Traffic Flow Prediction using Machine Learning Techniques - A Systematic Literature Review

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Subject Area: Computer Science.
Type of the Paper: Literature Review.
Type of Review: Peer Reviewed as per |C|O|P|E| guidance.
Indexed In: OpenAIRE.
DOI: https://doi.org/10.5281/zenodo.6479158
Google Scholar Citation: IJAEML

How to Cite this Paper:
Sathyan, Sigma, & Jagadeesha, S. N., (2022). Traffic Flow Prediction using Machine Learning Techniques - A Systematic Literature Review. *International Journal of Applied Engineering and Management Letters (IJAEML)*, *6*(1), 210-230. DOI: https://doi.org/10.5281/zenodo.6479158

International Journal of Applied Engineering and Management Letters (IJAEML)
A Refereed International Journal of Srinivas University, India.

Crossref DOI : https://doi.org/10.47992/IJAEML.2581.7000.0132

Received on: 07/04/2022
Published on: 25/04/2022

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ABSTRACT

Purpose: *Traffic control in large cities is extremely tough. To alleviate costs associated with traffic congestion, some nations of the world have implemented Intelligent Transportation Systems (ITS). This paper reviews the application of artificial neural network (ANN) and machine learning (ML) techniques and also their implementation issues in TFP. Techniques other than ML and ANN have also been discussed.*
Methodology: *The survey of literature on TFP (TFP) and ITS was conducted using several secondary sources of information such as conference proceedings Journals, Books, and Research Reports published in various publications, and then the kinds of literature that are reported as promising have been included. The collected information is then reviewed to discover possible key areas of concern in the TFP and ITS.*
Findings/Results: *Traffic management in cities is important for smooth traffic flow. TFP and ITS are drawing much attention from researchers these days. Application of ML, ANN, and other techniques are being tried to alleviate the traffic flow problem in cities. TFP using ITS employing ML techniques to overcome the problem of traffic congestion looks promising.*
Originality: *This review of literature is conducted using secondary data gathered from various sources. The information acquired will be useful to expand on existing theories and frameworks or to develop a new technique or modify to improve the accuracy of TFP. Tables containing categories of prediction, ML Pipelining, open-source ML tools available, standard datasets available have been included.*
Paper Type: *Literature Review.*
Keywords: TFP, machine learning, deep learning, Traffic Congestion, Shortterm, Longterm Prediction, Urban Traffic, ABCD Analysis, Public traffic Dataset, ML Simulation models, Traffic prediction Challenges

1. INTRODUCTION :

Traffic control in large cities is extremely tough. To alleviate costs associated with traffic congestion, some nations throughout the world have implemented Intelligent Transportation Systems (ITS). Models for predicting traffic flow (TF) are useful in the development of ITSs. ITS is a control and information system that makes use of integrated communications and data processing technology to improve human and commodities transportation, by enhancing safety, lowering road congestion, and effectively handling the occurrence of congestion, to achieve transportation policy goals and objectives – such as demand management or priority measures for public transportation [1-2].
In city transportation and area management, TFP has a wide range of applications. The TFP issue is a time series (TS) problem that involves estimating the urban road traffic flow at a future time using information gathered from one or more observation points during prior periods. This research aims to train the system to forecast traffic using a TFP algorithm. The system can make recommendations to the user based on their search. Traffic congestion is produced by the dynamic interactions of several causes. These aspects include variations in road architecture, traffic volume over time, weather data, accidents, road maintenance work, and so on. The public will profit from this system since users will

be able to see current TF and weather data on the roadways, minimizing the risk of urban road accidents and improving road safety [2].

This survey is about predicting the TF in an urban city using Machine learning (ML) tools. Machine learning is a branch of artificial intelligence that emphasizes on the creation of computer algorithms that increase their accuracy as they study or learn from massive amounts of data. The capacity of ML to learn from prior data sets while being flexible lends itself to a wide range of applications. ML concepts and their applications can be used to predict TF. Today's approaches are incapable of making precise forecasts when environmental variables change (for example, if changes in road structure or weather data or if there is construction or repair work) [3-4]. it is necessary to build a prediction system that integrates a wider range of variables that lead to traffic congestion. This survey focuses on analyzing how to properly describe TF in urban city road conditions with a focus on long-term or short-term predictions. By training ML tools with some historical and time-series data, the machine automatically learns how to predict the traffic [5]. In today's transportation systems, it's critical to be able to accurately estimate TF. It is a boost for many applications that require accurate information about future traffic patterns [6-7].

This communication has 12 sections. The following section includes the research objectives and goals. The third section includes the methodology performed. Section 4 gives an overview of TFP using ML. Section 5 discusses the literature published so far. A discussion about future works is in Section 6 and the research gap in TFP is identified in Section 7 and is followed by the research agendas. Section 9 explains the analysis of the research agenda. Section 10 contains the final research proposal on the chosen topic. ABCD analysis is shown in Section 11 and conclusions are drawn in Section 12.

