Using Machine Learning and Deep learning for traffic congestion prediction: a review

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Abstract:

Traffic congestion has long been a problem for many cities and commuters around the world, which causes long commuting hours, increased traffic accident rates, significant economic loss, etc. Correctly predicting traffic congestion can help alleviate several problems that traffic congestion is causing on a recurrent basis. With the advances in data collection, Artificial Intelligence (AI) becomes a perfect tool to be able to do short term and long term congestion forecasting. This paper reviews the latest developments in the Machine Learning and Deep Learning methodologies for traffic congestion prediction in a systematic way, over the last decade. The main finding have been structured based on different AI methodologies, data sets, and prediction time periods. The paper also discusses the advantage and drawbacks of the current AI methodologies, and talks about the research gap of implementing in real-life the AI methodologies for the traffic congestion prediction.

1. Introduction

With the acceleration of urbanization, decreased vehicle prices and increased population in many cities, traffic demand has been rapidly increasing in recent years. The urban road traffic resources cannot meet the increasing traffic demand, thus causing several traffic congestion problems [54]. Traffic congestion is a widely occurring phenomenon characterized by lower vehicle speeds, increased vehicular queuing and, sometimes, a complete paralysis of the traffic network [1]. Traffic congestion can cause many different problems, by reducing the traffic system efficiency, increasing the travel times and the delays to reach destinations; this can lead as well to safety and health concerns [19] while also causing air and sound pollution [43] or even affecting a city's effective functioning [47].

Forecasting the congestion level of a road network timely can prevent its formation and increase the efficiency and capacity of the road network [45]. This can, in turn, help alleviate or solve the impact of the aforementioned problems. In order to reduce the travel time of vehicles and solve the traffic congestion problem, a lot of effort has been placed into researching ways to forecast traffic congestion and to provide drivers with a more efficient route [10].

In the recent years, Artificial Intelligence (AI) has become increasingly popular and an extensive research work and applications have been taken within AI space. Shallow Machine Learning and Deep Machine Learning, as subsets of AI, have been used especially extensively within different smart city areas, which includes the research in traffic congestion prediction. In the last decade, given the extensive application of deep learning techniques, a growing number of researchers began to use deep neural networks to predict traffic congestion situations [54]. The successful development of deep learning (DL), which is based on artificial neural networks, has revolutionized many machine learning (ML) tasks, and traffic forecasting is no exception [37].

This paper systematically reviews and discusses different machine learning and deep learning based approaches for traffic congestion prediction. These different approaches utilize various data sources, and conduct traffic congestion predictions for different roads in different cities. The prediction time periods vary from real time to a few minutes to long term predictions. To be more specific, when reviewing the existing literature, we have investigated the following questions:

1. What machine learning or deep learning approach is most utilized recently?
2. What is the data source that has been used?
3. What is the prediction time period?
4. What is the outcome of the prediction modelling?

5. What issues or computational challenges have appeared?

The paper also discusses about the research gaps, and proposes a future direction for traffic congestion prediction.

2. Research Methodology

For the current mythology, we follow the steps below to review the current published literature:

1. Identify the relevant work in the field,
2. Study and assess the relevant work across multiple countries/venues/publication venues,
3. Analyse and summarise the relevant work and cluster together the work,
4. Find the research gaps in the current application of ML and DL work for congestion prediction,
5. Propose future directions which can be explored by research scientists in the field.

3.1. Identify Relevant Work

To conduct the literature review, this research utilised a wide array of online libraries and digital databases to identify and analyse relevant work within this field. Literature was identified and explored through IEEE Xplore, Elsevier, Springer, ResearchGate, ACM Digital Library, Gartner, and Google Scholar. To conduct the research, the following queries were utilised (note that even though forecasting and prediction are interchangeable, to maximise the results, both were searched for):

1. "Traffic Congestion Prediction" OR "Prediction of Traffic Congestion".
2. "Traffic Congestion Forecasting" OR "Forecasting of Traffic Congestion".
3. "Road Congestion Prediction" OR "Prediction of Road Congestion".
4. "Road Congestion Forecasting" OR "Forecasting of Road Congestion".
5. "Deep Learning models for traffic congestion prediction".
6. "Traffic Congestion Forecasting with trucks and buses".
7. "Urban city traffic prediction using neural networks".
8. "Traffic congestion prediction" OR "Forecasting traffic within urban cities".

The table below summarises the search results as follows:

Search Queries	IEEE	Springer	Google Scholar	Elsevier	ACM
Search results 1980-2022	1,100	16,775	170,000	3,651	56
Filtered – last 10 years	854	12,395	43,300	2,853	36
Relevance	69	156	1,855	109	33

Table 1 Summary of literature review.

Using these queries alone results in 191,582 articles aggregated within all these sources across all the years. Hence, these queries were further filtered with results from 2010 and onwards (discarding any results before this period) as well as papers only in English were explored. This is to ensure the latest, up to date and most applicable research is explored, and only relevant research gaps are explored. This reduced the results to roughly 2,200 publications. To further narrow down the research, results were sorted by relevance first, followed by year, through which roughly 118 total papers were studied. Out of which 91 were selected to explore in great depth through this literature review. These were selected due to their content, primarily including Recurrent Neural Networks, Transformer Models, Convolutional Neural Networks, Autoencoder Networks, Shallow Learning techniques including K Nearest Neighbour.

3.2. Retrieve Relevant Work

This paper uses Mendeley Reference Manager to manage the search result of the above queries. Some of the search results were not related to machine learning or deep learning, or were not related to traffic congestion prediction. In order to further filter the retrieved papers, a brief read through for all the found papers were conducted and only the papers related to using machine learning or deep learning models to predict traffic congestion were kept. Also, only articles written in English language were kept. As the number of articles from Google Scholar were big, this chapter mainly focused on the articles from IEEE, Springer, Elsevier and ACM. Any articles focusing on traffic congestion cause, traffic congestion estimation, traffic congestion propagation that were not closed related to traffic congestion prediction were excluded from this work.

3. Relevant Data Sources

Predicting traffic congestion utilising machine learning or deep learning requires 2 main steps. The first main step is collecting and processing data. The second step is applying machine learning or deep learning methodology for the traffic congestion prediction. The type, accuracy and completeness of the data source is of paramount importance of the traffic congestion prediction as it is the first step and the basis of the prediction. This section reviews and discusses different data sources used in the reviewed articles.

A wide library of data sources is considered for this research, to maximise accuracy, validity, and reliability of the research. As machine learning and deep learning require a large set of data to efficiently function and yield accurate results, datasets are collected and then processed to train and test the traffic management system model. The different types of datasets that will be considered, explored and investigated through this literature review are overviewed below. The most commonly used datasets are stationary data and probe data. Other datasets including weather data, pollution data, app data, social network data, events data, etc are also being used in machine learning or deep learning based traffic congestion prediction.

4.1. Stationary Data

Stationary data are gathered utilising stationary sensor stations that can operate all the time if no temporary failure is involved. The stations of data collection use a set of sensors installed in the roadway to detect the passage of vehicles [3]. The data reported by Bluetooth sensors included the Bluetooth ID of the device in the vehicle passing the sensor location and the time at which the device (vehicle) passed the sensor location [42]. This is an advantage when using the dataset as the exact location can be obtained. There are different stationary data from different countries and systems. Below are some of them.

