Casualties of Accidents - Time Series Forecasting

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Introduction

This project delves into a comprehensive analysis of road accidents spanning from 2005 to 2018, with a particular focus on forecasting potential casualties resulting from these incidents. By leveraging historical accident data, the aim is to predict future casualty trends, thereby enhancing road safety measures and informing policy decisions. Central to this endeavor is the exploration and application of advanced machine learning techniques, specifically Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU). These models are well-suited for handling sequential data and uncovering patterns over time, which is crucial for accurately forecasting road accident casualties. Through this project, we seek to improve the understanding of accident trends and contribute valuable insights for mitigating the impact of road traffic incidents.

Project Overview

In our project focused a detailed examination of road accident data from 2005 to 2018, with a focus on forecasting casualty figures associated with these incidents. The dataset, encompassing a wide range of variables including accident frequency, location, severity, and temporal factors, provides a rich foundation for analysis. The primary objective is to develop robust predictive models that can accurately estimate future casualties based on historical trends and patterns.

To achieve this, the project will employ several advanced machine learning techniques tailored for sequential data analysis: Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU). RNNs are designed to recognize patterns across sequences of data, while LSTMs and GRUs offer enhanced capabilities for handling long-term dependencies and mitigating issues like vanishing gradients that are prevalent in standard RNNs. By experimenting with these models, the project aims to identify the most effective approach for forecasting casualties.

The analysis will involve several stages, including data preprocessing, model training, and evaluation. Data preprocessing will address issues such as missing values and normalization to ensure high-quality input for the models. Each model will be trained using historical accident data, and performance will be assessed through metrics such as accuracy, precision, recall, and mean squared error. The goal is to compare the effectiveness of RNN, LSTM, and GRU in predicting casualties and to understand the implications of these predictions for road safety.

Ultimately, this project seeks to provide valuable insights into accident trends and casualty forecasts, contributing to improved road safety measures and informed decision-making. The findings are expected to support the development of targeted interventions and policies aimed at reducing the impact of road traffic accidents.

Results

(LSTM)

- This is a summary of (LSTM)

Model: "sequential_52"

Layer (type)	Output Shape	Param #
lstm_189 (LSTM)	(None, 1, 64)	16,896
dropout_149 (Dropout)	(None, 1, 64)	0
lstm_190 (LSTM)	(None, 1, 32)	12,416
dropout_150 (Dropout)	(None, 1, 32)	0
lstm_191 (LSTM)	(None, 1, 16)	3,136
dropout_151 (Dropout)	(None, 1, 16)	0
lstm_192 (LSTM)	(None, 8)	800
dense_46 (Dense)	(None, 1)	9

Total params: 33,257 (129.91 KB)
Trainable params: 33,257 (129.91 KB)
Non-trainable params: 0 (0.00 B)

