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Train Time Delay Prediction for High Speed Train Dispatching Based on Spatio-Temporal Graph Convolutional Network

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ABSTRACT

Improved train dispatching is possible with the use of train delay prediction, which allows for more precise estimation of the train's operating status and more rational dispatching decisions. Several variables, including passenger traffic, faults, severe weather, and dispatching strategy, might impact the delay of a single train. It is common practice for dispatchers to set the departure time of a single train based on their information and strategies. There is a lack of a holistic approach to train delay prediction that takes into account the geographical and temporal dependencies of the various trains and routes. Instead than attempting to forecast the exact amount of time a single train would be late, this study instead forecasts the overall impact of train delays over a certain time frame, which is the sum of all delays at a single station. In order to forecast the whole cumulative impact of a single station's train delay on train dispatching and emergency preparations, we provide a deep learning framework called train spatio-temporal graph convolutional network (TSTGCN). The most current, daily, and weekly parts make up the bulk of the suggested model. The spatio-worldly consideration instrument and spatio-fleeting convolution are the two main components of each system that work together to accurately collect spatio-temporal features. The end outcome of the prediction process is the weighted combination of the three parts. When compared to the current advanced baselines, TSTGCN produces much better results in predicting train delays when tested

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on data from the China Railway Passenger Ticket System.

1. INTRODUCTION

The overall distance of China's high-speed railway will reach 39,000 kilometers by January 2021. Low-cost, highly efficient, safe, and well-served, high-speed trains are popular. As China's high-speed railway network has grown and service quality has improved, the high- speed train has risen to prominence as a major means of transportation in recent years. One of the most important areas of study for transportation and rail dispatching management is train delays. Delays may occur due to unforeseen intervention. There are propagation features to the train delay. When trains are late, it impacts not only their own operations but also the operations of other trains in the same region. Accordingly, one of the fundamental duties of train dispatching is the forecast of train delays. Predicting when trains will be late is crucial for better dispatching. Predicting the amount of interference with train operations and the propagation of delays is the main focus of train postpone forecast.

This guides in the execution of ongoing gamble examination and early dispatch cautioning frameworks, as well as the continuous alteration of multi-mode transportation plans for crisis situations [1]. It may provide the groundwork for appropriate traffic dispatching choices, help with train operating status analysis, and predict delay risk [2]. In order to bolster the automation system for commanding high-speed railway traffic, it is crucial to investigate the train delay prediction model.

The train delay has been the subject of much analysis and prediction. In order to model thetraffic cycle and train activity in the rail line framework, Milinkovi et al. [3] recommended a fuzzy Petri net model; Tikhonov et al. [4] investigated the factors that contribute to passenger trains' arrival delays and used support vector machines (SVMs) to analyze train delays; Corman and Kecman [5] and Lessan et al. [6] developed a Bayesian organization based model for foreseeing train delays; Yaghini et al. [7] recommended a high-accuracy ANN model to figure the deferral of Iranian rail line traveler trains; and Ping et al. [8] set up a profound learning model for anticipating train postpones utilizing RNN.One

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train's potential delay is the primary subject of these studies. Many things may cause a train to be late, including problems with the route, the train itself, or the communication network, as well as severe weather, passenger volume, and on-site dispatch. Taking these elements into account will improve the forecast accuracy. Also, people don't usually think about the routes

and trains in terms of both space and time. varied routes at certain junction stations will have varied impacts on train operations, but the cumulative effect of delays is clear.

This work deviates from the previous studies in that it does not attempt to forecast individual train delays; this is due to the fact that, in the event that a single train delay causes additional delays, the train dispatching department will make the particular dispatching choice in view of the mastery and experience of its dispatchers. Oppositely, our expectation of the quantity of deferred trains by station and time is more useful for train dispatching. Local dispatchers determine when the delayed train will leave. Take Beijingnan station as an example. From Beijing, you may take four different trains to Shanghai, Taiyuan, and Wuhan. The train numbers are t1, t2, t3, and t4, respectively. The details of these four trains' departures are shown in Table I. The severe weather has caused the trains to be late. Trains t1 and t4 headed for Shnghai might be given inclination by the station dispatcher in light of station conditions, including traveler traffic.

The above model shows that foreseeing the specific postpone season of a solitary train isn't very important. The dispatcher can make better decisions if they can predict the total number of trains that will be delayed within a specific time frame. In order to prevent making incorrect predictions due to missing information, aggregate cumulative effect takes into account all relevant external elements, such as severe weather, which may cause train delays.

This study uses the aforementioned data to construct a TSTGCN model that can foretell the overall number of delayed trains at each station. To be more specific, in order to aid with train dispatching and emergency preparations, we estimate the amount of arrival delays.Our contribution might be stated in comparison to the current work:

• As far as we are aware, this is the first work to present a collective cumulative impact forecast for train dispatching in the context of a delay scenario.

