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A HYBRID APPROACH FOR EV CHARGING LOAD FORECASTING USING SIGNAL NOISE REDUCTION AND TIME SERIES ANALYSIS

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ABSTRACT

Vehicular Ad-Hoc Networks (VANETs) are a key component of intelligent transportation systems, enabling vehicles to communicate for safer and efficient traffic management. In India, rapid urbanization and increasing vehicle density have led to congestion and suboptimal route selection. According to recent reports, Indian cities witness over 30% higher average travel times due to traffic congestion. VANETs can optimize vehicle routing, improve network communication, and enhance road safety by analyzing traffic density, vehicle speed, and network conditions. The objective of this research is to predict optimal vehicle routes and traffic load patterns using machine learning. It aims to automate decision-making in vehicular networks for enhanced routing efficiency and network reliability. Traditionally, traffic and route management rely on manual monitoring using traffic signals, CCTV cameras, and periodic reports from traffic personnel. Vehicles follow pre-defined maps or human instructions to select routes, and charging stations depend on manual scheduling for load management. Manual systems are time-consuming, error-prone, and unable to adapt to real-time traffic fluctuations. They cannot predict congestion, optimize vehicle spacing, or balance charging loads dynamically. Human intervention limits scalability and often results in inefficient route selection and increased travel time. This research aims to overcome the limitations of manual systems by leveraging machine learning for real-time route and load optimization. Improvements include predictive accuracy, automated decision-making, adaptive traffic management, and efficient load distribution in vehicular networks, enabling scalable and reliable traffic solutions. The proposed system uses machine learning models for classification and regression. **GP Classifier** predicts whether a route or charging condition is optimal using Gaussian Process-based probabilistic modeling. **KNN Classifier** classifies load or route patterns based on similarities to historical data. **FusionMind Classifier**, a hybrid MLP+Random Forest model, captures complex patterns for accurate classification. For regression, **SGD, KNN, and FusionMind Regressors** forecast numerical values like vehicle spacing or charging load. These models enable predictive, adaptive, and automated traffic and charging management, reducing congestion and improving system reliability.

INTRODUCTION

The current international energy landscape is characterized by complexity and volatility, prompting countries worldwide to actively promote and develop renewable energy sources [1]. As China experiences a critical phase of rapid economic development, effectively coordinating and advancing the optimal integration of the “dual-carbon” goals with energy security has emerged as a pivotal issue in contemporary research. Studies indicate that the power production and transportation sectors are major contributors to carbon emissions, with the transportation sector alone accounting for over 25% of global carbon emissions [2]. In this context, EVs, as a form of clean energy transportation, are garnering increasing attention and support. However, the development of charging infrastructure has not kept pace with the growing demand for charging services, making the prediction of charging demand loads a prominent area of research. With the increasing popularity of new energy vehicles and other chargeable devices, forecasting user charging demand loads has become critically important within the power system [3]. This forecasting is directly linked to the rational allocation and efficient utilization of power resources and significantly influences production planning on the generation side, the precise scheduling of the power grid, as well as the stable operation of the power system and the reliability of the power supply [4]. Accurate predictions of charging demand can help mitigate the waste and scarcity of energy resources, ensuring the safety and stability of the power grid, enhancing the quality of power services, and meeting the ever-growing demand for charging [5]. Consequently, developing a scientific and robust prediction model for accurately forecasting user charging demand loads is essential for the sustainable development of the electric power industry and the stable operation of society [6].At present, the commonly used methods for charging demand load forecasting are machine learning and various combinations of models. In the realm of forecasting models, researchers both domestically and internationally have conducted numerous studies on EVs charging demand load forecasting. Derni Ageng et al. [7] proposed a short-term household load forecasting framework combining data preparation and LSTM networks, named LSTM-DP. Through interpolation and Savitzky Golay filtering for data preprocessing, the framework enhances the accuracy of next-hour load forecasting using LSTM.