2. RESEARCH OBJECTIVES AND TFP :

The research area is on Traffic Flow Prediction [TFP], focusing on urban road TFP using ML techniques. Many existing TFP models are unable to give accurate results in predicting traffic jams. This weakness has sparked interest in developing an ML model for TFP. ML methods can be quite versatile and effective in making this model. A literature review has been done to recognize ITS as well as Traffic Jam Prediction (TJP) and how ML can be used for TFP. The role of ML in TJP is also examined. The objectives of this study are:

1. How will emerging technologies, such as ML, improve the ITS?
2. The importance of ITS in urban cities.
3. Importance of urban road TFP Model.
4. What kinds of dataset are required for a TFP system?
5. To identify research gaps and attempt to provide a remedy.

3. METHODOLOGY FOLLOWED :

Various journal databases such as Elsevier, ScienceDirect, IEEE, Google scholar, and others have been used for this review purpose and shortlisted journals that used ML, Deep Learning (DL), and ANN to predict the urban road traffic jam. All study materials were collected initially and studied to find key threads across the articles.

4. OVERVIEW OF TJP IN ML :

In this section, using ML in ITS, with a particular emphasis on how ML increases perception, prediction, and management duties, among other things is addressed. Introduction to the ML methodologies, including terminology and ideas that are commonly found in the literature, are provided.

4.1 ITS:

The application of communication, information, transportation, and urban transport systems is commonly referred to as ITS. Traffic safety and efficiency are two main goals of ITS. Advantages of an ITS are a) Reduced intersection stalls and delays, b) Control and enhancement of speed, c) Enhancement of travel time, d) Management of capacity, and e) management of incidents [8]. In recent years, ITS has been receiving a lot of attention from academic and practitioner groups [9]. Figures 1 and 2 show a future ITS and various tasks performed coming under an ITS.

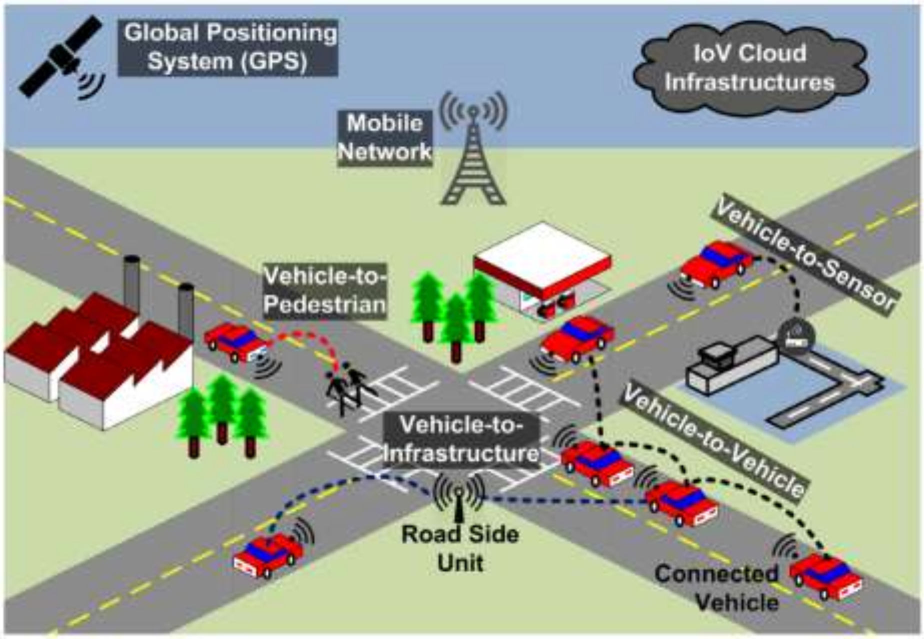

Fig. 1: Future Intelligent Transportation system overview [10].

