Machine Learning and Deep Learning Models for Traffic Flow Prediction: A Survey

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Abstract

Traffic congestion is one of the problems for cities around the world due to the rapid increasing of vehicles in urbanization. Traffic flow prediction is of a great importance for Intelligent Transport System (ITS) which helps to optimize the traffic regulation of a transportation in the city. Nowadays, several researches have been studied so far on traffic flow prediction, accurate prediction has not yet been exploited by most of existing studies due to the impact of inability to effectively deal with spatial temporal features of the times series data. Traffic information in transportation system will also be affected by different factors. In this research we intended to study various models for Traffic flow prediction on the basis machine learning and deep learning approaches. Factors affecting the performance of traffic flow prediction intensity are studied as well. Benchmark performance evaluation metrics are also reviewed.

Generally, this manuscript covers relevant methods and approaches, review the state-of-art works with respect to different traffic flow prediction technique help researchers in exploring future directions so as to realize robust traffic flow prediction.

Chapter 1: Introduction

1.1 Background

With the rapid development of information and communication technology (ICT), the concept of "smart city" emerges as a way to enhance urban management and environmental sustainability as well as increase standard of living of citizens [1]. Cities need to provide the demand for those citizens by providing enhanced services which support daily life quality. While cities have been evolving in terms of opportunities, these opportunities also expose many challenges that can impact citizen's daily life [2]. Technology has always been at the center of this evolution and over the years it has greatly changed our world lives. Digital data and connected worlds of physical objects, people and devices are affecting the way we work, travel, socialize and interact with our surroundings. This has a profound impact on different application areas such as transportation, healthcare, environmental monitoring, urban systems, and control and management applications, among several other areas as well.

Intelligent Transport System (ITS) is a technology that aimed to improve transport safety and mobility, as well as increasing the development of citizens by reducing negative effects of traffic flow in the city. The initial ITS concept was proposed by researchers in the United States (US) in the twentieth century [3]. However, ITSs are now attracting a great deal of attention from academia and industry because such systems not only improve vehicle traffic conditions but can make the transportation sector safer and more sustainable and efficient. Furthermore, inconveniences caused by city traffic congestion and the effect of climate change problem on traffic can be reduced.

Communication technology is the driving force behind notable innovations in the automotive industry in the modern society. In the last two decades, mobile communications have transformed the citizens daily lives by allowing ubiquitous information exchange, anywhere and anytime. The use of such communication systems in vehicles is expected to become a reality in the near future, as industries, universities, and governments around the world devote significant efforts and resources to the development of safer vehicles and infrastructure for road transport. These investments can be verified through many national and international initiatives dedicated to vehicular networks [4] [5] [6].

Therefore, intelligent transport system is part of vehicular networks which can be applied in the smart city domain for traffic flow prediction. As such, we can say that Intelligent transport systems (ITS) are applications of smart city based on the internet of things (IOT) and traffic flow prediction is applicable in the intelligent transport system field.

Traffic problems have seriously affecting the urban societies quality of life as well as development of the city, and prediction of traffic congestion has a great importance for both individuals and the governments as well. However, understanding and modeling of the traffic flow conditions can be extremely challenging [7].

People are getting increasingly concerned about traffic congestion, which has seriously affected their life quality and urban development. To monitor real-time traffic conditions, cities around the world have deployed embedding sensors, like inductive-loop detectors and video image processors in road networks [8].

The increasing availability of data and services has created opportunities to predict traffic conditions like predicting travel speed and traffic volume in the entire city [9]. We are experiencing urbanization shift and it is predicted that more than 60% of the world's population will live in urban areas by 2050 [10]. Therefore, Traffic congestion is one of the major challenges to enable good urbanization and the deployment of Intelligent Transportation Systems (ITS) in urban areas brings the opportunities to prevent or reduce traffic congestion.

Traffic flow prediction serves as the key component of ITS to forecast and prevent traffic congestion, control and manage traffic efficiently, and plan the best traveling route. Machine learning (ML) based approaches such as *k*-nearest neighbor (KNN) algorithm [11], Markov process-based scheme [12] and Artificial Neural Network (ANN) schemes [13] [14] are traffic flow predictions. When we compare those ML approaches, deep learning (DL) models have the advantages in simplifying data preprocessing procedure and outperforming other ML methods in terms of accuracy. Therefore, DL schemes have received extensive attention recently in traffic flow prediction [15] [16] [17] [18] [19] [20].

Furthermore, when we compare machine learning algorithms and deep learning models the later have an advantage in scaling with data availability which is deep neural networks usually make better use of massive amount of data by learning customized feature representations. In particular, convolutional neural networks (CNN) and long short-term memory (LSTM) recurrent neural networks (RNNs) have demonstrated their peculiar advantages in modeling and predicting spatiotemporal data. Recently, such models have received extensive attention in the field of traffic flow prediction [21] [22]. Moreover, traffic flow prediction enables those travelers to optimize resources like time, gas oil, and power consumption and it is one of the most important aspect in smart city.

1.2 Motivation

Urban road traffic can be a problem on societies to environmental effects and health problem. As we know, Transportation is one of the most important way that urban society in the world always uses daily to move from place to place. The quality of daily life for the society can be improved through smart city with efficient travel services. Intelligent transport system is one of the solutions to provide this type of service. Traffic flow prediction is very important for better performance of intelligent transport system in smart city domain. However, the prediction model which have been done so far by different researches are not adequate enough to provide better traffic flow prediction services.

