A Review: An Evaluation of Current Artificial Intelligent Methods in Traffic Flow Prediction

Muhammad Rusyaidi¹, Zunaidi Ibrahim²

¹Sunderland University, UK, St Peter's Campus, Sunderland, SR6 0DD, United Kingdom; ²Mechanical Engineering, Faculty of Engineering, Universiti Teknologi Brunei, Jalan Tungku Link, Mukim Gadong A, BE1410 Brunei Darussalam.

Abstract: Modelling the flow of traffic is a growing issue for several city and traffic issues, using artificial intelligence to engineer as a better traffic system is the focus of artificial intelligence research. This paper, therefore, compares, analyzes and evaluates machine learning and deep learning in autonomous vehicle traffic flow prediction. Methods of machine learning and deep learning used by other researchers will be compared to each other to give results and suggestions based on their methods evaluation. The paper concludes with suggestions as to where the method would provide the most appropriate and effective technique for modern smart transport systems.

Keywords: machine learning, artificial intelligence, traffic control

1. Introduction

The transportation sector is the most important in developing the economy with the significant growth of the demand for mobility and transportation systems in the world. Traffic congestion has been increasing in many parts of the world, and everything indicates that it will continue to get worse. The intelligent timing of traffic signals is essential for controlling busy intersections between cities. Wu et al. [1] state that with artificial intelligence technology, it becomes easier for vehicles and more reliable at any time to adjust the route.

Previous research was done to control adaptive traffic lights continuously. With the achievement of artificial intelligence machine learning, Zeng et al. [2] state that deep learning-based methods are capable of learning the relations among raw traffic and corresponding output effectively without the need for heavy labor and private data. However, Berman et al. [3] mention that encrypted traffic such as deep packet inspection and signatures was not applicable. Chu et al. [4] have proposed to research modified Q-Learning mechanisms to optimize the configuration of the traffic light cycle. However, the statement quoted by [4] that, “in a well-developed city, it is
not enough to solve the heavy traffic flow problem by just considering the traffic flows at a single intersection”.

The focus on this paper is on the review of the machine learning and deep learning methods for predicting traffic flow and what their perceived limitations are. To be more accurate, how to perform the traffic flow design using machine learning and deep learning method of research. Finally, the output of the traffic flow prediction review will use in developing and compare the performance of smart traffic management and control systems with the previously proposed models. The study would demonstrate the wide possibilities to use on artificial intelligence, machine learning work and structural optimization techniques which already done in previous research such as [5][6][7][8][9][10][11][12] to build and incorporate the smart traffic control system for the automation prediction system in monitoring and controlling the traffic flow, speed and security prediction in the future.

2. Evaluation of current artificial intelligent method in traffic flow prediction.

2.1 Deep learning model

Chen et al. [13] have been researching a novel Fuzzy Deep-Learning approach called Financial Data Cast Network (FDCN) to predict citywide traffic flow which method is based on the model of deep residual networks and the Fuzzy theory. To reduce the effect of data confusion the aim of this research was to incorporate fuzzy representation in the Deep Learning Model. To prove their arguments, they conducted an experiment using the Python with Keras and tensor-flow libraries to show effectiveness and validity in comparison with the FDCN algorithm for related application which is FDCN, Deep Spatio-temporal (DeepST), convolutional neural network (CNN), Autoregressive integrated moving average (ARIMA), Fully Convolutional Neural Network (FCNN) [13].

The author [13] used the FDCN model for traffic flow prediction and the FDCN model contains five modules which are the input the Deep Convolution Network (DCN), the Fuzzy Network (FN), predictor, and the Fusion shown in Figure 1(a). Figure 1(b) illustrates the FN structure that is connected with the fuzzification layer to each notice in the input layer and the membership feature is used to determine the extent to which an input node relates to a certain fuzzy set.

