Capstone Project Report - Impact of America's Involvement in Global Wars on United States GDP

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Github: https://github.com/sairin94/war-economic-prediction

Project Statement

Gross Domestic Product (GDP) is a crucial indicator in the economy of the United States and it represents the total dollar value of all goods and services produced over a specific time period and is an important measure of the overall economic activity within a country. The project titled "Impact of America's Involvement in Global Wars on United States GDP" aims to analyze and understand the multifaceted effects that U.S. involvement in major global conflicts (Korean War, Vietnam War, Persian Gulf War, War in Afghanistan, Iraq War and Russia Ukraine War) has had on the nation's economic growth and stability, as measured by GDP. This project employs a data analysis and a sophisticated deep learning model, which has been trained on historical economic data along with a range of economic indicators such as Consumer Price Index (CPI), Unemployment Rate (UNRATE), Personal Savings, Inflation Rate, Gross, Personal Consumption Expenditures (PCE), Gross Savings, Gross Saving as a Percentage of Gross National Income, Gross Domestic Investment, Net Saving as a Percentage of Gross National Income, military spending and Federal Funds Rate (FED FUNDS). A crucial boolean variable 'war' is added to show U.S. involvement in war. The primary focus of this project is to use the model to predict the U.S. GDP under varying scenarios of war involvement. By altering the war variable between 0 (no involvement) and 1 (active involvement), the project aims to observe and analyze the corresponding fluctuations in the predicted GDP. The overarching aim of the project is to understand whether America's involvement in global war has a significant effect on the GDP of the country.

Broader Impact Statement

The analysis and predictions regarding key economic metric GDP has broad implications for a diverse audience. Audiences who will find this study particularly insightful include economists, economic policy makers, historians, political scientists, investors, financial analysts, government officials, academics, students in related fields, and the general U.S. consumer base. Each group stands to gain a deeper understanding of the economic consequences of global conflicts, aiding in informed decision-making and enhancing knowledge in their respective fields.Lastly, the general U.S. consumer stands to gain a clearer picture of how global events can impact their economic environment, aiding in personal financial planning and understanding of the broader economy.

Ethical Concern

In the context of the project "Impact of America's Involvement in Global Wars on United States GDP" project, two key ethical issues merit close attention. Firstly, the potential for bias in the deep learning model is a significant concern. The model's ability to provide unbiased predictions hinges on the neutrality and representativeness of the data and algorithms it utilizes. Given the historical nature of the data encompassing various global conflicts and economic indicators, there's a risk that inherent biases in data collection, historical perspectives, or algorithmic design could skew results, potentially leading to misleading conclusions about the relationship between war involvement and GDP. This necessitates a vigilant approach to data selection and model programming. Secondly, the ethical use of data in such sensitive areas as war and economics requires a high degree of transparency and accountability. It's imperative that the methodologies, data sources, and inherent limitations of the study are communicated clearly and openly. This transparency is crucial to prevent misinterpretation of the findings and to ensure that the conclusions drawn from the project are used responsibly and ethically, respecting the complex interplay of economic, historical, and geopolitical factors.

Methods

Literature Review:

We possess a high-level understanding of what we aim to accomplish, but we need to explore how the academic community has approached the problem. To understand the effect of war on GDP, we have explored similar studies in this subject as listed below.

The paper "Economic Consequences of War on the U.S. Economy" by the Institute for Economics and Peace provides a foundational historical perspective. It meticulously analyzes the macroeconomic effects of U.S. government war spending since World War II, covering several major conflicts. The focus on the impacts of war financing on various economic factors like consumption, investment, unemployment, deficits, and inflation offers invaluable insights into the long-term economic patterns resulting from war involvement.

Tianyi Wang et al. in their paper "Recursive Deep Learning Framework for Forecasting the Decadal World Economic Outlook" offer a significant contribution by developing a deep learning framework to predict the GDP growth rate, including that of the United States. Utilizing data from 1980 to 2019 across 13 countries, their study tests multiple deep-learning models, with the LSTM model demonstrating superior performance.

