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TRAVEL DURATION PREDICTION BASED ON TRAFFIC SPEED AND DRIVING PATTERN USING DEEP LEARNING

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Abstract. *This paper shows our research progress based on travel duration to traffic speed using deep learning. The main purpose of this research is to predict travel duration from point A to point B and pinpoint route using neural networks, giving options of faster travel. Simply this paper's purpose is to provide travel duration prediction for less time to travel to a destination. We will harness deep learning algorithms for calculating and predicting travel duration from available information as parameters. We implemented a Global Positioning System (GPS) to provide speed parameters, and a traffic map will then provide information about traffic conditions as the other parameter for travel prediction. Waze Iframe will provide map information for deep learning algorithms to classify traffic conditions. Deep learning algorithms are able to give out sets of predictions from data sets in this research from data training.*
Keywords: Deep learning, Travel duration, GPS, Waze Iframe, Traffic condition, Travel prediction

1. **Introduction.** In the past few years, neural network has contributed a lot in the development of technological use. Neural network is an algorithm inspired by how the human brain recognizes a pattern. This kind of algorithm has helped determine complex patterns from a vast factor influencing the pattern recognizing process. Neural networks can solve problems based on learning techniques to understand and associate a non-linear map with an output of a pattern [1]. Travel pattern recognition can be categorized into a non-linear map problem, whereas travel patterns are needed to be able to calculate travel duration in many forms and factors. From the neural network, each travel pattern possible to approach from point A to point B can be shown from each pattern found from the neural network. Then each pattern will show possible routes to each point, providing crucial information to determine travel duration. Travel pattern is one of many factors affecting travel duration, besides travel patterns, there is also traffic condition and speed, distance from source and destination, etc. Several researches about neural network related in finding traffic speed only provide one key information to travel factor, since there are more than one factor affecting travel speed, pattern, and behavior, neural network can participate in developing an even more advanced application that is capable of providing precise travel information.

Besides neural networks, nowadays deep learning has become more common because of the big data era. Deep learning is a machine learning algorithm that utilizes a multilayered network method [2]. Deep learning utilizing multilayered networks is able to learn from

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a huge data set and extract any valuable to crucial information. Since factors may affect prediction calculation to deep learning and neural networks, non-parametric deep learning may also provide a huge contribution in travel prediction to this research. Non-parametric deep learning may predict and do regression from very abnormal and unpredicted traffic conditions [15]. Huge learning curve provides deep learning to recognize any architecture from any important features from an object, image, and any other [3].

Current state of traffic in Indonesia has progressively worsened each decade, affecting many factors of daily activities. For instance, office workers tend to be late to the office due to traffic jams that frequently occur. This situation will affect many factors of a company if traffic conditions worsen more in upcoming time. Office workers are only one example of the factor affected by traffic jams, while there are more factors that can be affected and will show a very huge impact to traffic jams. Besides traffic, each person's travel pattern is unique and different to each other. These differences may affect travel duration. Such things could be resolved or be reduced significantly by providing each individual with information, such as the speed that takes an individual from point A to point B, and the stage of traffic jam in which an individual chooses, by a various route that is recommended from an application that utilizes neural network as the basis of the prediction.

Neural network and travel duration prediction can provide useful information for such activities to reduce the negative impact of Indonesia's current state of traffic. There are a vast amount of possible factors affecting travel duration. By condoning repetitive training to a specified route from point A to point B we will be able to deepen any possible factors affecting travel prediction and calculate possible range of factors affecting travel prediction [13]. Whereas fixed parameters such as travel speed, and traffic condition will be recorded as data and will then be used for deep learning, other factors will be considered external factors and will not give a huge impact to prediction such as SAE (Stack Autoencoders) [16]. External factors will then be considered as factors that may affect travel prediction when the range of prediction to actual travel time data is gathered. This paper will discuss the theorem of deep learning, neural network, and color clustering used to support the development of applications for predicting travel duration based on several factors.

