Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Machine Learning for Traffic Flow Prediction and Management in Urban Civil Infrastructure

Dr. Rajesh Kumar[1]
[1]Assistant Professor, Department of Civil Engineering
Bakhtiyarpur College of Engineering, Bakhtiyarpur, Patna, Bihar, India

Reena Kumari[2]
[2]Assistant Professor, Department of Computer Science and Engineering
Bakhtiyarpur College of Engineering, Bakhtiyarpur, Patna, Bihar, India

Dr. Shashi Raj[3]
[3]Assistant Professor, Department of Computer Science and Engineering
Bakhtiyarpur College of Engineering, Bakhtiyarpur, Patna, Bihar, India

Neha Rani[4]
[4]Assistant Professor, Department of Civil Engineering
Government Engineering College, Bhojpur, Bihar, India

Rajnish Kumar Upadhyay[5]
[5]Assistant Professor, Department of Civil Engineering
Sershah Engineering College, Sasaram, Bihar, India

Abstract- One issue that all urban centres have in common is traffic congestion on the road networks. Comprehending the movement of traffic along road segments is imperative for generating workable remedies; yet, this is an expensive undertaking, particularly for developing nations. Based on historical traffic flow data, geometric data, and Google Distance Matrix API data, this study suggests a cost-effective method for a directional flow forecast model for metropolitan roads. The collected data was combined in time and space to serve as model estimation attributes. Devi- ating from classic probability estimates, a K- Nearest Neighbour regression method was utilised in the investigation. A test dataset was used to validate the model; the results indicated that the mean absolute error of prediction and the root mean square error were, respectively, 2.318 and 9.479. When the geometry of the road is known, lane flow can be estimated using the journey time and speed data obtained from the Google Distance matrix API.

Keywords— Google Distance Matrix, API, K- Nearest Neighbour Regression Method, Model Estimation.

INTRODUCTION

For traffic management and control systems, traffic flow is essential. Transport planners and policy makers will be able to plan and make decisions more effectively if traffic flow data for urban road networks is available. However, the collection of consistent traffic flow data for an urban road network in developing countries has been problematic due to budget gaps. The majority of affluent nations have access to flow data through embedded surveillance systems and traffic sensors in their road networks, which make poorer nations, choose to priorities this costly alternative. Traffic flow prediction has grown in importance as intelligent transportation technologies have advanced. The development of crowd sourced data mining has led to a phase-up of communication and detection procedures, making information on transit and mobility easier to extract. Because crowd sourcing makes it possible to continuously gather a huge number of data samples, its use has become more consistent and dependable. Reduced infrastructure investment leads to a low-cost alternative in the form of crowd sourced data, as these techniques rely on consumer services like phone calls, GPS navigation, retagged data transfer, and so on. Based on the aforementioned idea, the Google Distance Matrix API returns the journey time for a given origin and destination. Information and communication technology (ICT) is developing at a rapid pace, and with it, the idea of the "smart city," which aims to improve environmental sustainability, urban management, and citizen quality of life, is emerging. Cities must meet this demand from residents by offering improved services that improve the quality of everyday life. Cities have been offering more chances, but these have also brought up a number of difficulties that may affect citizens' day-to-day lives. At the forefront of this evolution has always been technology, which has profoundly altered our way of life over time. Our work, travel, social, and environmental interactions are being impacted by digital data and connected worlds of physical objects, people, and technology. Numerous application fields, including control and management applications, urban systems, environmental monitoring, transportation, and healthcare, are significantly impacted by this. By lessening the detrimental consequences of traffic in the city, the Intelligent Transport System (ITS) technology seeks to increase citizen development while also enhancing mobility and safety in transportation. Researchers in the United States (US) first introduced the idea of ITS in the twentieth century. But because these systems not only enhance vehicle performance but also have the potential to increase transportation sector safety, sustainability, and efficiency, ITSs are currently garnering a lot of interest from both academics and business. Consequently, intelligent transport systems are a component of vehicular networks that can be used for traffic flow prediction in the context of smart cities. Therefore, we can define intelligent transport systems (ITS) as internet of things (IOT)-based applications for smart cities, and traffic flow prediction has applicability in the field of ITS. More individuals have moved to metropolitan regions while rural depopulation has occurred in recent decades. By 2020, cities accounted for the centre of life for almost 56% of the world's population. Furthermore, projections indicate that by 2050, the population of 4.4 billion will have about doubled (The World Bank, 2020). The number of people living in close quarters in urban regions is correlated with an increase in the need for housing, infrastructure for basic services, healthcare, employment possibilities, and mobility. The infrastructure that is now in place is under a lot of strain, particularly from the need to provide practical and effective transit systems. Furthermore, not every kind of urban transit is sustainable. The most environmentally friendly options walking, cycling, and public transportation are not usually the most popular ones, according to an analysis of modal shares the proportion of people who use a given mode of transportation in a number of cities. For instance, reputable rankings list Vienna, Austria, as one of the world's most livable cities. When examining Vienna's modal share from 2014 to 2019, the data shows that 38% of all journeys were made on average using public transit, with walking and cycling coming in second and third, respectively. Despite the fact that this suggests a high level of acceptance for sustainable transportation, personal motorized cars accounted for 28% of all journeys (Heller, 2021).

