

Energy-Aware Routing Optimization for 5G Vehicular Fog Networks

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Abstract

The rapid expansion of 5G-enabled Intelligent Transportation Systems (ITS) is accelerating global vehicular connectivity, with projections exceeding 1.9 billion connected vehicles by 2030. Despite this growth, energy-efficient routing in dynamic fog-assisted vehicular networks remains a critical challenge. Traditional routing protocols such as Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), and Greedy Perimeter Stateless Routing (GPSR) rely on static heuristics and lack adaptability to fluctuating vehicle density, high mobility, and real-time fog node workloads, often leading to energy inefficiencies, load imbalance, and increased latency. To address these challenges, this study proposes an intelligent Classification and Regression Tree (CART)-based framework for predicting optimal load-balanced routes and energy efficiency scores using real-world vehicular network datasets. The proposed system integrates Decision Tree (DT), Support Vector Machine (SVM), and a novel Brain Branch model, which combines a Multi-Layer Perceptron (MLP) with Extra Trees (ET), within a user-friendly Tkinter-based graphical user interface (GUI) for real-time analysis. The pipeline incorporates data preprocessing, exploratory data analysis (EDA), load distribution modeling, and multi-model training. Among the evaluated approaches, the Brain Branch model demonstrates superior performance by effectively capturing complex routing patterns and energy dynamics. The proposed framework enhances routing precision, reduces unnecessary energy consumption, and enables efficient fog node selection with lower latency.

Keywords: 5G-enabled Intelligent Transportation Systems, Vehicular Ad Hoc Networks, Machine Learning, Latency Reduction, Multi-Layer Perceptron.

1. INTRODUCTION

As with the development of vehicular network (VN) system architecture, the dynamic and heterogeneous features of VN, coupled with rapid data flow within the topological structure of VN, impose significant challenges for sustaining network connectivity on the road, decision-making within the network set-up, timely data delivery, and network response time under the dynamic events [1]. Data communication management in VN has also become challenging due to limited bandwidth, line of sight, and intermittent communication among the vehicles and with the cloud [2,3]. Lane-changing across the road network can disrupt the overall network operation, resulting in network re-formation. This calls for an

adaptive and flexible network mechanism that can keep up with the dynamics of the network in order to maintain communication between the vehicles and the transport management system and to structure an intelligence-enabled network with ever-increasing traffic data demands that can react dynamically to events such as road accidents as demonstrated in Fig. 1.

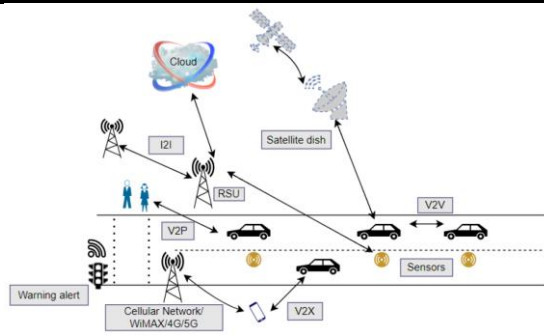


Fig. 1: Vehicular network

For instance, the nature of highway dynamics necessitates the development of a real-time, self-organizing mechanism to deal with the sudden events of vehicles entering and exiting the road. As the topological network structure is restricted by the road and its regulations, the network tends to adhere to a common structural formation considering the road structure layout. Therefore, adapting to road traffic and its dynamic challenges necessitates traffic analysis modeling and full network connectivity wherein using powerful communication techniques such as intelligent clustering (grouping) can support a flexible network structure and connection maintenance. A clustering approach can organize communication through the optimal management of vehicles having similar attributes into groups to reutilize the resources within the group and increase system operational capacity [4]. Several clustering protocols and algorithms have been designed to serve various VN applications. The research in routing algorithms and clustering approaches for VN has brought attention to the need to analyze and support cluster performance metrics, network connectivity, data dissemination, and reliability [5].

