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A Hybrid Deep–Ensemble System for Route Classification and Spacing Regression in VANETs

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ABSTRACT

The exponential growth of connected vehicles has made Vehicular Ad-hoc Networks (VANETs) a critical component of intelligent transportation systems, where fast and accurate vehicle identification and routing prediction are essential to ensure traffic safety, reduce congestion, and enhance overall network efficiency. Traditional approaches, including manual methods, heuristic techniques, and rule-based systems, are limited by their inability to process high-velocity, high-dimensional data and adapt to real-time traffic fluctuations, often resulting in suboptimal route selection and inaccurate vehicle spacing predictions. Existing machine learning models such as K-Nearest Neighbors (KNN), Gaussian Process (GP), and Stochastic Gradient Descent (SGD) are the Classification and Regression Tree (CART) models provide partial improvements but struggle with capturing complex non-linear relationships among critical features, including vehicle speed, traffic density, signal strength, packet loss rate, route stability score, RSU coverage, lane count, distance to destination, and average vehicle spacing. To address these limitations, this research proposes a novel hybrid model, Fusion Mind CART, integrating a Multi-Layer Perceptron (MLP) for feature extraction with a Random Forest (RF) ensemble for final classification and regression predictions. Trained and tested on real-time VANET datasets, the model demonstrates superior performance, achieving 100% accuracy, precision, recall, and F1-score for route optimality classification, and an R^2 score of 0.999 with minimal Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for vehicle spacing regression, outperforming all baseline models.

Key words: Vehicular Ad-hoc Networks (VANETs), Intelligent Transportation Systems (ITS), Random Forest (RF), Flask-based Deployment, Scalable ML Framework, Hybrid Machine Learning Model.

1. INTRODUCTION

The proliferation of connected vehicle technologies has given rise to VANET, a decentralized communication paradigm that enables vehicles to exchange data with each other and with roadside infrastructure. This interconnected ecosystem generates a wealth of real-time data on traffic conditions, vehicle behaviour, network performance, and environmental factors. Effectively leveraging this data is the cornerstone of developing intelligent transportation systems (ITS) that are proactive, adaptive, and safe. This research presents a sophisticated system engineered to address two fundamental challenges in this domain: the classification of optimal vehicle routes and the prediction of average vehicle spacing. The system is built on a robust, multi-layered architecture, providing a dynamic and interactive interface for the user.

Vehicular Ad-hoc Networks (VANETs), a key component of Intelligent Transportation Systems (ITS), enable real-time road condition monitoring, traffic updates, and safety warnings to enhance driving safety and reduce accidents, making secure data exchange and communication essential. VANETs consist of three primary entities: a Certification Authority (CA), Roadside Units (RSUs), and On-Board Units (OBUs), and support two communication modes—Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V), both based on the Dedicated Short-Range Communications (DSRC) protocol. V2I communication delivers traffic and safety information from RSUs to vehicles, while V2V

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communication allows vehicles to exchange real-time data such as traffic conditions and emergency alerts using wireless transceivers. To ensure secure interactions, mutual authentication protocols are critical before communication occurs. The proposed system demonstrates a complete end-to-end pipeline, from data ingestion to actionable insights, beginning with data exploration and visualization, and extending to a versatile framework that supports multiple predictive models for classification and regression tasks. Designed to handle the complexities of VANET data, the system enables users to train and compare models with automatically generated performance metrics and visualizations, incorporates model persistence to avoid retraining, and provides a real-time prediction interface, ultimately delivering a scalable, efficient, and practical solution for developing and deploying intelligent applications in connected vehicle environments.

