IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 1, May 2024

Predicting Traffic Flow with Neural Networks

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Abstract: *The monitoring and analysis of traffic flow has become crucial for transportation planners to best schedule road infrastructure repair projects as well as for people to better plan and manage their daily commutes. Therefore, one of the most crucial needs of traffic management systems is the capacity to precisely predict the type of traffic stream. In this study, we will give an intelligent approach to traffic flow prediction using actual data from the Central Road Research Institute (CRRI), India for the years 2018 and 2019. The suggested method is to train a neural network model to predict traffic flow on an hourly basis in the future. The simulation's conclusions provided a reliable forecast for the traffic statistics*

Keywords: Traffic Flow; Prediction; neural network; deep learning

I. INTRODUCTION

Due to recent population expansion and sharp declines in car prices, there has been a noticeable rise in traffic on the roads, which has raised demand for constant and unbroken road access at all hours. However, as road infrastructure ages, it becomes more and more in need of maintenance, which causes traffic jams, rerouting, and occasionally the entire route to close.

Under the direction of "Central Road Research Institute (CRRI), India," traffic data analysis is a crucial and important indicator for the nation's transportation and infrastructure plans. The centre gathers data on traffic movement in some of main roadways using either temporary or permanent inductive loops buried beneath the surface of the road.

By installing electronic recording devices on the road, traffic flow data along a specific national route, path, or intersection can be gathered. On an hourly basis, these devices can collect various data regarding passing vehicles, including speed, class, and acceleration/deceleration.

In order to help transportation planners make better judgments regarding constructing new roads or renovating existing ones based on the projection of traffic flow state in the short, medium, or even long term, a thorough and meticulous analysis of the data acquired can be used.

The challenge with merging is figuring out how to sift through the massive amount of data that has been gathered, identify relevant aspects from seemingly random entries, and predict the traffic flow situation for a specific date (day/hour).

II. STATE OF THE ART

Modern traffic management and control tactics are primarily driven by the growing application of intelligent transportation systems (ITS), the quick development of processing power, and adaptable mathematical techniques [1], [2]. Contributing to all major transport strategies is the primary goal of these kinds of systems. ITS entails gathering, processing, and analyzing data to guarantee an effective tool for decision-making.

Intelligent transport systems have made traffic flow prediction one of their core studies. A variety of techniques have been developed for this purpose, ranging from heuristics based on statistical analysis of historical data, such as the K-nearest neighbor algorithm, to auto-regressive linear models like autoregressive integrated moving average (ARIMA)[3], [4], [5] and linear and nonlinear regression. The ARIMA model can, however, need a lot of processing power. The multivariate time-series model was the focus of further studies [6].

It was discovered in [7] that neural networks can approximate any nonlinear function and that this makes them an effective tool for short-term traffic flow forecasting.

Based on simulated data, the artificial neural network (ANN) technique for short-term traffic flow prediction has also consistently performed well in [8]. However, it highlights how important it is to look into these methods more thoroughly using experimental data.

With differing degrees of success, researchers have also attempted a variety of deep neural network designs to estimate traffic flow [9], [10], [11], and [12]. The approach utilized in [9] to forecast traffic patterns at particular occasions demonstrated how deep learning yields accurate short-term traffic flow forecasts.

In order to estimate and predict the traffic status variables using machine learning approaches, data mining techniques were used in [13], [14]. Computational tools are used in data mining operations to extract valuable information from massive datasets. Combining these two methods, however, did not result in a noticeably better performance and is therefore not advised.

III. DATA SET

The Central Road Research Institute (CRRI), India has given us with an actual dataset, which we will use to train the suggested model outlined below. The dataset includes, on average, two-week intervals of observed traffic flow from the years 2018 and 2019.

The centre counts, categorise, and measures the speed of vehicles travelling along a specific roadway using two different kinds of devices that are placed on interesting roads.

- Single loop counters: keep track of the total amount of traffic passing through each lane.
- Multiple loop counters: keep track of the flow in each distinct lane.

The Dataset is made up of several distinct files, each of which has traffic data for a particular road at a given time. In addition, the dataset includes traffic classification for each lane based on the kind of vehicle (car, truck, etc.); for highways with several lanes, Table I shows an example of a recorded file. Table II outlines the five classes into which the vehicles are divided based on length.

The date (day and hour) of the start and finish of the recording, the number of lanes, the name of the road, etc. are all included in the meta-data of the files. Table III also describes how the traffic is classified according to the hourly quantity of vehicles.

TABLE I. SAMPLE DATA FROM A GENERATED FILE FOR A TWO-LANE ROAD WITH VEHICLE CLASSES.

