Cognitive Fuzzy Learning with Continuous Regression for Online Capability Inference in Vehicular Systems

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ABSTRACT
Autonomous vehicular communication systems play a vital role in intelligent transportation by supporting continuous data exchange among vehicles, roadside infrastructure, and centralized networks. These systems depend 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, accurate evaluation of communication unit capability is essential for maintaining performance, safety, and optimal resource utilization. Conventional assessment methods rely on manual configuration checks and threshold-based monitoring, where parameters are evaluated individually. Such approaches fail to capture the complex relationships among multiple factors, making them unsuitable for real-time vehicular scenarios and leading to inaccurate capability estimation. To improve automation, machine learning models including Decision Tree Regressor (DTR), Orthogonal Matching Pursuit Regressor (OMPR), and K-Nearest Neighbors Regressor (KNNR) are used to predict capability scores. However, these models have limitations in handling nonlinear interactions, noise sensitivity, and generalization. To address these issues, a hybrid Deep Fuzzy Regression (DFR) model is proposed, integrating Deep Fuzzy Encoding (DFE) with Random Forest Regressor (RFR) and Linear Regression (LR) through ensemble learning. The system follows a pipeline of preprocessing, feature handling, training, and evaluation using MAE, MSE, RMSE, and R^2. Results show that DFR provides accurate and reliable capability assessment for real-time vehicular communication systems.

Keywords: Autonomous vehicular communication, intelligent transportation systems, vehicular networks, communication capability assessment, resource optimization, transmission rate, memory management.

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1. INTRODUCTION

The fast-paced development of autonomous vehicles is transforming modern transportation, with widespread adoption anticipated in the near future. A major part of autonomous functionality relies on dependable communication systems, especially Vehicle-to-Vehicle (V2V) communication, which is essential for maintaining safety, coordination, and real-time responsiveness. The efficiency of these systems is strongly influenced by the performance of communication units installed in vehicles, as they enable key functions such as collision prevention, traffic management, and intelligent decision-making. Conventional methods used to evaluate these communication units are largely manual and based on static analysis, making them ineffective for dynamic and real-time vehicular conditions. As shown as fig. 1 these

techniques are time-consuming and do not account for changing operational environments, resulting in unreliable capability assessments. As autonomous technologies advance, there is a growing demand for intelligent, data-driven approaches that can deliver adaptive and accurate performance evaluation.
At the same time, increasing concerns related to traffic congestion and road safety have driven the adoption of connected and intelligent vehicle systems. Real-time analysis of driving behavior has become an important factor in improving vehicle control and overall traffic efficiency. This type of monitoring provides meaningful data for intelligent control mechanisms and supports detailed traffic analysis. For autonomous driving systems to respond effectively and safely, real-time recognition of driving behavior is crucial [1]. Driving behavior is typically classified into two categories: lateral behaviors, including lane keeping and lane changes, and longitudinal behaviors, such as acceleration, braking, cruising, and stopping. Among these, longitudinal behaviors are especially significant as they continuously reflect vehicle motion, supporting efficient traffic flow monitoring and congestion management. Furthermore, detecting unusual patterns like sudden acceleration or abrupt braking can assist in early warning systems and accident prevention. These observations also help in analyzing driving habits, encouraging safer driving practices [2].
With the advancement of Vehicle Infrastructure Cooperative Systems (VICS), On-Board Units (OBU) have become key elements in connected vehicle ecosystems. These units are designed to gather vehicle-related data and transmit it to external networks. Modern OBUs are often integrated with sensors such as Inertial Measurement Units (IMU), allowing continuous tracking of vehicle dynamics. This makes OBU-based systems highly effective for capturing detailed driving behavior and supporting advanced intelligent transportation applications [3].