Experimental results demonstrate superior performance compared to other methods. However, the LSTM model may face issues such as overfitting and sensitivity to hyperparameter selection. Additionally, Liu et al., [8] introduced an optimization method utilizing a differential evolution-improved Harris Hawk optimization (DE-IHHO) algorithm to tackle the hyperparameter selection challenge in bidirectional long short-term memory networks (BiLSTM) for short-term electricity load forecasting. While their approach markedly improves forecasting accuracy, the optimized BiLSTM model remains sensitive to initial parameter settings, and the increased computational complexity of the optimization algorithm may lead to prolonged training times. In general, the existing models above still cannot weaken certain nonlinear load sequences, leading to the inaccessibility of more accurate predicted values. To mitigate the impact of load data fluctuations on charging demand load forecasting, researchers both domestically and internationally frequently employ combined forecasting models based on signal decomposition algorithms. These models typically consist of three components: decomposition, prediction, and reconstruction. Initially, a signal decomposition algorithm is utilized to break down the charging load data into smoother load components. Subsequently, a prediction model is constructed for these components, and finally, the prediction results are reconstructed and combined to yield the final forecasts. Commonly used signal noise reduction methods include variational modal decomposition (VMD), empirical modal decomposition (EMD), and CEEMDAN. Among them, Zhang et al., [9] proposed a load forecasting model that integrates VMD with a Chaotic Grey Wolf Optimization (CGWO) algorithm and Support Vector Regression (SVR), addressing the nonlinear and non-stationary characteristics of power load data. Their results demonstrate that this model outperforms traditional methods across several performance indicators, confirming its efficacy in enhancing forecasting accuracy. However, the VMD method has notable limitations regarding sudden signals, and the CGWO algorithm may exhibit lower computational efficiency with large-scale datasets. Zheng et al., [10] introduced a hybrid forecasting model, termed SD-EMD-LSTM, which combines similar day selection, EMD, and Long Short-Term Memory (LSTM) networks. Their findings indicate that this model achieves high accuracy and stability in both one-day and one-week forecasting. Nonetheless, the EMD method can lead to modal mixing, and the model's complexity necessitates further improvements in computational efficiency. Shi et al., [11] developed a load forecasting method based on CEEMD and multi-model fusion, analyzing the stochasticity and complexity of load in regional integrated energy systems. Their results indicate high prediction accuracy when addressing non-stationary load sequences; however, the CEEMD algorithm may encounter modal aliasing and high computational complexity when decomposing high-frequency and low-frequency components, which can affect the model's real-time performance and efficiency. Chao et al., [12] developed a gated recurrent unit (GRU) neural network model, termed CEEMD-SSA-GRU, which is optimized using complete ensemble empirical mode decomposition (CEEMD) and the Sparrow Search Algorithm (SSA) to address the complexities associated with short-term power load forecasting. Their findings demonstrate that this model significantly outperforms others in forecasting accuracy; however, the training process is complex, and the computational cost of the optimization algorithm is substantial. Hu et al., [13] proposed a hybrid deep learning prediction model that combines EMD, CNN, and BiLSTM, analyzing the nonlinear and non-stationary characteristics of electric load. Their results show that this model achieves high accuracy and effectiveness in medium- and long-term load prediction. Nonetheless, EMD decomposition can lead to modal aliasing issues, and the CNN-BiLSTM model exhibits high computational complexity when processing large-scale data, which can adversely affect the model's real-time performance and efficiency. To address these challenges, this paper introduces the CEEMDAN-CNN-BiGRU-AM model, which fully utilizes the advantages of the CEEMDAN decomposition algorithm for signal noise reduction and the CNN- BiGRU model for feature extraction and time series processing. The CEEMDAN can decompose complex signals into simpler IMFs for time-frequency analysis and feature extraction. It improves upon traditional EMD methods by reducing mode mixing and enhancing stability in signal processing applications. The CNN component effectively captures local features of the load data through its convolutional and pooling layers, while the BiGRU component considers both past and future information when processing sequential data. By feeding sequence data into the two GRU models from beginning to end and from end to beginning, respectively, and subsequently merging the outputs, the BiGRU is able to capture sequential features more comprehensively. Finally, to optimize the extraction of key feature information, an AM is incorporated into the CNN-BiGRU model, enhancing its ability to capture significant feature information

