A deep learning-based approach to recognize passengers' transport mode and trip phases

A. SeyedHassan Hosseini[a,*], B. Guido Gentile[a],

C. Lory Michelle Bresciani Miristice [a], D. Francesco Viti [b]

[a] Department of Civil, Constructional and Environmental Engineering, Università di Roma La Sapienza, Rome, Italy
seyedhassan.hosseini@uniroma1.it, guido.gentile@uniroma1.it,
lorymichelle.brescianimiristice@uniroma1.it,

[b] Faculty of Science, Technology and Medicine 30 University of Luxembourg, Mobilab Transport Research Group, L-4364 Esch-sur-Alzette, Luxembourg
francesco.viti@uni.lu

* seyedhassan.hosseini@uniroma1.it

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 11, 2024

Keywords: (transport mode detection, trip phase recognition, convolutional neural network, GPS data)

1 INTRODUCTION

Detecting transit modes people use for daily movements and recognizing passengers' trip phases can provide valuable data for urban planning, transportation infrastructure development, and policy-making where commuters' journey data are essential. Mobile phones can aid in recording raw passenger trip information, benefiting from their widespread usage in people's daily lives. Since most people carry their smartphones during the day, the data collected can provide rich insights into mobility patterns, preferences, and behaviors. In recent years, deep learning models have demonstrated their capability to effectively address challenges in transport mode detection, particularly in classifying passenger trip chunks into different modes such as walking, cycling, metro, and in a car or bus. Convolutional and recurrent neural networks (Dabiri and Heaslip, 2018; Nawaz *et al.*, 2020) as a deep learning method can effectively extract complex patterns in the GPS data, enabling a more accurate classification algorithm to detect transit modes. Furthermore, machine and deep learning models were applied as a core component of trip phase recognition framework to detect different stages of passengers' journeys (Hosseini and Gentile, 2022; Hosseini et al., 2024).

2 METHODOLOGY

The first section of the methodology details the training procedure of a deep learning model using labeled GPS data, and the second section describes the use of the trained model for detecting passengers' trip stages.

2.1 Training deep learning model

In this research, Geolife (Zheng et al., 2008) and Sussex dataset as the main source of data (Gjoreski et al., 2018) were selected and cleaned by handling missing values, and dealing with outliers due to signal loss. Then coordinates were converted into meaningful representations, such as distances and speeds between GPS points. Our preprocessing approach is based on established steps from previous research in this field (Dabiri and Heaslip, 2018). We selected the same modes, namely walk, bike, bus, car, and train. In total, 6220 trips were selected and sampled into fixed-size GPS points (200 records) with one unique label. Speed, acceleration, jerk, and bearing rate are among the main features used in this study. To extract meaningful features from each data segment to train a deep learning model, data were fed into a 1D Convolutional Neural Network.

2.2 Trip phase recognition

The core objectives of this research study are twofold: First, we increase the prediction accuracy of previous research (Dabiri and Heaslip, 2018) by following the same steps. Second, an improved CNN model will be applied on GPS chunks to extract novel information from raw GPS data focusing on waiting time experienced at public transport stations and analyzing the accessibility level of bus stations from raw GPS trajectories saved by passengers. Bus-based trips were selected from Geolife data to be fed into our prediction trip phases framework. This study presents a novel framework for automatically estimating the duration and distance of the access and egress phases, as well as the waiting time at bus and metro stations, using raw GPS data from urban trajectories. Our prediction model was also trained with standing labeled data from Sussex to detect waiting time at public transit stops.

2.3 Bus and metro station detection

Raw GPS data can be used to determine the precise position of bus and train stations to analyze the quality of transit stops. More than 212 public transport-based journeys were captured from GeoLife dataset, with the conditions starting with walking or cycling, continuing with a bus or train, and then returning to walking and cycling, and a nearby search Api supported by Google was used to find the closest public transit stops ranked by distance.

3 RESULTS AND DISCUSSION

The results section comprises two main components. First, it discusses the improvements in model prediction of transport mode detection using a one-dimensional CNN. The second part describes the use of the random forest model to predict trip phases. Our future goal is to replace the random forest model with our new CNN model and report the results.

3.1 Transport mode detection

Table 1 demonstrates the efficacy of deep learning layers in extracting significant information from GPS segments. Notably, the prediction of walking segments achieved the highest recall rate at 92.18%.

Table 1: *Results of Best CNN Configuration*

Confusion matrix		Predicted						
		bike	bus	car	train	walking	sum	recall %
Actual	bike	836	25	3	0	60	924	90.47
	bus	20	1069	64	21	125	1299	82.29
	car	5	61	728	6	44	844	86.25
	train	5	23	24	652	55	759	85.90
	walking	36	61	14	7	1391	1509	92.18
	sum	902	1239	833	686	1675	4885	-
	precision %	92.68	86.27	87.39	95.04	83.04	-	-

Our results were also evaluated with previous research that used the GeoLife GPS trajectory dataset. Table 2 shows our model improved the final accuracy on test data by 2.84 percent and outperforms previous work in predicting transit mode.

