Traffic Pattern in Smart Cities

Subjects: Computer Science, Artificial Intelligence

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Smart cities have large-scale infrastructures that have been developed to monitor a wide variety of urban occurrences. This is done to improve the quality of urban life. In most instances, they place a very restricted and specific emphasis on (e.g., monitoring the traffic). They are expensive, need the management of specialists, and are not universally well-liked among residents since they focus on topics that are not (often) of public importance.

traffic pattern classification smart cities recurrent neural network accuracy

1. Introduction

Sensing is driving a shift in complexity away from hardware infrastructures and toward software infrastructures, which may open up new possibilities for citizen service options. This strategy has the potential to minimize the costs associated with development and management, improve the number of services that are given, and lessen public pessimism regarding smart cities in general [1]. For sensing and data fusion in relation to smart cities, there is a variety of opportunities and prospective new research pathways that have not yet been examined. Some of these opportunities pertain to smart cities, while others are related to sensing and data fusion. This is something that needs to be taken care of as quickly as humanly possible [2]. The following phase, which comes after identifying a fundamental collection of passive sensing features, is to identify the limits of information extraction from raw and primary data. The study focused on establishing the best deployment patterns, such as whether they should be dense and granular to capture the maximum amount of practical data or whether they should be sparse to keep costs low and reduce early expenditures in infrastructure [3]. There exist several projects with the objective of quantifying the city and the places that are located in close proximity to it to manage those territories eventually. Sensing is typically centered on monitoring specific phenomena, such as the volume of traffic, the quality of the air, and the state of public transit systems [4]. A sensing infrastructure is developed to keep an eye on the characteristics of the target. Possessing diverse sensory abilities (e.g., traffic intensity, air quality, and others) is essential. Even while they might use the same communications infrastructure, their capabilities are not always tied to one another in any situation [5]. The installation of a sensing infrastructure for a smart city calls for a large amount of planning in addition to initial and ongoing financial support. Both of these factors are necessary for successful deployment [6]. The management and operation of these systems both call for significant financial investments on the part of the business. Sensors of diverse sorts and deployments (for instance, sensors that measure the quantity of pollution in contrast to sensors that monitor the amount of traffic intensity) call for varying degrees of maintenance and operation [7]. It is possible to collect exact data despite this unpredictability; however, a variety of management and operating solutions are necessary. Non-dedicated sensing networks, also known as sensing capabilities made available by users and other organizations, can be considered for incorporation into city infrastructure and already do so [8]. These models create challenges throughout the integration process and may sometimes be imprecise, unstable, or unreliable.