Lane 1	Class 1	Class 2	Class 3	Class 4	Lane 2	Class 1	Class 2	Class 3	Class 4
181	85	45	34	17	202	46	63	52	41
389	182	152	42	13	136	46	41	25	24
418	156	124	87	51	118	42	45	19	12
438	205	140	52	41	134	52	43	24	15
316	132	85	67	32	370	196	92	45	37

TABLE II. VEHICLE CLASSIFICATION BASED ON THEIR LENGTH(L).

Class	1	2	3	4
Length	L <5.2m	5.2m <L <6.5m	6.5m <L <10.5m	L >10.5

TABLE III. DAILY TRAFFIC CLASSIFICATION BASED ON HOURLY SUM (S)

Class	4	3	2	1	0
Sum	s <200	200 <s <750	750 <s <2000	2000 <s <4500	4500 <s
Description	very low	low	medium	high	very high

A. Preparing the data

In order to get the dataset ready for feeding into the deep neural network that will be explained below, we will arrange it into a single matrix and convert the traffic count value into a category (very low, low, medium, high, very high).

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TABLE IV. DATASET SAMPLE

Count	Road name	Week day	Hour	Flow
309	RR 413 PK97 MEKNES	Sunday	16.0	low
790	RN 10 PK 19 Chtouka	Saturday	23.0	medium
20160	RN1 PK222.4 KENITRA	Tuesday	6.0	very high
220	RN 6 PK 71.38 KHEMISSET	Monday	5.0	low
30	RR401 PK65 KHEMISSET	Friday	4.0	very low
4201	RP3331 PK28 BENSLIMANE	Wednesday	7.0	high

B. Investigating data

As seen in Figs. 1 and 2, we will provide some statistical statistics regarding the dataset in this section.

Figure 1 makes it evident that there are two main times of increased traffic on the roads: between 11 and 14 and between 17 and 19. This could be attributed to an increase in the number of people travelling during rush hour to and from work, which results in these times experiencing the most traffic congestion. Additionally, Fig. 2 shows a discernible increase in traffic flow on the weekends, which may be related to people taking travels during that time.

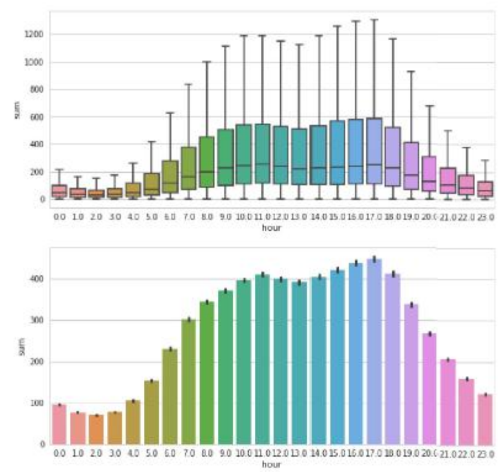

Fig. 1. Dataset statistics: grouped by hour

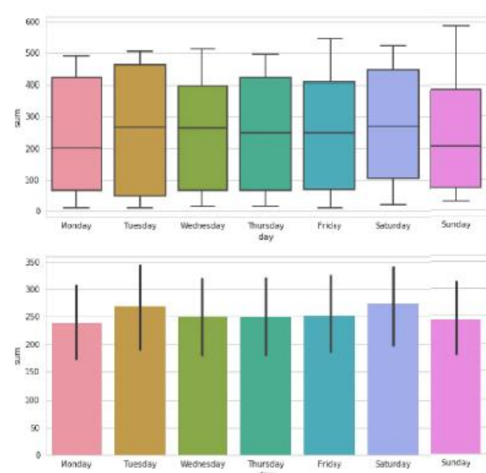

Fig. 2. Dataset statistics:grouped by days

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IV. DEEP LEARNING

Deep neural networks are general-purpose function approximators that have gained popularity recently in the machine learning field due to the enormous increase in computing power of contemporary machines, particularly graphic processing units, and the abundance of collected data that is available to train the models on. This resulted in a number of intriguing machine learning applications, including classification, natural language processing, image and audio recognition, and in this instance, data predictions based on prior observations.

A deep neural network may extract hidden characteristics and patterns from a given data set and identify unknown structure by using a multiple successive layer design that roughly resembles the biological nervous system [15], [16]. Complex non-linear functions are approximated using deep neural networks.

A hidden layer is made up of linked processors called neurons that each produce a sequence of real-valued activations. Each hidden layer carries out a non-linear translation from the preceding layer to the subsequent one.

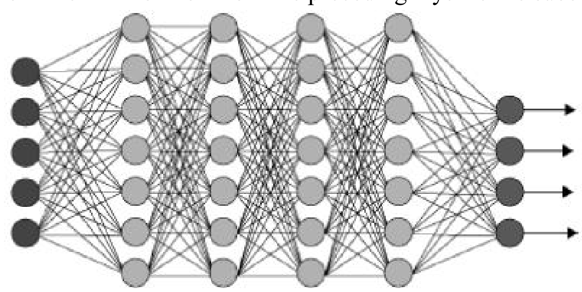

Fig. 3. Deep neural network architecture.