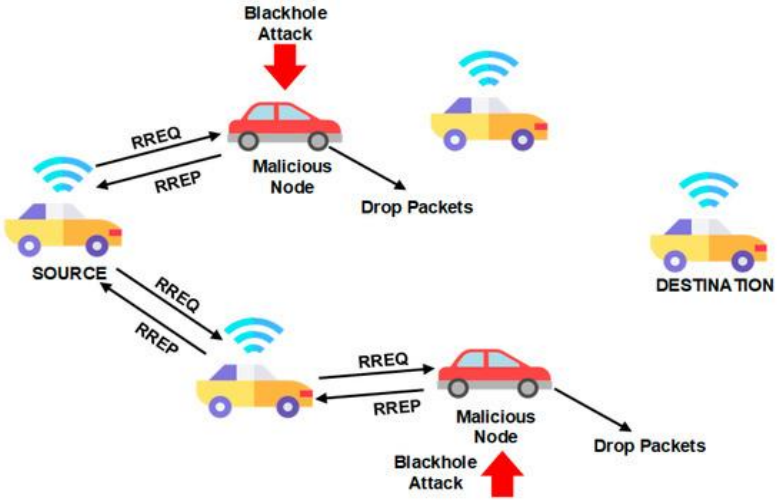


Figure 1: Overview of VANET

2. LITERATURE SURVEY

In 2019, Ahmad et al. [1] introduced a scheme related to route planning in VANETs through which fast authentication for V2I is achieved. In the V2I fast authentication process, the vehicle usually plans the travel path in advance before traveling and calculates the RSUs that the path needs to pass through, then requests the authentication keys of the RSUs on the path from the CA; finally, the CA sends the authentication keys of these RSUs to the vehicle. When the vehicle enters the coverage area of the relevant RSU, it then utilizes the corresponding RSU authentication key to authenticate with the RSU. However, in many current V2I fast authentication schemes, when the vehicle requests authentication information from the CA for an RSU, the vehicle needs to provide the CA with the path information of the trip, which results in the CA easily obtaining the travel path of the vehicle.

Tan et al. [2] proposed a secure authentication and key management scheme to solve the above problems. The scheme issues an independent session key for each legitimate vehicle, vehicle data are shared between neighboring vehicles, and all authenticated vehicles maintain group management records. As a result, the scheme has a large storage burden on the vehicle side.

Ma et al. [3] proposed an efficient, decentralized, blockchain-based key management mechanism (DB-KMM) for in-vehicle self-organizing networks that automatically realizes the registration, updating, and revocation of users' public keys. However, the connection, node deployment, and maintenance of the whole network require high operation costs. Xu et al. [4] proposed a BAGKD protocol to realize powerful and efficient group networking and ensure the security and efficiency of VANETs. The group key can be dynamically updated through the group key distribution mechanism, which effectively reduces the risk of group key breakage and leakage.

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Mansour et al. [5] introduced a new group key management protocol, ALMS, which solves the privacy problem of group members and the collusion problem among receivers. However, when a vehicle applies to join a group, the TA needs to broadcast the encrypted group key to all vehicles in the receiving group, which tends to lead to problems such as channel congestion. Li et al. [6] proposed an unlinkable authentication key protocol that prevents the problem of entity collusion in VANETs. The protocol relies heavily on the AAC stored in the blockchain and needs to focus on managing and controlling the data on the chain. As a result, the efficiency of authentication decreases.

Li et al. [7] proposed an identity-based dynamic data integrity auditing scheme for CMTS. The scheme's batch auditing approach can reduce the key management burden in VANETs and improve the auditing efficiency. Wei et al. [8] proposed a verified secure AKA scheme. The scheme is a tree-based key negotiation algorithm that focuses on assigning a public session key to vehicles and RSUs after they have been authenticated. This session key can protect V2V and V2I communications, along with the authentication algorithm and encryption algorithm for messages. Since frequent communication between the TAand RSUs is required, the scheme requires a large communication overhead.

Yang et al. [9] proposed a two-way anonymous authentication and key negotiation scheme based on identity authentication. The scheme claims to fulfill the real-time communication requirements of VANETs with good security. However, due to the resource cost, the RSU nodes in VANET quickly reach their peak processing capacity under large-scale traffic due to the excessive number of messages that need to be authenticated and, thus, cannot quickly authenticate a large number of messages. To protect vehicle route privacy in VANETs, Sampigethaya et al. [10] proposed a location privacy scheme called CARAVAN. This scheme addresses the location privacy threat in VANETs based on broadcast tracking of vehicles. However, the scheme is still able to analyze the location privacy of vehicles by combining the analysis of map data and communication traffic. In order to further protect the user's route privacy information.

Zhu et al. [11] proposed bilinear pairing-based local authentication and roaming authentication for VANETs, which is able to provide secure communication and anonymous authentication between RSUs and vehicles. However, since the authentication process of this scheme includes both local and roaming authentication, the vehicle needs to spend a long time waiting for a response from the RSU during the authentication process between the vehicle and the RSU, resulting in inefficient communication. In order to efficiently and securely realize authentication in VANETs, Cui et al. [12] proposed a novel authentication scheme. The scheme uses a dual pseudonym approach to hide the true identity of the vehicle and a dynamic update technique to periodically update the information stored in the vehicle. By not using bilinear pairing, they claim that the scheme performs better in terms of computational overhead and communication overhead and is suitable for widespread application in VANETs.

