A Path-Depended Passenger Flow Forecasting Model for Metro Rail Systems Using LSTM Neural Network

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Abstract: The primary goal of this work is to develop a framework for short term passenger flow prediction for metro rail transport systems. A reliable prediction of short-term passenger flow could greatly support metro authorities' decision process. Both inflow and outflow of the metro stations are strongly associated with the travel demand within metro networks. Sequestered station-wise analysis ignores the spatial correlations existing between the stations. This paper tries to merge the spatial with the temporal by employing an indirect method of computing flow through O-D estimates for the same. Path-depended station-pairs of O-D flow are considered for employing a customized LSTM network. Experimental results indicate that the proposed passenger flow prediction model is capable of better generalization on short-term passenger flow than standard models of learning compared. This work also establishes that O-D prediction provides an indirect estimation procedure for passenger flow. The specific use case for this work is Kochi Metro Rail Limited (KMRL). A highlight of the work is that the whole analytics and modelling procedures are written on a customized scalable big-data platform (Jaison Paul Data Analytics Platform) JP-DAP which was developed prior to this work.

1 INTRODUCTION

Metro railways are one of the new additions to intelligent transportation systems. Due to increasing population and ever extending city coverage, commuters rely more on public transit systems such as metro railways. Recently, with efficient, reliable and safe service, metro networks are experiencing a sharp hike in ridership. Short term traffic flow prediction is an integral component of the operational decision making pipeline. Short term passenger flow prediction aims at estimating the number of commuters given a specific station and a time interval, which is an important problem to address in metro transportation management (Li et al., 2017). Prediction of passenger flow information is of immense value in facility improvement, operation planning, revenue management, and even emergency evacuation. The literature supports both parametric and non-parametric models, parametric models include Auto-Regressive Moving Average(ARMA), seasonal ARMA, Kalman filtering, etc., while some frequently used non-parametric models are k-Nearest Neighbors algorithm (kNN) and spectral analysis. Recently, with incredible developments in artificial intelligence and explosive growth in computational power, there is a significant leap from analytical to data-driven modelling.

Since the operations of the metro, with an expanding user base, is a source of big data, analytical sandboxes designed to perform inferential procedures cannot be deployed as a real time solution as long as the scalability aspect is left unaddressed. The analytics presented here were therefore preceded by developing a customized distributed and scalable platform, JP-DAP. The models presented here were developed and run on the platform. The system is populated using the data received from KMRL (The project has a data sharing agreement with KMRL). In this work, propose an efficient and reliable travel pattern prediction through Origin-Destination (O-D) matrix estimation. This indirect approach is better than direct estimation of travel patterns which overlooks the spatial interconnections between stations. O-D distribution is distinct for different station-pairs since the usage distributions of stations are not identical.

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In the current trend most of the algorithms consider either entry flow or the exit. In this case, we have included origin-destination flow to make the flow path dependency between two stations. Here the case study has included the path from station A to station B, and also considered the direction flow from B to A. So that the mapping become 1:1.

The proposed model outperforms some widely used forecasting models such as the Support Vector Regressor (SVR), Bayesian regressor and Regression Tree.

The remainder of the paper is organized as follows. Section 1.1 describes the related work in the area. This section gives a comprehensive review of big data analytics in railway transportation. The following section 2 provides an intuitive analysis of the data, formats and basic architecture of JP-DAP. Section 3 provides a detail explanation about the fare card based learning for short term passenger flow prediction. Section 3.1 explains the proposed network architecture and passenger flow prediction model based on long short term memory (LSTM). Comparative analyses of the prediction performances are provided in Section 4. Finally, conclusions drawn and future research directions are discussed in Section 5.