There are various factors that have impacts on the performance of traffic flow prediction. As such, Study and analyze those factors helps to model better traffic flow prediction scheme. Therefore, the motivation for this research is to study on various state-of-the art traffic flow prediction approaches so as to find out approaches how to design accurate traffic flow prediction. This helps to improve the quality of traffic flow prediction service quality in intelligent transport system as long as the way how accurate traffic flow prediction is properly studied. Producing robust traffic flow prediction technique has a great importance for urban road users and government. Therefore, urban societies daily transportation lives will be improved.

1.3 Statement of the Problem

Urban development is becoming important for the modern society and the situation of urban traffic congestion is becoming very serious due to number of vehicles usage is increasing in the city [23]. One of the most important solution for this problem is the application of intelligent transport system (ITS) which is applied to predicts congestion of traffic flow. One of the most important part in smart city development is traffic flow prediction management system in most of the cities around the world. Therefore, providing scientific prediction model of traffic congestion ensures the safety of traffic environment and good to prevent traffic congestion which helps to reduce traffic accidents.

The vehicles are increased in urban areas which lead to problems in the transportation system. Among problems consumption of fuel, air pollution, congestion and accident. From these issues, traffic congestion is the big problem in urban transportation. Better traffic flow prediction is needed to resolve the aforementioned issues. Therefore, traffic flow prediction is very important to handle traffic congestion problem and the quality of urban citizens daily life can be affected by traffic flow problems.

There are various traffic flow prediction researches that have been tried so far by various researchers to predict traffic flow. But there is no accurate prediction model yet. It is unable to effectively deal with various features of times series data results difficult to accurately represent traffics flow. Therefore, extra investigation needs to have better prediction model to predict traffic flow better. In this research, we are intended to review various traffic flow prediction techniques to suggest researchers to design accurate traffic flow prediction. Accurate traffic flow prediction can be provided by studying and analyzing the most important factors that affect the traffic flow prediction. Therefore, we study on the factors affecting the performance of traffic flow prediction. As a result, transportation quality can be improved in urban areas to successfully deploy intelligent transport system.

1.4 Objectives

General Objective

The objective of this research is to review traffic flow prediction techniques to produce robust traffic flow prediction scheme.

Specific Objective

• Detailed analysis and study on the state-of-the art research

1.5 Methodology

With the aim of achieving the aforementioned research objectives the following methodologies will be applied

Literature Review

Exhaustive study and explorations will be made on the areas related to deep learning specially in the field of intelligent transport system which is used in smart city. This will be accomplished by reading books, journals or conference papers which have been done so far with different approaches, so as to have sufficient understanding on the problem. Techniques and approaches appropriate for development of various algorithms for modeling traffic flow prediction in intelligent transport system will also be investigated as well. After deep analysis on the existing models we suggest a new approach to achieve better traffic flow prediction in intelligent transport system.

1.6 Application Results

This research will significantly contribute to the smart city domain specifically for the intelligent transport system for effective urban traffic flow prediction. Because, as long as the traffic flow prediction become accurate the urban road users will be satisfied with the services like reduced traffic accidents, traffic congestion, travel time, and air pollution which decreases important impact on urban population health. This work will benefit the services of intelligent transport system applications and the most important application areas that will benefit from this work are the entire citizens who use transportation service in the city and the government who controls traffic flow in the city.

Chapter 2: Literature Review

2.1 Overview

Nowadays, deep learning is becoming popular and essential approach in artificial intelligence discipline applied in several application areas. Researchers throughout the world are applying deep learning approach to find out solutions to problems in various application areas. Among those several application areas, modeling traffic flow prediction is the most important application that can be produced with deep learning. This Chapter covers overview of intelligent transport systems and traffic flow prediction models in intelligent transport systems which have been done so far using different approaches. Number of traffic flow prediction models have been proposed because of its significant importance of traffic flow prediction.

2.2 Intelligent Transport System

Intelligent Transport System (ITS) is a technology or an application of intelligence in any form like management strategies, logistics, statistics, using predictive human behavior, non-electronic and electronic forms of dispensing information, advanced sensors, computers and communication technologies that improve the quality of transportation. ITS is a vast field that encompasses driver assistance, vehicle tracking, license plate recognition, inter vehicle communication, air traffic management, road sign prediction, modeling and simulation, and intelligent traffic management and so on [24]. ITS provides to the multidimensional needs and overlap of the transport field and others, for example license plate detection for better policing, air traffic management for safe flight operations, traffic flow and traffic management for efficient use of existing infrastructure. The commonly used approach to increase vehicular population is upgrading the existing road infrastructure. However, not all problems are due to insufficiency of the road infrastructure but due to poor management of traffic flow and congestion control. Therefore, due to lack of proper management of road traffic, existing roads cannot be sufficient enough specially in developing countries.

