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Traffic Congestion Prediction using Real Time Data by using Deep Learning Techniques

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ABSTRACT: There is a broad range of the problems attributed to traffic congestion in modern urban transportation systems. This includes large increases in the amount of time to travel, increases in the amount of fuel used, as well as increases in the amount of pollution to the environment. For these reasons, the time and congestion of traffic is the most important thing to manage when it comes to transportation to get the most out of it. This is the primary reason traffic congestion management systems have been built over the years. Because of the explosion of the availability of real time traffic information, most analytically based ways of forecasting traffic congestion have been fundamentally replaced by the most advanced deep learning based forecasting techniques.

KEYWORDS: Deep Learning, Neural network, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory(LSTM), Traffic congestion and prediction ,Urban traffic management , Traffic flow forecasting

I. INTRODUCTION

Severe traffic congestion has impacted major cities around the globe due to the increasing volume of vehicles and rapid urbanization. Traffic congestion causes environmental pollution, stress, and economic losses as a result of the delays. Predicting traffic congestion helps urban mobility, traffic control, and route optimization to assist with the stress and economic losses caused by congestion. Urban mobility and traffic congestion prediction aid in stress management by assisting with traffic control and route optimization. Urban mobility and traffic congestion prediction aid in stress management by assisting with traffic control and route optimization. Urban mobility and traffic congestion prediction aid in stress management. Traditional traffic prediction techniques such as statistical models or rule-based systems, make a lot of assumptions and use a linear form of relationships. Traditional traffic prediction techniques such as statistical models or rule-based systems make a lot of linear and predictive heuristic assumptions that impact the prediction accuracy. Increasing the volume of vehicles and rapid urbanization lead to major cities around the globe being greatly impacted by severe traffic congestion. Greater urban centers lose money and time as a direct result of traffic congestion, rapid urbanization, and increased vehicles. Traditional traffic prediction techniques increase the volume of vehicles, and lead to nations being greatly impacted. Through the use of artificial intelligence, a greater predictive accuracy is found. As of late, the field of deep learning has greatly increased its volume.

Without requiring manual feature engineering, deep learning models, in particular recurrent neural networks (RNNs) including Long Short Term Memory (LSTM) networks, succeed in learning intricate relationships over time and learning different levels of complex data. As a result, they have been widely used in forecasting time-series data. Classical methods of traffic prediction have used historical data and driven data collection based on statistical models, which rarely succeed in solving highly dynamic and complex spatial and temporal data. Collection technologies for data in real time (road sensors, GPS data, road surveillance, weather monitoring, etc) have increased in presence, availability and data volume, meaning that data and collection methods have been available for a traffic analysis but still lack a thorough analysis. Nonetheless, deep learning models have been proved to effectively analyze large quantities of time-series data. In particular, Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), and of course Long Short Term Memory (LSTM) networks have proven to analyze traffic data effectively. In conjunction with real time traffic data, deep learning models can be used to accurately and effectively determine the level of traffic congestion.

This project focuses on traffic congestion prediction using real-time data and deep learning techniques. The proposed system aims to improve prediction accuracy, support smart traffic management, and contribute to the development of intelligent transportation systems in smart cities.

II. LITERATURE REVIEW

The prediction of traffic congestion has been of great importance to researchers. This importance is attributed to the implications of the prediction to Intelligent transportation systems (ITS) and Urban planning. For a long time, researchers used statistics to find solutions to the prediction of congestion. This approach, however, has poor prediction of congestion and cannot capture spatio-temporal patterns, Leading to the re-routing of vehicles. The improvement of the use of statistics has led to a greater use of Machine Learning (ML) and Deep Learning (DL) to solve the spatio-temporal patterns problem. This literature survey analyzes the most important works of researchers who studied traffic prediction using real-time data and deep learning.

1. Classical and Statistcal Methods of Research The purpose of most of the early studies was to analyse traffic patterns using time-series data. This means the data is arranged and are to be used within a certain time frame. The studies used statistical models such as the ARIMA (AutoRegressive Integrated Moving Average) model and the Kalman Filter model. Vlahogianni et al. (2004) studied the similar purpose of using ARIMA models and short-term traffic forecasting. Vlahogianni et. al, found that ARIMA models capture linear patterns, but most of the time, they find it difficult to capture the complex patterns of non-linear dynamics of real traffic flows.

