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Network Traffic Prediction Model Considering Road Traffic Parameters Using Artificial Intelligence Methods in VANET

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ABSTRACT: Vehicular Ad hoc Networks (VANETs) are built on intelligent cars and may support vehicle-to-vehicle (V2V) and vehicle-to-roadside unit (V2R) communications. In this study, we offer a model for forecasting network traffic by taking into account the characteristics that might cause road traffic to occur. The suggested model incorporates a Random Forest-Gated Recurrent Unit-Network Traffic Prediction algorithm (RF-GRU-NTP) to estimate network traffic flow based on road and network traffic at the same time. This model is divided into three phases: network traffic prediction based on V2R communication, road traffic prediction based on V2V communication, and network traffic prediction taking into account both V2V and V2R communication. The proposed hybrid model, which is implemented in the third phase, selects the important features from the combined dataset (including V2V and V2R communications) using the Random Forest (RF) machine learning algorithm, and then applies deep learning algorithms to predict network traffic flow, with the Gated Recurrent Unit (GRU) algorithm providing the best results. The simulation results reveal that the proposed RF-GRU-NTP model outperforms previous network traffic prediction algorithms in terms of execution time and prediction errors.

***Keywords** – Vehicular network, network traffic prediction, road traffic prediction, regression methods, classification methods, machine learning algorithms, deep learning algorithms.*

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1. INTRODUCTION

VANET is an essential Intelligent Transportation System (ITS) technology that uses wireless communications to make the environment safer and transportation more efficient [1]. High-accuracy traffic flow forecast is a critical challenge in today's transportation systems. It may aid in path planning, making a better decision in picking the optimum route for people, and reducing traffic flow. Identifying where and when traffic will occur is a viable strategy for transportation management [2]. However, a novel viewpoint on network traffic flow suggests that traffic on the road may have an impact on network traffic. Vehicles on VANET may transmit packets to each other to predict traffic via V2V communications. As the number of cars and traffic on the road increased, so did the number of packets transmitted, resulting in increased network traffic. Previous research focused on road traffic and network traffic separately, which we addressed in our review of the literature. However, the majority of them handled the traffic issue on the road or in the network individually, however in this research, we will investigate the relationship between road and network traffic factors in order to anticipate network traffic. Intelligent methods using machine learning (ML) techniques are the best options for addressing traffic prediction challenges with the goal of predicting traffic flow. Some computational techniques, such as Bayesian modelling, fuzzy logic, hybrid modelling, Neural Networks (NN), and statistical modelling, are potential solutions aimed at improving prediction accuracy in data traffic flow [3]. The most important factor to consider in any of these scenarios is forecast accuracy. There are three kinds of machine learning techniques: Unsupervised Learning (training on unlabeled data), Supervised Learning (training on labelled data), and Reinforcement Learning are the three types of learning (it learns from the performance of the learning agent). Furthermore, these three categories of ML schemes sub-categorize various types of ML schemes, such as Transfer Learning and Online Learning [4].

Fig.1: Example figure

Deep learning (DL) methods for prediction issues are another interesting answer in the event of a huge and complicated dataset. It has several kinds of algorithms, the most well-known of which are Recurrent Neural Network (RNN) [5], [6] and Convolutional Neural Network (CNN) [7]. In general, the RNN contains two modules: Long Short-Term Memory (LSTM) [8] and Gated Recurrent Unit (GRU) [9], [10], where the LSTM method is comparable to the RNN in that it is designed to handle the vanishing issue. One of the most important characteristics of these algorithms is that they can learn dependencies for a long time with the goal of predicting in time-series datasets, and the GRU algorithm is similar to LSTM with more minor complications due to the number of its gates, which leads to it being faster than LSTM [11]. Furthermore, the Bi-directional Long Short-Term Memory (Bi-LSTM) technique may be utilised to extract more characteristics and bidirectional relationships. The process sequence in this kind of algorithm may be done in two directions (forward and backward) by employing two separate hidden layers [12].

