Deep Learning in Traffic Flow Control and Prediction for Traffic Management

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Abstract

A major issue in urban settings is the heavy traffic and vehicle congestion due to poor traffic control or overpopulation. Nevertheless, this issue emphasizes the significance of proper traffic flow control and prediction to improve traffic management. This study provides a systematic literature review of novel twenty (20) papers that used the deep learning approach to solve the complex traffic management problem. The several studies gathered showed that long short-term memory (LSTM) models are effective for urban traffic flow prediction. The related studies shows that additional datasets, and a hybrid model, lead to better prediction accuracies. Based from the result of systematic literature, after criteria was se, this study proposed an AT-Conv-LSTM model that uses environmental data and data from social media.

Keywords
Deep Learning, Traffic Flow Control, and Prediction, Traffic Management, Neural Networks

1. Introduction
Heavy traffic and vehicle congestion has been a major problem of urban environments since the dawn of motorized vehicles. Heavy vehicular congestion affects societies tremendously. These come in forms of economic effects due to the time wasted in traffic, or environmental effects due to air pollution and fuel burning, and more. Monitoring and controlling traffic with various technologies is an ongoing solution being studied and used today to manage urban vehicle traffic and improve road conditions (Gössling, 2020).

Literature review is a significant process involve in academic research. It is made up of planning the review, conducting the review, and reporting the review (Kitchenham et al. 2007). There are various methods and technologies used to identify traffic patterns and data to control traffic management to satisfactory levels. This study provides a systematic literature review of several selected published papers that have used a deep-learning approach in identifying traffic flow and controlling traffic, its methods, and several data.

Therefore, this study seeks to provide an amalgamation and review of the recent developments in using deep learning in traffic management and control. Specifically, different techniques and algorithms used in the collected studies are reviewed and explained. This study also reports the type of data in the dataset used in each study, as well as the specific field or context of traffic management focus. Finally, using the information from the studies collected, the paper proposes a system that improves a certain field in traffic management.

2. Data Collection

The sources of data in this study is based from collection of online databases of reputable publications (Xiao and Watson, 2019.) which includes arXiv (arxiv.org), IEEE Xplore (ieeexplore.ieee.org), ResearchGate (researchgate.net), Springer (link.springer.com), MDPI (mdpi.com), Hindawi (hindawi.com), and ScienceDirect (sciencedirect.com). To find the papers, the following steps were followed: (1) Choosing a reputable online database of papers; (2) Selecting papers to review are within the years 2017-2021; (3) Searching through papers that contain keywords, namely - traffic flow prediction, traffic accident detection, traffic flow prediction, traffic accident detection, safety critical event prediction, traffic signal control, traffic modeling, traffic monitoring system, traffic data imputation; (4) Filtering through selected papers through its abstract; (5) Obtaining a list of final filtered papers that are relevant to the objective of this study. The process of systematic literature review was based from backward search (Webster and Watson 2002) and forward search (Levy and Ellis 2006).

3. Systematic Literature Review

The selected papers are grouped and sorted for their relevance, as set on the criteria requirements. There were an initial amount of forty-two (42) papers gathered that fit the basic requirements of the study. After a more thorough observation of the abstract and content of the studies, the list was further reduced to twenty (20) studies. Published studies are chosen due to their relevance towards deep learning, traffic management, traffic control, and traffic prediction. These studies were found in the databases mentioned in the methodology. Furthermore, these studies are chosen based on their relevance to the deep learning application in traffic flow control and prediction.

The studies that were chosen for this research are listed in Table 1. These studies are chosen for their relevance towards traffic control and prediction using deep learning techniques. Thus, along with the study, the methods used by these studies are also enumerated. There are a variety of algorithms mentioned in these recent studies, including LSTM, variations of neural networks, and the like. These studies were collected from different reputable sources such as IEEE, ResearchGate, and Springer.