V. THE PROPOSED SYSTEM

Based on the recorded values in the previously mentioned dataset, we will present a deep neural network model in this study to forecast the traffic flow state in the future (very low, low, medium, high, and very high).

The Deep Neural Network Classifier (DNNC) in the proposed system has the architecture K-128-128-N, where N is the number of traffic classes to be predicted (in this example, 5). The network's input is the table IV pre-processed and normalized matrix. There are 128 hidden units spread over three hidden layers in the network.

$$h_i^j, i = 1..128, j = 1..3$$

Each layer's hidden layer count and the amount of neurons within it are quite experimental. Above the hidden layers with 5-dimensional outputs is a Softmax regression layer. The probability of each class in the output is estimated by the Softmax output layer. Equation.1 represents the Softmax [17] equation.

$$\sigma(z) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \qquad (1)$$

VI. EXPERIMRNT

We tested the accuracy of the predictions and made predictions using the most recent version of Keras in our studies. Keras offers three different activation function options: tanh, sigmoid, and relu. In our situation, we chose to employ the hyper tangent function, or tanh, since research has shown that it produces better results than the sigmoid function [18].

In order to optimise the weight and biases values, Keras also offers a wide range of optimisation algorithms, such as the stochastic gradient descent optimizer and the adaptive moment estimation algorithm [19]. We have selected the Adaptive Moment Estimation algorithm because it has been shown to converge more quickly and learn more quickly than other adaptive learning-method algorithms. Additionally, it addresses several issues with optimisation techniques, such as vanishing learning rate.

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The suggested model is tested on a system with installed ArchLinux. and Python (Version 3.6.4), Keras (Version 2.1.1), and Tensorflow (Version 1.4.0) as back-ends.

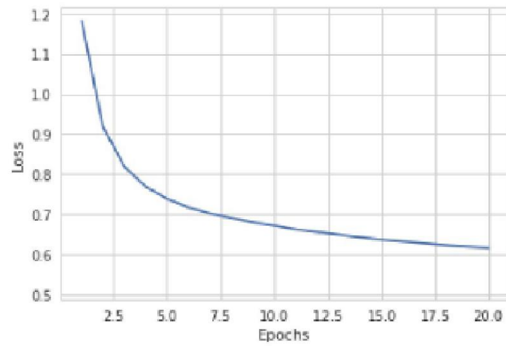

Fig. 4. Loss function changing process

The neural network's training phase saw a steady increase in the model's accuracy as it got better at projecting the traffic's future worth; eventually, the model's prediction accuracy reached 82%.

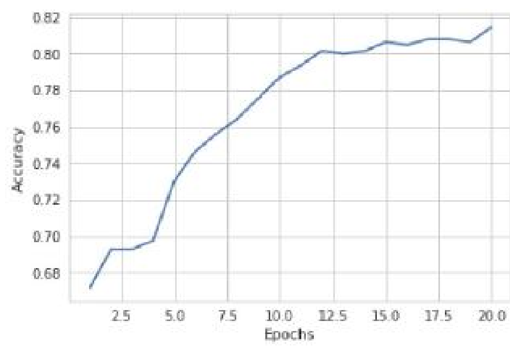

Fig. 5. the increase of the model accuracy during the training.

VII. SUMMARY AND PERSPECTIVES

For road traffic systems, accurate traffic forecasting is essential, especially for preventing congestion and maximising the effectiveness of scarce transportation resources during peak hours. The Central Road Research Institute (CRRI), India historical traffic data reveals a seasonal variation tendency that is present on numerous national roadways. It also discloses that a large quantity of data is absent or destroyed due to a variety of issues, including vandalism, hardware or software malfunction, and battery drain.

This paper's primary contribution is the creation of a deep learning architecture for traffic flow prediction on roads. It is possible to anticipate the amount of traffic on a certain road at a given time using the projected data.

It will also be used to reconstruct data that has been lost or damaged using the anticipated values. This makes it possible to complete the blanks in the traffic matrix that is used to determine the common traffic indicator, the Annual Average Daily Traffic (AADT). The results are unquestionably reliable, and the use and application on actual data is highly advantageous.

Future research may produce even better outcomes by combining neural networks with other prediction techniques. Additionally, it is advised to adjust the data's time parameter (hourly basis in our case) either upwards or downwards to determine the optimal duration for the learning process.

All Central Road Research Institute (CRRI), India road types were subjected to our technique without any consideration for their unique qualities or type. This compels us to classify the dataset earlier while accounting for various road features (such as type, size, and location).

VIII. RECOGNITION

Without the backing and assistance of the Central Road Research Institute (CRRI), India, this study paper would not have been feasible. The centre went above and beyond to give us the actual traffic statistics that we needed for our research, as well as to explain to us how they handle road traffic.

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