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Data-Driven State Estimation for Vehicular Networks Using Spatial Proximity and Deep Learning

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ABSTRACT

Modern vehicular networks generate massive amounts of real-time data encompassing vehicle speed, GPS location, signal strength, packet delay, congestion levels, and available bandwidth, which are crucial for proactive traffic management and network reliability. Traditional traffic monitoring systems rely on manual or threshold-based approaches to estimate vehicle priority and network congestion, often leading to delayed decision-making, inaccurate predictions, and inefficient resource allocation. These limitations are exacerbated in high-mobility scenarios where traffic density fluctuates rapidly, and vehicles interact dynamically with roadside units (RSUs), making conventional techniques insufficient for ensuring timely and safe routing decisions. Motivated by the need for a robust, real-time predictive framework, this research implements a machine learning pipeline that leverages both Classification and Regression Trees (CART) techniques to assess priority levels and traffic density accurately. Existing algorithms, such as Support Vector Machines with CART (SVM-CART) and Random Forest (RF) with CART (RF-CART), provide baseline predictive capabilities; however, they struggle with non-linear relationships, feature interactions, and overfitting under heterogeneous traffic conditions. To overcome these limitations, a Hybrid Stacked Ensemble (HSE-CART) is proposed, combining RF and Hierarchical Soft Tree (HSTree) models with linear Regression (LinR) for Regression and logistic regression (LR) for Classification as a final estimator. This hybrid approach captures complex dependencies, balances bias-variance trade-offs, and enhances both classification and regression performance. Overall, the research establishes a scalable, interpretable, and effective solution for high-mobility vehicular networks, supporting safer and more efficient traffic management in real-time environments.

Key words: Vehicular Networks (VANETs), Machine Learning, High-Mobility Environments, Predictive Modeling, Intelligent Transportation Systems (ITS), Classification and Regression Trees (CART).

1. INTRODUCTION

Network connectivity remains a critical challenge in Vehicular Ad Hoc Networks [1], as reliable communication between moving vehicles is essential for efficient and safe transportation systems as shown in figure. 1. Earlier analyses have explored connectivity under various roadway conditions, particularly focusing on highways with uninterrupted traffic flow [2]. However, real-world highway environments often include toll plazas, which introduce disruptions due to vehicle entry, exit, and temporary congestion, significantly affecting communication links among vehicles. To address this, connectivity probability is analyzed for a one-way highway scenario that includes toll plazas [3]. This metric represents the likelihood

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that vehicles can maintain direct communication and remain fully connected across the network. In this scenario, toll plazas are assumed to be uniformly distributed along the road. As vehicles approach these areas, congestion may occur, altering traffic flow and communication stability. Vehicles encountering sudden slowdowns or potential collisions can transmit alerts to nearby vehicles within communication range, enabling them to reduce speed and avoid further incidents [4].

This demonstrates how toll plaza regions directly influence both vehicle movement and network connectivity. Several parameters impact connectivity performance, including vehicle arrival patterns modeled using the Poisson process, traveling speed, communication range, and total road length. These factors collectively determine how effectively communication is maintained across the network. Simulation results validate the effectiveness of the analytical model and confirm its ability to represent real-world conditions [5]. Furthermore, the impact of different parameters on connectivity performance is systematically evaluated, providing insights into improving network stability in highway scenarios with toll plazas.