2. **Literature Review.**

2.1. **Deep learning.**
Deep learning can be categorized into machine learning algorithms. The big data era pushed the possibilities of deep learning in extracting information. Growth of available data, unsolved problems related, and any other learning methods has increased the use of deep learning [4]. Deep learning further improves neural networks since neural networks are categorized into neurons such as input layer, hidden layer, and output layer. Deep learning can extract such information from a neural network and train the network. Best weights are selected for each neuron available in order to train a neural network [3]. Collaboration between deep learning and neural networks can be categorized into Deep Neural Network (DNN), where DNN consists of supervised, unsupervised, and hybrid. Several papers discussed deep learning in the field of object prediction and any similar field, while this research will utilize deep learning in recognizing any travel route pattern from a neural network and learning the traffic pattern such as distance, traffic speed, traffic jams, based on data from Google Maps. Images from Google Maps with traffic conditions will provide data for deep learning to extract traffic speed information valuable to calculate and predict travel duration. Deep learning in recognizing traffic conditions may refer to route colors indicating each route's condition. The main advantage brought from deep learning is automatic feature selection from each data [6].

2.2. **Neural network.**
According to Park et al., neural networks are able to learn possible ways of associating and also map input layers such as non-linear problems and extract

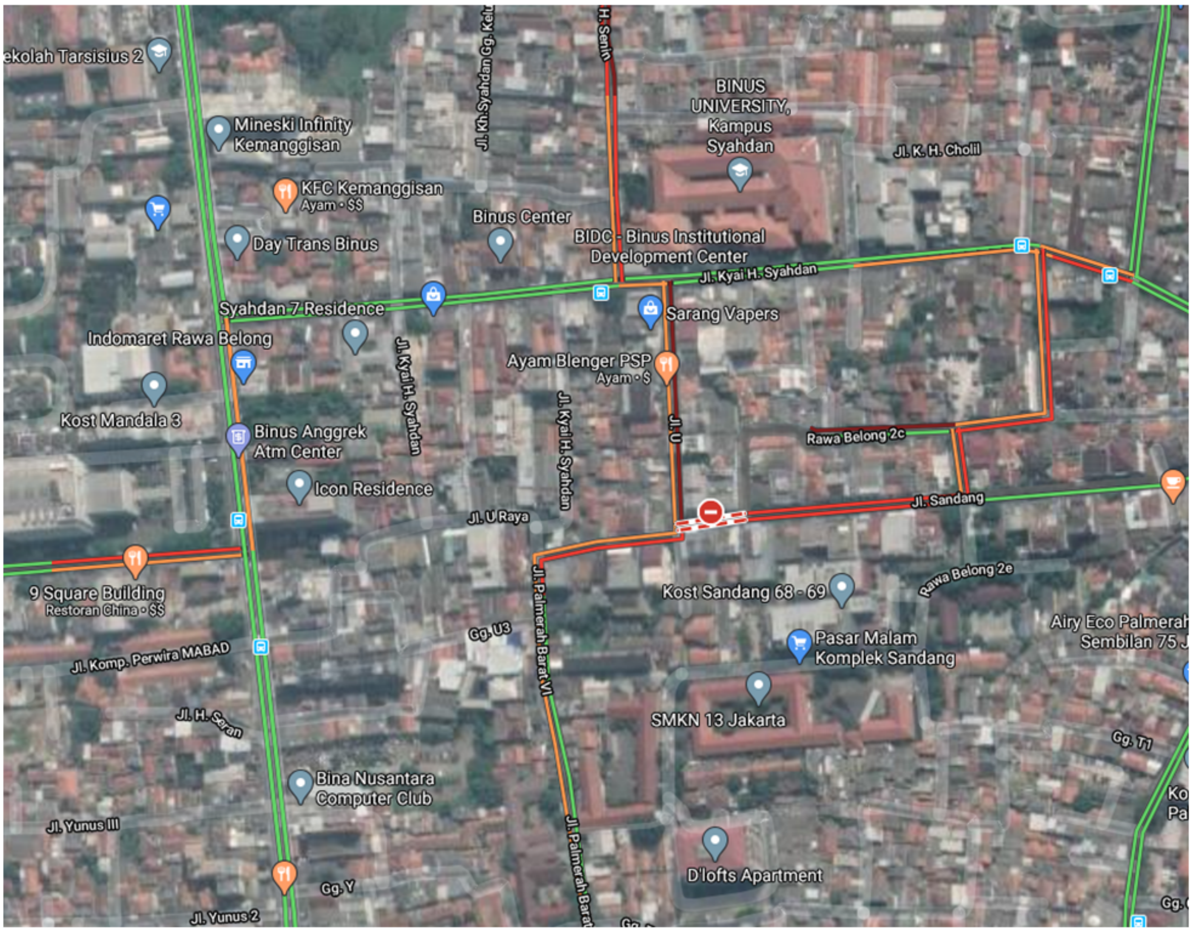

FIGURE 1. Google Maps showing traffic condition [5]