PeMS

One of the most commonly used stationary data is from Performance Measurement System (PeMS). In 2017, PeMS utilized over 39,000 detectors to collect real-time traffic data, these sensors cover the freeway system across all major metropolitan areas of the State of California, PeMS prepared over 10 years of (historical) traffic flow data [22]. PeMS data contains information of traffic flow, vehicle speed, traffic accident, etc [5]. There are many articles are based on the data from PeMS from several years ago until now. Fouladgar et al. [22], Bai et al. [5], Tu et al. [54], Xu et al. [57], Narmadha and Vijayakumar [37], etc all utilised PeMS data for machine learning or deep learning based traffic congestion prediction. Traffic flow counts data is mainly used from static traffic sensors placed around motorways or regular roads and represent perfect data sources for time series modelling, outlier and anomaly detection [73].

4.1.1. Other Stationary Data

Apart from PeMS, there are articles using stationary data provided by other organisations. Bui et al. [9] used traffic flow dataset from the vehicle detection system (VDS) in an urban area of South Korea. Bui et al. [9] used METR-LA, which is a well-known traffic speed dataset that had collected from the highway system of Los Angeles County. Florido et al. [21] used time series data collected by sensors belonging to the Spanish Directorate General for Traffic. Choi et al. [16] evaluated their proposed model by using the Bluetooth data collected in Brisbane, Australia, which contains the movement information of private vehicles. Chen et al. [12] used six weeks of structured vehicle passage records (VPRs) collected from surveillance cameras in Jinan, China. Vehicle ID, location, and timestamp can be extracted from VPRs using optical character recognition(OCR) [12]. Kwoczek et al. [27], wei Guan et al. [24] and Badura [4] also used stationary data collected from induction loop, magnetic sensor, etc.

4.2. Probe Data

Probe data can be collected from a much wider area, as long as there is GPS, GSM, etc. These data usually contains high spatial and temporal resolution [27]. Kwoczek et al. [27] used Floating Car Data (originated from millions of vehicles equipped with GPS sensors), GSM probe data and data from stationary sensor (e.g. loop detectors, camera sensors) for their research. Elleuch et al. [19] also conducted traffic prediction research based on Global Positioning Systems (GPS) traces. Among all the probe data, taxi GPS data are the most commonly used data. Chen et al. [13]

used TaxiBJ dataset that is trajectory data from Beijing taxicab GPS, including four time intervals: 1 July 2013 to 30 October 2013, 1 March 2014 to 30 June 2014, 1 March 2015 to 30 June 2015, 1 November 2015 to 10 April 2016. They obtained multi-attribute data sampling every 30 min on a grid map and obtained 48 samples per day [13]. Maniak et al. [34] used the data collected and provided to the NYC Taxi and Limousine Commission (TLC) by technology providers authorized under the Livery Passenger Enhancement Program (LPEP), which contain trip records from all trips completed in green taxis in NYC in 2013. Xu et al. [58] used the traffic data of urban taxis to study it in Beijing. Xu et al. [56] took the large dataset of taxi trajectories in Shanghai. Satrinia and Saptawati [46] predicted traffic speed with help of GPS data from history of taxi trip in Bandung city. The GPS data from taxi trip in Bandung city does not have data speed and sometimes the location detected from GPS device is less accurate so additional steps required in data preprocessing phase [46]. Apart from the taxi probe data, Osipov and Miloserdov [41] used "Yandex.Probki" that is one of the Internet services of the "Yandex" company, the data comes from mobile devices drivers equipped with GPS in Moscow, St. Petersburg and other major cities. Adetiloye and Awasthi [1] and Zhang et al. [62] also used GPS to conduct traffic congestion prediction.

4.3. Weather Data

Weather data is another useful data that have been used by many researchers to conducted the traffic congestion prediction research based on machine learning or deep learning. A multiple linear regression analysis (MLRA) model using weather data and traffic congestion data was implemented by Lee et al. [28]. Chen et al. [14] used resources including official websites of traffic management and operations, web-based map services (like Google map), weather forecasting websites, and local events (sport games, music concerts, etc.) websites. Chen et al. [13], Nguyen et al. [39] and Neelakandan et al. [38] all conducted the research taking weather data into consideration.

4.4. Pollution Data

Pollution and Air Quality datasets can yield a lot of information regarding current traffic scenarios on road. As most of the vehicles at present times are gasoline vehicles, a high pollution count at a particular road area can indicate a high amount of vehicle traffic flowing. One small problem with this condition is that it needs to be utilised against more data, primarily as large number of vehicles on the road does not mean a congestion has occurred, hence it must be used primarily with probe (GPS speed) or static data to yield more reliable results. Shahid et al. [47] used the air pollution dataset with pollutants parameters that are emitted by motor vehicles i.e. carbon monoxide, nitrogen dioxide, sulfur dioxide, particulate matter, and ozone. Other studies have looked at using ML and DL methods for air quality prediction both in isolation or in combination with other traffic simulation modelling [67]-[68]-[69]-[70]-[71]-[72].

SNS Data

SNS data contains a big amount of different kinds of information including the information that can be used to predict traffic congestion. As Adetiloye and Awasthi [1] stated, in their heterogeneous fusion model, they extend the homogenous model by integrating with qualitative data, i.e. traffic tweet information from Twitter data source. Nguyen et al. [39] also incorporated SNS(twitter) data to the environmental factors makes the predictive performance of Fusion-3DCNN CPA* Open image in new windowSNS higher than Fusion-3DCNN CPA by 3%.

4.5. Event Data

Events can affect traffic flow, thus can be used when predicting traffic congestion. In order to improve the prediction of their system, Chen et al. [14] applied a data fusion method to incorporate those unpredictable events. Kwoczek et al. [27] and Chen et al. [14] also conducted traffic congestion prediction research using data including events data.

4.6. Traffic Accident Data

Traffic accident can slow down the traffic flow, and it can be useful to incorporate traffic accident data into traffic congestion prediction dataset. Nguyen et al. [39] leveraged rainfall and traffic accident data, the predictive performance of Fusion-3DCNN CPA was increased by 3% compared to 3D-CNN. Multiple studies have modelled and used the traffic accident data sets around the world to predict either the traffic incident durations [81], the risk severity [85], the traffic demand estimation under non-recurrent congestions [82]-[83]-[91], or simply to combine both the traffic accident modelling and traffic simulation modelling into more complex architectures [75]-[76]-[80].

4.7. Bike Data

In some roads, bikes share the same road with other vehicles, and bike data can be useful for predicting traffic congestion in this case. Wang et al. [55] used the bike sharing data in Suzhou, China from April 1st, 2016 to April 1st, 2018. The public bicycle system in Suzhou is operated by Youon Company, in 2018, there are nearly 2,000 bike-sharing sites

[55].

4.8. App Data

Mobile and mobile apps are widely used in many countries and cities, the data collected from mobile apps can contain important information such as vehicle location, speed, etc. Chen et al. [14] managed to utilise web-based map services (like Google map) for their research. Authors in [43] managed to use app poll data on one of the roads nearby Telkom University. One important factor that needs to be considered when utilizing mobile app data is its relevant privacy agreement may need to be sought before the data is collected from the app.

