A Deep Learning Model to Predict Vehicles Occupancy on Freeways for Traffic Management

Muhammad Aqib[†], Rashid Mehmood[††], Ahmed Alzahrani[†], Iyad Katib[†], and Aiiad Albeshri[†]
mpervez@stu.kau.edu.sa RMehmood@kau.edu.sa asalzahrani@kau.edu.sa
iakatib@kau.edu.sa aaalbeshri@kau.edu.sa
[†]Department of Computer Science, FCIT, King Abdulaziz University, Jeddah, 21589, Saudi Arabia
[††]High Performance Computing Center, King Abdulaziz University, Jeddah, 21589, Saudi Arabia

Summary
Prediction of traffic conditions plays a key role in the current era's intelligent transportation system. It not only enables commuters to choose appropriate routes to reach their destinations but also helps authorities in making effective traffic management plans. All needed for this purpose is to use a method that could handle abundant traffic data and by making wise use of this data, it could help authorities to get an estimate of traffic conditions on road networks and to make effective traffic management plans. Deep learning approaches are the most appropriate choice for these kinds of problems and have extensively been used for traffic forecast. In this work, we are using deep neural networks to predict the traffic condition on highways by considering the spatio-temporal correlation in traffic data attributes. For our deep model, we are using historical traffic data collected from Performance Measurement System (PeMS) for a period of three months on a selected patch of a highway in California. We are using vehicles occupancy values collected from the vehicle detector stations (VDSs) to predict the occupancy on the freeway. Prediction results compared with the actual occupancy values not only give very high accuracy but also enables us to make use of these predicted values in performing different traffic management tasks.
Key words:
Deep Learning, Prediction, Intelligent Transport Systems, Deep Neural Networks, PeMS traffic data

1. Introduction

Inter and intra-city transportation networks are considered as the backbones of the countries and cities infrastructure to provide a healthy environment and to improve their living standards in addition to improve the economy growth rate. Due to this reason, transportation departments in the developed countries in general and in the big cities in particular are spending a lot of money to improve the infrastructure and using the latest technologies including the sensors, cameras, and other traffic monitoring systems to record traffic situation on road networks. With the development of intelligent transportation systems (ITS), it has now become easier than ever to collect traffic data including vehicles flow, speed, congestion and incidents reports and to make decisions not only to alleviate the road blockages and to reduce the number of accidents on roads but also to ensure the smooth vehicles flow. Traffic monitoring devices produce a large amount of data that could be used to analyze the traffic on those road networks. It also enables the transportation authorities to provide real-time traffic statistics that not only help travelers to make decisions but also the authorities to take necessary actions if needed, for example in case of emergency.

Traffic on a road network could be predicted by analyzing the data collected from the above mentioned and other traffic monitoring devices. For example, vehicles occupancy etc. could be predicted by using the historical data to analyze the traffic state on a road or freeway. For this purpose, researchers have been using different modeling approaches [1] in the past. Some other traffic prediction techniques includes Kalman filtering technique [2] which have been used by many researchers in past for this purpose [3], [4]. In addition to these approaches, autoregressive integrated moving average (ARIMA) [5]. ARIMA was considered as the most appropriate model for traffic prediction problems and a lot of work in traffic prediction was done using this technique. Also, many researchers proposed different variants of this technique including KARIMA [6], SARIMA [7] etc. Now due to the availability of huge amount of historic traffic data, and data processing capabilities, deep learning approach is used for this purpose and the prediction results obtained by using the deep learning models have proved it as a best choice for traffic predictions [8]–[12]. On the other hand, ARIMA and its variants are normally used by researchers to compare the prediction results obtained by using deep learning techniques.

Deep models are multi-layer architectures that extract the features from the input data and are capable to identify varieties of structures in the data without having any prior knowledge about the data. Deep models require a lot of input data for their training phase in which they automatically extract features from the data to learn. As it requires a large amount of data for training the network, therefore, it is considered a compute intensive and time-consuming job and requires a lot of time and resources for its training process. Due to its compute intensive nature, researchers have been avoiding using deep learning for prediction purposes in the past, but now due to the availability of large amount of data and also due to the

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availability of efficient computing resources, it is used for prediction purpose to get accurate predictions results with low error rates.