1.1 Related Works

In recent years, Intelligent transportation systems (ITS) have a significant role in smart cities. Short term traffic flow prediction plays an indispensable role in ITS (Ci et al., 2017). Hence considerable effort is made to develop efficient traffic flow prediction methods, which is backed by a large number of publications in this field. The purpose of short term traffic flow prediction is to facilitate dynamic traffic control proactively by monitoring the present traffic and foreseeing its immediate future (Tang et al., 2019). Apart from that, it provides accurate and timely traffic volume information for individual travelers, business sectors and government agencies (Tian and Pan, 2015). At the same time, any transportation network is a very complex system composed of many other factors such as weather conditions, region, etc.. Hence, the short-term traffic flow is highly non-linear and stochastic, which makes it a huge challenge to be predicted accurately (Tian and Pan, 2015). From previous studies, diverse deep learning methods have been applied to traffic flow prediction as they can capture the complex non-linear relations and the latent correlation features in traffic flow data. Furthermore, short-term passenger flow prediction for metro rail systems is a relatively new research field when compared to traffic prediction for ground transport.

A seminal work, Ahmed et al. (1979) proposed a model for short-term prediction of freeway traffic flow using Autoregressive Integrated Moving Average (ARIMA) (Ahmed and Cook, 1979). In 2009, Tsai et al. (Tsai et al., 2009) constructed two types of improved neural network models based on distinctive railway data for short-term railway passenger demand forecasting. The first is a neural network with several temporal units that interprets raw material using specific connections inside the network. The second method uses a parallel ensemble neural network, which processes various input data using various individual models. Both neural networks outperform traditional multilayer perception neural networks, according to the data. Later in 2013, Teresa Pamuła (Pamuła, 2013) developed a neural network model for accurate short term traffic flow forecasting with the data obtained from two video detectors located at the ends of a transit road in the city of Gliwice. In this work, tests were performed using three distinct classes of time series corresponding to: working days, Saturdays and Sundays. In (Sun et al., 2015) proposed a hybrid model of Wavelet Support Vector Machine (SVM). The method first decomposes the passenger flow data into different high frequency and low frequency series by wavelet and then prediction performed using SVM.

In 2018, Xiaoqing Dai et al. (Dai et al., 2018) developed a data-driven framework for short-term metro passenger flow prediction which utilizes spatio-temporal correlations. The travel demand within the metro networks are closely related to inflow and outflow of the metro stations. Hence, in this work they collect the O-D information from the smart-card data to explore the passenger flow patterns and propose a data driven framework for short-term metro passenger flow prediction. This method utilizes two forecasts as basic models, adaptive boosting and k-Nearest Neighbors (kNN) and then uses a probabilistic model selection method to combine the two outputs for better forecast.

From the literature survey, it was evident that LSTM based sequence prediction systems have not received much attention in metro related studies. Also, there are some existing gaps in metro passenger flow forecast such as unclear influencing factors, low accuracy, passenger congestion, unbalanced capacity and demand etc.(Zhang et al., 2020). A metro path defined to a travel from the origin station to alighting station of a passenger, which indicates the movement of a commuter within the metro network. Thus O-D flows is a potential feature to boost prediction (Dai et al., 2018). Therefore, in this work the O-D flows extracted from AFC data can be successfully utilized to describe different metro rail travel patterns. Hence the proposed forecasting framework, especially the LSTM method, can improve the performance of short-term transportation forecasting for metro rail.

2 EXPERIMENTAL ENVIRONMENT AND DATA SET

Kochi Metro rail (KMRL) (Metro Rail, 2017) network in Kerala, India, is selected as the use case for this research work. During the time interval considered, the metro line in the city covered only 16 stations with an average daily passenger volume of about 50,000. This dataset provides an insight into typical growth and demand pattern of a new-built metro system. The dataset is collected from Automatic Fare Collection (AFC)(Ampelas, 2001) system and covers 667 days, from 2017 (from June), 2018 and 2019 with a size of 5GB. A detailed description of AFC is given in Section 2.1.

The software ecosystem on which the experimental procedure and analysis were conducted consists of :

- Customized Hadoop based platform with Apache Spark integration and GPU support (JP-DAP)
- Python 3 with associated packages including Tensorflow, Keras and Scikit-learn for implementation of the analytic models.

