Short Term Traffic Flow Prediction Using Deep Learning Approach

MSc Research Project
Data Analytics

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Short Term Traffic Flow Prediction Using Deep Learning Approach

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MSc Research Project in Data Analytics

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Abstract

Intelligent transportation systems helps travellers reach their destination at an estimated time. Smart cities have deployed latest technologies to satisfy the needs of travellers through efficient navigation. Adverse weather conditions may lead to increase in traffic congestion as well as accidents. Rainfall, Snow and wet pavements are a major cause for the traffic flow during winter across all areas. Several methods have been researched at a deep level for predicting traffic flow and still an efficient method to satisfy real world traffic problems have not been identified. The accident and weather data are investigated in this paper to predict the flow of traffic in Leeds city. Three models were developed through deep learning neural network algorithm for predicting traffic flow. The predicted Deep neural network model is compared with the superior support vector machine model and the accuracy is higher for the Deep neural networks.

1 Introduction

The increase in traffic in developing countries is exponential and will continue to be so in the future. According to a latest survey approximately 60 percent of people will live in cities by 2050 and as a result, millions of cars will run on the roads leading to a critical strain on the intelligence transportation system. Large volume of traffic data is recorded by intelligent transportation system under all weather conditions. The recorded data is analyzed to assist in predicting slow moving traffic. Since no model exists that provides a 100 percent efficiency in predicting traffic flow, further research has been done in order to increase the accuracy in traffic prediction. The current system utilizes shallow techniques to predict traffic flow which is deemed inefficient. In the model discussed within this paper, deep learning algorithm will be applied to understand deep traffic patterns and make for more accurate predictions.

Deep Learning has attracted a lot of researchers which includes both academics as well as industries over the past few years. The traffic flow pattern along with weather data is processed through a deep algorithm to extract meaningful data by using multi layered architecture. Using stacked auto encoder a model has been developed by Lv et al. (2015) to perform complex operations and bring out a different patterns in the traffic flow. The limitation of this model is overcome by Koesdwiady et al. (n.d.) by using weather data by performing data fusion. However the major climate factors involved in predicting traffic data along with weather data using Deep Learning Neural Network has not been previously analysed within models, hence will be analysed within this model.

Weather acts as a key factor in traffic congestion. The important variables considered as causes of accidents due to weather include temperature, humidity, wind speed, fog and water level. These factors result in reduced visibility, pavement friction and lane obstruction, hence contributing to an increase in accidents. Over the last 10 years the number of accidents on highways constitute to around 22 percent of vehicle crashes due to adverse weather conditions, in which 14 percent of factors relating to weather conditions include rainfall and wet pavement. In 2013 two models was developed by Dunne and Ghosh (2013) to predict traffic congestion during rainy and non-rainy days. The dry model consists to traffic data and the wet model consists of traffic as well as weather data.

In this research, data from the city of Leeds is used to predict the traffic with respect to weather at three different time intervals - 15, 30 and 60 minutes. Deep Learning is applied to these models. Data prediction accuracy is higher at 15 Minute intervals, in comparison to those with support vector machines.

1.1 Research Question

How can the short term flow of traffic be predicted by incorporating traffic and weather data using Deep Learning approach?

1.2 Project Objective

The objective of this project is to develop a traffic model that brings high accuracy to satisfy real world traffic problems with respect to weather.

1.3 Paper Structure

The paper is organized into 6 sections as listed. Section 1 is the introduction to the paper. Section 2 describes the literature review based around traffic prediction dependent on climate conditions. Section 3 describes the methodology for predicting traffic. Section 4 lists the implementations models at different time intervals as discussed. In section 5 the model has been evaluated. Finally, in section 6 the paper concludes which is the best suited model and discusses future work that can be carried out.

2 Literature Review

2.1 Traffic Flow Prediction

One of the serious problems in developing countries is traffic flow prediction. There are many factors contributing to traffic flow and the key ones are weather, accidents and roadworks. Traffic flow prediction has been developing since the 1990s and currently many researchers are still progressing to identify a deep effective prediction.