2. LITERATURE SURVEY

Al-Hamid DZ et al. [6]. developed of a virtual model that represents the operation of an autonomous vehicular network. It also investigates the ability to re-orchestrate the topology through software definition while

running the various operational phases. Network self-formation, network expansion, retraction via vehicular members joining and leaving, and network self-healing when a topological rupture occurs as a result of a key member leaving the network are the key grouping phases. The communication approach is analyzed based on the status of network members and their ability to assume the various network roles. The concept is tested using both a Contiki-Cooja network simulator and a MATLAB analytical modeling tool to reflect the operation and performance of the grouping approach under various road scenarios. The outcome of the analysis reflects the ability of the group to be formulated within a measured latency considering the various network parameters such as communication message rate.

Blanco Fernández Y et al[7]. proposed a geocast routing approach that addresses challenges in highway environments by improving throughput and message delivery despite intermittent connectivity and GPS outages. Enhancements to the veins tool are discussed by Kilanioti et al. incorporating new caching and content distribution features along with machine learning algorithms for more effective VANET simulations. In another paper, Conrad et al. explore a customizable cyber-physical system (CPS) designed for the development and testing of intelligent vehicular systems, bridging theoretical concepts with practical applications. Song et al. use UAVs to extend the coverage of mobile edge computing (MEC) and propose a deep reinforcement learning-based SDN controller (DRL-SDNC) to optimize resource allocation, such as computational resources, bandwidth, and storage. The DRL-SDNC adjusts these resources based on task requirements and network conditions, enhancing efficiency and quality of service in UAV-assisted 5G networks.

Verma A et al[8]. presented survey is an attempt to cover various attack types on vehicular networks with existing security solutions available to handle these attacks. They will help researchers in getting in-depth information about the taxonomy of vehicular network security issues which can be explored further to design innovative solutions. These knowledge will also be helpful for new research directions, which in turn will help in the formulation of new strategies to handle attacks in a much better way.

Bowlin E et al[9]. provided by longer blockchains constitutes a nearly immutable, decentralized data structure that can store any data relevant to the applications. However, these chains must be adapted to the ad-hoc, resource-constrained environments found in VANETs. In the absence of abundant resources and reliable network connections, chain operation and maintenance must address the challenges presented by highly mobile nodes in novel ways, including situations such as emergency messaging that require real-time responses. Researchers have included different mechanisms to realize lightweight blockchains, such as adding reputation to existing consensus mechanisms, condensing the consensus committees, using geographical information, and monitoring a nodes behavior in attempts to adapt blockchains to these domains. They analyzes the challenges and gives solutions for these different mechanisms to realize lightweight blockchains for VANETs.

Peyman M et al[10]. discussed some of the most relevant optimization challenges in this area. Since most of the optimization problems are related to the need for real-time solutions or to the consideration of uncertainty and dynamic environments, the paper also discusses how some VANET challenges can be addressed with the use of agile optimization algorithms and the combination of metaheuristics with simulation and machine learning methods. The paper also offers a numerical analysis that

measures the impact of using these optimization techniques in some related problems. Our numerical analysis, based on real data from Open Data Barcelona, demonstrates that the constructive heuristic outperforms the random scenario in the CDP combined with vehicular networks, resulting in maximizing the minimum distance between facilities while meeting capacity requirements with the fewest facilities.

Juárez R et al[11]. presented a transformative dual-layer blockchain architecture, which was conceived to address the intricate security challenges pervasive in VANETs. The architecture pivots on a sophisticated reputation assessment framework, thus leveraging the principles of Bayesian inference and the analytical rigor of historical data to markedly diminish observational errors, as well as elevate the accuracy of reputation evaluations for vehicular nodes. A salient feature of our methodology is the implementation of an attenuation factor, which has been deftly calibrated to modulate the impact of historical behaviors on current reputation scores, thereby ensuring their relevance and alignment with recent vehicular interactions. Additionally, the numerical threshold serves as an indispensable mechanism, thus establishing a definitive criterion for the early identification of potentially malicious activities and enabling the activation of proactive security measures to safeguard the network's integrity. Empirical validation of our dual-layer blockchain model has yielded a remarkable 86% efficacy in counteracting malevolent behaviors, thus significantly outperforming extant paradigms.

