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Evaluating The Performance Of Lstm In Traffic Flow Prediction At Different Time Scales

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Abstract
This project presents a traffic prediction system leveraging deep learning techniques such as Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks to analyze and forecast vehicular traffic volume based on historical time-series data. Developed using Python and integrated within a Django web framework, the system utilizes traffic data that includes timestamp information to train models and predict traffic patterns across different hours of the day. The dataset undergoes preprocessing steps including feature extraction from timestamps, normalization using MinMaxScaler, and sequence generation for time-series forecasting. The models are trained using the Keras deep learning library, and their performance is evaluated using the Root Mean Squared Error (RMSE) metric. Among the models, LSTM has been configured with multiple hidden layers and dropout regularization to handle temporal dependencies and avoid overfitting. Users interact with the system through a web interface that allows them to initiate training for each model (RNN, GRU, LSTM) and visualize prediction outputs in comparison to actual traffic data. The system also includes a prediction module where users can simulate hourly traffic forecasts for a given year, with traffic levels categorized into "Low", "Mild", or "High" for intuitive understanding. This intelligent traffic forecasting tool can aid in smarter city planning, traffic control, and congestion management by offering accurate, real-time, and data-driven predictions.

I. INTRODUCTION

The rapid pace of urbanization and population growth has led to an exponential increase in the number of vehicles on roads, resulting in traffic congestion, delays, and a higher incidence of road accidents. In response to these challenges, intelligent traffic prediction systems have emerged as essential tools for smart city infrastructure. By leveraging advanced data analytics and machine learning techniques, these systems aim to forecast traffic conditions accurately, enabling better traffic management, route optimization, and urban planning. One of the most promising approaches in this domain is the use of deep learning techniques, particularly Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory networks (LSTM), which have shown remarkable effectiveness in time series prediction tasks.

This project focuses on the development of a web-based traffic prediction system using Django, a high-level Python web framework. The system utilizes historical traffic data to train three different deep learning models—RNN, GRU, and LSTM—each of which is designed to capture temporal dependencies and trends within the dataset. By integrating these models into a Django-powered web interface, the application provides an interactive and accessible platform for users to analyze traffic patterns and forecast future conditions based on specific parameters such as date, time, and location.

Traditional traffic forecasting methods, such as statistical models and rule-based systems, often fall short in capturing the nonlinear and dynamic nature of real-world traffic data. These approaches typically rely on assumptions of linearity and stationarity, which may not hold true in complex urban traffic environments. Deep learning, on the other hand, has the capacity to learn intricate patterns from large datasets without the need for extensive feature engineering. Among deep learning models, RNNs are specifically designed to handle sequential data, making them well-suited for traffic prediction. However, basic RNNs suffer from issues such as vanishing gradients, which can limit their ability to learn long-term dependencies. This is where advanced variants like GRU and LSTM come into play.

GRU and LSTM are improvements over traditional RNNs, designed to overcome the limitations of vanishing gradients and enable the network to retain information over longer sequences. LSTM networks achieve this through a gated cell structure that regulates the flow of information, allowing the model to learn both short- and long-term dependencies effectively. GRUs offer a simplified version of the LSTM with fewer parameters, which can lead to faster training times and comparable performance. In this project, all three architectures—RNN, GRU, and LSTM—are implemented and compared in terms of their prediction accuracy using Root Mean Squared Error (RMSE) as the evaluation metric.

The dataset used in this project contains traffic volume data recorded over time. Each record consists of fields such as timestamp, number of vehicles, and other contextual information. The data is preprocessed to extract relevant features, including year, month, day, and hour, which are then normalized using Min-Max scaling. The models are trained on a sequence of input data points, allowing them to learn temporal dependencies and predict the number of vehicles for future timestamps. The training process involves dividing the dataset into sequences of past observations, which serve as input for predicting the next time step.

II. Literature Survey

The growing complexities of urban traffic systems, driven by increased vehicle usage and population growth, have made traffic prediction a critical area of research in intelligent transportation systems (ITS). Accurate traffic forecasting is essential for enhancing mobility, reducing congestion, and supporting real-time traffic management decisions. Over the years, a range of techniques has been developed for traffic flow prediction, evolving from traditional statistical models to advanced deep learning approaches. This literature survey reviews notable research contributions and methodologies that have influenced the development of traffic prediction systems, particularly focusing on Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) models.

1. Traditional Statistical Methods

In the early stages of traffic prediction research, statistical techniques such as **Autoregressive Integrated Moving Average (ARIMA)** and **Kalman Filters** were widely used. These models are effective for linear, stationary time series data, but they often fail to capture the non-linear and dynamic nature of real-world traffic flow.

> **Ahmed and Cook (1979)** used a time series model for short-term freeway traffic flow prediction. Although it showed promise, it was limited by its assumption of linearity.

> **Okutani and Stephanedes (1984)** applied a Kalman filtering model for traffic estimation and prediction. This approach could update traffic estimates in real-time but struggled with noisy, non-linear data.