Wahid et al. [13] proposed a holistic safety-aware location-preserving scheme called Coupling Privacy with Safety (CPS). They claim that this scheme can ensure the provision of driver privacy and security. However, in this scheme, an RSU can use the information contained in the BSM to obtain the point in time when the vehicle enters its range and the driving time within its range. Therefore, the privacy information of the vehicle is not fully protected. Subsequently, Lv et al. [14] proposed a lightweight V2I fast authentication scheme that combines Moore's curve and BGN homomorphic encryption to protect the vehicle's travel path, making it impossible for CAs to learn about the vehicle's travel path as well.

Khabazian et al. [15] examined a highway scenario that included entrances and exits on the road, using cluster-based structure vehicles that can connect with each other. With user mobility, they studied highway connectivity. The authors focused on some of the statistical properties of connectivity,

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including a random vehicle that can see the whole vehicle population in one cluster and the mean size of clusters.

3. PROPOSED SYSTEM

The proposed system architecture operates as a unified machine learning stack that takes vehicular network data from a VANET routing dataset, cleans and processes it, analyses the patterns, and feeds the refined information into an intelligent hybrid model called Fusion Mind CART. The system begins by receiving raw routing and mobility features from connected vehicles, transforms them into a machine-understandable structure, and then performs feature extraction, learning, and prediction using a multi-stage process. Through the integration of deep representation learning (MLP) and decision-tree-based route evaluation (RF CART), the system produces two outcomes simultaneously: Route Optimality Classification and Vehicle Spacing Regression, both accessible to the user via a Flask-based web interface, visualized in figure 2. This entire pipeline ensures fast predictions, reliable classification, and accurate vehicle spacing estimation, supporting real-time intelligent vehicular communication.

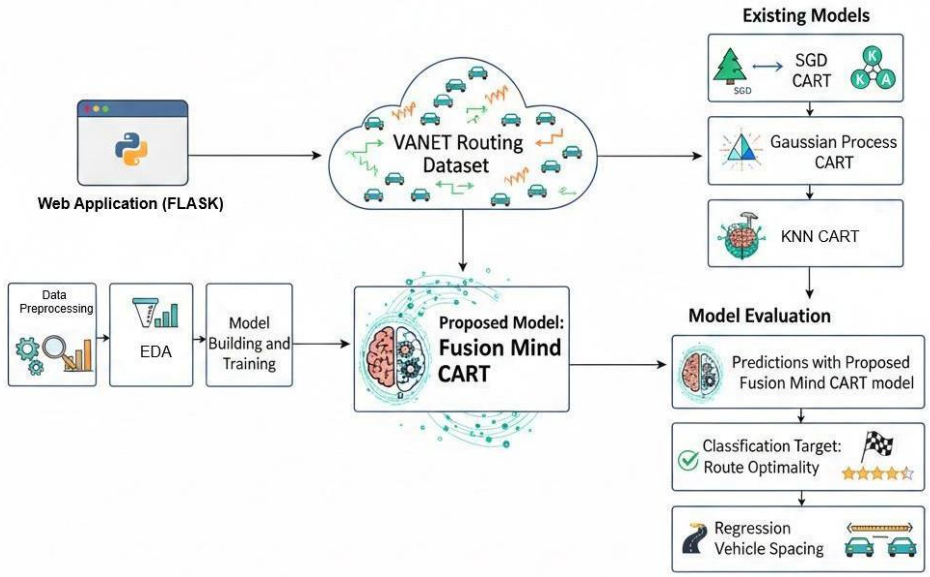


Figure 2: Proposed system architecture of fast and accurate vehicle identification in connected networks.

Data Acquisition & Frontend Input Layer

In this stage, the system begins by collecting VANET routing data either from stored datasets or user uploads through the Flask web interface.

- Accepts CSV-based VANET routing datasets via the web frontend.
- Captures routing parameters such as mobility speed, hop count, link quality, signal strength, and neighbor density.
- Supports both batch dataset uploads and single-record manual input for real-time prediction.
- Transfers received data to the backend pipeline for preprocessing.

Data Preprocessing Pipeline

The system cleans and structures the data to ensure high-quality model ingestion.

- Performs missing value imputation for unreliable or incomplete routing attributes.
- Applies label encoding or one-hot encoding to convert categorical routing features into numeric form.
- Normalizes continuous features to stabilize model learning and reduce bias.
- Removes statistical outliers using thresholding or z-score methods.