Zarie MM et al[12]. presented significant enhancements to vehicular networks to fulfill the demanding specifications by utilizing state-of-the-art technologies, including distributed edge computing, e.g., mobile edge computing (MEC) and fog computing, software-defined networking (SDN), and microservice. The work provides a novel vehicular network structure

based on micro-services architecture that meets the requirements of 6G networks. The required offloading scheme is introduced, and a handover algorithm is presented to provide seamless communication over the network. Moreover, a migration scheme for migrating data between edge servers was developed. The work was evaluated in terms of latency, availability, and reliability. The results outperformed existing traditional approaches, demonstrating the potential of our approach to meet the demanding requirements of next-generation vehicular networks.

Aziz S et al[13]. Proposed wireless communication between vehicles, the whole network can be sensitive towards cyber-attacks. In these attacks, sensitive information can be shared with a malicious network or a bogus user, resulting in malicious attacks on the IoV. For the last few years, detecting attacks in the IoV has been a challenging task. It is becoming increasingly difficult for traditional Intrusion Detection Systems (IDS) to detect these newer, more sophisticated attacks, which employ unusual patterns. Attackers disguise themselves as typical users to evade detection. These problems can be solved using deep learning. Many machine-learning and deep-learning (DL) models have been implemented to detect malicious attacks; however, feature selection remains a core issue. Through the use of training empirical data, DL independently defines intrusion features. We built a DL-based intrusion model that focuses on Denial of Service (DoS) assaults in particular.

Akwirry B et al[14]. proposed system assigns vehicles in the vehicle ad hoc network a trust value based on behaviour such as processing delay, packet loss and prior vehicle behavioural history. This will be done by selecting vehicles as watchdogs to observe the behaviour of neighbouring vehicles and evaluate the trust value. The second tier is to protect the watchdogs, which is done by watchdogs' behaviour history. The third security tier is to

protect the integrity of data used for trust value calculation. Results show that the proposed system is successful in identifying malicious vehicles in the VANET. It also improves the packet delivery ratio and end-to-end delay of the vehicle ad hoc network in the presence of malicious vehicles.

Shaikh RA et al[15]. proposed various extensions in the fuzzy risk-based decision model to achieve higher robustness, reliability, and completeness. They were presented the theoretical and simulation-based analysis and evaluation of the proposed scheme in a comprehensive manner. In addition, They have analytically cross verified the theoretical and simulation-based results. Qualitative comparison of the proposed scheme has also been presented in this work.

3. PROPOSED METHODOLOGY

The proposed system architecture is designed as an integrated analytical and predictive framework for optimizing energy-aware routing in 5G vehicular fog networks. The system begins by accepting vehicular network data through a Tkinter-based GUI, followed by preprocessing steps to handle missing values and encode categorical attributes. It then performs EDA to analyze key factors such as latency, node mobility, and traffic density, providing insights into network behavior. The processed data is divided into training and testing sets to ensure reliable model evaluation. Baseline models such as DT and SVM are implemented for initial analysis, followed by an advanced Brain Branch model for improved performance. The system is capable of performing dual predictions, including classification for optimal load balancing and regression for energy efficiency scoring. Finally, the GUI enables users to input new data and obtain real-time predictions, supporting efficient routing decisions with reduced energy consumption, balanced network load, and

improved overall network performance as shown in Fig. 2.

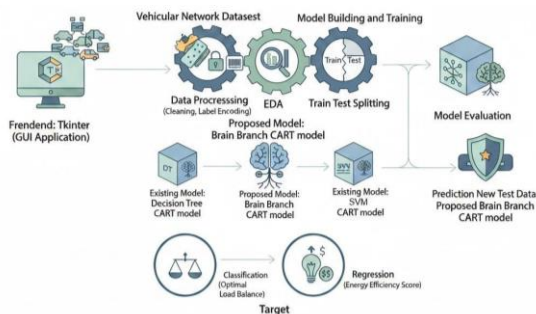


Fig. 2: Proposed system architecture of vehicular fog networks.