Table 1. Chosen studies and methods

Title of Study	Source	Method(s) Used
Applying Deep Learning to Detect Traffic Accidents in Real Time Using Spatiotemporal Sequential Data (Parsa 2019)	arXiv	Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)
Improving Urban Traffic Speed Prediction Using Data Source Fusion and Deep Learning (Essien et al. 2019)	IEEE	Long Short-Term Memory (LSTM)
A deep-learning model for urban traffic flow prediction with traffic events mined from twitter (Essien et al. 2020)	Springer	Bi-directional Long Short-Term Memory (LSTM) Stacked Autoencoder Architecture
Safety critical event prediction through unified analysis of driver and vehicle volatilities: Application of deep learning methods (Arvin 2021)	ResearchGate	Convolutional Neural Network (CNN) / Long Short-Term Memory (LSTM)
Modelling Smart Road Traffic Congestion Control System Using Machine Learning Techniques (Ata 2019)	ResearchGate	Artificial Neural Network (ANN)
Exploring Cooperative Multi-agent Reinforcement Learning Algorithm (CMRLA) for Intelligent Traffic Signal Control (Vidhate and Kulkarni 2017)	Springer	Cooperative Multi-Agent Reinforcement Learning Algorithm (CMRLA)
A Hybrid Deep Learning Model With Attention-Based Conv-LSTM Networks for Short-Term Traffic Flow Prediction (Zheng et al. 2020)	IEEE	Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Conv-LSTM, and Bi-directional LSTM

Title of Study	Source	Method(s) Used
Application of Artificial Intelligence in Traffic Control System of Non-Autonomous Vehicles at Signalized Road Intersection (Olayode et al. 2020)	ResearchGate	Artificial Neural Network (ANN)
Artificial intelligence for traffic signal control based solely on video images (Jeon and Sohn 2018)	ResearchGate	Convolutional Neural Network (CNN)
DynSTGAT: Dynamic Spatial-Temporal Graph Attention Network for Traffic Signal Control (Wu et al. 2021)	arXiv	Long Short-Term Memory (LSTM)
Road Network Guided Fine-Grained Urban Traffic Flow Inference (Liu et al. 2021)	arXiv	Road Aware Traffic Flow Magnifier (RATFM)
Detection Traffic Congestion Based on Twitter Data using Machine Learning (Zulfikar 2019)	ScienceDirect	Support Vector Machine (SVM)
Dynamic Traffic Modeling From Overhead Imagery (Workman and Jacobs 2020)	arXiv	Convolutional Neural Network (CNN)
Traffic Flow Prediction with Rainfall Impact Using a Deep Learning Method (Jia et al. 2017)	Hindawi	Long Short-Term Memory (LSTM) and Deep Belief Network (DBN)
Artificial Intelligence-Enabled Traffic Monitoring System (Mandal et al. 2020)	MDPI	Convolutional Neural Network (CNN)
Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning (Zhang et al. 2019)	ResearchGate	Convolution Neural Network (CNN) Deep Learning Framework, Spatio-Temporal Feature Selection Algorithm (STFSA)
Short-term travel time prediction by deep learning: A comparison of different LSTM-DNN models (Liu et al. 2017)	IEEE	Long Short-Term Memory (LSTM)
Traffic Flow Forecasting with Maintenance Downtime via Multi-Channel Attention-Based Spatio-Temporal Graph Convolutional Networks (Lu et al. 2021)	arXiv	Graph Convolutional Network (GCN)
Dynamic Spatiotemporal Graph Convolutional Neural Networks for Traffic Data Imputation with Complex Missing Patterns (Liang et al. 2021)	arXiv	Long Short-Term Memory (LSTM) / Graph Convolutional Network (GCN)
Classifying the traffic state of urban expressways: A machine learning approach (Cheng 2020)	ScienceDirect	Fuzzy-C Means (FCM)

5. Results and Discussion

The discussion in this section covers the topics presented in the review of the published papers selected which includes the following: (1) The context of Traffic Control and Prediction, (2) The deep learning methods utilized by the studies and their relevance, (3) the common datasets used in the studies, and (4) other unique methods used in the studies collected.

5.1 Traffic Flow Control and Prediction

The study of traffic flow is continuously growing due to its difficulty to manually calculate as various random factors may occur, such as driver behavior, time of day, sudden road obstruction, and more. Traffic flow and its prediction are paramount as they are directly connected to the movement of goods and people, thus directly affecting economic factors in a society (Dai et al. 2019). As more roads and cars are produced and the intervention of intelligent vehicles, the need to analyze traffic flow and its corresponding factors grow (Hu et al. 2020). Table 2 indicates the various contexts where traffic is often studied according to the related papers in this review. Each factor that is deemed related to controlling traffic is enumerated, along with the amount of studies gathered. Specifically, predicting the flow of traffic given certain data has been the most common context among the collected papers. Signal control follows, with five (5) out of twenty (20) papers collected.