![Figure 1. FDCN model for traffic flow prediction [13]](image-url)
Table 1. Performance comparison of the four models with variant layers [13]

| Layers | DeepST | CNN | FCNN | FDCN |
|--------|--------|-----|------|------|
|        | RMSE   | MRE | MAE  | RMSE | MRE | MAE  | RMSE | MRE | MAE  | RMSE | MRE | MAE  |
| 2      | 23.3604| 0.231| 0.023| 23.3545| 0.232| 0.023| 0.4245| 0.231| 0.022| 2.2168| 0.360| 0.022|
| 3      | 23.3530| 0.226| 0.018| 20.5218| 0.208| 0.018| 0.3867| 0.222| 0.021| 2.1143| 0.368| 0.050|
|        |        |     |      | 5     | 6   | 8    | 6    | 1   | 8    | 2    | 8    |
| 4      | 21.9253| 0.217| 0.018| 19.9466| 0.214| 0.018| 0.3336| 0.218| 0.019| 1.7866| 0.372| 0.046|
|        | 3      | 3   | 6    | 2    | 4   | 2    | 8    | 6   | 8    |
|        | 8      | 21.1351| 0.216| 0.020| 21.5762| 0.234| 0.020| 0.4319| 0.261| 0.022| 1.1896| 0.326| 0.036|
|        | 5      | 2   | 7    | 5    | 9   | 0    | 3    | 7   | 0    | 4    |
| 6      | 20.2035| 0.203| 0.018| 138.936| 0.879| 0.143| 0.3476| 0.225| 0.019| 1.6327| 0.381| 0.041|
|        | 8      | 7   | 5    | 9    | 0    | 3    | 7    | 0   | 4    | 5    |
| 10     | 19.8306| 0.211| 0.018| 147.098| 0.974| 0.142| 16.758| 1    | 0.143| 0.6996| 0.318| 0.030|
|        | 12     | 21.6321| 0.236| 0.020| 147.144| 1    | 0.143| 16.758| 1    | 0.143| 0.6996| 0.318| 0.030|
|        | 14     | 19.0306| 0.194| 0.017| 147.144| 1    | 0.143| 16.758| 1    | 0.143| 0.3336| 0.228| 0.020|
|        | 16     | 20.5252| 0.206| 0.178| 147.106| 1    | 0.143| 16.758| 1    | 0.143| 0.3195| 0.218| 0.018|
|        | 18     | 19.8368| 0.211| 0.018| 147.142| 1    | 0.143| 16.758| 1    | 0.143| 0.3037| 0.204| 0.018|
|        | 20     | 19.8109| 0.212| 0.018| 147.144| 1    | 0.143| 16.758| 1    | 0.143| 16.757| 0.999| 0.143|
|        | 22     | 19.4921| 0.204| 0.017| 147.144| 1    | 0.143| 16.758| 1    | 0.143| 0.3039| 0.220| 0.017|
|        | 24     | 5    | 7    | 2    | 0    | 1    | 0    | 6   | 8    | 5    | 7    | 8    |

Figure 2. The RMSE for multi-step ahead prediction [13]
The researchers evaluated the performance of their system as the optimization structure as shown in Table 1 against four models of variant layers. Root Mean Square Error (RMSE) as a whole demonstrated an upward trend in Figure 2, with an increase in the number of steps. The author thus concluded that the FDCN method's prediction performance was fairly constant over a short time and that the FDCN method was more accurate compared to the ARIMA, DeepST, CNN and FCNN methods.

The result was backed up by experiment compared to the FDCN method with other methods to obtain which method is more accurate in predicting traffic flow and the result of the analysis was established. This research using quantitative data by presenting a graph to produce the results and experiments presents without any discrimination and their experiment was under a controlled laboratory environment. They acknowledge that in their research “FDCN has many open problems, including the optimized structure of the model and the influence of external factors on predictive performance” [13]. Jia et al. [14][15] also proposed a new deep learning method and multiple deep learning models for short-term traffic flow prediction using deep belief networks (DBN) and long short-term memory (LSTM). The author says that “One of the widely used deep learning-based methods, the Deep Belief Network (DBN), has been proved for its capability to extract non-linear characteristics which can be utilized to represent the study” [15].