4.9. Traffic Signal Control data

An important data set that can be used for predicting the traffic congestion is the data collected from traffic signal controls placed inside intersections, together with data coming from loop detectors. These data sets can be used to reflect not only the level of congestion at each intersection, but also to make place for various traffic control strategies and optimization strategies that can be implemented [74]-[77]. Some recent studies event started incorporating parking utilization and how this can affect the traffic congestion surrounding the parking facilities that will be transformed in the future for more electric and autonomous vehicles utilization [78]-[79].

4.10. Other Data

There does exist some other form of useful data which this research could potentially utilise, depending on the performance of the models. One primarily dataset includes sound sensors to detect vehicle horns and other forms of engine noises, as very briefly discussed by Rao A. et al. in [65]. There are some other data that can be used to facilitate traffic congestion prediction, these data include data from CCTV footage [51], tolling system, survey data, etc. More recently the spatial layout of the road network has started to be integrated into the deep learning models for improving the prediction accuracy and this new hot topic area has opened the space for graph modelling approaches [86].
An important data regarding traffic congestion can be represented by the number of people waiting to use public transport, due to heavy congestion in the city, which can make public transport an attractive solution [90].

Last but not least, one needs to mention the data that will be generated by connected and autonomous vehicles which will be large and with a significant frequency; this type of data normally transmitted via dedicated connected vehicles devices equipped with DSRC will transmit not only the location of the vehicle in real time but will also be a good indication of congestion between vehicles when a flooding of messages will be exchanged between vehicles stuck in traffic. Preliminary analysis have been undertaken in the connected vehicle data [87]-[88]-[89] and this represents a unique and good starting point for investigating the congestion via transmitted messages between connected cars.

4. Applied AI Methodologies

The retrieved work and literature are reviewed through this section to analyse and explore the existing research within the field of traffic prediction. This work reviews the research primarily across Shallow Machine Learning Methods and Deep Learning Methods. The Machine Learning methods include approaches such as linear and logistic regressions, support vector regressions, decision trees, random forests, k-nearest neighbors algorithms, shallow artificial neural networks, reinforced learning, ensemble learning. The Deep Learning include sets of Recurrent Neural Networks (RNN), Transformers Networks, Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Autoencoder Networks (AN), Markov Chain Models and Generative Adversarial Networks (GAN). Alongside these, some studies combine shallow and deep learning to produce a more robust and a hybrid model, hence they are discussed within the final sections of the review as well.

5.1. Shallow Machine Learning Methodologies

Shallow Machine Learning based methodologies were implemented for traffic congestion prediction, which showed improved prediction result comparing with probabilistic reasoning or other non-AI approaches.

5.1.1. Linear Regression

Lee et al. [28] utilised multiple linear regression model to predict traffic congestion related to weather data, they used the mean absolute percentage error valuation method, and showed that the final multiple linear regression model has a prediction accuracy of 84.8%.

Putra et al. [43] proposed to conduct an app poll to traffic users on one of the roads nearby Telkom University, collected the traffic record, estimated the future traffic condition using linear regression, and then compared the predicted traffic condition with that of the actual traffic condition. The experiment result shows that the proposed method successfully predicts the traffic condition within the same class of level of service with the actual traffic condition [43].

However, linear regression may not always work for traffic congestion prediction. Linear regression is not suited for modeling relationships between traffic variables which are non-linear. Non-linear relationships can be modeled using other data driven techniques such as ANN, kNN and support vector regression (SVR) [42].

5.1.2. Logistic Regression

Deb et al. [17] utilised logistic regression model on the collected Uber movement data, and showed that it can accurately predict the time to travel between different nodes (locations) in Mumbai city with an accuracy of 85%. However logistic regression is not a suitable tool for congestion prediction in a time series approach.

5.1.3. Support Vector Regression (SVR)

Satrinia and Saptawati [46] proposed using Map Matching with topological information method in pre-processing phase; Map Matching has produced a new trajectory that has corresponded to the road, and from that new trajectories they calculated the speed for each road segment. Satrinia and Saptawati [46] utilized the Support Vector Regression (SVR) method for the traffic speed prediction, and the results indicated that Map Matching can help to obtain more accurate traffic speed and SVR has good performance to predict the traffic speed.

Philip et al. [42] claimed Support vector regression (SVR) models predict travel times with reasonable accuracy, especially when the amount of data is less or the variability in the data is high. Philip et al. [42] used travel times from prior 40 min to predict the travel time of the current interval, they built SVR, ANN and moving average models with 8 input values and compared the results obtained. They claimed that with suitable kernel functions and model parameters, the SVR model could be used to predict the travel time at the next instant quite accurately using previous travel time values, and the SVR model they used performed better than an Artificial Neural Network model and moving average approach under Indian traffic conditions [42].

5.1.4. Support Vector Machines (SVM)

Asencio-Cortés et al. [3] implemented SVM by using LibSVM free package and configured it with the SVM type as the C-SVC for classification tasks, the kernel as the polynomial of degree 1, and the cost parameter C as 1. Asencio-Cortés et al. [3] also used Stochastic Gradient Descent Optimization (SGD) that is an optimization technique that allows models, such as linear SVM or logistic regression, to be learned from high-dimensional data sets. They suggested SVM can be used for the classification problem and for traffic congestion prediction [3].

5.1.5. Decision Trees

The objective of the decision trees is obtaining rules or relationships that allow classification based on the attributes [3]. Florido et al. [21] claimed that Decision trees, artificial neural networks and nearest neighbors algorithms have been successfully applied to a particular location in Sevilla, Spain for traffic congestion prediction. Decision tree showed the best traffic congestion prediction result among the 3 models [21]. Elleuch et al. [19] claimed the fusion of predicted congestion state, the real time GPS information and the anomalous events using decisional tree has more improved the results.

Tamir et al. [53] presented a comparative study of traffic congestion prediction systems including decision tree, logistic regression, and neural networks. They used five days of traffic information (1,231,200 samples), the TensorFlow and the Clementine machine learning platforms for data preprocessing, training, and testing of the model [53]. They claimed that decision tree has better prediction performance and leads the other two methods with accuracy (97%), macro-average precision (95%), macro-average recall (96%), and macro-average F1_score (96%) in the python programming environment, and it outperforms logistic regression, and neural networks with an accuracy of 97.65% in Clementine environment [53]. Mystakidis and Tjortjis [35] claimed that Decision Trees were more accurate than Logistic Regression.

Gradient Boosting Decision Tree (GBDT)

Bai et al. [6] proposed a method for predicting urban road congestion based on the Spark platform parallel Gradient Boosting Decision Tree algorithm, and proved that the method proposed in their paper can effectively predict urban road congestion, reduce the running time, improve the prediction efficiency, and provide effective help for urban road management.

5.1.6. Random Forests

Liu and Wu [32] proposed to use random forest algorithm as it had the characteristics of high robustness, high performance and high practicability. They used the weather conditions, time period, special conditions of road, road quality and holiday as model input variables [32]. The results showed that the traffic prediction model established by using the random forest classification algorithm had a prediction accuracy of 87.5%, and the generalization error was low, and it could be effectively predicted, moreover, the calculation speed was fast, and it had stronger applicability to the prediction of congested condition [32].