1. LITERATURE REVIEW

Improving dynamic and distributed congestion control in vehicular ad hoc networks:

It is critical to consider Quality of Services while providing reliable communications in Vehicular Ad hoc Networks (VANets) (QoS). Congestion control solutions take into account two major QoS parameters: delay and packet loss. A Multi-Objective Tabu Search (MOTabu) approach is developed in this study to manage congestion in VANets. The suggested technique is distributed and dynamic, with two components: congestion detection and congestion management. Congestion is detected in the congestion detection component by monitoring the channel utilisation level. A MOTabu algorithm is used in the congestion control component to regulate transmission range and rate for both safety and non-safety massages while reducing delay and jitter. The suggested strategy's performance is then assessed using highway and urban scenarios utilising five performance metrics: packet loss, packet loss ratio, number of retransmissions, average latency, and throughput. The simulation results suggest that the MOTabu method outperforms other techniques like as CSMA/CA, D-FPAV, CABS, and so on. Congestion control utilising our method may contribute to more dependable settings in VANets.

A hybrid deep learning based traffic flow prediction method and its understanding:

Deep neural networks (DNNs) have recently shown that they can forecast traffic flow using huge data. While contemporary DNN models can outperform shallow models, it remains an unanswered question whether they can fully use the spatial-temporal aspects of traffic flow to increase their performance. Furthermore, our comprehension of them based on traffic statistics remains restricted. To increase forecast accuracy, this research offers a DNN-based traffic flow prediction model (DNN-BTF). The DNN-BTF model fully exploits traffic flow's weekly/daily periodicity and spatial-temporal properties. An attention-based approach that automatically learns to assess the relevance of historical traffic flow was developed, inspired by current work in machine learning. The convolutional neural network was also utilised to mine the spatial characteristics of traffic flow, while the recurrent neural network was used to mine the temporal information. We also demonstrated via visualisation how the DNN-BTF model interprets traffic flow data and challenges the traditional wisdom in the transportation sector that neural networks are merely a "black-box" approach. On a long-term horizon prediction job, data from the open-access database PeMS was utilised to verify the proposed DNN-BTF model. The experimental findings show that our strategy outperforms state-of-the-art methods.

Optimized structure of the traffic flow forecasting model with a deep learning approach:

Forecasting accuracy is critical for effective intelligent traffic management, particularly in terms of traffic efficiency and congestion reduction. The advent of the big data age opens up chances to significantly increase forecast accuracy. We present a new model, the stacked autoencoder Levenberg-Marquardt model, in this research, which is a form of deep architecture neural network technique aimed at improving forecasting accuracy. The Taguchi approach is used to construct an optimal structure and to learn traffic flow characteristics by layer-by-layer feature granulation using a greedy layerwise unsupervised learning algorithm in the proposed model. It is tested using real-world data from the M6 highway in the United Kingdom and compared to three current traffic predictors. To the best of our knowledge, this is the first time a deep learning-based traffic flow forecasting model with an optimal structure has been provided. The assessment findings show that the suggested model with an improved structure outperforms other models in traffic flow predictions.

Artificial intelligence for vehicle-to-everything: A survey

Advances in communications, intelligent transportation systems, and computing systems have recently created new prospects for intelligent traffic safety, comfort, and efficiency solutions. In several fields of scientific study, artificial intelligence (AI) has been extensively applied to enhance conventional data-driven

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methodologies. The vehicle-to-everything (V2X) system, in conjunction with AI, may gather data from many sources, broaden the driver's perspective, and forecast probable accidents, therefore improving driving comfort, safety, and efficiency. This study provides an extensive assessment of research efforts that have used AI to solve different research difficulties in V2X systems. We have summarised and classified the contributions of these research papers based on their application fields. Finally, we outline outstanding concerns and research difficulties that must be solved in order to fully realise the promise of AI in advancing V2X systems.