In this work, we are using deep learning to predict the vehicles average occupancy on highways. For predictions, we have used deep neural networks and have used five-minutes interval vehicles average occupancy data as an input to our deep learning model. Traffic data to be used as input to our deep model has been obtained from the Freeway Performance Measurement System (PeMS) [13]. We have used the historical data for three months in the year 2017 from September to November. Results obtained by comparing the predicted values with the actual occupancy values by using the well-known performance metrics shows that we have achieved high accuracy and the predicted results shows the accurate picture of traffic situation on the road by giving the accurate time vehicles are spending on the road while travelling to their destinations.

The rest of this paper is organized as follows. Section 2 reviews the traffic prediction work by other researchers. In Section 3, we have described our deep learning model by giving details about deep neural networks. We also have discussed the input dataset and data processing details in this section. Section 4 discusses the experimental results and finally, the discussion has been concluded in Section 5 with the directions for future work.

2. Literature Review

Many approaches have been developed to improve transportation. These include, for example, social media based approaches [14]–[16], big data based techniques [17]–[19], HPC based techniques [17], [19]–[21], vehicular networks (VANETs) and systems [22]–[25], modeling and simulations [26], [27], methods to improve urban logistics [17], [19], [20], [28], [29], and solutions based on autonomous vehicles and autonomic mobility systems [30]–[33]. A recent book has covered a number of topics related to smart transportation [34]. In addition to this, a lot of work has been done in transportation where researchers have used deep learning approaches for prediction purpose which is our focus in this paper. So, now we will discuss some of the works done in this area in detail.

An approach to predict traffic flow by using autoencoders has been proposed in [8]. They have used three months data to predict flow on week days. They have used mean relative error and root mean squared error for comparison and the results have been compared with the support vector machine (SVM) and an accuracy of up to 93% has been reported in this work. Authors in [35] have proposed an approach using convolution neural networks (CNN) and long short term memory (LSTM) for the prediction of traffic flow. They have used it to predict congestion on highways. They have predicted flow for 30-minutes interval and they also have obtained data from PeMS. RMSE has been used for results analysis in this work as well. They have used incidents data as well and prediction results also show high accuracy but overall dataset is not very big because they have used only two months data and accuracy could be increased by using a big input dataset.

An approach to predict vehicles average speed has been proposed in [36]. In this work, they first have used unsupervised learning technique and then supervised learning technique for results improvements. They have used deep belief networks and have used three months data for this work obtained from the Beijing Traffic Management Bureau. They have reported MAPE and RMSE values for results analysis. Their accuracy was high for small time interval but it is comparatively low for big time intervals. For example, they have reported 8.5 MAPE value for 30-min interval value which is comparatively low for speed value and could be improved. In another work [37] authors have combined CNN and LSTM to predict traffic flow on highways. They have used data for more than 12 months and have used MAE and MAPE values for analysis of prediction results and the results reported in their work are showing good accuracy.

In addition to the prediction of traffic flow or speed, it has also been used for the prediction of incidents as well as done in [38]. In this work they have used it for the prediction of crashes on the highways. They have used the vehicles speed data and have categorized it into different classes to represent congestion, free flow, jam flow etc. By using this approach, they have predicted the crashes on the road network. Although they have reported high accuracy but dividing the speed values in different threshold values does not really represents the correctness of predicted values. This could also be improved by using exact values with small frames to present a more accurate picture of the real condition on the road. In addition to this, dataset used in this work is very small and the accuracy reported in this work is comparatively low and can be improved.

In addition to traffic flow/speed/occupancy prediction approaches presented above, there are many studies [9], [11], [39]–[45], in which authors have used deep learning to predict traffic, or have used it for congestion evaluation in cities transport network. Another work [46] proposes a traffic flow prediction approach that considers the effect of weather conditions on the traffic flow as well. They have collected weather data from [47]. In some other works [48]–[50], authors have used some other approaches other than deep learning models to traffic flow prediction on crossings or to predict travel time prediction. Although, many researchers have reported very good prediction results by achieving high accuracy and low error rates but still there is need to explore in depth in this area to improve accuracy and to make use of latest technologies to get benefits of it for transportation management. Also, traffic flow or other attributes values could be used to predict the traffic conditions on the road networks, but because occupancy gives the time a vehicle takes while covering a distance in a unit of time, so it could be more helpful in identifying the traffic conditions e.g. to identify the congestion on the road or to see if the traffic is freely flowing.