Ali Lashgari's "Harnessing the Potential of Volatility: Advancing GDP Prediction" introduces an innovative machine learning approach to GDP prediction, which could be adapted to factor in the economic implications of war. By incorporating volatility as a model weight, this approach selects relevant macroeconomic variables for accurate GDP forecasting.

These literatures thus provide a comprehensive backdrop against which the project's models can be developed and refined.

Data Collection and Cleaning

The project involves gathering data on various macroeconomic factors such as the Consumer Price Index (CPI), Unemployment Rate (UNRATE), Personal Savings, Inflation Rate, Gross Domestic Product (GDP), Personal Consumption Expenditures (PCE), Gross Savings, Gross Saving as a Percentage of Gross National Income, Gross Domestic Investment, Net Saving as a Percentage of Gross National Income, military spending and the Federal Funds Rate (FED FUNDS). These datasets are sourced from multiple publicly accessible platforms, including the Fred Economic Data, Bureau of Labor Statistics, and Bureau of Economic Analysis.

Several challenges were encountered during the data cleaning process:

1. Varying Data Frequencies: The data received from different sources have varying frequencies. For instance, the Federal Funds Rate and Unemployment Rate are available on a monthly basis, Inflation Rate data are provided annually, while GDP, Gross Domestic Savings, Gross Investment, and Personal Consumption data are updated quarterly.

2. Presence of Missing Data: There are instances of missing data for certain years, months, or quarters due to unavailability in the referenced data sources.

3. Inconsistent Formats and Data Types: The data sources vary in format, and there are inconsistencies in the data types used. For example, dates are sometimes categorized as objects instead of the proper datetime format, and numerical columns are not always correctly labeled, posing challenges in data interpretation and usage.

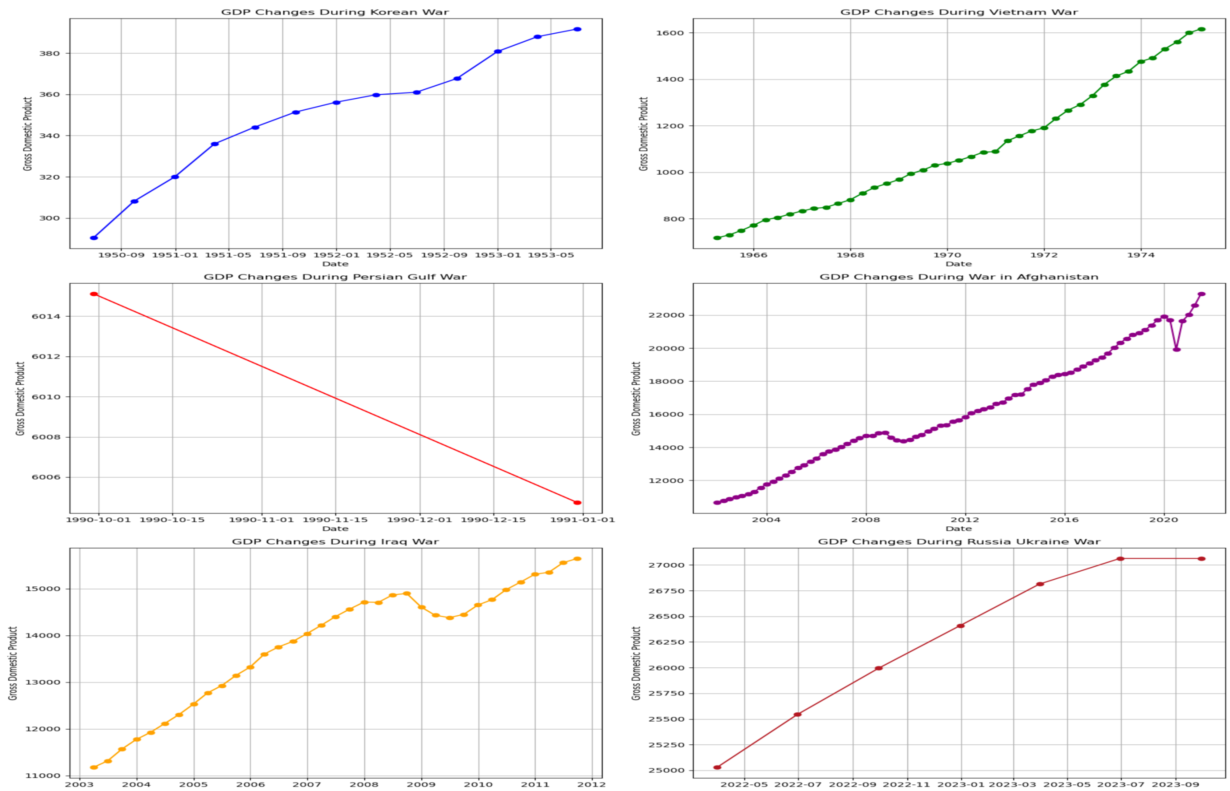
These challenges were meticulously addressed through a thorough cleaning and aggregation process, consolidating the data on a quarterly basis. The cleaned and aggregated data were then stored in a CSV file (war_final.csv) for subsequent analysis and modeling. The final aggregated dataset is compact, comprising approximately 307 records, making it manageable and efficient for detailed analysis and modeling.