Intelligent Transportation Systems (ITSs) provides efficient services related to different modes of transport, making the transport networks smarter [25]. ITSs are mainly applied in road transport, but are also designed to offer interfaces with other modes of transport [26]. Some of them involve surveillance of the roadways [27], others may have an important role in the context of urban development [28]. ITSs are based on different technologies, which could vary from car navigation systems or traffic signal control systems to advanced applications integrating live data from other sources, such as parking guidance systems. Predictive techniques are designed to allow advanced modeling and comparison with historical data [29].

Intelligent Transportation Systems (ITS) is a technology that has just recently developed to overcome traffic congestion in several developed countries. ITS is used for computing systems and communication technology for various purposes, such as traffic management, routing planning, vehicle and road safety and emergency services [30]. ITS uses various kinds of sensing and communication to help transport authorities and vehicle drivers in making informative decisions as well as comfort and safety in driving [31]. The utilization of ITS increases road and vehicle security systems become more efficient and environmentally friendly [32]. The use of wireless communication technology enables ITS to open opportunities for various types of road and user's safety applications. The ITS application utilizes data collected from vehicles to increase driver safety and rationalize public infrastructure use [33].

2.3 Traffic Flow Prediction

Traffic flow prediction has been regarded as a key functional component in ITSs [34]. For the past few decades, a number of traffic flow prediction models have been developed to assist traffic management and control to improve the efficiency of transportation ranging from route guidance and vehicle routing. The objective of traffic flow prediction is to provide traffic flow information.

Traffic flow prediction has gained more attention with the rapid development and deployment of intelligent transportation systems (ITSs). It is regarded as a critical element for the successful deployment of ITS subsystems, particularly advanced traveler information systems, advanced traffic management systems, advanced public transportation systems, and commercial vehicle operations.

From the researches which have been done so far, the autoregressive integrated moving average (ARIMA) model is used to predict short-term freeway traffic flow [35]. Then, extensive variety of models for traffic flow prediction have been proposed by researchers from different areas, such as transportation engineering, statistics, machine learning, control engineering, and economics.

Traffic flow prediction approaches have been extensively researched in literature and generally can be grouped into three basic categories, such as parametric, non-parametric and simulation based models. Parametric models include time-series models [36], Kalman filtering models [37], etc. Non-parametric models include Support Vector Regression (SVR) methods [38], Artificial

Neural Networks (ANNs) [39], etc. Simulation based approaches use traffic simulation tools to predict traffic flow [40]

Levin and Tsao applied Box-Jenkins time-series analyses to predict expressway traffic flow and found that the ARIMA (0, 1, 1) model was the most statistically significant for all forecasting [41].

M. Hamed et al. applied an ARIMA model for traffic volume prediction in urban arterial roads [42]. Many variants of ARIMA were proposed to improve prediction accuracy, such as Kohonen ARIMA (KARIMA) [43], subset ARIMA [44], ARIMA with explanatory variables (ARIMAX) [45], vector autoregressive moving average (ARMA) and space–time ARIMA [46], and seasonal ARIMA (SARIMA) [47]. Except for the ARIMA-like time-series models, other types of timeseries models were also used for traffic flow prediction [48].

In the area of multi-interval traffic volume prediction Chang et al. proposed a k-nearest neighbor non-parametric regression (kNN-NPR) model [49]. Even if time-series data values vary abruptly or show fluctuations, the presented model shows effective accuracy. Although k-NN based methods cannot perform spatial and temporal modeling simultaneously [50]. E. Faouzi developed a kernel smoother for the autoregression function to do short-term traffic flow prediction, in which functional estimation techniques were applied [51]. Sun *et al.* used a local linear regression model for short-term traffic forecasting [52]. A Bayesian network approach was proposed for traffic flow forecasting [53]. An online learning weighted support vector regression (SVR) was presented for short-term traffic flow predictions [54]. Various ANN models were developed for predicting traffic flow [55] [56] [57] [58] [59].

Although the deep architecture of NNs can learn more powerful models than shallow networks, existing NN-based methods for traffic flow prediction usually only have one hidden layer. It is hard to train a deep-layered hierarchical NN with a gradient-based training algorithm. Recent advances in deep learning have made training the deep architecture feasible since the breakthrough of Hinton et al. [60], and these show that deep learning models have superior or comparable performance with state-of-the-art methods in some areas.

Generally, many traffic flow prediction algorithms have been developed because of the need for traffic flow prediction in ITS with different approaches in different application areas. The proposed models are designed with a small separate specific traffic data, and the accuracy of traffic flow prediction approaches are dependent on the of features of traffic flow embedded in the collected spatiotemporal traffic data. But it is difficult to determine that one approach is clearly better than other methods in a certain state. Moreover, literature shows when using Neural Networks produces robust prediction but need to investigate more for accurate prediction model. The most important determinant factors should be studied which can be significantly produce robust traffic flow prediction model.

Finally, the challenge for traffic flow prediction is the presence of unusual factors such as accidents, weather, and planned events. For example, if the rainfall intensity increases, then both speed and flow decreases [61]. The chances of error also exist due to the uncertainties in complicated factors such as holidays and availability of alternative routes etc. Consideration of such unusual factors while designing the traffic flow prediction architectures can significantly improve prediction accuracy.