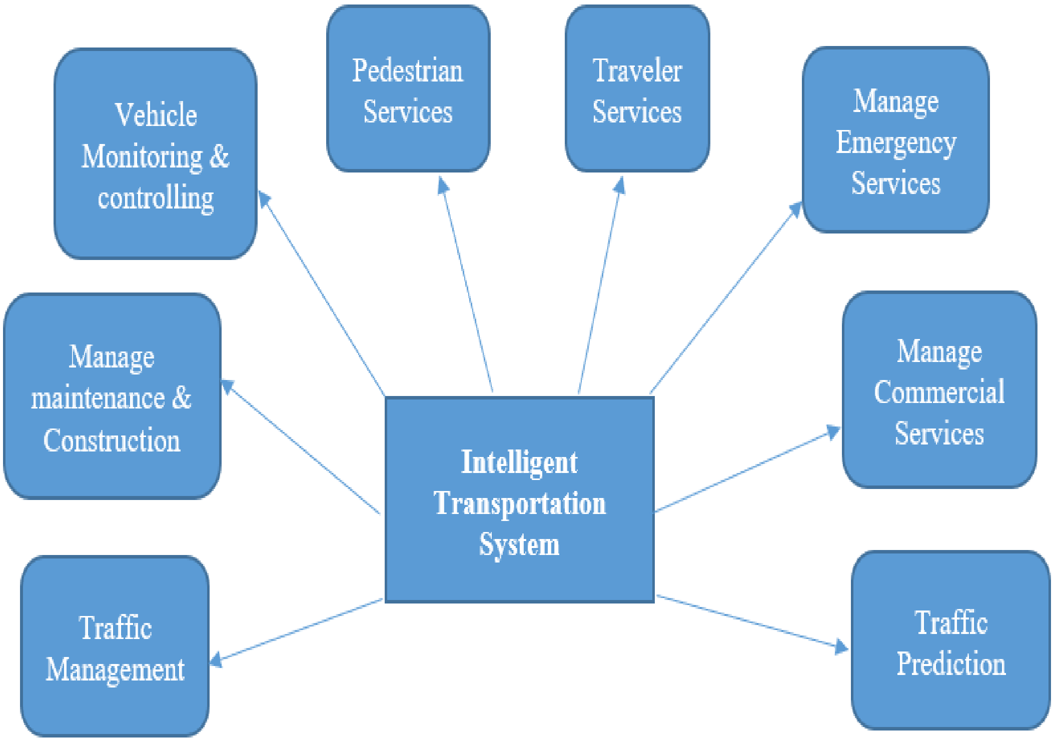

Fig. 2: Various tasks performed by an Intelligent Transportation Systems.

4.2 Machine Learning Predictions in ITS:

ML techniques have achieved a high level of performance on prediction challenges in ITS, primarily delivering tasks that may be classified into predicting TF, travel time, vehicle behaviour, user behaviour, and road occupancy [11-12]. Table 1 shows the various prediction category coming under traffic forecasting.

Table 1: Prediction Categories under Traffic Forecasting

Prediction Category	Description	Role of ML
Traffic Flow	TFP using Spatio-temporal dependencies.	Learning traffic patterns may use weather data, time-series data, historical data, accident-prone area data, road maintenance work information, etc.
Travel Time	Predicting the travel time for cars, buses, bikes, and other vehicles.	Learning traffic patterns based on temporal data. Extracting features & learning travel time patterns.
The behavior of Vehicle & User	Predicting lane changes, vehicle steering angle, pedestrian movements.	Learning & classifying driver's intentions, finding patterns from pedestrians, & future movement of vehicles [13].
Road Occupancy	Road density prediction for the urban region, predicting parking availability.	Modeling long or short-term predictions, learning parking occupancy patterns [14].

4.3 The role of machine learning in TFP:

Traffic forecasting is the process of anticipating the volume and density of TF to regulate vehicle movement, decrease congestion, and produce the ideal (lowest time- or energy-consuming) route. Traffic forecasting is critical for two types of organizations:

a) National/local authorities:

Many cities have embraced ITS in the last ten to twenty years to aid in the planning and administration of urban transportation networks. These systems make use of real-time traffic data and forecasts to increase transportation efficiency and safety by notifying users about current road conditions and altering road infrastructure. Using this method, the general public can be better informed about TF and weather data on the roadways, minimizing the risk of accidents and increasing overall road safety [15-16].

b) Logistics companies:

The logistics business is another area of use. Several enterprises rely on accurate scheduling and effective route planning, including transportation, delivery, and field service [17]. When it comes to travel, it's often not just about the present, but the future as well. For companies like these, accurate estimates of traffic and road conditions are critical to their planning and success. Figure 3 shows the traffic congestion in an urban area [18-19].

Traffic jams are generated by several elements that interact in a complex way. Factors such as variations in traffic, weather data, accidents, and maintenance work all contribute to fluctuations in traffic volume. Even with today's methods, environmental variables can't be predicted with any precision (for example, if changes in road structure or weather data or if there is construction or repair work). To reduce congestion on the road, it is necessary to construct a more accurate prediction system [20]. The primary goal of this study is to figure out how to accurately anticipate TF in urban road scenarios through machine learning techniques by using more of the underlying factors that contribute to traffic congestion as input into the forecasting process [21-22]. Figure 4 shows a Tree representation of ML algorithms used in TFP.

Fig. 3: The Traffic Congestion in an Urban Area [23].

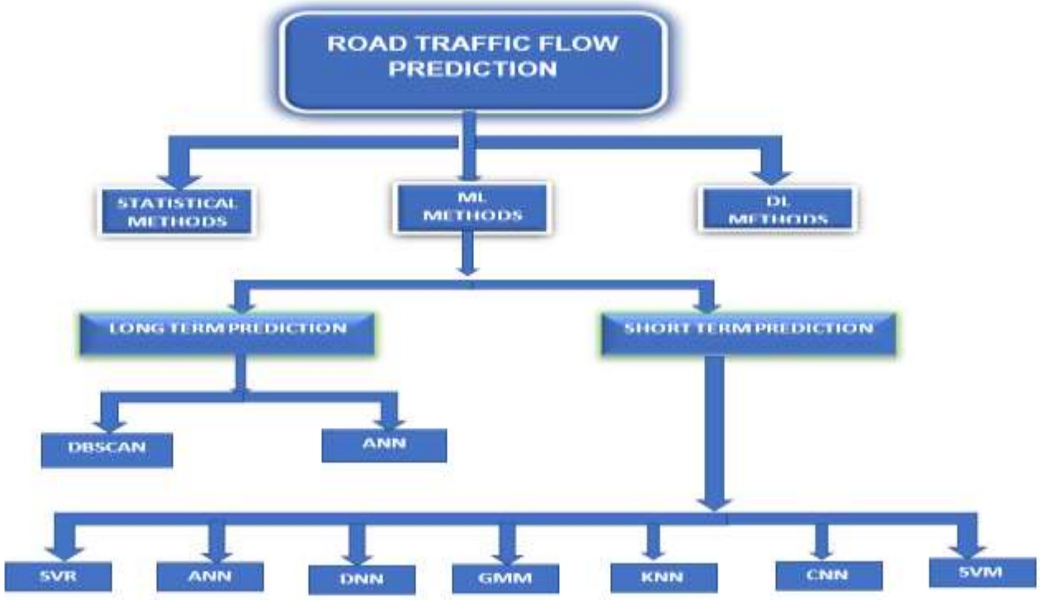

Fig. 4: ML Algorithms used in TFP.