Table 2. Contexts where traffic is studied

Study Context and Number of Research Papers Reviewed	**Reference Studies**
Traffic Flow Prediction -10	(Essien et al. 2019), (Essien et al. 2020), (Zheng et al. 2020), (Liu et al. 2021), (Zulfikar 2019), (Jia et al. 2017), (Zhang et al. 2019), (Liu et al. 2017), (Lu et al. 2021), (Cheng 2020)
Traffic Accident Detection -1	(Parsa 2019)
Safety Critical Event Prediction -1	(Arvin 2019)
Traffic Signal Control - 5	(Ata 2019), (Vidhate and Kulkarni 2017), (Olayode et al. 2020), (Jeon and Sohn 2018), Wu et al. 2021)
Traffic Modeling -1	(Workman and Jacobs 2020)
Traffic Monitoring System -1	(Mandal et al. 2020)
Traffic Data Imputation -1	(Liang et al. 2021)

5.2 Deep Learning in Traffic Management

Traffic management is essential due to its ability to keep goods and people moving (Dai et al. 2019). The ability to calculate features, their correlation, and predict the future from past data is best handed to deep learning models. Various models have been developed, tested, and used to alleviate traffic congestion and accurately predict traffic flow up to 1 hour forward. The following schematic in Figure 1 shows the commonly used methods in predicting and controlling traffic flow found within the chosen studies.

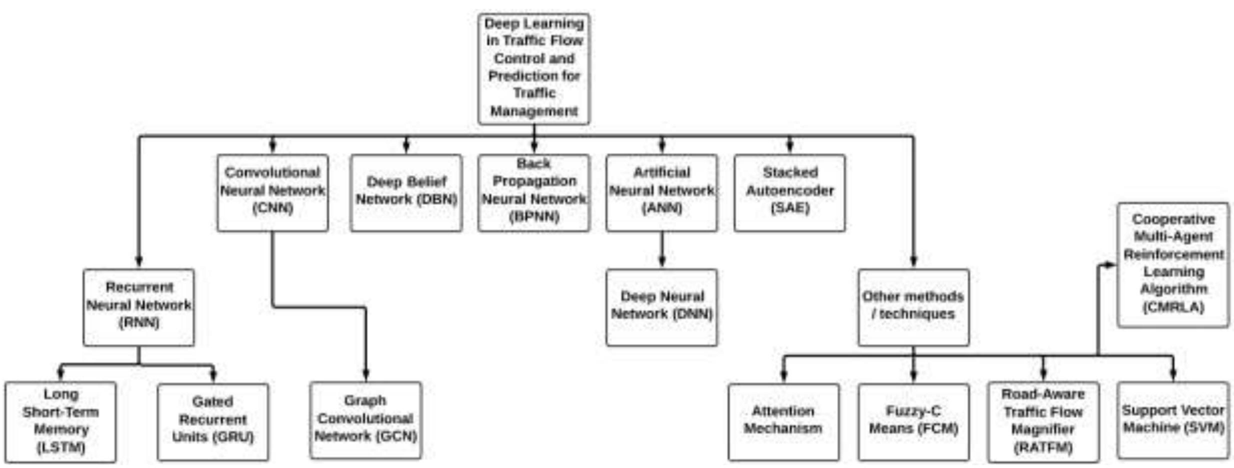

Figure 1. Schematic of deep learning methods commonly found in this review.

Convolutional Neural Network - Convolutional Neural Network (CNN) is a deep learning algorithm that can take in an input image and assign it a value (Iqbal et al. 2018). CNN can be beneficial in traffic management systems, where a model would have to deal with moving traffic constantly. It can extract vehicle images from the background from a video source and analyze them according to the researcher's specifications. The studies of Workman and Jacobs (2020) and Mandal et al. (2020) used CNN to segment traffic scenes to their own elements, mainly prioritizing vehicle density to extract different traffic variables such as traffic volume. Their application of CNN to their model is that it can count, spot, and recognize congestion build-up and the number of stationary vehicles. Another critical study from [16] where the standalone CNN performed well against SVR, KNN, SARIMA, and ANN models achieved a better 7.770 in the 10-minute category of traffic flow forecasting over the lowest model, SARIMA, which reached 10.470. The same research also showed a combined CNN with spatio-temporal feature selection algorithm, which performed better by achieving a higher precision prediction than the other algorithms. They had the best result of 7.931 compared to the standalone CNN that reached 9.806 in the 20-minute category of traffic flow forecasting.