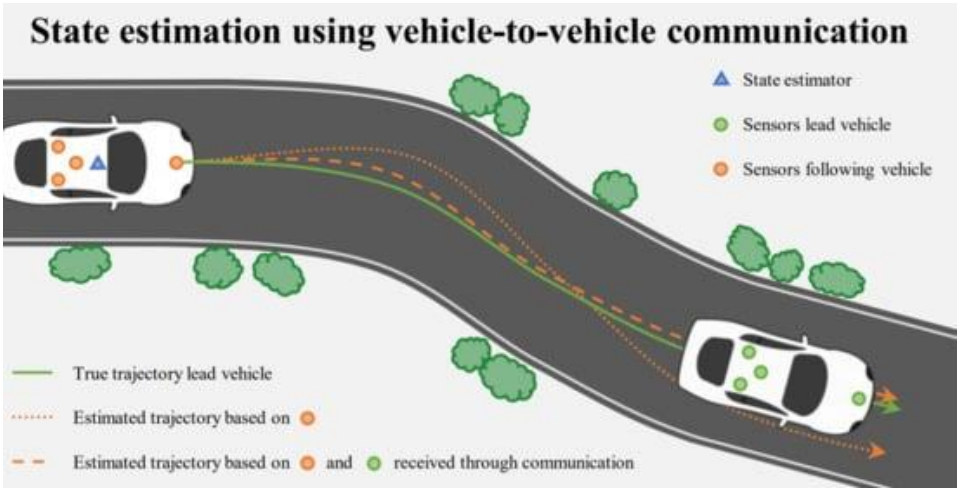


Figure. 1: State estimation using Vehicle to Vehicle (V2V) communication

2. LITERATURE SURVEY

Hussain et al. [6] aimed to study issues of network connectivity in vehicular ad hoc networks (VANETs) to avoid traffic congestion at a toll plaza. An analytical model was developed for highway scenarios where the traffic congestion could have the vehicles reduce their speed instead of blocking the flow of traffic. In this model, nearby vehicles had to be informed when traffic congestion occurred before reaching the toll plaza so they could reduce their speed to avoid traffic congestion. Once they had crossed the toll plaza they could travel on at their normal speed. The road was divided into two or three sub-segments to help analyze the performance of connectivity. The proposed analytical model considered various parameters that might disturb the connectivity probability, including traveling speed, communication range of vehicles, vehicle arrival rate, and road length.

Rekha Gangula et al. [7] proposed an intelligent intrusion prevention framework for network applications. The system integrated detection and prevention mechanisms within a unified architecture. The framework reduced attack propagation and improved response efficiency.

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Chango et al. [8] developed a comparison of neural network-based models for vehicular congestion prediction, with the aim of improving urban mobility and mitigating the negative effects associated with traffic, such as accidents and congestion. This research focused on evaluating the effectiveness of different neural network architectures, specifically Transformer and LSTM, in order to achieve accurate and reliable predictions of vehicular congestion. To carry out this research, a rigorous methodology was employed that included a systematic literature review based on the PRISMA methodology, which allowed for the identification and synthesis of the most relevant advances in the field. Likewise, the Design Science Research (DSR) methodology was applied to guide the development and validation of the models, and the CRISP-DM methodology was used to structure the process, from understanding the problem to implementing the solutions. The dataset used in this study included key variables related to traffic, such as vehicle speed, vehicular flow, and weather conditions.

Arya et al. [9] presented an approach to intrusion detection based on the distributed federated learning (FL) of heterogeneous neural networks for smart cities. It saved time and resources by using the most efficient intruder detection approach. First, vehicles used a federated learning technique to develop local, deep learning-based IDS classifiers for VANET data streams. They then shared their locally learned classifiers upon request, significantly reducing communication overhead with neighboring vehicles. Then, an ensemble of federated heterogeneous neural networks was constructed for each vehicle, including locally and remotely trained classifiers. Finally, the global ensemble model was again shared with local devices for their updating. The effectiveness of the suggested method for intrusion detection in VANETs was evaluated using performance indicators such as attack detection rates, classification accuracy, precision, recall, and F1 scores over a ToN-IoT data stream. The ID model showed 0.994 training and 0.981 testing accuracy.

Rekha Gangula et al. [10] proposed a deep learning and optimization-based intrusion detection method for IoT systems. The model combined deep neural architectures with optimization techniques. The approach improved detection accuracy and minimized computational overhead.

Rashid et al. [11] selected the problem of malicious node detection and proposed a real-time malicious node detection system using machine learning. They proposed a distributed multi-layer classifier and evaluated the results using OMNET++ and SUMO with machine learning classification using GBT, LR, MLPC, RF, and SVM models. The group of normal vehicles and attacking vehicles dataset was considered to apply the proposed model. The simulation results effectively enhanced the attack classification with an accuracy of 99%. Under LR and SVM, the system achieved 94 and 97%, respectively. The RF and GBT achieved better performance with 98% and 97% accuracy values, respectively. Since they had adopted Amazon Web Services, the network's performance had improved because training and testing time did not increase when more nodes were included in the network.

ul Hassan et al. [12] presented an intelligent cluster-based routing protocol to mitigate these challenges in VANET routing. The system operated through two pivotal phases: first, utilizing an artificial neural network (ANN) model to detect malicious nodes, and second, establishing clusters via enhanced clustering algorithms with appointed cluster heads (CH) for each cluster. Subsequently, an optimal path for data transmission was predicted, aiming to minimize packet transmission delays. Their approach integrated a modified ad hoc on-demand distance vector (AODV) protocol for on-demand route discovery and optimal path selection, enhancing request and reply (RREQ and RREP) protocols. Evaluation of routing

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performance involved the BHT dataset, leveraging the ANN classifier to compute accuracy, precision, recall, F1 score, and loss.

