Drivenet: Deep Learning approach for Traffic flow forecasting

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Abstract: Efficient traffic flow prediction is essential for effective traffic management and congestion reduction in urban areas. Traditional statistical models often fail to accurately capture the complex dynamics of vehicular traffic flow, especially under dynamic conditions. In this project, we propose a deep learning-based vehicular traffic flow prediction model that utilizes Long Short-Term Memory (LSTM) neural networks, AdaBoost, and gradient descent techniques to enhance prediction accuracy. To evaluate the model's accuracy, mean absolute error (MAE) and R2 score techniques are employed, comparing the predicted traffic flow with the actual traffic flow. Experimental results indicate that our model outperforms traditional statistical models, exhibiting lower MAE and higher R2 scores.

Keywords

Deep learning , Convolution neural networks , Computer vision techniques, Digital image processing

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I.INTRODUCTION

In order to improve traffic management, increase road safety, and increase overalltraffic efficiency, intelligent transportation systems place a high priority on the prediction of vehicular traffic flow. Becausetraffic patterns are dynamic and complex, projecting traffic flow accurately is a difficult endeavor. Traditional models frequently have trouble capturing the long-term trends and temporal dependencies present in traffic data. This research suggestsa strong prediction model using Long Short-Term Memory (LSTM) neural networks, a potent deep learning method capable of accurately modelling sequential data, to get over these constraints. The suggested model attempts to produce more accurate predictions by using past traffic flow data, which would allow transportation authoritiesand stakeholders to make better traffic management decisions. It draws attention to the difficulties in producing reliable traffic forecasts, such as the intricate and shifting nature of traffic patterns. The introduction also discusses the rationale for utilizing LSTM, highlighting how well it can simulate temporal dynamics and capture long-term interdependence. Urban areas frequently experience traffic congestion, which causes delays, higher fuel costs, and environmental pollution. Accurate forecasting of vehicle traffic flow has drawn a lot of attention recently as a means of reducing these problems and enhancing traffic management. The complexity and dynamic nature of traffic patterns are typically difficult to capture by traditional approaches to traffic flow prediction, which limits their ability to deliver accurate and timely forecasts. Therefore, there is anincreasing demand for sophisticated computational models that can successfully manage the underlying uncertainties

II. IMPLEMENTATION

Transportation issues are becoming more and more difficult as urbanisation advances and cars become more and more popular:

traffic flow is backed up, accidents are common, and the traffic environment is getting worse. It is crucial to use a vehiculartraffic flow prediction model to solve this problem. A system like that would make it possible to detect traffic early.to enhancethe system's accuracy and computational complexity performance. The first step of the suggested process entails gathering data from cameras and sensors placed close to traffic intersections. We gather a data set at each intersection that includes the time and the number of cars passing through the intersection. The first step of the suggested process entails gathering data from cameras and sensors placed close to traffic intersections. We gather a data set at each intersection that includes the time and the number of cars passing through the intersection. Several machine learningmethods, including Adaboost and decision trees, are used to anticipate the traffic at the various junctions' is one of the deep learning algorithms. Finally, the data is timeseries data because it is. The LSM evaluates the outcomes to obtain the highestlevel of accuracy.

A. Architecture

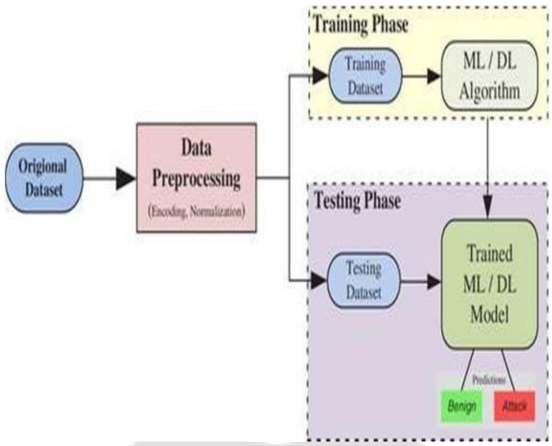

Fig.1

B. Usecase Diagram

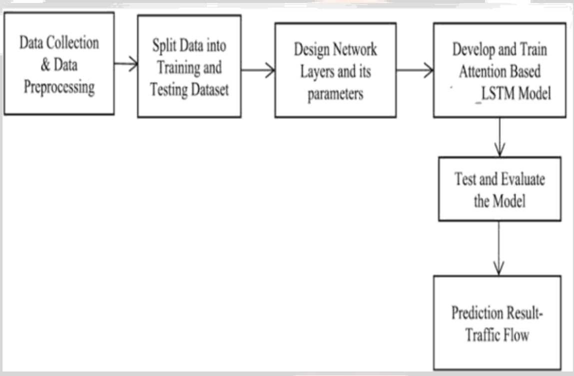

Fig.2

The project is being implemented primarily using 1 deep learning algorithm and 1 type of supervised machine learning algorithm. Those areRegression with Adaboost

C. The LSM Algorithm

The famous machine learning technique known as Adaboost, or Adaptive Boosting, combines a number of weak learners to produce a powerful prediction model.Typically, this consists of decision trees. Adaboost works by repeatedly training weak classifiers, each of which gives additional weight to the incorrectly categorised instances from the prior classifiers. This iterative procedureemphasises the challenging samples that the earlier classifiers had trouble correctly classifying, effectively increasing theirprominence in succeeding iterations. The Adaboost algorithm modifies the weights of the training samples in accordance with the classification accuracy of each iteration. It educates a fresh weak classifier is added to the ensemble using the new weights. Each weak classifier contributes a weighted vote throughout the prediction phase, and the final prediction is made by adding these weighted votes. Each classifier is given a weight based on the accuracy of its classification, with more accurate classifiers having a greater impact on the outcome prediction. As it successfully combines the

strengths of several weak classifiers to increase prediction accuracy, Adaboost has demonstrated to be a powerful method for tasks like classification, regression, and feature selection.