4.4 The Machine learning pipelining and interaction between stages of pipelining:

Table 2 and Figure 5 show various stages of pipeline.

Table 2: ML pipeline used for different tasks

ML Pipelining	Description
Data preprocessing	The data always needs preprocessing and data cleaning [24].
Feature Extraction	There are two types of feature extraction a) Manual-Handcraft extraction with human experts b) Using ML to extract the deep features and be done automatically [25].
Model Creation & Training	Regarding model training, ML has reached a huge status. The trained ML model can be used for regression, clustering classification, and decisions were made and that are used for ITS [26].
Test and Analysis	The process of evaluating the performance of a trained model on a training data set is referred to as model testing in ML. Testing outcomes can be evaluated using statistical indicators such as mean squared errors and receiver operating characteristic curves [27-28].

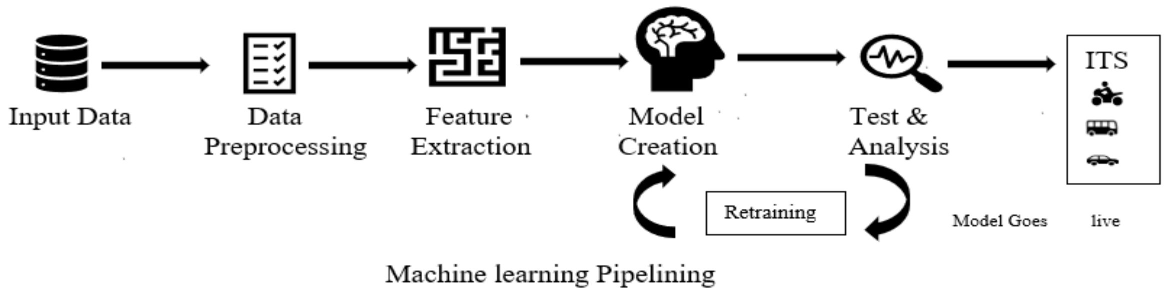

Fig. 5: The ML pipelining model in TFP.

4.5 TFPs and open challenges:

a) Short term predictions:
For the most part, today's solutions require a significant amount of data to function properly. This results in a smaller sample set for training and a more difficult learning experience than would be possible under normal traffic conditions since anomalous events (such as severe weather or temporary traffic restrictions) are not always predictable. Moreover, many cities face the difficulty of insufficient data due to the disparity in development levels between cities [29-30].

b) Long Term Predictions:
Short-to-medium-term forecasting is the main focus of existing traffic prediction systems [31]. Long-term prediction methods may require more information than historical knowledge [32-33].

c) Knowledge graph fusion:
Big data from multiple sources hides transportation domain knowledge. A large-scale transportation knowledge network's creation, learning, and deep knowledge search can help improve traffic forecast performance [34-35].

d) Real-time prediction:
As the name implies, the goal of this challenge is to evaluate data and assess traffic situations as quickly as possible. As data, model size, and parameter numbers grew, the problem became more severe. The challenge of creating an efficient and lightweight neural network that reduces network computation and increases network speed [36]. The question of how to develop an interactive model for traffic prediction remains unanswered [37-39].

e) Interpretability of models:
Neuronal networks are well-known for their reliability due to their complex structure, a high number of factors, and restricted transparency. A lack of interpretability in traffic projections could lead to problems. Insufficient research has been done to develop a more interpretable model of traffic prediction [40-41].

f) Benchmarking traffic prediction:
New models are proposed, typically in similar ways. In a recognized system with consistent huge datasets and experimental settings, comparing new traffic prediction algorithms has become problematic. Model design is also becoming increasingly sophisticated. Although most techniques have ablation studies, it is unclear how each component improves the algorithm. So, creating a replicable framework with a common dataset is critical [42-43].

g) Prediction under perturbation:
Contaminated data will affect the model's forecast accuracy. Existing techniques usually segregate data processing from model prediction [44]. A robust and accurate traffic forecast model in the presence of data noises and mistakes is crucial [45].

h) The optimal network architecture choice:
How to select the best network architecture for a specific traffic prediction assignment has not been thoroughly researched [46-48]. A road network graph can be used to represent traffic data in various works. Deep learning has yet to receive the attention it deserves in terms of in-depth research. Improved prediction performance using a network architecture also need to be studied [49-52].

4.6 TFP parameters:

To anticipate TFP, we consider a multi-parameters prediction approach that takes into account traffic patterns in a variety of ways [53].

a) Flow:

The amount of traffic that passes through a particular spot on the road in a given amount of time is referred to as the flow of traffic.

b) Speed:

The distance traveled per unit of time determines a vehicle's speed. In most cases, the speed of any vehicle on the road will differ from others around it due to factors such as the driver's position and the traffic conditions.

c) Day:

The day can be Sunday to Saturday.

d) Day of type:

The day of type is mainly described as public holiday, weekend, and working.

e) Clock time:

The clock time can be divided into hours, a total of 24 hours (1- 24 hour).

f) Weather condition:

Weather data such as sunny & rain can be taken to training and perdition purposes.