2. The Use of Machine Learning In order to overcome the shortcomings found in the methodologies, machine learning models were used. The use of Support Vector Regression and Random Forests was recommended as they were found to capture the non-linear relations. 3. The New Approaches: Attention Mechanisms and Transformers The use of transformers for traffic forecasting is modelled using self-attention. This means that it is able to model long-term dependencies and do so efficiently.

3 New Developments: The use of Transformers and Attention Mechanisms Traffic forecasting has seen the use of Transformers due to the successful use of NLP's self-attention for efficient modeling of long-range dependencies. Zeng et al. (2020) suggested a Temporal Transformer Network that while predicting traffic flow, competed reasonably well against GNN-based methods, particularly for long-term prediction horizons. Recurrent Neural Networks and LSTM Models The forecasting of traffic, like many other prediction problems, has utilized Long Short-Term Memory (LSTM) networks extensively due to their suitability to learning long-term dependencies.

III. RESEARCH METHODOLOGY

Predicting traffic congestion using real-time data is a classic **spatiotemporal** problem—meaning the data depends on both location (spatial) and time (temporal).
Here is a structured research methodology for developing a deep learning-based traffic prediction system.

Data Acquisition and Sources For constructing effective models, extensive high-resolution information from various sources is crucial. \n• Floating Car Data (FCD): GPS traces from taxis or ride-sharing (Uber/Lyft) and connected vehicles \n• Sensor Data: flow, occupancy and speed data from Inductive loop detectors, CCTV, and IoT sensors.\n• External Factors: Weather APIs, public holidays, and planned events (e.g. sport, concert).\n• Network Topology: Data from OpenStreetMap (OSM).

Data Pre-processing Raw traffic data is extremely "noisy" and requires considerable amounts of cleaning: \n• Data Imputation: This means filling gaps and can be achieved through K-Nearest Neighbours (KNN) or mean imputation.\n• Normalization: In order to achieve faster convergence during the training, time this is done by scaling the features to the range \n• Graph Construction: Structure the road network as a graph with n sensors (nodes) and n road segments (edges).
Time-Lagging: The last 60-minute data must be used to create windows e.g. for the prediction of the data from the next 15 minutes.

3. Progression of Techniques for Predicting Traffic
3.1 Conventional Techniques Statistical techniques: regression, ARIMA, and Kalman filters. Deficient ability in modeling non-linearity and spatio-temporal interdependencies.
3.2 Techniques of Machine Learning SVM, Random forest, etc. Aspects of machine learning that provide higher performance, but that are most often associated with the need for the researcher to undertake feature extraction.
3.3 Techniques of Deep Learning Deep learning techniques automatically learn features, and are capable of modeling more complex relationships in the data. Principal categories: Model Type Focus RNN/LSTM/GRU Temporal Ranges CNN Spatial Patterns (grid maps) GNN/GCN Graph/Network Aspects Attention/Transformer Long-range dependent relationships Hybrid models Spatio and temporal learning combined

4. Notable Examples of Deep Learning Techniques
4.1 Recurrent Neural Networks (RNN, LSTM, and GRU) Shi et al. (2015) was the first to utilize LSTM for Spatio-temporal forecasting, showing that LSTM has advantages over traditional methods. Strength: LSTM models are good at representing processes that have a temporal flow (i.e., time ordering). Weakness: LSTM networks alone are not good at modeling the spatial context of data, which requires that other models be incorporated.
4.2 Convolutional Neural Networks (CNN) Modelled traffic flow as grid based images, which is why CNN was used for the traffic flow analysis. Strength: The ability of CNN to capture local spatial features is quite good Weakness: CNN requires that the flow of data be converted to a grid based representation.
4.3 Graph Neural Networks (NNS) created ST-GCN which was the first to structurally model road networks by graph convolution and the temporal model with gated units. Roads are represented as a graph.