There are two methods involved in predicting traffic flow, these being Parametric and Non Parametric approaches. Non Parametric approach is the most famous and currently used in research. A multi resolution Finite Impulse Responses Neural network algorithm (FIRNN) is designed by Alarcon-Aquino and Barria (2006) through discrete wavelet transform. This framework analyses the discrete wavelet signals and transforms them into scaling and wavelet coefficients. Real world traffic data was applied to this model and it was found to have a higher accuracy considering only the FIRNN approach. Similarly, real world traffic data has been applied to Genetic Network Programming model (GNP) by Zhou et al. (2008). This model was developed to bring out the deep attributes in time related applications in the traffic database. These attributes are classified by GNP by applying rules to it on each round. The GNP technique was used in understanding the attributes in data and apply rules to it for each round and form small round pools. Association rules are applied to the data in the pools, which classifies the traffic data at low, medium or a high level. The rule was applied to separate lanes on the road and considered for prediction.

Neural Network is a popular technique involved in the traffic flow prediction by Chan and Dillon (2013), Vlahogianni and Karlaftis (2013), Kumar et al. (2013), Kumar et al. (2015). Fuzzy neural network is proposed by Bucur et al. (2010) for traffic prediction in urban areas using a self-adaptive predictor, which is based on time shifting. Small samples have been used for training the data with respect to weather and seasons. The data has been assigned with different weights and has been trained for short time horizons. The size of the data is small which is deemed the limitation of this model. The drawback of this model has been overcome in another model developed by Zhang et al. (2010). One year traffic data at 5 minutes intervals is used for predicting the data for one month in January using K nearest neighbour regression approach. This framework algorithms consists of 3 main stages; the historic data, state vector mechanism, and forecasting. K means is used in assigning the weights to the model and forecast is compared to real worlds traffic model. The accuracy of back propagation neural network is lower than of the Non parametric approach algorithm used for this urban area. If the Zhang et al. (2010) author included the traffic characteristics, road type and speed then the model would be more effective. This drawback has been overcome by Min and Wynter (2011) prediction using spatial-temporal correlation. The temporal dimension is analyzed by the time lag between the two links of traffic, and spatial dimension is analyzed by the neighbouring links of traffic characteristics. The advantage of this model is it provides greater accuracy in urban as well as express highway roads and is applied to real time traffic data, which is more volatile and predicted for 15 minutes accuracy. The challenge in this model is the fact that there are elements of missing data and the quality in this model changes from time to time. This model would have been more effective if it has included weather characteristics.

Smart Phones can help travellers reach their destinations through navigationand other apps. A service model has been developed by Horvitz et al. (2012) and referred as "James Bayes" for traffic forecasting in the Greater Seattle area. The methodology followed is the streaming intelligence in which a web service has been constructed to hold the traffic flow of data. More than 2 years of data has been used for prediction. The model predicted the bottleneck of the traffic and rendered the output in voice to the users. Bayesian methodology is used in forecasting for the prediction of over 30 minutes. The advantage of this model is includes weather characteristics and holidays.

Due to the development of technology large volumes of data is produced, and this data is stored efficiently as it is useful for analyzing and identifying patterns in the data. Chen et al. (2014) developed a big data framework model which is highly useful in storing the large volumes of data to which the Gaussian process regression is applied for prediction purposes. The drawback of the Zhou et al. (2008) model has been overcome in this model by analysing the large volume of data using K nearest neighbour to produce useful traffic data in a big data framework. Map-Reduce functions are performed on these useful traffic data through the Hadoop framework. The San Diego data-set used in the model consists of 62 sensors on a 5 minutes interval for the full 2010 year. The advantage in this model it can handle big data but it takes longer time to process. Peng et al. (2014) developed a model to run on cloud computing by using 10 physical servers and 30 virtual machines. The Hadoop watch predicted at a greater percentage of accuracy, by designing an application layer on traffic prediction to the system monitor. The advantage of this model is that it can run lag data over a short span of time.

