International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

IJIEMR Transactions, online available on 07th Jan 2023. Link
:http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=ISSUE-1

DOI: 10.48047/IJIEMR/V12/ISSUE 01/54

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

Volume 12, Issue 1, Pages: 579-588

Paper Authors
Mrs.M.Kavitha, K.Jhansi, Ch.Sumana, K.Tejaswini

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

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

Mrs.M.Kavitha, Associative professor, Dept. of Information Technology, Sridevi Women's Engineering College, Hyd. kavithareddy2414@gmail.com

K.Jhansi, B.Tech., Dept. of Information Technology, Sridevi Women's Engineering College, Hyd.

Ch.Sumana, B.Tech., Dept. of Information Technology, Sridevi Women's Engineering College, Hyd.

K.Tejaswini, B.Tech., Dept. of Information Technology, Sridevi Women's Engineering College, Hyd.

ABSTRACT: Vehicle-to-vehicle (V2V) and vehicle-to-side of the road unit (V2R) correspondences can be handled by VANETs, which are based on intelligent automobiles. In this paper, we present a model for anticipating network traffic that considers the points that could result in street traffic. The proposed model makes use of a Random Forest-Gated Recurrent Unit-Network Traffic Prediction method (RF-GRU-NTP) to anticipate the flow of network traffic in light of both organization and street traffic. There are three distinct phases to this model: street traffic forecast using V2V correspondence, organization traffic forecast using both V2V and V2R correspondence, and network traffic forecast using V2R correspondence. In the third stage, the proposed half breed model uses deep learning calculations to anticipate network traffic stream, with the Gated Recurrent Unit (GRU) calculation providing the best results. The Random Forest (RF) ML calculation is used to select the significant highlights from the combined dataset, including V2V and V2R correspondences. The simulation results demonstrate that the proposed RF-GRU-NTP model outperforms existing organization traffic forecast calculations in terms of execution time and expectation errors.

Keywords *– Network traffic expectation, street traffic forecast, relapse, arrangement, ML, and profound learning calculations are instances of vehicular organizations.*

1. INTRODUCTION

VANET is a significant Intelligent Transportation System (ITS) innovation that utilizes remote interchanges to work on the climate and transportation productivity [1]. In the present transportation frameworks, high-exactness traffic stream determining is a key undertaking. It might assist with way arranging, pursuing better choices on the best course for people, and limiting traffic stream. Recognizing where and when traffic will happen is a substantial transportation the board strategy [2]. In any case, a new viewpoint on network traffic stream suggests that street traffic might impact network traffic. Vehicles on the VANET might trade parcels to conjecture traffic through V2V associations. The quantity of parcels broadcast rose as the quantity of autos and traffic out and about expanded, bringing about expanded network traffic. Past examinations isolated street traffic from network traffic, which we tended to in our assessment of the writing. In any case, the greater part of them managed traffic issues out and about or on the organization all alone; nonetheless, in this review, we will dissect the connection among street and organization traffic qualities to foresee network traffic. Astute arrangements in light of machine learning (ML) procedures are the best options for handling traffic expectation troubles to expect traffic stream. Bayesian displaying, fluffy rationale, half and half demonstrating, Neural Networks (NN), and measurable demonstrating are a few potential systems for improving expectation precision in information traffic stream [3]. In any of these conditions, the most vital component to consider is expectation exactness. ML techniques are arranged into three kinds: The three sorts of learning are solo getting (planning on unlabeled data), oversaw getting the hang of (planning on named data), and backing learning (it gains from the presentation of the learning trained professional). Additionally, these three ML conspire classes divide a variety of ML plans, such as Internet Learning and Move Learning [4].