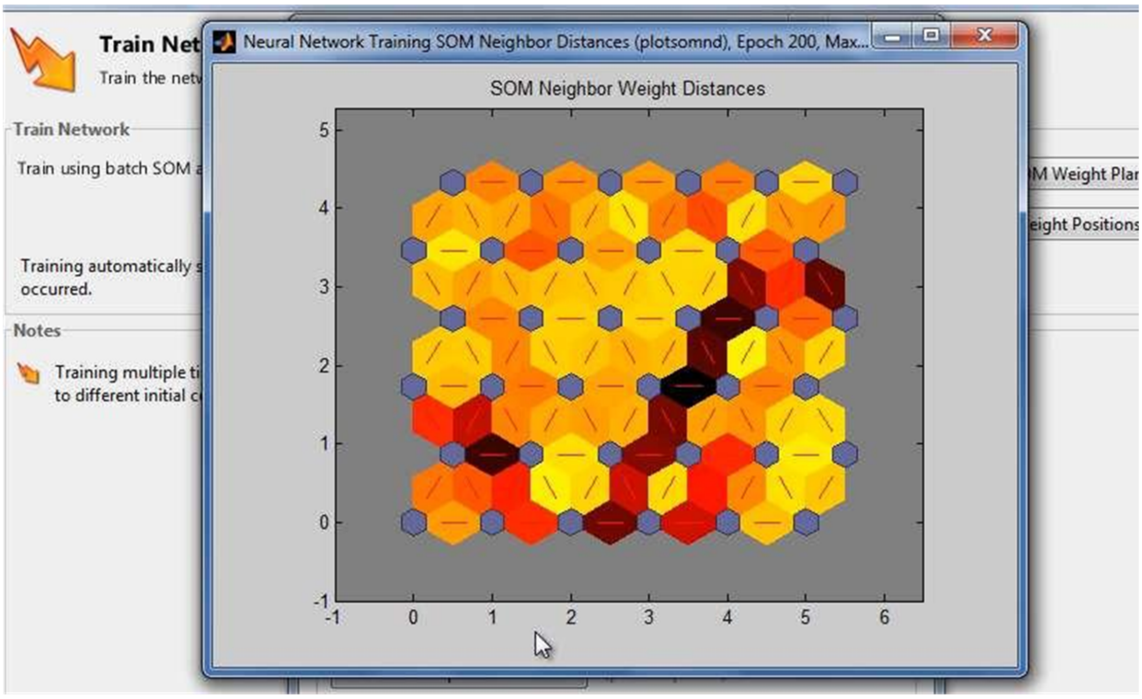

FIGURE 2. Color clustering example taken from Google

output in the form of patterns [7]. Meanwhile with neural networks, prediction of traffic flow information can be extracted from all datasets possible from deep learning creating deep neural networks. Traffic flow had a similarity with traffic prediction where several temporal and spatial factors may affect its output [19]. Lv et al. stated that from the past few decades, traffic flow and prediction of it may hold a crucial participation in the Intelligent Transportation System (ITS) [8].

Dai et al. stated that Recurrent Neural Network (RNN) is an artificial neural network with a hidden layer node oriented connection and closed loop [18], to ensure the accuracy of the prediction, information of the time sequence would be full-used by Recurrent Neural Network (RNN) [9]. However, RNN models in general when they are trained with long time lags shown to have problems in vanishing gradient and exploding gradient [14]. Kang et al. stated that to overcome such disadvantages, certain structures of RNNs such as LSTM were proposed [17]. Color clustering from learned data in deep learning from a data set may provide key information for a basic neural network in showing traffic patterns and route from starting point to the destination. Compared to other methods such as a structured recurrent neural network by considering each road segment as a node [20], the proposed neural network takes only the important data from current traffic conditions in real-time traffic.