The parametric approach in predicting the traffic flow has been implemented more than decades. Zhang et al. (2014) developed a hybrid model for analyzing the data collected on 5 minute intervals across 6 detectors starting from the "Sam Houston tollway until the Mark road" in Texas, USA. The data was collected in a highway for the northwest direction and the detectors were placed at a short range. There are three stages included in predicting the traffic data these are; spectral analysis, followed by the Arima model and the Garch model. Overall the performance of this model has a greater accuracy on predicting freeway traffic and it also captures the volatility in clustering of the Houston traffic flow data. The drawback of this model is that only one month of traffic data has been used for prediction purposes.

2.2 Weather On Traffic

Over the past several years there have been many methodologies applied to predict the traffic flow with respect to weather. climate plays an important role in determining the flow if traffic. Increase in traffic can be directly related to weather conditions in which rainfall or snow contributes to a major part.Mahmassani et al. (2009) developed an application through supervised statistical technique referred to as On-line support vector machine for regression. This model has 5 percent Mean absolute percentage error(MAPE), it results in higher performance level under atypical traffic conditions which includes climate characteristics. For the real world atypical traffic conditions is more useful. Similarly Tsirigotis et al. (2012) predicted traffic congestion through time series. The vector auto aggressive model has been predicted with a higher accuracy in comparison to the Arima model. The drawback of the previous model happens to be that only 3 days a week have been considered, this model however, overcomes this limitation but also has a drawback, whereby only rainfall has been considered as a climate parameter.

The Rainfall is the only parameter that was included in the Tsirigotis et al. (2012) model. Snow and wet pavement also contribute to adverse weather. Dunne and Ghosh (2013) developed a model through Neuro wavelet framework to predict traffic across dry and wet models. The dry model is preferred during sunny days and the wet model is ideal for rainy days. In the dry model only traffic data has been analyzed whereas in the wet model both traffic and weather data have been used. The drawback to this model is that it contains only 2 weeks worth of data and weekends are not counted. The wet model gives RMSE accuracy 4 percent whereas dry model gives an accuracy of 10 percent.

Speed is one of the major cause for accidents, and poor weather can multiply on highways are due to traffic speed according to the survey taken in 2014 by UK govt. Traffic speed is predicted using neural network algorithm on adverse weather conditions. Huang and Ran (2003) developed a model which results in 4.749 mean error for 15 minutes has accuracy in predicting traffic speed. Back propagation is applied within this model and has proved a greater accuracy. Similarly Yang et al. (2010) developed a model to predict the average vehicles speed during the traffic flow. The data-set is collected in 5 minutes interval over more than 65 sensors locations in the Taiwan city. The models are developed by collecting the average velocity data at each lane of the road. Neural network algorithm is applied on the collected data-set through vehicles via vehicular ad hoc network (VANET). The advantage of this model is that the accuracy is higher when weather data is incorporated.

Logistics transportation depends on timely delivery of goods to move from one place to another. But due to traffic and adverse weather conditions, there may be a need for alternative routes to ensure the goods are delivered on time. A traffic flow model developed by Gehrke and Wojtusiak (2008) using a natural induction system referred to as AQ21, applies attribution rules after learning. 15 years of data is used to predict the vehicle route during traffic. Two models were developed for improved quality in data and resulted in better prediction. The advantage of this model is that it uses plasma stimulation which predicts at a higher accuracy than naive agents.

Adverse weather conditions makes the travellers difficult to travel long distance. Overall safety in travelling depends on human factors, weather and traffic flow characteristics. Castro-Neto et al. (2009) developed a model consisting these important characteristics and designed a model considering supply and demand. Dyna smart framework model is implemented on this model. The limitation of this model is lack of real time traffic data and big data framework. Big data processing technology is used in predicting the traffic congestion. Lee et al. (2015) developed a hybrid approach, Multi linear regression algorithm to predict the traffic flow. Two months of data from Seoul was used in predicting the model.There are 48 weather forecasting variables used in predicting the traffic flow.

