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Traffic Prediction Using Deep Learning

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ABSTRACT

Traffic prediction plays one of the major role in intelligent transportation system(ITS). Accurate traffic prediction can assist the route planning, guide vehicle dispatching, and mitigate traffic congestion. This problem is challenging due to the complicated and dynamic spatiotemporal dependencies between different regions in the road network. In past days, an useful amount of research efforts has been devoted to this area, mainly deep learning method, greatly advancing traffic prediction abilities. The main purpose is to provide a comprehensive survey on deep learning-based approaches in traffic prediction from multiple perspectives.The Traffic problems like congestion of traffic is rising in cities around the world. Further some factors include increasing of urban populations, developing infrastructure, inefficient and uncoordinated traffic signal timings and a lack of real-time data.

I. INTRODUCTION

The development of smart devices, smart cities, smart transportation, and the internet of things has resulted in a massive increase in the amount of big data available. The next thought that came to the organization's mind was to find out how to put this huge data to good useful manner. This question prompted to conduct additional study into the use of large data collected in the transportation area in conjunction with AI techniques to develop helpful solutions. Intelligent Transportation Systems (ITS) aims to provide end users with innovative and advanced services that allow them to seamlessly use various modes of transportation and traffic management for timely and effective planning, as well as empower them to make better decisions in the latest multi-modular transportation system. The transportation authority, government, and public institutions will benefit much from having such a system because it can reasonably foresee transportation development . On a daily basis, we commute via public and private transportation. We take it for granted that the buses will arrive at their designated stops on time. Because of the ever-increasing population, the general public requires better travel experiences on commercial transportation.

II. OBJECTIVE

Deep learninggetting to know-based works invisitors prediction from multipleviews,such as, approaches, applications, datasets, experiments, analysis and future directions.Here we use classification for existing approaches, and describe their key design choices.We perform a comparative experimental study to evaluate different models, identifying the most effective component.

III. LITERATURE SURVEY

In Traffic Flow Prediction, big data: The traffic flow data which was provided by the author of a deep learning approach is useful for, the effective functioning of intelligent transport systems(ITS). Usually,it doesnow notappropriatemany of theprogramsinactualworld, for predicting the traffic situations usually. A Layered auto encoded design is used in deep learning concept. comparison of other data mining models has demonstrated in an efficient way.[2]

A transport traffic estimation technique has been introduced by the Mining Road Network Correlation for traffic estimation through the author of Compressive Sensing. This strategy has been tested with traffic data of over 4400 taxis from Shanghai town, China. The author suggests a different strategy to estimating different traffic flow that reduces the effort of people and increase automation. Accuracy estimations are used to validate this method [4].

IV. EXISTING SYSTEM

In previous systemsClassical methods which includes statistical methods and traditional machine learning methods are used. In closing years, machine learning knowledge of information, and deep learning strategies have been validated in

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the traffic prediction initiatives. The statistical methodsare to build a different type of data-driven statistical model for prediction. The most representative algorithms are Historical Average (HA), Auto-Regressive Integrated Moving Average (ARIMA), and Vector Auto Regressive (VAR).

V. PROPOSED METHOD

In proposed system, we used models and algorithms which comes under deep learning. We used CNN, LSTM and DNN networks. By using the regression techniques such as mean square error and root mean square error, we calculated the accuracy. Theproposed traffic system model representation is presented.In view of the proposed methodology the traffic model is considered as a set of nodes with corresponding inputs and output links. The traffic flow for a set of links will have an influence on the traffic flows of the output links. The traffic model is considered as a block-box fordecoding and modulating the machine inputs. As system is governed by a set of rules associated with the fixed and dynamic states which are mapped to the outputs.

VI. ALGORITHMS

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) is one of the most used algorithms in deep learning family and it is used to exploit the spatial structure of data(e.g., images) to learn the features of the data for the final model to learn something useful. CNN helps to learn the local features in the data. The CNN model is the deep model extension of FFBNN. Convolutional Layers contains more hidden layers and one of the convolutional layers at the input. A standardCNN hasthreeadditives, convolutional layers, pooling layers and a totallylinkedlayer. The CNN inherits all the features of an FFBNN model, except those convolutional layers are applied at the start of the normal ANN model and pooling layers are applied in between the ANN layers. Convolution is an operation between two functions, continuous or discrete which in practice.