LITERATURE REVIEW

Greenshield made the assumption that a linear speed-density relation would be represented by a parabolic flow-density relation in 1936. Transport experts improved on that by creating various mathematical models for continuous traffic flow that took into account both macroscopic and microscopic traffic flow characteristics. The detailed driver behavior models used in microscopic traffic simulators (e.g., MITSIMLab, AIMSUN,VISSIM) include lane-changing, gap-acceptance, car-following, and other disaggregate behavioral models. Using microscopic simulations is challenging in developing nations because of the varied character of current traffic and the difficulty in gathering data. The percentage of motorized two- and three-wheelers in developing countries' vehicle fleet is larger than that of four-wheelers. Because of this, the characteristics of traffic flow differ greatly from those of developed nations, where over 80% of vehicles are used for transportation. Additionally, it was noted that emerging nations had a large number of two-lane roadways. In two-lane roadways lane changing and passing man oeuvres typically performed when sight distance and gaps being available in the opposing traffic stream. As a result, when characterizing directional flow, one must take into account how opposite flow influences the directional flow. Chandra has observed that road width, shoulder width, and directional split are significantly affected on the free flow speed and capacity of two-lane highways. Furthermore, the temporal fluctuation of traffic flow is ignored by traditional methods of traffic flow analysis. While accidental analyses are feasible, using the conventional technique to examine long-term behavior is difficult. In order to include spatiotemporal characteristics in traffic flow prediction, researchers looked at time series analysis and machine learning methods. Deep learning is currently gaining popularity as a crucial method in the field of artificial intelligence that is used in many application domains. Deep learning techniques are being used by researchers worldwide to solve issues in a variety of application domains. The most significant application that deep learning can offer among those many application areas is traffic flow prediction modeling. It provides an overview of intelligent transport systems and the models used to estimate traffic flow in these systems, which have been developed thus far using various methodologies. The necessity of traffic flow prediction has led to the proposal of numerous models for this data.

Short-Term Traffic Flow Prediction Based on Online Sequential Extreme Learning Machine was proposed by Z. Ma et al. It is an adaptive prediction model built on the On-line Sequential Extreme Learning Machine (ELM) with Forgetting Mechanism variation of the Extreme Learning Machine (ELM). This model can adjust to changes in real time and update itself based on incoming input. Nevertheless, practical limits are found, such as the need for a large number of neurons and a big dataset size for initialization. Another plan incorporating network rebuilding and sequential updating is put up to increase the applicability.

A machine learning-based approach was proposed by Z. Bartlet et al. for the prediction of road traffic flow on urbanized arterial roads. Urbanized arterial roads are utilized for transportation of products and for connecting geographically significant places. To help reduce traffic flow congestion, it is essential to predict the flow of traffic on these highways. In this study, they used real datasets and machine learning models to anticipate traffic congestion on urbanized arterial roads.