The traffic congestion increases mainly due to weather and accident parameters. The intelligent transportation system predicts the traffic flow based on external factors and satisfies travellers in all terms including searching time and safety. Yu et al. (2013) Bayesian method is implemented to the traffic, weather and geometric data. Colorado data is used in this prediction by analyzing the data into two models. The comparison between two models is performed and a season model brings out better prediction.

3 Methodology

3.1 Design Process

The process flow diagram involved in the prediction of the traffic in this study is shown in Fig1. It involves 5 stages, in the first stage the data has been downloaded from the United Kingdom website which is an open data source data website "https://data.gov.uk/dataset/leeds-annual-traffic-growth". The traffic data consists of two .CSV files, one file contains traffic volume on different time intervals and next is camera location description. The weather data is downloaded from the Metro-Logical website "http://www.metoffice.gov.uk" The weather data is downloaded in .CSV file for the year 2014.

The next stage is the data pre processing, which involves combining the 2 sets of traffic and weather data. The traffic data consists of 23 loop detectors which count all vehicles travelling in their direction and its spread over different parts of Leeds city. The weather data is obtained on one hour time interval and its located near Leeds city. The camera location data and the traffic data is combined using the R programming language. The next step involves combining both the traffic and weather data. The traffic and weather data which is considered in this model, cover the loop detector which is near the weather station and consists of data on 15 minute intervals of time. The traffic data is messy and it is cleaned by treating the null values and outliers. The null values and outliers for the volume variable is imputed by Means of its corresponding variable which is costid, lane direction, time and direction description. The date-time variable is split into two columns and additional variable Month is added to it. In weather data the time has been converted into hh:mm:ss and rainfall variable consists of 'traces and its imputed by '.02'. The final traffic data consists of 5 loop detectors on 15 mins interval and weather data is incorporated within this. For the next stage, the traffic data is ready to run through the model. The final traffic data is trained for the periods June and July and then predicted for August month.

The next step involves building the model by applying Deep Neural Network and Support Vector machine algorithm through R programming language to perform the regression analysis on it. The data is normalized at this stage between 0 to 1 to perform better and to avoid over fit in the model. At the penultimate stage the data is predicted for test data using different iterations, by changing the neurons in hidden layers for better performance accuracy. The model is tuned till lowest Root Mean Square Deviation is obtained. The performance of the model is measured by RMSE, and lower the value results in higher accuracy. At the final stage the data is de-normalized to obtain its original volume since the data is in 0 to 1 scale.

3.2 Software Used

The software tools involved from the initial stage through to the final prediction are listed below:

1. Google Refine - Initial data cleaning of traffic and weather data.
2. Microsoft Excel - Initial data analysis and filtering of data.
3. R studio - Predicting the data for future analysis.