Fig.1: Example figure

Due to their extensive and intricate dataset, deep learning (DL) approaches to expectation problems are yet another fascinating arrangement. The Recurrent Neural Network (RNN) and the Convolutional Neural Network (CNN) are two of its most well-known calculations [5, 6]. In most cases, the RNN is made up of two modules: Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) [8, 10], with the LSTM method being similar to the RNN in that it is designed to handle the evaporating issue. The GRU calculation is similar to LSTM with additional minor confusions due to the number of its doors, resulting in it being quicker than LSTM [11]. This is one of the main features of these calculations, which can learn conditions that have been determined to foresee in time-series datasets for a considerable amount of time. In addition, additional characteristics and bidirectional affiliations can be extracted using the Bi-directional Long Short-Term Memory (Bi-LSTM) approach. Using two distinct secret layers, this kind of calculation's cycle arrangement can be completed in two headings—forward and reverse [12].

2. LITERATURE REVIEW

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

In Vehicular Ad Hoc Networks (VANets), it is essential to consider Quality of Services (QoS) when sending reliable communications. Control procedures should keep two important QoS boundaries in mind: delay and package misfortune. To reduce blockage in VANets, a Multi-Objective Tabu Search (MOTabu) procedure is proposed in this paper. Two sections make up the appropriated and dynamic approach that is being proposed: obstruct discovery and the board. The blockage recognition component examines the channel utilization level to identify clog. A MOTabu calculation is used in the blockage control section to control transmission reach and rate for both security and non-security rubs while reducing idleness and jitter. The proposed method's presentation is then evaluated using expressway and metropolitan scenarios and five execution metrics: throughput, normal idleness, the proportion of bundle misfortune, the number of retransmissions, and parcel misfortune. The recreation findings indicate that the MOTabu strategy outperforms other strategies like CSMA/CA, D-FPAV, Taxis, and so on. Using our technology, you can control clogs, which could lead to more secure VANet settings.

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

Recently, it has been demonstrated that massive amounts of information can be used to evaluate a traffic stream by deep neural networks (DNNs). Although current DNN models may outperform shallow models, it is unclear whether they can fully utilize the traffic stream's spatial-fleeting components to improve their presentation. In addition, they are difficult to interpret in light of traffic statistics. To work on gauge exactness, a DNN-based traffic stream expectation model (DNN-BTF) is proposed in this study. The weekly/everyday periodicity and spatial-fleeting features of traffic stream are fully utilized by the DNN-BTF model. A consideration-based method for determining the meaning of the previous traffic stream was developed, fueled by momentum ML research. The convolutional brain organization was also used to mine the topographical properties of the traffic stream, while the intermittent brain organization was used to mine the transient data. We also demonstrated how the DNN-BTF model perceives traffic stream data, challenging the transportation industry's common belief that brain networks are essentially a "black-box" approach. On a drawn-out skyline expectation task, information from the open-access data set PeMS was used to approve the proposed DNN-BTF model. The results of the analyses show that our method outperforms cutting-edge approaches.

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

When it comes to increasing traffic productivity and reducing congestion, gauging accuracy is crucial for efficient traffic executives. The upcoming large information period presents opportunities to significantly improve forecast accuracy. The stacked autoencoder Levenberg-Marquardt model, an original brain network design strategy aimed at ensuring accuracy, is the model we present in this paper. The Taguchi method is used to create an optimal design and learn traffic stream qualities through layer-by-layer highlight granulation and a ferocious layerwise solo learning calculation in the proposed model. It is compared to three other traffic indicators in the Assembled Realm that use actual information from the M6 highway. A comprehensive learning-based traffic stream estimating model with an ideal construction has never been advertised before, as far as we are aware. The evaluation shows that, when it comes to anticipating the flow of traffic, the new model outperforms the previous ones.

Artificial intelligence for vehicle-to-everything: A survey

New avenues for savvy traffic security, solace, and proficiency arrangements have been opened up by ongoing advancements in correspondence, advanced transportation frameworks, and PC frameworks. In a variety of logical domains, artificial intelligence (AI) has been extensively utilized to advance conventional information-driven approaches. The vehicle-to-everything (V2X) framework can, in conjunction with artificial intelligence, collect data from a variety of sources, broaden the driver's perspective, and anticipate potential accidents, thereby enhancing driver comfort, safety, and proficiency. A comprehensive analysis of research drives that have utilized simulated intelligence to respond to various examination challenges in V2X frameworks is provided in this report. Based on their application areas, the commitments of these examination distributions have been compiled and summarized. Finally, we discuss irritating issues and exploration difficulties that need to be resolved in order to fully comprehend simulated intelligence's capacity for V2X framework creation.

