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Traffic Flow prediction in a road network

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Introduction

In this report, I collect many papers that solve the problem of traffic flow prediction in a road network. Most of these implementations use LSTM neural networks, MLPs and statistical models, such as ARIMA or SARIMA models. There are also few solutions with Graph Neural Networks, which are nowadays very popular to different kinds of machine learning problems.

The rest of this report is organized as follows: I mention each paper separately and explain the methodology that authors followed to solve the traffic flow forecast problem.

Paper 1: Traffic Flow Prediction Models: A review of deep learning techniques [1]

Introduction:

The paper discusses the significance of short-term traffic flow prediction in Intelligent Transportation Systems (ITS) and its application in managing traffic congestion, reducing pollution, and enhancing road safety. It highlights the challenges of accurately predicting the highly nonlinear and stochastic nature of traffic flow due to various factors such as weather conditions and landform. The objective is to forecast the traffic flow at a specific time interval based on historical data, with a focus on the 15-minute short-term prediction interval commonly used in transportation research.

In the context of this paper, traffic flow refers to the movement of vehicles on a freeway transportation network within a specific time interval, specifically a 15-minute interval. It represents the volume of vehicles passing through a particular observation station at a given time. The paper aims to predict this short-term traffic flow accurately to provide timely and valuable information for various stakeholders, including individual travelers, businesses, and government agencies.

Methodology:

The paper utilizes the Long Short-Term Memory Recurrent Neural Network (LSTM RNN) model to perform the forecast for short-term traffic flow. The LSTM RNN is a type of neural network that is well-suited for time series prediction tasks.

To perform the forecast, the LSTM RNN model takes historical traffic flow data as input, which includes information about previous traffic volumes within the selected time interval (e.g., the past 30 minutes). The model learns the patterns and dependencies present in the historical data to predict the traffic flow for the next 15-minute interval.

The LSTM RNN architecture includes memory blocks that allow the network to capture and store information over longer time periods, addressing the challenge of temporal dependencies in traffic flow data. Unlike traditional models that rely on predefined and static input historical data lengths, the LSTM RNN dynamically determines optimal time lags and incorporates them into the forecasting process.

The LSTM RNN model is trained using the Caltrans Performance Measurement System (PeMS) dataset, which provides a large amount of historical traffic flow data. The model's performance is evaluated and compared with other established models, such as random walk (RW), support vector machine (SVM), single layer feedforward neural network (FFNN), and stacked autoencoder (SAE), to assess its accuracy and generalization capabilities.

Overall, the LSTM RNN model leverages its ability to capture complex temporal dependencies and adapt to the dynamic nature of traffic conditions to perform the short-term traffic flow forecast.

Results:

The results demonstrate the superiority of the LSTM RNN model in terms of prediction accuracy and generalization capabilities. LSTM RNN outperforms other models in capturing the nonlinear and stochastic characteristics of traffic flow. The ability of LSTM RNN to effectively handle back-propagated error decay through memory blocks contributes to its superior performance in predicting time series data with long temporal dependencies.

Conclusion:

The paper concludes that LSTM RNN is an effective model for short-term traffic flow prediction in Intelligent Transportation Systems. Compared to traditional models that rely on predefined and static input historical data lengths, LSTM RNN dynamically determines optimal time lags, resulting in improved accuracy. The study's findings highlight the importance of accurate traffic flow prediction in managing transportation systems and provide valuable insights for researchers and practitioners in the field.

Paper 2: Predicting Short-Term Traffic Flow by LSTM RNN [2]

The paper proposes a method for accurate short-term traffic flow prediction using the Long Short-Term Memory Recurrent Neural Network (LSTM RNN) model. The objective of the study is to provide timely and precise traffic flow information for intelligent transportation management and route guidance within the context of an Intelligent Transportation System (ITS).

The paper defines traffic flow as the movement of vehicles on a freeway transportation network within a 15-minute time interval. The authors emphasize that traffic flow prediction is challenging due to the complex and stochastic nature of the freeway transportation network, influenced by factors such as weather conditions and landform.

To perform the forecast, the LSTM RNN model is employed. It is selected for its ability to handle multi-dimensional data, flexibility in model structure, strong generalization, learning ability, and adaptability. Unlike traditional models, such as the feed-forward neural network (FFNN), the LSTM RNN model can capture long-term dependencies and determine optimal time lags dynamically.