MACHINE LEARNING FOR TRAFFIC FLOW PREDICTION

Machine learning is stochastic and non-linear; using its principles to estimate traffic flow has become an optimistic strategy. Three more general categories of models linear parametric models, non-linear parametric models, and non-linear non-parametric models could be distinguished among the models used to estimate traffic flow in the literature. The Kalman filter model, time series prediction models, exponential filtering models, historical average prediction models, and exponential filtering models are quite common when evaluating linear parametric models. Researchers that study the non-linear parametric behavior of traffic flow have used models based on wavelet analysis, cellular automata, fuzzy regression, and models based on catastrophe theory. However, because of their linearity and parametric approach, the aforementioned approaches' weaknesses led to poor traffic flow prediction performance. As a result, the researchers have concentrated on machine learning-based non-linear non-parametric techniques. In this regard, it was possible to see the use of the k-nearest neighbor regression model, the random forest regression model, the support vector regression model, the Gaussian process regression model, and the models based on artificial neural networks. With the quick development and implementation of intelligent transportation systems, traffic flow prediction has drawn increased attention (ITSs). It is recognized as a vital aspect for the successful deployment of ITS subsystems, particularly advanced traveler information systems, advanced traffic management systems, advanced public transit systems, and commercial vehicle operations. The autoregressive integrated moving average (ARIMA) model is used to predict short-term motorway traffic flow based on the research that has been conducted thus far. Subsequently, a wide range of models for the prediction of traffic flow have been put forth by scholars in several fields, including transportation engineering, statistics, machine learning, control engineering, and economics. Numerous studies have been conducted on traffic flow prediction techniques, which can be broadly classified into three groups: parametric, non-parametric, and simulation-based models. Time-series models, Kalman filtering models, and other models are examples of parametric models. Support Vector Regression (SVR) techniques, Artificial Neural Networks (ANNs), and other models are examples of non-parametric models. Traffic simulation tools are used in simulation-based methodologies to forecast traffic flow. In order to predict the flow of traffic on motorways, Levin and Tsao used Box-Jenkins time-series analyses. They discovered that the ARIMA (0, 1, 1) model was the most statistically significant for all forecasts.

MACHINE LEARNING IN TRAFFIC MANAGEMENT IN URBAN CIVIL INFRASTRUCTURE

In order to accomplish control, prediction, or classification tasks, machine learning entails discovering patterns in unprocessed data (Bengio et al., 2017). There are many different models in the field of machine learning that can be used to solve different types of problems. The most important thing to remember is to distinguish between supervised, semi-supervised, and unsupervised learning tasks. The foundation of supervised learning is a labelled data collection. As a result, the data set contains known input and output. Tasks using partially labelled data that is, where not all outputs are available for pattern recognition are referred to as semi-supervised learning tasks. Lastly, tasks involving unsupervised learning deal with data sets that lack labels. Moreover, the nature of the data permits a further distinction between machine learning jobs. The literature makes a distinction between difficulties involving clustering, regression, and classification in this context (Campesato, 2020). To identify a car or a bike on a given image is an example of a transportation classification problem in its most basic form, where the labels are represented as categories. The data set that addresses this binary classification problem has two labels, such as label 0 for a car and label 1 for a bike. Data sets including several categories can be used to train classification models; they are not restricted to binary representations (see to publications like Gupte et al., 2002; Boukerche et al., 2017).Regression problems, on the other hand, are learning challenges in which continuous values constitute the label. For instance, traffic dynamics are learned from input data and appropriate labels to estimate traffic flow or trip times in the upcoming hour (e.g., Smith and Demetsky, 1994; Xu and Jiang, 2020; Kwon et al., 2000). Finally, when a data collection does not contain labels, one of the most famous strategies is clustering e.g., finding clusters of macroscopic traffic patterns (Ambühl et al., 2021). Linear regression (LR), logistic regression, random forest (RF), support vector machines (SVM), gradient boosting techniques, and artificial neural networks are popular examples of these machine learning models. Neural networks of many forms, including Multi-Layer Perceptrons (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short Term Memory (LSTM) neural networks, have been proposed over time. Furthermore, newer studies mix many designs to create model ensembles that perform better than standalone systems. Keep in mind that this is not a comprehensive list and that new techniques are being created all the time to replace outdated ones. It is important to remember about other subfields in transportation, such reinforcement learning, which has also received recent attention. Additionally, machine learning approaches have been applied to the management of traffic in urban perimeters/corridors in order to: (a) directly estimate or predict traffic variables like flow, speed, or journey durations; or (b) perform data fusion to estimate the traffic state or corresponding variables. Yao et al. (2017), for instance, use SVM models to estimate speed in an urban corridor over the short term. These models' effectiveness is evaluated in comparison to GPS data obtained from taxis. An additional study by Polson and Sokolov (2017) forecasts traffic flow at various points along an urban corridor. The work uses an attention model in conjunction with deep neural networks to determine the importance of the input. Performance is evaluated in comparison to open-source database loop detector data.