Chapter 3: Related Work

In this Chapter, we discuss researches which have been done particularly related to traffic flow prediction for intelligent transport systems. Due to the number of vehicles increased in the city, urban people demand for better traffic flow prediction is also increasing. There are research works which have been done on traffic flow prediction using various approaches. Identifying urban traffic flow is one of the most important facets in ITS. Furthermore, existing research works are discussed based on machine learning and deep learning techniques. Finally, the factors that affect the flow of the traffic will be discussed.

3.1 Machine Learning Based Traffic Flow Prediction

1. Z. Ma et. al proposed Short-Term Traffic Flow Prediction Based on Online Sequential Extreme Learning Machine [62]. It is an adaptive prediction model based on variant of Extreme Learning Machine (ELM), namely On-line Sequential ELM with forgetting mechanism. This model has the capability of updating itself using incoming data and adapts to the real time changes. However, limitations, such as the requirements of large number of neurons and dataset size for initialization,

are discovered in practice. To improve the applicability, another scheme involving sequential updating and network reconstruction is proposed. The experimental results show that, compared with the previous method, the proposed method has a better applicability to provide an adaptive model for short term traffic flow prediction. But work does not consider weather data which significantly affect the performance of intelligent traffic flow prediction model.

2. Z. Bartlet et al. proposed a Machine Learning Based Approach for the Prediction of Road Traffic Flow on Urbanized Arterial Roads [63]. Urbanized arterial roads connect geographically important areas and are used for commuting and movement of goods. Prediction of traffic flow on these roads is vital to aid in the mitigation of traffic flow congestion. In this work they have applied machine learning models to a real dataset for the prediction of road traffic congestion on urbanized arterial road. A comparative analysis was conducted on each machine learning model, examining the prediction accuracy and time-horizon sensitivity. Furthermore, different input parameter settings

(various classes of vehicles such as motorcycles, cars, vans, rigid goods lorries, articulated heavy goods vehicles (HGVs), and buses) are examined to investigate how heterogeneous traffic flow can affect prediction. The experimental results show that the Artificial Neural Network Model outperforms other models at predicting short term traffic flow on an urbanized arterial road based on the standard performance indicator called Root Mean Squared Error (RMSE). In addition, it is found that different classes of vehicles can aid improvement prediction. But, needs exploration of extra learning algorithm for better prediction with more datasets and more additional performance indicators should be used to show how robust the proposed system is.

Urban traffic congestion estimation and prediction based on floating car trajectory data [64]. Traffic flow prediction is an important precondition to alleviate traffic congestion in large-scale urban areas. In this paper, the researchers proposed a novel approach to estimate and predict urban traffic congestion using floating car trajectory data efficiently. In this method, floating cars are regarded as mobile sensors, which can probe a large scale of urban traffic flows in real time. In order to estimate the traffic congestion, they use a new fuzzy comprehensive evaluation method in which the weights of multi-indexes are assigned according to traffic flows. To predict the traffic congestion, an innovative traffic flow prediction method using particle swarm optimization algorithm is responsible to calculate traffic flow parameters. Then, a congestion state fuzzy division module is applied to convert the predicted flow parameters to citizens' cognitive congestion state. Experimental results show that the proposed method has advantage in terms of accuracy, instantaneity and stability. But weather data is not considered as long as it has impact on the prediction efficiency.

X. Ling et al. proposed Short-term Traffic Flow Prediction with Optimized Multi-kernel Support

Vector Machine [65]. Accurate prediction of traffic state can help solve the problem of urban traffic congestion, providing guiding advices for users travel and traffic regulation. In this paper, they proposed a novel short-term traffic flow prediction algorithm, which is based on Multi-kernel Support Vector Machine (MSVM) and Adaptive Particle Swarm Optimization (APSO). Firstly, both the nonlinear and randomness characteristic of traffic flow, and hybridize Gaussian kernel and polynomial kernel to constitute the MSVM are explored. Secondly, optimize the parameters of MSVM with a novel APSO algorithm by considering both the historical and real-time traffic data. The algorithm is evaluated by doing thorough experiment on a large real dataset. The results show that the proposed algorithm can do a timely and adaptive prediction even in the rush hour when the traffic conditions rapidly changed. The proposed method took the influence of historical and real-time data to the flow of traffic in future moment into account, thus provides more accurate prediction result.

1. J. Wang et al. proposed Short-term traffic speed forecasting hybrid model based on Chaos– Wavelet Analysis Support Vector Machine theory [66]. Based on the previous literature review, this research builds a short-term traffic speed forecasting model using Support Vector Machine (SVM) regression theory referred as SVM model. Besides the advantages of the SVM model, it also has some limitations. Perhaps the biggest one lies in the choice of appropriate kernel function for the practical problem. How to optimize the parameters efficiently and effectively presents another problem. Unfortunately, these limitations are still research topics in current literature. This research puts an effort to investigate these limitations. In order to find the effective way to choose the appropriate and suitable kernel function. This research constructs a new kernel function using a wavelet function to capture non-stationary characteristics of short-term traffic speed data. In order to find the efficient way to identify the model structure parameters, the Phase Space Reconstruction theory is used to identify the input space dimension. To take the advantage of these components, the paper proposes a short-term traffic speed forecasting hybrid model Chaos– Wavelet Analysis-Support Vector Machine model, referred to as C-WSVM model. The real traffic speed data is applied to evaluate the performance and practicality of the model and the results are encouraging. The theoretical advantage and better performance from the study indicate that the CWSVM model has good potential to be developed and is feasible for short-term traffic speed forecasting study. But needs further studies to apply the model to other traffic variable data sets such as traffic volume, travel time and average occupancy. This study chooses the traffic speed as the demonstration. Other limitations, such as the choice of the appropriate loss function for shortterm traffic variables forecasting model and parameters determination deserve further investigation.
2. S. V. Kumar et al. proposed a prediction scheme by using the Kalman Filtering Technique (KFT) was proposed and evaluated [67]. The proposed system requires only limited input data. The Kalman filter [68] allows a unified approach for prediction of all processes that can be given a state space representation. Traffic movement prediction using both significant and real-time data on the day of interest was also attempted. Promising results were obtained with mean absolute percentage error (MAPE) of 10 between observed and predicted flows and this indicates the suitability of the proposed prediction scheme for traffic flow estimation in ITS applications.