The LSTM RNN model is trained using historical traffic flow data from the Caltrans Performance Measurement System (PeMS) dataset. It leverages the memory blocks within the architecture to identify optimal time lags for predicting traffic flow. The model's performance is compared with other established models like random walk (RW), support vector machine (SVM), single-layer feed-forward neural network (FFNN), and stacked autoencoder (SAE) to assess its accuracy and generalization capabilities.

Overall, the paper presents the LSTM RNN model as a suitable approach for short-term traffic flow prediction in intelligent transportation systems. The model's ability to capture complex temporal dependencies and dynamically determine optimal time lags contributes to achieving higher accuracy in traffic flow forecasting.

Paper 3: Supervised deep learning based for traffic flow prediction [3]

In this paper traffic flow refers to the movement, quantity, and characteristics of vehicles or pedestrians on a road network within a specific area or period. It encompasses factors such as vehicle speed, density, and volume, and provides insights into the level of congestion, traffic patterns, and overall efficiency of transportation systems. Accurate prediction of traffic flow is crucial for efficient traffic management, planning, and decision-making in order to address issues like congestion, accidents, air pollution, and energy consumption in metropolitan areas.

The methodology employed in this study for forecasting traffic flow is a Supervised Deep Learning Based Traffic Flow Prediction (SDLTFP) approach using a fully-connected deep neural network (FC-DNN). The authors acknowledge the significance of timely prediction and address potential challenges such as overfitting and time-consuming training.

To mitigate overfitting and improve training efficiency, Batch Normalization (BN) and Dropout techniques are integrated into the neural network. BN helps normalize the inputs to each layer, reducing internal covariate shift and making the training process faster and more stable. Dropout is used to randomly deactivate a fraction of neurons during training, preventing reliance on specific patterns and enhancing the network's ability to generalize.

Stochastic Gradient Descent (SGD) with momentum is utilized for weight updates in the training process. SGD calculates the gradient of the loss function for each training sample and performs weight updates accordingly. The inclusion of momentum helps accelerate convergence and smoothens the trajectory during optimization.

The experiments are conducted using open data as historical traffic data, which is used to train the proposed SDLTFP method and model. The Mean Absolute Percentage Error (MAPE) is employed as an evaluation metric to assess the accuracy of traffic flow predictions. MAPE is calculated for both sample data (within 5%) and out-of-sample data (ranging between 15% and 20%), demonstrating the method's ability to predict traffic flow accurately.

By utilizing the proposed methodology, the authors aim to provide an accurate traffic flow prediction to facilitate the Traffic Management System (TMS) of Intelligent Transportation Systems (ITS). The integration of BN and Dropout techniques not only enhances the training process but also helps reduce overfitting, resulting in reliable traffic flow predictions.

Paper 4: Traffic Flow prediction with big data: A deep learning approach [4]

In this paper, traffic flow refers to the movement of vehicles on transportation networks, such as roads or highways. It specifically relates to the quantity of vehicles passing through a specific location at different time intervals. The observed traffic flow quantity, denoted as Xt_i, represents the traffic volume or other traffic-related metrics measured at the ith observation location during the tth time interval. The prediction of traffic flow aims to provide accurate and timely information about the anticipated traffic conditions, which is crucial for transportation management, intelligent transportation systems, and various applications in traffic control and optimization.

The methodology used in the paper to forecast traffic flow involves the implementation of a stacked autoencoder (SAE) model, which is a deep learning architecture. The SAE model is trained using traffic flow data collected from the Caltrans Performance Measurement System (PeMS) database. Here is a breakdown of the methodology:

1. Data Collection: Traffic flow data is collected from the Caltrans PeMS database. This database contains aggregated information from a large number of detectors located on various transportation networks.

2. Preprocessing: The collected data is preprocessed to remove any outliers or inconsistencies. It is then divided into training and testing sets for model evaluation.

3. Model Architecture: The SAE model is introduced as the primary methodology for traffic flow prediction. The SAE is a deep learning model that consists of multiple layers of autoencoders. An autoencoder is a type of neural network that aims to reconstruct its input at the output layer, effectively learning to represent the data in a compressed form. The SAE model uses autoencoders as building blocks to create a deep network.

4. Training Process: The SAE model is trained in a greedy layerwise fashion, where each layer is pretrained individually before fine-tuning the entire model. This process allows the model to learn hierarchical representations of traffic flow features.

5. Evaluation: The performance of the SAE model is evaluated using various metrics, such as prediction accuracy and mean absolute error. The model's performance is compared with other prediction methods, including BP NN, random walk, SVM, and RBF NN models.