3. Methodology

In this section, we will discuss in detail about the methodology we have used for prediction purpose. This includes discussion about the dataset we have used for prediction purpose, processing of input dataset so that it could be used as input to our deep learning model and the architecture of our deep learning model along with its configuration details.

3.1 Input Dataset

In this section we will discuss the dataset we are using as an input to our deep learning models for traffic modeling. This data is obtained from PeMS [13] and it provides enough information that could be used for different prediction and analysis purposes. This includes aggregate flow, average occupancy, average speed and other values for all the lanes collected by using the sensors, cameras and other devices at the vehicle detector stations (VDSs). In addition to aggregate values, it provides lane wise data as well i.e. for example, it provides lane wise occupancy values as well for up to 8 lanes on the selected patches of the freeways in California State USA. It provides near-real-time data and historical traffic data. We are using historical data in this work and it is available for different corridors. We are using the dataset for corridor 01A: Los Angeles I-5. The length of this corridor is 13.784 miles and two directions on this corridor are denoted by I5-N and I5-S. For I5-N, there are 26 vehicle detector stations (VDSs) to collect the data about the vehicles traveling on this route. On the opposite direction, i.e. I5-S, there are 25 such stations for data collection. This is a five-minutes interval data and therefore we are using five-minutes interval occupancy values for prediction. In this work, we are using only data collected in one direction, i.e. I5-N for a duration of three months starting from September 2017 to November 2017. In Fig. 1, we have given an overview of the occupancy values recorded at a specific vehicle detector station on November 26, 2017. Low occupancy values show that there was no congestion on the road as we can see after the mid night hours. But during the peak hours, occupancy values start increasing and it reaches to the highest values around noon. Because it is weekend (Sunday), therefore the graph is not showing the high occupancy values in the morning peak hours. Although the values are higher than the early morning values but still these are not indicating the heavy traffic on the roads.

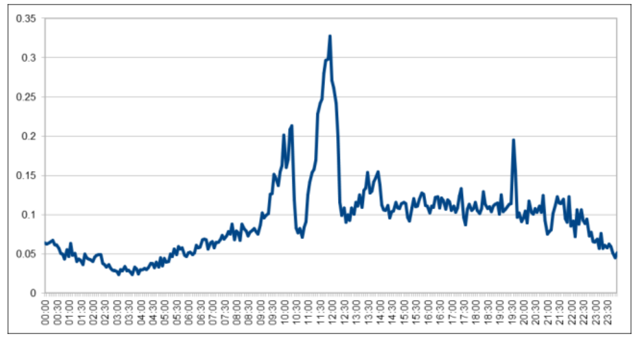

Fig. 1 An overview of vehicles average occupancy values on a week day.

3.2 Input Data Processing

As we have described in the previous section, our input dataset contains a list of input parameters. So, the challenge here is to carefully analyze the dataset and to select some of them based on the requirements of our deep learning models. Therefore, before using this data as input to our deep learning model, we have to extract the required information from the data and then to process some or all of its attributes to extract useful information. This process is called data parsing. In this process, we process the dataset attributes values to extract some other useful information and make new attributes to be used as input to our deep learning model. In this work, we have used some of the attributes values without making any change in their values e.g. "StationId" and have processed some of them e.g. "timestamp" to extract some other useful information. We have used "timestamp" attribute to extract hours, minutes, days, months, year, and day of week values. Extraction of useful attributes is a complicated process and it requires in-depth understanding of the input dataset attributes and their effect on the training process. In this case, we not only studied and analyzed the effect of each attribute in the dataset to make a balanced dataset, but also executed our deep model with different configuration and with different lists of input parameters values. Then by analyzing the results, we identified the attributes that were not useful for our deep model and also realized that we need some other attributes to improve the accuracy. With the help of this long process, we finalized the input parameters for our input dataset. For example, from "timestamp" attribute, we extracted different other attribute values e.g. time, day, month, etc. and used these new attributes as input to our deep model in combination with other attributes. After this we have converted the data from long format to wide format based on the occupancy values. To deal with different issues in the input dataset, e.g. dealing will null values, all NAs in the dataset are replaced with the values obtained by using a predefined criteria. Finally, the data is normalized and divided into the training, testing, and prediction subsets to be fed to our deep neural network model. We have divided the input dataset into three subsets for training, testing, and prediction in the ratio of 8, 1, 1 respectively. This means that first 80% of the input dataset has been used for training of the deep learning model, next 10% was used for testing purpose, and the rest 10% has been used to make prediction.