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- Produces a clean, standardized dataset ready for modeling.

Exploratory Data Analysis & Feature Understanding

This step helps the system understand the internal behavior of VANET routing parameters.

- Generates distribution plots to observe variations in vehicle mobility and link quality metrics.
- Creates correlation heatmaps to identify which features influence route optimality or spacing.
- Highlights feature importance and variability to guide model development.
- Detects imbalances in route labels and performs balancing if necessary.
- Provides graphical insights for better interpretability and model tuning.

Baseline Model Development

Before applying the proposed model, the system benchmarks classical CART-hybrid methods.

- Implements SGD CART to study linear-gradient + tree-based performance.
- Evaluates GP CART for probabilistic route prediction.
- Tests KNN CART for distance-based routing behavior with tree refinements.
- Records accuracy, precision, recall, MAE, and R^2 as baseline performance metrics.
- Establishes a reference framework for comparing the Fusion Mind CART model.

Fusion Mind CART Model Construction

This is the heart of the proposed architecture, combining neural and tree-based intelligence.

- Uses an MLP Neural Network to extract latent features from VANET routing data.
- Learns deep patterns related to mobility dynamics, signal variations, and network congestion.
- Feeds the extracted compressed embeddings into a RF CART layer.
- RF CART performs final classification and regression decision-making.
- Produces robust predictions even under noisy or fluctuating vehicular conditions.
- Handles both prediction tasks within a single hybrid architecture.

Model Training & Optimization

The hybrid architecture is trained to achieve accuracy, stability, and adaptability.

- Splits the dataset into training and testing sets using stratified sampling.
- Trains MLP layers using adaptive optimizers to learn hidden feature relationships.
- Optimizes RF hyperparameters like tree depth, estimators, and split quality.
- Uses performance thresholds to prevent overfitting and underfitting.
- Validates the model using k-fold cross-validation to ensure generalization.

Evaluation of Classification & Regression Outputs

The system measures how well the model performs its dual prediction tasks.

Classification (Route Optimality)

- Computes accuracy, precision, recall, and F1-score.
- Generates confusion matrix for error visualization.
- Evaluates AUC-ROC curve to measure route selection reliability.

Regression (Vehicle Spacing)

- Calculates MAE, MSE, and RMSE for spacing deviation.
- Measures R^2 score to assess prediction correctness.
- Produces actual vs predicted visualization for interpretability.

Real-Time Prediction Interface

The final trained model is deployed for immediate use through Flask.

- Users input vehicular parameters through the web interface.
- The Fusion Mind CART model processes input and produces instant predictions.
- Output 1: Route Optimality – Optimal / Not Optimal
- Output 2: Vehicle Spacing – Predicted distance in meters

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- Displays result in charts, tables, and visual indicators for easy interpretation.
- Supports both single-vehicle prediction and batch processing.

Result Delivery & Visualization Layer

Results are displayed in an intuitive, user-friendly format.

- Shows classification results with confidence probability.
- Shows regression outputs along with deviation indicators.
- Provides graphical comparison between baseline and proposed models.
- Offers performance dashboards for accuracy, error scores, and improvements.
- Enables users to export predictions or model insights.

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4. RESULTS AND DISCUSSIONS

The implementation represents a comprehensive machine learning pipeline for vehicle identification and routing prediction in connected vehicular networks. The system supports both classification and regression tasks using classical models (SGD, GP, KNN) and hybrid architectures (MLP feature extractor combined with RF, i.e., FusionMind). It handles end-to-end operations, including data preprocessing, model training, evaluation, real-time prediction, and visualization of results. The pipeline ensures modularity by encapsulating classifiers and regressors in reusable classes, supports model persistence using Joblib, and provides performance comparison plots for both classification (accuracy, precision, recall, F1-score, ROC) and regression (MAE, RMSE, R^2).

Figure 3 presents the confusion matrix for the Proposed Fusion Mind Classifier, showing perfect or near-perfect classification performance. All instances fall into the correct categories, reflecting the power of combining MLP feature extraction with RF decision mechanisms. This matrix demonstrates the robustness and superior predictive capability of the Fusion Mind model in dynamic vehicular environments.