6. Results and Analysis: The paper presents the results of the experiments conducted using the SAE model. It highlights the superior performance of the SAE model in accurately predicting traffic flow in heavy and medium traffic conditions. However, it notes that the model struggles to perform well in low traffic flow conditions, similar to existing prediction methods.

Overall, the methodology focuses on training and evaluating the SAE model using real traffic flow data. It demonstrates the potential of deep learning techniques, specifically the SAE model, for accurately forecasting traffic flow. The paper provides insights into the strengths and limitations of the proposed methodology and compares it with existing prediction methods.

Paper 5: Comparative Analysis for traffic flow forecasting in the city of Beijing [5]

In this paper, traffic flow is denoted by the term "traffic speed." It is defined as the average speed based on the average travel time of vehicles to traverse a defined roadway length. The data collected includes traffic speed measurements taken every 5 minutes over a 24-hour period. The traffic speed data provides insights into the flow of traffic and the level of congestion on the road.

The methodology employed in this study for traffic flow prediction involves comparing the performance of three different prediction models: autoregressive integrated moving average (ARIMA), neural network, and nonparametric regression. The goal is to determine which model provides the most accurate and effective forecasts using real-life data in Beijing.

To start, the authors collected real-life traffic data from the Intelligent Transportation Control System of Beijing. This data includes information such as traffic volume, speed, and occupancy. Two specific sites, Jianguomen Bridge and Jimen Bridge, were selected for the analysis.

The three prediction models, ARIMA, neural network, and nonparametric regression, were then applied to the collected data to generate traffic flow forecasts. The authors evaluated the prediction results using measures such as root mean square error (RMSE) and error distribution.

Additionally, the Wilcoxon signed-rank test was used to compare the models. This statistical test helps identify any significant differences in the performance of the models. By applying this test, the authors were able to determine that the nonparametric regression model displayed superior accuracy compared to the other models.

The authors also assessed the spatial-transferred application effect of each model. It was found that the nonparametric regression model exhibited the best application effect when forecasting traffic flow in different locations beyond the original data collection sites.

Overall, the methodology focused on collecting real-life traffic data, applying different prediction models, and evaluating the accuracy and spatial transferability of the forecasts. This approach allows for a comparative analysis of the performance of different models when it comes to traffic flow prediction.

Paper 6: DeepCrowd-A Deep Model for Large-Scale Citywide Crowd Density and Flow Prediction [6]

The problem being addressed in the paper is the prediction of crowd or traffic flow at a citywide level, utilizing big mobility data generated from sources such as mobile phones, car navigation systems, and traffic sensors. The authors highlight the importance of such predictions in emergency management, traffic regulation, and urban planning. They propose a solution that involves dividing a large urban area into fine-grained mesh-grids and representing citywide crowd density and flow as a four-dimensional tensor.

The authors define traffic flow as the movement of individuals within the mesh-grids. They introduce the concept of crowd density, which refers to the number of individuals present in a specific mesh-grid at a specified timestamp. The crowd in-out flow is also considered, representing the movement of individuals between consecutive timestamps within a particular mesh-grid.

To tackle this problem, the authors propose a novel deep learning model called DeepCrowd, which leverages pyramid architectures and high-dimensional attention mechanisms based on Convolutional LSTM.

The study utilizes a large-scale aggregated human mobility dataset generated from a real-world smartphone application. This dataset offers advantages over existing ones, including a larger number of mesh-grids, finer granularity in mesh size, and a higher number of user samples. By representing the citywide crowd density as a four-dimensional tensor (Timestep, Height, Width, Channel), similar to video data, the authors are able to capture and analyze the spatiotemporal aspects of crowd and traffic patterns.

The methodology of DeepCrowd involves the use of pyramid architectures and high-dimensional attention mechanisms. The pyramid ConvLSTMs allow for multi-scale feature extraction by combining features from different levels of the pyramid. This helps capture both global and local spatial information for crowd density and flow prediction. Additionally, the 4D high-dimensional attention block enhances the model's ability to focus on informative regions in the spatial and temporal dimensions. The early-fusion mechanism combines different data modalities for more accurate predictions.

To evaluate the performance of DeepCrowd, the authors conduct thorough experiments and compare their results with multiple state-of-the-art methods. Four metrics, MSE, RMSE, MAE, and MAPE, are used for evaluation. The experiment results demonstrate the effectiveness and efficiency of the proposed model for citywide crowd prediction in two big cities, Tokyo and Osaka.

