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Traffic Flow Prediction Using Machine Learning and Deep Learning Techniques: A Web-Based Application

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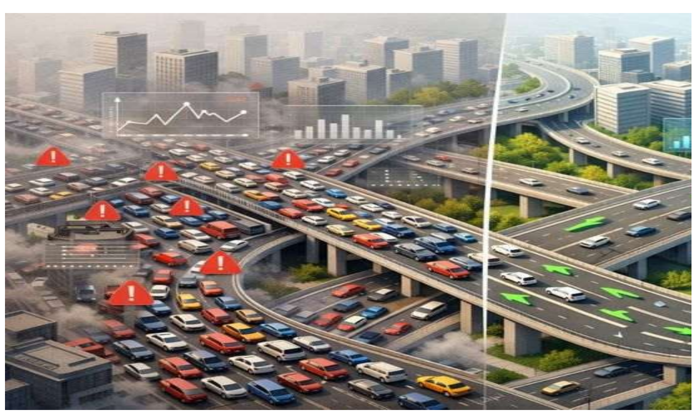
ABSTRACT: Rapidurbanizationandincreasingvehicledensity havesignificantlyintensifiedtrafficcongestionin metropolitan and semi-urban regions. Efficient trafficmanagementrequiresaccurateshort-term and long-term traffic flow prediction to support intelligent transportation systems. This paper presents a web-based traffic flow prediction system built using Long Short-Term Memory (LSTM)neuralnetworks.Thesystemistrainedon city-wisehistoricaltrafficdatasetsandiscapable of learning complex temporal dependencies presentintrafficpatterns.MultipleLSTMmodels are developed and trained for different cities, including Kalaburagi, Delhi, Mumbai, Pune, Hyderabad, and Kolkata. A Flask-based backend integrates the trained models with a lightweight webinterface,enablinguserstoobtainreal-time traffic flow predictions. Experimental results demonstrate that the proposed LSTM-based approach achieves superior prediction accuracy compared to conventional machine learning methods,highlightingitssuitabilityforsmartcity trafficplanningandcongestionmitigation.
Keywords: TrafficFlowPrediction,LSTM,DeepLearning, Time-Series Forecasting, Flask, Intelligent Transportation Systems.

I. INTRODUCTION

Traffic congestion has become a persistent challengeinmodernurbanenvironmentsdueto rapid population growth, increased vehicle ownership,and constrained road infrastructure. Congestionresultsineconomiclosses,increased fuel consumption, environmental pollution, and commuter dissatisfaction. Accurate traffic flow prediction is therefore a critical component of intelligenttransportationsystems(ITS),enabling proactivetrafficcontrol,routeoptimization,and infrastructure planning.

Traditional traffic prediction techniques, such as statistical regression models and classical machinelearningalgorithms, oftenfailtocapture the nonlinear and temporal characteristics inherent in traffic data. Deep learning techniques, particularly Long Short-Term Memory(LSTM)networks,haveproveneffective in modeling sequential data with long-term dependencies. This work proposes an LSTM-based trafficflow prediction system deployed as a web application, allowing real-time prediction and accessibility for practical usage.



II. LITERATURE SURVEY

Early approaches to traffic flow prediction relied onstatisticalmodelssuchaslinearregressionand ARIMA. While these methods are computationally efficient, they struggle with nonlinear traffic behavior and varying temporal patterns.Machine learning approaches, including SupportVectorMachines(SVM)andfeedforward Artificial Neural Networks (ANN), improved prediction accuracy but exhibited limitations in capturing long-term temporal dependencies.