Studies of Arvin (2021), Zheng et al. (2020), Jeon and Sohn (2018) and Zhang et al. (2019) show that convolutional Neural Network (CNN) performs well as a deep learning algorithm for its purpose, but it cannot select a vast number of regions in object detection. Multiple studies involving CNN have used variants of CNN or combinations of CNN, one variant would be the R-CNN which was created to combat the inability of CNN, it is now allowed to capture a significant amount of region proposals per image but comes with the cost of taking a considerable amount of time and delay from real-time. Fast and Faster R-CNN was introduced as a quicker object detection algorithm to mitigate the problems of R-CNN by having the convolution operation done a single time per image, and a feature map will be generated. An extension of Faster R-CNN named Mask R-CNN, whose main difference was having a third output for the object mask, was also used in the research of traffic queue detection in the study of Mandal et al. (2020). Its accuracy of 90.5% shows that Mask R-CNN compares favorably well with YOLO who has an accuracy of 93.7% despite a slight performance decrease over the other. Though YOLO was able to outperform CNN, it can be noted that despite a marginal difference between YOLO, CNN is still a viable option as it can be a cheaper and more reliable option when implementing a Smart Traffic Management System.

Long Short-Term Memory - Another significant field in deep learning is Long Short-Term Memory or LSTM. Its significance is because of how well it performs in the process, the classification, and the prediction of outcomes established on time series data. An example of the efficiency or effectiveness of LSTM can be seen in the studies of Parsa (2019), Essien et al. (2019), Arvin (2021), Workman and Jacobs (2020) and Liu et al. (2017) . However, one unique study worth mentioning would be the study involving an LSTM Stacked Autoencoder (SAE) that uses a traffic, weather, and tweet dataset (Arvin 2021). It can be seen that when their proposed LSTM model utilized all three datasets, it managed to show remarkable development in prediction accuracy with a 5.5049% in MAE or Mean Absolute Error in comparison to using only the traffic dataset that resulted in a 9.4763% in MAE, and to utilizing both traffic and weather datasets that lead to an MAE of 8.0927%. With that in mind, it can be said that adding more datasets may lead to better prediction accuracy when it comes to using an LSTM model. The previous statement is also supported by another study that involves the prediction of traffic flow while considering the impact of rainfall. The study mentioned that the prediction accuracy of deep learning is improved when using data inputs that come from multiple sources (Jia et al. 2017).

Models based on Long short-term memory may be efficient for time-scaled data, but it is also worth mentioning that LSTM models lack in some other areas. In the study that implements both Gated Recurrent Units (GRU) and Long Short-Term Memory for detecting traffic accidents, it can be observed that the slightly superior deep learning technique is the GRU. The reason for this slight superiority is because the GRU model performed better in the sense that it managed to memorize data, both on a long and short-term scale. In contrast, the LSTM model was only capable of memorizing data on a long-term scale. Nevertheless, despite the slight difference in their performance, the performance of both models was still of excellence because of their capability to achieve both a favorable rate of detection and false alarms. Specifically, the LSTM model attained 96% accuracy, 73.8% detection rate, and 3.0% false alarm rate. On the other hand, the GRU model had 95.9% accuracy, a 75% detection rate, and a 3.2% false alarm rate. It can be seen that the difference in their performance is slight but is still worth mentioning (Parsa 2019).

LSTM models on their own have been observed to perform excellently. However, another thing worth looking into would be LSTM models' performance when combined or when performing with other deep learning techniques. In the study of Zheng et al. (2020) they used Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), a Hybrid Conv-LSTM Network with attention mechanism, and a Bi-directional LSTM Network. The Attention mechanism is of significant help when it comes to improving the prediction performance because it was designed to assign different weights at different times to differentiate the significance of flow sequences, or in other words, to divert its attention to more important sequences. They compared the performance of the proposed model AT-Conv-LSTM with different existing algorithms for the prediction of traffic flow such as Long Short-Term Memory (LSTM), Stacked Autoencoders (SAE), Support Vector Regression (SVR), Diffusion Convolutional Recurrent Neural Network (DCRNN), and Deep Neural Network – Based Traffic Flow (DNN-BTF). This study shows that when LSTM is combined with both a Convolutional Neural Network and an Attention Mechanism, it can perform remarkably well compared to other algorithms.