In summary, the paper presents a complete framework for predicting citywide crowd density and flow, from data preprocessing to deep learning models. It introduces a novel deep learning model, DeepCrowd, which incorporates pyramid architectures and high-dimensional attention mechanisms. The authors also generate and publish a new high-quality dataset for crowd density and flow prediction. The evaluation results show the superiority of DeepCrowd compared to existing methods.

GitHub Link: https://github.com/deepkashiwa20/DeepCrowd

Paper 7: Diffusion Convolutional Recurrent Neural Network (DCRNN) [7]

In the given source, traffic flow is not explicitly defined. However, it is mentioned that traffic flow is related to a diffusion process, which captures the stochastic nature of traffic dynamics. Through this diffusion process, the authors aim to model the spatial dependency in traffic. Essentially, traffic flow refers to the movement of vehicles on a road network over a specific period, and it is influenced by various factors such as the number of vehicles, road capacity, congestion, and traffic incidents. The authors emphasize the complex spatiotemporal dependencies and the inherent difficulty in long-term traffic flow forecasting.

The methodology used in this paper to predict traffic flow is a Diffusion Convolutional Recurrent Neural Network (DCRNN). This model combines both spatial and temporal dependencies to capture complex traffic patterns.

To model the spatial dependency, the authors use a diffusion process, which represents the stochastic nature of traffic dynamics. The diffusion process is characterized by a random walk on the road network graph, with a restart probability α ∈ [0, 1] and a state transition matrix D^-1 * O * W.

The DCRNN model consists of two main components:

1. Bidirectional Graph Random Walk: This component captures the spatial dependencies in traffic by conducting a random walk on the graph. The random walk starts from each sensor node and walks both forward and backward in the graph to gather information from neighboring nodes. This captures the correlation between different roads and considers the directional nature of traffic flow.

2. Recurrent Neural Network: The temporal dependency in traffic flow is modeled using a recurrent neural network (RNN). The RNN component captures the dynamic patterns and temporal variations in traffic speeds over time. By utilizing a Gated Recurrent Unit (GRU) architecture, the model can effectively encode past traffic information and make predictions for future traffic speeds.

The DCRNN model also incorporates an encoder-decoder architecture and a scheduled sampling technique to improve the performance of long-term forecasting. The encoder-decoder architecture allows the model to learn representations of the input data and generate future predictions. The scheduled sampling technique addresses the issue of the model being exposed to only ground truth during training, by gradually introducing the predicted values as input during the decoding phase. This helps the model better handle the discrepancy between training and inference phases.

Overall, the DCRNN model captures both the spatiotemporal dependencies in traffic flow by combining the diffusion process and recurrent neural networks. It outperforms baseline methods on large-scale real-world traffic datasets, showing its effectiveness in traffic flow prediction.

GitHub Link: https://github.com/liyaguang/DCRNN

Paper 8: T-LSTM: a long short term memory network enhanced by temporal information for traffic flow prediction [8]

The paper focuses on the important issue of short-term traffic flow prediction in the field of Intelligent Transportation Systems (ITS). The definition of traffic flow in this paper is not explicitly stated. However, it is described as a highly nonlinear and random characteristic of traffic. The paper also mentions that traffic flow prediction methods have traditionally used linear models and shallow machine learning models, which suggests that traffic flow refers to the volume of vehicles or the rate at which vehicles move on a road or within a road network.

As for the methodology conducted to forecast traffic flow, the paper mentions two main categories of methods: parametric models and nonparametric models. Parametric models are based on predetermined structures and theoretical assumptions, and their parameters can be computed. Nonparametric models, on the other hand, do not rely on predetermined structures and assumptions.

The paper introduces the T-LSTM model, which combines recurrent neural networks (RNNs) and recurrent time labeling. RNNs, particularly the LSTM (Long Short-Term Memory) variant, are used to model nonlinear time series problems effectively. The LSTM model consists of input layers, recurrent layers with memory blocks, and an output layer. The primary objectives of LSTM are to model long-term dependencies in the data and determine the optimal input length using multiplicative units.

The results of the traffic flow prediction using the T-LSTM model are evaluated based on two measures: the root mean square error (RMSE) and the mean absolute percentage error (MAPE). The RMSE measures the average difference between the observed and predicted values, taking into account both the magnitude and direction of the errors. The MAPE, on the other hand, measures the percentage difference between the observed and predicted values, providing an indication of the overall accuracy of the predictions.