Background

Vehicular Ad-Hoc Networks (VANETs) are an integral part of modern intelligent transportation systems, allowing vehicles to communicate with each other and roadside infrastructure to enhance traffic management, road safety, and driving efficiency. In India, rapid urbanization and a significant increase in vehicle density have caused severe traffic congestion, with urban centers experiencing over 30% longer travel times compared to uncongested conditions. Traditional traffic management relies on static signals, manual monitoring, and human-guided routing, which fail to adapt to dynamic traffic patterns. VANETs can provide real-time data on vehicle speed, traffic density, route conditions, and network performance, enabling smarter, automated decisions for vehicle routing and load balancing. Applications include real-time navigation optimization, traffic flow control, congestion prediction, accident prevention, and efficient charging station scheduling.

Problem Definition

Before the integration of machine learning, vehicular networks faced numerous limitations. Traffic management relied heavily on manual observation through CCTV cameras, traffic personnel, and pre-defined signals, which could not account for real-time traffic fluctuations. Route selection often followed static maps or human judgment, leading to congestion and suboptimal travel times. Vehicles were unable to adapt dynamically to changing network conditions, and charging stations struggled to balance loads efficiently. Overall, the absence of predictive and automated systems resulted in inefficiencies, increased travel delays, and reduced road network reliability.

Research Motivation

The motivation for this research arises from the need to improve traffic and route management in highly congested urban areas of India. By leveraging machine learning, vehicles can autonomously determine optimal routes, predict traffic loads, and adjust to real-time conditions. Automated decision-making reduces human intervention, enabling scalable and adaptive traffic solutions. Enhancing prediction accuracy and load balancing contributes to safer and more reliable transportation networks. The research aims to bridge the gap between conventional manual monitoring and intelligent, data-driven vehicular network management.

Objective

The primary objective of this research is to develop a machine learning-based system capable of predicting optimal vehicle routes and traffic load patterns within VANETs. It seeks to automate routing decisions, optimize vehicle spacing, and forecast congestion in real time. The system also aims to balance charging station loads efficiently, reduce travel delays, and improve overall network reliability. Classification and regression models are employed to provide accurate, adaptive, and actionable insights for traffic and charging management.

Applications

This research has practical applications in several areas of intelligent transportation. VANETs enhanced with machine learning can provide real-time route optimization for vehicles, reducing congestion and travel time. Traffic authorities can monitor and predict high-density zones to manage flow efficiently. Charging stations benefit from predictive load distribution, ensuring equitable energy supply. Navigation systems can integrate dynamic routing suggestions for optimal travel. Emergency services gain faster access during high traffic conditions. Fleet management becomes more efficient through adaptive scheduling. Urban planners can analyze traffic patterns for better infrastructure development. Overall, the system improves safety, reliability, and efficiency across vehicular networks.

Significance

The significance of this research lies in transforming conventional traffic and route management into an intelligent, automated, and predictive system. By integrating machine learning models like GP Classifier, KNN Classifier, and FusionMind Classifier, VANETs can make informed routing decisions while maintaining vehicle safety and network efficiency. Predictive regression models further enhance the system by forecasting vehicle spacing and charging station loads. This approach reduces congestion, improves travel time, and ensures balanced resource allocation across vehicular networks. The research contributes to sustainable urban transportation solutions, enhanced traffic safety, and the advancement of smart city infrastructure