Figure 1 : Summary of LSTM

- " Model loss " metric that indicates how well or poorly a model is performing

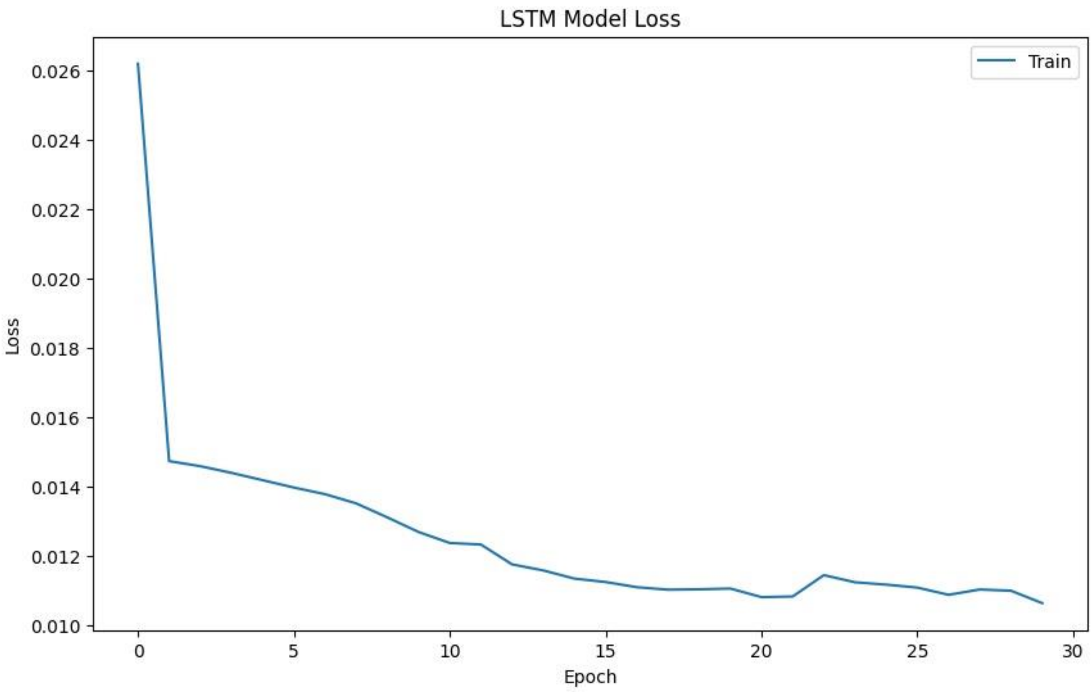

Figure 2: LSTM Model Loss

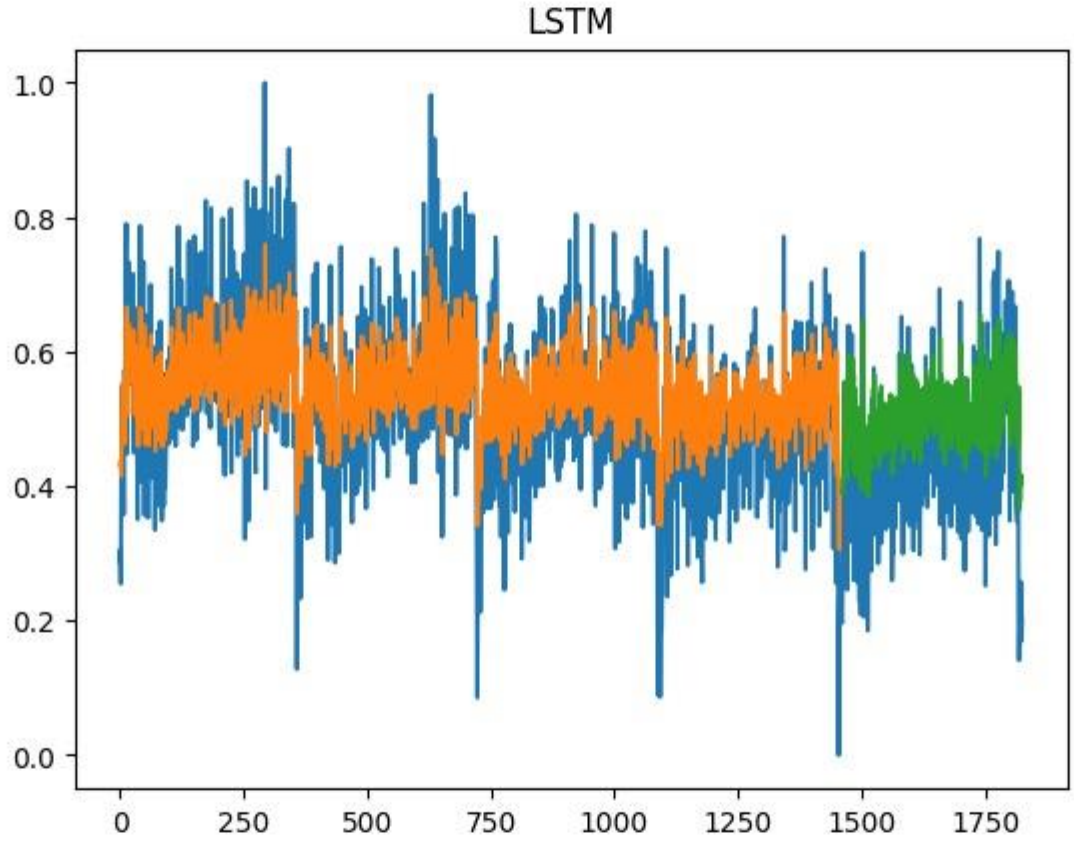

Figure 3 : LSTM

(GRU)

- This is a summary of (GRU)

Model: "sequential_54"

Layer (type)	Output Shape	Param #
gru_14 (GRU)	(None, 1, 128)	50,304
dropout_154 (Dropout)	(None, 1, 128)	0
gru_15 (GRU)	(None, 64)	37,248
dropout_155 (Dropout)	(None, 64)	0
dense_48 (Dense)	(None, 1)	65

Total params: 87,617 (342.25 KB)
Trainable params: 87,617 (342.25 KB)
Non-trainable params: 0 (0.00 B)