These methods laid the groundwork for more complex modeling techniques, but their limitations prompted researchers to explore data-driven machine learning approaches.

2. Machine Learning Approaches

With the rise of computing power and the availability of large-scale traffic datasets, machine learning models such as **Support Vector Machines (SVMs)**, **k-Nearest Neighbors (k-NN)**, and **Decision Trees** gained popularity.

> **Vanajakshi and Rilett (2004)** explored SVM for predicting short-term traffic flow and demonstrated improved performance over ARIMA models.

Wu et al. (2004) used neural networks for traffic prediction, showing that non-linear models could better learn from historical data patterns compared to traditional linear models.

Existing System

The existing systems for traffic prediction have undergone significant transformation over the past few decades. Various methodologies, platforms, and technologies have been employed to anticipate traffic conditions with the goal of improving urban mobility, minimizing congestion, and enabling smarter infrastructure planning. Most of these systems fall under traditional statistical models, machine learning-based solutions, and, more recently, deep learning approaches. Despite the evolution of predictive capabilities, existing systems still face several limitations in terms of accuracy, adaptability, and real-time usability.

1. Traditional Systems

Traditional traffic forecasting systems primarily rely on statistical and time-series models such as:

ARIMA (AutoRegressive Integrated Moving Average)

Kalman Filtering

Bayesian Networks

These models are used to analyze historical traffic flow data and make short-term predictions. While they are mathematically interpretable and computationally inexpensive, they fail to capture the non-linear, dynamic, and complex patterns often present in real-world traffic data. Moreover, these models assume stationarity and linearity, which are not always applicable in modern traffic scenarios.

Limitations:

Poor accuracy in highly dynamic or irregular traffic conditions.

Inability to model complex, non-linear relationships.

Require extensive manual feature engineering and assumptions about data distribution.

III. Proposed System

The proposed system aims to develop a **deep learning-based web application** for traffic flow prediction that leverages the power of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). It is built using the **Django framework**, providing an intuitive and interactive user interface for traffic analysts, city planners, and the general public to monitor and predict traffic congestion with high accuracy.

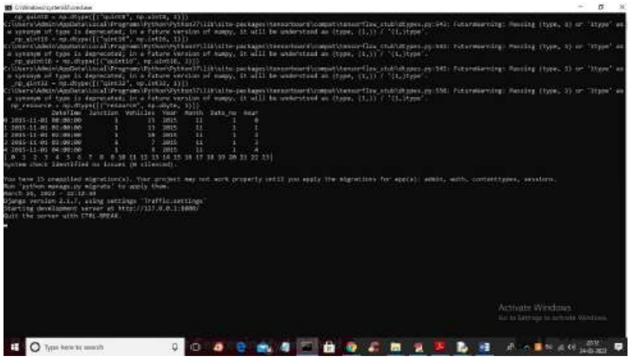
The system is designed to overcome the limitations of existing methods by incorporating advanced neural networks that can learn long-term dependencies in sequential traffic data. It also enables users to visualize and compare the performance of different models and make future traffic predictions for specific time intervals.

IV. Results

Evaluating the Performance of LSTM in Traffic Flow Prediction at Different Time Scales

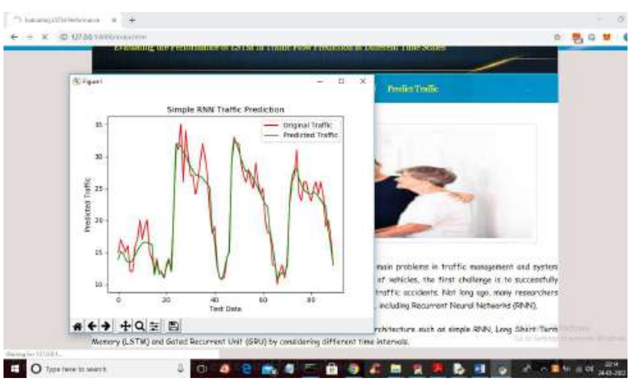
In this project we are using ‘traffic.csv’ dataset to train 3 different traffic prediction algorithms such as Simple RNN, GRU and LSTM. This dataset contains Junction ID from 1 to 4 but it don’t have area name so you can give value between 1 to 4 or u can give 4 different area name. First we will train all algorithms with that dataset and then calculate its RMSE value and in all algorithms LSTM giving less RMSE error.