Proposed Brain Branch CART model

The Brain Branch CART model enhances traditional decision-tree learning by introducing parallel branching logic inspired by layered neural decision pathways. Instead of relying on a single split path, it creates multiple “brain-like” decision branches, each specializing in different vehicular attributes such as mobility, load patterns, and energy usage. This multi-branch structure allows the model to more accurately classify optimal load balance and predict energy efficiency scores, ensuring adaptive and intelligent routing across 5G vehicular fog networks as shown in Fig. 3.

Ingestion of Pre-processed Vehicular Features: The model receives cleaned, normalized, and encoded vehicular network features, including mobility speed, fog node load, channel conditions, distance metrics, and energy indicators. These structured inputs ensure that the Brain Branch CART model operates on consistent and noise-reduced data, forming a reliable foundation for routing decisions.

Initialization of Brain-Inspired Multi-Branch Framework: Instead of creating a linear decision pathway, the model initializes parallel branching layers that mimic brain-like evaluations. Each branch specializes in a category of vehicular attributes mobility, load, or energy allowing the model to capture

complex interactions among them. This multi-branch design strengthens contextual understanding before making routing decisions.

Feature Projection into Specialized Sub-Branched: The input features are projected into multiple specialized branches where each branch extracts unique decision patterns. For instance, mobility branches detect patterns in vehicular speed changes, while energy branches focus on consumption behavior. This separation enables more precise learning of multi-dimensional routing behaviors.

Branch-Wise Decision Node Formation: Each branch begins constructing its own CART nodes using optimal split rules to maximize information gain. These nodes evaluate relationships between features like fog load thresholds, energy variations, or latency constraints. The branch-level nodes allow the system to maintain granularity and reduce decision ambiguity.

Cross-Branch Interaction for Deep Evaluation: The branches exchange selected decision outcomes to refine the tree’s understanding of vehicular dynamics. For example, mobility branches may influence load-balance branches when high-speed vehicles require low-latency routing. This interaction creates a collaborative decision structure, improving prediction reliability.

Intermediate Fusion of Branch Outputs: Intermediate decisions from different branches are fused to create a unified decision signature. This fusion is crucial for balancing competing objectives such as minimizing latency, optimizing fog utilization, and conserving energy. The fused representation forms a strong candidate for final classification and regression operations.

Formation of Brain Branch CART Decision Pathways: The fused decisions allow the model to build enhanced and deeper CART pathways that incorporate multi-branch

intelligence. These pathways integrate both hierarchical splits and cross-branch insights, resulting in robust routing decision logic tailored for dynamic 5G environments.

Classification of Optimal Load Balance: The Brain Branch CART model produces a classification output that predicts the optimal load distribution across fog nodes. By processing branch-specific insights, the classification ensures efficient workload placement even during traffic spikes or vehicular bursts.

Regression for Energy Efficiency Score Prediction: Simultaneously, the regression branch estimates the energy efficiency score, indicating how effective a routing path is regarding energy usage. The brain-inspired structure enables fine-grained energy modeling that adapts to fluctuating vehicular conditions and fog resource availability.

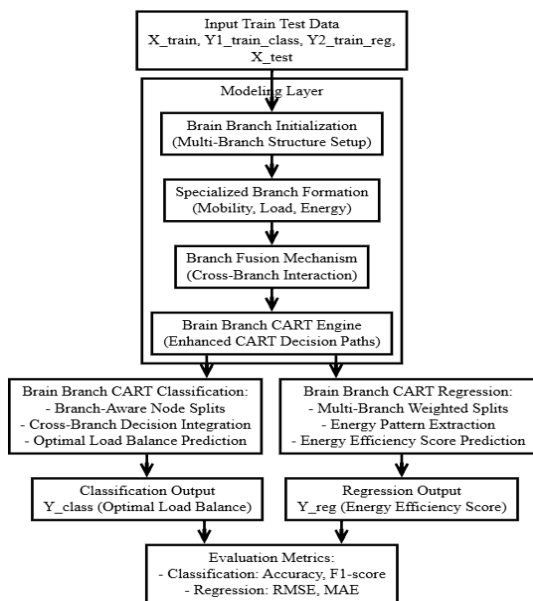


Fig. 3: Internal workflow of proposed brain branch CART model.