On the hardware side, the computational nodes were configured with Intel Xeon E3 series server-grade processor with 4 cores and 32 GB RAM and NVIDIA Quadro P1000 graphics card with 4GB of GPU memory. The data are received through system APIs and are appropriately transformed into forms suitable for analysis and visualization. The structured information is stored in Hive database. Spark (Zaharia et al., 2010) is responsible for the computation and transformation process, with distributed memory computing. Details of JP-DAP is provided in Section 2.2.

2.1 Automated Fare Card Data

The compiled data used for this research work is provided by by the AFC Analysis Department of KMRL. The data is stripped of sensitive private attributes and anonymized by the department before making it available for analysis. The detail data format is shown in Table 1.

2.2 Big Data Platform

In this section, the description of the big data platform called Jaison Paul Data Analytics Platform (JP-DAP)(Mulerikkal et al., 2022) built on Hadoop with supporting analytics components is given. This is a prior work done which is already communicated. The system accepts data from a spectrum of distinct sources associated with the metro presently. The architecture has been designed to provide enough leeway to seamlessly integrate other modes of transport as well as the future expansions in the metro itself. The data is received through system APIs. The core analysis covered by a set of internal APIs within the platform .

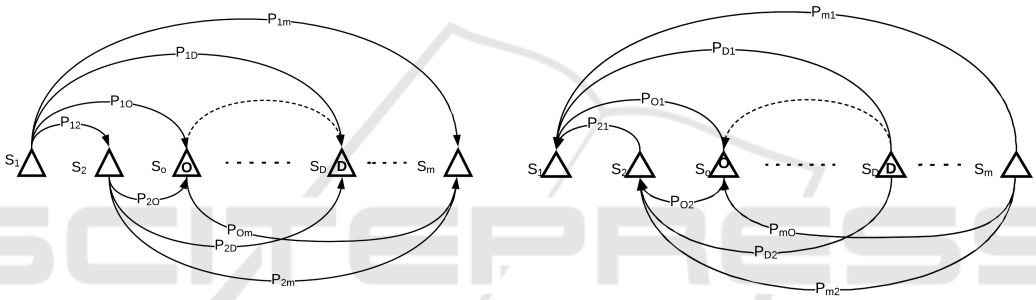
3 SHORT TERM PASSENGER FLOW PREDICTION FROM O-D FORECAST

Short term passenger flow prediction is an important aspect of usage trend analysis and provides a very useful feature for deciding staffing pattern and train schedules. For effective metro system management and to help commuters adjust their travel timings or in extreme cases, assist emergency management an effective passenger flow prediction is required (Dai et al., 2018). The passenger counts in both up and down directions of each station provide its distinct behavioral travel pattern. The passenger count can be station wise or pair-wise total entry and total exit. For the analysis of passenger flow, different time frames are considered and day-wise prediction is performed.

An accurate short term passenger flow at each (O-D) path can be predicted by combining the legacy information of both inflow and outflow of each metro station (Dai et al., 2018). Hence, for time series forecasting for each path, the O-D information is extracted from AFC data. The entire travel paths, both forward and backward of the metro system is shown in Fig. 1(a) and Fig. 1(b). In the figure, S_O and S_D are the target origin and destination stations. Hence the path connecting S_O and S_D is the targeted path. The proposed model is trained for predicting the passenger flow of the targeted O-D based on legacy O-D data. The O-D matrix of the metro system consisting of m stations is shown in equation 1. Where P_{ij} represents the total count of passengers from station i to station j for a predefined time window.

Table 1: Dataset Description.