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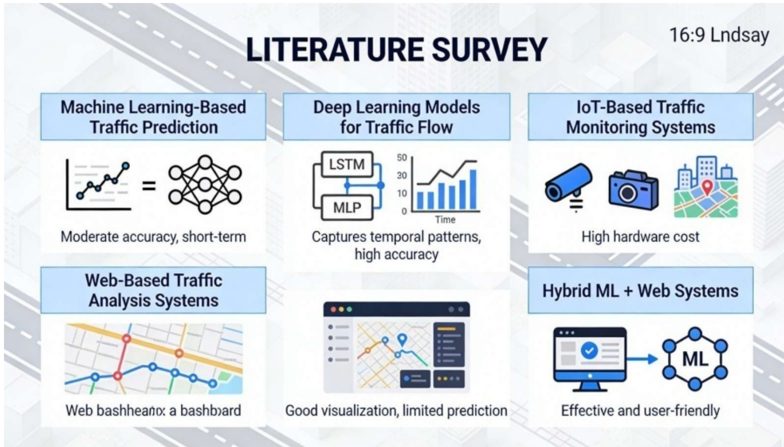
Recentstudieshighlighttheeffectivenessof recurrent neural networks (RNN) and LSTM architectures in traffic forecasting. LSTM networks are capable of retaining historical information over extended time intervals, making them well-suited for traffic time-series data. Several works report improved performance of LSTM-based models over traditionalapproaches.However,manyexisting studies focus primarily on model accuracy and lack real-time deployment or user-accessible interfaces.Thepresentworkbridgesthisgapby integratingLSTM-basedpredictionwithaweb-based application.



III. PROBLEM STATEMENT

Despite significant advancements in traffic flow prediction techniques, existing systems face several challenges:

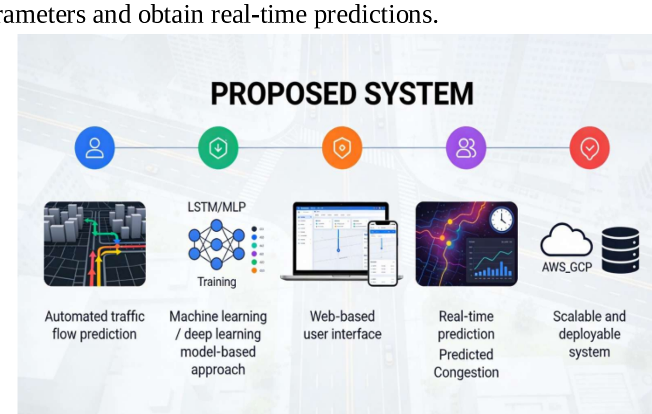
- Inadequate modeling of long-term temporal dependencies
- Reduced prediction accuracy under dynamic traffic conditions
- Limitedsupportforreal-timeprediction and deployment
- Lack of user-friendly, web-based interaction platforms

Theselimitationsnecessitatethedevelopmentof anintelligent,LSTM-basedtrafficflowprediction system that supports real-time accessibility and practical usability.

IV. PROPOSED SYSTEM AND METHODOLOGY

A. Overview of the Proposed System

The proposed system predicts future traffic flow using LSTM deep learning models trained on historical traffic datasets. City-specific datasets are used to train independent models, enabling localized traffic prediction. A web-based interface allowsuserstoselectcity-specificparameters and obtain real-time predictions.



B. System Components

The system architecture comprises three primary layers:

- User Interface Layer – Handles user interaction and input collection
- Backend Processing Layer – Manages data preprocessing, model loading, and prediction logic

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- LSTMPredictionLayer–Performstraffic flow forecasting using trained LSTM models

C. UserInterface Layer

TheuserinterfaceisdevelopedusingHTML, CSS,andJavaScript.Itprovidesasimpleand intuitive platform for users to input parameterssuchascity,time,anddate.The interface communicates with the backend through HTTP requests and displays predicted traffic flow values in real time.

D. BackendProcessingLayer

The backend is implemented using the Flask web framework. It validates user inputs, performs data normalization using pre-trained scalers, and selects the appropriate city-specific LSTM model. The backend also ensures efficient communication between the frontend and the prediction model.

E. LSTM-BasedPredictionLayer

The prediction layer forms the core of the system and utilizes PyTorch-based LSTM models.Themodelsaretrainedonsequential traffic data using sliding window techniques to capture temporal dependencies. Separate models are maintained for different cities to improve prediction accuracy.