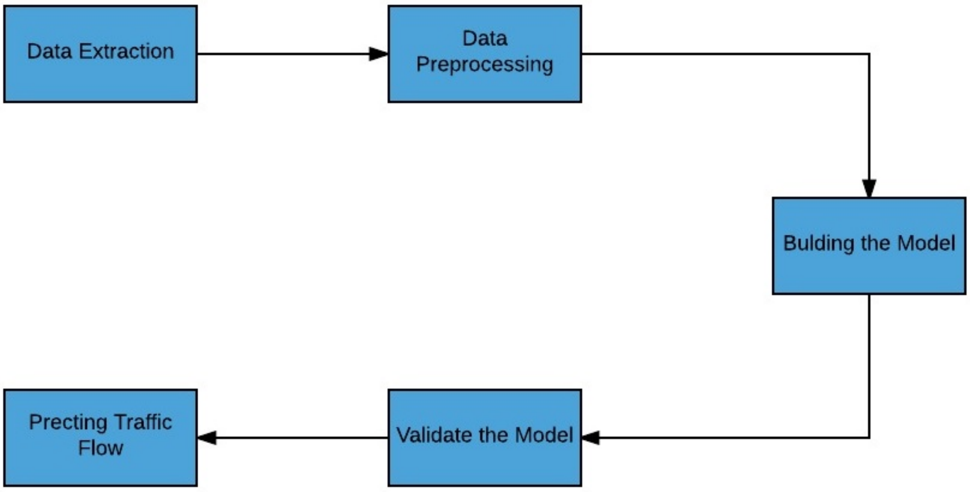

Figure 1: Process Flow Model

4. Tableau - Visualizing the predicted volume against actual volume with respect to date.

4 Implementation

4.1 Traffic Dataset

The Leeds city traffic and weather data set is downloaded from the United Kingdom website, and it is cleaned for a period of 3 months from June to August at 15 Minutes intervals. Both the data-sets are combined into a single data-set, that is then trained for the periods June and July and then predicted for the August Month. Three models are developed on 15 Minutes interval traffic data and predicted using the deep learning neural network algorithm. In the first model i have predicted traffic flow for one month. In the the second model i have predicted a day ahead on 15 minutes interval. For the last model i have predicted for particular location. In the initial analysis it can be visualized more vehicles enters the city between 7am and 8am and leaves the city by 4pm to 5pm. The fig2 shows blue line represents the people entering the city and Orange line represents people leaving the city.

Two months of data inclusive of all days is trained and is tested for August month by applying SVM and DNN algorithm using R programming language. The parameters included in the traffic data-set are date, time, month, camera location description, lane direction, direction description, cost-id, fog, rainfall, wind direction, temperature, wind speed, relative humidity, cloud cover and volume. These parameters are in different scales,as a result normalization has been performed on min max scale to yield for a

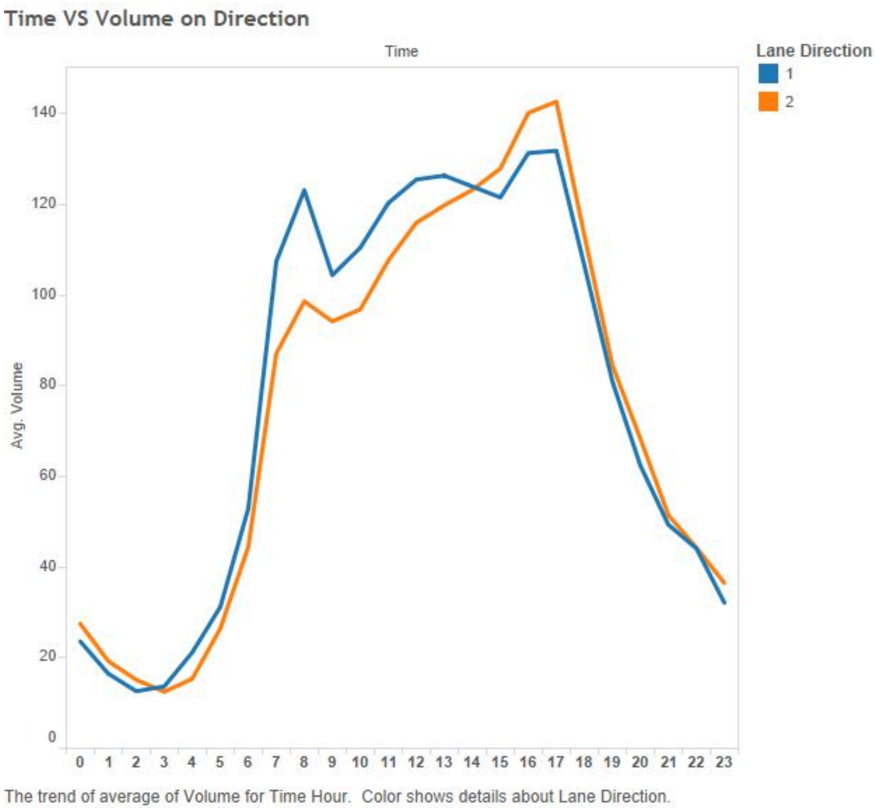

Figure 2: Time Vs Volume On Direction

accurate predictions. Three different models were developed and applied using deep neural network algorithm and the performance of the model is compared with support vector machine algorithm.

