

Short-Term Urban Rail Passenger Flow Prediction using TCN-LSTM Model

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Abstract. Predicting short-term passenger flow in urban rail transit systems is crucial for efficient operation and management. The TCN-LSTM model, which combines Temporal Convolutional Networks (TCNs) and Long Short-Term Memory (LSTM) networks, offers a robust solution for this task. TCNs provide an expansive receptive field, enabling the model to capture long-range dependencies and trends in passenger flow data. Meanwhile, LSTMs are adept at handling sequential data, refining the temporal features extracted by the TCN layers to account for short-term dependencies and fluctuations. This hybrid approach leverages the strengths of both architectures, resulting in a model that can accurately predict passenger volumes, accommodating regular traffic patterns and sudden changes in rider behavior. The implementation of the TCN-LSTM model in urban rail transit systems leads to optimized train schedules, improved service efficiency, and enhanced passenger experiences. By enabling more dynamic and responsive transit management, this model plays a pivotal role in addressing the challenges of modern urban transportation.

Keywords: Short-time passenger flow; forecast; TCN-LSTM model; prediction accuracy.

1. Introduction

Until December 31, 2023, China boasts a total of 306 urban rail lines spanning an impressive length of 10,165.7 kilometers. With a staggering count of 37.59 million trains in actual operation and a remarkable tally of 29.44 billion passenger trips, accompanied by an astounding figure of 17.66 billion passenger stops and an astonishing record of 241.8 billion passenger trips [1]. In 2023, China's urban rail transit system has made significant advancements, as evidenced by the expansion of lines and stations. This not only signifies infrastructure enhancement but also reflects the acceleration of urbanization. The extension of new routes and mileage further enhances the coverage and efficiency of the transportation network. Simultaneously, the substantial increase in passenger volume and turnover underscores the pivotal role played by rail transit in meeting public travel demands. However, with rapid growth in passenger traffic, effectively mitigating congestion during peak periods and enhancing service quality will be key areas for future focus. In conclusion, the substantial surge in passenger volume and turnover underscores the pivotal role played by rail transit in meeting public travel demands. With the continuous advancement of China's urbanization level, the passenger flow of rail transit has been consistently increasing, particularly during peak hours on weekdays, thereby exacerbating the issue of overcrowding among passengers. Short-term passenger flow forecasting primarily serves to provide real-time information and facilitate dynamic scheduling, thus serving as a crucial measure for urban rail transit to alleviate congestion and enhance service quality [2].

By analyzing and mining historical data as well as real-time data, passenger flow forecasting predicts the future changing trend of passenger flow, providing a scientific basis for traffic management and operation. Accurate prediction of passenger flow can assist traffic management departments in effectively allocating resources and dynamically scheduling operations, enabling early warning and effective response to potential congestion scenarios, thereby enhancing the operational efficiency and service level of rail transit systems. Particularly during emergencies and peak periods of passenger flow, accurate forecasts provide timely decision support to ensure the safety and smooth travel experience for passengers. Therefore, urban rail transit passenger flow forecasting not only serves as a crucial means to alleviate traffic congestion but also plays an indispensable role in

optimizing transportation resource allocation, improving operational efficiency, and enhancing the quality of urban public transport services [3].

The Particle Swarm Optimization-Variational Mode Decomposition-Long Short-Term Memory (PSO-VMD-LSTM) model is employed by Zhang Wanning to forecast passenger flow, while Variance Component Model (VCM) is utilized to decompose the raw passenger flow data into multiple Intrinsic Mode Function (IMF), representing distinct frequency components of the data and aiding in capturing intricate time series features. Subsequently, the hyperparameters of the LSTM model are optimized using the PSO algorithm to ensure optimal performance when handling each IMF. Through this multi-level processing approach, the model significantly enhances prediction accuracy and robustness, establishing an efficient short-term passenger flow prediction scheme for urban rail transit [4]. Zhao utilized the Improved Particle Swarm Optimization - Long Short-Term Memory (IPSO-LSTM) combined model for short-term passenger flow prediction in urban rail transit, incorporating the genetic algorithm's variation mechanism, introducing an adaptive variation function, and optimizing the iteration times, learning rate, and number of hidden layer neurons of the LSTM model through an IPSO algorithm [5].

