Temporal and Event Based Traffic prediction using Deep Neural Network

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Abstract - Traffic congestion has been a major cause of severe negative economic and environmental effect for metropolitan regions throughout the world in the contemporary period. Future traffic prediction is one of the most effective techniques to reduce traffic congestion. Since its start in the late 1970s, the discipline of traffic prediction research has progressed significantly. We enter the era of deep neural networks as theoretical and technical developments arise. Deep neural networks acquired popularity owing to their enormous prediction capacity, which may be attributed to their complex and deep structure. Despite the prominence of deep neural network models in traffic prediction, academic reviews of these approaches are uncommon. We introduce an RNN-based deep neural network for traffic prediction in this research. We'll take care of everything.

Key Words: Deep neural network, RNN algorithm

1.INTRODUCTION

Almost every major city in the globe has traffic congestion. Subways, and other traffic control systems are both costly and complex to build. Understanding traffic on highways may help us improve our daily lives. Our research use deep learning algorithms to recognize traffic patterns, which aids in the resolution of traffic congestion issues. We employ the RNN algorithm to estimate traffic by gathering data from both public and private transportation, as well as certain exceptional events.

We studied about deep neural network architecture used in traffic flow prediction in detail. It takes into account not only traffic flow and speed for a particular time and place of traffic information, but also events linked with traffic flow and speed. Because it does not consider the Event component in the traffic dataset, our suggested technique has a greater prediction accuracy than the other scheme.

2. RELATED WORK

[1] The work done by author David Alexander Tedjopurnomo, Zhifeng Bao, Baihua Zheng, Farhana Murtaza Choudhury, and Kai Qin IEEE VOL. 34, NO. 4

In this modern era, traffic congestion has become a major source of severe negative economic and environmental impact for urban areas worldwide. One of the most efficient ways to mitigate traffic congestion is through future traffic prediction. The research field of traffic prediction has evolved greatly ever since its inception in the late 70s. Earlier studies mainly use classical statistical models such as ARIMA and its variants. Recently, researchers have started to focus on machine learning models because of their power and flexibility. As theoretical and technological advances emerge, we enter the era of deep neural network, which gained popularity due to its sheer prediction power which can be attributed to the complex and deep structure. Despite the popularity of deep neural network models in the field of traffic prediction, literature surveys of such methods are rare. In this work, we present an up-to-date survey of deep neural network for traffic prediction. We will provide a detailed explanation of popular deep neural network architectures commonly used in the traffic flow prediction literatures, categorize and describe the literatures themselves, present an overview of the commonalities and differences among different works, and finally provide a discussion regarding the challenges and future directions for this field.

[2] The work done by KYUNGEUN LEE 1, MOONJUNG EO1, EUNA JUNG 1, YOONJIN YOON 2, AND WONJONG RHEE Digital Object Identifier 10.1109/ACCESS.2021.3071174

In modern transportation systems, an enormous amount of traffic data is generated every day. This has led to rapid progress in short-term traffic prediction (STTP), in which deep learning methods have recently been applied. In traffic networks with complex spatiotemporal relationships, deep neural networks (DNNs) often perform well because they are capable of automatically extracting the most important

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features and patterns. In this study, we survey recent STTP studies applying deep networks from four perspectives. 1) We summarize input data representation methods according to the number and type of spatial and temporal dependencies involved. 2)We explain a wide range of DNN techniques from the earliest networks, including Restricted Boltzmann Machines, to the most recent, including graph-based and meta-learning networks. 3) We summarize previous STTP studies in terms of the type of DNN techniques, application area, dataset and code availability, and the type of the represented spatiotemporal dependencies. 4) We compile public traf_c datasets that are popular and can be used as the standard benchmarks. Finally, we suggest challenging issues and possible future research directions in STTP.