Open-Source ML Tools:

Table 3 lists various open-source tools available for TFP. All the listed tools are run on Linux, Mac OS, and Windows and are cost-free. Most of the tools are written in the languages Python, C, C++, Java, Python.

Table 3: List of various Open-Source ML tools for TFP

Name of the tool	Description	Tasks performed
ScikitLearn	Scikit-learn is a Python toolkit that simplifies the process of constructing machine learning algorithms. It provides a Python programming language library.	The various task performed are 1. Classification, 2. regression, 3. clustering, 4. preprocessing, 5. model selection, 6. dimensionality reduction [54].
PyTorch-Python	PyTorch is a machine learning library for Python that is built on the Torch framework. In addition to being an ML library, torch is a Lua-based computer platform and scripting language.	Autograd Module Optima Module, nn Module
Tensor Flow	Programmers can use TensorFlow's JavaScript library to aid with machine learning. The APIs will enable you to build and train the models.	Provides a library for dataflow programming.
Weka-ML	ML techniques help in Data mining.	1. Data preparation 2. Classification 3. Regression 4. Clustering 5. Visualization 6. Association rules mining [55].
Google Colab	It will assist you in developing ML applications using PyTorch, Keras, TensorFlow, and OpenCV libraries. Google-Colab is a cloud service that supports Python.	Supports libraries of 1. PyTorch, 2. Keras, 3.TensorFlow, and 4. OpenCV

ApacheMahout	It assists mathematicians and data scientists with algorithm execution.	1. Preprocessors 2. Regression 3. Clustering 4. Recommenders 5. Distributed Linear Algebra.
ML - Accors.Net	It provides libraries for image and audio processing.	1. Classification 2. Regression 3. Distribution 4. Clustering 5. Hypothesis Tests & 6. Kernel Methods 7.Image, Audio & Signal. & 8.Vision [56].
ML- Shogun	Shogun includes a variety of ML methods and data types. These ML libraries are used in research and education.	1. Regression 2. Classification 3. Clustering 4. Support vector machines. 5. Dimensionality reduction 6. Online learning, etc [57].
Keras.io-API	Keras is a neural network programming interface. It's a Python-based tool that makes it easy to conduct research quickly.	API for neural networks
ML- Rapid Miner	It's a platform for ML, data preparation, predictive analytics, deep learning, and text mining. It can be used for research, education, and application development.	1. Data loading 2. Transformation 3. Data preprocessing & 4. Visualization.

4.7 Public Datasets:

Accurate traffic forecasting requires high-quality datasets. For the purpose of making the predictions, we have compiled all of the publicly available datasets in Table 4.

Table 4: List of datasets that are freely accessible for Traffic Prediction.

Application Task	Source	Description
TF	PeMS	PeMS is an acronym for the California Transportation Agency's Performance Measurement System (PeMS), which display on the map and collected in realtime by over 38000 independent detectors [58].
	PeMSD3:	Flow data from 9/1/2018 to 11/30/2018 is included in this collection of 358 sensors.
	PeMSD7	Includes data on TF collected from 883 sensor stations between July 1st and August 31st of this year.
	PeMSD4	From January 1st to February 28th, 2018, 3848 sensors were installed on 29 roadways in the San Francisco Bay Area, totaling 59 days of data [59] [60].
	NYC Bike:	The CitiBike system in New York City provides the data for this visualization. A total of 13,000 bikes and 800 docking stations are available. Citibikenyc.com/system data is where you can find the original data [61].

	T-Drive:	A massive quantity of Beijing taxicab trajectories from February 2nd , 2015 to June 3rd, 2015. Use these repositories to determine the TF in an area. At https://www.microsoft.com/en-us/research, you can find the original source.
Speed	PeMSD-BAY	The data spans six months, from January 1 to June 30 of this year, and comes from 325 sensors located throughout the San Francisco Bay Area.
	METR-LA	From March 1st to June 30th, 2012, 207 sensors on Los Angeles County's roadways recorded data on traffic speed.
	SZ-taxi	From the 1st of January until the 31st of January, 2015, this is Shenzhen's taxi movement. The research region includes 156 important roads in Luohu District. Calculations of TF on each road are performed every 15 minutes to ensure accuracy.
	LOOP	Loop detectors on four interconnected freeways are used to get this information from 323 sensor stations [62].
Other open datasets	https://kaggle.com/	Contains datasets of traffic predictions.
	https://worldwidescience.org	A gateway to global science consists of national and international scientific databases and portals. Consists ofmore than 400 sample records of software requirements specification documents.
	https://zenodo.org/record/	PURE (PUblic REquirements dataset) is a collection of 79 publicly available natural language requirements papers that were gathered from the Web.
	Madrid	A realistic, publicly available, and heterogeneous dataset for the simulative evaluation of highway vehicular networks.
	https://midas.umich.edu/research-datasets/	This collection includes MIDAS-managed campus datasets as well as other U-M and external datasets of interest to MIDAS researchers.