Shi employed the Principal Component Analysis-Long Short-Term Memory (PCA-LSTM) model for short-term passenger flow prediction in urban rail transit, extracting key features from historical passenger flow data using PCA, simplifying input information, and training/predicting extracted feature data with a long short-term memory network LSTM model [6]. A short-term passenger flow forecasting model was established. The K-means Clustering-Long Short-Term Memory-Error Correction (K-LSTM-ECM) Model by Wang Jinfeng integrates K-means clustering, LSTM, and ECM to accurately forecast short-term passenger flow in urban rail transit [7]. By combining the strengths of K-means clustering and LSTM, the K-LSTM-ECM model effectively captures the unique characteristics of passenger flow data and significantly enhances prediction accuracy. Furthermore, the introduction of ECM further strengthens the robustness of the model, reduces prediction errors, and ensures stable and reliable results.

The Meng Ge model utilizes the Particle Swarm Optimization - Fuzzy Support Vector Regression (PSO-FSVR) approach to accurately forecast passenger flow in urban rail transit systems [8]. The optimization process of PSO and the training time of SVR are lengthy, resulting in high computational complexity. Additionally, the PSO-FSVR model is highly sensitive to initial parameter selection and hyperparameter tuning, while SVR exhibits inefficiency when processing large-scale datasets. The Residual Convolutional Neural Network - Gated Recurrent Unit (ResCNN-GRU) model for urban rail transit passenger flow prediction, based on a self-concern mechanism, is an advanced prediction method that combines ResCNN, GRU, and the self-concern mechanism [9]. However, its high computational complexity, difficulty in parameter tuning, substantial demand for large amounts of high-quality data, limited interpretability of results and risk of overfitting constrain its practical applicability in certain scenarios.

To summarize, the combined model possesses the inherent advantages of the basic model. The TCN-LSTM model offers significant advantages for short-term passenger flow prediction in urban rail transit systems. By combining the expansive receptive field of Temporal Convolutional Networks (TCNs) with the sequential data handling capabilities of Long Short-Term Memory (LSTM) networks, this hybrid model excels in capturing both long-range dependencies and immediate temporal dynamics within the data [10]. This dual capability enables it to accurately forecast passenger volumes, accommodating regular traffic patterns and responding to anomalies or sudden changes in rider behavior. Such precise predictions are crucial for optimizing train schedules, enhancing service efficiency, and improving passenger experience by enabling more dynamic and responsive transit management. This article optimizes the model by incorporating additional information such as time stamps, station details, passenger volume to achieve a more accurate short-term prediction of urban rail transit passenger flow.

2. Methods

2.1. Data Source

The present study focuses on the swipe data of urban rail transit in Hangzhou, collected from January 1 to 7, 2019. The dataset utilized is characterized by its objectivity and accuracy. During the process of data cleaning and outlier detection, the number of swipes on a given day is initially extracted and consolidated from multiple CSV files to ensure chronological order. Subsequently, features such as hour and day of the week are derived from the time column to capture periodic patterns in the time series. To mitigate the impact of eigenvalue range, standardization is applied to normalize the number of swipes, hours, and days of the week, thereby scaling the data between 0 and 1. This step enhances algorithmic performance. The Isolation Forest algorithm, an unsupervised learning technique based on tree structures that effectively identifies outliers, is then employed for outlier detection on this standardized dataset.

Detected outliers are flagged within the dataset with a label -1 assigned to them while normal data points receive a label 1. Finally, scatterplot visualization is utilized where normal data points are represented in blue while abnormal data points are depicted in red, thus providing a visual representation of both outliers present in the dataset as well as their distribution (Figure 1).