4.2 Model A - One Month Prediction

In this model deep neural network and support vector machine algorithm are applied to measure the performance of traffic data. In this model all the 15 variables are used in training the June and July data for predicting the August data. The data is converted into matrix and normalization process through max min scale(0,1). The trained and tested data is converted into H2o to perform the deep learning algorithm. H2o is a virtual machine which performs machine learning algorithm on clusters. H2o is initiated on the system by connecting to the clusters and allocating 3GB to it. Two hidden layers and the neurons are selected through trial and error approach method. The neurons are selected by 2/3 of of the input vale, hence for 15 input variables i am running the model by assisting 20 neurons in the first layer, these values are amended until a better level of accuracy has been reached. The "Tanh" activation function is used in this model since it gives stronger gradients in the value(0,1). For the svm model the data has been converted into numbers by assigning individual values for the factors. The data is run by support vector machine algorithm to predict the accuracy. The accuracy is measured by RMSE as .0957 in deep learning technique, this lies on a normalized scale between 0 and 1. Deep learning has a higher accuracy for predicting traffic when compared to the SVM method which as .1850 RMSE value. In this model the data is predicted for 31 days including all detector locations.

4.3 Model B - One Day Prediction

This model has been developed to predict next day traffic using the latest 2 months data. Similar to the previous model both algorithms have been applied and the models tuned for greater accuracy. For the DNN model the data is used in training was similar to the data used in model A. In this model deep learning neural network used two hidden layers and trial and error approach has been followed to obtain better accuracy. The neurons (20,10) gave the lowest RMSE 0.204. For the SVM model the data has been completely converted into numbers by assigning values for factors. This model is predicting the one day traffic prediction, so in data variable only one day will be available, similarly the fog data is same for the whole day. These values will not be useful in prediction. Hence the day and fog data has been removed form this model as there are no different values in these columns. The predicted root mean square value is .10697 on the normalized scale of 0 to1. For SVM the model predicted .1970 which is higher when compared with DNN model.

4.4 Model C - Location Prediction

This model is designed to predict the traffic based on one camera location. June and July data is used for training the model and the predictions is done for August. The DNN used the same data in this model but in the SVM model two variables 'Description' and 'Sea Level' were removed as there are no change in value in these columns. The two algorithms were used in the prediction, deep neural network algorithm was performed by considering 2 hidden layer and the neurons used were 20 and 7, which was selected by the trial and error approach for a higher accurate prediction. Support vector machine has tuned the model for a improved accurate predictions. The RMSE of the SVM model is compared with the DNN model and it was found to be 0.1124 on a normalized scale form 0 to 1. Overall the accuracy of this model is higher when compared with SVM model which has .1299 RMSE value.

5 Evaluation

In deep learning, the neurons and hidden layers are the key element in producing the higher accuracy. The neurons are selected based on the input given, followed by a trial and error approach. The epochs and momentum stable remains the same in the models. The SVM is tuned by changing the Kernel in the model. The Kernel function splits the input depending on their similarity. The H2o is connected to clusters and 3 GB is allocated to the system for increased performance. Each time the deep learning model was run the process took approximately one minute to display the output. The efficiency of this DNN model is very high in terms of accuracy and as well as in implementation when compared with the support vector machine algorithm. The predicted values are on the normalized scale. The traffic flow prediction is measured using root mean square value. Overall deep neural network performed better when compared with SVM algorithm on all models.