Silva and Martins [50] claimed that the models that would produce the best results for the problem in question were Multiple Regression, KNearest Neighbors (KNN), Neural Network (Multilayer perceptron), Random Forest and Support Vector Machine (SVM). They suggested that the model that was better suited for the designated task would be the Random Forest model, since it had the best scores all around and a really low response time, which gave it a solid advantage over the similar scoring KNN that took almost 10 min to complete a task [50].

Shenghua et al. [48] proposed a short-term traffic congestion prediction method based on the random forest algorithm. They used the traffic data of high-speed road in the PeMS database of the United States for the simulation experiment; the experimental results showed that the accuracy of their method was 94.36%, which proved the excellent performance of their method [48].

Chen et al. [15] proposed a mixed forest prediction method considering the spatio-temporal correlation characteristics of urban road traffic state is constructed by improving the existing random forest algorithm. The optimal combination of eigenvectors and the number of decision trees for classified forest, regression forest, post classified forest and mixed forest algorithm were selected [15]. The results showed that the model is effective and has the prospect of big data application [15].

5.1.7. K-Nearest Neighbors Algorithm (K-NN)

Kwoczek et al. [27] used an adaptation of the K-Nearest Neighbors (K-NN) algorithm; they looked for the most similar past PSEs (cases) among historic observations, in order to derive a prediction of the impact of the second wave of traffic. Kwoczek et al. [27] stated that for the use of the K-Nearest Neighbors algorithm, one of the issue was the optimal choice of the parameter k, that was the number of closest training examples to be considered in the feature space.

Florido et al. [21] claimed that Decision trees, artificial neural networks and nearest neighbors algorithms have been successfully applied to a particular location in Sevilla, Spain for traffic congestion prediction. NN showed the worst traffic congestion prediction result among the 3 models [21].

5.1.8. Shallow Artificial Neural Network (Shallow ANN)

While ANN can be either shallow machine learning or deep machine learning depending on the number of hidden layers, the research project conducted in this section utilized shallow machine learning methodology with one hidden layers.

Florido et al. [21] claimed that Decision trees, artificial neural networks and nearest neighbors algorithms have been successfully applied to a particular location in Sevilla, Spain for traffic congestion prediction. The ANN was composed of as many inputs as features, one hidden layer with seven neurons, with a feed forward topology, a sigmoid activation function and a back propagation-based learning paradigm. The ANN result was better than NN, but worse than decision tree [21].

Najada et al. [36] developed three time-series models ARIMA, BATS, TBATS, and a neural network model and apply them to their created VANET data to analyze and predicted the total number of nodes in a cluster (density) and the average speed of the nodes. The created dataset and developed models could assist in predicting cluster density and average node speed to detect congestion, which would enhance route navigation Najada et al. [36].

5.1.9. Reinforcement Learning

Surya and Rakesh [52] proposed work based on the application of the reinforcement learning by considering the parameters waiting time of the vehicle and exit rate was exploited to minimize the traffic congestion, the proposed work mainly considered flow rate of the traffic and waiting time of vehicles. By using this algorithm they could identify that waiting time of the vehicles considerably reduced so as congestion also [52].

Ji and Jin [26] introduced a novel KG reasoning traffic congestion prediction framework built based on a reinforcement learning and claimed that by training a reinforcement learning-based agent to learn relation reasoning paths, it is possible to predict the congestion propagation on real-time traffic data in an efficient manner.

5.1.10. Ensemble Learning

Asencio-Cortés et al. [3] stated an ensemble algorithm is an approach to increase the prediction accuracy by combining the results from multiple classifiers. The basic approach of ensemble analysis is to apply the aggregated classifiers (internal classifiers) multiple times using either different models, or using the same model on different subsets of the training data, the results from different classifiers are then combined into a single-robust prediction [3].

XGBoost: is an ensemble learning method used by Ran et al. [44] who proposed a combined model based on K-means and XGBoost, and used average speed and traffic flow as the input of the model. According to the prediction experiment of I15-N expressway traffic data in PeMS database, the combined model outperforms other models and the predictive accuracy of the combined model reached 94.47% [44].

Xu et al. [56] combined the random search and Dual_XGBoost algorithms to predict traffic congestion, and they took the Shanghai transportation as a case study. The result showed that their method was faster in model training, more flexible in predicting time and more sensitive to changes in the long-term features, however, some road congestion could not be discovered, or it could cause errors in calculating the average road speed as it could not distinguish whether a vehicle was driving on an elevated road or a road based on GPS signals alone [56].

Shallow Machine Learning Methodology	Proposed Articles
Linear Regression	Lee et al. [28] Putra et al. [43]
Logistic Regression	Deb et al. [17]
Support Vector Regression (SVR)	Satrinia and Saptawati [46] Philip et al. [42]
Support Vector Machines (SVM)	Asencio-Cortés et al. [3]
Decision Trees	Florido et al. [21] Elleuch et al. [19] Tamir et al. [53] Mystakidis and Tjortjis [35] Bai et al. [6]
Random Forest	Liu and Wu [32] Silva and Martins [50] Shenghua et al. [48] Chen et al. [15]
K-Nearest Neighbors Algorithm (K-NN)	Kwoczek et al. [27] Florido et al. [21]
Shallow Artificial Neural Network (Shallow ANN)	Florido et al. [21] Najada et al. [36]
Reinforcement Learning	Surya and Rakesh [52] Ji and Jin [26]
Ensemble Learning	Ran et al. [44] Xu et al. [56]

In

Table 2 we present a summarized information regarding the works around shallow machine learning methodologies for traffic congestion prediction.

Shallow Machine Learning Methodology	Proposed Articles
Linear Regression	Lee et al. [28] Putra et al. [43]
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Shallow Artificial Neural Network (Shallow ANN)	Florido et al. [21] Najada et al. [36]
Reinforcement Learning	Surya and Rakesh [52] Ji and Jin [26]
Ensemble Learning	Ran et al. [44] Xu et al. [56]

Table 2 Summary of shallow ML works

5.2. Deep Learning Methodologies

As Xu et al. [57] stated, the traffic data changes all the time, some short-term events such as concerts, sports events or traffic accidents will also bring uncertainty to the data, so the traffic data belongs to non-linear data. The traditional time series method and machine learning models are better at learning from linear data than nonlinear data; they can only improve from the time features of data, and they often can't deal with the spatial correlation of the prediction variable [57]. The inherent non-linear relationships and spatiotemporal autocorrelation remain big challenges [11]. Moreover, the families of less frequently addressed and more complex problems are those that include moving and interval data sensors to make predictions beyond single points on the roads [2]. To solve the aforementioned non-linear temporal spatial characteristics of traffic data, Deep Learning Methodologies were implemented by many research projects to predict traffic congestion.

5.2.1. Deep Artificial Neural Network (Deep ANN)

The research projects conducted in this section all utilized deep machine learning methodologies with several hidden layers.

Wang et al. [55] proposed a neural network model with training data as bike-sharing, holiday and meteorology data for Suzhou. They predicted the traffic flow of the bike sites through relevant categorical variables to verify the application of the entity embedding in traffic problems [55]. The research results showed that entity embedding can effectively increase the continuity of categorical variables and therefore, improve the prediction efficiency for the neural network models [55].

Elleuch et al. [19] proposed a system utilising ANN that did not only take into account the historical GPS data but also the real time unpredictable events which have impacts on traffic jams such as accidents. The result demonstrated the efficiency of the proposed model in forecasting traffic congestion [19].