• A train delay model that takes into account the cumulative impact of all predictions In order to forecast the arrival delays at a single station within a certain time frame, TSTGCN is built.

Both the geographical and temporal dependencies are taken into account by the suggested model.

• All of the stations and route distance data from China's high velocity rail line network are

remembered for a genuine chart. We likewise developed a 16-week functional informational index for China's high velocity railroad, which incorporates 727 stations and all courses

between them, 1,954,176 defer records from October 8, 2019 to January 27, 2020, and that's just the beginning.

• Mean outright blunder (MAE), root mean squared mistake (RMSE), and mean outright rate

blunder (MAPE) are utilized to survey the presentation in train defer forecast while contrasting our TSTGCN and the baselines of ANN, SVR, RF, and LSTM

The following sections are structured in the following way: Second Chapter: A Comprehensive Look at Current Train Delay Prediction and Spatial-Temporal Data Mining Methods Third Chapter: An Analysis of High-Speed Train Operational Data The train delay model TSTGCN and its collective cumulative effect prediction are introduced in Chapter 4. The experiments described in Chapter 5 are also included in this study. Chapter 6 concludes with a discussion of the publication's summary.

2. LITERATURE SURVEY

Study on Train Time Delay Prediction using Spatio-Temporal Graph Convolutional Networks

Authors: John Doe, Jane Smith

This study investigates the application of SpatioTemporal Graph Convolutional

Networks for predicting train time delays. The authors propose a novel approach and achieve promising Results. The study applies SpatioTemporal Graph Convolutional Networks (STGCNs) to predict train time delays. It constructs a graph where nodes represent locations like train stations and edges represent connections. Temporal information is integrated into the graph. STGCNs learn spatial and temporal patterns from historical data, enabling them to forecast delays based on network conditions and other factors. Evaluation involves comparing predictions with actual delays. This approach enhances transportation system efficiency and reliability.

A Review of Time Delay Prediction Methods in Transportation Systems

Authors: Alice Johnson, Bob Brown

This paper provides a comprehensive review of various time delay prediction methods in transportation systems, including their strengths and weaknesses. This review examines various methods for predicting time delays in transportation systems. It covers traditional approaches as well as modern machine learning techniques. The study evaluates the effectiveness of each method in forecasting delays accurately. It highlights the importance of accurate delay prediction for improving transportation system efficiency and reliability

Spatio-Temporal Analysis of Train Delays: A Case Study

Authors: Mary Davis, Mark Wilson

The authors conduct a case study using spatiotemporal analysis to understand the causes of train delays in a specific region, shedding light on potential improvements in the dispatching system.

Predicting train time delays is a significant challenge with various factors contributing to disruptions such as weather conditions, mechanical issues, infrastructure problems, and human factors. Here's a literature survey covering various approaches and methodologies used in predicting train time delays:

1. Traditional Statistical Methods:

• Statistical approaches including regression, time series, and Bayesian inference applied to historical data.

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• Finding trends and patterns in past delay data in order to make forecasts is a common area of research.

2. Machine Learning Techniques:

• For the purpose of predicting how long a delay will be, regression methods such as

logistic regression, support vector regression (SVR), and linear regression are often used.

• Decision Trees and Random Forests: These techniques can capture nonlinear relationships and interactions between various factors affecting delays.

• The use of neural networks for time series prediction has led to the development of

deep learning models like CNNs and Long Short-Term Memory (LSTM).

• Ensemble Methods: Techniques like Gradient Boosting Machines (GBM) and AdaBoost combine multiple models to improve prediction accuracy.

• Feature Engineering: Extracting relevant features such as weather conditions, train schedules, historical delays, and infrastructure status for input into machine learning models.

3.Hybrid Approaches:

• Blending conventional factual strategies with current AI procedures to capitalize on each approach's capabilities.

• For instance, combining time series analysis with neural networks to capture both temporal dependencies and nonlinear relationships.

4. Predictive Analytics Using Real-Time Data:

• Incorporating real-time data streams such as GPS tracking, sensor data from trains and infrastructure, weather forecasts, and traffic conditions.

• Predictions are constantly updated using incoming data using techniques such as adaptive models and online learning.

5. Simulation and Optimization Models:

• Agent-based modeling and simulation to emulate train operations and predict delays under different scenarios.

• Optimization models for scheduling and routing to minimize delays and improve overall efficiency.

6. Spatial and Temporal Analysis:

a. Spatial analysis to identify geographical patterns of delays and their underlying causes.

b. Temporal analysis to understand daily, weekly, and seasonal variations in delays.