2. Smart Cities

Herrera, J. C. et al. [9] have discussed that the evaluation of traffic data obtained via GPS-enabled mobile phones depends on the type of data collected, the application used to collect and analyze it, and the evaluation goals. Generally, traffic data obtained via GPS-enabled mobile phones can provide useful insights into the movement of traffic, including the frequency of certain routes, the average speed of vehicles on a particular route, or the average wait times encountered at traffic lights. Furthermore, GPS-enabled mobile phones can provide real-time updates regarding traffic delays, route changes, or other traffic-related events, making them invaluable tools for navigating congested urban areas. Kim S., et al. [10] have discussed that optimal vehicle routing with real-time traffic information uses the most up-to-date real-time information from traffic sensors and GPS data to create the most direct and efficient route to reach a destination. Real-time traffic information can be used to identify and avoid traffic jams, back-ups, and road works that may slow down traditional routes—ultimately resulting in a much faster and more efficient route. Leontiadis I. et al. [11] have discussed the effectiveness of an opportunistic traffic management system for vehicular networks is Limited. It relies on available capacity in the network to determine when and where vehicles should be allowed to transit. This means that the system is reactive—traffic congestion may still occur, and efficiency is determined by the amount of available capacity in the network. Further, these systems are vulnerable to inaccurate assumptions about the road network and the possibility of malicious interference with the transmissions. Doolan R. et al. [12] discussed the Vanet-enabled eco-friendly road characteristics-aware routing for vehicular traffic, a routing algorithm developed for determining an optimal route in congested road networks. The algorithm considers road characteristics such as length, width, number of lanes, turns, intersection types, average speed limit, traffic load, etc. It also considers the availability of green and sustainable transportation modes such as electric and hybrid vehicles. These factors calculate the fastest route with the least pollution impact. The goal of this routing algorithm is to reduce emissions, improve fuel efficiency, and minimize overall congestion. Nadeem T. et al. [13] have discussed Car-to-car communication, or vehicle-to-vehicle (V2V) communication, as a technology that wirelessly collects and shares data between vehicles on the road. This data is then used to facilitate communication between vehicles to share important information about traffic conditions, road hazards, and other timely information to help them operate safely on the roads. This technology can reduce traffic congestion and increase safety while driving. Yildirimoglu, M. et al. [14] has discussed the experienced travel time prediction for congested freeways is usually higher than the normal travel time. Congested freeways can experience extended travel times up to double the normal time. Wang Y., et al. [15] have discussed that Dynamic traffic prediction based on traffic flow mining is a method of predicting future traffic patterns by analyzing data mined from traffic flow sensors. This method utilizes machine learning algorithms, such as support vector machines, decision trees, neural networks, and deep learning, to create a model that can detect patterns in the data and make predictions about future traffic volumes and speeds. The predictive model can then be used to plan for changes in traffic flow, such as lane reductions and new road construction, and suggest optimal routes for drivers. Guardiola, I. G. et al. [16] has discussed the functional approach to monitoring and recognizing patterns of daily traffic profiles involves collecting a variety of data such as the amount of time spent on each website, the number of visitor interactions, the average speed of page loading, the amount of time spent on each page, and the type of pages visited. After collecting the data, it can then be analyzed to identify any patterns in the behavior of your users. For example, if you see a pattern of peak activity during certain times of the day, you can monitor the traffic and adjust your marketing strategy accordingly. You can also use this data to identify patterns that can be used to improve the user experience, such as speeding up page loading times or tailoring content to be more relevant to the user. Abdullah, S. M., et al. [17] has discussed the Soft GRU-Based Recurrent Neural Networks (RNNs) for Enhanced Congestion Prediction Using Deep Learning is a type of artificial neural network that uses deep learning techniques to predict traffic patterns and congested regions in urban areas. These soft GRU-based RNNs use transfer learning to learn complex patterns in the data quickly and accurately, allowing quick and accurate congestion prediction. These networks use various features such as historical traffic information, weather data, and geographical characteristics of urban areas to provide accurate predictions. The use of these networks for congestion prediction has helped make traffic control easier and more efficient. Logeshwaran J. et al. [18] have discussed a novel architecture of an intelligent decision model for efficient resource allocation in 5G broadband communication networks is a system that integrates machine learning, optimization techniques, and real-time data analytics into an efficient resource allocation module. This system is designed to provide optimal utilization of network resources while meeting the demand of multiplex subscribers over a fixed time window. It incorporates predictive analysis tools to facilitate the dynamic allocation of resources based on historical data and user requirements. This model also enhances the scalability and reliability of 5G networks by allocating resources efficiently and without compromising the network's performance. Ultimately, this architecture is envisioned to provide optimal network performance while offering a flexible and efficient resource allocation with minimal user intervention.

Logeshwaran et al. [19] have discussed an energy-efficient resource allocation model for device-to-device communication in 5G wireless personal area networks that involves allocating radio resources to minimise energy consumption while achieving the desired data rate. Specifically, resource allocation strategies can include techniques such as frequency reuse, power control, and scheduling of transmissions to maximize channel utilization and minimize energy consumption. Other methods used are modulation sub-carrier allocation, antenna configuration, and Beamforming. Energy-efficient resource allocation techniques consider the available spectrum utilization of the channel, the interference between users, traffic demand, and the mobility of users, and use advanced algorithms such as game theory, optimization theory, and machine learning to distribute the resources effectively. Singh et al. [20] have discussed Cloud-Based License Plate Recognition for Smart City Using Deep Learning. This system uses deep learning technology to identify car license plates from images captured in smart city surveillance cameras. This system enables automated license plate recognition (ALPR), increasing efficiency in traffic violation enforcement, enhancing public safety, and tracking vehicles to enforce traffic and security regulations. The system is cloud-based, meaning that data is stored and processed in the cloud and therefore does not require any physical hardware setup.

