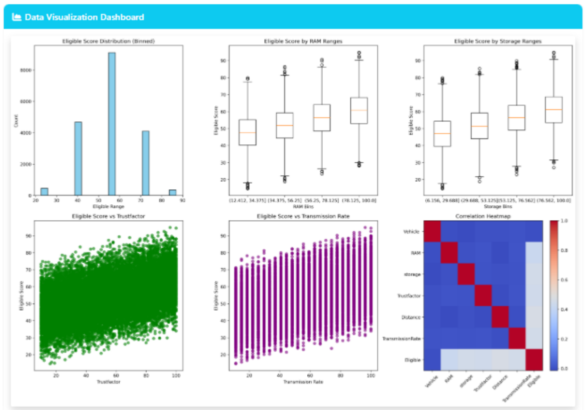


Figure 3: EDA for vehicle communications

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 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 Transmission Rate. The purple vertical bands indicate Transmission Rate values clustered around 40, 70, and 100, with Eligible scores varying widely (40-70). The plot suggests no strong linear correlation, but higher Transmission Rate 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.

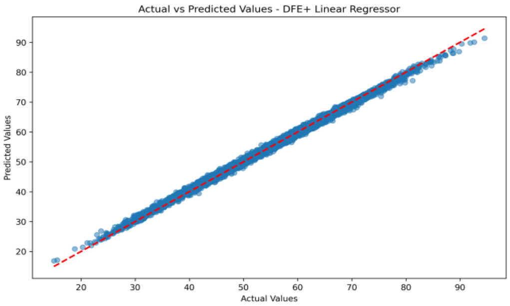
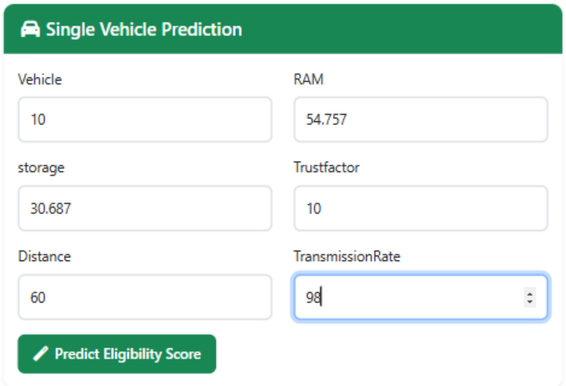


Figure 4: Scatter plot of actual vs predictions obtained using DFR model.

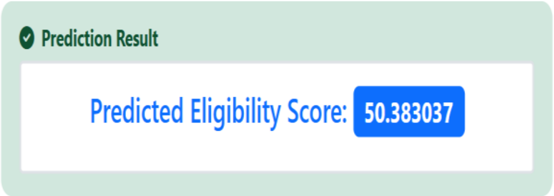
Figure 4 illustrates the relationship between actual and predicted values obtained using the DFE + Linear Regressor model. The data points closely align along the diagonal reference line, indicating a strong agreement between predicted and actual values. This alignment reflects high prediction accuracy and minimal deviation across the entire range of values. The consistency of the distribution suggests that the model effectively captures the underlying data patterns. The figure demonstrates the model's reliability and excellent generalization performance.


Single Vehicle Prediction

Vehicle: 10
RAM: 54.757
storage: 30.687
Trustfactor: 10
Distance: 60
TransmissionRate: 98

Figure 5: Single Vehicle Prediction Interface for Single Input Analysis.

Figure 5: 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 provides an easy and interactive way to analyze individual vehicles' eligibility scores based on the input features.


Prediction Result

Predicted Eligibility Score: 50.383037

Figure 6: Prediction Result of the Test Data.

Figure 6: 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
Proposed 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.
- **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

The research introduces a machine learning–driven framework for predicting the capability of vehicular communication units using regression models trained on onboard unit datasets. A set of models, including DTR, OMPR, KNNR, and a hybrid DFR approach that integrates DFE with LR, were implemented and evaluated using MAE, MSE, RMSE, and R^2 score. The results indicate that conventional models such as DTR and OMPR deliver relatively low predictive performance, with R^2 values of 0.1590 and 0.2094, suggesting weak generalization. KNNR shows a notable improvement, achieving an R^2 score of 0.8033, demonstrating its effectiveness in capturing local data structures. The proposed DFR model achieves the best performance, with an R^2 score of 0.9961 and very low error values (MAE = 0.0006 and MSE = 0.0001), indicating highly accurate predictions. These outcomes demonstrate that combining fuzzy-based feature representation with regression models enhances the ability to model complex relationships in vehicular communication data. Moreover, the system is designed with a modular structure and a web-based interface, enabling scalable deployment and supporting real-time capability assessment in intelligent transportation environments.

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