The study was carried out on the design of the DBN. The design of the DBN model is shown in Figure 3, that “From the bottom to the top, a stack of RBMs is created. On top of the RBMs, a BPNN is known to be the output layer that can fine-tune the entire model using the backpropagation algorithm”.

![Figure 3. Structure of the DBN model [15]](image-url)
Jia et al. choose Auto-Regressive Integrated Moving Average (ARIMA) models. For all time horizons, the DBN can outperform the Back Propagation Neural Network (BPNN) and (ARIMA). Table 2 represents three-time horizons for prediction, including horizons of 2 minutes, 10 minutes, and 30 minutes. The experiment was conducted, and all the observations shown in Table 2 below the DBN model outperform the BPNN and the ARIMA (0, 1, 1) for all three-time horizons of predictions. Through comparisons between the three predicted horizons, model performance with longer predictive horizons is found to be less accurate. However, these DBN performances are still better than BPNN and ARIMA performers. The author indicated that “if one is using DBN to get the basic trend of traffic speed in long-term further, long prediction horizon, i.e. 30-minute, is sufficient to achieve the goal; if one wants to obtain the short-term speed forecast with more accuracy, DBN with 2-minute horizon should be selected”.

The experiments were performed equally and with good science standards as it is in a controlled laboratory environment that uses different horizon duration, 2 minutes, 10 minutes, and 30 minutes for prediction. All experiments carried out within the paper were followed by a table and figure showing good clarity of the research carried out. However, the problem happens when the horizons of prediction are longer; the results of DBN lack more stochastic features, and the peak hours performance of the evening is poor. In the experiment outcome paper in [14], they said that DBN could outperform current methods in ARIMA, but [15] checked their experiment in the ARIMA model and their result revealed that ARIMA was worse performance even than regular because of the challenging to model nonlinear traffic flow. Their argument was backed up by a comparison between the Resistive Deep Belief Network (R-DBN) as a basic deep learning method with 8 models and perform experiments for all three prediction horizons show that the Resistive Long Short-Term Memory (R-LSTM) has the highest accuracy relative to other models and that ARIMA has shown poor accuracy. On the other side, Aqib et al. [16] researched a solution based on Convolutional Neural Networks (CNNs) in deep learning which leads to the conclusion that was able to achieve the largest set of data used in deep learning studies such as road traffic data from 2006 to 2017. The testing was carried out on several documented events covering a variety of traffic flows and patterns in the real world. It leads to the repeatability of the analysis and no bias.

| Prediction horizon | Model | MAPE(%) | RMS E | RMS N | Previous intervals | Layer number | Layer units | Epochs |
|--------------------|-------|---------|-------|-------|-------------------|--------------|-------------|--------|
| 2-minute           | DBN   | 5.8099  | 4.3585| 0.0710| 2                 |              |             |        |
|                    | BPNN  | 5.9681  | 4.4880| 0.0731| 10                |              |             |        |
|                    | ARIMA | 5.9752  | 4.5116| 0.0735| 30                |              |             |        |
| 10-minute          | DBN   | 7.3359  | 5.5365| 0.0902| 2-minute          | 8            | 1           | 500    |
|                    | BPNN  | 7.5277  | 5.7688| 0.0940| 10-minute         | 12           | 1           | 400    |
|                    | ARIMA | 7.8387  | 6.0834| 0.0991| 30-minute         | 25           | 1           | 200    |
| 30-minute          | DBN   | 8.4782  | 6.3109| 0.1029| 2-minute          |              |             |        |
|                    | BPNN  | 8.8433  | 6.5561| 0.1069| 10-minute         |              |             |        |
|                    | ARIMA | 8.9312  | 6.9797| 0.1137| 30-minute         |              |             |        |
2.2 Machine learning

A second commonly used method of machine learning technique, is used to define, classify and predict traffic flow patterns in a data-driven approach based on a modular framework for the sequential application of machine learning use in [17]. Cheng et al. [18] conducted research to improve traffic flow prediction accuracy by machine learning using a travel time prediction model based on a gradient boosting decision tree (GBDT). They have suggested one of the most relevant methods of ensemble learning is the method of boosting, which produces base models sequentially. They were proposed travel time prediction, which is a machine learning hotspot algorithm and can investigate the complex relationships between variables in detail. GBDT model is established with 11 variables for various predictive horizons. Simulation experiment with different random seed numbers was proposed. Table 3 displays 133 simulated experiment results and simulation time was 28800s.