Visualizing and understanding recurrent networks

Recurrent Neural Networks (RNNs), and in particular a variation with Long Short-Term Memory (LSTM), are gaining traction as a consequence of successful applications in a broad variety of machine learning issues using sequential input. However, although LSTMs provide excellent outcomes in practise, the source of their effectiveness and limits remain unknown. We want to overcome this gap by offering an analysis of their representations, predictions, and error kinds using character-level language models as an interpretable testbed. Our tests, in particular, show the presence of interpretable cells that maintain track of long-term dependencies such as line lengths, quotations, and brackets. Furthermore, our comparison with finite horizon n-gram models identifies long-range structural relationships as the cause of the LSTM benefits. Finally, we analyse the remaining flaws and offer topics for additional research.

3. METHODOLOGY

Previous research focused on road traffic and network traffic separately, which we addressed in our review of the literature. However, the majority of them handled the traffic issue on the road or in the network individually, however in this research, we will investigate the relationship between road and network traffic factors in order to anticipate network traffic. Intelligent methods using machine learning (ML) techniques are the best options for addressing traffic prediction challenges with the goal of predicting traffic flow.

Disadvantages:

1. As the number of cars and traffic on the road increases, so does the number of packets delivered, resulting in increased network traffic.
2. Reduced forecast accuracy in data traffic flow.

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In this study, we offer a model for forecasting network traffic by taking into account the characteristics that might cause road traffic to occur. The suggested model incorporates a Random Forest-Gated Recurrent Unit-Network Traffic Prediction algorithm (RF-GRU-NTP) to estimate network traffic flow based on road and network traffic at the same time. This model is divided into three phases: network traffic prediction based on V2R communication, road traffic prediction based on V2V communication, and network traffic prediction taking into account both V2V and V2R communication. The proposed hybrid model, which is implemented in the third phase, selects the important features from the combined dataset (including V2V and V2R communications) using the Random Forest (RF) machine learning algorithm, and then applies deep learning algorithms to predict network traffic flow, with the Gated Recurrent Unit (GRU) algorithm providing the best results.

Advantages:

1. The suggested RF-GRU-NTP model outperforms in terms of execution time.
2. The suggested RF-GRU-NTP model outperforms previous network traffic prediction algorithms in terms of prediction errors.

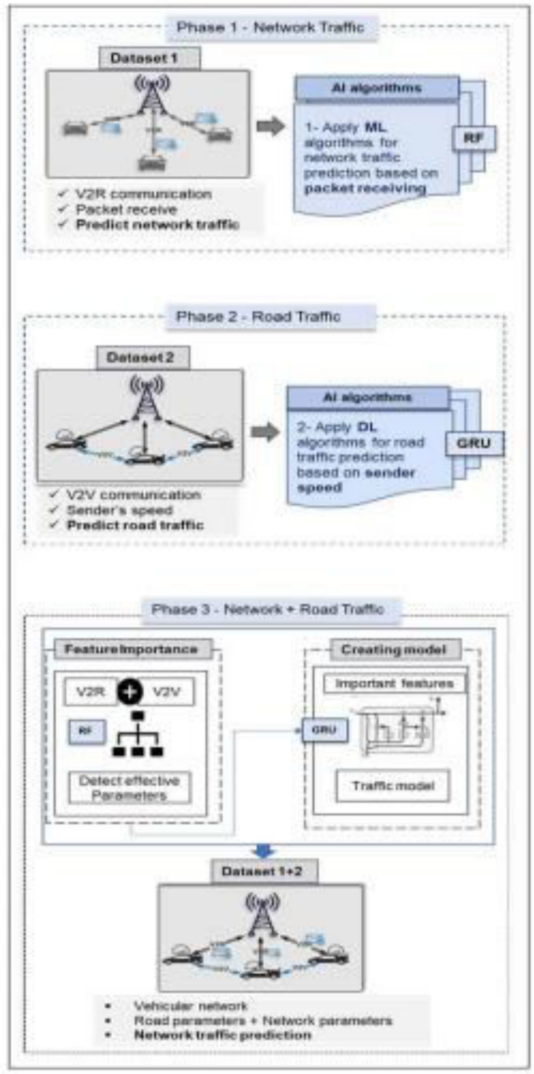

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: Using this module, we will import data into the system.