Visualizing and understanding recurrent networks

Due to their usefulness in a wide range of ML problems, including consecutive information, recurrent neural networks (RNNs) and, particularly, variants with long-short-term memory (LSTM) are becoming increasingly common. However, despite the fact that LSTMs typically produce exceptional results, the sources of their viability and constraints are unclear. We really want to conquer this issue by giving an examination of their depictions, conjectures, and bungle types utilizing interpretable individual level language models as a testbed. Long-term conditions like line lengths, statements, and sections are monitored by interpretable cells, as demonstrated by our tests. In addition, we find that the LSTM benefits are derived from drawn-out underlying linkages, in contrast to restricted skyline n-gram models. Finally, we examine the remaining issues and suggest areas for future review.

3. METHODOLOGY

Past examinations isolated street traffic from network traffic, which we tended to in our assessment of the writing. Nonetheless, the heft of them managed traffic issues out and about or on the organization all alone; be that as it may, in this review, we will examine the connection among street and organization traffic qualities to anticipate network traffic. Astute arrangements in light of machine learning (ML) strategies are the best choices for handling traffic expectation challenges to expect traffic stream.

Disadvantages:

1. The number of delivered packets increases with the number of vehicles and traffic on the road, which in turn increases network traffic.
2. decreased accuracy of data traffic flow forecasts.

In this paper, we present a model for anticipating network traffic that considers the factors that could result in street traffic. The proposed model uses a Random Forest-Gated Recurrent Unit-Network Traffic Prediction method (RF-GRU-NTP) to anticipate the network traffic stream in light of both organization and street traffic. There are three distinct phases to this model: traffic forecast using V2V correspondence, organization traffic expectation using both V2V and V2R correspondence, and network traffic expectation using V2R correspondence. In the third stage, the proposed half-and-half model uses deep learning calculations to anticipate network traffic stream, with the Gated Recurrent Unit (GRU) calculation providing the best results. The Random Forest (RF) ML calculation is used to select the significant highlights from the joined dataset, including V2V and V2R correspondences.

Advantages:

1. In terms of execution time, the proposed RF-GRU-NTP model excels.

2. In terms of prediction errors, the proposed RF-GRU-NTP model beats existing network traffic prediction algorithms.

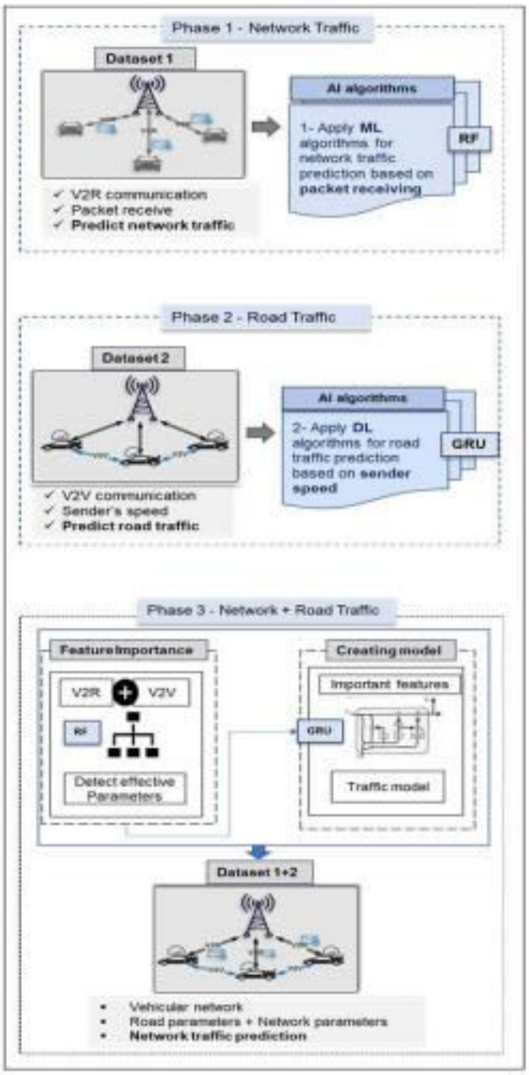

Fig.2: System architecture

MODULES:

We designed the modules indicated below to carry out the aforementioned project.