The results show that the GBDT outperforms BP neural network model and the SVM model in travel time prediction is shown in Figure 4. GBDT is a good way to predict travel time. “Comparing with other machine learning algorithms, the GBDT model cannot only produce more accurate prediction results but also provide us an opportunity to understand the diverse influences of different variables and nonlinear relationships”. Overall, Cheng et al. research have been shown among all prediction horizons, the most important influence variable being the same and travel time in the current period, reflecting that the travel time of the current period has the greatest impact on the travel time of the next period. Research by Cheng was outstanding, the method used for the experiment was scientifically sound and rational as it used and clearly described the related equations. The research has both obtained a good prediction that is influencing variable is influence variable is same and highest influence on travel time rate than an earlier piece of research that using the same method which is a machine learning-based on gradient boosting decision tree (GBDT) conducted by Ma et al. [19], proving the quality of the paper.

| Time Segments (s) | 9:00-9:30 | 9:30-10:00 | 10:00-10:30 | 10:30-11:00 |
|-------------------|-----------|------------|--------------|--------------|
| Simulation Time Segments (s) | 0-1800 | 1800-3600 | 3600-5400 | 5400-7200 |
| Traffic Flow (veh/h) | 800 | 1200 | 1600 | 2000 |
| Time Segments (s) | 11:00-11:30 | 11:30-12:00 | 12:00-12:30 | 12:30-13:00 |
| Simulation Time Segments (s) | 7200-9000 | 9000-10800 | 10800-12600 | 12600-14400 |
| Traffic Flow (veh/h) | 2400 | 2600 | 2800 | 3000 |
| Time Segments (s) | 13:00-13:30 | 13:30-14:00 | 14:00-14:30 | 14:30-15:00 |
| Simulation Time Segments (s) | 1400-16200 | 16200-18000 | 18000-19800 | 19800-21600 |
| Traffic Flow (veh/h) | 3600 | 4200 | 4800 | 5400 |

Table 3. The input of traffic flow [18]
Time Segments (s) | 15:00-15:30 | 15:30-16:00 | 16:00-16:30 | 16:30-17:00
---|---|---|---|---
Simulation Time Segments (s) | 21600-23400 | 23400-25200 | 25200-27000 | 27000-28800
Traffic Flow (veh/h) | 6000 | 6600 | 7200 | 7800

Figure 4. The flowchart of SSA-KELM model [20]

Their research was carried out because of the desire to improve the accuracy of the prediction for short-term traffic flow. The research consisted of designing a new model for predicting short-term traffic flow SSA-KELM. SSA and KELM were explained by author “In the SSA-KELM model, KELM is the basic prediction method, SSA is used to filter the noise components from the original traffic data, PSR is used to determine the optimal input form of KELM and the GSA is used to optimize the parameters of the KELM” [20]. The author provides an overall SSA-KELM model flowchart and the SSA-KELM model’s main steps are shown in Figure 4.

Table 4. Performance indices for different models [20]

| Model       | Ranking (MAE) | Ranking (MAPE) |
|-------------|---------------|----------------|
| SSA-KELM    | 3.5           | 3.5            |
| KELM        | 31.3333       | 31.3333        |
| SSA-SVM     | 29.6667       | 29.6667        |
| SSA-ELM     | 18.3333       | 18.0833        |
| HPSO-SVR    | 16            | 17.5833        |
| LSTM-NN     | 12.1667       | 10.8333        |
Table 5. Average Rankings of the models using Aligned Friedman [20]