- Processing: Using this module, we will read data for processing.
- Splitting data into train and test: Using this module, data will be separated into train and test.
- Model generation: Using this module, we will generate models. Deep Learning - CNN, CNN+LSTM, LSTM, BiLSTM, RNN, GRU, and CNN with KFoldVaildation and Machine Learning - Random Forest, Decision Tree, KNN, Support Vector Machine, and Voting Classifier are used to build the model.
- User registration and login: Using this module will result in registration and login.
- User input: Using this module will provide input for prediction
- Prediction: the final projected value will be presented

4. IMPLEMENTATION

ALGORITHMS:

CNN: A CNN is a kind of network architecture for deep learning algorithms that is primarily utilised for image recognition and pixel data processing jobs. There are different forms of neural networks in deep learning, but CNNs are the network design of choice for identifying and recognising things.

CNN+LSTM: A CNN-LSTM model is made up of CNN layers that extract features from input data and LSTM layers that forecast sequences. In general, the CNN-LSTM is utilised for activity identification, picture labelling, and video labelling.

LSTM: LSTM is an abbreviation for long short-term memory networks, which are utilised in Deep Learning. It is a kind of recurrent neural networks (RNNs) that may learn long-term dependencies, particularly in sequence prediction tasks.

BiLSTM: A bidirectional LSTM (BiLSTM) layer learns the bidirectional long-term relationships between time steps in a time series or sequence data. When you want the network to learn from the whole time series at each time step, these dependencies might be advantageous.

RNN: Recurrent neural networks (RNNs) are the cutting-edge algorithm for sequential data, and they are employed in Apple's Siri and Google's voice search. It is the first algorithm to recall its input thanks to its internal memory, making it ideal for machine learning issues involving sequential data.

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GRU: Gated recurrent units (GRUs) are a recurrent neural network gating technique established in 2014 by Kyunghyun Cho et al. The GRU functions similarly to a long short-term memory (LSTM) with a forget gate, but with fewer parameters since it lacks an output gate.

Random Forest: A Supervised Machine Learning Algorithm that is commonly utilised in Classification and Regression applications. It constructs decision trees from several samples and uses their majority vote for classification and average for regression.

Decision tree: A decision tree is a non-parametric supervised learning technique that may be used for classification and regression applications. It has a tree structure that is hierarchical and consists of a root node, branches, internal nodes, and leaf nodes.

KNN: The k-nearest neighbours method, often known as KNN or k-NN, is a non-parametric, supervised learning classifier that employs proximity to create classifications or predictions about an individual data point's grouping.

SVM: Support Vector Machine (SVM) is a supervised machine learning technique that may be used for both classification and regression. Though we call them regression issues, they are best suited for categorization. The SVM algorithm's goal is to identify a hyperplane in an N-dimensional space that clearly classifies the input points.