- Information investigation: We will bring information into the framework utilizing this module.
- Handling: We will peruse information for handling utilizing this module.
- Data separation into train and test: Data will be divided into train and test using this module.
- The development of models: Models will be made with this module. The model is built using machine learning and deep learning techniques like Random Forest, Decision Tree, KNN, Support Vector Machine, and Voting Classifier, as well as CNN, CNN+LSTM, LSTM, BiLSTM, GRU, and CNN with KFoldVaildation.
- User registration and login: Using this module will need you to register and login.
- User input: Using this module will offer prediction input.
- The ultimate anticipated value will be displayed as a prediction.

4. IMPLEMENTATION

ALGORITHMS:

CNN: A CNN is a type of deep learning network design that is typically used for pixel information handling and picture recognition tasks. While there are a few different types of brain organizations used in deep learning, CNNs are the most widely used organization engineering for continuously perceiving objects.

CNN+LSTM: CNN layers gather highlights from input information, while LSTM layers foresee groupings in a CNN-LSTM model. The CNN-LSTM is frequently utilized for action acknowledgment, picture naming, and video marking.

LSTM: Deep Learning makes use of long short-term memory networks, which are referred to as LSTM. It is a type of recurrent neural network (RNN) that can predict errands and learn long-distance connections in succession.

BiLSTM: A bidirectional LSTM layer learns the drawn out bidirectional connections between's time steps in a period series or succession of information. These conditions might be helpful when you maintain that the organization should gain from the entire time series at each time step.

RNN: Repetitive brain organizations (RNNs) are the most evolved estimation for successive data and are used in Apple's Siri and Google's voice search. It is the primary calculation for remembering its feedback due to its internal memory, making it ideal for ML issues requiring consecutive information.

GRU: Gated recurrent units (GRUs) are a repetitive brain network gating approach created by Kyunghyun Cho et al. in 2014. The GRU behaves similarly to a long short-term memory (LSTM) with a neglect door, but with fewer boundaries, because it misses the mark on yield entryway.

Random Forest: A Regulated ML Calculation is a sort of ML calculation that is in many cases utilized in characterization and relapse applications. It assembles choice trees from a few examples, utilizing the larger part vote in favor of characterization and the normal for relapse.

Decision tree: For classification and regression, a decision tree is a type of non-parametric supervised learning approach. It includes a progressive tree structure with a root hub, branches, inside hubs, and leaf hubs.

KNN: A non-parametric, directed learning classifier, the k-nearest neighbors method, also known as KNN or k-NN, makes use of nearness to make predictions or characterizations about the collection of individual data of interest.

SVM: SVM is a controlled ML calculation that can be used for grouping as well as relapse. Whatever we call them, they are more well-organized. Finding a hyperplane that clearly identifies the information focuses in an N-layered space is the goal of the SVM method.

International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
www.ijiemr.org

Voting classifier: A voting classifier is an ML assessor that trains and predicts relying upon the results of many base models or assessors. For every assessor yield, collecting models may be matched democratic choices.