Long Short-Term Memory (LSTM)

Long time series have long data dependencies. To examine these long-term dependencies the traditional neural primarily based network isn't enough to do the process. Here a recurrent neural network (RNN) based Long Short-Term Memory (LSTM) are used. An RNN is similar in structure to a feed forward neural network except that the output of every neuron unit is fed back to its input, which makes it a recurrent fee learner. LSTM is a more advanced form of RNN. LSTM is a more advanced form of RNN. LSTM is a memory block structure which are controlled by memory cells through their respective input, output forget gates and peepholes connections. Data flow and operations in Long Short-Term Memory (LSTM) unit structure contains the forget, input, output, and update gate.

Deep Neural Networks (DNN)

The principalreasonof a neural communityis toacquirea hard and fastof inputs,perform progressively complex calculations on them, and give output to solve real world problems like Classification. We mainly restrict ourselves to feed forward the neural networks. we've gotanenter, an output, and awayof sequentialfactsin a deepnetwork. Initially, DNN creates a map of virtual neurons and later assigns random numerical values or weights to connections between them. The weights and inputs are then multiplied and returns an output between 0 and 1. When these particular community cannot apprehenda particularsample, aset of ruleswouldregulatethe weights. Deep neural networks are especially classes of machine learning algorithms which are equivalent to the artificial neural network (ANN).

VII. SYSTEM ARCHITECTURE

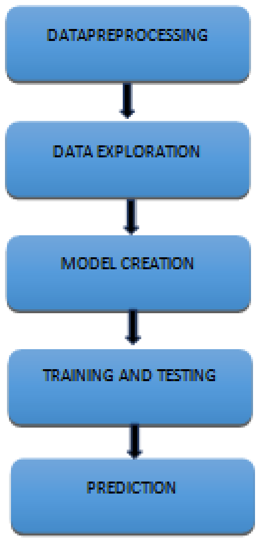

Figure -7.1

VIII. DATA SET

This dataset contains total 48120 observations of the number of vehicles each hour in four different junctions:

i. DateTime
ii. Junction
iii. Vehicles
iv. ID

Sno.	Date Time	Junction	Vehicles	ID
0	2015-11-01 00:00:00	1.0	15	20151101001
1	2015-11-01 00:00:00	1.0	13	20151101011
2	2015-11-01 00:00:00	1.0	10	20151101021
--	------------	-----	-----	-------
--	------------	-----	-----	-------
48117	2017-06-30 21:00:00	4.0	16	20170630214
48118	2017-06-30 22:00:00	4.0	22	20170630224
48119	2017-06-30 23:00:00	4.0	12	20170630234

Table – 8.1

IX. LIBRARIES

1.1 Pandas:

Pandas is the most popular python library that is used for the data analysis. Itprovides highly optimized performance with back-end source code is purely writteninC orPython.Wecananalyze datainpandaswith

1. Series
2. Dataframes

9.2 JupyterNotebook

Jupyter Notebook is a JSON document, following a versioned schema, and contains an ordered list of input/output cells which can contain code, text mathematics, plots and rich media, usually ending with the ".ipynb" extension.A Jupyter Notebook is an open-source web application that allows one to create and share documents that contain live code, equations, visualizations, and narrative text. The Uses include data cleaning and transformation, numerical simulation, statistical modelling, data visualization, machine learning, and much more.

9.3Keras

The Keras is an open-source neural-network library written in Python. It is capableof running on the top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or PlaidML. It is Designed to enable fast experimentation with deep neural networks, it focusesonbeinguser-friendly,modular,andextensible.Kerascontains verynumerousimplementationsofcommonlyusedneural-networkbuildingblockssuchaslayers, objectives, activationfunctions, optimizers,andahostoftoolstowork with image and text data easier to simplify the coding necessary for writingdeepneuralnetworkcode.