Voting classifier: A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

5. EXPERIMENTAL RESULTS

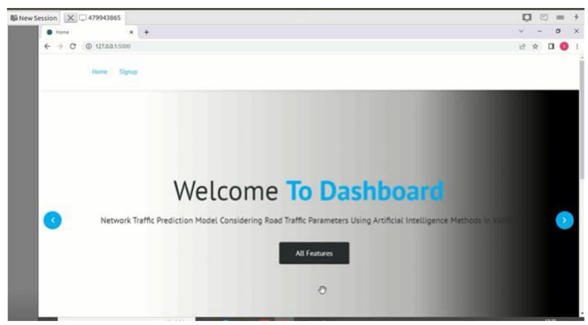

Fig.3: Home screen

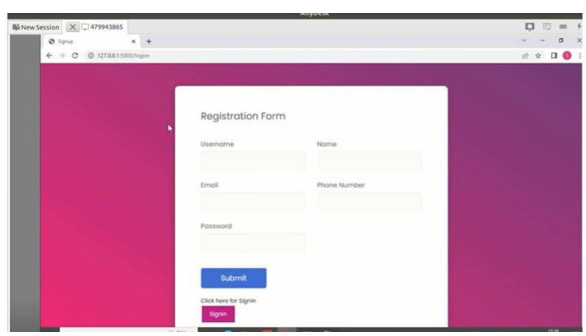

Fig.4: User registration

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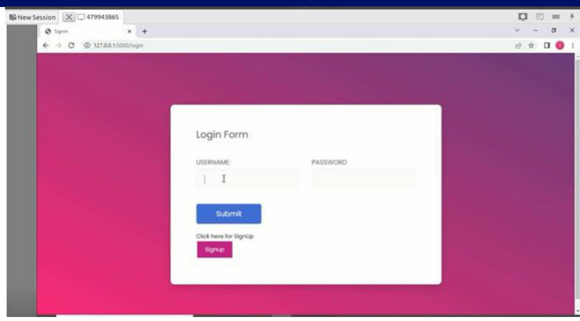

Fig.5: user login

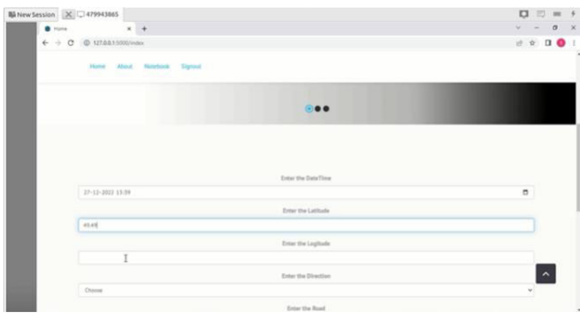

Fig.6: User input

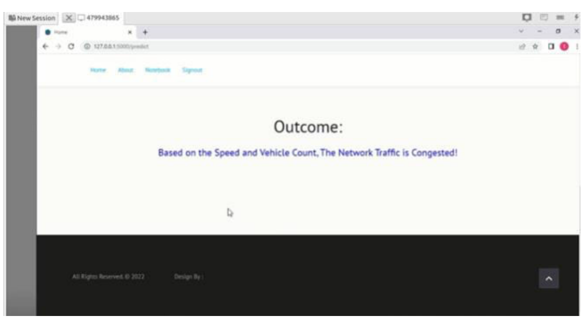

Fig.7: Prediction result

6. CONCLUSION

We presented an RF-GRU-NTP model in this research with the goal of predicting network traffic flow based on traffic in the road and network at the same time. We split our investigation into three stages. We concentrated on network traffic prediction in the initial phase. To forecast network traffic flow, we utilised the V2R dataset and received packets delivered by cars to RSUs as a network parameter. Then, we experimented with several machine learning techniques, such as the RF, NB, KNN, and SVM algorithms, and assessed them using classification metrics. After all assessments, the RF had superior performance in predicting network traffic flow, although our goal was "packet reception." In the second phase, we attempted to estimate road traffic flow using the V2V dataset, using the "sender speed" as our aim to identify road traffic. We expected that if the senders' speed was less than 60 km/h, traffic would occur on the road. As a result, we used several deep learning algorithms, such as the LSTM, GRU, and Bi-LSTM. Finally, we examined the findings using several regression assessment criteria, and based on the results, the GRU was the best algorithm for predicting road traffic. Then, in the third step, we used machine learning and deep learning algorithms to achieve our goal of network traffic flow while accounting for road traffic flow. We merged V2V and V2R datasets for this purpose and utilised the RF technique to identify features. We discovered the most critical characteristics, which were "packet receive" and "receiver speed," which may influence "sender speed" and network traffic flow. The network traffic flow was then projected using the suggested RF-GRU-NTP model. As a consequence, we compared our findings to pure algorithms such as LSTM and Bi-LSTM to ensure that the proposed model performs well in network traffic flow prediction. The suggested model's major difficulty was merging two datasets in order to apply machine learning and deep learning algorithms with the goal of predicting network traffic using various sorts of characteristics. This is, to the best of our knowledge, the first study that forecasts network traffic flow based on road traffic flow. However, when the number of cars increases, the amount of data created by them takes the form of big data, which we will incorporate in our future work.

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