

Comprehensive Approaches to Traffic Flow Prediction

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Abstract. Intelligent transportation systems require traffic flow prediction, and anomaly detection is the key to ensuring accuracy. Using traditional statistical models to handle complex traffic scenarios is becoming increasingly challenging as urbanization accelerates. Consequently, to enhance the precision of forecasting traffic flow and detecting anomalies, various deep learning techniques, and emerging methods have been introduced. The purpose of this paper is to examine how traditional and deep learning methods, as well as emerging technologies, can be used to predict traffic flow and detect anomalies, including techniques such as the autoregressive integrated moving average model (ARIMA), K-nearest neighbor (KNN) algorithm and convolutional neural network (CNN). The result shows that emerging technologies can improve system performance in multiple traffic environments by accurately extracting features from complex data. The research of this paper provides a theoretical basis for the traffic management department and helps to realize a safer and more efficient advanced transportation system.

Keywords: Traffic flow prediction, Traditional methods, Anomaly detection, Emerging approaches.

1. Introduction

The urban population is growing at an annual rate of 1.8% due to the ongoing acceleration of global urbanization [1], so the use of urban vehicles is placing an increasing burden on transportation systems. Urban governance in various countries is faced with many problems such as inefficient public transportation systems, frequent accidents, and increased greenhouse gas emissions, which seriously affect the travel efficiency and quality of life of residents, and bring challenges to the sustainable development of cities [2]. Therefore, accurate traffic flow prediction is considered a key factor in solving these difficulties. Through traffic forecasting, urban traffic management departments can implement early intervention measures to help the public make more reasonable travel choices, thereby reducing the pressure on the transportation system and improving travel experience and satisfaction.

Traffic flow forecasting methods have significantly changed in recent years as a result of the continual improvement of data monitoring technology and the advancement of science and technology. Traditional statistical methods used to be an important part of traffic flow prediction, but They have gradually been eliminated due to limitations such as the insufficient ability to capture complex nonlinear relations. Deep learning methods and a series of emerging methods, with their powerful feature learning capabilities and adaptability to massive data, have brought new opportunities to the field of traffic flow prediction and anomaly detection, demonstrating significant advantages.

The paper offers a comprehensive analysis of the impact of traditional methods and deep learning methods on various traffic flow prediction problems. Specifically, this article will explain from the following perspectives: Firstly, this paper analyzes the performance of different models in traffic flow prediction and discusses the advantages and limitations of traditional methods and deep learning methods in this problem; Secondly, explores how emerging methods can improve the conventional models and deep learning approaches to enhance the accuracy of traffic flow forecasting; Finally, the application of traditional methods, deep learning methods and emerging technologies in anomaly detection techniques is evaluated. These discussions could provide important references and guidance for research and practice in related fields.

2. Traffic-flow prediction

Traffic flow prediction constitutes a critical element in the domains of traffic system design, traffic regulation, and the management of intelligent vehicle systems [3], which usually refers to the estimation of vehicle flow or traffic conditions on roads during a specific period in the future. It can assist relevant personnel in corresponding traffic management and traffic control, and also help travelers make more convenient choices. Consequently, traffic flow prediction is a significant area of study within the discipline of traffic engineering. This research domain has evolved from traditional statistical approaches to the adoption of machine learning and deep learning methodologies, thereby developing a range of effective predictive models.

2.1. Traditional methods

Initial traffic flow forecasting utilizing conventional techniques predominantly depended on established statistical approaches, including the ARIMA model, seasonal time series models, exponential smoothing models, and linear regression models [4]. These methods extract trends and seasonal features from historical traffic flow data through time series analysis. Among them, the Kalman filter and integrated autoregressive moving average are the most studied statistical techniques for predicting time series data. Pavlyuk [5] made use of the assumptions of the ARIMA model, space-time model, multi-spatial state model, and other model specifications to predict the traffic of small sections, and found that ARIMA could flexibly understand the operation mode of traffic and the flow relationship between adjacent locations and roads. Emami et al. [6] employed the Kalman filtering algorithm to forecast traffic flow near intersections in the context of connected vehicles. The research results showed that when the penetration rate exceeded 20%, the performance of the Kalman filter was good. Many experiments have confirmed that ARIMA models have good predictive performance for random traffic flow, but their ability to handle nonlinear and complex patterns is limited [7]. For example, ARIMA models typically assume that the data is stationary, which often does not hold in actual traffic flow data. In addition, traditional methods have high data requirements, especially in cases where the amount of data is insufficient or there are missing values, and the prediction performance will significantly decrease. Therefore, the emphasis in traffic flow prediction research is progressively transitioning from conventional statistical learning approaches to deep learning methodologies.