LITERATURE SURVEY

Torres et al. [14] first proposed the CEEMDAN algorithm, which builds upon the EMD algorithm by continuously averaging the new signal through the addition of adaptive Gaussian white noise. The EMD algorithm decomposes the original signal into IMFs based primarily on the local eigentime scales of the original signal, resulting in a series of IMF components that span from high to low frequencies [15]. In contrast, the CEEMDAN method incorporates the IMF components of white noise into each decomposition step, computing unique IMF components for enhanced accuracy. The noise introduced by the CEEMDAN method diminishes progressively, resulting in reduced residual noise within the eigenmode components and consequently lowering the reconstruction error [16]. Additionally, each stage of decomposition employs a global stopping criterion, thereby enhancing the overall efficiency of the decomposition process. The CEEMDAN decomposition process is as follows: GRU, an advanced variant of recurrent neural networks, was proposed by Kyung Hyun Cho [27] in 2014 as a simplification of LSTM networks, aimed at enhancing the efficiency of sequence data processing. Compared to traditional RNNs, the GRU introduces a unique gating mechanism that enables the network to adaptively filter and retain essential information, thereby capturing long-term dependencies in sequences with greater accuracy [28].The core innovation of the GRU lies in the optimization of its internal structure. Unlike the gating mechanism in LSTMs, the GRU employs two gates: the update gate and the reset gate. The update gate functions as an information filter, determining the extent to which the current information should be retained for future time steps. In contrast, the reset gate decides whether to discard previous information to accommodate new input. This gating mechanism is designed to provide the GRU with increased flexibility and efficiency in processing sequential data, thereby enhancing the overall performance of the model [29]. In the GRU architecture, the reset gate plays a key role at moment t. It regulates the way in which the current input Xt is fused with the hidden state Ht−1 of the previous moment, which is manifested in the decision of how much information needs to be forgotten or retained. A higher value of the reset gate indicates a higher weighting of Ht−1 in determining the current state, and correspondingly a lower weighting of the current input Xt [30]. When Xt and Ht−1 are introduced, they are first multiplied at the element level by their respective weight matrices WXr , and subsequently, processed by a sigmoid function to obtain the output of the reset gate, Rt . This process efficiently regulates the ratio of information fusion between the hidden state and the current input at the previous moment. After the computational training in the above steps, the GRU will use this information to compute H~t , which will help to further compute the next Ht . This is done by multiplying the output of the reset gate at time t with the hidden state at time *t-1* on an element-by-element basis [25]. A value of about 0 indicates that the hidden state information at moment t-1 should be selectively ignored or "forgotten"; on the contrary, a value of about 1 implies that the hidden state information at moment *t-1* should be stored [32]. After unit-by-unit multiplication, the computed values are fused with the inputs at time t. Finally, the full connectivity layer is set up with appropriate settings. Finally, a suitable activation function is set up in the fully connected layer to process the results obtained in the previous step to obtain the candidate hidden states. The BiGRU model is a deep learning architecture consisting of two GRU layers that process the input sequences in forward and reverse directions, respectively. This design allows BiGRU to capture both past and future information in the sequence, thus effectively capturing long-distance dependencies [35]. Each GRU layer decides which information is retained or forgotten through the update gate and reset gate mechanisms, which in turn updates the hidden state and outputs the results. This integration of bi-directional information flow provides BiGRU with enhanced sequence analysis capabilities

SYSTEM ANALYSIS

EXISTING SYSTEM

In the existing system, electric vehicle (EV) charging load prediction is generally performed using **traditional forecasting methods** such as basic statistical analysis and conventional time-series models. Techniques like **ARIMA, linear regression, and simple moving averages** are commonly used to estimate future charging demand.

These methods rely mainly on historical charging data but often ignore the presence of **noise, irregular fluctuations, and external influencing factors** such as weather conditions, traffic patterns, and charging station availability. As a result, prediction accuracy may decrease, especially when the data contains significant noise or variability.