Database Entry	Description / Contents
Stations	All working station information (till Feb 2019) Aluva, Pulinchodu, Companypady, Ambattukavu,Muttom, Kalamassery, Cochin University, Pathadipalam, EdapallyChangampuzha Park, Palarivattom, JLN Stadium, Kaloor, Lissie, M.G Road, Maharaja's College
Equipment Type	Mode of Taking Tickets have done (3 Modes) EFO (Excess Fare Office) TOM (Ticket Office Machine) GATE (AFC Gates)
Equipment ID	Unique ID of each Machines
Fare Product	E-Purse, SJT (Single Journey Ticket), Free Exit Ticket, Paid Exit Ticket, Staff Card
Fare Media	EMV (using Kochi One Card) , QR (Normal Paper Ticket), RPT (RF-ID Paper Ticket)
Ticket Card Number	Unique Ticket ID Information
Transaction Type	Top-up, Issue , Adjustment, Entry, Exit ,Cancel
Transaction Time	YYY-MM-DD HH:MM:SS Format



(a) Forward Path of Passengers for Different O-D's (b) Backward Path of Passengers for Different O-D's

Figure 1: Passenger Flow Paths in Metro System.

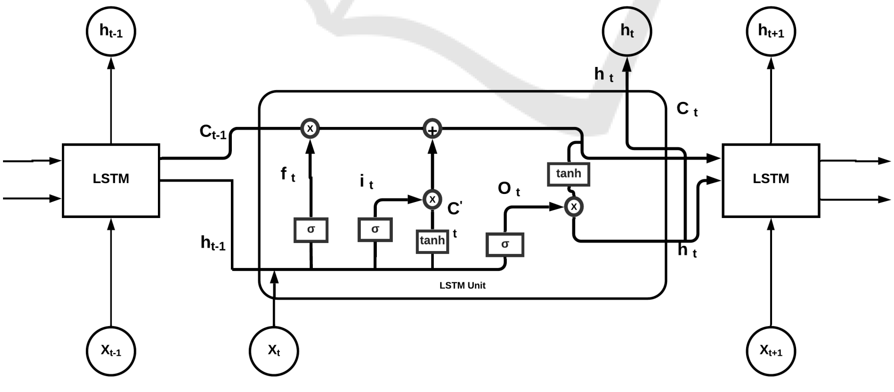


Figure 2: Illustration of the Inner Structure of an LSTM Layer.

$$OD_{Matrix} = \begin{bmatrix} 0 & P_{1,2} & P_{1,3}.....P_{1,m} \\ P_{2,1} & 0 & P_{2,3}.....P_{2,m} \\ P_{3,1} & P_{3,2} & 0......P_{3,m} \\ . & . & . \\ . & . & . \\ P_{m,1} & P_{m,2} & P_{m,3}.....0 \end{bmatrix} \quad (1)$$

In the proposed method, a feature matrix comprised of O-D information based on the time window is computed over a period of time, forming a 2-D time sequence. A Recurrent Neural Network (RNN) is trained to make short term O-D predictions from a sequence collected over a span of d consecutive time windows.

$$Feature_{Matrix} = \begin{pmatrix} P_{1,1_{t-d+1}} & \cdots & P_{1,m_t} \\ \vdots & \cdots & \vdots \\ P_{1,m_{t-d+1}} & \cdots & P_{1,m_t} \\ P_{2,1_{t-d+1}} & \cdots & P_{2,1_t} \\ \vdots & \ddots & \vdots \\ P_{m,m_{t-d+1}} & \cdots & P_{m,m_t} \end{pmatrix} \quad (2)$$

3.1 Long Short-Term Memory (LSTM)

Neural networks outperform most of the traditional machine learning techniques because of its unique non-linear adaptive processing ability(Xiao and Yin, 2019). The inability of traditional neural networks in handling long sequences due to undesirable behaviour of training gradients hindered their application on structured learning problems until the path-breaking invention of LSTM networks (Hochreiter and Schmidhuber, 1997). Literature amply supports the application of LSTM for traffic flow prediction(Xiao and Yin, 2019). The architectural checks to prevent gradients from going haywire are implemented using input, output and forget gates, which regulate the flow of gradients through the neural units (LSTM cells) (Ci et al., 2017). The LSTM cell unit is depicted in Fig. 4.