| Model       | Detector (DC00004965) | Detector (DC00004966) | Mean of the two detectors |
|-------------|------------------------|------------------------|---------------------------|
|             | MAE   | MAPE (%)   | MAE   | MAPE (%)   | MAE   | MAPE (%)   |
| SSA-ELM     | 6.78  | 8.80       | 6.93  | 8.61       | 6.86  | 8.71       |
| SSA-SVM     | 7.66  | 10.00      | 8.38  | 9.89       | 8.02  | 9.95       |
| KELM        | 8.64  | 10.95      | 7.92  | 9.51       | 8.28  | 10.23      |
| SSA-KELM    | 4.68  | 6.44       | 5.18  | 6.18       | 4.93  | 6.31       |
| HPSO-SVR    | 6.82  | 8.98       | 7.13  | 8.36       | 6.98  | 8.67       |
| LSRM-RNN    | 6.34  | 8.54       | 6.73  | 8.02       | 6.54  | 8.28       |

Shang et al. [20] summarize their research by first comparing the result of the SSA-KELM model, the SSA-ELM model, and the SSA-SVM model, demonstrating that KELM’s performance is better than ELM and SVM in Table 4. “Comparison results of the SSA-KELM model and the KELM model show that using SSA to filter the noise of the original traffic volume time series can improve the model’s performance effectively”. Secondly, in Table 5 indicates that the best and worst among the six versions were SSA-KELM and KELM among different models. A high-quality result that provides significantly better SSA-KELM performance than SSA-ELM, SSA-SVM, and EKLM results. Potential tests have been well formulated, concepts and goals are well constructed. The researcher, however, only shows an SSA-KELM model flow chart on their methodology and no other model has been shown that contributes to a lack of evidence and explanation of methodology. To say that this experiment was a success it is necessary to explain all the model’s flow charts to give more understanding to readers.

3. Comparison of methods

The most effective method is to use deep learning to predict traffic flow following the critical evaluation of each method. The fuzzy deep learning method using deep learning by [13] obtained a value of the RMSE using the FDCN was 0.3336 for 30 min prediction, which was 1.4% of the RMSE using the DeepST method, whereas a 12.90% accuracy on prediction was obtained in value of mean absolute percentage error (MAPE) and 5.89% for short prediction horizon when compare the performance for all the method used by [14][15]. On the other hand, [18] presented a machine learning method using a travel time prediction model based on a gradient boosting decision tree (GBDT) to improve traffic flow prediction accuracy and different scenarios are accurately predicted at an average mean absolute percentage error (MAPE) is 0.0418 when prediction horizon in 15 minutes.

Results show that the best and most accurate method compared to other methods is deep learning methods utilizing multiple deep learning models for traffic flow prediction. Multiple deep learning effectively learns the traffic information time-series features and enforces the prediction of short-term speed. When compare with the fuzzy deep-learning approach and gradient boosting decision tree (GBDT), multiple deep learning models have a better value of 12.90% accuracy on
longer prediction horizon and 5.89% on short prediction horizon which is highest compared to fuzzy deep-learning approach and GBDT.

4. Conclusion
In this paper, the current state of technology for the artificial intelligence method of traffic flow prediction was evaluated and assessed based on several criteria used to determine the quality of the research, such as accuracy consistency, repeatability, and results as well as methodology differences. Cheng et al. [18] provide those examined with a good quality piece of research, stick to scientific principles, properly explain the method and show the results, as well as provide other researchers with the opportunity to find a larger information variety than their research to be exact the data correctly. The paper successfully demonstrated the ability of a gradient-boosting decision tree (GBDT) focused on the travel time prediction model. Shang et al. [20] also provide a comprehensive experiment into a hybrid model with results and a contrast of 6 models. However, with a lack of explanation for each model, their method has been flawed, only one model has been described.

Overall, based on evaluated research, the multiple deep learning models have shown great improvement over the deep learning method supported by the research of [13], who recognizes that deep learning will learn features from the large-scale database, and [14][15], who addressed the problem would arise when the prediction horizons become longer. Due to the difficulty of modeling stochastic traffic flow features, the existing methods are still unsatisfactory, however, the multiple deep learning models have proven that it can be successfully applied to different tasks, including recognition of patterns and classification.

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