Final Output Delivery and Routing Decision Support: The model outputs both the classification (Optimal Load Balance) and the regression score (Energy Efficiency). These outputs guide real-time routing strategies in 5G vehicular fog environments, enhancing

network stability, reducing congestion, and optimizing energy consumption.

4. Result Description

The results of the proposed Energy-Aware Routing Optimization system demonstrate the effectiveness of the implemented pipeline in handling vehicular network data and generating accurate predictions. The system successfully integrates preprocessing, analysis, and prediction within a unified graphical interface. The visual outputs generated during EDA provide clear insights into data distribution, relationships between features, and network behavior under varying conditions. The interface enables seamless interaction, allowing users to upload datasets, visualize patterns, and observe routing performance metrics in real time. The combination of graphical analysis and predictive modeling ensures improved understanding of energy consumption patterns and load balancing in 5G vehicular fog networks.

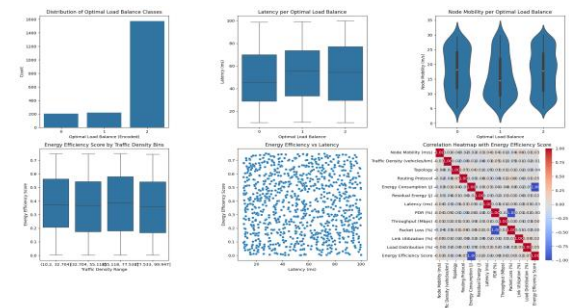


Fig. 4: Data Analysis.

Fig. 4 provide a comprehensive understanding of the underlying patterns and distributions within the vehicular network dataset. Various visualization techniques such as count plots, box plots, violin plots, scatter plots, and correlation heatmaps are used to examine categorical distributions, statistical variability, feature relationships, and dependencies among attributes. These visualizations reveal important insights into network behavior, including traffic density, latency variations, energy consumption trends, and routing

protocol distribution. The analysis supports better interpretation of data characteristics, which plays a crucial role in improving model performance and routing optimization in 5G vehicular fog networks.

Fig. 4 (a) Count Plot: The count plot illustrates the distribution of categorical variables such as routing protocols and topology types within the dataset. It highlights the frequency of occurrences for each category, showing how data samples are distributed across different routing protocols like AODV, DSR, and GYTAR. The visualization confirms the presence of multiple routing strategies and their representation in the dataset, supporting balanced analysis across different network configurations.

Fig.4 (b) Box Plot: The box plot represents the statistical distribution of numerical features such as latency, energy consumption, and throughput. It displays median values, quartiles, and outliers, providing insight into variability and dispersion in the dataset. The presence of outliers indicates variations in vehicular behavior under different traffic and mobility conditions. This visualization helps in identifying anomalies and understanding the spread of network performance metrics.

Fig. 4 (c) Violin Plot: The violin plot combines the features of a box plot and density plot to represent the distribution of data across different variables. It shows the probability density of features such as latency and energy consumption, highlighting areas with higher concentration of values. The shape of the plot

reflects how data is distributed across the range, providing a deeper understanding of feature behavior in the vehicular network.

Fig. 4 (d) Box Plot: This additional box plot focuses on another subset of numerical features, reinforcing the analysis of data variability and distribution. It emphasizes consistency in feature values and highlights the presence of extreme values across different parameters. The visualization supports comparative analysis of multiple network attributes, contributing to better feature understanding.

Fig. 4 (e) Scatter Plot: The scatter plot represents the relationship between two continuous variables such as node mobility and latency or throughput and energy consumption. It shows how changes in one variable affect another, revealing patterns and correlations within the dataset. Clustering of points indicates strong relationships, while dispersion reflects weaker associations. This visualization is useful for understanding dependencies among network parameters.

