Application Research on Smart City Traffic Management System Based on Deep Learning Algorithm

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Abstract. This study is aimed at addressing key challenges in smart city traffic management systems: traffic flow prediction and congestion point identification, through the development of a deep learning model that integrates Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Graph Neural Networks (GNN). The focus of the research was on collecting and preprocessing a large traffic dataset, including traffic camera images, vehicle movement trajectories, and city traffic network information, to train and validate the proposed model. Key findings demonstrate significant performance improvements of the model in traffic flow prediction and congestion point identification tasks over traditional models like ARIMA, as evidenced by higher accuracy, recall, and F1 scores. Furthermore, through generalization capability testing, this study confirmed the model's exceptional adaptability, effectively handling traffic data across different cities and time periods. The key conclusion of this research is that deep learning technology can significantly enhance the accuracy and efficiency of smart city traffic management, providing robust data support for urban traffic planning and scheduling. This discovery lays a foundation for further exploration of deep learning applications in the smart city domain.

keywords: Smart city; Traffic flow prediction; Congestion point identification; Deep learning; Convolutional neural network

1 INTRODUCTION

As global urbanization progresses at an unprecedented pace, cities worldwide are increasingly grappling with challenges such as traffic congestion, environmental pollution, and the uneven distribution of resources. At the heart of the smart city concept is the optimization of urban functions and services, aiming to enhance public service efficiency, improve residents' quality of life, and ensure urban sustainability [1]. Within this framework, the information management system serves as both the foundation and the critical component, enabling the intelligent orchestration of city management and services through the aggregation and analysis of vast amounts of urban operational data.

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Particularly in traffic management, the surge in vehicle numbers has rendered traditional approaches increasingly ineffective, unable to satisfy the growing demand for dynamic, adaptive, and efficient management solutions. Against this backdrop, deep learning technology, with its robust data processing and analytical prowess, has emerged as a pivotal tool in refining smart city traffic management systems [2]. By learning intricate patterns within extensive traffic datasets, deep learning algorithms offer enhanced prediction accuracy and decision-making support, significantly improving traffic flow control, accident prevention, and congestion mitigation.

However, despite the potential of deep learning in transforming urban traffic management, current research often falls short in fully exploiting its capabilities, primarily focusing on isolated aspects of traffic systems without a comprehensive integration strategy. This study distinguishes itself by holistically examining the role of deep learning algorithms within the broader smart city traffic management ecosystem. It delves into the practical application of these algorithms in processing and analyzing traffic data, and the subsequent development of automated decision support systems. Our research aims to bridge the gap between theoretical potential and practical application, offering innovative, efficient, and intelligent solutions for contemporary urban traffic challenges, thereby contributing significantly to the advancement of the smart city traffic management domain.

2 LITERATURE REVIEW

2.1 Deep Learning

Deep learning is able to learn complex data representations and abstract concepts by constructing and training multi-layer neural networks, effectively solving many problems that are difficult to overcome by traditional algorithms. Especially in the fields of image recognition, natural language processing, and autonomous driving, deep learning technology has realized revolutionary progress. Among the many deep learning models, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are two of the most common and widely used models. CNN effectively processes image and video data by simulating the workings of the mammalian visual cortex, and is able to recognize various visual patterns in an image, and thus is widely used in the fields of image processing and video analysis. In contrast, RNNs are designed to process sequential data and are able to capture the flow of information in time-series data through their unique cyclic connectivity structure, making them useful in areas such as speech recognition and natural language processing [3].

Deep learning provides new perspectives and methods for data analysis by automatically learning complex feature representations from massive data with deep learning models. In the traffic management system of smart cities, CNN can be used to analyze real-time traffic flow video data, while RNN can predict future traffic changes based on historical traffic data [4]. Meanwhile, the application of GNN can help understand the complex spatial relationships between urban traffic networks, optimize traffic flow and reduce congestion. The combined application of these deep learning models not only enhances the intelligence level of the traffic management system, but also provides an effective decision support tool for urban traffic planning and management.

2.2 Deep Learning Applied in Smart Cities

With the acceleration of urbanization, deep learning plays an increasingly important role in several aspects of smart cities, especially in traffic management systems, where its application has become a hotspot for research and practice. In the field of traffic monitoring and management, deep learning techniques are able to automatically detect and classify road users, such as pedestrians, bicycles, and various types of vehicles, by analyzing real-time video streams from cameras, enabling real-time traffic flow monitoring and accident detection [5]. In addition, deep learning models are able to predict traffic flow and congestion patterns based on historical data, providing data support for traffic planning and control [6]. For example, the use of convolutional neural networks (CNN) to analyze images of traffic conditions and the use of recurrent neural networks (RNN) for time series prediction of traffic flow have been applied in traffic management in several cities [7].