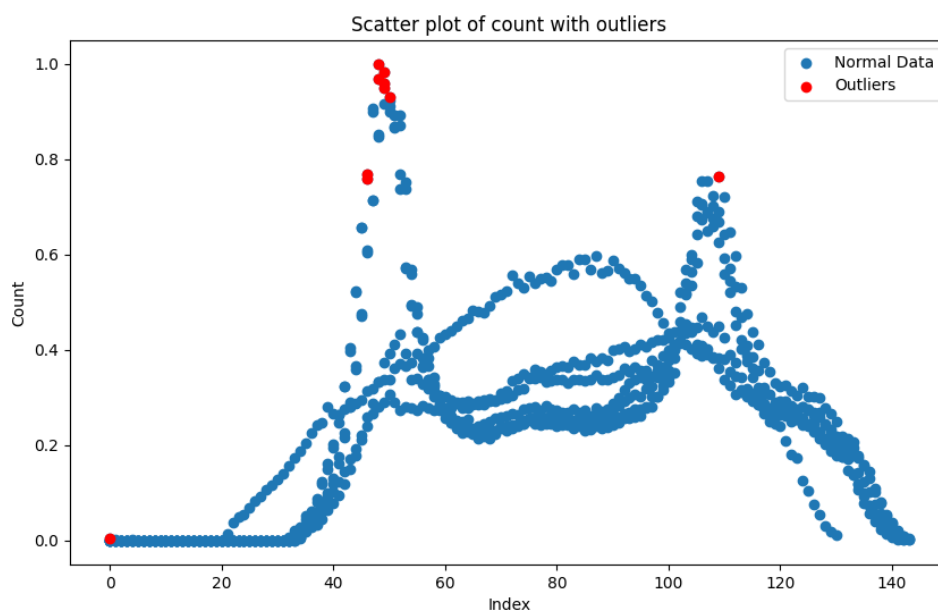


Fig 1. Outlier detection results

The data presented in Figure 2 clearly indicates distinct peak arrival times during the morning hours of 8:00-10:00 and evening hours of 18:00-20:00 on working days (September 2 - September 4, September 7) and rest day (September 5), representing a double-peak passenger flow pattern. Conversely, on rest days (September 1) and rest day (September 6), there is a noticeable single peak period from 18:00 to 20:00 in the evening, indicating a single-peak passenger flow pattern. These observations highlight prominent characteristics of non-linearity, non-stationarity, and mutation within the weekly passenger flow patterns.

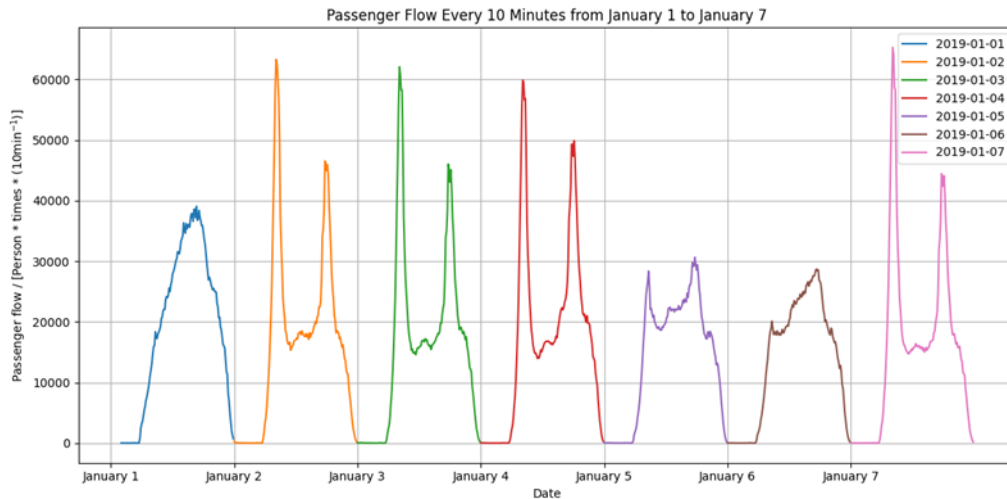


Fig 2. Time distribution of passenger traffic in one week

2.2. Method Introduction

The LSTM is a specialized form of recurrent neural network (RNN), initially proposed by Sepp Hochreiter in 1997. This architecture was specifically designed to address the issue of gradient vanishing or exploding that traditional RNNs encounter when processing lengthy time series data, enabling it to effectively retain information over extended temporal contexts. At the core of LSTM lie its distinctive gating mechanisms, encompassing input gates, forget gates, and output gates, which empower the network with selective information assimilation or disregard capabilities, thereby preserving crucial long-term dependencies while discarding irrelevant information (Figure 3).