Olayode et al. [40] proposed an artificial neural network (ANN) predictive model using traffic flow variables from the South African Road transportation system as a case study. These traffic data sets comprised of several different classes of vehicles, the speed of each category of vehicles on the road, the traffic density, the time, and traffic volume as input and output variables [40]. The results obtained from this research study showed an ANN model training and testing performance of 1.0000 and 0.99975, and the results of this study contribute significant insights into the modeling and prediction of vehicular traffic flow, which will assist urban planners and transportation researchers in transportation and urban planning [40].

5.2.2. Deep Auto Encoder

Xu et al. [58] presented an auto encoder (SAE) model based on deep learning for short-term traffic congestion. They used the Softmax regression according to the temporal and spatial distribution characteristics of traffic flow [58]. The results showed that the performance of the model proposed was better than that of other models for workday traffic forecasting, and for non-workday traffic forecasting, the performance of their model was better than that of the shallow network model, and it was closer to that of RNN and LSTM in depth learning [58].

5.2.3. Convolutional Neural Network (CNN)

Hossain and Uddin [25] presented an approach that predicted traffic conditions for the future by through relationship between two sorts of datasets according to time sequence that determined groups of traffic states with similar patterns. They found that working with a maximum amount of data sets was beneficial, and the proposed ConvNet neural network was real affection for images classification or segmentation [25].

Bartlett et al. [8] proposed an online dynamical framework using CNN. The experiment results showed that both short and long-term temporal patterns improved prediction accuracy, the proposed online dynamical framework improved predication results by 10.8% when compared with a deep gated recurrent unit model [8]. The main disadvantage of their online learning framework was the eventual loss of the long-term temporal patterns embedded within the training data [8].

PCNN

Chen et al. [12] proposed a novel method named PCNN, which is based on a deep convolutional neural network, modeling periodic traffic data for short-term traffic congestion prediction. PCNN had two pivotal procedures: time series folding and multi-grained learning. It first temporally folded the time series and constructs a 2-D matrix as the network input, such that both the real-time traffic conditions and past traffic patterns are well considered; then, with a series of convolutions over the input matrix, it was able to model the local temporal dependency and multiscale traffic patterns [12]. Experimental results on a real-world urban traffic data set confirmed that folding time series data into a 2-D matrix was effective and PCNN outperformed the baselines significantly for the task of short-term congestion prediction [12].

FDCN

CNN - FDCN Chen et al. [13] developed the FDCN model to predict traffic flow. The proposed method incorporated the fuzzy method and the deep residual convolution network to extract features for more accurate traffic flow prediction [13]. Experimental results indicated that the FDCN method was more powerful in its representation capability than existing methods, however, the FDCN has many open problems, including the optimized structure of the model and the influence of external factors on predictive performance [13].

TCN

Chen [11] proposed a Multi-Task Time-Series Graph Network (MTG-Net) framework, which used a Temporal Convolutional Network (TCN) to capture the temporal relationships and models the correlations between regions dynamically with graph attention network (GAT). Temporal Convolutional Networks, or simply TCN, is a variation of Convolutional Neural Networks for sequence modelling tasks, by combining aspects of RNN and CNN [11]. Experiments on real traffic congestion data demonstrated effectiveness of their approach over state-of-the-art methods [11].

3D-CNN

Nguyen et al. [39] proposed a deep learning approach based on 3D-CNN to utilize many urban sensing data sources wrapped into 3D-Raster-Images, for which, the spatial and temporal dependencies of the data can be entirely preserved. They successfully showed the positive impacts of using environmental factors such as rain, traffic accident, and social networking contents in enhancing predictive performance [39].

SG-CNN

Tu et al. [54] proposed a traffic congestion prediction model named SG-CNN which training process is optimized by road segment grouping algorithm. The experiments demonstrated that their proposed model has higher accuracy rate than other models [54].

Graph Convolutional Network (GCN)

Xu et al. [57] proposed a Graph Convolutional Network (GCN) prediction model based on long-term, short-term, and spatial features. The combination of GRU and GLU was used to train the model to learn the short-term features of traffic data, and GCGRU was proposed to learn the long-term features of traffic data [57]. They claimed their model can ensure that the training effect is good in a short training time and the training efficiency is the highest [57].

5.2.4. Recurrent Neural Network (RNN)

Fandango and Wiegand [20] built the models with Structural Recurrent Neural Network(SRNN), GRU and LSTM architecture and used 6 months of data from California Transportation Department. They were unable to observe improvements from GRU and SRNN models by including an iterative approach [20].

Osipov and Miloserdov [41] proposed to use recurrent neural networks (RNN) with controlled elements for predicting traffic congestions on the basis of geographic information systems (GIS). In comparison with the forecast of the Internet service, the recurrent network with controlled elements showed on average a more accurate result [41].

Gu et al. [23] proposed a architecture fused by entropy-based grey relation analysis (EGRA) and a two-layer RNN-based structure. The experimental result illustrated the future speed of the target lane sections is highly affected by the previous speeds of adjacent lane sections, especially the upstream lane sections [23].

ARNN

Choi et al. [16] proposed Attention-based Recurrent Neural Network model for urban vehicle trajectory prediction. In this proposed model, they used attention mechanism to incorporate network traffic state data into urban vehicle trajectory prediction and used the Bluetooth data collected in Brisbane, Australia, which contains the movement information of private vehicles [16]. The result showed that ARNN model have better performance compared to RNN model [16].

LSTM

Long Short Term Memory (LSTM) is a subset of RNN, many researches were conducted using LSTM. Chen et al. [14] proposed to use the stacked long short-term memory model to learn and predict the patterns of traffic conditions. Experimental results showed that the proposed model for traffic condition prediction had superior perfor- mance over multilayer perceptron model, decision tree model and support vector machine model [14].

Fandango and Wiegand [20] built the models with Structural Recurrent Neural Network(SRNN), GRU and LSTM architecture and used 6 months of data from California Transportation Department. Though not statistically verified, combining an iterative strategy with the LSTM architectures appeared preliminarily to have a positive impact on the accuracy of predictions on all the four metrics used: MSE, MAE, MAPE, and SMAPE [20].

Yi et al. [61] applied long-short term memory for analyzing data in Gyeongbu Expressway of Korean transportation system. Experiments indicated promising results for predicting short term traffic flow in highway systems [61].

Zhang et al. [63] proposed an Attention-based long short-term memory (LSTM) recurrent neural network. They evaluated the prediction architecture on a real-time traffic data from Gray-Chicago-Milwaukee (GCM) Transportation Corridor in Chicago land [63]. It was demonstrated that the proposed method outperforms baselines significantly [63].

Yi and Bui [59] took VDS data into account by applying a deep learning approach using LSTM-RNN model to predict traffic flow. They first tried to understand the traffic condition by applying visualization techniques, then, based on the traffic condition, they appied an appropriate deep learning model for predicting traffic flow [59]. The results indicated the effectiveness of the proposed model, and the limitation of the study was that the configuration of the proposed model(LSTM) could not minimize the square error for all VDS datasets [59].

Shin et al. [49] proposed a long short-term memory (LSTM)-based traffic congestion prediction approach based on the correction of missing temporal and spatial values. The proposed prediction method applies pre-processing that consists of outlier removal using the median absolute deviation of the traffic data and the correction of temporal and spatial values using temporal and spatial trends and pattern data [49]. The mean absolute percentage error (MAPE) of the proposed method was found to be the best of the compared models, at approximately 5% [49].