2.2. Deep learning methods

The core idea of deep learning methods is to automatically extract effective features from large amounts of data by building deep neural networks, thereby improving the accuracy and efficiency of predictions. Feature learning no longer requires manually providing created features, they will automatically learn other complex features [8]. Deep learning is an artificial intelligence paradigm that has sparked great interest in academia and demonstrated greater potential than traditional statistical learning prediction methods. A deep belief network (DBN) represents an early methodology in deep learning that has been employed for the prediction of traffic flow. Huang et al. [9] used a stacked restricted Boltzmann machine for greedy layer-by-layer training, followed by fine-tuning to achieve unsupervised feature learning of DBN. When traffic flow is low, the predicted results of DBN may not be able to keep up with fluctuations in the number of vehicles. However, during peak periods of high traffic flow, DBN's

predictions match the actual flow very well, indicating that DBN can effectively learn the patterns of the transportation system and demonstrate potential in predicting during peak periods. Deep learning architectures, such as long short-term memory networks (LSTM) and convolutional neural networks (CNN) have also been used to anticipate traffic flow. Yang et al. [10] proposed LSTM+, which can flexibly capture time dependence in data and memorize long-term and short-term timing information, thereby improving the accuracy of prediction. Zhao et al. [11] utilized a Temporal Convolutional Network (TCN) architecture characterized by causal convolution and a one-dimensional fully convolutional network structure to forecast traffic flow. They also added dilated convolution and residual layers to the TCN model, which properly projected the total number of cars at the intersection for the following 15 minutes based on past traffic flow data sequences. The advantage of deep learning models is that they can automatically extract key features from complex data, thus reducing the need for manual feature engineering and achieving more efficient operation. Furthermore, deep learning approaches can manage big datasets, are highly adaptable, and can produce accurate predictions in a variety of traffic scenarios. However, the overfitting problem caused by the complexity of the model and the sensitivity to the parameter threshold range will affect the prediction effect of the deep learning method, resulting in prediction errors. As a result, hybrid models and more advanced technologies are being investigated.

2.3. Emerging methods

The study discovered that by combining multiple deep learning models, the advantages of each model in different aspects can be fully utilized to improve the overall prediction performance. For example, the combination of deep learning methods such as CNN and LSTM, particle swarm optimization (PSO), and bidirectional long- short-term memory (Bi LSTM) could improve the performance of predictive models. Bharti et al. [12] combined PSO and Bi LSTM to create the PSO-BI LSTM model. The Bi LSTM model is used to capture contextual information over time and is paired with PSO to produce more accurate traffic flow predictions. After examining traffic flow data from the inner ring road in India, it was discovered that the model can reliably estimate traffic flow under various scenarios. Gu et al. [13] created an improved Bayesian deep learning combination model (IBCM-DL) that incorporates three types of sub-predictors: ARIMA, recurrent unit neural networks (GRUNN), and radial basis function neural networks (RBFNN). ARIMA and RBFNN are used to efficiently handle seasonal changes and trend analysis, while GRU-NN can handle missing data and adapt to dynamic changes. The actual traffic statistics of the Beijing expressway show that the model has better performance and more accurate results. Furthermore, researchers should include the robustness, interpretability and generalization ability of various emerging models as one of the important test criteria, so as to make more accurate traffic flow prediction through multi-faceted evaluation.

3. Anomaly detection in traffic flow prediction

Traffic data is typically collected by sensors, such as ultrasonic sensors, infrared detectors, and satellite positioning systems for traffic flow prediction. However, these data are often subject to the influence of inaccuracies, incompleteness, and outlier values. Therefore, data cleaning must be carried out before data analysis, and the identification of outliers constitutes a crucial component of the data cleaning process. In traffic flow forecasting, anomaly recognition is used to identify traffic events or data points that are significantly different from normal traffic patterns. These anomalies may arise from a multitude of factors, including traffic congestion, vehicle malfunctions, and emergency situations. If these abnormal events are not identified promptly or significant outliers are removed from the data, the accuracy of the predictive model may decline, thereby affecting the decision-maker of the relevant authorities. Therefore, the implementation of an effective anomaly detection method is crucial for enhancing the performance of traffic flow prediction models.

3.1. Traditional methods

The early methods of anomaly detection are mainly based on the statistical principle [14]. A statistical model of typical traffic patterns is developed by calculating the mean and standard deviation of traffic using historical data. This approach facilitates the establishment of thresholds for the identification of outliers. Common statistical methods include the box-whisk method, extreme student deviation test (ESD), and Grubbs test. Among them, the core idea of the Grubbs test is to set a strict critical value for the recognition of outliers by determining the significance level and reducing the possibility of wrong discrimination. Wu et al. [15] employed the Grubbs test methodology to identify anomalous passenger flow patterns during the closure of subway stations. The findings from the experiments indicate that, compared with other algorithms, the Grubbs test has a more accurate ability to identify stations and passenger flow affected by subway station closure, and can provide more targeted adjustment strategies and passenger flow guidance schemes for subway operation. In addition, the seasonal autoregressive integral moving average (SARIMA) model and KNN algorithm are also widely used in univariate time series anomaly detection. Almeida et al. [16] used the SARIMA model for anomaly detection and observed that the SARIMA model was superior to the ANN model. However, the SARIMA model also suffers from the drawback of needing to be retrained every hour to improve accuracy. Djenouri et al. [17] extended the KNN algorithm to flexible data placement (FDP) to detect outliers in the probability of traffic flow distribution. The model calculates the distance between the new traffic distribution probability and each FDP in the historical database to determine whether the newly observed traffic distribution probability is an outlier. Compared with existing algorithms such as the Dirichlet process mixture model (DPMM) and principal component analysis (PCA), KNN FDP shows better performance in processing large urban traffic flow data. However, statistical models typically assume that data follows a specific distribution (such as a normal distribution), and the model's fit may be significantly affected by outliers, which could cause a reduction in its performance. Moreover, the strong spatiotemporal dynamics of traffic flow data make it difficult to adapt traditional methods. This leads to a decrease in model accuracy, particularly in real-time or near-real-time anomaly detection scenarios.