To run project double click on ‘run.bat’ file to start python DJANGO webserver and to get below screen



In above screen server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below home page

In above screen click on 'Train Simple RNN' link to train RNN and get below output



In above graph x-axis represents test data and y-axis represents traffic volume and red line represents original test traffic value and green line represents predicted value and we can see both line are fully overlap but still some gap or difference is there between original and predicted values of RNN and now close above graph to get below output

In above screen with Simple RNN we got 3.56 RMSE value and now click on 'Train GRU' link to train GRU and get below output

In above screen we can see with GRU also little difference is there between original test value and predicted values but GRU has little less difference compare to Simple RNN and now close above graph to get below output

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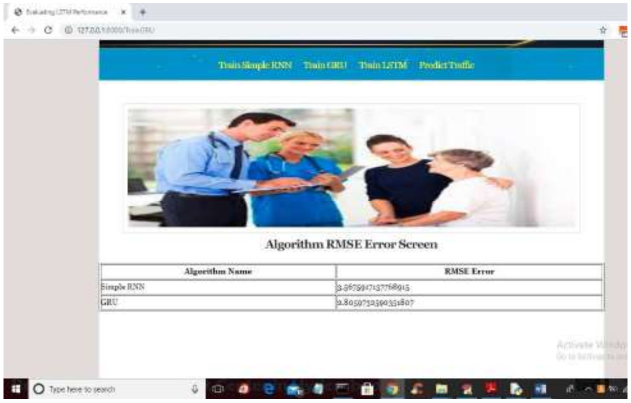


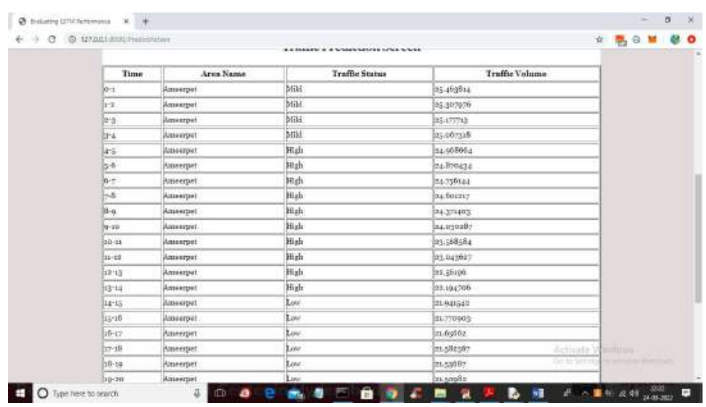
In above screen with GRU we got less RMSE error as 2.86 compare to Simple RNN and now click on ‘Train LSTM’ link to get below output

In above LSTM prediction we can see LSTM has less prediction difference compare to Simple RNN and GRU and now close above graph to get below output

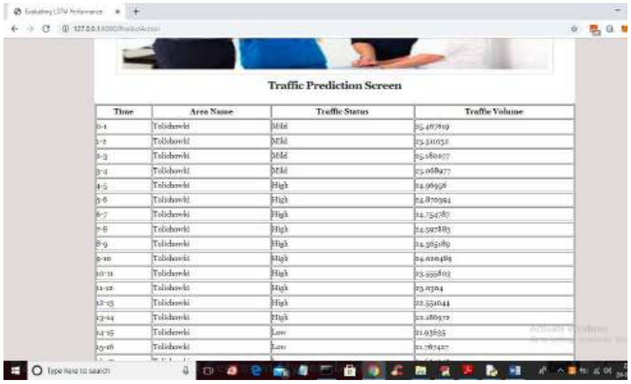
In above screen we can see with LSTM we got less RMSE compare to other algorithm and now click on ‘Predict Traffic’ link to get below screen

In above screen enter some area name to get below output

In above graph x-axis represents hours from 0 to 23 and y-axis represents traffic volume and now close above graph to get below output



In above screen you can see traffic status and similarly you can enter other name and get output



V. Conclusion

The implementation of a traffic prediction system using Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models presents a significant step forward in intelligent transportation solutions. With the increasing complexity of urban traffic and the rapid growth in the number of vehicles, the need for a robust and accurate prediction mechanism has become more critical than ever. This system leverages deep learning algorithms trained on historical traffic data to forecast traffic patterns with high precision, thus enabling proactive decision-making for both commuters and city planners.

The system effectively processes and transforms time-series data to capture temporal dependencies using LSTM, GRU, and RNN models. Each model contributes uniquely: RNN offers simplicity, LSTM handles long-term dependencies effectively, and GRU provides computational efficiency with comparable performance. Together, these models offer a comparative understanding of different deep learning approaches to traffic forecasting. Moreover, by visualizing the prediction results and evaluating them through metrics such as RMSE, users gain clarity on model performance and reliability.

Through this project, not only is traffic congestion prediction improved, but it also lays the groundwork for smarter urban planning, better emergency response strategies, and optimized travel routes. The use of Django as the backend framework ensures a scalable and interactive platform, while technologies like Keras and TensorFlow support robust model development. The system's modular architecture allows for future scalability and real-time data integration.

In conclusion, this traffic prediction system represents an innovative blend of machine learning and web technologies to solve real-world problems. As future enhancements are incorporated—such as real-time data feeds, multi-city support, and intelligent traffic signal control—this system has the potential to significantly impact the way we manage and interact with urban transportation infrastructure, making our cities more efficient, sustainable, and commuter-friendly.

REFERENCES

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5. **Yu, B., Song, H., & Guan, H. (2016).** *A deep learning approach to urban traffic flow prediction based on time-series data.* Big Data Analytics, 1(1), 1–10Explores deep learning techniques including RNN and LSTM for urban traffic forecasting, supporting the comparative methodology used in this project.