DEVELOPMENT TOOLS

The Deep Learning Platform offers an interface that makes it simple to construct deep learning architectures using pre-built, optimised libraries or components. A decent deep learning platform should include a number of important features, including automatic gradient computations, parallelization, easy coding, minimal computations, and optimised performance. Prominent corporations like Google, Microsoft, Nvidia, and Amazon are heavily investing in the development of deep learning platforms that utilise Graphic Processing Units (GPUs) to expedite large-scale computations. TensorFlow is the most popular and frequently utilised platform among users among all of the ones that are currently in use, which is why we are using it for our research.

(i) TensorFlow- The Google Brain Team unveiled this platform around the end of 2015. The languages that it supports, including Python, C++, R, and Java, contribute to the tool's popularity. Moreover, it enables excellent data scalability while working with one or more CPUs and GPUs. TensorFlow can therefore be trusted by an individual with a tablet or by a large-scale distributed system. Nonetheless, researchers recommended using server-grade multi-thread implementation of TensorFlow. it treats any model as a directed acyclic graph (DAG), in which the edges represent multi-dimensional arrays known as tensors between the nodes, which represent mathematical operations. TensorFlow is used in a variety of applications, including object detection, time-series analysis, voice recognition, video analysis, and distribution visualisation. Additionally, TensorFlow facilitates distributed training, offers mobile users reduced latency, and integrates with SQL tables with ease. TensorFlow's features, such as its substantial built-in support for deep learning and mathematical function for neural networks, make it more appropriate for the majority of deep learning models.

(ii) Deeplearning4J- Developed by Skymind, Deep Learning for Java (DL4J) is a feature-rich, open-source distributed deep learning framework for the JVM that has been integrated into the Java ecosystem by the Eclipse Foundation. With support for Java and Scala APIs, DL4J is intended to be both open source and commercial-grade. It can function in distributed environments by connecting with other deep learning frameworks like TensorFlow, Caffe, and Theano, and it can import models from these and other platforms. Restricted Boltzmann machines, deep belief networks, deep stacking autoencoders, recursive neural networks, and other implementations are also included. In many other platforms, these implementations would need to be created from scratch or via sample code.

(iii) Theano- Sadly, Theano, a well-liked deep learning platform created mostly by academics, is no longer supported as of version 1.0.0 (November, 2017). Theano is a Python library that was started in 2007 with the primary goal of assisting scientific research applications. It is designed to optimise code compilation and execute mathematical operations on multi-dimensional arrays. More specifically, Theano was made to outperform existing Python libraries, such as NumPy, in terms of creating symbolic graphs and optimising execution speed and stability. Theano offers tensor operations, GPU computation, operates on Python 2 and 3, and supports parallelism via BLAS and SIMD support.

(iv)Torch- Another framework for scientific computing, Torch focuses mostly on GPU-accelerated computation. It is written in C and offers LuaJIT, a scripting language derived from Lua. Additionally, Windows implementations of Torch are not officially maintained; instead, it is mostly supported on Mac OS X and Ubuntu 12C. However, applications for the iOS and Android mobile platforms have been created. A large portion of the Torch documentation and different algorithm implementations are community-driven and available on GitHub. A recent benchmarking research showed that, despite its GPU-centric implementation, Torch is still best suited for several network types but does not significantly outperform the competition (CNTK, MXNet, and Caffe) in single- or multi-GPU computing.

(v) Caffe and Caffe2- Caffe was built by Berkeley AI Research (BAIR) and the Berkeley Vision and Learning Centre (BVLC) at UC Berkeley to provide expressive architecture and GPU support for deep learning and especially image classification, originating in 2014. Caffe is a pure C + + and CUDA library, which may also be operated in command line, Python, and MatLab interfaces. It is compatible with mobile platforms and bare CUDA devices. It has also been expanded to work with Spark in the Apache Hadoop environment. Building upon the original Caffe project, Caffe2 is a component of Facebook Research and Facebook Open Source. It supports a number of build platforms, including Mac OS X, Windows, Linux, iOS, and Android, and it implements an extra Python API.