Additionally, this system can identify license plates from video streams, providing faster and more accurate results than still images. Furthermore, deep learning models such as convolutional neural networks (CNN) allow this system to accurately recognize license plates in various conditions, including weather changes, different times of day, changes in lighting, and more. Wenget al. [21] have discussed a Decomposition Dynamic Graph Convolutional Recurrent Network (DDGCRN) for traffic forecasting, a deep learning model designed to predict future traffic conditions in a given region. DDGCRN combines a graph convolutional network (GCN) and a recurrent neural network (RNN) to capture both the spatial and temporal features of the traffic. The GCN part of the DDGCRN encodes the traffic data from different sources, such as traffic sensors, historical data, and geographical information, into a vector representation. The RNN part of the DDGCRN then combines the vector representation and temporal features to forecast future traffic demand. For example, the RNN can consider holiday effects, seasonal changes, and other temporal factors. Djenouri et al. [22] discussed that Federated deep learning is a type of distributed machine learning technique that enables multiple parties to train a shared model securely without sharing their underlying data. It is increasingly used in edge-based applications in the smart city due to its data privacy, scalability, and cost-efficiency benefits. With federated deep learning, potentially sensitive data can stay within its original user's systems, allowing for improved shared insights and data-driven applications. By utilizing local edge devices, federated deep learning can enable applications ranging from waste management to advanced energy forecasting.

Walch, M. et al. [23] has discussed the Floating Car Data–Based Short-Term Travel Time Forecasting with Deep Recurrent Neural Networks. Incorporating Weather Data is a forecasting methodology that uses Floating Car Data (FCD) combined with deep recurrent neural networks and weather data to predict travel time for short-term trips. This approach combines data from the floating car (e.g., location) and local and global weather information to provide better prediction accuracy than traditional models that lack a weather factor. By incorporating weather data into the model, the system can make predictions that are more accurate than those of traditional methods. Furthermore, this approach can capture much finer route detailsthan other models, allowing it to provide more specific predictions for each vehicle. Maheswari, K. G., et al. [24] has discussed the Optimal cluster-based feature selection for intrusion detection systems in web and cloud computing environments using hybrid teacher learning optimization, and deep recurrent neural networks can occur through various methods. These methods include expert knowledge-based rules, feature selection algorithms, and random forest-based models. Expert knowledge-based rules utilize domain-specific knowledge, rules, and other manual information to identify the important features of the dataset. Feature selection algorithms use mathematical models to determine the optimal feature subset from the dataset. Random forest-based models use decision tree-like structures to identify important features with the strongest predictor ability. All these methods will help identify optimal features for intrusion detection systems and improve the performance of intrusion detection systems, especially in a dynamic and unpredictable environment. Rezaee et al. [25] discussed the IoMT-Assisted Medical Vehicle Routing Based on UAV-Borne Human Crowd Sensing and Deep Learning in Smart Cities is a type of intelligent optimization approach which combines Internet of Things (IoT) technology, UAV-borne human crowd sensing, and deep learning technology to help guide medical vehicles to their destinations more efficiently. It utilizes IoT sensors installed on medical vehicles to collect road data such as traffic conditions and congestion to dynamically generate optimized routes. It combines UAV-borne human crowd sensing to collect updated information about the real-time situation on roads or in areas of interest. Finally, it utilizes deep learning to analyze the collected data to generate intelligent recommendations and alerts that enable medical vehicles to make more accurate decisions on routes to maximize efficiency and reduce travel time. This approach is especially useful in smart cities where traffic conditions are constantly changing. Asha, A., et al. [26] has discussed the Optimized RNN-based performance prediction of IoT and WSN-oriented smart city application using an improved honey badger algorithm is an advanced method of predicting the performance of smart city applications using an enhanced version of the honey badger algorithm and a Recurrent Neural Network. This improved version of the honey badger algorithm combines reinforcement learning, dynamic programming, and evolutionary computation to increase the accuracy of the performance predictions. The Recurrent Neural Network, part of the method, is used to handle the temporal elements of the prediction and increase the accuracy of the predictions.