While using the occupancy data for prediction, we observed that that vehicles 5-minutes interval average occupancy provided by PeMS were very small. Therefore, the output values that were used as labels while training were in decimals. Most of the values were in the form of $a \times 10^{-b}$ where $b \geq 2$. So, our model was unable to identify the difference between them and it was unable to predict the correct occupancy values. After getting almost the same results with low accuracy rate from different model configurations, we analyzed the difference between all the models and input datasets. Also, we compared these results with the vehicles flow and average speed data.

So, in this work, we have adopted a new data parsing approach where we only changed the output labels without making any change in the input dataset. Dataset used in this work was changed in such a way that we have changed the output labels by using the defined criteria. Let us consider that O be the set of our output labels and l be the length of the output dataset then $O = \{o_i | o_i \in \mathbb{N}, 1 \leq i \leq l\}$. Let a be any positive integer $a \in \mathbb{Z}^+$, then the new set of output values could be defined as $O_{new} = \{a \times o_i | o_i \in \mathbb{N}, 1 \leq i \leq l\}$. This way, we changed the output labels, and this will also affect our predicted values and they will also not be reflecting the original set of output labels O. Instead it will be representing the new set of output labels O_{new} and we can convert them to represent the original values by dividing all the values by the same positive integer a.

We have used a set of 17 attributes values as an input to our deep learning model. This includes "station Id" which gives a numeric value to identify each vehicle detector station on the freeway. It also includes an attribute "day" which gives the numeric value for the day of a month in "dd" format. "month" value gives the numeric month value in "mm" format and "year" is a four-digit numeric value in the form "yyyy". We also have extracted clock hours values from the data and "hours" provides these values ranging from 0 to 23. "weekday" is also an important input attribute and it is helpful in identifying the day of the week. For example, it may help while dealing with the weekends data or week days data or to collect the data on a specific day (e.g. Monday) in a month or year. Rest are the five-minutes interval occupancy values and are named as occup_00, occup_05, …, occup_55. Here occup_00 defines the average occupancy value calculated at a VDS during the first five minutes of an hour. Similarly, occup_55 defines the average occupancy value at a VDS during the last five minutes of the hour.

3.3 Deep Learning Model

In a neural network, many neurons are used in such a way that the output of a neuron could be used as an input to the other neurons in the network as shown in Fig. 2. Here the left most layer is the input layer and the right most layer is the output layer. Number of neurons in input layer is the number of input parameters in our input dataset whereas we are predicting vehicles occupancy for a specific time interval, so the output layer returns only one single neuron considered as an output or predicted occupancy value. In this deep model used in traffic modeling section, n is the number of parameters used as an input to our deep model. On the other hand, there is only one output parameter. Although we have shown four hidden layers in Fig. 2, but it may change depending upon the training strategy. As for example, we have used five hidden layers in our deep learning model. We have given number of hidden layers in our deep learning model while giving other specification details. Similarly, number of hidden units are also given with the number of hidden layers. As, we have executed our deep model with different configurations settings, so number of hidden units used in our model to get the highest accuracy value could also be different from those shown in the figure as we have defined later while giving details about the model configurations.

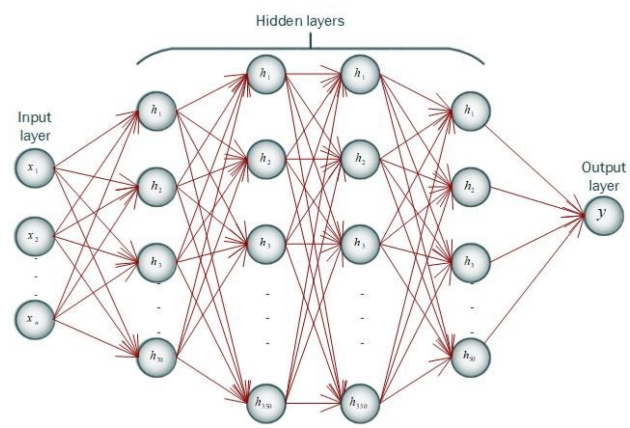

Fig. 2 An overview of deep learning model for vehicles occupancy prediction.