3.2. Deep learning methods

Deep learning techniques have increasingly garnered interest in the field of anomaly detection, attributed to the growing volume of data and advancements in computational capabilities. In the context of traffic analysis, CNN and LSTM have become the two most effective deep learning architectures. CNN, due to its expertise in processing spatial information, has become an ideal tool for analyzing traffic camera or satellite image data, and detecting traffic congestion and road anomalies. The purpose of its design is to imitate the human visual cortex and recognize visual patterns, such as the density of vehicles or irregular surface conditions on roads. Khan et al. [18] constructed a CNN model using the Keras library and evaluated the trained model on 30 test videos. The test dataset showed a model accuracy of around 82%. As a result, the proposed CNN-based deep learning model can effectively detect abnormal events like traffic accidents from traffic flow, resulting in better predicting future traffic conditions. Zhu et al. [19] also use CNN to detect abnormal situations in traffic flow, such as traffic jams, illegal parking, and sudden natural disasters, with remarkable recognition effect and high efficiency. For LSTM, when there is a significant difference between real-time traffic data and LSTM forecast data, LSTM can adjust the parameters of the model to better adapt to the current data trend, thus improving the adaptability of subsequent forecasts. Tian et al. [20] proposed an improved LSTM model that integrated the traffic prediction technology for dealing with missing data, which could more accurately deal with the traffic flow lacking data. Fitters et al. [21] proposed outlier-enriched LSTM (OE-LSTM). Through the application of spatiotemporal correlation analysis, this methodology is capable of identifying outliers within traffic flow data and assessing the interrelationships among them. The experimental findings indicate that the OE-LSTM framework demonstrates efficacy in traffic flow datasets. However, deep learning models may exhibit a high degree of accuracy on certain data sets, but their adaptability may be limited when faced with diverse traffic scenarios or different environmental conditions, and the model

may be sensitive to certain types of anomalies while ignoring others. Therefore, researchers are developing transfer learning or multi-model fusion strategies to address the aforementioned issues.

3.3. *Emerging methods*

With the development of technology, new anomaly detection methods continue to emerge. The latest student teams-achievement divisions (STAD) method proposed by Yin et al. [22] uses a unique sampling method and a detection algorithm based on a twin multilayer perceptron, enabling STAD to extract a small but representative sample from each category. These samples were subsequently used to train a twin multilayer perceptron model to effectively distinguish between normal and abnormal traffic. The results showed that STAD maintains an accuracy and detection rate of more than 95% in anomaly detection. He et al. [23] proposed a combination model, which combined the LSTM model and Q-learning algorithm to build an agent. This algorithm can self-learn, so that it can adapt to the actual situation more flexibly, and improve the ability to detect abnormal data. According to the experimental results, the model performs better than other models in various parameter configurations, with an accuracy close to 90%. Michau et al. [24] proposed an innovative unsupervised transfer learning (UTL) method for fault detection in industry. The purpose of this model is to mine the common structure between data sets for cluster analysis or dimensionality reduction. Empirical findings indicate that the proposed methodology is capable of effectively detecting anomalies that were not present during the training phase. In order to enhance the precision of anomaly extraction, it is essential to identify distinct spatiotemporal characteristics of traffic anomalies, thereby facilitating anomaly detection from a data-driven standpoint.

4. Conclusions

The management of traffic flow is gaining significance in light of rapid urbanization and the rising demand for transportation. It is essential for fostering sustainable development and enhancing the quality of life for urban residents. The efficient operation of urban traffic systems is closely related to the accuracy of traffic flow prediction. Advanced prediction model plays an essential part for building accurate traffic flow prediction and anomaly detection system. Deep learning models show the ability to efficiently identify complex dynamic characteristics of traffic flow in several studies. However, the majority of the contributions are centered on the application level, and there is a lack of theoretical depth. Thus, the development path of traffic flow prediction may be hampered by the use of only deep learning models. This has prompted researchers to gradually explore the effectiveness of hybrid models and unsupervised methods. This study presents an analysis of the benefits and drawbacks associated with conventional statistical techniques. A range of contemporary deep learning architectures and their applications in traffic flow prediction and anomaly detection are further described. In addition, the paper examines the growing trend of hybrid methodologies that is gaining more popularity. With the continuous evolution of artificial intelligence algorithms, adaptive and intelligent decision support systems should be developed by researchers to achieve more flexible traffic management and efficient resource allocation, thereby better addressing future transportation challenges.

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