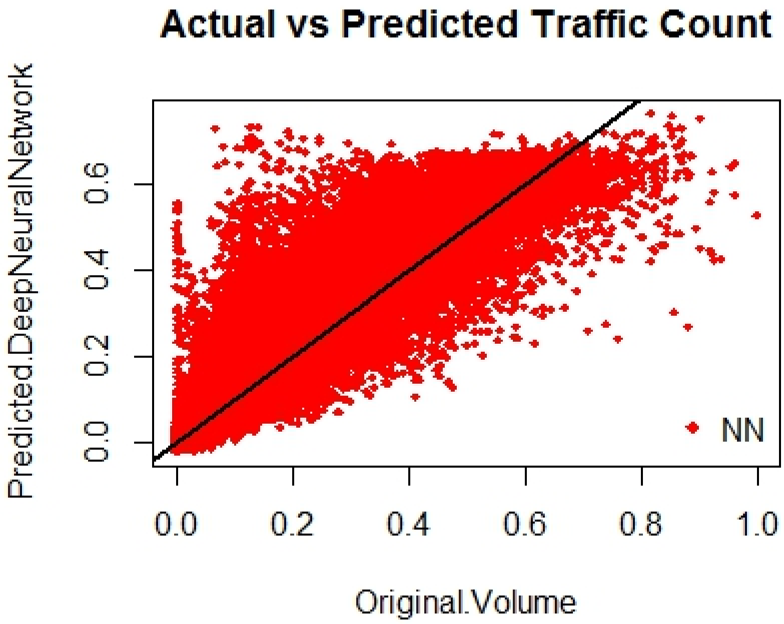

Figure 3: Model A - One Month Prediction

5.1 Model A - One Month Prediction

Two Algorithms have been applied in this model to measure better accuracy using RMSE value. The activation function ”Tanh” is used in this model. Two hidden layers with ”21 and 17” neurons were selected on a trial and error approach, which resulted in a lower RMSE level. The SVM model shows a lack of prediction accuracy in comparison to the deep learning model. The scatter plot displays the actual vs predicted traffic volume data derived from the DNN model. The RMSE value for deep learning and support vector machine is .0957 and .1850 respectively. The DNN model predicted better, the predicted model plot is shown below. The correlation between the actual and predicted values is 78 percent and its shown in fig 3.

5.2 Model B - One Day Prediction

Deep learning and support vector machine algorithm is applied to this model to predict traffic a day ahead. The data used is for the past 2 months and the same procedure is followed for this model but there is change in the neurons but not in the hidden layer. The neurons which produced higher accuracy were (20,10). The root mean square value for the deep learning and SVM is .1069 and .1950 respectively. The actual vs predicted value for a day ahead traffic for the neural network is shown below. The co-relation between the actual vs predicted traffic data is 73 percent and its shown in fig 4 .

