Intelligent Traffic Management System for Smart Cities

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Abstract

rapid urbanization and the growing population in smart cities pose significant challenges to the management of urban traffic. In recent years, there has been an increasing interest in developing intelligent traffic management systems that leverage advanced machineries, such as the Internet of Things (IoT), and machine learning (ML), to enhance the efficiency and effectiveness of traffic management in smart cities. This paper proposes an intelligent traffic management (ITM) system for smart cities that integrates various computing paradigms to provide real-time traffic information, optimize traffic flow, and improve road safety. The suggested system utilizes an innovative system for the predicting the traffic flows with the goal of enhancing the current level of traffic management in smart cities. An enhanced convolutional autoencoder network is incorporated into the proposed system as a means of extracting the spatial representations contained in traffic flows. Additionally, by the utilization of a refined gated learning module, it possesses the capability of accurately recording temporal dynamics. Our system is evaluated using real-world traffic data, and the results demonstrate its effectiveness in improving traffic flow and reducing congestion in smart cities. Our system has the potential to significantly enhance the performance of traffic management systems in smart cities, decrease traffic crowding, and progress the safety of roads in smart cities.

Keywords: Deep Learning; Intelligent system; internet of things (IoT); smart cities;

1. Introduction:

Traffic management is a crucial aspect of smart cities, as it plays a significant role in ensuring the safety and efficiency of transportation systems. Smart cities use advanced technologies and data analytics to optimize traffic flow, reduce congestion, and enhance public safety. One of the primary technologies used in traffic management in smart cities is the Internet of Things (IoT). IoT sensors can be installed in roads, streetlights, and other infrastructure to collect real-time data on traffic conditions, such as vehicle speed, traffic density, and vehicle types [1]. This data can be analyzed using machine learning algorithms to provide insights that can help traffic managers make informed decisions about traffic flow and congestion. Another key technology used in traffic management is intelligent transportation systems (ITS), which use real-time data and analytics to manage traffic flow and improve safety. ITS can be used to monitor traffic conditions and adjust traffic signals, reroute traffic in case of congestion, and provide real-time information to drivers about traffic conditions [2].

Smart cities also use a range of other technologies to manage traffic, such as predictive analytics, automated parking systems, and electric vehicle charging stations. For example, predictive analytics can be used to forecast traffic congestion based on historical data, allowing traffic managers to take preemptive measures to prevent gridlock. In addition to technology, smart cities also implement policies and programs to promote sustainable transportation, such as public transit, cycling infrastructure, and car-sharing programs [3]. By encouraging alternative modes of transportation, smart cities can reduce congestion and air pollution, while improving public health and quality of life.

DOI: https://doi.org/10.54216/JISIoT.030104
Received: March 18, 2021 Accepted: June 11, 2021

Intelligent traffic management (ITM) is a relatively new discipline that uses cutting-edge technologies and data analysis to make transportation networks more effective, secure, and environmentally friendly. Timely reliable and safe transportation of people and goods is a primary goal of the Smart Transportation business, and its success depends on efficient and trustworthy traffic management. The Internet of Things (IoT) plays a pivotal role in bettering traffic management in transportation by providing real-time data on traffic conditions, allowing for better decision-making and more effective regulation of traffic flow [1]. Devices that are connected can collect data on factors such as traffic quantities, journey times, automobile speeds, and locations. Specialized algorithms for machine learning can be used to this data to identify patterns, flag anomalies, and predict future traffic patterns. The information can be used for safer streets, less congestion, and better control of traffic flow. Services such as automated problem management, individualized route planning, and real-time traffic data [2] are all possible thanks to the Internet of Things used by transportation firms.

Machine learning (ML) is increasingly being used in the development of intelligent traffic management systems. With the growing number of vehicles on the roads, the need for efficient traffic management has become critical. ML algorithms can analyze vast amounts of data in real-time to provide insights that can be used to optimize traffic flow, reduce congestion, and improve public safety. One important use of ML in traffic management is in traffic prediction. ML algorithms can analyze historical data on traffic patterns and use this information to predict congestion in real time. By using these predictions, traffic managers can make informed decisions about routing and traffic signal timing, which can reduce congestion and improve traffic flow. Another use of ML in traffic management is in incident detection and management. ML algorithms can be trained to detect incidents such as accidents or road closures in real time. Once an incident is detected, the algorithm can automatically suggest alternative routes to drivers or adjust traffic signal timing to reduce congestion in the affected area.