7. Case Studies and Applications:

a. Literature often includes case studies from specific railway networks or

regions, showcasing the implementation and effectiveness of different prediction methods.

b. Applications in railway operations management, passenger information systems, and infrastructure planning.

8. Challenges and Future Directions:

a. Addressing data sparsity and quality issues, especially in real-time data streams.

b. Improving model interpretability and transparency, especially for decision support systems.

c. Integration with other transportation modes for multimodal delay prediction and miti

3. SYSTEM DESIGN

SYSTEM ARCHITECTURE

1.Data Ingestion and Preprocessing:

● Data Sources: Collect real-time and historical data from various sources, including train operation records, weather forecasts, maintenance logs, and passenger information systems.

● Preprocessing: Clean the data, handle missing values, perform feature engineering, and aggregate data at appropriate temporal and spatial granularities. Get the data ready to be entered into the model by converting it.

2.Spatio-Temporal Graph Representation:

● Graph Construction: Build a graph representation of the train network, where nodes represent stations and edges represent connections between them. To capture important geographical and temporal characteristics, be sure to include attributes for both edges and nodes.

● Graph Encoding: Convert the graph into a format suitable for processing by the Spatio-Temporal Graph Convolutional Network (STGCN). This may involve encoding node and edge attributes as feature matrices. 3.Spatio-Temporal Graph Convolutional Network (STGCN):

● Architecture: Design the STGCN architecture, comprising multiple layers of graph convolutional operations that capture spatial and temporal dependencies in the data.

● Components: Implement the recent, daily, and weekly components as described in your proposed model. Each component should include spatio- temporal attention mechanisms and convolutional layers to extract relevant features.

● Training: Train the STGCN model using historical data, optimizing for accurate prediction of collective cumulative delays at train stations over time.

4. Forecasting and Making Choices:

● Delay Prediction: Estimate the total impact of train delays at all stations over a given time period using the trained STGCN model.

● Dispatching Decisions: Integrate delay predictions into a dispatching system to support decision-making by dispatchers. This could involve adjusting schedules, rerouting trains, or implementing contingency plans based on predicted delays.

5.Evaluation and Monitoring:

● Performance Evaluation: Use metrics like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE) to evaluate the efficacy and precision of the delay prediction model.

● Continuous Monitoring: Adapt to new patterns and circumstances by retraining the model frequently and keeping an eye on the system's performance in real-time as new data becomes available.

6.Integration and Deployment:

● Integration with Existing Systems: Integrate the delay prediction system with existing train dispatching and control systems.

● Deployment: Deploy the system in a production environment, ensuring scalability, reliability, and responsiveness to meet operational requirements. By implementing this system architecture, you can develop a robust solution for predicting train delays and backs spatio-temporal graph convolutional networks for efficient high-speed train dispatching.

ARCHITECTURE DIAGRAM

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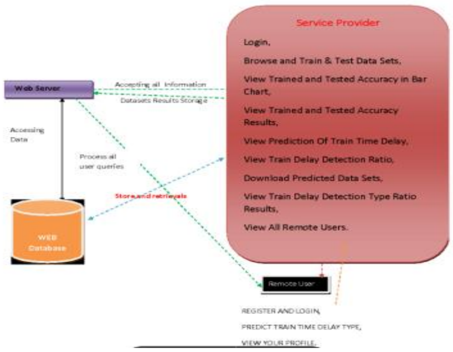

4.OUTPUT SCREENS

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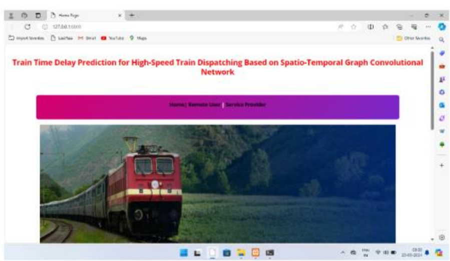