We are executing our deep model with different batch sizes and with different number of epochs. Therefore, instead of running our deep model with only one batch size and a fixed number of iterations, we have developed a setup to run it multiple with different combinations of configuration values. The purpose to do this is to find the batch size and the number of epochs that gives us the higher accuracy. This way, we have selected the best suitable configuration values (e.g. batch sizes, number of epochs) for our deep learning model. In addition to this, we make different input dataset combinations with slight input parameters changes and run

them using all the possible configuration combinations. This way we can identify the parameters that influence the accuracy and thus we can change our input dataset accordingly. In the following paragraph we have presented our deep model configurations details.
Number of input parameters, as discussed before is 17, and our model is predicting the occupancy i.e. numeric value, so number of output parameters is 1. We are presenting the results of our model executed with five hidden layers and number of hidden units in those hidden layers were 17, 85, 425, 425, and 85 respectively. We have executed our model with batch sizes of 100, 200, 500, and 1000. Each of these batch sizes were executed with three different values of number of iterations (epochs) which were 100, 500, 1000. We are using *Rectifier Linear Unit (ReLU)* as activation function which can be defined as $f(x) = \ln(1 + e^x)$. Also, *Adam* optimizer has been used for optimization purposes. In this work, we have used *Keras* [51] and *TensorFlow* [52].

3.4 Performance Metrics

For evaluation of our results, we have used three well known performance metrics to analyze the prediction results. These include mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). These have been defined below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|V_i - P_i| \quad (1)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|V_i - P_i|}{V_i} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(V_i - P_i)^2} \quad (3)$$

Here, N represents the size (number of values predicted by the model) of dataset used for prediction purpose, V is the set of actual values used for comparison with the predicted values, and P is the set of values predicted by our DL model.

4. Experiments and Analysis

In this section, we are presenting the prediction results obtained by computing the performance metrics values by comparing the actual and the predicted vehicles average occupancy values.
As we have mentioned in Section 3.3, we have executed our deep model with different configuration settings, but here we are presenting the results obtained by executing the model with only two batch size values 500, and 1000. Results obtained by executing the model with these batch sizes and three different epochs values have been presented in this section.

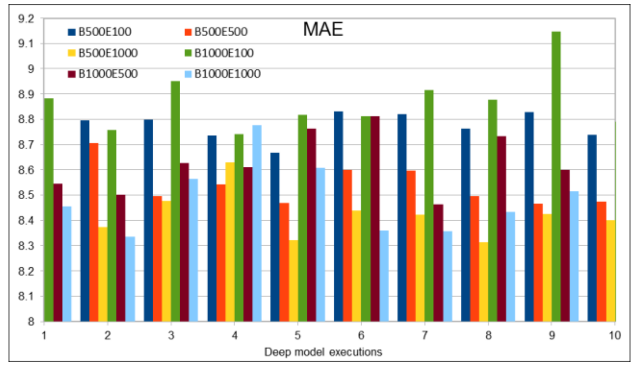

Fig. 3 Comparison of MAE values using different configuration values.

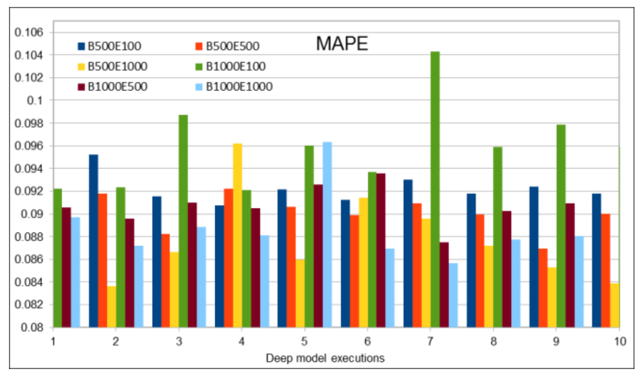

Fig. 4 Comparison of MAPE values using different configuration values.

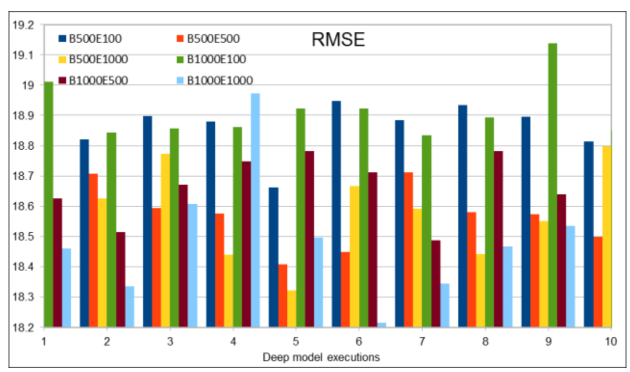

Fig. 5 Comparison of RMSE values using different configuration settings.