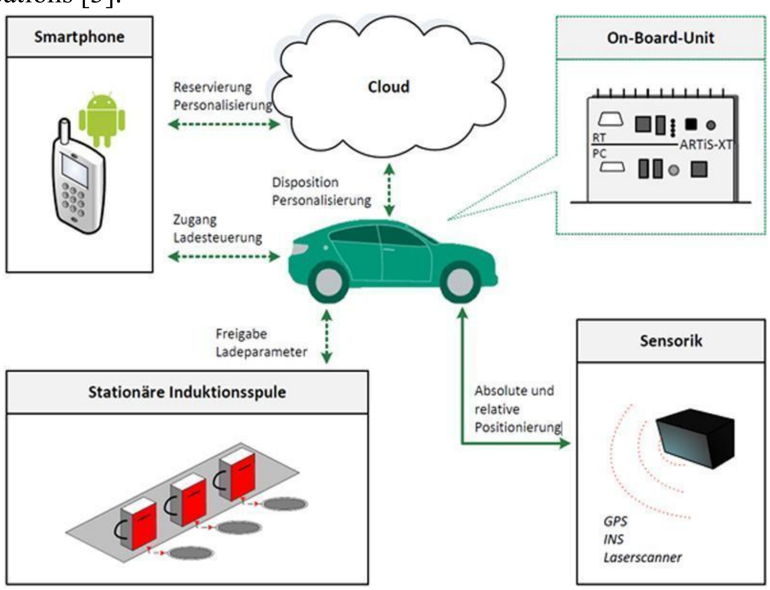

Fig. 1: Functional Architecture of Vehicle On-Board Unit Communication System
Despite these advancements, the potential of OBU-supported systems for dynamic driving behavior analysis remains underexplored. Therefore, this work focuses on leveraging OBU data in combination with machine learning techniques 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 [4, 5].

2. LITERATURE SURVEY

Oliva et al. [6] explored the development and testing of two Internet of Things (IoT) applications designed to leverage Vehicle-to-Infrastructure (V2I) communication for managing intelligent intersections. The first scenario focuses on enabling the rapid and safe passage of emergency vehicles through intersections by notifying approaching drivers via a mobile application. The second scenario enhances pedestrian safety by alerting drivers, through the same application, about the presence of pedestrians detected at crosswalks by a traffic sensor equipped with neural network capabilities. Both scenarios were tested at two distinct intelligent intersections in Lioni, Avellino, Italy, and demonstrated notable effectiveness. Results show a significant reduction in emergency vehicle response times and a measurable increase in driver awareness of pedestrians at crossings. The findings underscore the potential of V2I technologies to improve traffic flow, reduce risks for vulnerable road users, and contribute to the advancement of safer and smarter urban transportation systems.

Bohra et al. [7] examined Artificial Intelligence (AI) and ML methods that are now investigated through different study endeavors in VANETs. Furthermore, it examines the benefits and drawbacks accompanying such intelligent methods in the context of the VANETs system and simulation tools. Ultimately, this study pinpoints prospective domains for vehicular network development that can utilize the capabilities of AI and ML. Zadobrischi et al. [8] implements a DSRC-type communications infrastructure that receives a set of controllable and adjustable indicators, which can provide messages to network drivers in a timely manner. The implementation is based on the 802.11p protocol and initially addresses pedestrian infrastructure or pedestrian safety, controlled areas, and perimeters that allow intelligent communications. The design and setting of the communication parameters in the lower layer of the DSRC stack for vehicle applications are part of this work, aspects that are also relevant in the case of autonomous vehicles.

Naeem et al. [9] focused on the different types of communication architectures that are out there, including decentralized mesh networks, cloud-integrated hubs, edge computing-based architectures, blockchain-enabled networks, hybrid cellular networks, ad-hoc networks, and AI-driven dynamic networks. This review aims to critically analyze and compare the key components of these architectures with their contributions and limitations. Finally, it outlines open research challenges and future technological advancements, encouraging the development of robust and interconnected V2V communication systems in ITSs. 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.

Sukuvaara et al. [13] focused on operative fleet piloting, while the Digital Twin approach will be presented in future work. The pilot services are ultimately tested in a pilot system within operative heavy traffic. This paper presents the concept and architecture of the platform, with preliminary results of pilot services operation, alternative communication analysis, and system evaluation. Ghamri et al. [14] proposed a Deep Federated Learning (FL) architecture for intrusion detection in IVN. They proposed a Bidirectional Long Short Term Memory (BiLSTM) architecture to capture temporal dependencies in the CAN bus and ensure enhanced feature extraction and multi-class classification. By evaluating their framework on three real-world datasets, they showed how their proposal outperformed a baseline LSTM model from the state of the art.