[3] The work done by author Junyi Li, Fangce Guo, Yibing Wang, Lihui Zhang, Xiaoxiang Na, Simon Hu *Member, IEEE*

A key problem in short-term traffic prediction is the prevailing data missing scenarios across the entire traffic network. To address this challenge, a transfer learning framework is currently used in the literature, which could improve the prediction accuracy on the target link that suffers severe data missing problems by using information from source links with sufficient historical However, one of the limitations in these transfer-learning based models is their high dependency on the consistency between datasets and the complex data selection process, which brings heavy computation burden and human efforts. In this paper, we propose an adaptive transfer learning method in short-term traffic flow prediction model to alleviate the complex data selection process. Specifically, a self-adaptive neural network with a novel domain adaptation loss is developed. The domain adaptation loss is able to calculate the distance between the source data and the corresponding target data in each training batch, which can help the network to adaptively filter inconsistent source data and learn target link related information in each training batch. The Maximum Mean Discrepancy (MMD) measurement, which has been fully validated and applied in transfer learning research, is used in combination with the Gaussian kernel to measure the distance between datasets in each training batch. A series of experiments are designed and conducted using 15-minute interval traffic flow data from the Highways England, UK. The results have demonstrated that the proposed adaptive transfer learning method is less affected by the inconsistency between datasets and provides more accurate short-term traffic flow prediction.

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3. PROPOSED SYSTEM

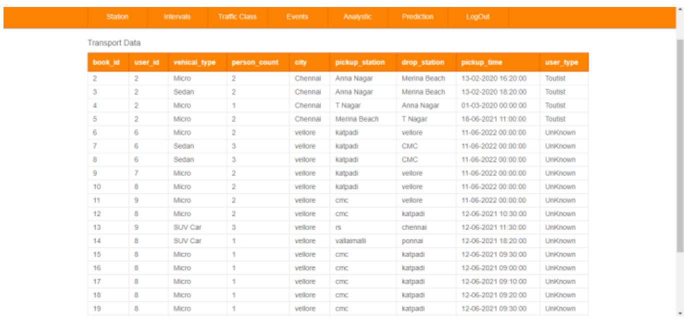
Our proposed system rebuilds the current RNN (Recursive Neural Network Model) to enable a traffic prediction system. It examines not only traffic flow and speed for a particular time and location, but also events connected with traffic flow and speed. The events might be religious or political celebrations, as well as natural disasters or tragedies. These events are also time-related. The event information and traffic data are mapped using temporal details and sent into the RNN, which then extracts the traffic congestion pattern. Our suggested approach takes into time, location, and event to provide more accurate traffic congestion forecast. Because the previous approach does not consider the Event, the forecast accuracy is greater. We predict traffic using both public and private transportation. Furthermore, we employ exceptional events to ensure the authenticity of our project.

3.1 MODULES

1. Fetch Transport Data
2. Event Mapping
3. Pattern Initialization
4. RNN Modeling
5. Traffic Prediction

MODULE 1: Fetch Transport Data

Because tourists will not employ the same transportation provider, our technology incorporates data from many domains. For data collection in a domain context, we employ a web API technique for data extraction. The acquired data is processed to extract the location, time, and then relevant information, which is then stored on database for future data analysis.



book_id	user_id	vehical_type	person_count	city	pickup_station	drop_station	pickup_time	user_type
2	2	Micro	2	Chennai	Anna Nagar	Merina Beach	13-02-2020 16:20:00	Toutist
3	2	Sedan	2	Chennai	Anna Nagar	Merina Beach	13-02-2020 18:20:00	Toutist
4	2	Micro	1	Chennai	T Nagar	Anna Nagar	01-03-2020 00:00:00	Toutist
5	2	Micro	2	Chennai	Merina Beach	T Nagar	18-06-2021 11:00:00	Toutist
6	6	Micro	2	vellore	katpadi	vellore	11-06-2022 00:00:00	UnKnown
7	6	Sedan	3	vellore	katpadi	CMC	11-06-2022 00:00:00	UnKnown
8	6	Sedan	3	vellore	katpadi	CMC	11-06-2022 00:00:00	UnKnown
9	7	Micro	2	vellore	katpadi	vellore	11-06-2022 00:00:00	UnKnown
10	8	Micro	2	vellore	katpadi	vellore	11-06-2022 00:00:00	UnKnown
11	9	Micro	2	vellore	cmc	vellore	11-06-2022 00:00:00	UnKnown
12	8	Micro	2	vellore	cmc	katpadi	12-06-2021 10:30:00	UnKnown
13	9	SUV Car	3	vellore	rs	chennai	12-06-2021 11:30:00	UnKnown
14	8	SUV Car	1	vellore	vallaimalli	ponnai	12-06-2021 18:20:00	UnKnown
15	8	Micro	1	vellore	cmc	katpadi	12-06-2021 09:30:00	UnKnown
16	8	Micro	1	vellore	cmc	katpadi	12-06-2021 09:00:00	UnKnown
17	8	Micro	1	vellore	cmc	katpadi	12-06-2021 09:10:00	UnKnown
18	8	Micro	1	vellore	cmc	katpadi	12-06-2021 09:20:00	UnKnown
19	8	Micro	1	vellore	cmc	katpadi	12-06-2021 09:30:00	UnKnown