F. LSTMModel Architecture

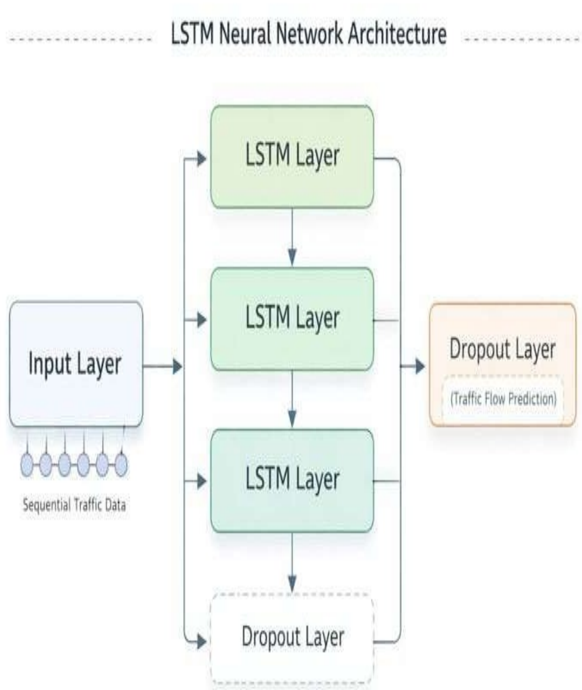

Figure2:ArchitectureoftheLSTMNeural Network

The architecture consists of an input layer, one or more stacked LSTM layers, dropout layers to mitigate overfitting, and a fully connected dense layer that outputs the predicted traffic flow value.

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V. WORKFLOW

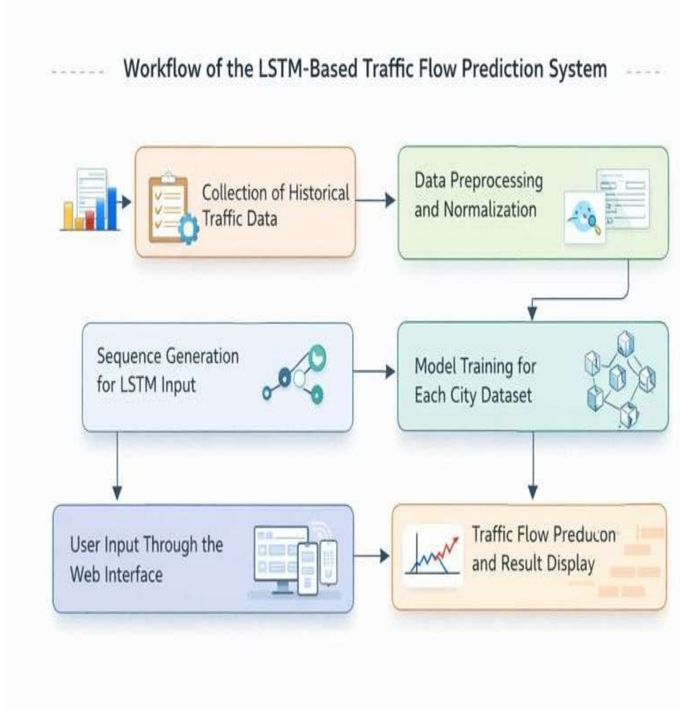
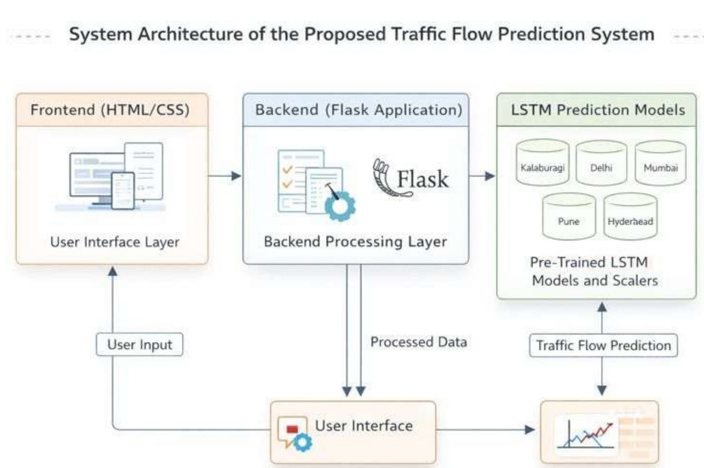


Figure3:WorkflowoftheLSTM-BasedTraffic Flow Prediction System

Thesystemworkflowincludesthefollowing steps:

1) Collectionofhistoricaltrafficdata
2) Datapreprocessingandnormalization
3) SequencegenerationforLSTMinput
4) Modeltrainingforeachcitydataset
5) Userinputthroughthewebinterface
6) Trafficflowpredictionandresultdisplay