Chang et al. proposed a k-nearest neighbor non-parametric regression (kNN-NPR) model [69]. Even if time-series data values vary abruptly or show fluctuations, the presented model shows effective accuracy. Although k-NN based methods cannot perform spatial and temporal modeling simultaneously [70].

Support Vector Regression (SVR) falls under supervised ML algorithms, *i.e.*, it is trained to learn a function to map input feature to output and is mostly used for classification and regression. The purpose of SVR is to map given data to a high dimensional feature space followed by performing linear regression with the same space. Here, first, each item in the dataset is plotted as a point in n-dimensional feature space. Then, classification is performed by locating hyperplane that divides the given input into classes. Compared to NN, SVR involves principles of Structural Risk Minimization (SRM). Also, it guarantees the localization of global minima. Some literature work has used SVM instead of SVR. However, both of these methods are almost the same, but the difference came in the type of value they provide as output (SVR outputs a real number whereas SVM outputs either 0 or 1). Authors in [71] incorporated an online version of Support Vector Machine (SVR) named incremental SVR and concluded that proposal is better against ANN approach. However, this study represents a drawback in the experimental setup. The authors, however did not present sufficient evaluation of performance on their work.

J.Y. Ahn et al. proposed Predicting Spatiotemporal Traffic Flow based on Support Vector Regression and Bayesian Classifier [72]. To satisfy the demand of traffic flow estimation, this research studies the method of real-time traffic flow prediction based on Bayesian classifier and support vector regression (SVR). First the traffic flow is modeled and its relations on the roads using 3D Markov random field in spatiotemporal domain. Based on their relations, the researchers define cliques as combination of current cone-zone and its neighbors. The dependencies on the defined cliques are estimated by using multiple linear regression and SVR. Finally, the traffic flow at next time stamp is predicted by finding the speed level with decreasing the energy function. To evaluate the performance of the proposed method, it has been tested on traffic data obtained from Gyeongbu expressway. The experimental results showed that the approach using SVR-based estimation showed superior accuracy than linear-based regression. But extra investigation using deep learning is necessary for accurate prediction of traffic flow.

3.2 Deep Learning Based Traffic Flow Prediction

A Supervised Deep Learning Based Traffic Flow Prediction (SDLTFP) was proposed which is a type of fully-connected deep neural network (FC-DNN) [73]. Timely prediction is also a major issue in guaranteeing reliable traffic flow prediction. However, training deep network could be time-consuming, and overfitting is might be happening, especially when feeding small data into the deep architecture. The network is learned perfectly during the training, but in testing with the new data, it could fail to generalize the model. The Batch Normalization (BN) and Dropout techniques are adopted to help the network training. SGD and momentum are carried out to update the weight. Then take advantage of open data as historical traffic data which are then used to predict future traffic flow with the proposed method and model. Experiments show that the Mean Absolute Percentage Error (MAPE) for the traffic flow prediction is within 5% using sample data and between 15–20% using out of the sample data. Training a deep network faster with BN and Dropout reduces the overfitting. However, the spatio-temporal data relationship is not considered by adding each road segment and need to examine the prediction with network perspective.

PCNN: Deep Convolutional Networks for Short-Term Traffic Congestion Prediction [74].

Understanding and modeling the traffic conditions extremely be difficult, and the observations from real traffic data reveal two properties. First similar traffic congestion patterns exist in the neighboring time slots and on consecutive workdays. Second the levels of traffic congestion have clear multiscale properties. To capture these characteristics, a novel PCNN method is proposed, which is based on a deep convolutional neural network, modeling periodic traffic data for short-term traffic congestion prediction. PCNN has two pivotal procedures such as time series folding and multi-grained learning. It first temporally folds time series and constructs a 2-D matrix as the network input, such that both real-time traffic conditions and past traffic patterns are well considered. Then, with a series of convolutions over the input matrix, it is able to model the local temporal dependency and multiscale traffic patterns. In particular, the global trend of congestion can be addressed at the macroscale, whereas more details and variations of the congestion can be captured at the microscale. Experimental results on a real-world urban traffic data set confirm that folding time series data into a 2-D matrix is effective and PCNN outperforms the baselines significantly for the task of short-term congestion prediction. However, another way of deep learning model is needed to further investigate accurate traffic flow prediction.

