ijraset

IJRASET

International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL
FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

www.ijraset.com

Call: ◎08813907089 | E-mail ID: ijraset@gmail.com

Vehicular Traffic Flow Prediction Model using Deep Learning

M Sunny[1], G Goutham[2], G Pratyush[3], G Rohith Reddy[4], Prof. V. Sravanti[5], Dr. Md. Thayyaba Khatoon[6]

[1, 2, 3, 4]*Artificial Intelligence & Machine Learning, Department Of Computer Science & Engineering, Malla Reddy University, Hyderabad, Telangana, India*

[5]*Guide*
[6]*Hod*

Abstract: The necessity for better informed judgements based on information and communication technology to sense the city and gauge its pulse was brought about by the sustainable growth of cities. The characterisation of vehicular traffic flows and the forecasting of urban mobility are crucial components of this "smart cities" idea. A Despite the fact that traffic shows seasonal trends, these patterns may not always is accurate. We discovered that the suggested methods, statistical algorithms like SARIM, and neural network algorithms, such as FFNN, LSTM, CNN, and hybrid LSTM-CNN, are significantly good at predicting the short-term traffic counter data, even when atypical traffic conditions are seen.

I. INTRODUCTION

In order to improve traffic management, increase road safety, and increase overall traffic efficiency, intelligent transportation systems place a high priority on the prediction of vehicular traffic flow. Because traffic 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 suggests a 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 authorities and 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 an increasing 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 vehicular traffic flow prediction model to solve this problem. A system like that would make it possible to detect traffic early.to enhance the 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 learning methods, 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 highest level of accuracy.
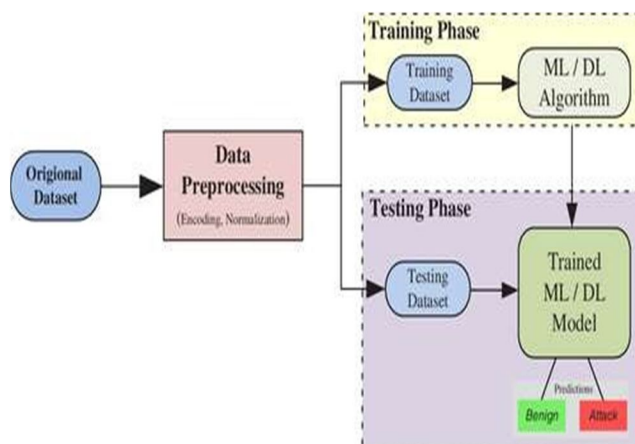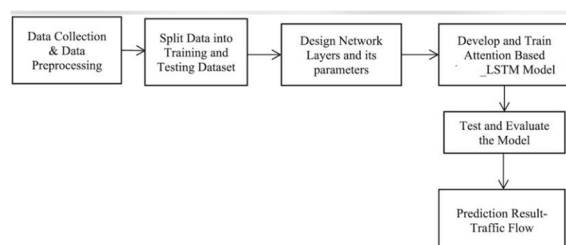
A. Architecture