There are many factors to consider when it comes to traffic flow prediction with the help of deep learning, and among those is the weather. In the previous study that involved using traffic datasets, weather datasets, and tweets, it can be observed that the weather dataset helped in improving the prediction accuracy (Essien et al. 2020). With that in mind, in another study, the researchers proposed two models, R-DBN, and the R-LSTM, both of which are Deep Belief Network (DBN) models and LSTM models that have integrated rainfall. The study shows that compared to their non-rainfall-integrated counterpart, they showed better performance for the R-LSTM model compared to the LSTM model. The results also show that the R-LSTM model is better compared to the R-DBN model. Still, both models showed superior performance compared to other models such as the Back-Propagation Neural Network or BPNN and the Auto-Regressive Integrated Moving Average model or the ARIMA. This study shows that the LSTM model is better than the DBN model and that having data input from multiple sources leads to better prediction accuracies (Jia et al. 2017).

Spatio-Temporal - Spatio-temporal data plays a significant part in traffic flow prediction for analyzing and predicting traffic involves both space and time Zhang et al. 2019). They proposed a CNN-based short-term prediction model for traffic flow, and with that, they used a spatio-temporal feature selection algorithm or STFSA. The algorithm selects certain features from the provided dataset and translates them into a two-dimensional or 2D matrix. In this specific study, spatio-temporal data is of even more significance because the CNN needs to learn the selected features before creating the traffic flow prediction model. For evaluation, the researchers compared the actual traffic flow data with the results they had predicted. In addition to that, the researchers also evaluated other baseline models and compared them to their proposed model. The comparisons and evaluations show that the proposed model CNN + STFSA performs the best in predicting traffic flow.

5.3 Datasets

When dealing with studies related to traffic management and traffic prediction, using multiple datasets to train the models varying from social media tweets in the study of Essien et al. (2020) and Zulfikar (2019) or a government agency dataset such as PeMS dataset. Datasets can be acquired from public sites, and in some studies, they would procure their own datasets (Essien et al. 2019), wherein they would use. In Table 3 are the different types of datasets used by the 20 research papers we gathered.

The table of datasets used in the gathered related literatures, as shown in Table 3, suggests that the most common form of data collection is numerical data, images, and surveillance videos. With most freeways and junctions equipped with a CCTV camera, obtaining such files from agencies or personally capturing them yourselves is doable. Out of the twenty (20) gathered related literature, three (3) had the same form of dataset collection, using overhead imagery to gather data for their model (Jeon and Sohn 2018), (Mandal et al. 2020), (Zhang et al. 2019). It is also worth mentioning that a unique form of dataset collection is with Twitter, the dataset used by Essien et al. (2020) and Zulfikar (2019) to train their models. With its vast number of online users, Twitter can be a great source of data as there are Twitter pages that offer such traffic updates despite having to filter out subjective tweets or tweets that intend to express sarcasm. Twitter can be a mine for obtaining data for studies such as traffic prediction.

Table 3. Datasets used in the Gathered Related Literatures.

Dataset	Type	Content
Traffic Data	Accident, traffic Spatio-temporal, weather condition, and congestion status data	Images, Reports, and Videos
Numerical Dataset	Hourly Observation from January 1, 2017, to September 7, 2017	Traffic (speed, traffic flow, and vehicle density data) and Weather Characteristics (rainfall and temperature data)
Categorical Dataset	Tweets and Weather Dataset	Traffic Updates from Twitter Pages and Weather Dataset