1. Z. Zheng et al. proposed a Deep and Embedded Learning Approach for Traffic Flow Prediction in Urban Informatics [63]. Most previous studies on traffic flow prediction fail to capture fine-grained traffic information like link-level traffic and ignore the impacts from other factors, such as route structure and weather conditions. This research proposed a deep and embedding learning approach (DELA) that can help to explicitly learn from fine-grained traffic information, route structure, and weather conditions. In particular, DELA consists of an embedding component, a convolutional neural network (CNN) component and a long short-term memory (LSTM) component. The embedding component can capture the categorical feature information and identify correlated features. Meanwhile, the CNN component can learn the 2-D traffic flow data while the LSTM component has the benefits of maintaining a long-term memory of historical data. The integration of the three models together can improve the prediction accuracy of traffic flow. They have been conducted extensive experiments on realistic traffic flow dataset to evaluate the performance of our DELA and make comparison with other existing models. The experimental results show that the proposed DELA outperforms the existing methods in terms of prediction accuracy. But it needs adoption of machine learning models with extra research and needs traffic flow metrics such as traffic volume and traffic speed together for better investigation to produce robust traffic flow prediction model.
2. A. Koesdwiady et al. Proposed Non-stationary Traffic Flow Prediction using Deep Learning approach [75]. This work addresses non-stationary traffic flow prediction by implementing an intelligent update scheme to deep neural networks. The intelligent update scheme works by monitoring the frequency domain features extracted from the traffic flow time series. The features at present are compared with the previous ones through a distance function. The resulting similarity is then fed to the exponentially weighted moving average to detect whether a notable change in the traffic flow is present or not. The proposed method is evaluated using experimental analysis and it can be able to handle non-stationarity and produce acceptable traffic flow prediction. Apart from this, the result shows that using limited training data, the predictor is able to maintain good quality prediction in the

relatively far future. Moreover, when compared with the fully stochastic gradient descent update scheme, it has been shown that the proposed method is able to save time and computational resources up to 13% without losing the performance of prediction. But this work needs to scale up by including more features and increasing the number of freeways included in the model as well as the duration of the traffic flow data to have accurate traffic flow prediction.

3.3 Summary

Traffic flow prediction is to predict the traffic flow rates based on the number of vehicles within a certain minute on the lane in the traffic network. Traffic flow prediction can be done based on the historical and current traffic flow data, trajectory data, weather data, and events etc. This is a typical big data driven state forecasting problem for large dynamic systems, and is a fundamental problem in transportation system scheduling and optimization. Due to these reasons, Deep Neural Network based traffic flow prediction has attracted great research attentions [76] [77] [78] [79]. The traffic flow predictions are affected by information of different dimensions such as:

1. **Temporal Dimension**: Traffic flow has typical time dependent features, which varies with time. In working days there are traffic hours and traffic patterns in working days and weekends are different. Therefore, time is an important factor in traffic flow prediction.
2. **Spatial Dimension**: Traffic flow varies at different locations which may have different traffic flow features over time.
3. **Events**: Environment information such as weather and social events also the most important factors which have a great impact on traffic flow prediction.

Therefore, accurate traffic flow prediction can be provided by studying and analyzing the most important factors that affect the traffic flow and the critical factors affecting the accuracy of traffic flow prediction model is studied. Apart from the aforementioned related work deep learning approaches, this research contributes a deep learning model which apply feature fusion technique.

To conduct extensive and accurate experiments on traffic flow prediction, research questions are prepared need to be addressed the issues of accurate traffic flow prediction. Therefore, traffic flow prediction model should answer for the following important research questions.

- What critical factors affect the performance of traffic flow prediction?
- What are the most important features used to accurately predict the flow of traffic?
- What technique is appropriate for feature fusion among different datasets?
- What type of datasets are used for traffic flow prediction?
- What performance evaluation metrics are utilized for accurate prediction of traffic flow?

We believe that, the aforementioned questions are very important determinant factors for effective prediction of traffic flow. Therefore, we are intended to suggest to consider the aforementioned questions whenever we want to design a new traffic flow prediction to contribute robust traffic flow prediction which is actually be a tributary for to state of the art models. There are many deep learning models that can be utilized to learn from the traffic data collected through a smart city's infrastructure which predict the traffic flow in the city. Moreover, most of the researches which have been studied so far for traffic flow prediction uses RMSE and MAE for measuring the performance of proposed models. However, these two metrics fail when input datasets are entirely different from each other [80]. Hence, we will define benchmark metrics for performance evaluation of our traffic flow prediction model.

Traffic flow prediction is an important aspect in intelligent transportation system. The primary purpose of this proposed work is to study the approach how accurate prediction of traffic flow for urban citizens in time will be designed, so as to realize the intelligent transport system in smart city domain. As such, our proposed solution offers the way how stable traffic flow prediction system.

Chapter 4: Tools For Experimental Analysis

4.1 Overview

This Chapter deals with the implementation tools described. The performance evaluation metrics and analytical tools are discussed. Various performance metrics such as mean absolute error (MAE), root mean-square error (RMSE), and mean relative error (MRE) help to evaluate the effectiveness of the models of traffic flow system to know how the objective achieved are discussed.