Additionally, traditional models struggle to handle **large-scale and complex datasets**, which are common in modern smart grid and EV charging infrastructure systems.

Limitations of the Existing System

- Sensitive to **noisy and irregular data**
- Limited ability to capture complex patterns in EV charging behavior
- Lower prediction accuracy in dynamic environments
- Poor scalability for large datasets
- Lack of advanced data preprocessing techniques

PROPOSED SYSTEM

The proposed system introduces an **advanced EV charging load prediction framework** that integrates **signal noise reduction techniques with time-series modeling**. The system first removes unwanted noise from charging load data using signal processing methods such as **wavelet transform or filtering techniques**.

After noise reduction, the cleaned data is processed using **advanced time-series forecasting models** or machine learning methods to accurately predict future charging load demand.

The proposed system may utilize models such as:

- Long Short-Term Memory (LSTM) networks
- Recurrent Neural Networks (RNN)
- ARIMA with enhanced preprocessing
- Hybrid machine learning forecasting models

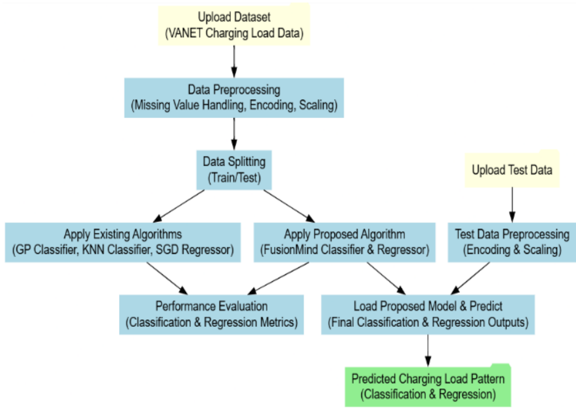
By combining **signal denoising with time-series modeling**, the system improves prediction accuracy and reliability. This helps energy providers and charging station operators optimize **energy distribution, charging infrastructure planning, and grid stability**.

Advantages of the Proposed System

- Improved prediction accuracy through **noise reduction techniques**
- Ability to capture **complex temporal patterns** in EV charging demand
- Efficient handling of large-scale EV charging datasets
- Better support for **smart grid energy management**
- More reliable forecasting for **charging infrastructure planning**

IMPLEMENTATION

The research begins with the acquisition of a relevant dataset containing vehicular network data, including features such as vehicle speed, traffic density, lane count, route stability scores, signal strength, and distance to destination, along with target variables for classification and regression tasks. Once the dataset is collected, preprocessing is performed, which includes handling missing values, encoding categorical variables, and normalizing numerical features to prepare the data for machine learning. Following preprocessing, existing algorithms such as KNN classifiers and regressors are applied to establish baseline performance, which allows comparison with the proposed models. The proposed algorithm, FusionMind—a hybrid MLP plus Random Forest model—is then trained on the processed dataset to capture complex patterns in both classification and regression tasks. Performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score for classification, and MAE, RMSE, and R^2 for regression. Finally, the trained models are used to predict outcomes on new, unseen test data, demonstrating the practical applicability of the research in optimizing vehicular routes and load distribution. This step-by-step methodology ensures that the research pipeline is reproducible, reliable, and capable of handling both real-time and batch predictions in vehicular networks.



DATA PREPROCESSING

Data preprocessing in this research involves several critical steps to ensure the dataset is clean, consistent, and suitable for modeling. Initially, the dataset undergoes **null value removal** to handle incomplete records, which could otherwise bias model training. Categorical features, such as route type or road priority, are transformed using **label encoding**, converting string labels into numerical values that machine learning models can process. For regression targets, numerical features are scaled using techniques such as standardization to normalize the data range. Additionally, feature extraction is applied to identify the most informative variables and reduce dimensionality, ensuring the model focuses on relevant patterns. This preprocessing also includes detection of datetime variables or unusual outliers and applying necessary transformations to make the dataset uniform. By completing these steps, the dataset is structured for effective model learning, minimizing errors due to inconsistent formats, missing values, or unscaled features.