Recurrent neural network (RNN) architecture known as Long Short-Term Memory (LSTM) was created with the goal of addressing the vanishing gradientproblem and capturing long-term dependencies in sequential data. . LSTMnetworks use memory cells and gating mechanisms to efficiently store and retrieveinformation over lengthy periods of time, incontrast to standard RNNs which struggle to maintain information over longdurations. Memory cells, input gates, output gates, and forget gates make up an LSTM network. The network may recallprevious information because the memory cells function as a memory unit. The input gate decides whether information should besaved by controlling the flow of data into the memory cells. The memory cells' extraneous data is selectively deleted by theforget gate. The output gate controls how information is transferred from memory cells to the output layer or the subsequent time step. These gates allow LSTM networks to learn and remember information over long sequences, which makes them more effective

RESULTS

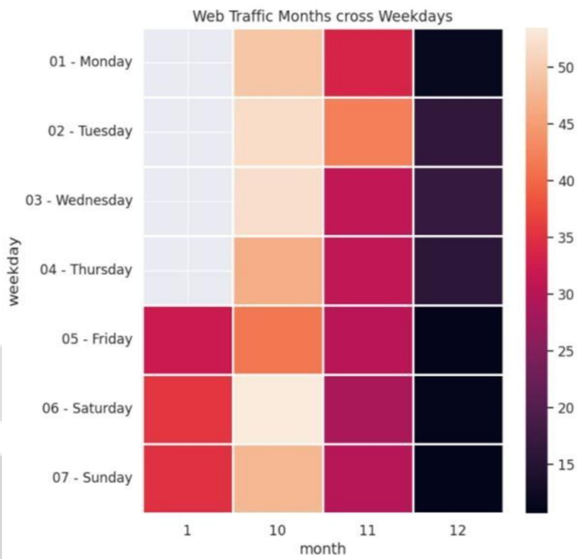

Fig.3

A. Training Data

```
# design network
model = Sequential()
model.add(LSTM(50, input_shape=(trainx.shape[1], trainx.shape[2])))
model.add(Dense(1))
model.compile(loss='mae', optimizer='adam')
# fit network
history = model.fit(trainx, trainy, epochs=10, batch_size=8, validation_data=(testx, testy), verbose=2,
```

```
Epoch 1/10
2650/2650 - 18s - loss: 27.9575 - val_loss: 27.4948 - 18s/epoch - 7ms/step
Epoch 2/10
2650/2650 - 11s - loss: 27.4286 - val_loss: 27.2704 - 11s/epoch - 4ms/step
Epoch 3/10
2650/2650 - 13s - loss: 27.0966 - val_loss: 26.8027 - 13s/epoch - 5ms/step
Epoch 4/10
2650/2650 - 13s - loss: 26.5757 - val_loss: 26.2216 - 13s/epoch - 5ms/step
Epoch 5/10
2650/2650 - 10s - loss: 26.0178 - val_loss: 25.6762 - 10s/epoch - 4ms/step
Epoch 6/10
2650/2650 - 10s - loss: 25.6024 - val_loss: 25.2800 - 10s/epoch - 4ms/step
Epoch 7/10
2650/2650 - 10s - loss: 25.2323 - val_loss: 24.8356 - 10s/epoch - 4ms/step
Epoch 8/10
2650/2650 - 11s - loss: 24.6890 - val_loss: 24.1695 - 11s/epoch - 4ms/step
Epoch 9/10
2650/2650 - 10s - loss: 23.9795 - val_loss: 23.4072 - 10s/epoch - 4ms/step
Epoch 10/10
2650/2650 - 10s - loss: 23.2620 - val_loss: 22.7048 - 10s/epoch - 4ms/step
```

B. Accuracy score

Fig.4

Model Accuracy Score: 0.8867545545565

III. CONCLUSION

We draw the conclusion that the LSTM algorithm we employed to analyse our observation our observation got the highest accuracy rating. Movement of people and things is essential to existence. Travel israpidly expanding as a result of rising population and the need to provide human social welfare. The number of automobiles is growing as technology advances daily. Management of vehicle movement is essential given the increasing rate of vehiclegrowth. Vehicle management aids inreducing travel expenses and length of trip. Having precise background knowledge is crucial for creating a precise vehicular management system. One of the most crucial pieces of information needed to create an accurate vehicle managementsystem is traffic flow. In order to capture the non- linearity of traffic flow prediction, deep learning LSTM models for traffic forecasting have demonstrated promising results. While employing individual deep learning models to estimate traffic flow hasa number of benefits, there are also some serious drawbacks. Research is alreadybeginning to shift away from deep learning architectures and towards hybrid andunsupervised techniques. This review discussed the various deep learning architectures currently in use for predicting traffic flow as well as the growing appeal ofhybrid techniques.

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