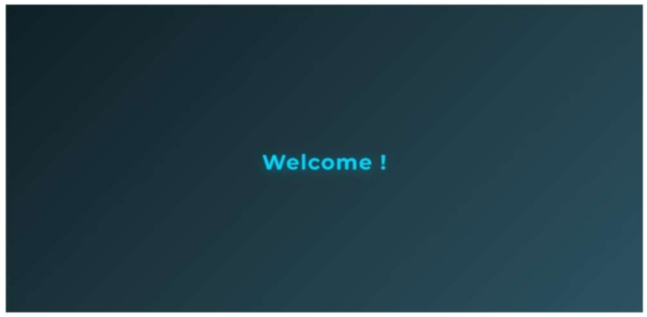
VI. SYSTEM ARCHITECTURE

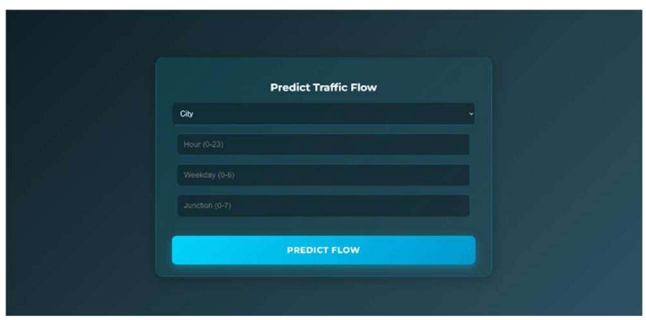


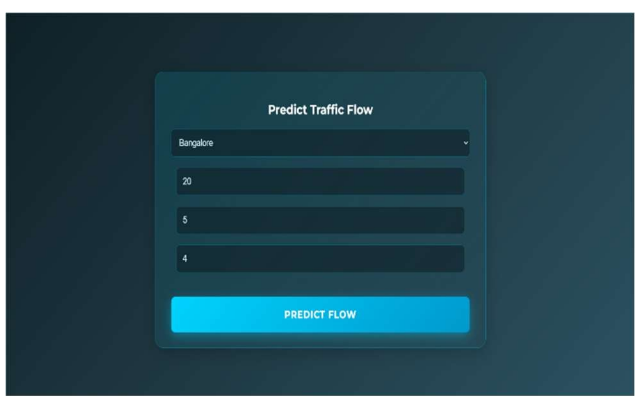
The architecture integrates the frontend interface, Flask backend, trained LSTM models, and pre-trained scalers. This modular design ensures scalability, maintainability, and efficient real-time prediction.

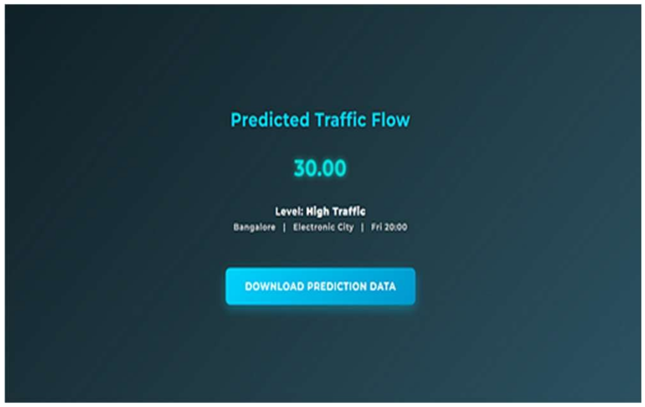
VII. RESULTS AND DISCUSSION

ExperimentalevaluationindicatesthattheLSTM-based models effectively capture temporal variations in traffic data and produce accurate predictions across multiple cities. Compared to traditional machine learning techniques, the proposed approach demonstrates reduced prediction error and improved robustness. The web-based implementation enhances accessibility and allows real-time usage, making the system suitable for practical deployment.









VIII. CONCLUSION

This paper presented a web-based traffic flow prediction system using Long Short-Term Memory networks. By leveraging deep learning techniques and city-specific historical datasets, the proposed system achieves accurate and reliable traffic forecasting. The integration of LSTMmodelswithaFlask-basedwebapplication enables real-time prediction and user accessibility, supporting intelligent transportationsystemsandsmartcityinitiatives.