Majumdar et al. [33] introduced long short-term memory networks for the prediction of congestion propagation across a road network based on vehicle speed data from traffic sensors at two sites across a 5-min period within a busy town. Analysis of both univariate and multivariate predictive models showed an accuracy of 84–95% depending on the road layout [33]. This accuracy showed that long short-term memory networks are suitable for predicting congestion propagation on road networks and may form a key component of future traffic modelling approaches for smart and sustainable cities around the world [33].

Yi and Bui [60] proposed a deep learning model with the long short term memory network based on the HyperNet framework has presented for learning the temporal variation of traffic datasets at main regions of highway traffic systems. They took data from the Korean highway system into account as a case study to evaluate the proposed approach [60]. The evaluation indicated promising results of the proposed framework for learning multiple datasets of the traffic highway systems [60].

CPM-ConvLSTM
Di et al. [18] proposed CPM-ConvLSTM, a spatiotemporal model for short-term prediction of congestion level in each road segment. Their model is built on a spatial matrix which incorporated both the congestion propagation pattern and the spatial correlation between road segments. The preliminary experiments on the traffic data set collected from Helsinki, Finland proved that CPM-ConvLSTM greatly outperforms 6 counterparts in terms of prediction accuracy [18].

PLSTM
Zheng et al. [64] proposed a novel method named PLSTM to further explore the characteristics of traffic conges- tion propagation and predict short-term traffic congested states, which was a long short-term memory (LSTM) neural network for modeling traffic propagation. The experimental results had validated the rationality of input series on improving prediction accuracy and the effectiveness of PLSTM [64].

LSTM-SPRVM
Li et al. [29] proposed a deep prediction model named LSTM-SPRVM based on deep learning algorithms, machine learning algorithms, and Spark parallelization technology for the prediction of traffic congestion features in the future. Traffic congestion features such as average speed, road occupancy rate, and traffic flow density were used, and the experimental results showed LSTM-SPRVM was better than other existing deep learning models in terms of prediction accuracy [29].

ConvLSTM
Bai et al. [5] designed a two-layer network based on the Convolutional Long-Short Term Memory (ConvLSTM) to predict road network congestion. The experiments showed that in all locations where congestion often occurs, the proposed method significantly outperforms baseline models including Linear Regression, Autoregressive Integrated Moving Average, Support Vector Regression, Random Forest, Gradient Boosting Regression, Long-Short Term Memory and generally outperforms the Convolution-based deep Neural Network modeling Periodic traffic data [5]. The results showed that the proposed model can accurately capture the temporal and spatial characteristics of traffic [5].

5.2.5. Multi-task Learning (MTL)
Zhang et al. [62] proposed a deep learning based Multi-task Learning (MTL) model to predict the network-wide short-term traffic speed. The deep learning based MTL model provides a better performance compared with four other deep learning based models (i.e., STL-GRU, STL-LSTM, Conv-GRU and TCN) and three conventional models (i.e., v-SVM, k-NN and EFNN) [62]. Zhang et al. [62] claimed the proposed MTL approach with the nonlinear Granger causality analysis and Bayesian optimization was a promising way to carry out the network-wide short-term traffic speed prediction.

5.2.6. Multi Layer Perceptron (MLP)
Lira et al. [30] proposed to use Multi Layer Perceptron (MLP) for traffic congestion prediction. The approach showed that the identification and usage of the traffic state, congestion and free flow helped to reduce the error of the velocity prediction. The MLP neural network produced better predictions of the future velocity when comparing to random forests [30].

MLP Ensemble Regression Model
Shahid et al. [47] proposed an approach of ensemble regression model technique in which the first regression model's result is boosted using Boosting ensemble method and is passed to the next regression model. The experimental results validate the overall efficiency of the integrated approach we proposed. The results showed that SVR ensemble Multi-layer perceptron (MLP) gives the most accurate results, and the effectiveness of the proposed framework which

decreases the error rate by 2.47% [47].

5.2.7. Extreme Learning Machine (ELM)

Ban et al. [7] proposed to use feed-forward neural network (SLFN) model, which is an Extreme Learning Machine (ELM) to predict traffic congestion. Their experiment results showed that ELM algorithm provided good generalization performance at extremely fast learning speed compared with other state-of-art algorithms, and it obtained high accuracy in practical prediction application [7]. In addition, quick training and good fitting resulted on their own large scale traffic data set proved ELM algorithm worked well on large data sets [7].

5.2.8. Elman Neural Network

Neelakandan et al. [38] proposed an efficient IoT-based traffic prediction using optimized weight Elman neural network (OWENN) algorithm and traffic signal control system using Intel 80,286 microprocessor for a smart city. The performance of the proposed system was compared with the existent ENN, CNN, NN, and ANFIS methods in terms of accuracy, f-measure, MAE, and RMSE metrics, the test findings revealed the high degree of efficiency of the suggested relative to traditional approaches [38].

5.2.9. Back-Propagation Neural Network (BPNN)

Wei Guan et al. [24] proposed a feed forward back-propagation neural network (BPNN) model, and a data-driven congestion analysis approach, which consisted of loop detector data processing, traffic simulation, and artificial intelligence to predict the urban temporal-spatial congestion evolution. A case study in Tianjin, China was conducted, and the case study result showed that the evening peak has more serious traffic congestion than the morning peak, the prediction accuracy of feed forward back-propagation neural network (BPNN) increased with the time interval aggregation level increasing, and the prediction accuracy was 85.7% with 30 min interval aggregation [24].

5.2.10. Graph Neural Network (GNN)

Spatial-Temporal GNN (ST-GNN)

Bui et al. [9] focused on ST-GNN models for traffic prediction by learning hidden patterns of spatial-temporal graphs, and proposed a new taxonomy of ST-GNN by dividing existing models into four approaches such as graph convolutional recurrent neural network, fully graph convolutional network, graph multi-attention network, and self-learning graph structure. [9] claimed ST-GNN models provided the capability of traffic forecasting with promising results.

5.2.11. Decentralized Deep Learning

Fouladgar et al. [22] proposed a decentralized deep learning-based method where each node accurately predicted its own congestion state in realtime based on the congestion state of the neighboring stations. historical data from the deployment site was not required, which made the proposed method more suitable for newly installed stations [22]. Extensive experiments conducted on the designed benchmark reflected a successful congestion prediction [22].

5.2.12. Hierarchical Spatial-Temporal State Machine (HSTSM)

Maniak et al. [34] introduced a novel biologically inspired universal generative modelling technique called Hierarchical Spatial-Temporal State Machine (HSTSM). The HSTSM modelling approach incorporated many soft computing techniques including: deep belief networks, auto-encoders, agglomerative hierarchical clustering and temporal sequence processing [34]. A case study for the modelling and prediction of traffic based on taxi movements was described, where HSTSM was used to address the computational challenges arising from analysing and processing large volumes of varied data [34].