5. LITERATURE SURVEY: RELATED WORKS :

In the previous sections, the resources referred from [1- 62] with regard to various aspects of the research topic are indicated. In the following, we present the brief details of the literature survey carried out with regard to the research work reported in the literature on the proposed topic.

Kumar, B. R., et al. [63], provides a model for traffic volume forecast that can be utilized in Transportation Planning, Management, and Assessment. Various TFP methods are proposed, such as historical, real time, and time-series analysis, but the precision and efficiency of time in forecasting are difficult and pose contradictions. Real-time traffic prediction with ANN and SVR is used to produce an efficient traffic prediction. This work uses observed data from Hyderabad to construct a model for traffic volume prediction along Nizampet Road in Nizampet.

Kumar, K., et al. [64], proposed an Artificial Neural Network (ANN) to anticipate short-term TF based on historical traffic data. It takes into account characteristics including the volume of traffic, speed, density, as well as time of day and week. Previous studies in the literature have used average TF speed as an input variable, while this study uses the speed of each vehicle type as a separate input variable. The results reveal that the Artificial Neural Network performs consistently even when the time interval for TFP is raised from 5 minutes to 15 minutes and produces satisfactory results even when the speeds of each category of vehicles are treated individually as input variables.

Kim, Y. J., et al. [65], presented a multifactor pattern recognition model, combining a Gaussian mixture model clustering algorithm with an artificial neural network, which is used to predict urban TF. System design takes into account aspects such as road geography and environmental conditions to predict TF. The results of the experiments show that the proposed model is more accurate than the conventional methods used in making predictions.

Lana, I., et al. [66], discuss various literature surveys and report that most of the work in this field has been on short-term prediction models. When describing TF in urban road scenarios, this paper looks at how to do it right. It focuses on the long term. A clustering stage is used to look for commonalities or patterns in the TF data that each road sensor collects. This allows for the creation of prediction models for each of these patterns. Individual prediction models are supposed to be part of the MoveUs platform, a European Commission-funded project, which will help traffic managers and road users better plan their trips. The platform will also help people plan their trips more effectively.

Salamanis, et al. [67], explain both normal and abnormal traffic situations, and offer a traffic prediction model. Traffic patterns are identified using DBSCAN, a density-based clustering technique, which uses distinct prediction models for each cluster that depicts a traffic pattern in both normal and abnormal conditions. An ARIMA model from TS analysis was used in conjunction with the k Nearest Neighbor and Support Vector Regression techniques from the ML area.

Wu, Y., et al. [68], present a Deep Neural Network (DNNs) which can anticipate TF using huge data. While contemporary DNN models outperform shallow approaches in terms of performance, fully exploiting the spatial-temporal aspects of TF is still an open topic. Our comprehension of them is also limited. This research presents a DNN-BTF model to increase prediction accuracy. The DNN-BTF model fully exploits TF spatial-temporal periodicity. Convolutional Neural Networks were used to mine spatial characteristics, whereas Recurrent Neural Networks were utilized to mine temporal features. And also visualized how the DNN-BTF model understands TF data, challenging the notion that neural networks are a “black-box” approach in transportation. The suggested DNN-BTF model was tested on a long-term horizon prediction task using data from PeMS.

Ma, D., et al. [69], provide an advanced strategy based on pattern matching prediction. First, clustering algorithms separate historical data into groups based on patterns. It is then trained using Convolutional Neural Networks and Long-Short-Term Memory (CNNs-LSTM) for each group. The degree of similarity between the target day and each group is calculated for each time point, and the predictor trained by the group with the highest degree of similarity is chosen. Using a Seattle case study, they show how choosing the right predictor can enhance prediction accuracy.

Rahman, F. I. [70], describe three sets of weather-related parameters which are combined with ML algorithms to better anticipate TF. This study uses three ML methods: KNN, SVM, and ANN. However, choosing the best ML TFP model for a given set of data is difficult. The influence of selecting each core component of three ML algorithms on prediction accuracy is shown in this research. Five months of historical TF data are weather trained. Then, a month's TF is estimated. KNN outperforms SVM and ANN in one-hour TFP.

A deep learning-based spatiotemporal neural network model is proposed by Jia, T., et al [71]. To accurately estimate citywide TF for each road segment based on an extensive investigation of TF patterns. Convolutional networks with densely linked connections are used to learn spatial dependences and handle spatial sparsity while recurrent convolutional networks are used to learn temporal dependences. In their model, they aim to aggregate the outputs of those hybrid networks by utilizing different weights, which is further strengthened by external information such as the day of the week. The model was trained and validated using taxicab trajectory data from Wuhan, China.

Cui, Z., et al. [74], say due to time-varying traffic patterns and complex spatial dependencies on road networks, traffic forecasting is a difficult application of spatiotemporal forecasting. For this, a unique deep learning framework called Traffic Graph Convolutional Long Short-Term Memory Neural Network (TGC-LSTM) that learns the interactions between highways in the traffic graph and forecasts the network-wide traffic condition is proposed and define traffic graph convolution based on physical network architecture. The proposed traffic graph convolution and spectral graph convolution are discussed.

5.1 Summary of Related Work:

Table 5: Summary of findings from 2009-2021 presented by various authors.