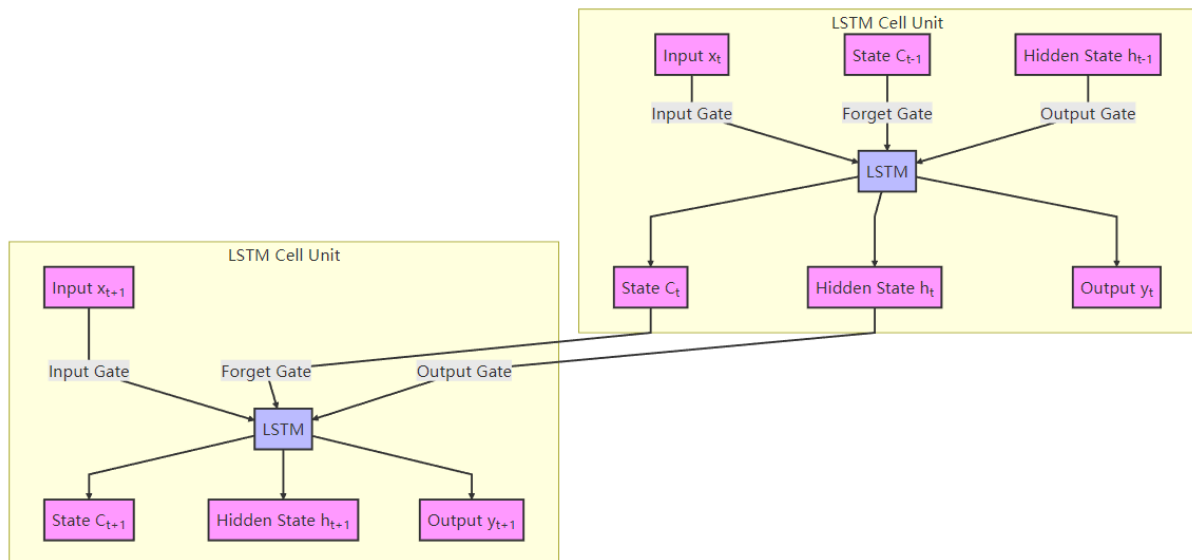


Fig 3. LSTM network structure diagram

LSTM is extensively utilized, particularly in the domain of natural language processing (NLP). For instance, within language models, machine translation, text generation, and speech recognition systems, LSTM efficiently processes and predicts data associated with lengthy texts. It excels at comprehending context, sentence structure, and semantic coherence in extensive conversations. Moreover, LSTM finds widespread application in time series forecasting tasks such as stock price prediction, climate change modeling, and healthcare monitoring systems that require analysis and prediction of intricate patterns within long-term time series data.

At time x_t input data is the actual measured ridership of urban rail transit; The output of y_t at time is the passenger flow estimated by LSTM neural network model. The output of the LSTM cell

unit at time h_t represents the hidden state of the current moment. The state of LSTM cell units in time C_t is used to regulate and transmit memory information and capture the timing characteristics of input data.