3. Proposed Method.

3.1. Waze live map.

Waze map is one of Waze's plugins providing information about route, traffic condition, and such information will be necessary in calculating and providing traffic duration prediction. Waze map will point out parameters such as latitude and longitude position based on mobile Global Positioning System, each parameter then can be analyzed using deep learning to understand the live condition of each travel route's traffic condition from Waze Live Map providing traffic condition with color clustering. Waze Live Map has a role of giving datasets to the deep learning algorithm implemented together with the API, parameters sent by the API will be stored and pinpoint travel prediction calculated with several other aspects. Data will flow continuously each second providing accurate future prediction, even though it might not reach 100% due to unpredictable external factors affecting its performance. Each data extracted from both Waze map and color clustering algorithm then can be stored to a storage to contain all datasets as shown in Figure 3.

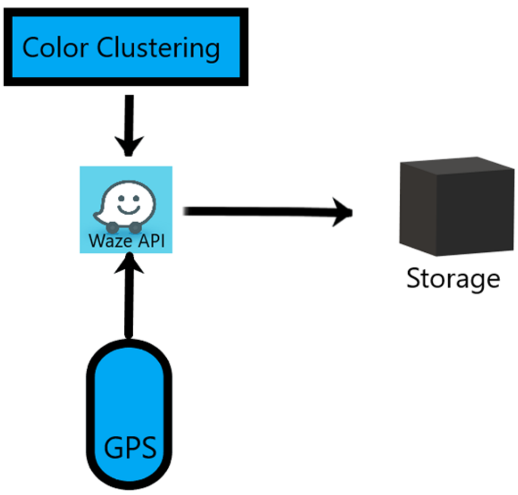

FIGURE 3. Block diagram of Waze API implementation

3.2. **Global positioning system.** Global Positioning System in each mobile phone using Internet connection will then provide information specific and different from Waze Live Map API. Waze will provide latitude and longitude information, where GPS will provide travel speed (km/h). Data then can be processed together with Waze API and color clustering algorithm and then prediction data will be stored as shown in Figure 4.

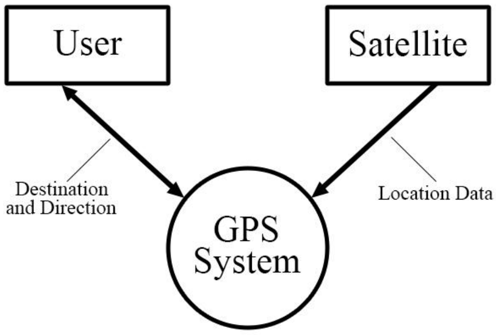

FIGURE 4. Context diagram for GPS system [11]

3.3. **Color clustering algorithm.** Color clustering algorithm will work by analyzing and cluster traffic speed color in Waze Live Map providing images of live conditions to the traffic. Each color will be clustered based on current position from GPS and Waze API providing latitude and longitude positioning. Then both parameters will be set as the cluster center to analyze the surrounding color cluster category, where red means heavy traffic jam, orange means crowded traffic, yellow means light traffic, and green means smooth traffic and so on.

Deeper clustering to the color options can be deepened by using multi-stage clustering since a more specific color to traffic jam intensity can be determined to a more precise level. Color clusters will analyze the traffic condition and classify it into more precise color clusters. Both color clustering algorithms may bring their own purpose into this research.

$$\Psi_\sigma(X) = \sum_{k=1}^{n} \phi(X - X_k) \tag{1}$$

Proposed color clustering algorithm used is the K-Means algorithm, by splitting iteratively several subgroups of color. $\Psi_\sigma(X)$ is considered as the potential field function for the scale size of σ, then n represents sets of color points, X, X_k as the color points, and then each subgroup of color will be iterated based on the sets of color points available.

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} \omega_{ik} \left\|x^i - \mu_k\right\|^2 \tag{2}$$

J as the objective function, k represents the number of clusters, while m represents the number of cases. Centroid for the cluster is represented by μ_k, x^i represents the cluster, and $\|x^i - \mu_k\|^2$ will be used as the distance function. The iteration will continue until no changes are found to the centroid for each cluster. After no changes are found, each data point will be assigned to the closest centroid.

Objective functions provide steps for keeping the intercluster data points similar and at the same time also as different as possible. Each iteration will alter the color subgroups based on the centroid data until there are no changes to the subgroup of color cluster (intercluster).