Figure 1: Transport data fetched.

MODULE 2: Event Mapping

In this module, gathered traffic data is mapped to an event if it occurs within a specific time frame. It initially gathers event information through event calendars, which contain the event as well as its date and time, and traffic information, which also contains the date and time. The traffic data and event-related information with the same date and time are combined to generate a new dataset.

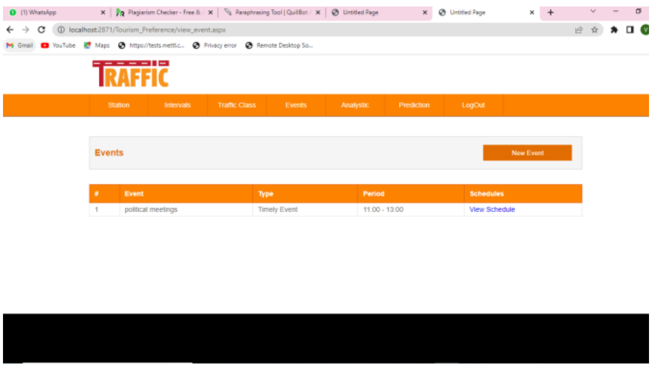


Figure 2: Event mapping

MODULE 3: pattern Initialization

We must first indicate the pattern and classes for which we are executing the learning process. This module allows us to create N number of intervals, we use the starting and ending time to declare four primary intervals of the traffic they are: morning, afternoon, evening, and night. Then we must specify the number of classes for which we are learning. we have four different types they are low traffic, medium traffic, high traffic, and extremely high traffic. along with their acceptable thresholds.

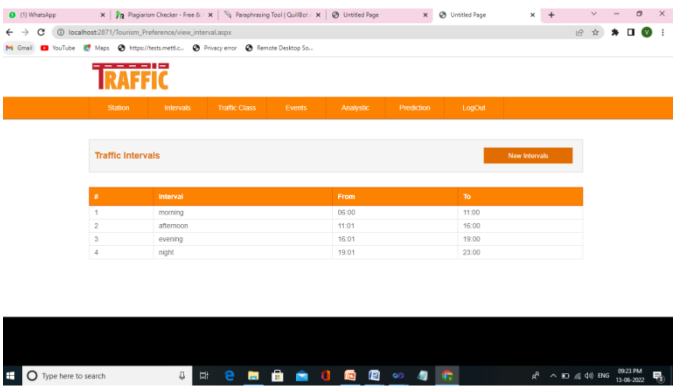


Fig 3: Pattern Initialization

MODULE 4: RNN Modeling

This is our most important module, and it leverages the data from the preceding modules to learn and construct patterns for classes based on the declarations made during the pattern initialization process. When the data fulfill the specified threshold, the RNN Modeling process reads the data one by one and assigns weight to the classes. Each traffic class has been assigned two weights: one without event limitations and another for the event to occur on a specific date.