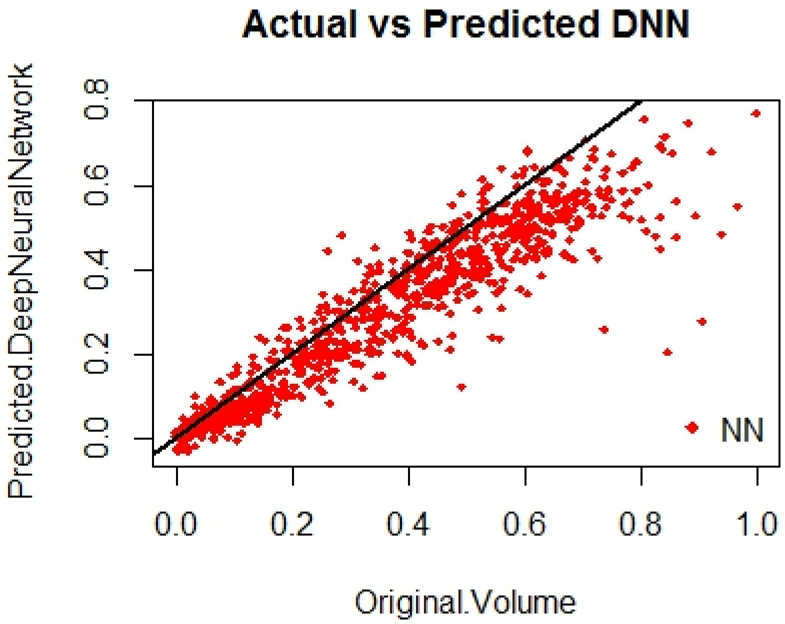

Figure 4: Model B - One Day Prediction

5.3 Model C - Location Prediction

This model performed better when compared to the Model A and B, but it predicted at a particular location. Deep learning and SVM algorithms are applied similarly to the previous model but the neurons used in 2 hidden layers are (20,7). The RMSE value for these two model are 0.1111 and 0.1987, in which the lower value belongs to the deep learning technique. The correlation between the actual and predicted traffic data is shown in the fig 5. This model has predicted one months traffic data on 15 minute intervals for a particular camera location at a higher level of accuracy in comparison to the SVM model.

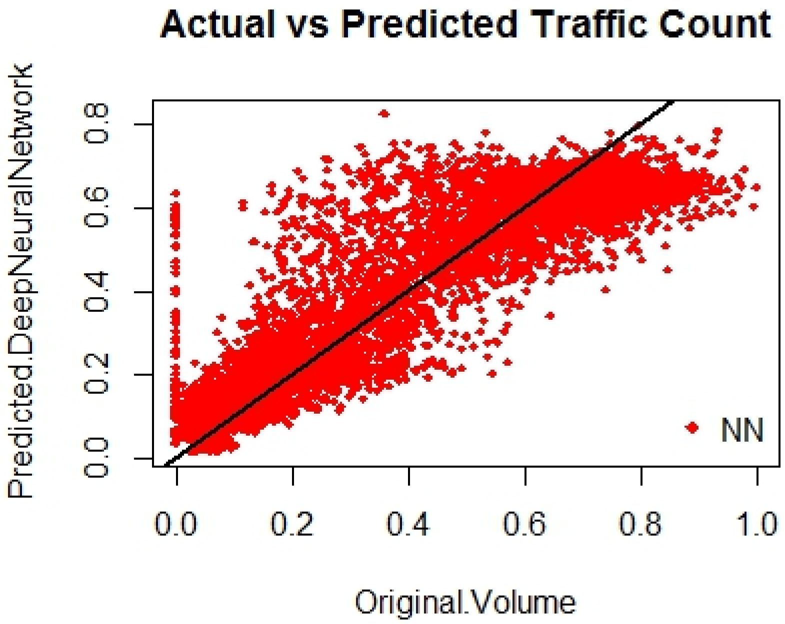

Figure 5: Model C - Location Prediction

	Deep Neural Network	Support Vector Machine
Model A	.0957	.1850
Model B	.1204	.1970
Model C	.1124	.1299

Figure 6: Comparison Of RMSE values by DNN and SVM Algorithms on Different models

6 Conclusion and Future Work

The performance using the deep learning approach for Leeds traffic flow prediction is higher when compared to other models, which perform shallow traffic predictions. This method performs multilayer procedures for processing the data and brings out greater results by deeply analysing the traffic pattern. The advantage of using this model is that it performs deep computations in a short span of time by assigning different hidden layers and neurons. Overall the model has been tuned to obtain greater performance with respect to weather when compared with other algorithms. The models predicted better when compared with each other. The RMSE for all the models developed by deep learning are relatively close.

The intelligent transportation system has started deploying the latest algorithm to improve the traffic prediction and ensures the needs and development of smarter cities have been improved. However, more research is deployed only for traffic prediction rather than the incorporation of weather data. Rainfall and snow lead to an increase in traffic congestion, and this paper developed a model to overcome the issue faced in the real world traffic. RMSE is used for checking the accuracy of the model by comparing the original values with predicted values.

In the future accident data should be considered along with traffic and weather data and it should run on different models using deep learning algorithm and their performance should be evaluated for better prediction accuracy. This is because, after climatic conditions, accident data is the next factor which impacts traffic congestion.

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