Peyman et al. [13] discussed how some VANET challenges could be addressed with the use of agile optimization algorithms and the combination of metaheuristics with simulation and machine learning methods. The paper also offered a numerical analysis that measured the impact of using these optimization techniques in some related problems. Their numerical analysis, based on real data from Open Data Barcelona, demonstrated that the constructive heuristic outperformed 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.

Marwah et al. [14] proposed hybrid whale dragonfly optimization approach (H-WDFOA-VANET) was compared with industry standard models, such as rider integrated cuckoo search (RI-CS) and enhanced hybrid ant colony optimization routing protocol (EHACORP). With the proposed method, throughput could be increased. The proposed system had energy consumption values of 2.00000 mJ, latency values of 15.61668 s, and a drop at node 60 of 0.15759. Additionally, a higher throughput was achieved with the new method. With the suggested method, it was possible to meet the energy consumption targets, delay value, and drop value at node 60. The proposed method reduced the drop value at node 80 to 0.15504, delay time to 15.64318 s, and energy consumption to 2.00000 mJ. These outcomes demonstrated the effectiveness of their proposed method. Thus, the proposed system was more efficient than existing systems.

Manderna et al. [15] presented an innovative method for creating an AI-based NIDS that used Deep Learning methods. The suggested model specifically incorporated the Self Attention-Based Bidirectional Long Short-Term Memory (SA-BiLSTM) for classification and the Cascaded Convolution Neural Network (CCNN) for learning high-level features. The Multi-variant Gradient-Based Optimization algorithm (MV-GBO) was applied to improve CCNN and SA-BiLSTM further to enhance the model's performance. Additionally, information gained using MV-GBO-based feature extraction was employed to enhance feature learning. The effectiveness of the proposed model was evaluated on reliable datasets such as KDD-CUP99, ToN-IoT, and VeReMi, which were utilized on the MATLAB platform. The proposed model achieved 99% accuracy on all the datasets.

3. PROPOSED SYSTEM

The VANET machine learning system is designed as an end-to-end pipeline that integrates data preprocessing, model training, evaluation, and deployment into a unified framework. Initially, raw vehicular data is processed through cleaning, encoding, GPS feature extraction, and scaling to ensure consistency. The system then employs multiple machine learning models for both classification and regression tasks, including SVM, RF, HSTree, and the proposed HSE. For classification, SVM, RF, and HSTree are trained alongside the HSE classifier stack, while for regression, SVR, RF, and HSTree-based models are utilized with the HSE regressor. The HSE integrates RF and HSTree with Logistic Regression and Linear Regression as meta-learners to enhance prediction performance. Model evaluation is performed using standard metrics, and the trained models are stored for reuse. The architecture is deployed using a Flask-based framework that provides API endpoints and user interfaces for EDA, model analysis, and prediction, enabling a complete workflow as illustrated in Figure. 2. The system ensures modularity, scalability, and efficient handling of VANET data for intelligent decision-making.