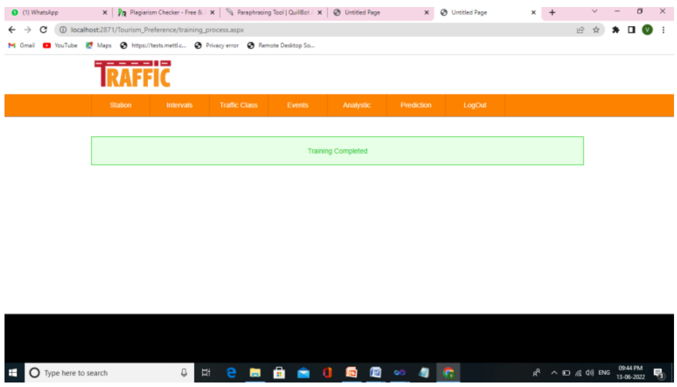


Fig 4: RNN modeling

MODULE 5: Traffic Prediction

Finally, this module use traffic classifications and weights to forecast traffic on a certain day and time. Even if we enter the date and time, the module utilises the time data to determine whether the pattern group is morning, afternoon, or evening. Our solution checks the weight of the courses based on the selected group and indicates if the traffic is high or low for that group. And it determines the weight it needs to take based on the date information. If any events occur on the specified date, the weight assigned to the event in that specific class is used to classify the input.

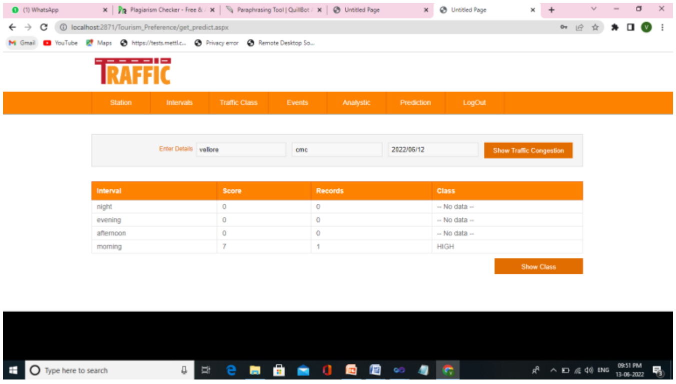


Fig 5: Traffic prediction

4. ARCHITECTURAL AND DATAFLOW DIAGRAM

4.1 ARCHITECTURAL DIAGRAM

The overall system architecture diagram illustrates the structure of our entire project in a very clear and effective graphical style. It usually always contains every component or module of our developing projects, as well as the workflow of the components and the associated data resources.

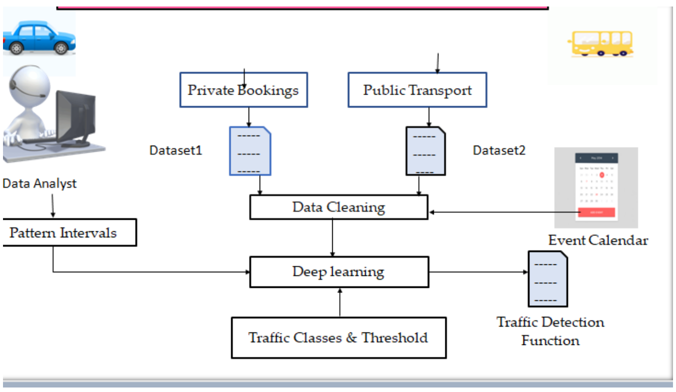


Fig 6: Architectural Diagram

4.2: USE CASE DIAGRAM

A use case is a collection of situations that describe a user's engagement with a technology. The link between actors and use cases is depicted in a use case diagram. Use cases and actors are the two fundamental components of a use case diagram. A user or another system that will interact with the modelled system is represented by an actor. A use case is a system's external view that depicts an action that a user could take to achieve a job.

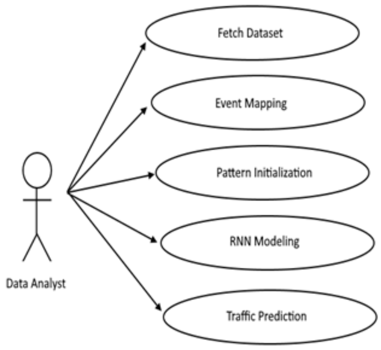


Fig 7: Use case diagram

4.3 ACTIVITY DIAGRAM

Activity diagrams are graphical representations of processes include step-by-step activities and actions that allow for selection, iteration, and concurrency. Activity diagrams in the Unified Modeling Language may be used to depict the business and operational step-by-step workflow of system components. The activity diagram is the total control flow.