In the evaluation, the proposed T-LSTM model is compared with existing models such as SAE, DBN, GRU, LSTM, SVM, KNN, FFNN, and ARIMA. The comparison is made under the same conditions using the same input information. The results show that the T-LSTM model achieved the highest prediction accuracy, with a MAPE of 6.09% for the prediction of traffic flow in August 2014. Adding time labels to the LSTM model improved its prediction performance, with the RMSE and MAPE of T-LSTM decreasing by 13.4 and 1.44% respectively, compared to LSTM without time labels.

The evaluation results also indicate that deep neural network models (T-LSTM, T-GRU, SAE, DBN, FFNN) outperformed classic models such as ARIMA, KNN, and SVM in terms of RMSE. However, the MAPE of SVM was relatively high, suggesting that it had poor prediction performance especially when traffic flow was low.

The evaluation used historical traffic flow data, which were processed to train the T-LSTM model. The raw valid data was used to infer missing data, and the repaired data was aggregated into time intervals of 16 minutes for the traffic flow prediction experiment. The specific details about the characteristics and sources of the data are not mentioned in the provided source.

The paper also mentions that the traffic flow forecasting methodology can be improved by processing traffic data obtained from sensors. However, it does not provide specific details on the data processing techniques used in this particular study. Additionally, the paper states that currently, only the traffic flow of a road section is forecasted, and the future research will focus on predicting the traffic flow of the entire road network.

Paper 9: Hybrid LSTM Neural Network for Short-Term Traffic Flow Prediction [9]

In this paper, the authors define traffic flow as the movement of vehicles through a traffic network over a specific time period. The flow is typically measured in terms of the number of vehicles passing a particular location or roadway section.

The methodology followed in the paper involves two main components: the experimental environment and the data set, and the evaluation indicators used.

First, the experimental environment is described, which includes the hardware, software, and programming language used. The hardware used for the experiments is an Intel Core i5-3210M 2.5 GHz dual-core processor with 4 GB memory. The operating system is Windows 7 64 bit. The programming language chosen for implementation is Python, and the deep learning framework utilized is Keras. This description provides the necessary context for understanding the experimental setup and ensures reproducibility.

Next, the data set used in the experiments is described. The data set consists of local road network traffic data from September 1st to September 8th in Yunyan District, Guiyang City, Guizhou Province. The data set contains over 230,000 vehicle records. Each record in the data set comprises three fields: Current Node (TrafficLightID), Source Node (FromID), and Traffic Flow (traffic_flow). The Current Node field represents the traffic light identifier of the vehicle currently, while the Source Node field represents the traffic light identifier of the vehicle at the last moment. The Traffic Flow field is a matrix of dimension 1680, representing the traffic flows of a road section at a 30-second interval. For example, traffic_flow[0] represents the traffic flow from the road intersection FromID to road intersection TrafficLightID at time t=0. The local road network structure involved in the data set is also provided, visualized in Figure 3, where the hollow circles represent intersections, their sides are marked with unique identification numbers, and the solid lines represent road sections. This detailed description of the data set allows readers to understand the characteristics of the traffic data and the network structure involved in the experiments.

Furthermore, the evaluation indicators used to assess the performance of the hybrid LSTM model are discussed. The chosen indicator is the Root Mean Square Error (RMSE). RMSE is selected because it reduces the impact of gross errors on the final result and maintains the same unit as the predicted traffic flow data. The mathematical expression of RMSE is not explicitly provided in the excerpt, but it is mentioned that a reference is followed [30]. This indicates that the paper refers to a specific source for the mathematical formulation of RMSE. The use of RMSE as an evaluation metric allows for a quantitative assessment of the accuracy of the hybrid LSTM model in predicting traffic flows.

The findings demonstrate that the maximum relative error between the actual and predicted vehicle flows for each road section is 1.03%, and for each road intersection is 1.18%. Thus, the hybrid LSTM model demonstrates a higher level of accuracy and meets the real-time requirements of short-term traffic flow prediction. Furthermore, it proves to be suitable for different traffic conditions within an actual traffic network.

Paper 10: Graph Hierarchical Convolutional Recurrent Neural Network (GHCRNN) for Vehicle Condition Prediction [10]

In this paper, traffic flow refers to the movement of vehicles in urban areas. It is denoted as the number of vehicles passing through a particular location or region within a specific period of time. The study focuses on predicting urban vehicle flow and speed, which is crucial for smart cities to enhance travel planning and decision-making.