5. EXPERIMENTAL RESULTS

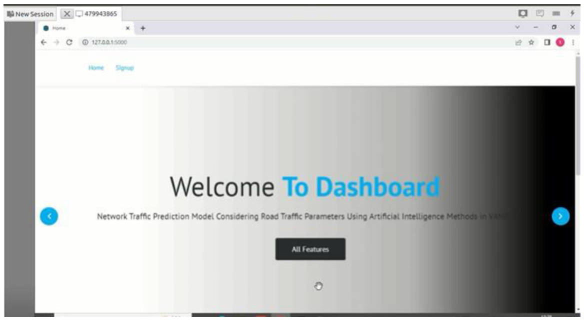

Fig.3: Home screen

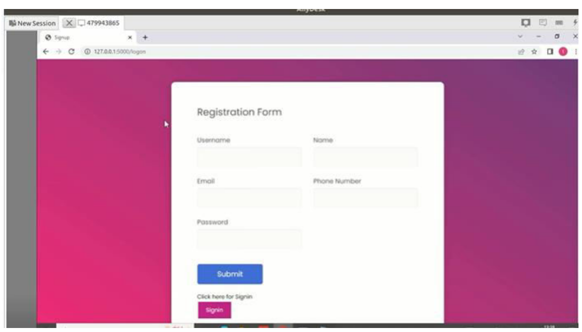

Fig.4: User registration

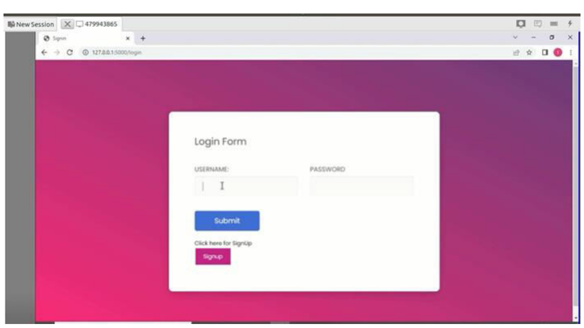

Fig.5: user login

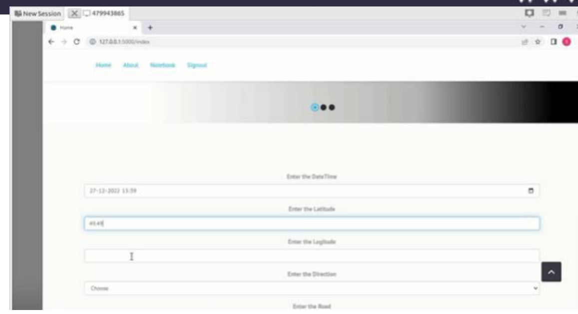

Fig.6: User input

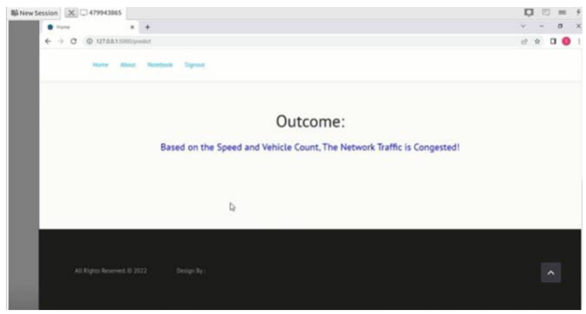

Fig.7: Prediction result

6. CONCLUSION

A RF-GRU-NTP model was presented in this review to speculate on the network traffic stream in light of both network and outside traffic at the same time. There were three parts to our review. We initially concentrated on the expectation of network traffic. To anticipate the flow of network traffic, we used the V2R dataset and received bundles transported via vehicles to RSUs as an organizational boundary. Then, at that point, utilizing order measurements, we tried various AI draws near, including the RF, NB, KNN, and SVM calculations. In spite of the way that our point was "bundle gathering," the RF outflanked the others in guaging network traffic stream. We attempted to appraise street traffic stream involving the V2V data in the subsequent stage, utilizing the "source speed" as our objective to distinguish street traffic. We expected traffic on the course in the event that the shippers' speed was under 60 km/h. We used the LSTM, GRU, and Bi-LSTM, among other profound learning calculations, as a result. Finally, we looked at the data using a variety of relapse assessment rules and determined that the not entirely certain calculation was the best one for estimating street traffic. Utilizing AI and deep learning techniques to achieve our point of organization traffic stream while also representing street traffic stream was the final stage. For this, we joined V2V and V2R datasets and used the RF method for managing track down features. "Bundle receipt" and "beneficiary speed," which may have an impact on "source speed" and the organization's traffic stream, were our primary distinctions. The organization's traffic stream was then evaluated using the proposed RF-GRU-NTP model. To confirm that the recommended model is effective at anticipating network traffic stream, we compared our findings to unadulterated calculations like LSTM and Bi-LSTM. The most difficult part of the proposed model was connecting two datasets so that AI and deep learning calculations could be used to monitor network traffic based on different properties. According to our knowledge, this is the first study to evaluate network traffic stream using street traffic stream. However, as the number of automobiles increases, so does the amount of information they produce, which we will incorporate into our subsequent work.