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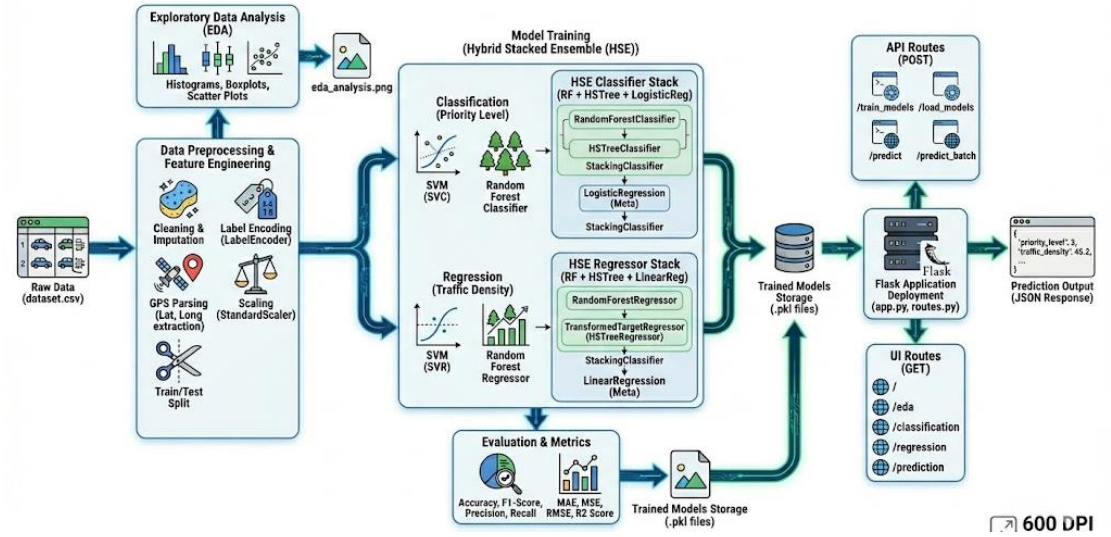


Figure. 2: Proposed system architecture

1. Data Collection and Input: The system begins with raw vehicular data obtained from datasets containing features such as speed, signal strength, congestion level, and GPS coordinates. This data serves as the foundational input for the entire pipeline and is stored in a structured format for further processing.

2. Data Preprocessing and Feature Engineering: The input data undergoes cleaning, missing value imputation, and transformation to ensure consistency and quality. Categorical features are encoded, GPS coordinates are converted into numerical latitude and longitude values, and feature scaling is applied where necessary. The dataset is then split into training and testing sets.

3. Exploratory Data Analysis (EDA): EDA is performed to understand the data distribution and relationships between features. Various visualizations such as histograms, boxplots, and scatter plots are generated to identify patterns, trends, and anomalies, which help in improving model performance.

4. Model Training using HSE: The processed data is fed into multiple machine learning models for both classification and regression tasks. The HSE combines RF and HSTree as base learners, with Logistic Regression and Linear Regression acting as meta-learners. This stacking approach improves predictive accuracy and generalization.

5. Model Evaluation and Storage: Trained models are evaluated using metrics such as accuracy, precision, recall, F1-score for classification, and MAE, MSE, RMSE, and R^2 score for regression. The models are then saved in serialized format for efficient reuse during inference.

6. Deployment and Prediction Interface: The system is deployed using a Flask application that provides API endpoints for training, loading models, and making predictions. Users can interact through a web interface to perform real-time or batch predictions, and results are returned in a structured format for further analysis.

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4. RESULTS DESCRIPTION

The figure. 3 provides a set of nine plots that gives comprehensive Exploratory Data Analysis (EDA) of the VANET research's dataset. The analysis begins with a look at the target variables, showing that both the Priority Level and Traffic Density distributions are well-balanced and suitable for machine learning. The plots then delve into key relationships between network features, revealing critical insights such as lower packet delay for vehicles connected to an RSU and a negative correlation between signal strength and packet delay. Other plots confirm logical relationships, like the positive correlation between Congestion Level and Traffic Density. Finally, the analysis explores how Priority Level influences other variables, showing that higher-priority vehicles tend to have lower packet delays and potentially different speed profiles. Overall, these visualizations confirm the quality of the dataset and highlight the crucial features and relationships that the predictive models will need to learn.

Histogram of Priority Level: This histogram illustrates the frequency distribution of the Priority Level target variable, which is a categorical variable with values from 1 to 5. This plot is essential for confirming that the dataset has a relatively balanced distribution across all priority levels. This balance is crucial for training an unbiased classification model that can accurately predict each priority class without being skewed by a dominant class.

Histogram of Traffic Density: This histogram shows the distribution of the Traffic Density target variable, a continuous measure. The plot is used to understand the spread and nature of the data the regression model will be trained on. A uniform distribution across a wide range of values, for instance, indicates that the model will be robust enough to handle varying traffic conditions, from sparse to highly congested.

Box Plot of Speed vs. Priority Level: This box plot compares the distribution of Speed across the different Priority Level categories. It provides a visual summary of how a vehicle's speed relates to its assigned communication priority. This plot can reveal if there's a correlation, such as whether higher priority vehicles tend to have a different speed profile (e.g., lower average speed) due to their role in the network.