With reference to Figure 2, the equations listed below describe how an LSTM unit works at every time step t. The expressions f_t, i_t, $\widetilde{C}_t$, O_t and C_t represent the forget gate, input gate, candidate cell state, output gate and cell state respectively. C_t combines past information with present input. The final cell output is represented by h_t where the typically used activation function is $tanh$ (Xiao and Yin, 2019). $\sigma(x)$ and $tanh$ are the standard activation functions used in neural networks as given in equation 9 and 10. And W and b are the weight vector matrix and bias vector respectively.

$$f_t = \sigma(w_f.[h_{t-1}, x_t] + b_f) \quad (3)$$
$$i_t = \sigma(w_i.[h_{t-1}, x_t] + b_i) \quad (4)$$
$$\widetilde{C}_t = \tanh(w_c.[h_{t-1}, x_t] + b_c) \quad (5)$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{c}_t \quad (6)$$
$$O_t = \sigma(w_o.[h_{t-1}, x_t] + b_o) \quad (7)$$
$$h_t = O_t * tanh(C_t) \quad (8)$$
$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (9)$$
$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (10)$$

The transmission of information in the hidden state are controlled by the input gate, the forget gate and the output gate (Han et al., 2019). The input and forget gates decide the strength of input and previous state signals used in deciding the state of the cell. The output gate modulates the non-linearly transformed state and can helps local control of the output signal propagated. LSTMs are highly effective in passenger flow prediction as observed in (Han et al., 2019). The goal of this work is to implement a path-dependent passenger flow forecasting model. The detailed explanation of proposed LSTM network for path-dependent passenger flow forecasting is given in the following Section.

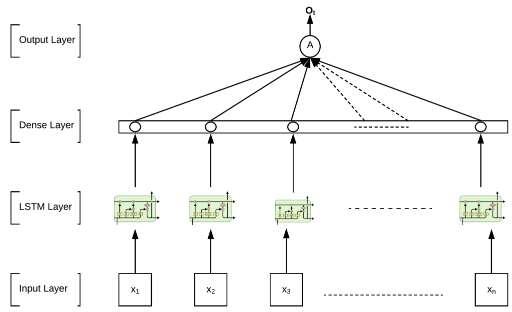


Figure 3: Architecture of LSTM.

3.2 Path-Dependent Passenger Flow Prediction Model Based on LSTM

The passenger flow forecasting is defined as predicting future passenger volume y, from the historical passenger flow at each station. Localized passenger flow analysis of O-D pairs is an important technique in spatio-temporal traffic analysis and is of great assistance in service scheduling and logistics management. We use LSTM model to forecast the traffic through O-D paths. Suppose the input passenger flow sequence of a certain O-D path is $x = (x_1, x_2, x_3 ... x_n)$, the vector sequence of the memory cell in LSTM is $h = (h_1, h_2, h_3 ... h_n)$, the output predicted y is the final predicted passenger flow sequence for the O-D path. For training the model, feature matrix is collected from O-D information as given in equation 2. The inflow and outflow of at each station is the aggregated result of predicted path-dependent passenger flows. The feature matrix is scaled in the range of $0to1$ before being fed to the model. The architecture of the proposed LSTM neural network is shown in fig 3. The input layer size is same as the input feature matrix sequence length.

The proposed model consists of an LSTM layer followed by a dense layer. The intermediate output of the LSTM does a revealing representation of the temporal correlations existing in the passenger flow sequence. Hence the dense layer performs better than when the sequence is directly fed to it. The dense functions as a regressor for the scaled passenger flow output. The network requires a single neuron in the output layer with a linear activation to predict the passenger flow at the next time step. The optimization of the dense layer is gradient descent and the loss function is Mean Squared Error (MSE). Since it is a single dense layer network the computation done by it can be summarized by the equations below:

$$\begin{gathered} O_{final} = f(W_i * X_i + B) \\ X_i : \; input\ matrix \\ W_i : \; weight\ matrix, B : bias \end{gathered} \tag{11}$$

All the analytical procedures are performed in JP-DAP software platform using relevant APIs and deep learning libraries such as Google TensorFlow(Ci et al., 2017). The other internal libraries used from the JP-DAP platforms are ML-lib, Scikit-learn, OpenCV. The LSTM model can be generalized to other complex metro systems connecting other modes of transport with O-D matrix providing relevant insights for the future research.