In this research, a novel ML model for automated and efficient prediction of traffic flow as way to improve the traffic management tasks in smart cities. Once the system receives the traffic samples, the spatial patterns are captured and extracted by an upgraded convolutional autoencoding module. Then, our system learn the temporal representations via an improved gated learning networks. Subsequently, both temporal and spatial representations are combined to generate the final prediction about the future traffic flow.

The remaining of this study is planned as follows: The second section provides a literature overview on the use of ML in IoT traffic control applications. The third section discusses the rationale behind the proposed system 's technique. The experiments conducted for this paper and their contexts are discussed in the fourth section. The major conclusions of this work are discussed in the fifth section.

2. Related Work

The researcher is making a significant amount of effort to build intelligent machine-learning solutions to improve traffic management in light of the ongoing progress in ML. For instance, the work [1] proposed an approach for traffic control in wireless networks that eliminates the need for traditional routing protocols. The authors used a deep learning model to predict the optimal route for data packets based on real-time network conditions such as traffic load and link quality. This approach aimed to improve the efficiency and reliability of wireless networks while reducing network congestion and latency. The paper provides a detailed description of the proposed architecture and evaluates its performance using simulations. The work [2] developed a reinforcement learning agent to learn the optimal timing and sequencing of traffic lights based on real-time traffic data. it tried to improve traffic flow, reduce congestion, and decrease travel time for vehicles. It provided a detailed description of the proposed architecture and evaluates its performance using simulations. The results show that the proposed approach outperforms traditional traffic light control methods in terms of traffic flow, travel time, and fuel consumption. The work [3] developed an algorithm for channel assignment in Software Defined Networking (SDN) based Internet of Things (IoT) networks, whereby a DL model was applied to predict the traffic load on different channels and dynamically assign channels based on real-time traffic conditions. The paper provided a detailed description of the proposed algorithm and evaluates its performance using simulations. The work [4] reviewed the recent advancements in deep learning techniques for network traffic control systems. they discussed the challenges faced by traditional traffic control methods and highlight the potential of deep learning in addressing these challenges. They provided an overview of the different deep learning architectures used for traffic control systems, involving recurrent models, convolutional models, and graph models. The authors also discussed the applications of ML in different areas of traffic control, such as traffic light control, routing, and channel assignment. The work [5] developed an approach for short-term traffic forecasting, which take the historical traffic data to train an LSTM model to predict the traffic flow soon. The paper provided a detailed

DOI: https://doi.org/10.54216/JISIoT.030104
Received: March 18, 2021 Accepted: June 11, 2021

description of the LSTM model and assessed its performance using real-world traffic data. The work [6] developed a system for a managing traffic in smart cities that considers context-awareness. The authors suggest incorporating different data sources, such as sensor data, social media data, and weather data, to provide a comprehensive understanding of the traffic situation in real-time. The work [7] developed an approach for extracting relevant information from traffic camera images in a big data environment. The authors suggested using threshold-based image extraction schemes to identify and extract relevant features, such as the number of vehicles and their speed, from traffic camera images. they aimed to improve the accuracy and efficiency of traffic management systems by providing real-time insights into traffic conditions. The paper [8] investigated that UAVs can be used for a variety of applications in smart cities, such as emergency response, and package delivery. The authors aimed to improve the quality of transportation systems by providing real-time insights into traffic conditions and enabling proactive management. The paper [9] proposed a real-time traffic management system that integrates IoT and big data technologies to collect traffic data in real-time and analyzing the data using big data analytics to provide insights into traffic conditions. This approach improved the efficiency and effectiveness of traffic management by providing real-time insights into traffic conditions and enabling proactive management. The paper [10] provided a comprehensive overview of the challenges and innovative approaches in developing traffic management systems for smart cities from a communications-oriented perspective. The authors suggested that the design and implementation of such systems require an interdisciplinary approach that incorporates various communication technologies, such as wireless networks, the IoT, and cloud computing.

3. Methodology of the proposed ITM System

In this section, we will examine the practice of our ITM system for the powerful forecasting of traffic flows in smart cities. Figure 1 presents a diagrammatic representation of the proposed system's organizational structure. The proposed model, as can be seen, is composed of two primary building blocks: the first of which learns the spatial information that is present, and the second of which learns the temporal characteristics of the traffic patterns. A comprehensive explanation of each component of our model is provided in the subsequent paragraphs.