REFERENCES

[1] N. Taherkhani and S. Pierre, ‘‘Improving dynamic and distributed congestion control in vehicular ad hoc networks,’’ Ad Hoc Netw., vol. 33, pp. 112–125, Oct. 2015.

[2] Y. Wu, H. Tan, L. Qin, B. Ran, and Z. Jiang, ‘‘A hybrid deep learning based traffic flow prediction method and its understanding,’’ Transp. Res. C, Emerg. Technol., vol. 90, pp. 166–180, May 2018.

[3] H.-F. Yang, T. S. Dillon, and Y.-P. P. Chen, ‘‘Optimized structure of the traffic flow forecasting model with a deep learning approach,’’ IEEE Trans. Neural Netw. Learn. Syst., vol. 28, no. 10, pp. 2371–2381, Oct. 2016.

[4] W. Tong, A. Hussain, W. X. Bo, and S. Maharjan, ‘‘Artificial intelligence for vehicle-to-everything: A survey,’’ IEEE Access, vol. 7, pp. 10823–10843, 2019.

[5] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, ‘‘Empirical evaluation of gated recurrent neural networks on sequence modeling,’’ Dec. 2014, arXiv:1412.3555.

[6] A. Karpathy, J. Johnson, and L. Fei-Fei, ‘‘Visualizing and understanding recurrent networks,’’ Jun. 2015, arXiv:1506.02078.

[7] M. Coşkun, Ö. Yildirim, U. Ayşegül, and Y. Demir, ‘‘An overview of popular deep learning methods,’’ Eur. J. Techn., vol. 7, no. 2, pp. 165–176, Dec. 2017.

[8] K. Greff, R. K. Srivastava, J. Koutník, B. R. Steunebrink, and J. Schmidhuber, ‘‘LSTM: A search space odyssey,’’ IEEE Trans. Neural Netw. Learn. Syst., vol. 28, no. 10, pp. 2222–2232, Oct. 2016.

[9] R. Jozefowicz, W. Zaremba, and I. Sutskever, ‘‘An empirical exploration of recurrent network architectures,’’ in Proc. Int. Conf. Int. Conf. Mach. Learn., Jun. 2015, pp. 2342–2350.

[10] P. Sun, A. Boukerche, and Y. Tao, ‘‘SSGRU: A novel hybrid stacked GRUbased traffic volume prediction approach in a road network,’’ Comput. Commun., vol. 160, pp. 502–511, Jul. 2020.

[11] P. T. Yamak, L. Yujian, and P. K. Gadosey, ‘‘A comparison between ARIMA, LSTM, and GRU for time series forecasting,’’ in Proc. 2nd Int. Conf. Algorithms, Comput. Artif. Intell., Sanya, China, Dec. 2019, pp. 49–55.

[12] Z. Cui, R. Ke, Z. Pu, and Y. Wang, ‘‘Deep bidirectional and unidirectional LSTM recurrent neural network for network-wide traffic speed prediction,’’ Jan. 2018, arXiv:1801.02143.

[13] R. Jia, P. Jiang, L. Liu, L. Cui, and Y. Shi, ‘‘Data driven congestion trends prediction of urban transportation,’’ IEEE Internet Things J., vol. 5, no. 2, pp. 581–591, Apr. 2018.

[14] F. Falahatraftar, S. Pierre, and S. Chamberland, ‘‘A centralized and dynamic network congestion classification approach for heterogeneous vehicular networks,’’ IEEE Access, vol. 9, pp. 122284–122298, 2021.

[15] A. Lazaris and V. K. Prasanna, ‘‘Deep learning models for aggregated network traffic prediction,’’ in Proc. 15th Int. Conf. Netw. Service Manage. (CNSM), Halifax, NS, Canada, Oct. 2019, pp. 1–5.