EXPLORATORY DATA ANALYSIS (EDA)

Exploratory Data Analysis is conducted to understand the distribution and relationship between features and target variables. Initially, the dataset is visualized using histograms, scatter plots, violin plots, and correlation heatmaps to detect patterns, anomalies, and feature importance. After this analysis, the data is prepared for modeling by splitting it into training and testing subsets. The **train-test split** ensures that models are evaluated on unseen data, preventing overfitting and providing a realistic measure of performance. In this research, the data split is stratified for classification targets to maintain the same proportion of optimal and non-optimal routes in both training and test sets. For handling class imbalance,

TRAIN-TEST SPLIT

The train-test split divides the preprocessed dataset into two distinct subsets: a training set used to fit the models, and a testing set reserved for evaluating model generalization. The split is commonly done at a ratio of 80% for training and 20% for testing, though this can be adjusted depending on dataset size. Stratification is applied for classification tasks to preserve the class distribution, ensuring that both optimal and non-optimal route categories are proportionally represented. Additionally, the training set can be further augmented using SMOTE to balance minority classes. The testing set is kept strictly unseen to prevent overfitting, and preprocessing steps such as scaling are applied consistently across both subsets. This approach ensures that model performance metrics accurately reflect the predictive capability on real-world data.

MODEL BUILDING

EXISTING ALGORITHM: KNN CLASSIFIER AND REGRESSOR

The K-Nearest Neighbors (KNN) algorithm is a non-parametric method used for both classification and regression tasks. For classification, it assigns a label to a test sample based on the majority label among its k nearest neighbors in the feature space. For regression, the algorithm predicts a numerical value by averaging the values of the k closest neighbors. KNN relies on distance metrics such as Euclidean or cosine similarity to determine the proximity between data points, making it intuitive and simple to implement. It does not assume any underlying data distribution, which makes it flexible for real-world vehicular datasets where traffic patterns can be highly irregular.

KNN works by storing all training samples and making predictions by computing distances between a new input and the stored samples. In classification, the label with the most votes among the nearest neighbors is chosen, whereas, in regression, the predicted value is the mean of the neighbors' values. Despite its simplicity, KNN requires careful selection of the hyperparameter k, as small values can lead to overfitting while large values may oversmooth predictions. Feature scaling is crucial because distance-based calculations are sensitive to the magnitude of features.

The algorithm follows a straightforward architecture: input features → distance computation → neighbor selection → majority vote (classification) or averaging (regression) → output prediction. While effective for smaller datasets and capturing local patterns, KNN suffers from high computational cost during prediction, memory-intensive storage of all training data, and sensitivity to noisy data points. Its predictive capability diminishes with increasing dimensionality due to the curse of dimensionality, and it cannot easily handle dynamic feature interactions without additional preprocessing.

PROPOSED ALGORITHM: FUSIONMIND CLASSIFIER AND REGRESSOR

The FusionMind algorithm is a hybrid machine learning model designed for both classification and regression tasks in vehicular networks. It combines the strengths of a Multi-Layer Perceptron (MLP) and Random Forest (RF) to capture both nonlinear relationships and ensemble-based feature interactions. For classification, FusionMind predicts optimal routes, vehicle spacing categories, or charging station conditions by analyzing traffic patterns, network connectivity, and vehicular density. For regression, it forecasts numerical outputs such as travel time, network load, and vehicle spacing with higher accuracy than conventional models. By leveraging the MLP's ability to model complex, high-dimensional patterns and the RF's capability to reduce overfitting and improve robustness, FusionMind achieves adaptive, reliable predictions. The hybrid structure enables the algorithm to generalize well across varying traffic scenarios and adapt to both real-time and historical vehicular datasets.