Autoencoders are a type of ML that can be used for modeling traffic flow data. An autoencoder consists of an encoder that maps the input data to a compacted representation (latent space) and a decoder that maps the compressed representation back to the original input data. By doing so, autoencoders can learn a compressed representation of the input data that captures the most important features and patterns of the data. Autoencoders have been used for modeling traffic flow data by using the traffic flow data as input and training the autoencoder to reconstruct the same data at the output. The compressed representation obtained from the encoder can be used for visualization, clustering, or anomaly detection. The autoencoder can also be used to generate new traffic flow data that is like the training data, which can be used for generating synthetic data or augmenting the training dataset. thus, our system use AutoEncoder (AE) learn spatial features of traffic flow data, which are later passed to predictive module network to improve the performance of traffic flow prediction at the present location. So, the input of AE is traffic flow $X_u = \{x_{u1}, x_{u2}, \dots, x_{um}\}$ and, with $x_{ui}, x_{di} \in R^d$. The AE process inputs as follows:

$$z_i = f(w_z * (x_{ui} + x_{di}) + b_z), \tag{1}$$

$$y_i = g(w_y * z_i + b_y). \tag{2}$$

Where * denote convolutional kernel.

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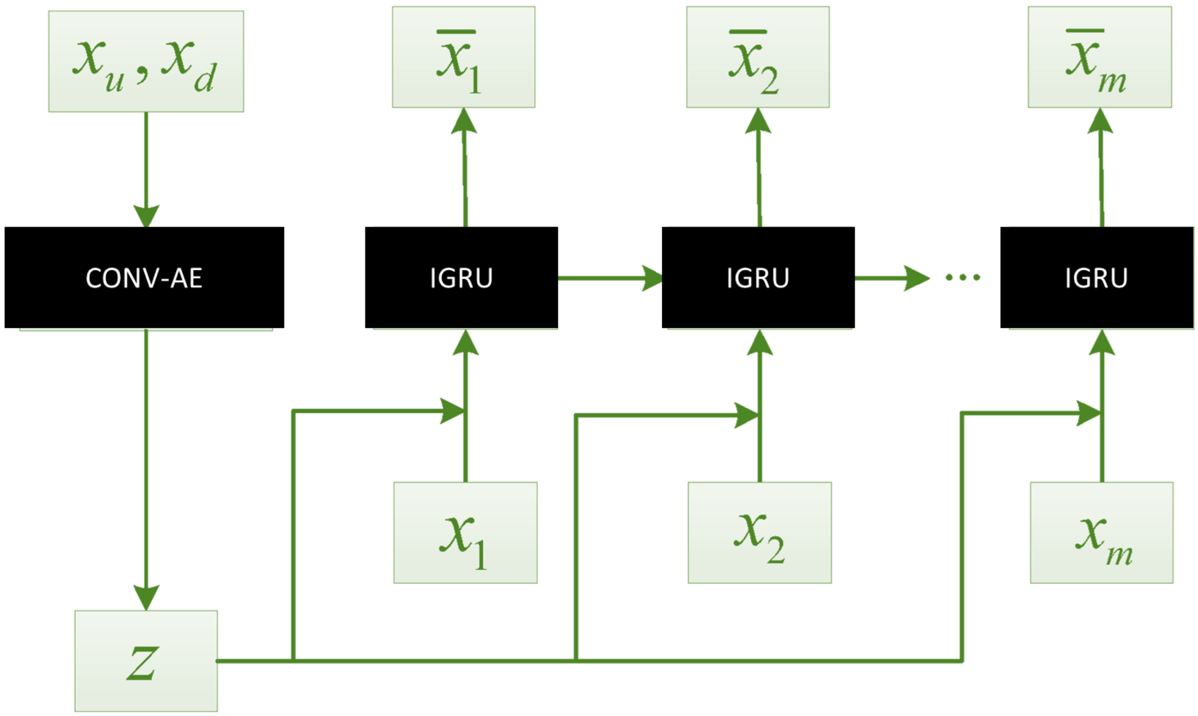

Figure 1: Illustration of the architecture of the proposed ML-based ITM system.