Author	Types of prediction	Prediction Interval Time	Parameters used	Data set	Simulation Model	ML /DL Algorithm used/Comparative Model	Prediction Error Evaluation Criteria
Kumar, B. R., et al. (2020) [63]	Short-Term Prediction	5 Mins	Volume, Travel Time, Speed, Distress Rating, Road width.	videography survey along the Nizampet	ANN (R-Software and MATLAB)	SVR ANN	R^2 MAE MSE RMSE Chi-Square
Kumar, K., et al (2013) [64]	Short-Term Prediction	5 minutes to 15 minutes	Time, speed, Day (Monday to Friday only)	Data samples were collected using video cameras	ANN Model	Artificial Neural Network (ANN)	MSE NMSE MAE Chi-Square
Kim, Y. J., et al (2015) [65]	Short-Term Prediction	5 to30 Mins	Environmental variables (e.g., average straight line, number of crosswalks, bus stops), traffic volume, travel time, speed and Weather Condition.	ITS detectors, GIS and MIS data bases	Multifactor pattern recognition model (MPRM).	Gaussian Mixture Model (GMM)clustering with an artificial neural network (ANN).	MAE
Lana, I., et al. (2016) [66]	Long-term prediction	Hour Based	Speed, Occupancy or TF, No. of vehicles in the specific time, Day of the Week, Day Type (Working, weekend,	Data from road sensors. Historical Weather data	DBSCAN model	density-based clustering algorithm (DBSCAN)	-

			public holiday)				
Salamanis., et al. (2017) [67]	Short-Term Prediction	5 minute and 1 hour	All days of the week, weekdays, Only weekends. All hours, Normal hours, Abnormal hours	Performance Measurement System (PeMS): The traffic dataset & the incident dataset, GPS-Vehicle Detection Stations (VDS),	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm evaluation framework in C++	The k-Nearest Neighbor (KNN), Support Vector Regression (SVR), Autoregressive integrated moving average (ARIMA) model from Time series analysis was trained and tested. Density-based spatial Clustering of Applications with Noise (DBSCAN) algorithm	RMSE NRMSE
Wu, Y., et al. (2018) [68]	Long-term prediction	Hour Based	weekly/daily periodicity and Spatial & Temporal feature	PeMS	Hybrid model-Deep neural networks (DNN-BTF) model	Convolutional neural network (CNN)and Recurrent Neural Network (RNN)	MAE MRE RMSE
Ma, D., et al. (2018) [69]	Short-Term Prediction	5 Mins	Day of the week, Historical Data Clustering based on workdays and weekends.	sensors on an arterial road	Convolutional Neural Networks and Long-short-term-memory (CNNs-LSTM) model.	deep neural network (DNN)	APE MAPE
Rahman, F. I. (2020) [70]	Short-Term Prediction	1 Hour	Day, day type (holiday, working, weekend), Clock time, weather data (sunny,	Transportation Infrastructure Ireland (TII) www. accuweather and	All the three algorithm models developed	KNN SVM ANN	R^2 MAPE

			not sunny, raining, not raining) precipitation value and temperature value.	www. wunderground.com.			
Jia, T., et al. (2020) [71]	Short-Term Prediction	10 Mins	spatiotemporal patterns, including recent, daily, weekly, Workday, holiday	GitHub Historical Data taxicab trajectory data from Wuhan, China.	Python	Deep neural networks (DNN)	RMSE MAE
Nadia Shamshad., et al (2020) [72]	Long-short term	1 hour for long	Weather data	PEMS, VDS,	Long-Short Term Memory (LSTM) Model	Artificial neural network (ANN), Support Vector Machine (SVM)	RMSE
Tselentis, D. I ., el al (2015) [73]	Short-Term Prediction	30Min	Travel speed Spatial data Volume Weather data	Camera	ARIMA	ARIMA Bayesian model	RMSE MAPE
Cui, Z., et al(2019) [74]	Short-Term Prediction	15 Min	Flow occupancy	LOOP data and INRIX	Traffic Graph Convolutional Long short-Term memory neural network - TGC-LSTM	Graph convolutional recurrent neural network.	RMSE MAE MAPE
Xu, Y., et al(2016) [75]	Short-Term Prediction	10 Min	Spatio-temporal	LOOPS	Variable Selection-based Support Vector Regression (VS-SVR) mode	ARIMA, MARS, Spatio-Temporal Bayesian MARS, AR	RMSE MAPE
Kumar, K. et al(2015) [76]	Short-Term Prediction	15 Mins	Day of week, Time of day, Category	Camera Video	Sensitivity Model	ANN and Sensitivity Model	RMSE R MAE

			of vehicles divided in 8 parts				
Qu, W., et al (2020) [77]	Short-Term Prediction	30 Minutes Before with Next 5 minutes prediction	Multi-dimensional data : 1. Cycle by cycle 2. TF rates 3. Queue length 4. Signal timing 5. Day of the week 6. Holiday or not	Video Camera	KNN+ Elman	Clustering, KNN, BP, Elman neural network	RMSE CCPO

6. DISCUSSION AND FUTURE WORKS :

The aim of this review is to give a general awareness of ITS and TFP. Different strategies for predicting TF for ITS have been discussed in various studies. Research on seasonal TFP has been the primary focus of certain studies, in addition, high-accuracy methods are necessary to forecast urban TF. Most researchers rely on datasets that are freely accessible to illustrate the evaluation or understanding of their work. The model's accuracy may suffer when it comes to real-world datasets. It is also emphasized that developing a TF forecast system that can address all parameters is a difficult task. The primary aim of this review article is to provide a review of ML-based TFP and its use in ITS. It is possible that the use of ML-DL techniques will aid in the appropriate handling of traffic forecasting. According to peer-reviewed articles, an important research topic is how to construct a model that can capture the temporal and spatial aspects of TF while also predicting the complicated condition of the future. The combined use of hybrid learning models in the implementation of traffic forecasting in ITS is still a research area that requires further investigation.