Jain et al. [27] discussed the Research on artificial neural networks (ANNs) for smart cities towards Sustainable Development Goal (SDG)-11 has grown rapidly in recent years due to the potential for improved services and outcomes in urban areas. Research themes include the development of ANN architectures for predictive analytics and forecasting, the development of ANNs for efficient use of energy resources and water, and the development of ANNs for improved governance and decision-making in smart cities. Other research themes include the development of ANNs for anomaly detection and data-driven urban planning. Innovative research trends include the development of ANNs that incorporate predictive models, such as Bayesian Networks, to identify complex problems and solutions in urban areas. Additionally, research on the use of ANNs for social network analysis and data-driven urban speciation has been conducted. Research concerning the role of ANNs in urban energy management and intelligent transportation systems is also an important area of focus. Vasudha et al. [28] discussed Carriageway edge detection for unmarked urban roads using deep learning techniques is the application of advanced computer vision and image processing techniques to identify and detect the edges of the road to aid an autonomous vehicle in its navigation while driving in an urban environment. The deep learning approach uses convolutional neural networks (CNNs) to analyse images or videos of the road ahead to detect objects, features, and other important cues that can be used to determine the route the car should take. This approach relies on accurately identifying features such as lane markings, spots, and other distinct features of the road to accurately identify and navigate around them. Nazari et al. [29] discussed that Deep learning has become an essential technology for the future of smart cities. It can be used to develop algorithms to solve complex problems such as traffic optimization, energy management, water quality management, and public safety. Deep learning can improve urban governance, plan smart city infrastructures, and optimize resource utilization. It can also be used to create more efficient and cost-effective smart city services such as parking management and smart waste management. Additionally, deep learning can help increase the accuracy and reliability of surveillance data collected for public safety, and it can be used to develop advanced public services such as intelligent conversational agents. In short, deep learning can offer numerous advantages to improve people’s overall quality of life in smart cities.

Abbaset al. [30] discussed that the Harris-Hawk-Optimization-Based Deep Recurrent Neural Network is designed to secure the Internet of Medical Things (IoMT) consisting of devices, such as implanted medical devices, connected to the Internet. The Harris-Hawk-Optimization-Based Deep Recurrent Neural Network is a bi-level optimization approach that combines deep recurrent neural networks with an optimization algorithm inspired by the behavior of the Harris Hawk. The optimization algorithm is based on a process known as the Hawk-Eye search, which allows the network to explore the input space more efficiently and accurately and to detect malicious activities more precisely. The network can identify suspicious missing data, detect suspiciously connected devices, identify malicious activity, and provide security alerts. The Harris-Hawk-Optimization-Based Deep Recurrent Neural Network also helps to protect against data leakage and unauthorized access. Xiao et al. [31] discussed the smart cities use a variety of predictive technologies to predict the availability of parking in a given area. This is done through the collection and analysis of data from sources such as sensors, traffic cameras, and vehicle tracking software. The predictive models developed by smart cities help city planners and decision-makers plan the best parking strategies for a given area, such as dynamic pricing, improved enforcement, or creating new parking spaces altogether. Predictive models also allow drivers to locate and reserve parking spots in real time easily.

Redhuet al. [32] discussed the Short-term traffic flow prediction based on optimized deep learning neural networks, which use deep learning algorithms to optimize traffic flow prediction accuracy. It involves building neural networks with multiple layers to learn from historical traffic data to predict future traffic. The prediction process is iterative, and the deep learning algorithm can adapt to changes in traffic flow and trends. This type of prediction helps traffic engineers manage congested roadways and advise drivers on the best route. Sereyet al. [33] discussed the Pattern recognition and deep learning technologies are enablers of Industry 4. 0, or the fourth industrial revolution. They enable machines that can rapidly analyze data and make decisions previously limited to human brains, from sorting through large volumes of data to completing complex tasks. They can identify trends, predict outcomes, and generate insights with unprecedented speed and accuracy. Pattern recognition and deep learning can be used in various industries, such as computer vision, natural language processing, robotics, driverless cars, healthcare, and finance. By combining large amounts of data from multiple sources, these technologies allow for more intelligent solutions and discoveries previously impossible.

Based on the above comprehensive analysis, the following issues were identified. They are,

- Incomplete or biased data interpreting traffic volume and Variation in Traffic Congestion Levels across Different Periods
- Complexity in Differentiating Street Traffic Types and Data Security and Privacy Considerations
- Lack of Standardization of Systems and limited Accessibility of High-Quality Historical Data
- Difficulties in Modeling for Unforeseen Events and Geographical Constraints on System Performance
- Inaccuracy of Interpretation for Motorists on Pedestrians, or Cyclists and the limitations in Updating Emergency Services in Timely Manner.

The novelty of this approach is that it uses a deep recurrent neural network for traffic pattern classification in smart cities. Compared to traditional methods, this allows for a more accurate and comprehensive classification of traffic patterns, as the deep learning approach can learn patterns from sequences of data to identify, classify, and predict traffic patterns. Furthermore, the model can adapt to changes in the road network and other factors that may impact traffic, allowing for more accurate predictions. Additionally, the use of recurrent neural networks is advantageous as it can capture both spatial and temporal data, allowing for a more comprehensive approach.

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