4. **Experimental Result.** Implementation of the algorithm is implanted to a mobile device using *Waze Iframe* API showing current traffic condition and GPS tracking exact latitude and longitude position for the deep learning algorithm, while *Waze Iframe* provides data for color clustering algorithm based on Figure 5 showing current position of the driver in heavy traffic. Both current speed and color cluster data are inserted to the database and used as information for deep learning algorithms and to predict travel prediction as shown in Figure 5.

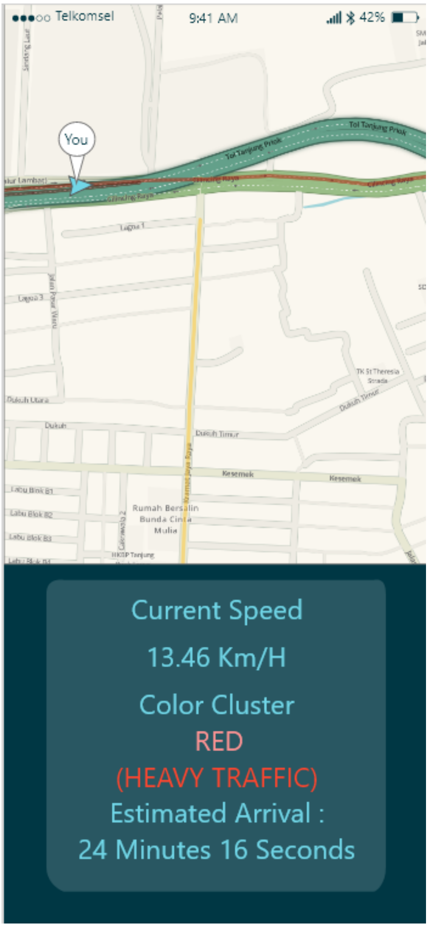

FIGURE 5. Travel duration prediction mobile

The application implemented GPS positioning and was able to detect the current speed of the driver as well as the color clustering algorithm selecting the current traffic speed color which is red and categorized as heavy traffic. With previous data training based on the deep learning algorithm, the application is able to conduct calculation and provide estimated travel prediction. By doing data recording each second provided by GPS data and color clustering data from *Waze Iframe*, the database will be altered to contain all data, where new data inserted will replace old data where old data has been learned to deep learning algorithms.

5. **Conclusion.** One of the fundamental things that could cause traffic jams is weather, accidents, and other sort of things that frequently happen on the roads. People tend to find out whether they can reach their destination as efficiently and save time as much as possible. However, driving patterns for every person are not the same, whether one should drive slowly or fast. In this paper, we have implemented driving duration prediction based on traffic speed and driving pattern gathered from data gathering activity. Hence through *Waze Iframe* API showing current traffic conditions and GPS tracking individual travel speed, along with a deep learning algorithm, we can predict travel duration. Experimental

results show that travel speed and traffic speed could categorize the road condition, which leads to calculation of estimated travel time of the user to reach from point A to point B. Several deep learning and neural network algorithms used such as color clustering algorithm combined with several parameters to calculate and predict travel duration can train all the data to provide a more precise prediction.

Furthermore, the purpose of the research is to develop an application to predict travel duration by recognizing traffic patterns and conditions. For the future work, additional prediction features can be added in the development of the neural network such as weather conditions, since prediction may be affected by a vast amount of factors. More considered factors in predicting may result in a more accurate result and be able to counter unexpected outcomes due to changes of prediction factors.

REFERENCES

[1] J. Tang, F. Liu, Y. Zou, W. Zhang and Y. Wang, An improved fuzzy neural network for traffic speed prediction considering periodic characteristic, *IEEE Trans. Intelligent Transportation Systems*, vol.18, no.9, pp.2340-2350, 2017.

[2] T. Kagawa and N. P. Chandrasiri, Analysis of driving skills based on deep learning using stacked autoencoders, *The 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, Yogyakarta, pp.1-4, 2017.

[3] W. Budiharto, A. A. S. Gunawan, J. S. Suroso, A. Chowanda, A. Patrik and G. Utama, Fast object detection for quadcopter drone using deep learning, *The 3rd International Conference on Computer and Communication Systems (ICCCS)*, Nagoya, pp.192-195, 2018.

[4] A. Sevik, P. Erdogmus and E. Yalein, Font and Turkish letter recognition in images with deep learning, *International Congress on Big Data, Deep Learning and Fighting Cyber Terrorism (IBIGDELFT)*, Ankara, Turkey, pp.61-64, 2018.