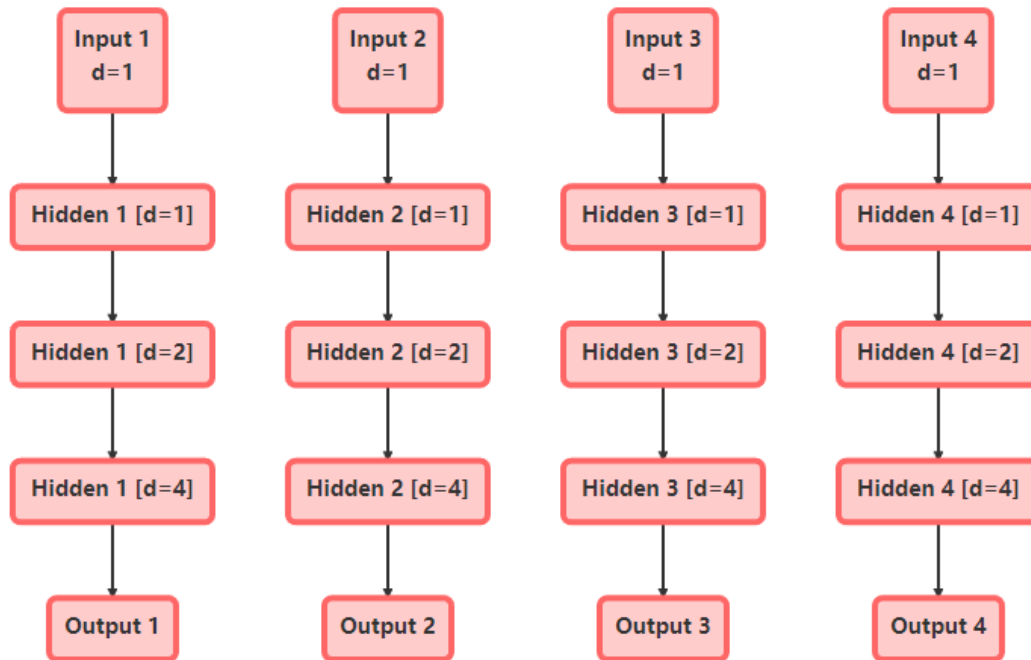


Fig 4. Comprehensive causal convolutional networks

It is crucial to ensure that the output of the current time step solely depends on the present and past inputs, without any access to future information. This is particularly significant in time series prediction problems as it prohibits the model from utilizing future data in practical applications (Figure 4).

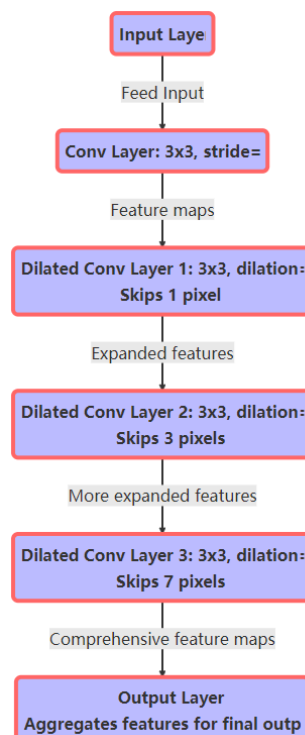


Fig 5. Dilated Convolutional Network

A Dilated Convolutional Network is a type of convolutional neural network that utilizes dilated convolutions to exponentially expand the receptive field of the network's filters without increasing the number of parameters or computational cost. This approach enables the network to capture long-range dependencies in data, such as time series or spatial hierarchies in images, making it highly effective for tasks requiring extensive contextual information while maintaining computational efficiency (Figure 5).

3. Results and Discussion

3.1. Model Fitting Results

Figure 6 illustrates the performance of the time series prediction model on the training dataset, specifically comparing the model's predicted values with the actual observed values. The horizontal axis represents the sample index, reflecting continuous observation points of the time series data ranging from 0 to approximately 800. The vertical axis displays a normalized ridership count scaled between 0 and 1 to eliminate scale differences and optimize training.

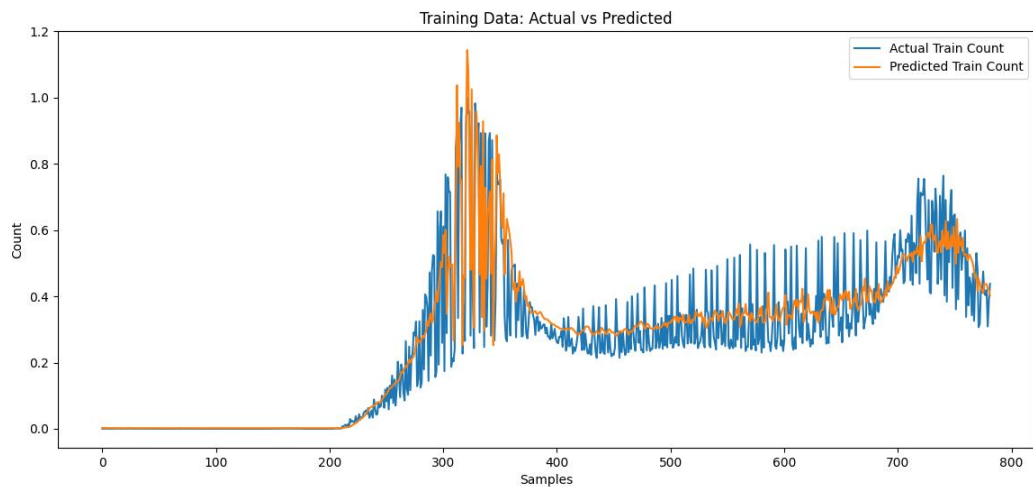


Fig 6. Predict the results of the model's training data

In this figure 6, the blue line represents the Actual Train Count, while the orange line depicts the Predicted Train Count generated by the model. By comparing these two lines, we can intuitively evaluate both the model's ability to capture time series dynamics and its prediction accuracy.