Dataset	Type	Content
SHRP2 NDS	7566 baseline, 1307 near-crash events, and 617 crash events	Various Images of crash events
Weather and Traffic Dataset	Weather Speed and Traffic Speed	Video of Traffic Speed and Data of Weather Speed
Footage of Vehicles	Images and Videos of Stationary Vehicles and Arriving Vehicles	Number of Vehicles Arriving and Stationary Vehicles
PeMS Traffic Data	Numerical data of Vehicle Congestion	Various traffic congestion at different hours of the day
Traffic Data	Arrival date, arrival time, vehicle direction, class number of vehicles, etc.	Log reports
Overhead Imagery	Aerial Images, 1000 Traffic Cameras Images (500 congested and 500 non-congested)	Various traffic densities at different hours of the day. Images of Junctions with varying vehicle density.
Surveillance Footage	Synthetic/Real World Intersection Surveillance Footage and Records	Videos of traffic densities on intersections at different hours of the day
XiAn, ChengDu, and TaxiBJ-P1	Road Network Information	Various Images of Chinese Roads
Categorical Dataset	Tweets	Various tweets specifying speed or traffic flow in a junction
Dynamic Traffic Dataset	Dynamic Traffic Speeds	Hourly Speed Data over Road Segments
Traffic and Environmental Dataset	Traffic Data and Multisource Environmental Data	Data on traffic congestion and weather data
Numerical Dataset	Travel Time Data	Duration of Travel
PeMS-BAY	Traffic Flow Recording at 5-minute intervals	Vehicles passing California Bay Area
METR_LA/INRIX-SEA	Traffic Speed Data	Road networks within Los Angeles Freeway / Seattle
Numerical Dataset	Traffic Flow and Speed Data	Vehicles passing the North-South Shanghai Elevated Expressway

5.4 Other Methods

As for other significant methods used, Artificial Neural Network or ANN shows a lot of advantages with its ability to think independently compared to other artificial intelligence methods and its accuracy during the prediction of time and finding the correlation between input and output of the analysis of data (Ata 2019). Olayode et al. (2020) used ANN in the study [8] in eliminating or reducing the traffic volume in a set area with the help of traffic data from Mikros Traffic Monitoring firm or MTM. The ANN model used Levenberg-Marquadt as the training algorithm due to the ANN's reliability on having a large dataset to provide accurate information. The method is fast and easy to be applied to large datasets. The data gathered from the study concluded that the ANN model can predict the traffic flow of vehicles efficiently, considering vehicle speed and class description. The data was based on the training solutions, testing, and validation, all matching when received, and the low value of MSE showed the high accuracy of the values. Support Vector Machine or SVM is highly used for classification, and it was used in the study of (Zulfikar 2019) to detect congestion in social media text information using machine learning. Using the library libSVM with the Sigmoid Kernel, Linear Kernel, and Polynomial Kernel, they compared which kernel will have the highest accuracy. The study concluded that the libSVM could maintain a high accuracy rate of more than 95% in all three kernels in determining the location and time of congestion, and it was cross-checked with applications and utilized Google maps for validation

The Fuzzy-C Mean or FCM is an algorithm to classify results distributed to a multilayered data space into the set number of specified categories in the study of Cheng (2020) to classify the urban traffic state by using the loop detector data for Shanghai. Data showed that the improved FCM method increased by 10.10%, 5.45%, 30.92%, and 35.66% compared to the traditional FCM method, SVM method, decision tree method, and KNN method when cross-checked with the data gathered in determining traffic congestion. It was then concluded that the improved FCM clustering approach works exceptionally well in determining urban traffic state and is very much feasible. The FCM is viable in determining or understanding the traffic status of a specified road network, and it may also be used in future studies which apply more datasets such as real-world traffic data.

Other significant methods used were the Gated Recurrent Units or GRU in the study of Parsa et al. (2019) to detect traffic accidents as it was comparable to LSTM in performing well with sequential data. GRU could achieve high detection rates with low false alarm rates. It was concluded that GRU might perform better than LSTM in detection rate and similarly in false alarm rates. It also excels in capturing both long-term and short-term dependencies. Graph Convolutional Network or GCN was altered and used in the study of Liang et al. 92021). They created a novel deep learning architecture, called Dynamic Spatiotemporal Graph Convolutional Neural Networks (DSTGCN), to provide precise and robust results for the different missing patterns. They concluded that the model achieves better performance than current methods in different missing patterns, and it provides solid results with a wide range of missing ratios.