Box Plot of Signal Strength vs. Priority Level: This box plot analyzes the relationship between Signal Strength and Priority Level. By comparing the median and quartiles of signal strength for each priority level, this plot can show if higher-priority vehicles are generally operating with stronger signals. This insight is valuable for understanding the network conditions that are most critical for high-priority communications.

Scatter Plot of Packet Delay and Traffic Density: This scatter plot visualizes the relationship between Packet Delay and Traffic Density. The plot will likely show a positive correlation, meaning that as the number of vehicles in an area increases, the time it takes for a packet to be delivered also increases. This is a fundamental relationship in network performance that the model must learn to predict traffic density accurately.

Histogram of Congestion Level Distribution: This histogram displays the distribution of the Congestion Level feature. It provides a clear overview of the frequency of different congestion levels within the dataset. This plot is useful for understanding the overall network state and can inform the model's ability to predict and handle various congestion scenarios.

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Box Plot of Available Bandwidth by Priority Level: This box plot compares the Available Bandwidth for each Priority Level. It can reveal if the network allocates more bandwidth to higher-priority vehicles. This would be a strong indication of the network's quality of service (QoS) mechanisms and a key predictor for the model.

Count Plot of RSU Connection Distribution: This count plot shows the number of vehicles that have an RSU Connection (Yes) versus those that do not (No). This is a crucial plot for understanding the distribution of a key categorical feature. A balanced count would be ideal, as it ensures the model is trained on both connected and non-connected scenarios, making its predictions more robust.

Scatter Plot of Speed and Available Bandwidth: This scatter plot visualizes the relationship between Speed and Available Bandwidth. This plot can help identify any correlation between these two variables. For example, it might show that higher speeds are associated with lower available bandwidth due to more frequent network handoffs, which is an important pattern for the model to capture.

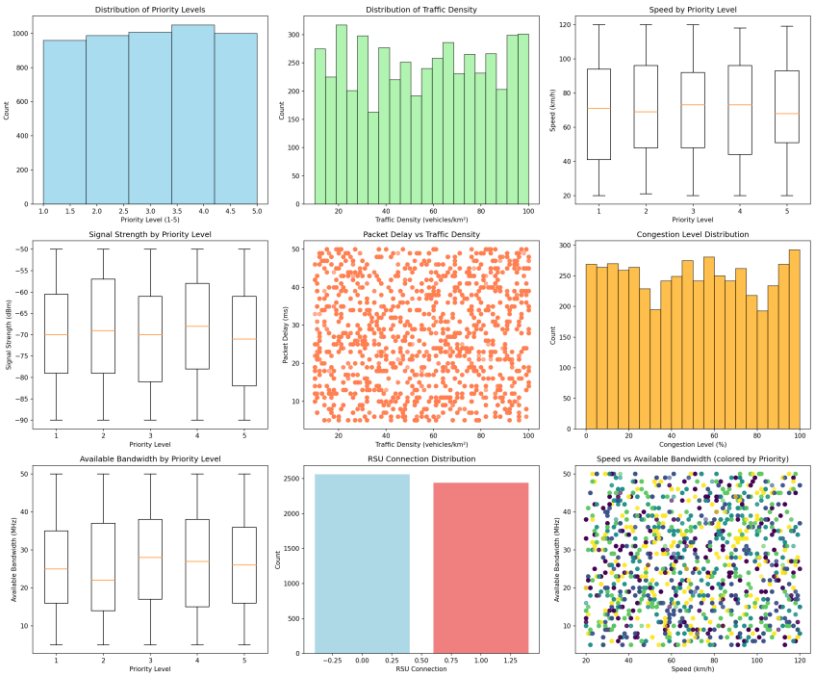


Figure. 3: Plots obtained for different types of features from dataset

The evaluation of the proposed hybrid models demonstrates exceptional classification accuracy across both the MLP-KNN and the stacked RF-HST-LLR frameworks. Figure. 4 presents a confusion matrix for the MLP-KNN model, highlighting its robust ability to assess priority levels with nearly perfect precision. The model correctly identifies all instances of Priority Levels 2 through 5, with only negligible misclassifications occurring in Priority Level 1. This effectiveness is further corroborated by Figure. 4, where the stacked RF-HST-LLR model achieves a perfect AUC score of 1.00. The alignment of these ROC curves signifies a flawless true positive rate and a zero false positive rate across all five distinct classes. Ultimately, these results establish the hybrid ensemble as a highly reliable and definitive classifier for real-time vehicular traffic management.