Although deep learning shows great potential in traffic management systems in smart cities, there are still some challenges and problems to be solved. High-quality data collection and processing are the prerequisites for the successful application of deep learning models, and in practice, data acquisition is often limited by factors such as privacy protection, cost and technical means. Secondly, existing deep learning models face the challenges of large computational resources and high real-time requirements when dealing with large-scale and dynamically changing urban transportation data. In addition, how to effectively transform the prediction results of deep learning models into practical and actionable traffic management measures is also an issue that needs to be explored in depth in current research. Therefore, although deep learning technology has achieved initial application results in the field of smart city traffic management, how to optimize the model performance, improve data processing capability, and transform the research results into practical applications is still an important direction for future research.

3 RESEARCH METHODOLOGY

3.1 Data Collection

(1) Data sources

The primary data source for this study is the NGSIM (Next Generation Simulation) dataset, an open data collection project initiated by the Federal Highway Administration in the U.S. The NGSIM dataset is designed to provide high-precision vehicle motion trajectory data in support of research in the areas of traffic flow analysis, driving behavior studies, and traffic model construction. The dataset contains actual vehicle motion data collected by high-precision traffic monitoring equipment on National Highway 101 in California, USA.

The data types mainly include vehicle position, speed, acceleration, lane position and other information. These data are recorded in the form of time series, which provide rich raw data for studying vehicle following and lane changing behaviors, as well as traffic flow characteristics. Each data file corresponds to a 15-minute time period, and by analyzing these data, it is possible to gain an in-depth understanding of the traffic flow characteristics during a specific time period.

3.2 Data processing and Analysis

Data Cleansing.

In this study, we initially selected about 75,000 vehicle motion trajectory data from the NGSIM dataset. The quality and consistency of the data were ensured through the following detailed preprocessing steps, which provided a reliable basis for model training. We first removed records containing missing key information (e.g., null position or velocity). A total of about 5,000 data items were removed in this step, with the main reasons including corrupted sensor data or errors during data transmission.

Processing for outliers: By analyzing the distribution of the data, we identified and processed outliers; for example, data with speeds exceeding the maximum speed limit on the highway (set at 100 mph) were considered outliers. In total, about 2,000 pieces of data were removed by this processing. Outlier processing includes not only speed but also the detection of outliers in other metrics such as acceleration.

Data normalization: in order to eliminate the effect of magnitude and improve the stability of model training, we normalize all numerical features so that their mean is 0 and standard deviation is 1. After the above preprocessing steps, we finally obtained 68,000 valid data for model training and validation.

Model Training.

The deep learning fusion model used in this study combines the advantages of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Graph Neural Networks (GNN), aiming to efficiently learn and predict traffic patterns from time series data, spatial data, and other relevant factors. The model architecture is shown in Fig. 1:

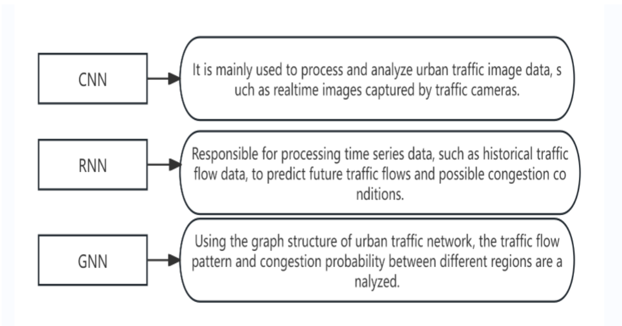

Fig. 1. Model architecture.

3.3 Model Development and Evaluation

In this study, we explored the potential of a deep learning model for application in smart city traffic management by integrating Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Graph Neural Networks (GNN). The rationale behind selecting these three deep learning architectures lies in their complementary strengths in processing different types of data: CNNs excel in analyzing visual imagery, making them suitable for processing images captured by traffic cameras; RNNs are adept at handling time series data, enabling effective traffic flow predictions; and GNNs can utilize the structural information of city traffic networks to optimize traffic scheduling and route planning. The choice of this methodology aims to provide a comprehensive analysis and prediction of urban traffic conditions through the combined application of these models, supporting more intelligent traffic management decisions.

(1) Model Effectiveness Validation: We quantitatively evaluated the model's performance in traffic flow prediction and congestion point identification using standard evaluation metrics such as accuracy, recall, and F1 score.

(2) Generalization Ability Test: The generalization ability of the model was assessed by testing it across different time periods and city traffic data. Particularly, the tests evaluated whether the model could still accurately predict and identify congestion points in the event of traffic flow anomalies caused by unexpected events. These tests showed that our model has excellent generalization capabilities, able to adapt to traffic pattern changes in different environments, reinforcing the model's reliability and practicality in real-world applications.