[5] *Google Maps Showing Traffic Conditions*, https://www.google.com/maps/place/Jakarta+Pusat,+Kota+Jakarta+Pusat,+Daerah+Khusus+Ibukota+Jakarta/@-6.201502,106.7841003,728m/data=!3m1!1e3!4m5!3m4!1s0x2e69f436b8c94b07:0x6ea6d5398b7c82f6!8m2!3d-6.1805113!4d106.8283831!5m1!1e1, Accessed on 5 August 2020.

[6] C. Siripanpornchana, S. Panichpapiboon and P. Chaovalit, Travel-time prediction with deep learning, *IEEE Region 10 Conference (TENCON)*, Singapore, pp.1859-1862, 2016.

[7] J. Park et al., Real time vehicle speed prediction using a neural network traffic model, *The 2011 International Joint Conference on Neural Networks*, San Jose, CA, pp.2991-2996, 2011.

[8] Y. Lv, Y. Duan, W. Kang, Z. Li and F. Wang, Traffic flow prediction with big data: A deep learning approach, *IEEE Trans. Intelligent Transportation Systems*, vol.16, no.2, pp.865-873, 2015.

[9] J. Zhao, Y. Gao, Y. Qu, H. Yin, Y. Liu and H. Sun, Travel time prediction: Based on gated recurrent unit method and data fusion, *IEEE Access*, vol.6, pp.70463-70472, DOI: 10.1109/ACCESS.2018.2878799, 2018.

[10] *Color Clustering Example*, https://www.mathworks.com/videos/iris-flower-clustering-with-neural-clustering-tool-68796.html, Accessed on 7 August 2020.

[11] *Context Diagram for GPS System*, http://shivone2011.blogspot.com/2010/11/context-diagram-for-gps-system-pg-83.html, Accessed on 7 August 2020.

[12] *Color Clustering K-Means Algorithm*, https://towardsdatascience.com/k-means-clustering-algorithm-applications-evaluation-methods-and-drawbacks-aa03e644b48a, Accessed on 7 August 2020.

[13] A. Khosravi, E. Mazloumi, S. Nahavandi, D. Creighton and J. W. C. van Lint, Prediction intervals to account for uncertainties in travel time prediction, *IEEE Trans. Intelligent Transportation Systems*, vol.12, no.2, pp.537-547, 2011.

[14] Y. Gu, W. Lu, X. Xu, L. Qin, Z. Shao and H. Zhang, An improved Bayesian combination model for short-term traffic prediction with deep learning, *IEEE Trans. Intelligent Transportation Systems*, vol.21, no.3, pp.1332-1342, DOI: 10.1109/TITS.2019.2939290, 2020.

[15] A. Koesdwiady, R. Soua and F. Karray, Improving traffic flow prediction with weather information in connected cars: A deep learning approach, *IEEE Trans. Vehicular Technology*, vol.65, no.12, pp.9508-9517, 2016.

[16] J. Lemieux and Y. Ma, Vehicle speed prediction using deep learning, *IEEE Vehicle Power and Propulsion Conference (VPPC)*, Montreal, QC, pp.1-5, 2015.

[17] D. Kang, Y. Lv and Y. Chen, Short-term traffic flow prediction with LSTM recurrent neural network, *IEEE the 20th International Conference on Intelligent Transportation Systems (ITSC)*, Yokohama, pp.1-6, DOI: 10.1109/ITSC.2017.8317872, 2017.

[18] G. Dai, C. Ma and X. Xu, Short-term traffic flow prediction method for urban road sections based on space – Time analysis and GRU, *IEEE Access*, vol.7, pp.143025-143035, DOI: 10.1109/ACCESS.2019.2941280, 2019.

[19] Z. Liu, Z. Li, K. Wu and M. Li, Urban traffic prediction from mobility data using deep learning, *IEEE Network*, vol.32, no.4, pp.40-46, DOI: 10.1109/MNET.2018.1700411, 2018.

[20] Y. Kim, P. Wang and L. Mihaylova, Structural recurrent neural network for traffic speed prediction, *ICASSP 2019 – 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Brighton, United Kingdom, pp.5207-5211, DOI: 10.1109/ICASSP.2019.8683670, 2019.