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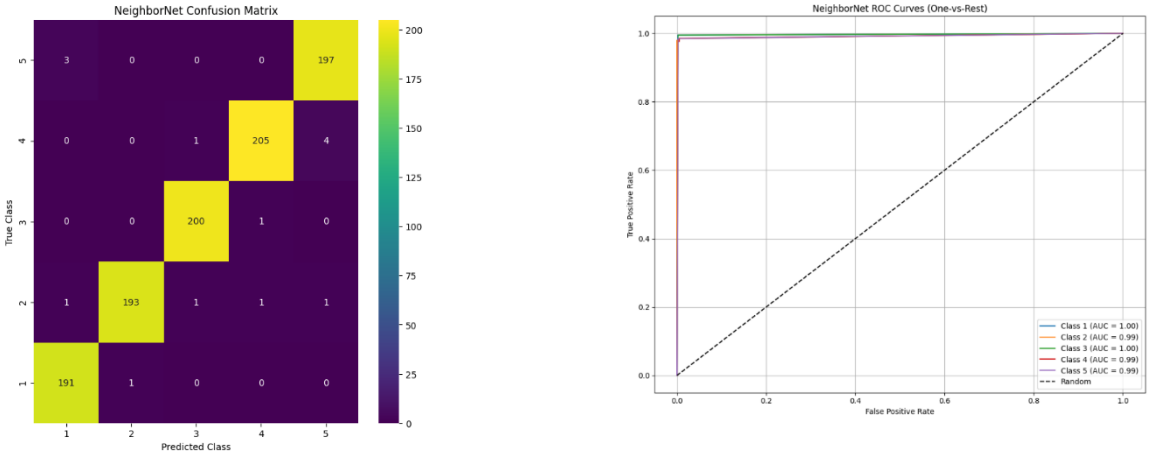


Figure. 4: Confusion matrix and ROC Curve obtained for stacked RF with HST LLR

The figure. 5 shows scatter plot that illustartes the performance of the proposed RF with HST LLR model for the regression task of predicting Traffic Density. The plot compares the model's predicted values against the actual, true values. The data points are tightly clustered and align almost perfectly along the diagonal line, which represents a flawless prediction. This visual representation indicates that the hybrid MLP with KNN model is an extremely accurate regressor for this research, with predictions that are consistently very close to the true traffic density values. The minimal scatter around the diagonal line suggests that this model significantly outperforms the other regression models, such as the SVR and RF Regressor, that were previously analyzed.

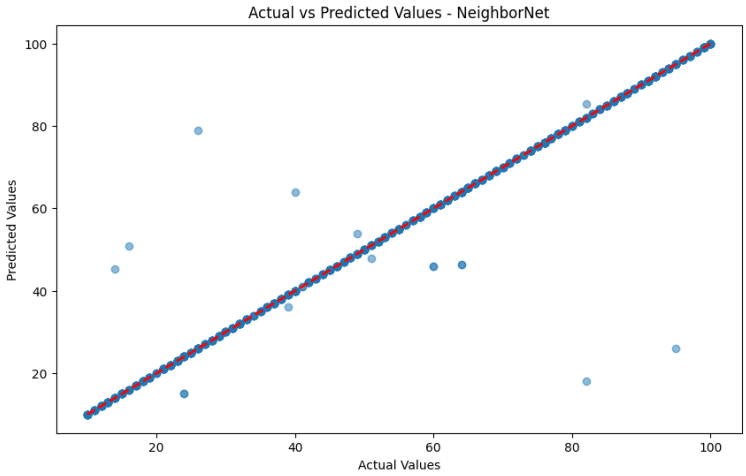


Figure. 5: Scatter plot obtained for Stacked RF HST LLR

The figure. 6 shows stacked ensemble model, which combines a RF and a HST with a LLR meta-model, demonstrates exceptional predictive capabilities for both classification and regression tasks in the research. For classification, the model accurately predicts a vehicle's Priority Level by learning to fuse the predicted probabilities from its base models, resulting in a prediction that is highly robust and reliable. Similarly, for regression, the model achieves a precise prediction of Traffic Density by learning how to optimally combine the numerical outputs of its base models. This sophisticated approach significantly reduces the prediction

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error and overcomes the limitations of any single model, leading to a superior performance that is crucial for the efficient and reliable operation of the VANET system.