Fig. 4 (f) Correlation Heatmap: The correlation heatmap displays the correlation coefficients between all numerical features in the dataset. It provides a color-coded matrix where strong positive and negative relationships are clearly visible. Features such as latency, throughput, and packet loss show varying degrees of correlation with energy consumption and load distribution. This visualization helps in identifying influential features that impact routing efficiency and energy optimization in the system.

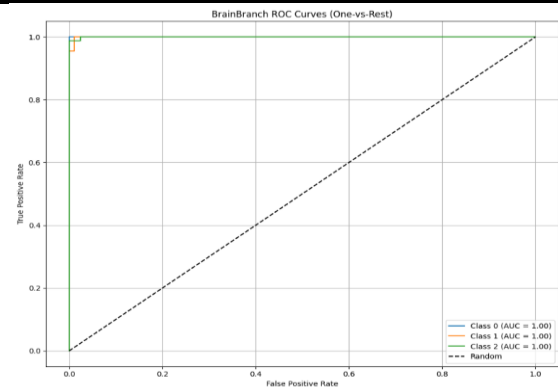
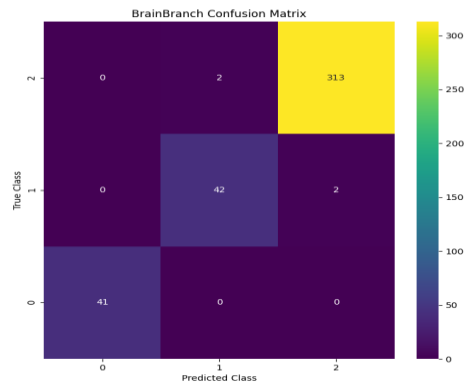


Fig. 5: Obtained confusion matrix and ROC curves from Brain Branch model.

The confusion matrices and ROC curves presented in Fig. 5 evaluate the classification performance of different models for Optimal Load Balance prediction. The confusion matrices show the distribution of correctly and incorrectly classified instances across all classes, indicating the level of prediction accuracy achieved by each model. The ROC curves illustrate the trade-off between true positive rate and false positive rate, highlighting the ability of each model to distinguish between classes. The comparative visualization demonstrates the variation in classification strength among the DT, SVM, and Brain Branch models. The confusion matrix for the Brain Branch model shows highly accurate classification with minimal misclassification across all classes. The diagonal dominance indicates strong prediction consistency. The ROC curve is positioned closest to the top-left corner, representing excellent true positive rates and low false positive rates. This confirms superior classification performance in identifying optimal load balance categories.

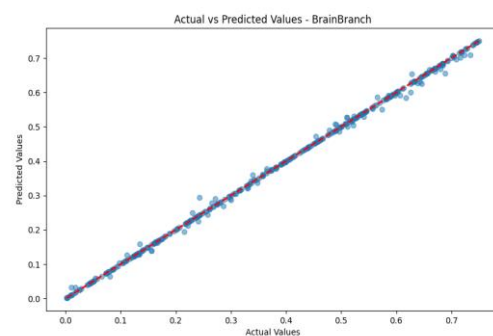


Fig. 6: Obtained scatter plot from Brain Branch model.

The scatter plots presented in Fig. 6 represent the regression performance of different models for predicting Energy Efficiency Score. Each plot shows the relationship between actual and predicted values, where closer alignment to the diagonal line indicates higher prediction accuracy. The distribution of points reflects how well each model captures underlying patterns in energy consumption and network behavior. The comparison across DT, SVM, and Brain Branch models highlights differences in prediction precision and consistency, with tighter clustering indicating improved regression performance. The scatter plot for the Brain Branch model shows a tight clustering of points along the diagonal reference line. The predicted values closely match the actual values with minimal deviation. This indicates high regression accuracy and strong learning of underlying energy efficiency patterns in the dataset. The distribution confirms the model's

effectiveness in predicting continuous outputs with high precision.

Table 1: Performance evaluation obtained using existing DT, SVM classifiers and proposed hybrid Brain Branch classification model.