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 procedure emphasises the challenging samples that the earlier classifiers had trouble correctly classifying, effectively increasing their prominence 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 gradient problem and capturing long-term dependencies in sequential data. . LSTM networks use memory cells and gating mechanisms to efficiently store and retrieve information over lengthy periods of time, in contrast to standard RNNs which struggle to maintain information over long durations. Memory cells, input gates, output gates, and forget gates make up an LSTM network. The network may recall previous information because the memory cells function as a memory unit. The input gate decides whether information should be saved by controlling the flow of data into the memory cells. The memory cells' extraneous data is selectively deleted by the forget 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
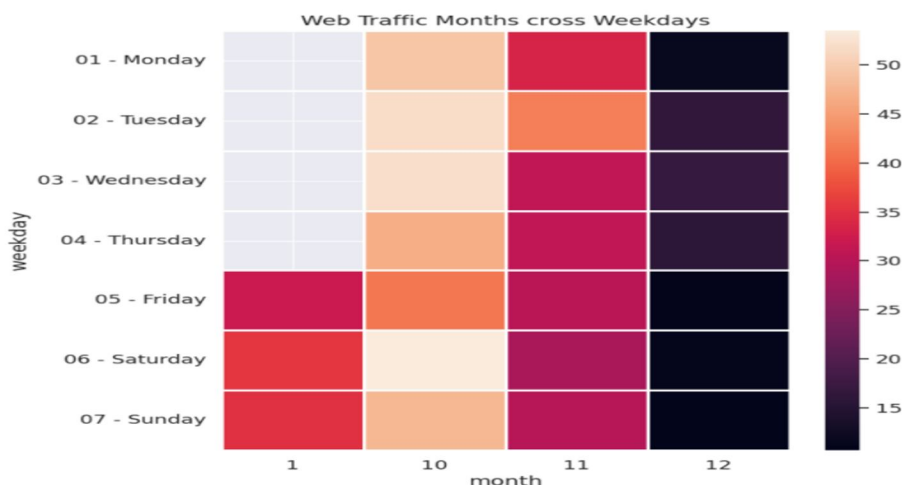
III. RESULTS

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
```
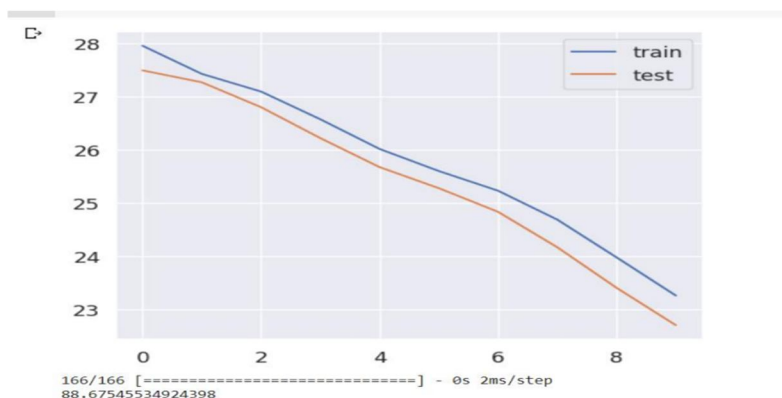
B. Accuracy Score

Fig 4

Model Accuracy Score: 0. 88675455453565

IV.   CONCLUSION

We draw the conclusion that the LSTM algorithm we employed to analyse our observation got the highest accuracy rating. Movement of people and things is essential to existence. Travel is rapidly 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 vehicle growth. Vehicle management aids in reducing 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 management system 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 has a number of benefits, there are also some serious drawbacks. Research is already beginning to shift away from deep learning architectures and towards hybrid and unsupervised techniques. This review discussed the various deep learning architectures currently in use for predicting traffic flow as well as the growing appeal of hybrid techniques.

REFERENCES

[1]   Moor, and K. Papaiannaki,"Toward the accurate identification of network application", PAM'05, pp.41-54, USA, 2005.

[2]   H. Patrick et al. "ACAS: Automated Construction of Application Signatures", Proceedingsof the 2005 ACM SIGCOMM workshop on Mining network data, pp: 197 – 202, Philadelphia, Pennsylvania, 2005.

[3]   T. S. Tabatabaei and S. Krishnan, "Towards robust speech signal processing", Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, Istanbul, Oct2010.

[4]   Chen, C., Li, K., Teo, S. G., Zou, X., Li, K., & Zeng, Z. (2020). Citywide traffic flow prediction based on multiple gated spatio- temporal convolutional neural networks. ACM Transactions on Knowledge Discovery

[5]   Ballard, D. H. (1987). Modular learning in neural networks. Aaai, 279– 284. https://www.aaai.org/Papers/AAAI/1987/AAAI87-050.pdf [Google Scholar]

INTERNATIONAL JOURNAL
FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 ◯ (24*7 Support on Whatsapp)