Figure 4 : Summary of GRU

- " Model loss " metric that indicates how well or poorly a model is performing

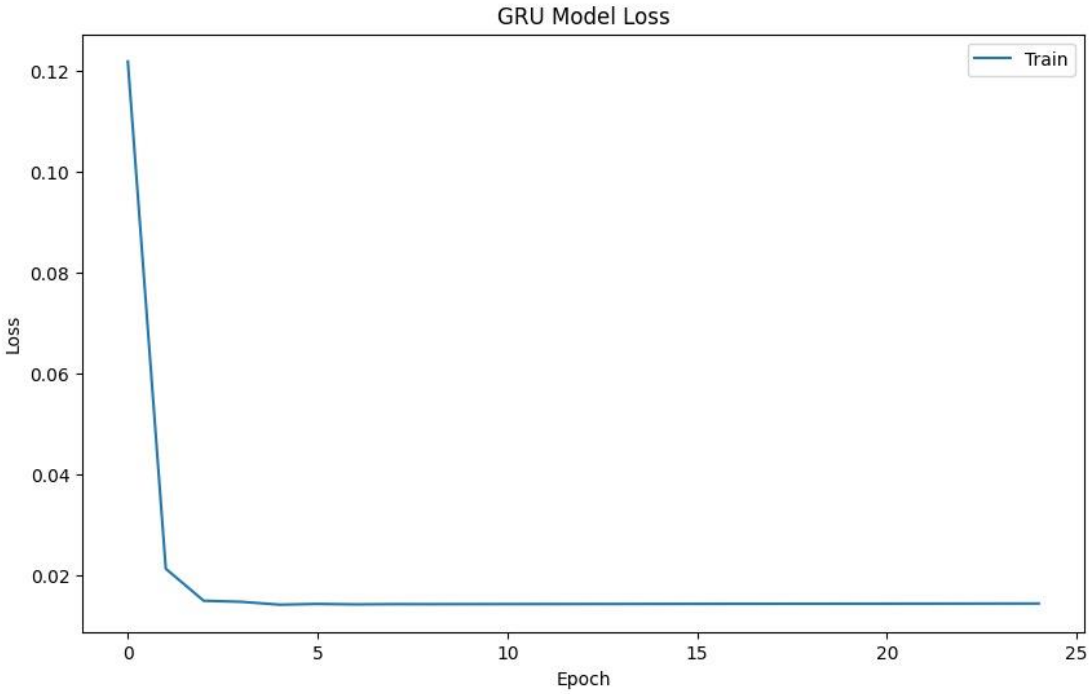

Figure 5: GRU Model Loss

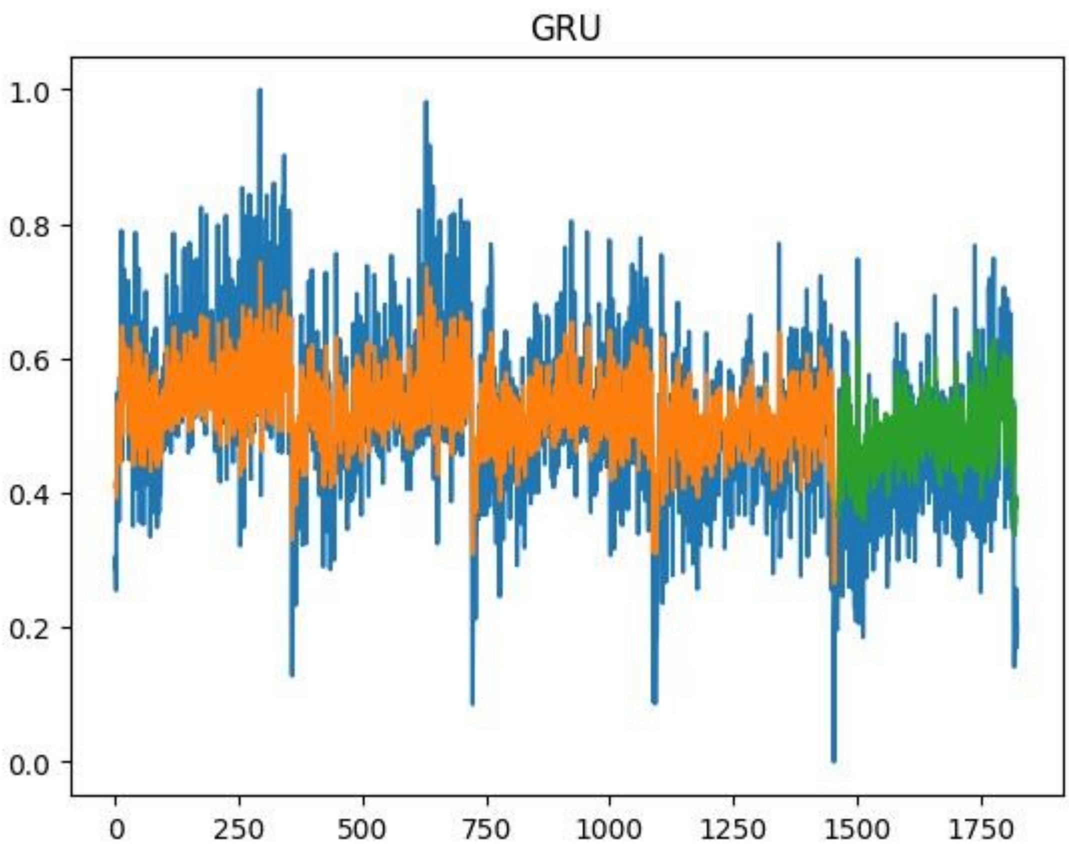

Figure 6: GRU

Task Schedule

Name	Tasks
Abdullah AlOwais	EDA , Cleaning
Reshoof Alzweaid	EDA , Report
Maryam Jathmi	Model training , Presentation

Conclusion

In conclusion, our Time Series of Number of Casualties project has successfully developed a predictive model that estimates the number of casualties for the upcoming month using historical data on accident dates and casualty figures. By leveraging this model, we can anticipate future casualty numbers with greater accuracy, providing valuable insights for traffic safety authorities and policymakers. This forecasting capability enables more effective planning, resource allocation, and targeted safety interventions, ultimately contributing to enhanced road safety and reduced accident impacts. The project demonstrates the power of data-driven predictions in addressing road safety challenges and underscores the importance of proactive measures in mitigating risks and improving public safety outcomes .