CONCLUSION

The application of machine learning concepts to traffic flow prediction on urban two-lane roadways has proven successful. The study assesses the application of the non-linear non-parametric methodology for flow prediction, departing from conventional ways of linear parametric approaches. Using spatiotemporal inputs, the study creates a traffic flow estimation model based on K-Nearest Neighbor regression. The model uses road geometry data and travel time and speed data from the Google Distance Matrix API as inputs. With a linear correlation of 0.97, K-Nearest Neighbor regression was able to provide a greater prediction accuracy. At K = 3 neighbors, the prediction error was at its lowest. The N-Fold cross-validation approach was u The Intelligent Transport System (ITS) is a system designed to increase mobility and safety in transport. It improves citizen development by lessening the negative effects of city traffic flow. Researchers are interested in ITSs because they can make transportation safer, more sustainable, and effective in addition to improving traffic conditions for cars. Reduce the annoyances brought on by the city's traffic jams and the effects of the climate change issue. Reducing traffic congestion in the city can be accomplished with accurate traffic flow prediction. Predicting short-term traffic flow is a crucial component of intelligent transportation systems.

REFERENCES

[1]. Dai, X., Fu, R., Lin, Y., et al.: DeepTrend: A Deep Hierarchical Neural Network for Traffic Flow Prediction (2017).

[2]. Japan International Cooperation Agency; Oriental Consultants Co., LTD. Urban Transport System Development Project For Colombo Metropolitan Region.

[3]. Amini, S., Gerostathopoulos, I., Prehofer, C.: Big Data Analytics Architecture for Real-Time Traffic Control.

[4]. Chatzimilioudis, G., Konstantinidis, A., Laoudias, C., Zeinalipour-yazti, D.: Crowdsourcing with smartphones. IEEE Internet Comput. 16(5), 1–7 (2012).

[5]. M. O. K. Yamamoto T., "Ocial web site of vehicle information and communication system (VICS), https://trid.trb.org/view/574444," Japan, 2017.

[6]. K. Osama Mohammed, "A Machine Learning Approach to Short-Term Trac Flow Prediction: A Case Study of Interstate 64 in Missouri," IEEE International Smart Cities Conference (ISC2), 04 March 2019.

[7]. Y. a. Y. L. M. Chen, "Mining moving patterns for predicting next location," Inf. Syst., vol. 54, p. 156– 168, Dec. 2015.

[8]. Z. X. Y. a. S. V. U. X. Zhan, "Citywide trac volume estimation using trajectory data," IEEE Trans. Knowl. Data Eng., Vols. 29, no. 2, p. 272–285, Feb. 2017.

[9]. X. L. J. J. J. O. a. L. S. Y. Tan, "A study of best practices in promoting sustainable urbanization in China," J. Environ. Manage.," vol. 193, p. 8–18, May 2017.

[10]. S. F. G. Z. Y. a. B. Y. B. Yu, "k-nearest neighbor model for multiple-time-step prediction of shortterm trac condition," J. Transp. Eng. , Vols. 142, no. 6, 2016.

[11]. A. a. E. K. E. Ko, "3D Markov process for trac ow prediction in real-time Sensors," Vols. 16, no. 2, 2016.

[12]. J. a. S. Sun, "Neural network multitask learning for trac ow forecasting," in in Proc. IEEE Int. Joint Conf. Neural Netw. (IJCNN), Jun. 2008.

[13]. Chen, "Research on trac ow prediction in the big data environment based on the improved RBF neural network," IEEE Trans. Ind. Informat, Vols. 13, no. 4, p. 2000–2008, Aug. 2017.

[14]. S. H. H. a. K. X. W. Huang, "Deep architecture for trac ow prediction: Deep belief networks with multitask learning," IEEE Trans. Intell. Transp. Syst., Vols. 15, no. 5, p. 2191–2201, Oct. 2014.

[15]. D. W. K. Z. L. a. F.-Y. W. Y. Lv, "Trac ow prediction with big data: A deep learning approach," IEEE Trans. Intell. Transp. Syst., Vols. 16, no. 2 , p. 865–873, Apr. 2015.

[16]. L. Y.-L. L. a. F. W. Y. Duan, "An ecient realization of deep learning for trac data imputation," Transp. Res. C, Emerg. Technol., vol. 72, p. 168–181, Nov. 2016.