Capturing temporal dependencies in traffic flow data refers to the ability to model and analyze how traffic patterns change over time. Temporal dynamics play a crucial role in traffic flow data analysis as traffic patterns can vary significantly over short periods. Capturing temporal dynamics involves analyzing time-series data to detect trends, periodicity, and seasonality in traffic flow. This information can be used to develop accurate predictive models and optimize traffic flow in real time. Techniques such as time-series analysis, autoregressive integrated moving averages (ARIMA), and neural networks have been used to capture temporal dynamics in traffic flow data. By capturing temporal dynamics in traffic flow data, transportation planners and managers can make informed decisions to improve traffic flow, reduce congestion, and enhance road safety. To this end, improved Gated Recurrent Unit (IGRU) is introduced to learn temporal dependencies in sequential data by applying gated learning that allow it to selectively update or forget information from previous time steps. Following the same concept of standard GRU, the IGRU the advantage of gating mechanisms to selectively update and reset the network's memory, which empowers the network to capture long-term dependencies in the data. To use the IGRU for in our system, the latent space of the autoencoder is divided into sequences of fixed length. Each sequence would correspond to a time window of the traffic flow data, with the IGRU taking as input the flow measurements at each time step within the window. The GRU would then be trained to predict the flow measurements at the next time step, given the previous measurements within the window. The network would learn to capture temporal dependencies in the data, such as daily or weekly patterns in traffic flow. Mathematically speaking, the gating calculation IGRU gates are expressed as shown below:

$$Z_t = swish(W^z x_t + V^z h_{t-1} + b_z) \tag{3}$$

$$r_t = swish(W^r x_t + V^r h_{t-1} + b_r) \tag{4}$$

The hidden state, h_t, and candidate state, $\tilde{h}_t$ are followingly computed as follows:

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t \tag{5}$$

$$\tilde{h}_t = tanh(W^c x_t + V^c (r_t \otimes h_{t-1})) \tag{6}$$

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whereby, the W^z, W^r, and W^c represent the parameters, while V_z, V_r, and V_c indicate the parameters of gates. The b indicates the bias parameters. By the end of the mode, we apply a Huber loss function to be used to update the parameters of our system during the training. The Huber loss is calculated as follows:

$$\text{Huber } (x) = \begin{cases} \frac{1}{2}x^2 & \text{for } |x| \leq \delta, \\ \delta|x| - \frac{1}{2}\delta^2 & \text{otherwise.} \end{cases} \tag{7}$$

where $\boldsymbol{\delta}$ represents a flexible parameter that plates wherever the transformation occurs.

A. Results and Discussion

Our tests employed the PeMSD7 traffic dataset to evaluate the suggested model's practicability. It covers the time period of May 2012 - June 2012 and includes speed measurements from 39,000 sensors in District 7 of California at a resolution of 5 minutes or/and 30 seconds. With a 5-minute interval being used as the norm in our studies, the road graph's primary nodes cover 288 data points daily. Linear interpolation was used to fill in the gaps for the missing data points. In addition, the Z-Score technique was used to standardize the input variables. According to the d_{ij} distances between every pair of traffic stations, we determine the road graph's adjacency matrix. We may write down the following expression for the edge weight w_{ij} in the adjacency matrix W:

$$w_{ij} = \begin{cases} \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right), & i \neq j \text{ and } \exp\left(-\frac{d_{ij}^2}{\sigma^2}\right) \geq \epsilon \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

The functioning of our ITM system is assessed according to three common indicators that calculated the variation between the system's predictions, $\hat{Y}$, and ground truth Y. These indicators are computed as follows:

$$Mean\ Square\ Erro(MSE) = \frac{1}{n}\sum_{i=1}^{n} \left(Y_t - \hat{Y}_t\right)^2 \tag{9}$$

$$Mean\ Absolute\ Error\ (MAE) = \frac{1}{n}\sum_{i=1}^{n} \left|Y_t - \hat{Y}_t\right| \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1} \left(Y_t - \hat{Y}_t\right)^2}{\sum_{i=1} (Y_t - \bar{Y})^2} \tag{11}$$