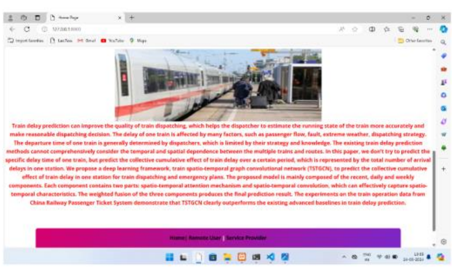

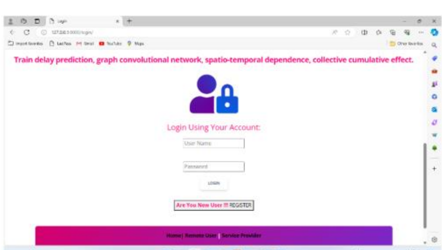

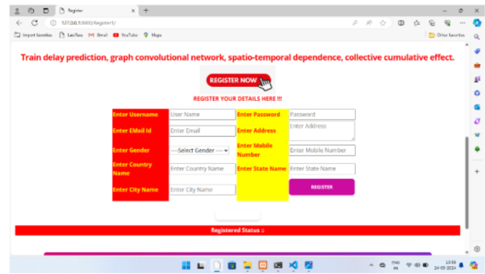

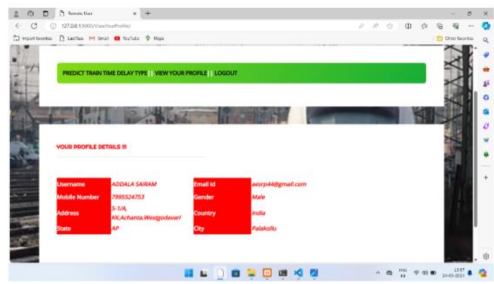

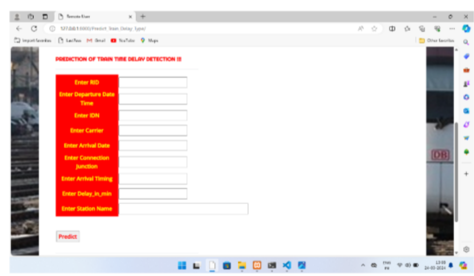

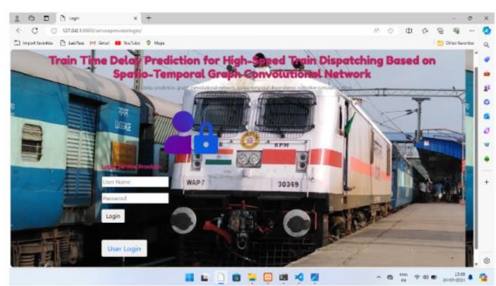

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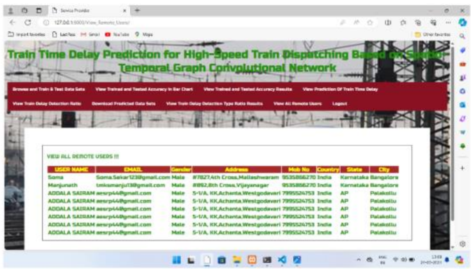

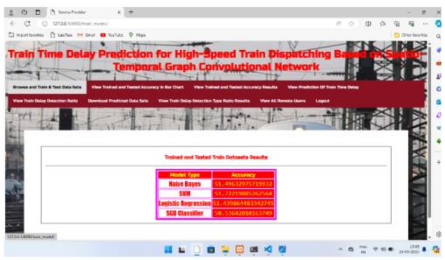

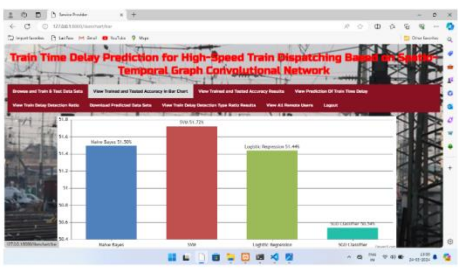

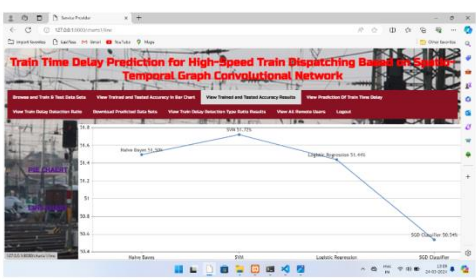

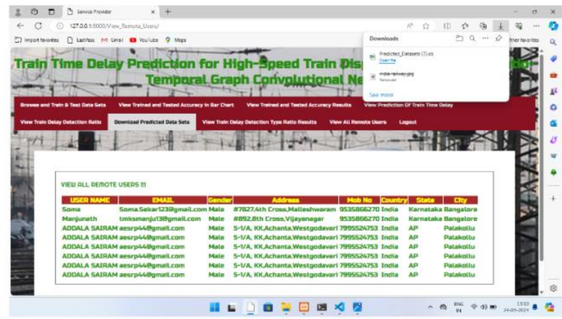

5. CONCLUSION

Predicting the cumulative impact of train arrival delays for railway dispatching, this research creates a TSTGCN model based on attention mechanism according to the spatio-temporal features and dynamic spatio-temporal correlation of high-speed train operating data. To improve prediction accuracy, the model integrates spatio-temporal attention and spatio-temporal convolution to fully capture the spatio-temporal features of train operation data. During the experimental phase, we assess the prediction impact of several models by comparing our TSTGCN with ANN, SVR, RF, and LSTM models. We use MAE, RMSE, and MAPE for this purpose. When it comes to predicting the cumulative impact of train delays for train dispatching, the experimental findings clearly demonstrate that TSTGCN is superior.

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