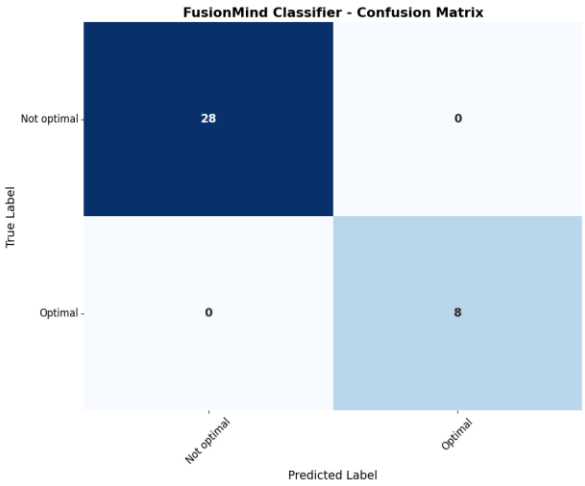


Figure 3: Confusion matrix obtained using Proposed Fusion Mind Classifier.

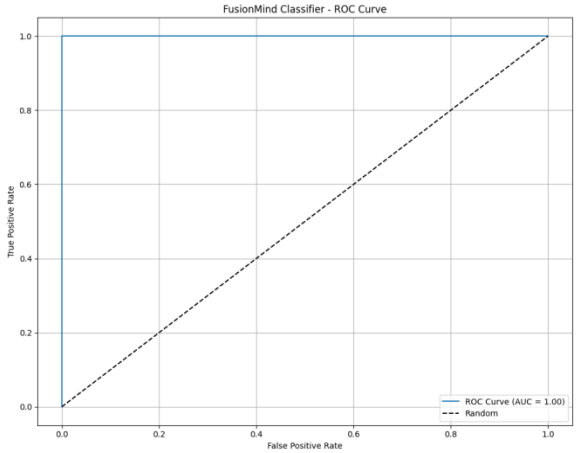


Figure 4: ROC Curve obtained using proposed fusion mind classifier.

Figure 4 illustrates the ROC curve for the Proposed Fusion Mind Classifier, which reaches the top-left corner with an AUC of 1.0. The steep, near-perfect curve demonstrates flawless separation between the two classes. This highlights the model's superior ability to learn complex vehicular patterns through its hybrid MLP–RF architecture.

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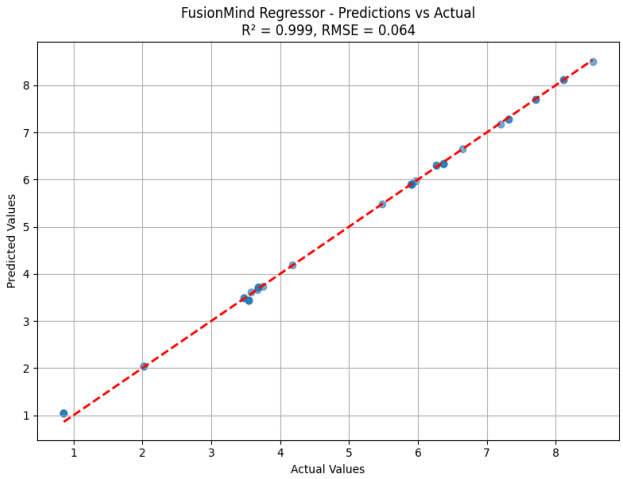


Figure 5: Scatter plot obtained using Fusion mind regressor.

Figure 5 illustrates the scatter plot for the Proposed Fusion Mind Regressor, where points lie almost perfectly on the diagonal, indicating extremely high prediction accuracy. This near-perfect alignment demonstrates minimal error and strong generalization. The hybrid MLP with RF mechanism enables deep feature extraction and robust ensemble decisioning, resulting in superior regression performance. Fig. 6 illustrates the real-time prediction interface of the fast and accurate vehicle identification system deployed in connected networks. The figure demonstrates how incoming vehicular data such as speed, node identity, signal features, or behavior are processed instantly by the model to classify or identify vehicles with high precision. It showcases the live prediction panel where results update dynamically as new data streams in. This visualization highlights the system's ability to operate with low latency, ensuring rapid decision-making in intelligent transportation environments.