Upon analyzing this chart, it is evident that in most intervals, the model accurately follows the trend of actual data, demonstrating excellent fitting and predictive capabilities. Particularly in sections where data changes more gradually, the model predictions exhibit high consistency with actual observations.

Table 1. Training set and test set results

	Value
Train MSE	0.00757
Train MAE	0.05680
Test MSE	0.00224
Test MAE	0.04146

Mean Squared Error (MSE) for the training set is 0.00757, which indicates a low average prediction error and suggests that the model fits the training data well (Table 1). A low MSE value typically signifies minimal variance between the predicted and actual values. The testing set MSE of 0.00224 is remarkably lower than that of the training set, suggesting excellent generalization capability of the model. Lower MSE on the test set than the training set can occur if the test data

exhibits less variability or if it aligns well within the model's most accurate prediction range. Mean Absolute Error (MAE) for the training set is 0.05680, reflecting the average absolute deviation between the predicted and actual values, providing a direct measure of error magnitude. The testing set MAE of 0.04146 shows a reduction from the training set, further confirming the model's high accuracy on new, unseen data and indicating reliable and precise predictions.

3.2. Comparison Results

Figure 7 clearly demonstrates the exceptional performance of the TCN-LSTM model in accurately predicting short-term passenger flow in urban rail transit systems. On the left side of the graph, the blue line represents the observed passenger counts from the test data, while the orange, green, and red lines correspond to predictions generated by the TCN, LSTM, and TCN-LSTM models respectively. Notably, it is evident that the predictions derived from the TCN-LSTM model (red line) closely align with actual data (blue line), particularly in regions where passenger flow exhibits significant fluctuations. This underscores the superior accuracy of this model in capturing both peak values and volatile trends within dataset.

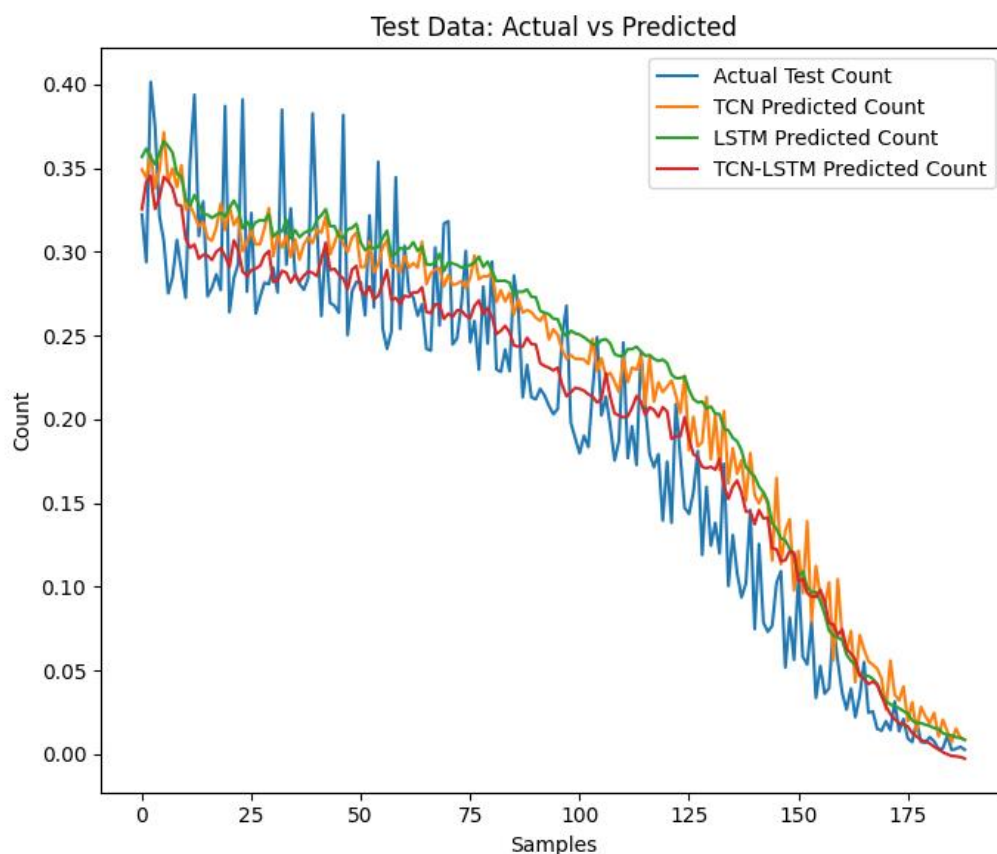


Fig 7. Comparison of prediction accuracy between mixed model and single model

In contrast, the TCN model (orange line) and the LSTM model (green line) display larger deviations from the actual values, especially during peak traffic periods and other instances of high variability (Figure 7).