In Fig. 3, Fig. 4, and Fig. 5, we have presented the MAE, MAPE, and RMSE values respectively, calculated by comparing the predicted and the original occupancy values. We have executed our deep learning model 10 times with each model configuration settings. The purpose, to execute the model multiple times (10 times) with each configurations setup was to see the variation in the prediction results. This could also help us in identifying the minimum, maximum, and average error values. We can see the variations in the error rates while analyzing the predicted values using the result obtained by using the defined performance metrics. If we discuss the MAPE values, we can see that the minimum MAPE value obtained by executing the model 10-times was less than 0.084 which was obtained while executing the model with a batch size of 500 with 1000 epochs, whereas the maximum value was 0.104 which was obtained while executing the model with a batch size of 1000 with 100 epochs. Similarly, we have calculated MAE and RMSE values as well as shown in the figures. If we compare the MAPE values, we can say that we have obtained comparatively good results (not in all cases) while using the batch size of 500 with 1000 epochs. Same trend is reflected by the results in the case where we have calculated MAE values. For RMSE values, in some cases, we have obtained better RMSE values with these configurations, but in some cases as we can see in the graph, this metric is showing good results obtained from other combinations of batch sizes and numbers of epochs.

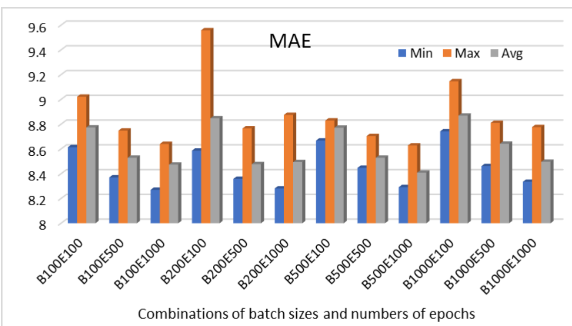

Fig. 6 Comparison of Min, Max, and Avg MAE values by executing the model using 12 different configuration settings.

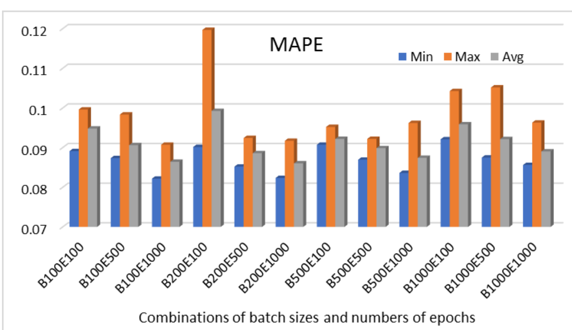

Fig. 7 Comparison of Min, Max, and Avg MAPE values by executing the model using 12 different configuration settings.

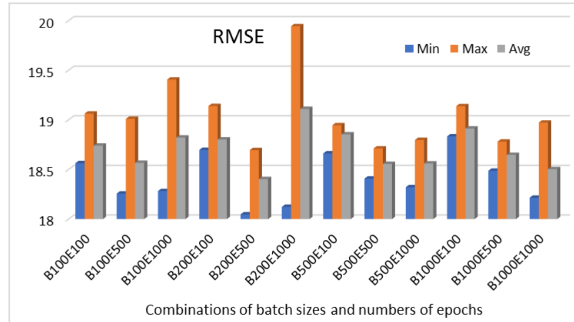

Fig. 8 Comparison of Min, Max, and Avg RMSE values by executing the model using 12 different configuration settings.