IX. FUTURE ENHANCEMENTS

1) Integrationofreal-timetrafficsensorand IoT data
2) Development of hybrid CNN–LSTM architectures
3) Cloud-baseddeploymentforscalability
4) Mobileapplicationintegration
5) Interactive traffic visualization dashboards

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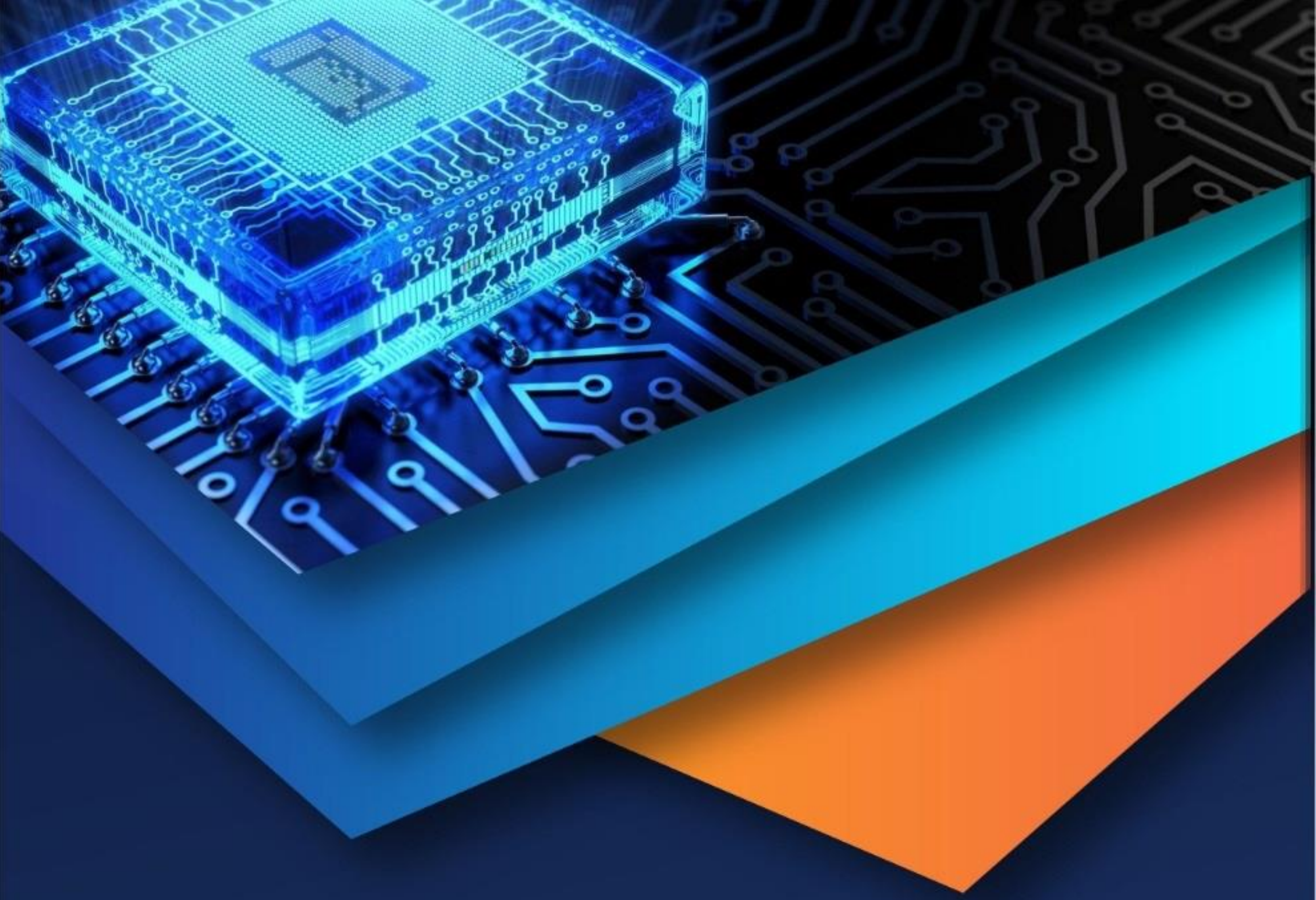

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