6. Proposed System

According to this review, the proposed system for controlling and predicting traffic flow would utilize spatio-temporal factors present in traffic data. Thus, historical data must be taken along with corresponding road networks present near the location, including traffic direction, traffic flow within a certain time, and factors such as unexpected events. Future traffic flow should be predicted using these data and parameters using an LSTM approach due to its ability to process and predict based on sequential data. Although this approach has been repeatedly studied, studies on predicting traffic flow where a road obstruction is present are scarce. To further increase the model's accuracy, attention gates are to be included within the LSTM model, which increases efficiency and decreases processing time (Lu et al. 2021). In addition to that, the proposed system shall use environmental data that comes from multiple sources and data from social media platforms. The reason for this is because additional datasets improve the prediction accuracy of LSTM models, as shown in the studies of Essien et al. (2020) and Jia et al. (2017). Another concept that we would like to incorporate into the proposed system would be combining the LSTM model with CNN and an attention mechanism. The reason behind this addition would be due to the significant difference in performance between the AT-Conv-LSTM model and the LSTM model, as seen in the previous study (Zheng et al. 2020).

The flow of the model can be seen in Figure 2: (1) The multisource input of historical spatio-temporal data of a certain location at certain and different times, and data from social media. (2) AT-Conv-LSTM model analyzes patterns between traffic volume, its relation to location, and its relation to the current time. (3) AT-Conv-LSTM model predicts traffic flow in the next 60 minutes in 15-minute intervals.

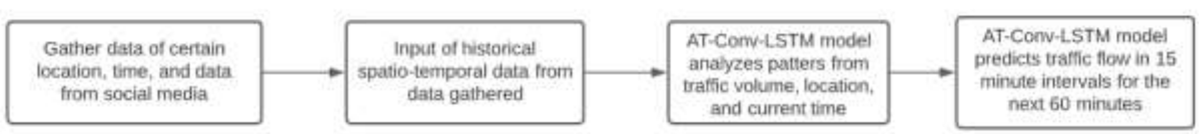

Figure 2. Conceptual framework of the proposed system

7. Implication and Conclusion

Based on the studies that the researchers have gathered and reviewed, the researchers can conclude that they will be proposing an AT-Conv-LSTM model that uses multisource environmental data and data from social media platforms because of the improvement that these features have shown to provide. It was shown that using an LSTM model combined with CNN and an attention mechanism shows superior performance compared to a standalone LSTM model (Zheng et al. 2020). It was also shown in the studies of Essien et al. (2020) and Jia et al. (2017), that using more datasets leads to better prediction accuracy, which is why the researchers believe that the proposed model should use both environmental data and data from social media. Instead of using other models such as a DBN or a GRU-based model, we chose an LSTM based model because it performed better than a DBN-based model (Jia et al. 2017) and only had a slightly lower performance with the GRU-based model Parsa et al. (2019). Despite the GRU model having a slightly better performance than the LSTM model, the researchers still chose the LSTM model to be combined with CNN and an attention mechanism because no related literature involved the hybrid of a GRU-based model CNN, and attention mechanism.

8. Limitation and Future Research

In this paper, several studies of Parsa et al. (2019), Essien et al. (2020), Zheng et al. (2020) and Jia et al. (2017) that the performance of an LSTM based model was confirmed to be of excellence, and in traffic flow control and prediction, which resulted in the formulation of the proposed conceptual framework in this study. Nevertheless, the limitations of this paper stem from the lack of studies regarding an AT-Conv-GRU model or an AT-Conv-DBN model selected in the review process. This study needs to gather further review on hybrid models. It is also recommended that future researchers feature new forms of data rather than pure traffic flow data such as data from other sources like social media posts.

References

Arvin, R., Khattak, A.J. and Qi, H., Safety critical event prediction through unified analysis of driver and vehicle volatilities: Application of deep learning methods. *Accident Analysis & Prevention*, vol. 151, p.105949, 2021.

Ata, A., Khan, M.A., Abbas, S., Ahmad, G. and Fatima, A., Modelling smart road traffic congestion control system using machine learning techniques. *Neural Network World*, vol. 29(2), pp.99-110, 2019.

Cheng, Z., Wang, W., Lu, J. and Xing, X., Classifying the traffic state of urban expressways: A machine-learning approach. *Transportation Research Part A: Policy and Practice*, vol. 137, pp.411-428, 2020

Dai, G., Ma, C. and Xu, X., Short-term traffic flow prediction method for urban road sections based on space–time analysis and GRU. IEEE Access, vol. 7, pp.143025-143035, 2019.

Essien, A., Petrounias, I., Sampaio, P. and Sampaio, S., Improving urban traffic speed prediction using data source fusion and deep learning. I*n 2019 IEEE International Conference on Big Data and Smart Computing (BigComp)* (pp. 1-8), February 2019.