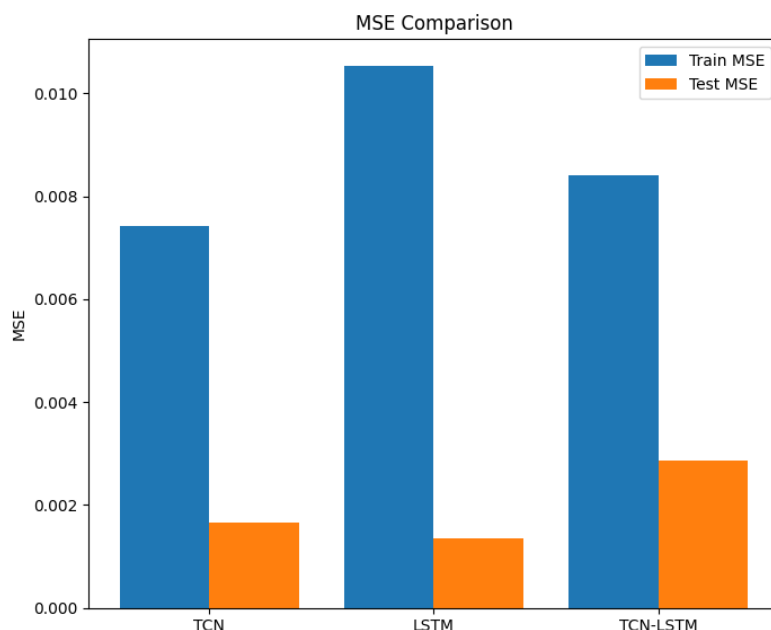


Fig 8. MSE performance of different models on training set and test set of short-term passenger flow prediction task of urban rail transit

The TCN-LSTM model exhibits the lowest MSE metrics across both training and test datasets, highlighting its robust generalization capabilities from training environments to practical applications. This not only illustrates a superior fit to the training data but also delineates its enhanced proficiency in accurately predicting unseen data (Figure 8).

Although the LSTM model outperforms the standalone TCN model in terms of MSE, it does not reach the efficacy levels of the hybrid TCN-LSTM model. This suggests that while LSTMs effectively capture temporal dependencies within data sequences, integrating TCN layers significantly augments the model's ability to process longer sequences and manage abrupt changes more efficiently. On the other hand, the elevated MSE values linked with the TCN model signal its suboptimal performance in addressing the complexities of the dataset, especially in adapting to rapid fluctuations in data (Figure 8).

This detailed evaluation reaffirms the strategic advantage of amalgamating TCN and LSTM architectures to proficiently manage the intricate and dynamic datasets commonly associated with urban rail systems. The hybrid TCN-LSTM model thus stands out as an indispensable asset for transit authorities aiming to enhance operational efficiency and improve passenger satisfaction through precise and reliable short-term traffic forecasts.

4. Conclusion

The TCN-LSTM model stands out as a revolutionary advancement in the field of predictive analytics, particularly for urban rail transit systems. This model uniquely combines TCN and LSTM networks, harnessing their strengths to enhance the accuracy of short-term passenger flow predictions. The ability of the TCN-LSTM model to accurately forecast passenger volumes is incredibly valuable for transit authorities. It enables more efficient resource allocation, reduces congestion, and significantly improves the overall passenger experience by anticipating and managing the flow of commuters more effectively.

As urban populations increase and the demand on public transportation systems intensifies, the integration of such sophisticated predictive technologies becomes indispensable. For urban centers looking to optimize their transit operations and adapt to rapid changes in commuter patterns, the TCN-LSTM model offers a robust solution. By leveraging this advanced technology, transit authorities can

ensure smoother operations and a higher quality of service, making urban transportation systems more resilient and responsive to the needs of a growing commuter base.

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