5.2.13. Online Deep Neural Network

Chan et al. [10] proposed a design that utilizes an online deep neural network with the sliding window strategy for traffic prediction and routes vehicles through roads that are weighted based on two factors — predicted road travel time and the presently detected mean vehicle speed. The proposed online multi-factor deep learning approach showed that a newly initialised neural network can competently learn and predict traffic congestion using the spatiotemporal traffic information such as the speed pheromone, density pheromone, and forecasted density pheromone incrementally [10]. These improvements could be seen from the results above where the MVR method displayed over 37% reduction in mean travel time and more than 34% reduction in CO2 and fuel emissions [10].

5.2.14. Generative Adversarial Network (GAN)

Badura [4] proposed a model based on a generative deep neural network. In order to train this network the following methods were used: algorithms prepared for Restricted Boltzmann Machine and Deep Believe Network, as well as neighbourhood network [4]. These architectures and methods adapted to the real dependencies of traffic much better and more accurately than traditional structures and methods of learning [4].

5.2.15. Hybrid Deep Learning Methodologies

Liu et al. [31] used traffic flow data in vehicle-road collaboration environment, and proposed KNN clustering algorithm, ARIMA model and Back Propagation Neural Networks model to detect current road congestion, forecast road congestion in real time and planned the best travel plan for users.

Adetiloye and Awasthi [1] proposed a Big data fusion framework based on homogenous and heterogeneous data for traffic congestion prediction. The homogeneous data fusion model fused data of same types (quantitative) estimated using machine-learning algorithms: back propagation neural network, random forest, and deep belief network; and applies extended Kalman filter for the stochastic filtering of the non-linear noisiness while reducing the estimation and measurement errors [1]. In the heterogeneous fusion model, they extended the homogenous model by integrating with qualitative data, i.e. traffic tweet information from Twitter data source [1]. The strength of proposed work was the use of Big data fusion for traffic congestion prediction in near real-time situation on the basis of the traffic travel times of road vehicles on urban motorways, and the limitation was lack of adequate system tools to seamlessly integrate data from various sources for real-time traffic information [1].

Ranjan et al. [45] proposed a hybrid neural network architecture formed by combing Convolutional Neural Network, Long Short-Term Memory, and Transpose Convolutional Neural Network to extract the spatial and temporal information from the input image to predict the network-wide congestion level. Their experiment showed that the proposed model could efficiently and effectively learn both spatial and temporal relationships for traffic congestion prediction [45]. Their model outperformed two other deep neural networks (Auto-encoder and ConvLSTM) in terms of computational efficiency and prediction performance [45].

Sunindyo and Satria [51] explored possibility to use the CCTV footage to perform traffic prediction. The traffic data was modeled using both Multi-layer Perceptron (MLP)/ANN and Long Short-term Memory (LSTM) [51]. This study proved that automatically processed CCTV footage was indeed a viable option for traffic congestion prediction [51].

Narmadha and Vijayakumar [37] proposed hybrid neural network algorithms such as Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) network for short term traffic flow prediction based on multivariate analysis. Widely referred datasets Performance Measurement Systems (PEMS) and Mesowest were used to evaluate this model. Experiment results showed that CNN-LSTM Hybrid prediction model achieves high accuracy compared with other models [37].

The combination of Deep learning techniques with other outlier removal and or incident text encoding represents a hot topic especially in 2022 for incident duration prediction and severity classification [81]-[84]-[85].

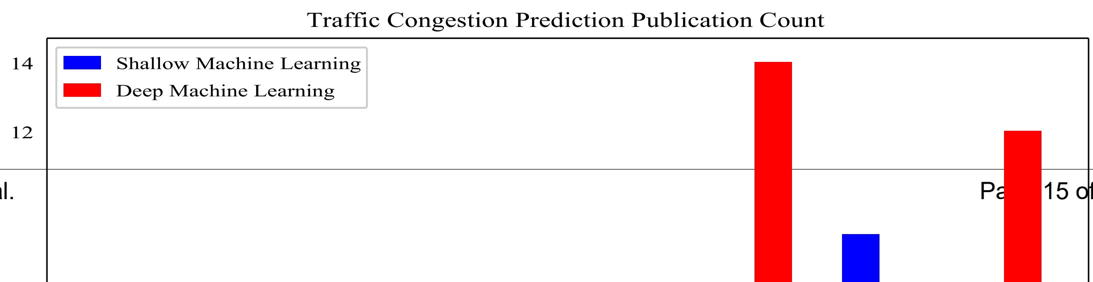
Table 3 presents a summary for what was mentioned above for deep learning methodologies for traffic congestion prediction.

Table 3 Summary of Deep learning methodologies for trafic congestion prediction

Deep Learning Methodology	Proposed Articles
Deep Artificial Neural Network (Deep ANN)	Wang et al. [55] Elleuch et al. [19] Olayode et al. [40]
Deep Auto Encoder	Xu et al. [58]
Convolutional Neural Network (CNN)	Hossain and Uddin [25] Bartlett et al. [8] Chen et al. [12] Chen et al. [13] Chen [11] Nguyen et al. [39] Tu et al. [54] Xu et al. [57]
Recurrent Neural Network (RNN)	Fandango and Wiegand [20] Osipov and Miloserdov [41] Gu et al. [23] Choi et al. [16] Chen et al. [14] Yi et al. [61] Zhang et al. [63] Yi and Bui [59] Shin et al. [49] Yi and Bui [60] Majumdar et al. [33] Di et al. [18] Zheng et al. [64] Li et al. [29] Bai et al. [5]
Multi-task Learning (MTL)	Zhang et al. [62]
Multi Layer Perceptron (MLP)	Lira et al. [30] Shahid et al. [47]
Extreme Learning Machine (ELM)	Ban et al. [7]
Elman Neural Network	Neelakandan et al. [38]
Back-Propagation Neural Network (BPNN)	wei Guan et al. [24]
Graph Neural Network (GNN)	Bui et al. [9]
Decentralized Deep Learning	Fouladgar et al. [22]
Hierarchical Spatial-Temporal State Machine (HSTSM)	Maniak et al. [34]
Online Deep Neural Network	Chan et al. [10]
Generative Adversarial Network (GAN)	Badura [4]
Hybrid Deep Learning Methodol	Liu et al. [31] Adetiloye and Awasthi [1] Ranjan et al. [45] Sunindyo and Satria [51] Narmadha and Vijayakumar [37]

5. Findings

Data is critical for machine learning and deep learning based traffic congestion prediction models. Most of the traffic congestion prediction research projects were conducted utilising stationary data or probe data. PeMS is the most widely used stationary data, and taxi GPS data is the most widely used probe data. Apart from these, weather data and pollution data both play important role in traffic congestion prediction models. Event data and traffic accident data can also be directly related to traffic congestion prediction. In the recent years, SNS data and app data have become increasingly popular, and have shown their effectiveness in traffic congestion prediction. Other data that can be useful for traffic congestion prediction includes bike data, CCTV footage data, tolling system data, etc.