7. RESEARCH GAP :

It is concluded that the present training models, approaches, and journal publications appear to be falling short in addressing the benefits and issues associated with ITS from the literature review. There is a shortage of studies on the application of technology to the forecast of TF. There is a need to simplify the approaches and also to enhance their accuracy. As a result of recent improvements in ITS, researchers have been encouraged to implement TFP with various ML approaches. Some of the algorithms in the ML techniques have a number of difficulties when it comes to implementing the complexity of TFP systems. One way to ensure that TFP systems live up to their promise in practice is to boost the technology that addresses these problems. Doing the literature review, find out that various aspects of TFP systems do not effectively utilize statistical methods. This study points out the following research gaps and makes recommendations for filling them.

- **Research Gap 1:** Which ML algorithm gives good accuracy in TFP.
- **Research Gap 2:** Many categories and types of algorithms are available in Deep learning and ML. Different techniques and strategies are available in ML and deep learning for classifying and filtering the data. Identify the best among the available algorithms that will serve the purpose.
- **Research Gap 3:** User interface design is needed to display the studied results.
- **Research Gap 4:** Further explore the availability of dataset repositories**.**
- **Research Gap 5:** Possibility of designing new algorithms for TFP.

8. RESEARCH AGENDAS :

(1) Literature review lacks a comprehensive comparative study to identify the best technique among the available ones. Hence, a comparative study of all the reported techniques will be made and identify

ML techniques or algorithms that are ideal for creating Short-Term TFP models in a city with a high accuracy and prediction rate, and a lower false-positive score?
(2) To find out what are different datasets and open-source tools are available for TFP and which one is more suitable for short-term prediction.
(3) What technologies are being researched to automate the process of TFP in an ITS.
(4) How advanced is research in Deep Learning and ML for TFP?
(5) Possibility of finding an alternative technique suitable for short-term TFP.
(6) Creation of User Interface Design.

9. ANALYSIS OF RESEARCH AGENDAS :

Materials have to be identified to determine the technique's efficacy. The various techniques and methodologies can be utilized to collect and process data to create an intelligent TFP system that produces the desired outcome. We should choose the best method that is compatible with all elements of the external interaction. In order to build a framework for integrating ML algorithms, the most appropriate hardware and software should be used. There should be a requirement to scan and assess innovative systems in ML to improve the outcome of Smart TFP systems.

10. FINAL RESEARCH PROPOSAL ON CHOSEN TOPIC :

Attempts will be made to find an alternate approach for Intelligent Transportation Systems using historical and weather-related Short-Term TFP in a city using ML techniques and others.

11. ABCD ANALYSIS OF RESEARCH PROPOSAL :

The ABCD analysis is used to evaluate the features of concepts and procedures when assessing the value of the business in society [78] [79]. Nowadays a big data-driven TFP is done [80]. It is primarily utilized to ascertain the numerous elements affecting the selected determinant issues, which are classified into four categories: advantages, benefits, constraints, and disadvantages which are shown in Table 5.

Table 5: The ABCD Listing

Advantages	Benefits
➢ It incorporates a sophisticated mechanism for intelligent TFP. ➢ People are alerted well in advance about traffic congestion based on past data. ➢ Using a prediction system helps a person to make the best judgments during their travel. ➢ A solution that eliminates all of the difficulties faced globally in conventional road traffic.	➢ All across the world, it's a big help to drivers. ➢ A traffic prediction system helps to forecast future traffic jams in a metropolitan region. ➢ This traffic prediction information could be used by individuals, businesses, and the government to make informed decisions about TF. ➢ Minimizes traffic congestion, vehicle speed, lowers carbon emissions, can reduces road accidents, and enhances traffic operations.
Constraints	**Disadvantages**
➢ Data accessibility and data format vary. ➢ An accurate forecast may be affected by other global factors. ➢ More Expense. ➢ The transition from a traditional model of transportation to an intelligent one. ➢ Data preparation is needed because of the increased size of the data.	➢ Prediction accuracy is highly based on the quality of the data that can be gathered. ➢ One of the most difficult tasks in data management is dealing with unstructured data. ➢ To acquire information, there is no standard format to follow. ➢ Data must be verified for veracity and validity. ➢ To properly examine the results of traffic prediction, daily monitoring is necessary.

12. CONCLUSION :

In this study, a brief overview of TFP is presented. There is great progress and application activity in the field of TFP. Predicting and forecasting TF from both spatial and temporal data is drawing much attention these days. Predictions are made using both parametric and nonparametric approaches. ML and ANN are reported to be the quickest and accurate ways of predicting TF.

13. ACKNOWLEDGEMENTS :

The suggestions made by the reviewers and the editorial team are gratefully acknowledged.

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