How FusionMind Works

FusionMind first preprocesses the input features and feeds them into two parallel streams: the MLP captures nonlinear and deep feature interactions, while the Random Forest independently learns decision-tree-based feature splits. The outputs from both streams are then combined using a weighted ensemble or concatenation mechanism to produce the final prediction. For classification, the combined output undergoes a softmax or majority voting step to determine the predicted category. For regression, the outputs are averaged or weighted to produce the predicted numerical value. This dual-stream architecture allows the model to capture complementary patterns that single models like KNN or standard MLPs may miss, providing higher accuracy and robustness in real-time vehicular decision-making.

Algorithm Steps (Architecture)

1. Input preprocessing: normalize and encode vehicular features.
2. Parallel learning: feed data to MLP and Random Forest models simultaneously.
3. Feature extraction: MLP extracts deep patterns; RF captures decision-tree insights.
4. Fusion step: combine MLP and RF outputs using weighted averaging or ensemble voting.
5. Output prediction: classify route/load categories or predict numerical values for regression.

Advantages of FusionMind

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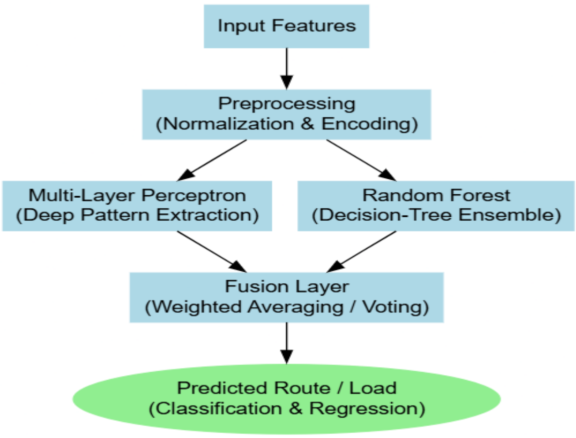
- Captures both linear and nonlinear relationships.
- Reduces overfitting with Random Forest ensemble component.
- Provides robust and reliable predictions for dynamic traffic conditions.
- Handles high-dimensional and heterogeneous vehicular data efficiently.
- Supports both classification and regression in a single hybrid framework.
- Adapts to real-time traffic scenarios and historical data patterns.
- Improves predictive accuracy over conventional models like KNN or standalone MLP.



CONCLUSION:

The conducted study demonstrates that advanced hybrid machine learning models, particularly the FusionMind architectures combining MLP feature extraction with Random Forests, significantly outperform conventional models in both classification and regression tasks for VANET routing and charging load prediction. For classification, traditional models such as SGD, GP, and KNN achieved moderate to good accuracy, but only the FusionMind Classifier attained perfect results, highlighting the effectiveness of deep feature extraction combined with ensemble learning in capturing complex patterns in vehicular network data. Similarly, in regression tasks, while SGD, GP, and KNN regressors showed limitations in predicting average vehicle spacing or load forecasts, the FusionMind Regressor achieved near-perfect metrics, demonstrating robustness and superior generalization. Overall, the results emphasize that integrating neural network-based feature learning with ensemble models can substantially enhance predictive performance in dynamic vehicular network environments.

FUTURE SCOPE:

Future work can focus on extending this framework to real-time VANET environments with live traffic and sensor data to improve the adaptability of models under highly dynamic conditions. Incorporating additional data sources, such as weather conditions, road incidents, or vehicle-to-infrastructure communication metrics, could further enhance prediction accuracy. Research can also explore other hybrid architectures, including attention-based neural networks or graph neural networks, to model spatial and temporal dependencies more effectively. Optimizing the models for low-latency deployment on edge devices or embedded vehicular systems is another promising direction, enabling real-time decision-making for route optimization and traffic management. Finally, expanding the dataset across different regions and road types would allow better generalization and validation of the models' applicability in diverse vehicular scenarios

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