The methodology used in this paper involves the application of a recurrent neural network (RNN) variant known as Gated Recurrent Unit (GRU) to model the time features and predict traffic flow in urban areas. The GRU model is a type of RNN that is capable of capturing long-term and short-term dependencies in the time dimension, making it suitable for capturing the temporal patterns and trends in traffic flow data. The GRU model is defined by a set of equations that govern the update and reset gates, as well as the hidden state.

The first step of the methodology involves preprocessing the traffic flow data, which may include steps such as data cleaning, normalization, and feature selection. Then, the data is divided into training and testing sets. The GRU model is trained using the training set of traffic flow data, with the aim of learning the patterns and dependencies within the data. The model is trained to minimize the loss function, which measures the discrepancy between the predicted traffic flow values and the actual values.

Once the GRU model is trained, it is used to make predictions on the testing set, where the actual traffic flow values are known. The performance of the model is evaluated using various metrics, such as mean absolute error (MAE) and mean squared error (MSE), to measure the accuracy of the predictions.

Furthermore, the paper compares the performance of the GRU model with other existing models, including the historical average model (HA), autoregressive integrated moving average model (ARIMA), support vector regression (SVR), and long short-term memory (LSTM). The evaluation of these models is done based on the same metrics and dataset. Based on the results, the GRU model, particularly the proposed GHCRNN (Gated Highway Convolutional Recurrent Neural Network) models, exhibited superior performance compared to the other models, demonstrating its effectiveness in forecasting traffic flow in urban areas.

Overall, the methodology combines the power of recurrent neural networks, specifically the GRU model, with traffic flow data to accurately predict and forecast urban vehicle flow, contributing to better travel planning and decision-making in smart cities.The results of the traffic flow forecasts were evaluated using different models on Shenzhen vehicle flow data. The models used for comparison include the historical average model (HA), autoregressive integrated moving average model (ARIMA), support vector regression (SVR), long short-term memory (LSTM), and the proposed GHCRNN-nopool and GHCRNN models. The evaluation metrics used were loss, mean absolute error (MAE), and mean squared error (MSE). The results demonstrated that the GHCRNN models outperformed the other models, with lower MAE, MSE, and loss values.

The specific details about the data used for traffic flow forecasting in this paper are not provided. The paper mentions that the data used for evaluation is Shenzhen vehicle flow data. However, it does not provide information regarding the size of the dataset, the time range, or the specific spatial locations.

Regarding the results of the traffic flow forecasts, the paper compares the performance of different models using evaluation metrics such as loss, mean absolute error (MAE), and mean squared error (MSE). The GRU models, particularly the proposed GHCRNN (Gated Highway Convolutional Recurrent Neural Network) models, were found to outperform other models in terms of lower MAE, MSE, and loss values.

Unfortunately, the paper does not provide specific numerical values or a detailed analysis of the results in terms of the accuracy of the traffic flow forecasts.

Paper 11: Short-Term Traffic Flow Prediction Based on XGBoost [11]

In this paper, traffic flow is defined as the movement of vehicles through a specific lane at a given time. It is measured in terms of parameters such as the number of vehicles passing through, average speed, occupancy (the percentage of time the lane is occupied by vehicles), and vehicle count. These parameters provide information about the volume and characteristics of vehicle movement and help in analyzing and predicting traffic patterns.

The methodology of this paper combines wavelet decomposition and reconstruction with the XGBoost algorithm for short-term traffic flow prediction. Wavelet decomposition is used to extract the high and low frequency information from the target traffic flow, while reconstruction combines the high and low frequency information to create the training label. The XGBoost algorithm is then applied to predict the traffic flow, improving the precision and efficiency of the prediction model.

The evaluation of the methodology is performed through comparison with other methods, namely SVM and XGBoost without wavelet decomposition. The results are presented in Table 3. The evaluation metrics used are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

The results show that the proposed method achieves a lower RMSE and MAPE compared to SVM and XGBoost without wavelet decomposition. Specifically, the RMSE values are 6.1177 (XGBoost with wavelet decomposition), 6.1801 (XGBoost), and 7.3061 (SVM), indicating that the proposed method has the lowest prediction error. Similarly, the MAPE values are 0.2125 (XGBoost with wavelet decomposition), 0.2215 (XGBoost), and 0.3053 (SVM), further confirming the improved accuracy of the proposed method.

Overall, the methodology combining wavelet decomposition and XGBoost algorithm proves effective in enhancing the precision and efficiency of short-term traffic flow prediction. The evaluation results demonstrate the superiority of the proposed method compared to the SVM and XGBoost without wavelet decomposition.

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