In addition to this, as we have executed our deep model 10 times with each combination of different combination values, so we also have calculated minimum, maximum, and average error values for each configuration set up. Minimum, maximum, and average values are shown in Fig. 6, Fig. 7, and Fig. 8. If we compare the MAE results, we can say that the results with batch 500, and epoch 1000 have shown the good result where minimum and average MAE values are very close and also the maximum MAE value is comparatively close to these values. Similar trend is seen when we talk about MAPE values in Fig. 7, where this combination has show good results but model with batch size 100 and epochs 1000 have shown even better results. This is even different in RMSE case (Fig. 8) where error values represented by B200E500 have shown the lowest error rate. Although there is variation in results but there is not a big difference between the minimum and maximum error values which is very important and because average error values are close to minimum values and shows that in most of the cases our model have shown low error rates as compared to few cases where error rate is high. One important thing is that although in some cases error values are high but this is because we have multiplied the labels by a constant number (1000), this also increases the error rate especially in the case of MAE. So, if we convert the values back to the original values and then calculate the error values, then the error values will be even less than the reported error values.

5. Conclusion

In this work, we have presented a deep neural network-based approach to predict vehicles occupancy on highways using the data collected from the vehicle detector stations in California. Our deep model is capable of learning spatial and temporal correlation from the input traffic data. To check the consistency of our deep model while predicting occupancy values, we repeated the training, testing and prediction process multiple times (10 times) to analyze the output generated by each combination of configuration settings. We also calculated minimum, maximum, and average error rate for each of our model configurations. We have reported higher accuracy of our model by using the well know performance metrics.

In future, we would like to include other traffic data features and we may combine different features like flow, speed, occupancy etc. to make overall traffic behavior predictions, and we can use other deep models to further improve the accuracy. Also, we can use these models and datasets for real-time predictions and traffic incidents predictions.

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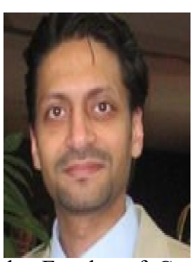
Muhammad Aqib received the MCS degree in computer science from University of Arid Agriculture Rawalpindi, Pakistan and MS degree in computer science from King Abdul Aziz University, Jeddah, Saudi Arabia where he is currently pursuing the Ph.D degree in computer science. His research interests include deep learning, big data, in-memory computing, high performance computing, GPU computing, access control policies and fog cloud computing.

Rashid Mehmood (M'06–SM'10) is currently a Research Professor of big data systems and the Director of research, training, and consultancy with the High Performance Computing Center, King Abdulaziz University, Saudi Arabia. He has gained qualifications and academic work experience from universities in U.K., including Swansea, Cambridge, Birmingham, and Oxford. He has over 20 years of research experience in computational modeling and simulation systems coupled with his expertise in high-performance computing. His broad research aim is to develop multi-disciplinary science and technology to enable a better quality of life and Smart Economy with a focus on real-time intelligence and dynamic system management. He has published over 150 research papers, including five edited books. He is a Founding Member of the Future Cities and Community Resilience Network. He has organized and chaired international conferences and workshops in his areas of expertise, including EuropeComm 2009 and Nets4Cars 2010–2013. He has led and contributed to academia-industry collaborative projects funded by EPSRC, EU, and U.K. regional funds, and Technology Strategy Board U.K. with the value over £50 million. He is a member of the ACM and OSA, and the former Vice-Chairman of the IET Wales SW Network.

Ahmed Alzahrani received the B.S. degree in computer science from King Abdul Aziz University in 2000, and the M.S. degrees in information security from University of Glamorgan, Cardiff, UK in 2005. He received the Ph.D. degree in computer networks from University of Bradford, UK in 2009. He is currently an Associate Professor with the Computer Science Department, and the current Vice Dean of Deanship of Graduate Studies for academic affaris, King Abdul Aziz University. His current research interests include computer networs, networks security, quality of service routing, quantum computing, deep learning, big data, in-memory computing, and high performance computing.



Iyad Katib received the B.S. degree in statistics/computer science from King Abdul Aziz University in 1999, and the M.S. and Ph.D. degrees in computer science from the University of Missouri-Kansas City in 2004 and 2011, respectively. He is currently an Associate Professor with the Computer Science Department and the current Vice Dean and the College Council Secretary of the Faculty of Computing and Information Technology, King Abdulaziz University (KAU). He is also the Director of the KAU High Performance Computing Center. His current research interest is on computer networking and high-performance computing.

Aiiad Albeshri received the M.S. and Ph.D. degrees in information technology from the Queensland University of Technology, Brisbane, QLD, Australia, in 2007 and 2013, respectively. He has been an Assistant Professor with the Computer Science Department, King Abdulaziz University, Jeddah, Saudi Arabia, since 2013. His current research interests include security and trust in cloud computing and big data