4 EXPERIMENTAL RESULTS AND ANALYSIS

This section presents the experiment outcomes of the proposed model and discusses them in comparison with other conventional machine learning algorithms like SVR, Regressor and Regression Tree.

LSTM model is implemented using Keras library (Chollet et al., 2015) on top of Google's TensorFlow machine learning framework (Abadi et al., 2016). To analyze the passenger flow at each station and also to find the anomalies present in the data, box plot analysis is performed. All those points outside the min and max are considered to be the outliers in the data. Outlier removal is performed as part of pre-processing.

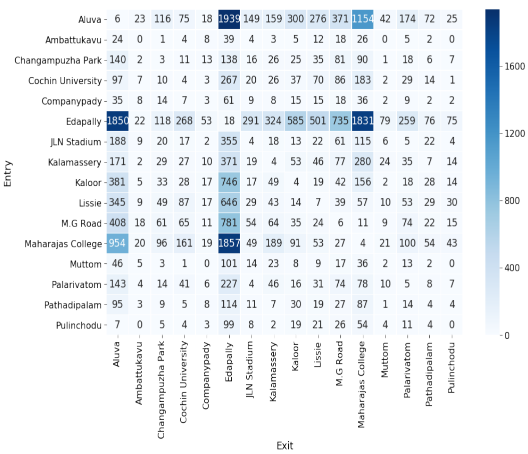


Figure 4: Heat-map of Origin-Destination Matrix.

Further, the heatmap of O-D matrix for Kochi metro stations per day is shown in Fig 4. From the heatmap for a single day it is can be inferred that, the frequent travel paths in the Kochi metro network or the path-dependent stations are (Edappally-Aluva), (Maharajas-Aluva), (Aluva-Edappally), (Aluva-Maharajas), (Edappally- Maharajas), (Maharajas-Edappally). Different machine learning models such as the SVR, Bayesian Regressor and Regression Tree are trained along with LSTM network using scaled metro data. For training the models, 60% from the whole data set is selected randomly and the rest 40% is used for validation and testing the network. LSTM is trained using stochastic gradient descent algorithm. For more efficient passenger flow prediction model, the maximum number of epochs set to be 1000. From the experimental analysis of the fare card dat based learning (AFC), the model is best fit when it has 250, 40 and 6 neurons respectively. Conventionally, the model training is stopped if the loss of validation dataset does not decrease after five loops. The single step training and validation loss of the proposed LSTM model is shown in Figure 5(a). Figure 5(b) provides the valid versus prediction result of data points. Moreover, we train our models by minimizing the mean square error for 500 epochs with a batch size of 100. The optimizer learning rate is experimentally fixed to 0.05. In any time series forecasting method, performance metric is an indispensable part. The accuracy assessment methods for passenger flow prediction is given in the following subsection.

4.1 Performance Metric

The statistical test indicators that we used to compare the performance of the traffic flow prediction models are Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It is defined as follows:

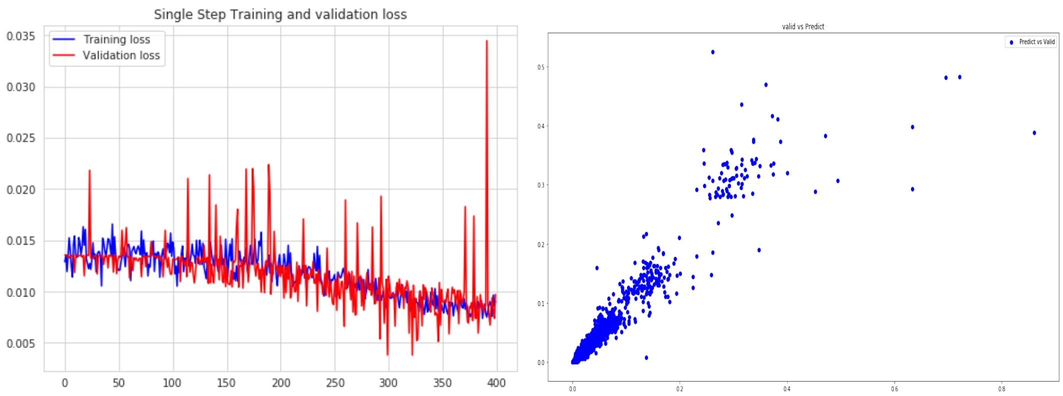
$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_t - x_t)^2 \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_t - x_t)^2} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_t - x_t| \tag{14}$$

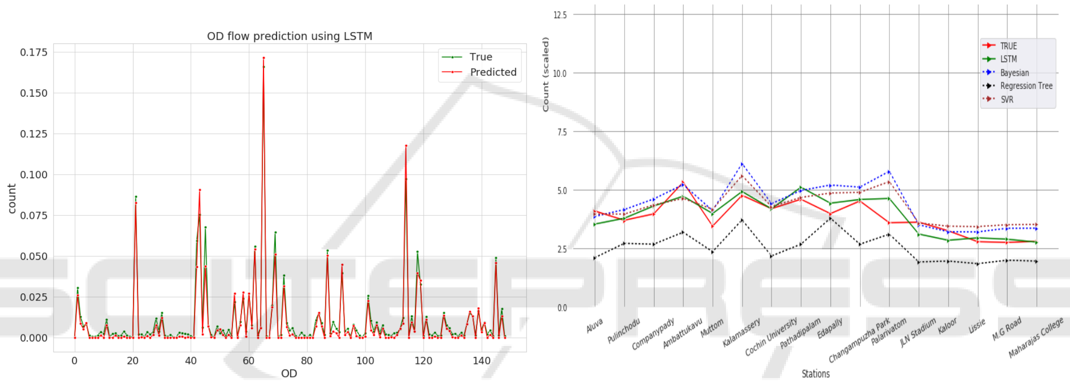
4.2 Evaluation and Inferences

The evaluation results of different models using O-D is shown in Table 2. The model is compared with a trained SVR model, Bayesian Regressor and Regression Tree. With reference to Table 2, it is ob-



(a) Single-step Training and Validation Loss (b) Vaild vs Prediction based on the data-points(Passenger Day Count)

Figure 5: Single-step Training and Validation Loss of LSTM and Valid vs Predction on datapoints.



(a) Short Term Path-wise Passenger Flow Prediction using LSTM (b) Short Term Station-wise Passenger Flow Prediction using LSTM

Figure 6: Path-wise and Station-wise Passenger Flow Prediction using LSTM.

Table 2: Accuracy Metrics for Time Series Forecast.

Model		MSE	RMSE	MAE
SVR(kernel)	Linear	0.0023	0.0486	0.0476
	Polynomial	0.0084	0.0924	0.0899
	RBF	0.0031	0.0553	0.0541
Bayesian Regressor		0.00018	0.01376	0.003435
Regression Tree		0.00072	0.02688	0.01099
LSTM		**0.00015**	**0.01253**	**0.003539**

served that the best kernel for the SVR model is linear. Also, the performance of the model is evaluated using accuracy measuring metrics such as MSE, Root Mean Square error (RMSE), Mean Absolute Error (MAE). From the experimental analysis and results obtained, proposed passenger flow prediction model using LSTM outperforms most of the traditional machine learning techniques. The LSTM model is designed using all possible paths existing in the current metro system. The time series prediction of passenger count using the LSTM neural network is shown in Figure 6(a). The inflow and outflow of each station is the aggregated result of predicted O-D flows as depicted in Figure 6(b).