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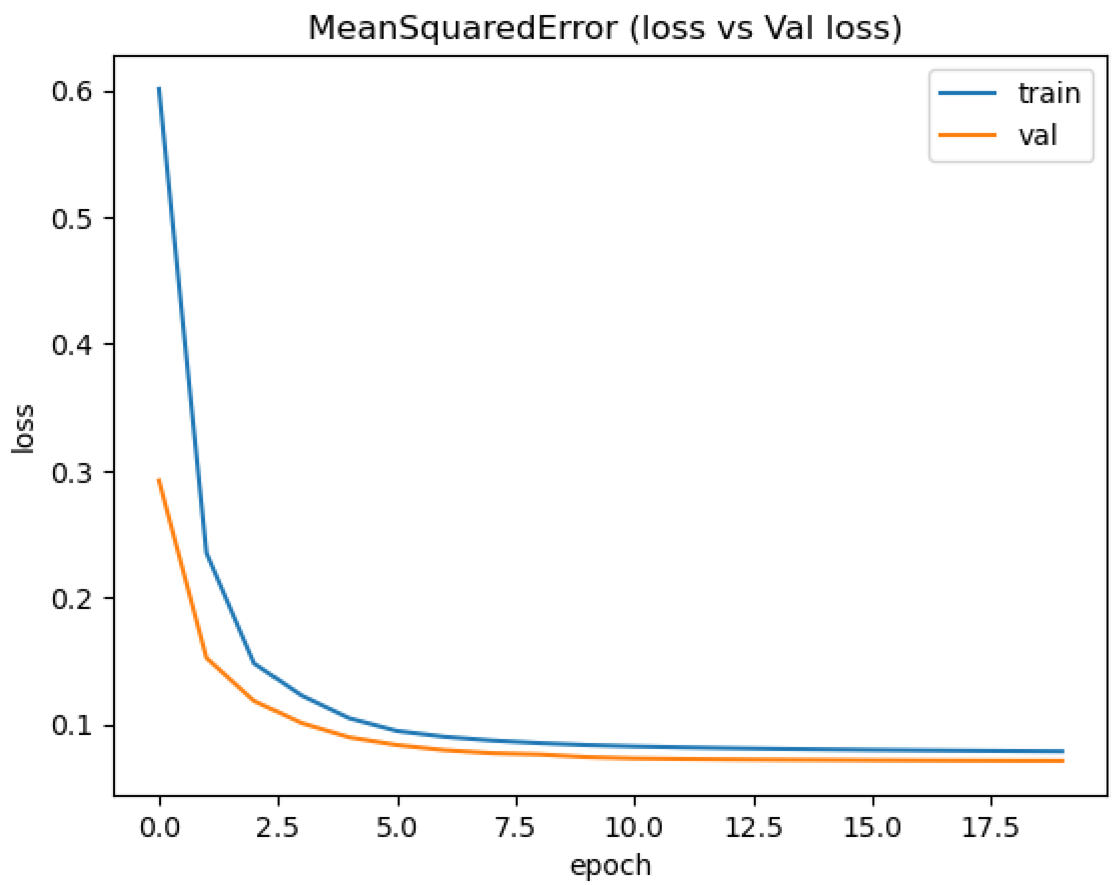

Figure 2: Illustration of the learning curves of the proposed system

To comprehend the competitive power of our ITM system, Table 1 presents the quantitative results attained from investigational assessments between the proposed system and the cutting-edge methods (ARIMA, support vector regressor (SVR), full connected LSTM(FC_LSTM), Multi-layer perceptron (MLP)) in the literature. It's worth noting that the proposed approach can outperform alternative methods in terms of predictive power. Because our model so well captures the spatio-temporal aspects of traffic flow and their relationship, the network's prediction abilities are greatly enhanced.

Table 1: comparative analysis of how well various ML techniques can predict PeMSD7.

	MAE	**MSE**	R^2
ARIMA	0.55±0.109	0.396±0.121	0.748±0.073
SVR	0.532±0.14	0.427±0.071	0.798±0.126
MLP	0.527±0.083	0.383±0.155	0.84±0.091
FC-LSTM	0.504±0.083	0.241±0.108	0.863±0.066
Proposed	0.216±0.138	0.134±0.086	0.945±0.073