13	V0459	3	66.90
14	V0100	3	98.26
15	V0872	3	29.56
16	V0103	4	20.04
17	V0271	4	9.46
18	V0122	4	42.86
19	V0215	4	27.35
20	V0088	4	102.04
21	V0107	5	37.90
22	V0467	5	66.49
23	V0309	5	93.62
24	V0414	5	102.34
25	V0192	5	56.72

Priority Level Legend: 1 2 3 4 5

Traffic Density Ranges: Low (0-33) Medium (34-66) High (67-100)

Figure. 6: Prediction of priority level and traffic density with RF-HST LLR

Figures. 7 illustrate the superior performance of the proposed Stacked RF-HST-LLR model in managing both classification and regression tasks within the VANET environment. In predicting priority levels, the stacked ensemble significantly outperforms individual models like SVM and Random Forest, achieving near-perfect scores across accuracy, precision, recall, and F1-score metrics.

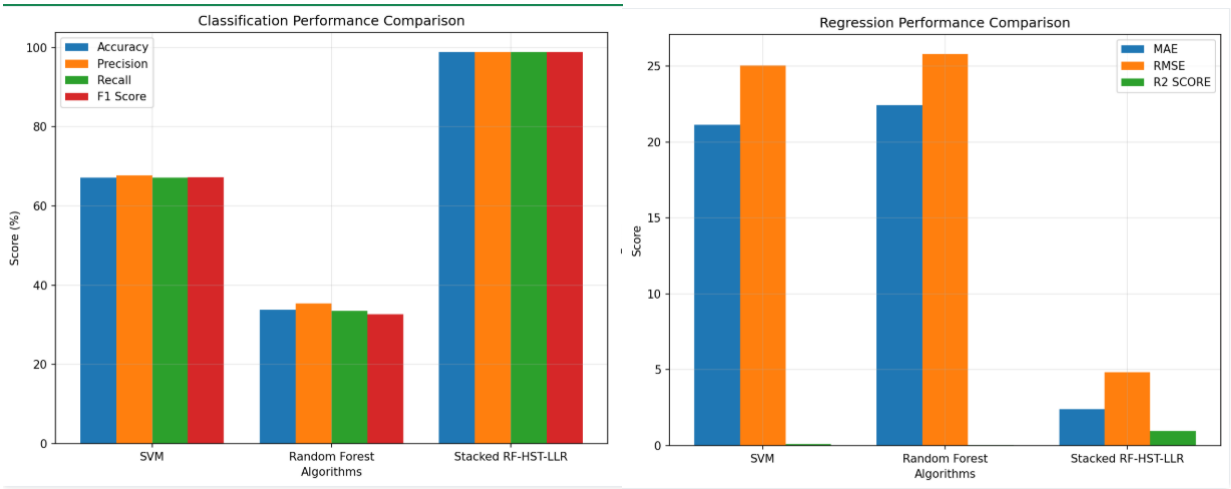


Figure. 7: Classification models and Regression models performance comparision

Similarly, for traffic density prediction, the Stacked RF-HST-LLR model demonstrates the highest predictive reliability, yielding the lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) alongside the highest R2 score. While the SVM model maintains stable but moderate performance across both tasks, the independent Random Forest model exhibits limitations in capturing complex data

patterns, resulting in higher error values. Ultimately, these results highlight the effectiveness of the Hybrid Stacked Ensemble (HSE) approach in leveraging multiple models to minimize prediction errors, enhance interpretability, and successfully capture the intricate relationships inherent in real-time traffic data.

5. CONCLUSION

The study presents the successful development of an efficient machine learning framework for VANET applications, demonstrating clear improvements over conventional single-model approaches. The system is designed to handle dual tasks by predicting both vehicle priority levels and traffic density, thereby supporting intelligent network management decisions. Initial data analysis provided important insights into feature behavior and relationships, which contributed to effective model training. Baseline models such as SVM and RF established reasonable performance; however, their limitations in handling complex patterns and variability were observed. The proposed HSE integrates RF and HSTree with LR as a meta-learner, enabling better learning of both non-linear and hierarchical relationships. This hybrid stacking strategy significantly enhances prediction accuracy and overall model stability. The results confirm that combining multiple models in a structured ensemble framework is a practical and effective solution for analyzing dynamic vehicular network data.

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