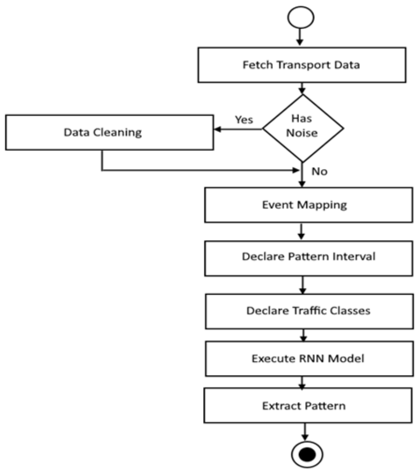


Fig 8: Activity diagram

5.RESULT AND OBSERVATIONS

Traffic classes are weighted to anticipate traffic on a specific day and time. Even if we enter a date and time, this module uses the time data to determine whether it is morning, afternoon, or evening. Our solution checks the weight of the classes based on the selected group and indicates if traffic is high or low in that group. And, using the date information, it determines which weight to allocate to each event that occurs on the specified date. The weight assigned to the event on that particular class is used to classify the input.

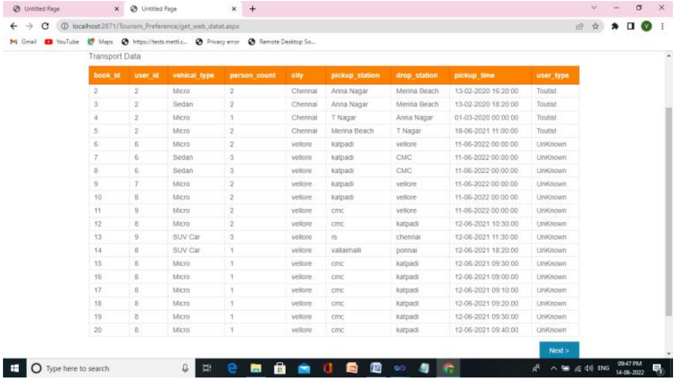


Fig 9: Traffic data

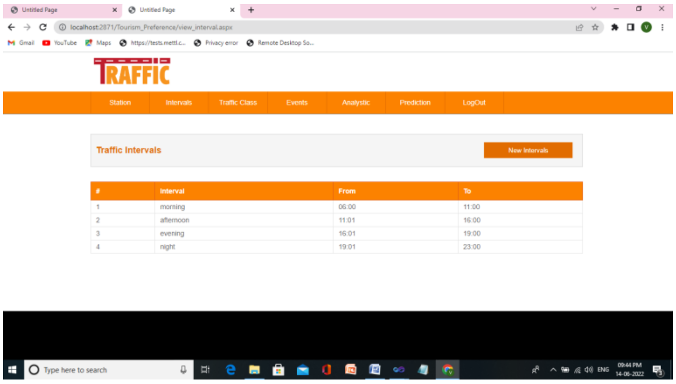


Fig 10: Traffic intervels

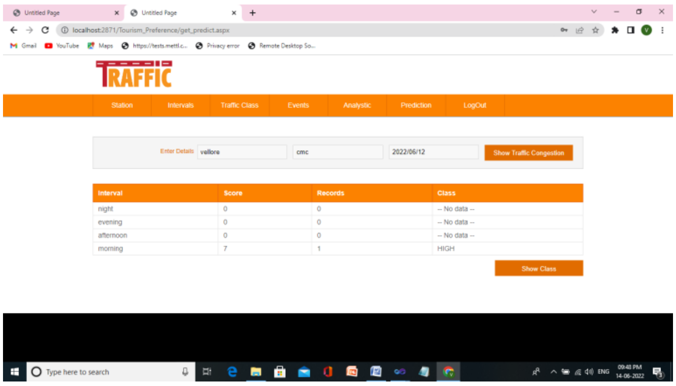


Fig 11: Traffic prediction

6.CONCLUSION

Our execution certifies that we successfully executed our project work and tested it in various scenarios within the time frame specified. Our project divides the labour of design, implementation, testing, and documentation into tiers so that we can finish on schedule. The outcomes obtained are in line with our expectations, thus we determined that our project was successfully completed. We had to include a screen photo and coding of the project in our documentation as evidence of completion.

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