Algorithm	Accuracy	Precision	Recall	F1-score
DT Classifier Model	21.25	17.88	66.67	27.27
SVM Classifier Model	49.75	52.98	78.08	48.10
Brain Branch Model	99.00	98.27	98.27	98.27

Table 1 presents the performance evaluation of the DT Classifier, SVM Classifier, and the proposed Brain Branch model based on Accuracy, Precision, Recall, and F1-score. The DT model shows relatively low accuracy and precision, indicating limited classification capability despite moderate recall. The SVM model demonstrates improved performance across all metrics, reflecting better handling of data patterns and class separation. The proposed Brain Branch model achieves the highest values across all evaluation metrics, with near-perfect accuracy, precision, recall, and F1-score. This clearly indicates superior classification performance and effective learning of complex relationships in the vehicular network dataset.

Table 2: Performance evaluation obtained using existing DT, SVM regressors and proposed hybrid Brain Branch Regression model.

Model/Metric	MAE	MSE	RMSE	R2-score
DT Regressor Model	0.0001	0	0.0	0.7638

SVM Regressor Model	0.000	0	0.0	0.9672
Brain Branch Model	0.000	0	0.0	0.9990

Table 2 presents the performance comparison of the DT Regressor, SVM Regressor, and the proposed Brain Branch model using evaluation metrics such as MAE, MSE, RMSE, and R2-score. The DT Regressor shows moderate performance with a relatively higher MAE and an R2-score of 0.7638, indicating limited fit to the data. The SVM Regressor demonstrates improved performance with near-zero error values and a higher R2-score of 0.9672, reflecting better prediction accuracy and model generalization. The proposed Brain Branch model achieves the best results with negligible error values and an R2-score of 0.9990, indicating an almost perfect fit between predicted and actual values. This clearly shows the superiority of the proposed model in accurately estimating energy efficiency scores in the vehicular network dataset.

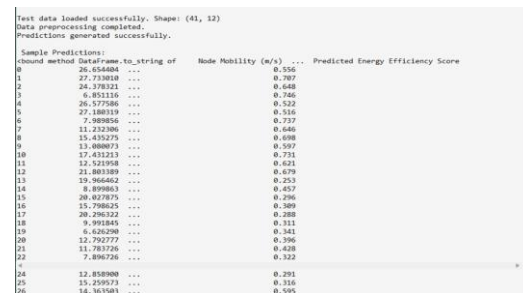


Fig. 7: Predictions on Test Data

The results presented in Fig. 7 illustrates the model predictions generated on unseen test data from the vehicular network dataset. The figure compares the predicted outputs with the corresponding actual values for both classification (Optimal Load Balance) and regression (Energy Efficiency Score). The alignment between predicted and actual values indicates the level of accuracy achieved by the

trained model. A close match between these values demonstrates that the model has effectively learned the underlying patterns in mobility, traffic density, and energy-related features. This visualization confirms the reliability of the system in generating accurate predictions for real-time routing and energy optimization in 5G vehicular fog networks.

5. Conclusion

This study presented an intelligent CART-based framework for energy-efficient and load-balanced routing in 5G-enabled ITS. By addressing the limitations of traditional routing protocols such as AODV, DSR, and GPSR particularly their reliance on static heuristics and inability to adapt to dynamic vehicular environments the proposed system offers a more flexible and data-driven solution. The integration of multiple ML models, including DT, SVM, and the proposed Brain Branch model (MLP combined with ET), enabled effective prediction of optimal routes and energy efficiency scores. The inclusion of a Tkinter-based GUI further enhances the practical usability of the framework by allowing real-time analysis and visualization. Among all models, the Brain Branch approach demonstrated superior performance, effectively capturing complex patterns in vehicular mobility, load distribution, and energy dynamics. The framework significantly improves routing precision, reduces unnecessary energy consumption, balances fog node workloads, and minimizes latency. Overall, this work contributes a scalable and intelligent solution for next-generation ITS, supporting more efficient and sustainable vehicular communication systems.

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