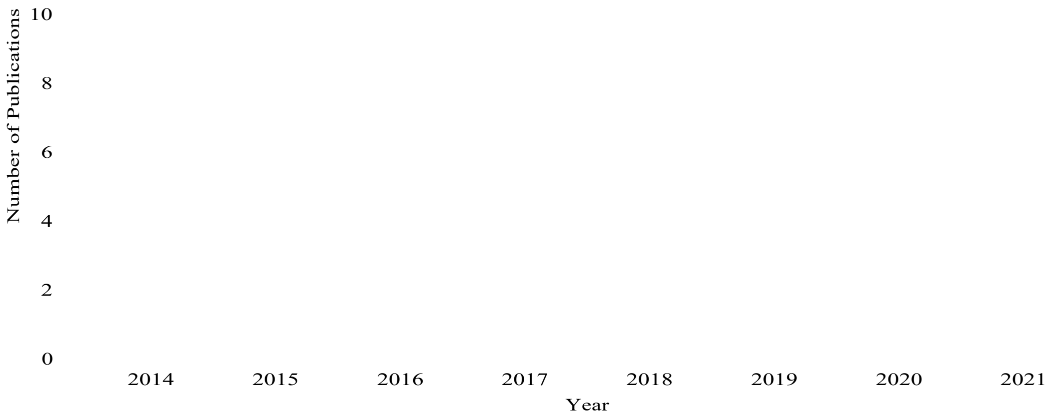


Figure 1: Traffic Congestion Prediction Publication Count.

Based on the statistics shown in the graph above for our selected publication analysis, we can see that the number of research conducted for shallow machine learning or deep learning based traffic congestion prediction has increased a lot in the recent years. Before 2016, there were more research conducted for shallow machine learning based traffic congestion prediction. Since 2016, deep learning based traffic congestion prediction has become increasingly popular. From 2021-2022 there has been no traffic congestion prediction research conducted based on shallow machine learning, all the research projects were conducted in deep learning.

Although the neural network has been criticized as the internal relationships of hidden layers are generally unknown [55], we can see it still has become the most popular way to predict traffic congestion in the recent research. Among all the deep learning methodologies, RNN is the most frequently used one, and CNN is the second most frequently used one. Within RNN, LSTM is the most popular deep learning based model for traffic congestion prediction. In 2021, multiple new deep learning methodologies were proposed for traffic congestion prediction, these include Multi Layer Perceptron (MLP), Elman Neural Network, Graph Neural Network (GNN), etc. Although they all claimed a promising traffic congestion prediction result was obtained based on these deep learning methodologies, it is hard to tell which methodology produced the best result as the datasets that were used are different.

Advantages:

Using Machine Learning or Deep learning can result in several advantages especially around large data sets, which are collected from multiple sources, that would require a long time to manually filter and arrange. Datasets that come from multiple sources of transportation can be used for gaining insights into the behavior of one mode and the repercussions that it has on other interconnected modes. Predictions across all modes can provide an accurate insight in recurrent versus non-recurrent transport conditions in the network, while leveraging operators to make informed decisions. The subsequent and indirect advantages are towards the improvement of traveler satisfaction, better planning operations, less time to solve incidents and take decisions, etc.

Limitations

Some of the main limitations of deploying and using ML and DL techniques at scale reside in the computational complexity that requires strong hardware and software support. Their implementation requires several steps of data collection, cleaning, sorting, outlier removal, training, validating, testing and re-training when new data comes along and the old models become obsolete. ML models require continuous maintenance and the data quality is extremely important which often is not the case, especially when failures occur across the network or across the utilized sensors. There are other limitations in terms of types of data required: flow, speed, occupancy, patronage, incident, events, etc. which often needs to be integrated across multiple systems.

6. Future directions and Research Gaps to be filled

In the recent years, traffic congestion prediction has become increasingly important. A lot of research projects have been conducted for it. Various datasets have been utilised for traffic congestion prediction, from stationary and probe data, to weather and pollution data, then to event and SNS data, etc. It is not necessarily that the more types of datasets utilised for machine learning or deep learning based traffic congestion prediction, the better result will be obtained. However, by increasing the types of datasets, and by adopting a suitable machine learning or deep learning based methodology for traffic congestion prediction, a better prediction result can be possible achieved.

A variety of machine learning and deep learning based methodologies have been conducted for traffic congestion prediction, with a trend of the popularity of the adoption of deep learning based methodologies in the recent years. In 2021-2022, many new deep learning based methodologies were proposed for traffic congestion prediction, and achieved good prediction results. There are still many deep learning methodologies have not been tested and utilised fortraffic congestion prediction. There is a big opportunity to test and compare the rest of deep learning methodologies to see how they perform against traffic congestion prediction. Semi-supervised deep learning can be especially useful here as it can utilise more types of datasets than supervised deep learning.

Another research gap is that most literature only considers traffic congestion prediction based on average vehicle speed or average traffic volume; only a very small subset of literature has explored combining both attributes together to develop a more robust and reliable prediction model. Although this research gap is not of high importance or significance, it is still a gap nonetheless, and hence must be explored and aimed to be filled soon.

Data sources and the final dataset is at the fundamental level of constructing a machine learning/deep learning traffic congestion prediction model. Most of the literature that exists, makes use of strong, reliable, and well-captured datasets, however, majority of them do not combine multiple data sources (i.e., static data, probe data, event data, weather data, etcetera) to form a stronger dataset, with more diverse range of data and input attributes.

Furthermore, most of the existing research within the field, does not perform any secondary tasks after successfully predicting the traffic congestion level. Very few studies aim to re-route traffic or offer any solutions to reduce the congestion level/overcome the problem, hence leaving a large research gap open.

Many papers within this research's review also collect static and probe data of vehicles, GPS receivers and other wireless trackers, yet almost no paper mentioned regarding how they ensure user's authority is obtained in collecting the data, and then how they will safely store and utilise the data. No details regarding encryption of data nor protection of data are provided by any literature, hence this leaves a very critical and a very important research gap required to be filled.

A future direction in which machine learning and deep learning will be widely utilised are digital twins for smart cities as more and more data will be integrated in a hybrid approach. Studies have already started at integrating and adopting such methodologies [66] and more future developments will follow with more data availability and accesibility.

A high-level quick list of the research gaps above is shown below.

- No practical or physical deployment of the models – either be in existing navigation applications or any physical online dashboards
- Much of the existing traffic congestion predictions are based off either average vehicle speed or average traffic volume – almost no papers discuss both together (except 2-3 papers)
- Only 2-3 papers have combined multiple input data sources to produce their dataset – majority of them only utilise one form of data and ignore others (i.e. static data only or probe data only or event data only; very small amount of literature utilises multiple sources at once)
- Little focus on re-routing of traffic after successful congestion prediction - most papers do not handle re-routing or doing any particular tasks with the predicted traffic congestion
- Very little research conducted in privacy and ethical concerns with general data collection methods – most research either utilises publicly available data sources but no research describes methods to ensure safe and ethical utilisation of this data, ensuring to prevent any misuse of data

7. Conclusions

Traffic and traffic congestion is one of the most prevalent problems of our modern society. Vehicles on our road rise sharply at alarming levels daily, causing delays and stress for drivers stuck within traffic jams every day. In the past, some research projects utilised probabilistic reasoning such as fuzzy logic, hidden markov models, for solving the traffic congestion prediction. But in more recent years, an increasing number of research projects used machine learning or deep learning based methodologies for traffic congestion prediction. In the last five years more specifically, deep learning based methodologies for traffic congestion prediction has become especially popular. There are still a lot of opportunities to utilise other machine learning or deep learning based methodologies for traffic congestion prediction. A high interest is currently given to spatial-temporal modelling by considering network characteristics from the model. On top of that, more types of datasets can be utilised for traffic congestion prediction. Semi-supervised deep learning models can be a good way to utilize more types of datasets for traffic congestion prediction.

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