Essien, A., Petrounias, I., Sampaio, P. and Sampaio, S., A deep-learning model for urban traffic flow prediction with traffic events mined from twitter. World Wide Web, pp.1-24, 2020.

Gössling, S., Integrating e-scooters in urban transportation: Problems, policies, and the prospect of system change. Transportation Research Part D: Transport and Environment, vol. 79, p.102230, 2020.

Iqbal, S., Ghani, M.U., Saba, T. and Rehman, A., Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN). Microscopy research and technique, vol. 81(4), pp.419-427, 2018.

Jeon, H., Lee, J. and Sohn, K., Artificial intelligence for traffic signal control based solely on video images. Journal of Intelligent Transportation Systems, vol. 22(5), pp.433-445, 2018.

Jia, Y., Wu, J. and Xu, M., 2017. Traffic flow prediction with rainfall impact using a deep learning method. Journal of advanced transportation, 2017.

Kitchenham, B. and Charters, S., Guidelines for performing systematic literature reviews in software engineering, 2007.

Levy, Y. and Ellis, T.J., A systems approach to conduct an effective literature review in support of information systems research. Informing Science, vol. 9, 2006

Liang, Y., Zhao, Z. and Sun, L., Dynamic spatiotemporal graph convolutional neural networks for traffic data imputation with complex missing patterns. arXiv preprint arXiv:2109.08357, 2021.

Liu, L., Liu, M., Li, G., Wu, Z. and Lin, L., Road network guided fine-grained urban traffic flow inference. arXiv preprint arXiv:2109.14251, 2021.

Liu, Y., Wang, Y., Yang, X. and Zhang, L., October. Short-term travel time prediction by deep learning: A comparison of different LSTM-DNN models. In 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) (pp. 1-8). IEEE, 2017.

Lu, Y., Kamranfar, P., Lattanzi, D. and Shehu, A., Traffic Flow Forecasting with Maintenance Downtime via Multi-Channel Attention-Based Spatio-Temporal Graph Convolutional Networks. arXiv preprint arXiv:2110.01535., 2021.

Mandal, V., Mussah, A.R., Jin, P. and Adu-Gyamfi, Y., Artificial intelligence-enabled traffic monitoring system. Sustainability, vol. 12(21), p.9177, 2020.

Olayode, O.I., Tartibu, L.K. and Okwu, M.O., Application of Artificial Intelligence in Traffic Control System of Non-autonomous Vehicles at Signalized Road Intersection. Procedia CIRP, vol. 91, pp.194-200, 2020.

Parsa, A.B., Chauhan, R.S., Taghipour, H., Derrible, S. and Mohammadian, A., Applying deep learning to detect traffic accidents in real time using spatiotemporal sequential data. arXiv preprint arXiv:1912.06991, 2019.
Vidhate, D.A. and Kulkarni, P., August. Exploring Cooperative Multi-agent Reinforcement Learning Algorithm (CMRLA) for Intelligent Traffic Signal Control. In International Conference on Smart Trends for Information Technology and Computer Communications (pp. 71-81). Springer, Singapore, 2017.
Webster, J. and Watson, R.T., Analyzing the past to prepare for the future: Writing a literature review. MIS quarterly, pp.xiii-xxiii, 2002.
Workman, S. and Jacobs, N., Dynamic traffic modeling from overhead imagery. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 12315-12324), 2020.
Wu, L., Wang, M., Wu, D. and Wu, J., October. DynSTGAT: Dynamic Spatial-Temporal Graph Attention Network for Traffic Signal Control. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management (pp. 2150-2159), 2021.
Xiao, Y. and Watson, M., Guidance on conducting a systematic literature review. Journal of Planning Education and Research, vol. 39(1), pp.93-112.2, 2019.
Zhang, W., Yu, Y., Qi, Y., Shu, F. and Wang, Y., Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning. Transportmetrica A: Transport Science, vol. 15(2), pp.1688-1711, 2019.
Zheng, H., Lin, F., Feng, X. and Chen, Y., A hybrid deep learning model with attention-based conv-LSTM networks for short-term traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 2020.
Zulfikar, M.T., Detection traffic congestion based on Twitter data using machine learning. Procedia Computer Science, vol. 157, pp.118-124, 2019.

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