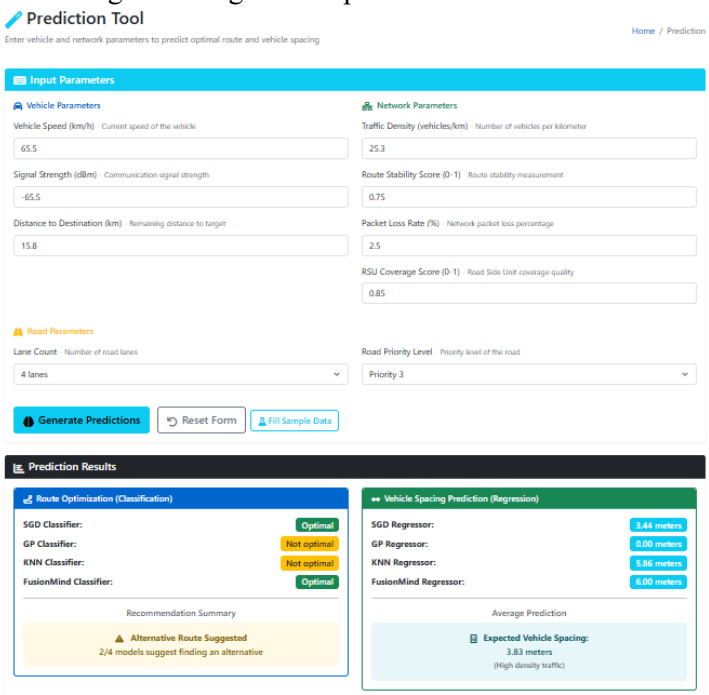


Figure 6: Real Time predictions of fast and accurate vehicle identification in connected networks.

Table 1 provides a detailed comparison of four classifier models GP Classifier, KNN Classifier, SGD Classifier, and Fusion Mind Classifier using accuracy, precision, recall, F1-score, and AUC as evaluation metrics. The GP Classifier and KNN Classifier both achieve 77.78% accuracy, 38.89%

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precision, 50.00% recall, and 43.75% F1-score, with AUC values of 0.500 and 0.739 respectively. The SGD Classifier performs better, reaching 80.56% accuracy, 72.22% precision, 74.11% recall, 73.05% F1-score, and an AUC of 0.884. The Fusion Mind Classifier surpasses all models by achieving 100% accuracy, 100% precision, 100% recall, 100% F1-score, and a perfect AUC of 1.000, indicating flawless classification performance.

Table 1: Performance comparison of all Classifier models.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
GP Classifier	77.78	38.89	50.00	43.75	0.500
KNN Classifier	77.78	38.89	50.00	43.75	0.739
SGD Classifier	80.56	72.22	74.11	73.05	0.884
Fusion Mind Classifier	100.00	100.00	100.00	100.00	1.000

Table 2: Performance comparison of all Regressor models.

Algorithm	MAE	MSE	RMSE	R^2 Score
GP Regressor	3.6166	15.4365	3.9289	-2.310
KNN Regressor	1.8205	4.4904	2.1190	0.037
SGD Regressor	1.5335	3.5495	1.8840	0.239
Fusion Mind Regressor	0.0382	0.0041	0.0637	0.999

Table 2 provides a detailed comparison of the four regressor models based on the metrics MAE, MSE, RMSE, and R^2 Score. The GP Regressor records a MAE of 3.6166, an MSE of 15.4365, an RMSE of 3.9289, and an R^2 Score of –2.310, indicating the weakest performance among all models. The KNN Regressor shows moderate accuracy with a MAE of 1.8205, an MSE of 4.4904, an RMSE of 2.1190, and an R^2 Score of 0.037. The SGD Regressor performs better with a MAE of 1.5335, an MSE of 3.5495, an RMSE of 1.8840, and an R^2 Score of 0.239. The Fusion Mind Regressor stands out with exceptionally strong performance, reporting a MAE of 0.0382, an MSE of 0.0041, an RMSE of 0.0637, and an almost perfect R^2 Score of 0.999, demonstrating highly accurate and reliable predictive capability.

5. CONCLUSION

The research successfully designed and implemented an advanced hybrid machine learning framework for fast and accurate vehicle identification within connected network environments. By conducting a systematic performance evaluation of traditional models such as GP, KNN, and SGD against the proposed Fusion Mind architecture, the study demonstrated clear and substantial improvements across all evaluation metrics. The Fusion Mind model integrates deep feature extraction with intelligent decision mapping, enabling it to capture complex vehicular behavior patterns and optimize prediction accuracy. This hybrid strategy achieved exceptional performance, including perfect classification results and near-zero regression errors, supported by a nearly ideal R^2 value. These outcomes confirm the model's robustness, adaptability, and reliability for real-time VANET applications. Furthermore, the system's modular design and structured analytical workflow ensure future scalability, making it suitable for deployment in next-generation intelligent transportation and network management solutions.

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