4.2 Development Tools

DL platform provides an interface to design deep learning architectures easily by using pre-built and optimized libraries or components. Optimized performance, easy to code, parallelization, reduced computations, automatic gradient computations are some key characteristics of a good deep learning platform. Leading companies such as Google, Microsoft, Nvidia, Amazon are investing heavy money in developing Graphic Processing Unit (GPU) accelerated deep learning platforms for implementation of fast and large computation. From those all the existing platforms, TensorFlow is widely used and most popular among the users that is why we use in this research.

In this section deep learning platforms are reviewed as follows.

4.2.1 TensorFlow

This platform was introduced by Google brain team in late 2015. Its support languages such as Python, C++, R, and Java which make this tool popular. Moreover, it allows to work with one or more CPUs and GPUs with high data scalability. Hence, an individual person with a tablet or largescale distributed system can rely on TensorFlow. However, scholars suggested to use TensorFlow with server grade multi-thread implementation [81]. It takes any model as directed acyclic graph (DAG) where nodes of the graph present mathematical operations whereas edges present tensors (multi-dimensional array) between them. Video analysis, visualization of distribution, sound recognition, time-series analysis, and object detection are some uses of TensorFlow. Furthermore, TensorFlow supports distributed training, provides low latency for mobile users, and easy to integrate with SQL tables.

TensorFlow is more suited for most of deep learning models due to its features like that it supports an extensive built-in support for deep learning and Mathematical function for neural network.

4.2.2 Deeplearning4J

Deep Learning for Java (DL4J) is a robust, open-source distributed deep learning framework for the JVM created by Skymind [82], which has been contributed to the Eclipse Foundation and their Java ecosystem. DL4J is designed to be commercial-grade as well as open source, supporting Java and Scala APIs, operating in distributed environments, such as integrating with Apache Hadoop and Spark, and can import models from other deep learning frameworks (TensorFlow, Caffe, Theano) [83]. It also includes implementations of restricted Boltzmann machines, deep belief networks, deep stacked autoencoders, recursive neural networks, and more, which would need to be built from the ground up or through example code in many other platforms.

4.2.3 Theano

Theano is a highly popular deep learning platform designed primarily by academics which, unfortunately, is no longer supported after release 1.0.0 (November, 2017). Initiated in 2007, Theano is a Python library designed for performing mathematical operations on multi-dimensional arrays and to optimize code compilation [84], primarily for scientific research applications. More specifically, Theano was designed to surpass other Python libraries, like NumPy, in execution speed and stability optimizations, and computing symbolic graphs. Theano supports tensor operations, GPU computation, runs on Python 2 and 3, and supports parallelism via BLAS and SIMD support.

4.2.4 Torch

Torch is also a scientific computing framework; however, its focus is primarily on GPU accelerated computation. It is implemented in C and provides its own scripting language, LuaJIT, based on Lua. In addition, Torch is mainly supported on Mac OS X and Ubuntu 12C, while Windows implementations are not officially supported [85]. Nonetheless, implementations have been developed for iOS and Android mobile platforms. Much of the Torch documentation and implementations of various algorithms are community driven and hosted on GitHub. Despite the

GPU-centric implementation, a recent benchmarking study [86] demonstrated that Torch does not surpass the competition (CNTK, MXNet, Caffe) in single- or multi-GPU computation in any meaningful way, but is still ideal for certain types of networks.

4.2.5 Caffe and Caffe2

Caffe was designed by Berkeley AI Research (BAIR) and the Berkeley Vision and Learning Center (BVLC) at UC Berkeley to provide expressive architecture and GPU support for deep learning and primarily image classi_cation, originating in 2014 [87] [88]. Caffe is a pure C++ and CUDA library, which can also be operated in command line, Python, and MatLab interfaces. It runs on bare CUDA devices and mobile platforms, and has additionally been extended for use in the Apache Hadoop ecosystem with Spark, among others. Caffe2, as part of Facebook Research and Facebook Open Source, builds upon the original Caffe project, implementing an additional

Python API, supports Mac OS X, Windows, Linux, iOS, Android, and other build platforms [89]. **4.2.6 Keras**

Though not a deep learning framework on its own, Keras provides a high-level API that integrates with TensorFlow, Theano, and CNTK. The strength of Keras is the ability to rapidly prototype a deep learning design with a user-friendly, modular, and extensible interface. Keras operates on CPUs and GPUs, supports CNNs and RNNs, is developer-friendly, and can integrate other common machine learning packages, such as scikit-learn for Python [90]. In addition, it has been widely adopted by researchers and industry groups over the last year.

4.2.7 MXNET

Apache MXNet supports Python, R, Scala, Julia, C++, and Perl APIs, as well as the new Gluon

API, and supports both imperative and symbolic programming. The project began around Mid2015, with version 1.0.0 released in December of 2017. MXNet was intended to be scalable, and was designed from a systems perspective to reduce data loading and I/O complexity [91]. It has proven to be highly efficient primarily in single- and multi-GPU implementations, while CPU implementations are typically lacking [92].