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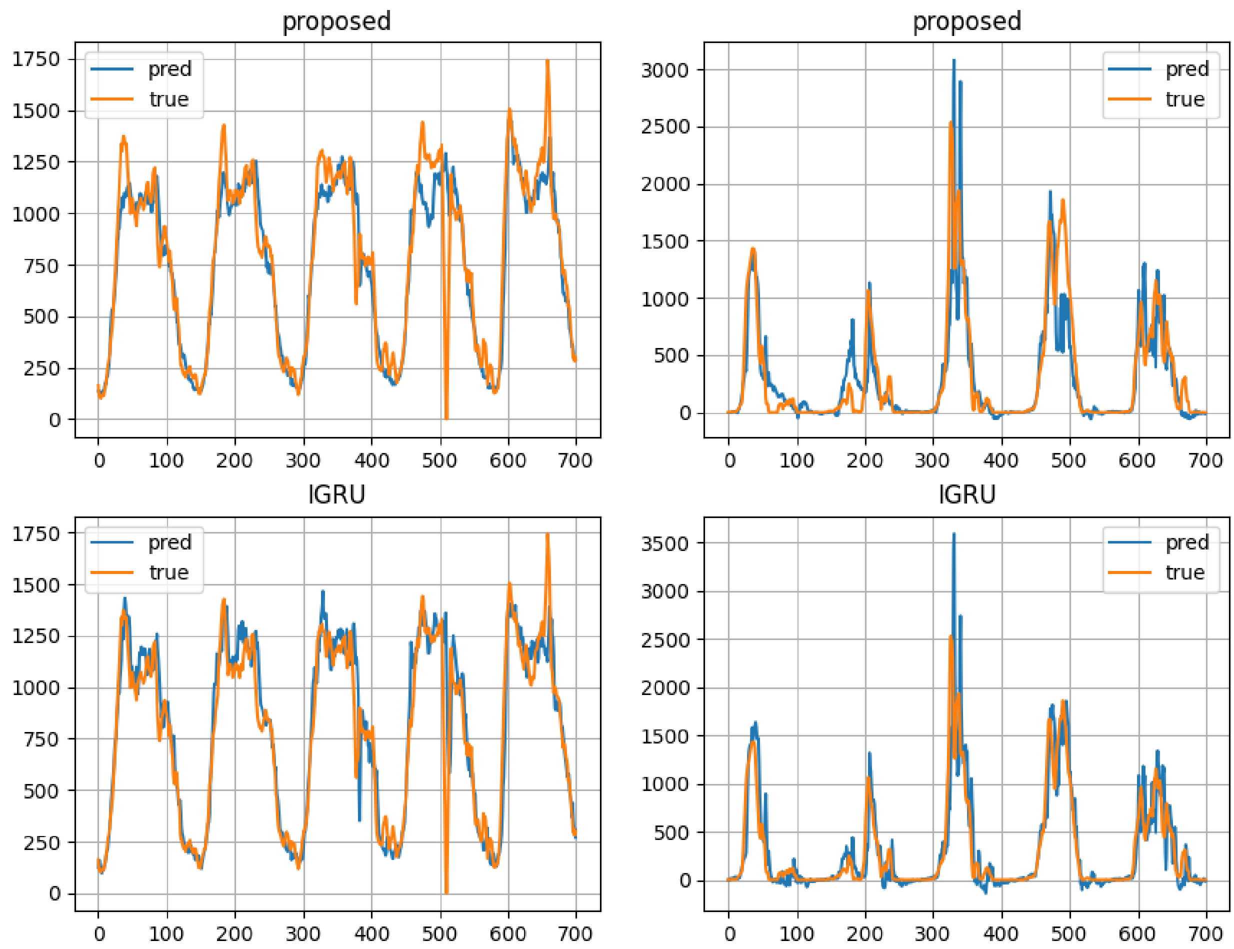

Figure 3: visualization of predictions of the proposed system and IGRU against actual traffic flow.

In addition, we use the training curves shown in Figure 3 to evaluate the model's consistency as it is being trained. It's worth noting that even while being trained, the proposed model keeps a consistent learning behavior. The model also converges quickly under a variety of loss functions. Figure 4 compares the model predictions to the actual data, providing further evidence for the suggested model's accuracy. The reliability of the model as a tool for enhancing ITM activities is shown by the prediction curves' demonstration of its ability to accurately estimate traffic flows.

4. Conclusion

This work presents an intelligent system for predictive modeling traffic flows in smart cities to give the decision-makers a set of valuable insights about the future state of the traffic sector, and thereby help them to avoid possible issues. The chronological patterns and the spatial patterns of smart city traffics are seized as corresponding sets for enhanced forecasting. The effectiveness and competitiveness of our system were confirmed experimentally in comparison to state-of-the-art methods. Our approach is a viable tool for deployment in a real-world ITM system since it captures a supplementary set of representations of traffic flows.

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Received: March 18, 2021 Accepted: June 11, 2021

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