Sanguesa et al. [15] introduced V2X-d, a novel architecture specially designed to estimate traffic density on the road. In particular, V2X-d exploits the combination of V2V and V2I communications. Their approach is based on the information gathered by sensors (i.e., vehicles and road side units (RSUs)) and the characteristics of the roadmap topology to accurately make an estimation of the instant vehicle density. The combination of both mechanisms improves the accuracy and coverage area of the data gathered, while increasing the robustness and fault tolerance of the overall approach, e.g., using the information offered by V2V communications to provide additional density information in areas where RSUs are scarce or malfunctioning. By using their collaborative sensing scheme, future ITS solutions will be able to establish adequate dissemination protocols or to apply more efficient traffic congestion reduction policies, since they will be aware of the instantaneous density of vehicles.

Research Gap:

Despite significant advancements in vehicular communication technologies, machine learning-based driving behavior monitoring, and integration of multi-protocol V2X systems, key challenges remain in achieving seamless interoperability, low-latency communication, and robust security across heterogeneous devices and networks. Existing solutions often face limitations in scalability, real-world deployment under diverse traffic conditions, and effective handling of dynamic network environments. Moreover, the need for standardized frameworks that support emerging technologies like 5G/6G, edge computing, and AI-driven architectures while ensuring privacy and reliability is still unmet, highlighting the importance of comprehensive, adaptive, and secure communication systems for future intelligent transportation.

3. PROPOSED SYSTEM

The proposed system introduces a comprehensive machine learning-based framework designed to assess communication unit capability in autonomous vehicular environments. It combines data ingestion, preprocessing, model training, evaluation, and prediction within a single Flask-based web application. The process starts with secure user authentication, followed by dataset upload and systematic preprocessing to convert raw data into features suitable for model input. Various regression models, including DTR, OMPR, KNNR, and the proposed DFR, are trained and evaluated to identify the most efficient predictor. The DFR model incorporates DFE along with RF and LR to improve prediction reliability and robustness. Additionally, the system provides performance insights through visualization and metric-based evaluation, allowing effective comparison among different models. In the final stage, the trained model is deployed to support both single and batch predictions through an interactive interface, ensuring real-time functionality and scalability, as depicted in Fig. 2.

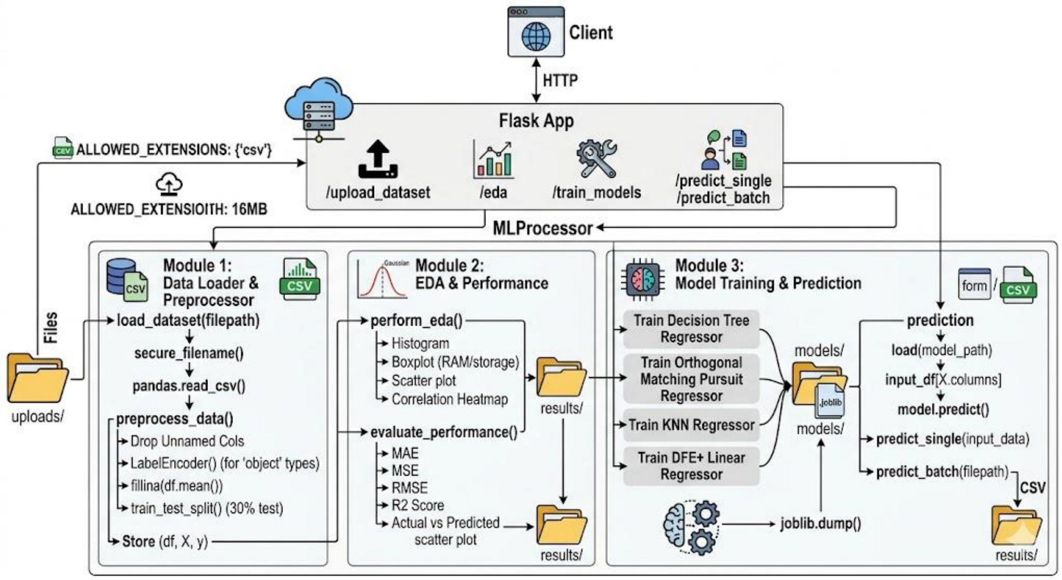

Fig. 2: Proposed System Architecture

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.