Table 2 - *Comparison with previous research*

Model	**Test Accuracy (%)**
Best CNN model in our study	87.64
(Dabiri and Heaslip, 2018)	84.8
(Zheng et al., 2008)	76.2

3.2 Trip phase recognition (passengers and bus station side)

In this paper, the MAPE method was used to calculate the errors of the final results, which is defined as the mean of the absolute percentage errors between the predicted and actual values for access time and distance and egress time and distance for each single trip. MAPE was calculated using this formula (Hyndman and Koehler, 2006).

$$MAPE = \left(\frac{1}{n}\right) \times \sum \left|\frac{actual - forcast}{actual}\right| \times 100 \tag{1}$$

Table 3. *Results of trip phases*

Phase	Prediction Accuracy	MAPE
Access Time	0.8567	0.1432
Access Distance	0.8608	0.1391
Egress Time	0.9469	0.0530
Egress Distance	0.9286	0.071

To understand, the accessibility level of each public transit stop and the distribution of passengers' waiting time, 71 trips were found with a similar address ID, and it means that all trips attracted by one single bus station. Figure 1 shows a better visualization of actual and predicted values for each phase where x-axis defines the range of time and distance in the dataset and y-axis shows the probability density defined as the probability per unit value of variables on x-axis.

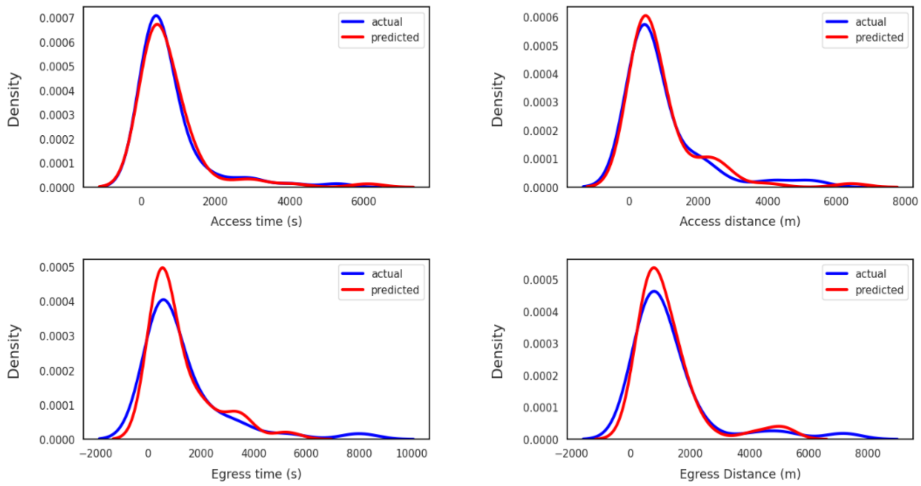

Figure 1 - *Kernel Distribution Estimation of Access and Egress Phases of 71 Trips Attracted by Single Bus Stop*

Figure 2 - *Kernel Distribution Estimation of Waiting Time (19 Trips)*

Finally, Figure 2 demonstrates a kernel distribution of waiting time at stop level for 19 trips attracted by one single bus station. Our proposed framework can present the distribution of waiting time at each bus station where there is GPS data.

4 CONCLUSIONS

This research presents a novel and robust approach for identifying trip modes using just GPS data and deep learning algorithms. Raw GPS data are fed into a CNN network after preprocessing procedures. The comparison demonstrates that the suggested technique can significantly boost identification accuracy on the same dataset. Furthermore, an automated trip phase detection framework to extract meaningful data from passengers' trips was presented.

5 REFERENCES

1. Dabiri, S. and Heaslip, K., 2018 ‘Inferring transportation modes from GPS trajectories using a convolutional neural network’, *Transportation research part C: emerging technologies*, 86, pp. 360–371.

2. Gjoreski, H. *et al.*, 2018 ‘The university of sussex-huawei locomotion and transportation dataset for multimodal analytics with mobile devices’, *IEEE Access*, 6, pp. 42592–42604.
3. Hosseini, S.H. *et al.*, 2024 ‘GPS-Based Trip Phase and Waiting Time Detection to and from Public Transport Stops Via Machine Learning Models’, *Transportation Research Procedia*, 78, pp. 530–537.
4. Hosseini, S.H. and Gentile, G., 2022 ‘Smartphone-Based Recognition of Access Trip Phase to Public Transport Stops Via Machine Learning Models’, *Transport and Telecommunication*, 23(4), pp. 273–283.
5. Hyndman, R.J. and Koehler, A.B., 2006 ‘Another look at measures of forecast accuracy’, *International journal of forecasting*, 22(4), pp. 679–688.
6. Nawaz, A. *et al.*, 2020 ‘Convolutional LSTM based transportation mode learning from raw GPS trajectories’, *IET Intelligent Transport Systems*, 14(6), pp. 570–577.
7. Zheng, Y. *et al.*, 2008 ‘Understanding mobility based on GPS data’, in *Proceedings of the 10th international conference on Ubiquitous computing*, pp. 312–321.