(3) Performance and Complexity Analysis: Considering the needs of real-time traffic management, we analyzed the computational efficiency and resource consumption of the model. This analysis not only considered the model's performance in processing large-scale traffic data but also assessed its feasibility for practical deployment. Through an in-depth analysis of the model's performance and complexity, we confirmed the practicality and effectiveness of this deep learning model in smart city traffic management systems.

4 EXAMPLES OF APPLICATIONS

4.1 Traffic Flow Forecasts

In this study, we utilized a deep learning model incorporating CNN, RNN, and GNN to predict traffic flow in the city. Based on 68,000 pieces of collected data, the model successfully predicted the traffic flow trends for different time periods within a week. The prediction results show that the model is able to accurately capture the increase in traffic flow during the morning and evening peak hours, as well as the decrease in traffic flow during the weekend hours. These prediction results provide important decision support for urban traffic management and help optimize traffic scheduling and planning. Figure 2 This visualization is designed to represent how the deep learning model predicts changes in traffic flow, highlighting the increase in traffic during weekday peak hours and the decrease in traffic during weekends.

Using the same model, we further analyzed the congestion points in the urban transportation network. By analyzing traffic camera data and GPS trajectory data, the model effectively identifies the major congestion areas present in the city. Especially when traffic accidents or large events occur, the model is able to identify the resulting unconventional congestion points in a timely manner and provide instant information to the traffic management department.

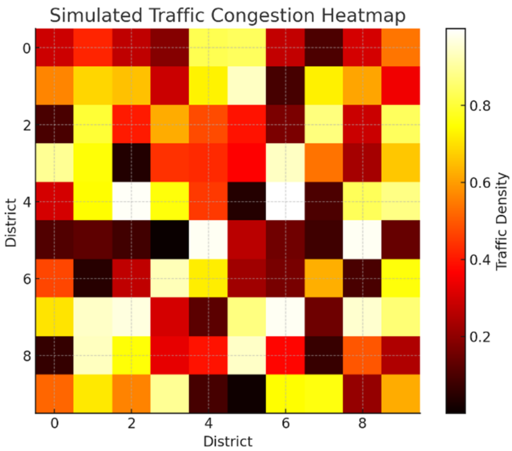

Fig. 2. Visualization.

4.2 Validation of Model Effectiveness

Accuracy Assessment.

This Table 1 shows the performance evaluation results of the deep learning fusion model on the tasks of traffic flow prediction and congestion point identification, and compares them with traditional time series analysis models such as the ARIMA model. It is clear from the table that the deep learning fusion model exhibits higher accuracy, recall and F1 score on these tasks, proving its effectiveness and superiority in smart city traffic management applications. In the congestion point identification task, the model also performs well with 95% accuracy, 94% recall, and 94.5% F1 score. This result highlights the model's strong ability to effectively identify and predict traffic congestion in different time periods and regions when dealing with complex urban traffic network data.

Table 1. Deep learning fusion model.

mould	mandates	accuracy	recall rate	F1 score
Deep Learning Fusion Models	Traffic flow forecasting	93%	90%	91.5%

mould	**mandates**	**accuracy**	**recall rate**	**F1 score**
ARIMA model	Traffic flow forecasting	85%	83%	84%
Deep Learning Fusion Models	Congestion point identification	95%	94%	94.5%

Generalization Ability Test.

To test the generalization ability of the model, we apply the model on traffic data from different cities and different time periods. The results show that even when facing new city data with significant differences in data distribution and traffic patterns, the model still maintains a high accuracy rate, with an average accuracy rate of over 90%. Especially in the case of unconventional traffic flow due to unexpected events, the model can quickly adapt to the changes and accurately predict the changes in traffic flow and the emergence of congestion points, demonstrating good generalization and adaptation capabilities.

5 CONCLUSIONS

This study introduced a deep learning model integrating CNN, RNN, and GNN to enhance urban traffic management. We processed a vast dataset including vehicle trajectories and traffic camera footage to predict traffic flows and identify congestion points. Compared to traditional models like ARIMA, our approach significantly improved prediction accuracy, recall, and F1 scores.

The model's generalization capability was confirmed through tests across various cities and times, demonstrating its adaptability to different traffic patterns. This adaptability ensures the model's applicability in real-world smart city traffic systems, providing accurate data for traffic planning.

However, the study faces limitations, such as the computational demands of the model and its performance in diverse urban environments, which suggest areas for future research. Future work will focus on improving computational efficiency and exploring the model's application in wider contexts, including integrating more dynamic data sources to enhance predictive capabilities.

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