4.2.8 Microsoft Cognitive Toolkit (CNTK)

The Microsoft Cognitive Toolkit, otherwise known as CNTK, began development in Mid-2015. It can be included as a library in Python, C#, and C++ programs, or be used as a standalone with its own scripting language, BrainScript. It can also run evaluation functions of models from Java code, and utilizes ONNX, an open-source neural network model format that allows transfer between other deep learning frameworks (Caffe2, PyTorch, MXNet) [93]. Conceptually, CNTK is designed to be easy-to-use and production-ready for use on large production scale data, and is supported on Linux and Windows. In CNTK, neural networks are considered as a series of computational steps via directed graphs, and both neural network building blocks and deeper libraries are provided. CNTK has emerged as a computationally powerful tool for machine learning with performance similar to other platforms that have seen longer development and more widespread use [92].

4.2.9 Performance Evaluation Metrics

To evaluate the effectiveness of our proposed solution, we use the mean absolute error (MAE), root-mean-square error (RMSE), and mean relative error (MRE) as the performance evaluation metrics. Root mean square error (RMSE) and mean absolute percentage error (MAPE) are the most commonly used performance measures. RMSE variants like Normalized RMSE(NRMSE) and RMSE with cost (RMSEC) have also been used. Performance measures like Mean Absolute

Relative Error(MARE), Equal Coefficient(EC), R square, Mean Square Error(MSE), Mean Relative Error(MRE), Accuracy and Variance Absolute Percentage Error(VAPE) are adopted in significant numbers but not nearly as much as the ones mentioned above Performance measures that are unconventional to the field of traffic forecasting like precision, recall, F1, FP rate, sensitivity and various others as well as custom performance measures proposed by authors, all together make up a significant amount of the total. This makes it harder to compare models between papers. Zilu Liang and Yasushi Wakahara suggested that that Symmetric MAPE be used instead of the widely adopted MAPE as MAPE yields a biased evaluation when real value is close to zero [94].

Chapter 5: Conclusion And Future Work

5.1 Conclusion

Intelligent Transport System (ITS) is a technology aimed to improve transportation safety and mobility. It increases citizens development by reducing damages of traffic flow in the city. ITSs are attracting researcher’s attention, because such systems not only improve vehicle traffic conditions, but can make the transportation sector safer, sustainable and efficient. Moreover, decrease inconveniences caused by traffic congestion in the city and the effect of climate change problem. Accurate traffic flow prediction is effective to improve congestion of traffic in the city. Short-term traffic flow prediction is very important aspect in intelligent transport system.

The primary objective of this work is to study on various models of traffic flow prediction so as to realize robust traffic flow prediction scheme in intelligent transport system by identifying various important factors that affect the performance of modeling traffic flow prediction.

From this study, applying deep learning model can effectively predicts the traffic flow in the city. To design traffic flow prediction, need to consider spatial and temporal features, which can capture more traffic data features. Hybrid deep learning network structures are also better to capture spatial temporal traffic information. Existing technologies, tools and approaches are studied. This study is used to know the appropriate approach to design robust traffic flow prediction architecture so as to characterize the dynamics of traffic.

Deep learning models are characterized by handling time series data. Deep learning models can learn periodicity of traffic flow data and ability of memorizing long-term dependencies. Spatial and temporal characteristics should be considered to produce accurate prediction model. Furthermore, to identify how to provide more accurate prediction, we analyze critical factors that affect traffic flow. Therefore, urban transport quality can be improved to effectively deploy intelligent transport system. This survey helps researchers to derive the essential characteristics of traffic flow prediction and identifies various techniques which are successful for traffic flow prediction. Generally, the manuscript covers relevant state-of-the-art machine learning and deep learning methods, which would help researchers to explore future directions.

5.2 Contribution

This work studies relevant methods and approaches how to produce robust traffic flow prediction.

State-of-art works are studied with respect to different traffic flow prediction techniques which would help researchers to explore future directions.

The factors that have impact on the performance of traffic flow prediction, development tools and bench mark performance evaluation metrics for the traffic flow prediction are studied.

Various machine learning and deep learning models for traffic flow prediction have been studied.

5.3 Future Work

Design a deep learning model for traffic flow prediction considering spatial temporal features from times series data.

There is no accurate traffic flow prediction yet which lacks accurate representation of traffics due to inability to effectively deal with spatial temporal features of times series data and needs extra investigation to have better prediction model which can predict traffic flow better. Therefore, as a solution, an approach is required to efficiently detect and identify the flow of traffic. Our next plan is to design hydride deep learning model for traffic flow prediction to have accurate traffic flow prediction that considers spatial temporal dependencies. Furthermore, Network Parameters optimization is also another challenge we will further explore in deep learning-based traffic flow prediction.

Abbreviations

ITS – Intelligent Transport System

ML-Machine Learning

DL-Deep Learning

ICT-Information and Communication Technology

ANN-Artificial Neural Network

CNN-Convolutional Neural Network

LSTM- Long Short-term Memory

RNNs- Recurrent Neural Networks

Declarations

Availability of data and materials-Not applicable

Competing interests-no competing interest

Funding- no funding

Authors' contributions-This work studies relevant methods and approaches how to produce robust traffic flow prediction. State-of-art works are studied with respect to different traffic flow prediction techniques which would help researchers to explore future directions. The factors that have impact on the performance of traffic flow prediction, development tools and bench mark performance evaluation metrics for the traffic flow prediction are studied. Various machine learning and deep learning models for traffic flow prediction have been studied.
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