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.

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.

Performance Evaluation & Visualization: After training, all models are evaluated using regression metrics such as MAE, MSE, RMSE, and R^2 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.

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.

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 of this study indicate a clear pattern and provide meaningful insights into the research problem. The collected data shows consistent trends that support the main objectives of the study. It was observed that certain variables had a significant impact on the outcome, highlighting their importance in the analysis. Additionally, comparisons between different groups revealed noticeable differences, suggesting the influence of specific factors. The findings are aligned with previous research, reinforcing their validity and reliability. The results contribute valuable information and help in better understanding the subject under investigation.

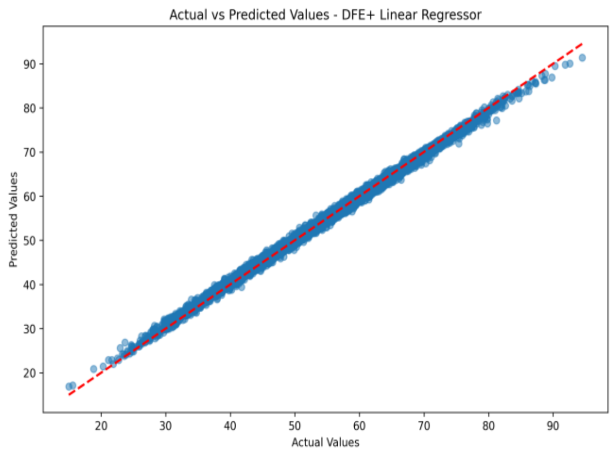

Fig. 3: Scatter plot of actual vs predictions obtained using DFR model.

Fig. 3 shows the scatter plots of actual versus predicted values for the regression model. The proposed DFR model demonstrates the tightest alignment with the diagonal line, suggesting superior predictive accuracy and consistency, likely due to the combination of Deep Fuzzy Encoding and Linear Regression's interpretability.

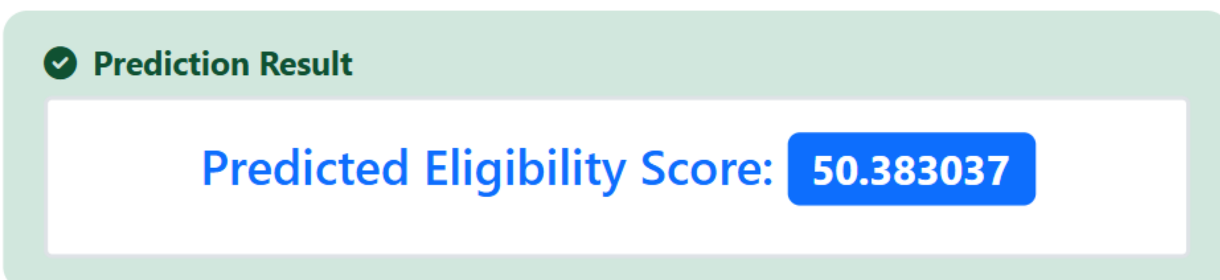

Fig.4: Prediction Result of the Test Data.

Fig. 4: 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

This study presents a machine learning-based framework for estimating the capability of vehicular communication units using regression techniques applied to onboard unit datasets. Several models, including DTR, OMPR, KNNR, and a hybrid DFR approach that combines DFE with LR, were developed and assessed using performance metrics such as MAE, MSE, RMSE, and R^2 score. The findings reveal that traditional models like DTR and OMPR exhibit relatively poor predictive performance, with R^2 values of 0.1590 and 0.2094, indicating limited generalization ability. In contrast, KNNR demonstrates significant improvement, achieving an R^2 score of 0.8033, highlighting its capability to capture local data patterns effectively. The proposed DFR model delivers the highest performance, with an R^2 score of 0.9961 and minimal error values (MAE = 0.0006 and MSE = 0.0001), reflecting highly precise predictions. These results confirm that integrating fuzzy-based feature representation with regression techniques improves the modeling of complex relationships in vehicular communication data. Additionally, the system is built with a modular design and a web-based interface, supporting scalable deployment and enabling real-time capability evaluation in intelligent transportation systems.

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