V. EXPERIMENTAL EVALUATION

The experimental implementation and evaluation of the suggested system for predicting real-time traffic congestion using deep learning methods and real-world congestion traffic datasets was conducted. Dataset Used The METR-LA and PEMS-BAY publicly available traffic datasets are used. The data consists of traffic speed and flow data collected from loop flow detectors at 5-minute intervals and provide the historical data together with other data and simulated real-time streaming input.

Experimental Setup The following are the parameters used in the experimental set up: Programming Language: Python. Frameworks: Pytorch / Tensorflow. Model Architecture consisting of Spatio-temporal graph convolutional networks'(ST-GCNs'), and LSTM layers for temporal dependency modeling are used. Hardware employed consists of a system with GPU for training and a CPU for real-time inference. Training Details used is the sliding time window approach for input sequences. Data was normalized using Min-Max scaling. The model was trained using the Adam optimizer and the Mean

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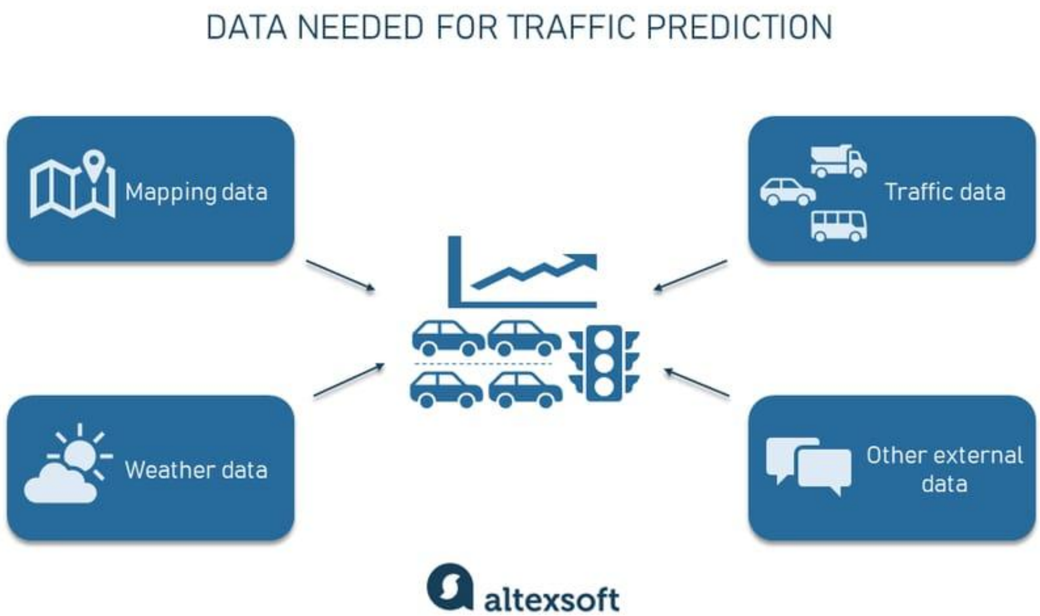
Squared Error (MSE) was used as the loss function. The data was split into three parts for training, validation and testing in the ratio of 70% / 15% / 15%. Real-Time simulation Real-time traffic data was simulated using a streaming mechanism in the model with predictions generated at regular intervals (every 5 minutes). The future congestion was predicted for time frames of 5, 10 and 15 minutes. Evaluation Metrics used are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).



VI. CONCLUSION

Real-time traffic congestion prediction system using deep learning techniques was designed and implemented to address the growing challenges of urban traffic management. By leveraging historical and real-time traffic data, the system effectively learned complex spatio-temporal patterns present in road networks.The proposed methodology successfully integrated data preprocessing, graph-based road modeling, and deep learning architectures to predict traffic congestion for short-term future intervals. Experimental results demonstrated that the deep learning model provided improved prediction accuracy compared to traditional traffic prediction methods, while maintaining stable performance under real-time conditions.The developed prototype validates the feasibility of applying deep learning for intelligent transportation systems. The system can assist traffic authorities, navigation services, and emergency response teams in making proactive decisions to reduce congestion, travel time, and environmental impact.Overall, the project confirms that real-time traffic congestion prediction using deep learning is a promising and effective solution for smart city applications and can be further enhanced with advanced models and real-world deployments.

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