X. RESULTS

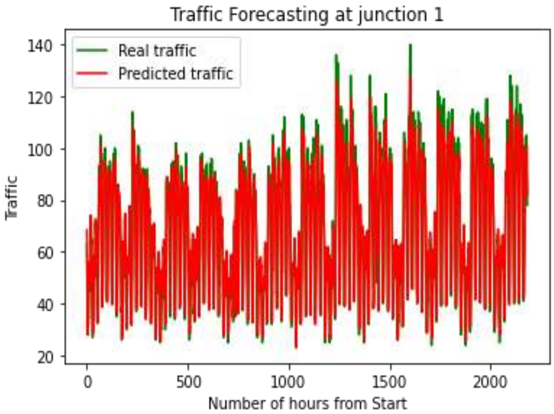

Figure – 10.1

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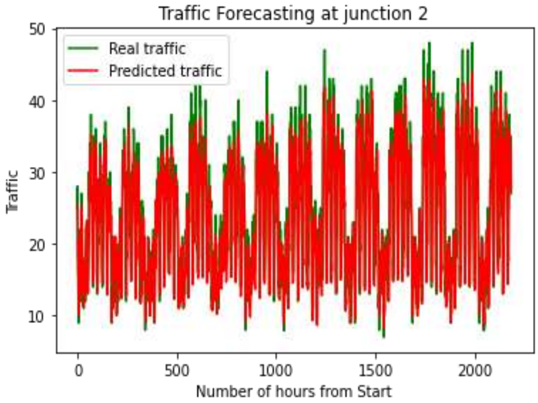

Figure – 10.2

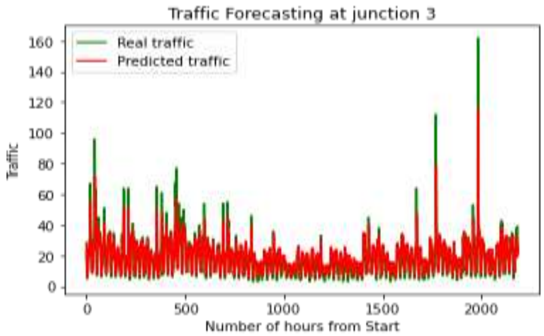

Figure – 10.3

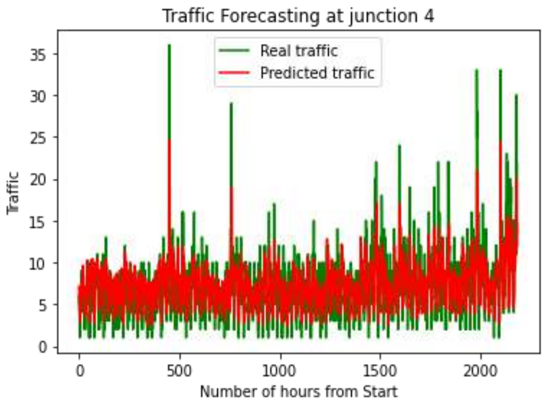

Figure – 10.4

XI. CONCLUSION

A topological breakdown of the highway network is used to report the bi-directional flow function of the individual roadways, taking into account net inflows and outflows.

Furthermore, utilising statistical and neural-based machine learning models with different loss functions and training optimisation methodologies,suggest that objective function is optimised and compared for the constraints. Finally, for improved prediction accuracy, we describebest fitting machine learning model parameters for suggested flow goal functions. The deep learning models are also tested for features that are time dependent in the experiments in a distinct experiment instance. Despite the fact that, every flow time series is time dependent, the order in which the input data is delivered to the models with respect to time matters, because the models exploit data.

Experiments show that shallow machine learning techniques can be used if the data is sparse enough to be categorically predicted, as in the case of SVR and RFR, and that if the data is not sparse enough to be categorically predicted, the patterns in the data must be learned properly using FFBNN and LSTM based deep learning techniques, as the latter performed better in highly correlated sparse data scenarios or conditions. Furthermore, the proposed network breakdown for machine learning implementation has an impact on the final model's performance, which in our tests outperformed without an objective function to account for traffic network flow-links.

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