5 CONCLUSION AND FUTURE WORK

This work attempts to tackle the problem of flow prediction for metro rail transport using path-dependent station pairs to increase the accuracy of the prediction. By examining the observations it was found that LSTM network in conjunction with a non-linear dense prediction layer performed better than other models. Experimental results have derived that that incorporation of spatial information is a performance enhancer and blazes a direction worth further exploration. Moreover unlike conventional ML methods the intermediate features generated by the LSTM convey the temporal structure more effectively. The extraction of OD matrix is computational bottleneck in this process. We identify employment of distributed computational methods as a potential future work for solving this problem. Another intended area of future work is to further explore is the effect of external factors like weather conditions and bring them into the scope of the model.

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REFERENCES

Abadi, M., Agarwal, A., and Barham, P. (2016). TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from tensorflow.org.

Ahmed, M. S. and Cook, A. R. (1979). *Analysis of freeway traffic time-series data by using Box-Jenkins techniques*. Number 722.

Ampelas, A. (2001). Automatic fare collection. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*.

Chollet, F. et al. (2015). Keras. https://keras.io.

Ci, Y., Xiu, G., and Wu, L. (2017). A short-term traffic flow prediction method based on long short-term memory network. In *International Conference on Green Intelligent Transportation System and Safety*, pages 601–608. Springer.

Dai, X., Sun, L., and Xu, Y. (2018). Short-term origin-destination based metro flow prediction with probabilistic model selection approach. *Journal of Advanced Transportation*, 2018.

Han, Y., Wang, C., Ren, Y., Wang, S., Zheng, H., and Chen, G. (2019). Short-term prediction of bus passenger flow based on a hybrid optimized lstm network. *ISPRS International Journal of Geo-Information*, 8(9):366.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8):1735–1780.

Li, Y., Wang, X., Sun, S., Ma, X., and Lu, G. (2017). Forecasting short-term subway passenger flow under special events scenarios using multiscale radial basis function networks. *Transportation Research Part C: Emerging Technologies*, 77:306–328.

Metro Rail (2017). Kochi metro rail Ltd., Kerala, India.

Mulerikkal, J., Thandassery, S., Dixon K, D. M., Rejathalal, V., and Ayyappan, B. (2022). Jp-dap: An intelligent data analytics platform for metro rail transport systems. *IEEE Transactions on Intelligent Transportation Systems*, 23(7):9146–9156.

Pamuła, T. (2013). Short-term traffic flow forecasting method based on the data from video detectors using a neural network. In *International Conference on Transport Systems Telematics*, pages 147–154. Springer.

Sun, Y., Leng, B., and Guan, W. (2015). A novel wavelet-svm short-time passenger flow prediction in beijing subway system. *Neurocomputing*, 166:109–121.

Tang, L., Zhao, Y., Cabrera, J., Ma, J., and Tsui, K. L. (2019). Forecasting short-term passenger flow: An empirical study on shenzhen metro. *IEEE Transactions on Intelligent Transportation Systems*, 20(10):3613–3622.

Tian, Y. and Pan, L. (2015). Predicting short-term traffic flow by long short-term memory recurrent neural network. In *2015 IEEE international conference on smart city/SocialCom/SustainCom (SmartCity)*, pages 153–158. IEEE.

Tsai, T.-H., Lee, C.-K., and Wei, C.-H. (2009). Neural network based temporal feature models for short-term railway passenger demand forecasting. *Expert Systems with Applications*, 36(2):3728–3736.

Xiao, Y. and Yin, Y. (2019). Hybrid lstm neural network for short-term traffic flow prediction. *Information*, 10(3):105.

Zaharia, M., Chowdhury, M., Franklin, M. J., Shenker, S., Stoica, I., et al. (2010). Spark: Cluster computing with working sets. *HotCloud*, 10(10-10):95.

Zhang, Z., Wang, C., Gao, Y., Chen, J., and Zhang, Y. (2020). Short-term passenger flow forecast of rail transit station based on mic feature selection and st-lightgbm considering transfer passenger flow. *Scientific Programming*, 2020.