Hybrid Deep Belief Network in Traffic Flow Prediction

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Contributor: Gouse Pasha Mohammed , Naif Alasmari , Hadeel Alsolai , Saud S. Alotaibi , Najm Alotaibi , Heba Mohsen

Accurate and timely traffic flow prediction not just allows traffic controllers to evade traffic congestion and guarantee standard traffic functioning, it even assists travelers to take advantage of planning ahead of schedule and modifying travel routes promptly. The presented hybrid deep belief network (AST2FP-OHDBN) model initially normalizes the traffic data using min–max normalization.

intelligent transportation system | smart cities | traffic flow prediction

1. Introduction

As a new form of intellectually complex mechanism, with high interaction and integration among multidimensional heterogeneous physical substances in network atmospheres [1][2], the cyber-physical system (CPS) compiles control, computing, and communication technologies to offer a practicable solution to and advanced technologies for the new generation of intelligent transportation system (ITS). This therefore is the key advancement direction of the CPS and resolves the issues of intellectual real-time target control and optimal dispatch of ITS [3]. Meanwhile, the issue of dense functions of large-scale data-computing and optimum control-scheduling methods in large-scale ITS is resolved by the speedy advancement of cloud computing (CC) technology. The basic principle of this was dispensing computing tasks on a great number of cloud-distributed computers; ITS management departments could then match CC sources to ITS cloud-controlled applications, evaluating storage systems and computers as required [4]. The implementation of CPS and CC technology makes it possible to attain, transfer and compute traffic data practically, and the implementation of the dynamic matrix method and artificial intelligence (AI) method could forecast traffic data in the next moment in advance [5].

Real-time precise short-time traffic flow forecasting could provide traffic guidance for traffic participants by selecting a suitable travel route, and aid the traffic controllers to have a fair control strategy for relieving traffic congestion [6]. Traffic flow becomes a time sequence data, having robust cyclicity and regularity that were considered as the base for precise estimation. However, its uncertainty and randomness raise prediction difficulties. Therefore, short-time traffic flow forecasting becomes necessary and challenging one in research domains and transport management [7]. Over the last few years, more techniques were deployed for forecasting short-term traffic flow, such as the autoregressive integrated moving average (ARIMA), fuzzy theory, artificial neural network (ANN), and Kalman filter. Such techniques proved to be helpful in deriving traffic flow temporary tendency and forecasting the future traffic flow. It was discovered from the literature that AI-related methods have been extensively utilized for object analytics and detection in ITS. However, such AI-enabled methods need precise perception [8]. However, prevailing approaches produce several mistakes at the time of execution, which may not applicable for realistic data analytics in ITS.

During the past few decades, several research proposals were suggested for enhancing self-learning approaches to dynamic and complex applications of the transport system [9]. Self-learning methods for traffic prediction could be widely split into 2 parts: nonparametric and parametric. In this context, a nonparametric method termed deep learning (DL) was found to be helpful for traffic flow forecasting with multidimensional features [10]. DL was a subset of machine learning (ML) that depends on the idea of deep neural network (DNN) and it was broadly utilized for object recognition, data classification, and natural language processing (NLP).

2. Hybrid Deep Belief Network in Traffic Flow Prediction

Zhang et al. [11] suggest a short-term traffic flow forecasting technique on the basis of a CNN-DL structure. In the presented structure, the optimum input duration lags and spatial data volumes were fixed by a spatio-temporal feature selection algorithm (STFSA), and the chosen spatio-temporal traffic flow features were derived from actual data and transformed into a 2-dimensional matrix. The CNN later studied such features for framing a predictive method. In [12], a hybrid technique compiling FNN and fuzzy rough set (FRS) can be suggested for imputation of missed traffic data. At first, FNN can be utilized for data classification; next, the KNN technique can be employed for determining optimal number of data leveraged to predict missing data in every category; lastly, the FRS was leveraged for imputing missed values. In [13], deep feature learning techniques were recommended for predicting short-term traffic flow in the succeeding multiple steps, utilizing supervised learning approaches. In order to reach traffic flow forecasting for the following day, an advanced multiobjective PSO method is implemented for optimizing certain variables in DBN. The modified method could foster the accuracy of the prediction fallouts and bolster their multiple step prediction capability.

Huang et al. [14] suggest a single-stage DNN-YOLOv3 (you only look once)-DL, that depends on the Tensorflow structure for improvising this issue. The network framework can be maximized by presenting the ideology of spatial pyramid pooling, afterward, the loss function was redefined, and a weight regularization technique was presented, in which, the statistics and real-time detections of traffic flow are applied efficiently. The optimization method uses the DL-CAR dataset for experimentations and end-to-end network training with datasets in various cases and weathers. In [15], a traffic flow detection method depending on DL on the edge node is suggested. Initially, the authors suggest a vehicle detection approach on the basis of the YOLOv3 method trained with a high volume of traffic data. They subsequently then pruned the method for ensuring competence on the edge equipment.

In [16], a novel end-to-end hybrid DL network method, termed M-B-LSTM, was suggested for short-term traffic flow forecasting in this work. In the M-B-LSTM method, online self-learning networks can be built as a data map layer for learning and equalizing the traffic flow statistic dispersal to reduce the impact of overfitting issues and distribution imbalance at the time of network learning. Feng et al. [17] suggest a new short-run traffic flow forecasting technique depends on an adaptive multikernel SVM (AMSVM) with spatial–temporal co-relation, termed

AMSVM-STC. Initially, explore the randomness as well as nonlinearity of traffic flow, and hybrid polynomial kernel and Gaussian kernel for constituting the AMSVM. Secondly, the variables of AMSVM are optimized with the adaptive PSO method and recommends a new technique to constitute the hybrid kernel's weight adjust adaptively in accordance with changing tendency of realistic traffic flow.

Xia et al. [18] presents a short-term traffic flow predictive approach which integrates community detection-based federated learning with graph convolutional network (GCN) for alleviating the time consuming trained, superior communication costs, and data privacy risks of global GCNs as the count of data improves. The federated community GCN (FCGCN) is attain accurate, timely, and safe traffic state predictive from the period of big traffic information that is an important for the effective function of intelligent transportation methods. Lin et al. [19] examines a process for screening spatial time-delayed traffic sequence dependent upon the maximal data coefficient. The selective time-delayed traffic sequence is changed as to traffic state vector in that traffic flow was predictive by implementing the integration of SVM and KNN techniques. The authors utilize the presented infrastructure to real-world traffic flow predictive. Chen et al. [20] introduces a new location GCN (Location-GCN). The location-GCN resolves this problem with added a novel learnable matrix as to GCN process, utilizing the absolute value of this matrix for representing the various control levels amongst distinct nodes. Afterward, the long short-term memory (LSTM) was utilized in the presented traffic predictive system. Besides, Trigonometric function encoder was utilized in this case for enabling the short-term input series for transferring the long-term periodical data.

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