Exploratory Data Analysis

Analysis of Impact Of Wars On Country's GDP

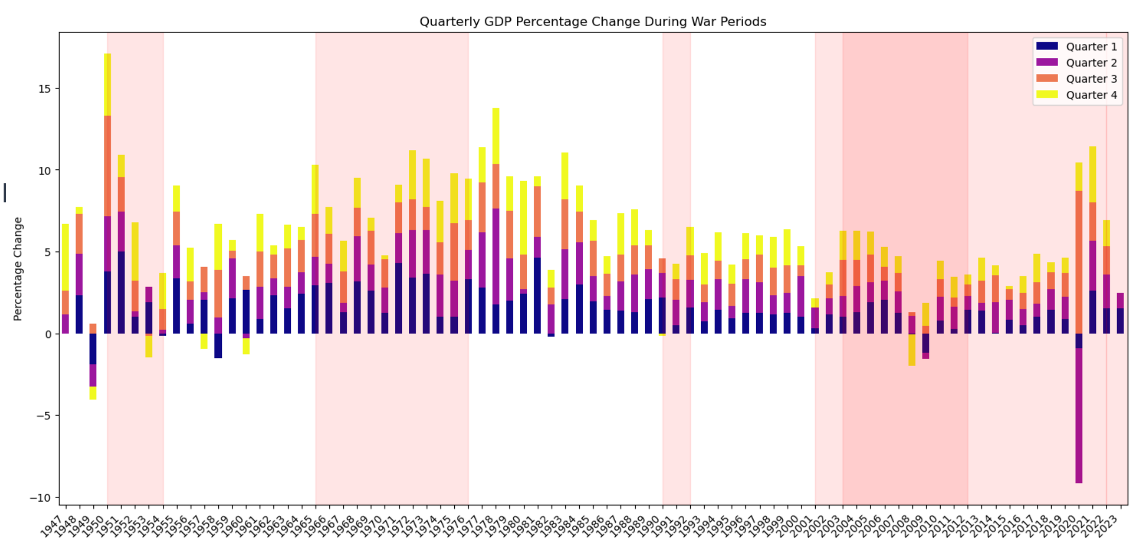
1. It can be seen from Figure 1, a steadily increasing GDP trend during several conflicts. These conflicts include the Korean War, Vietnam War, War in Afghanistan, Iraq War and Russia Ukraine War. However there was a notable dip in GDP during some periods of War in Afghanistan and Iraq War. Additionally there was a decreasing trend during the Persian Gulf War.

Figure1



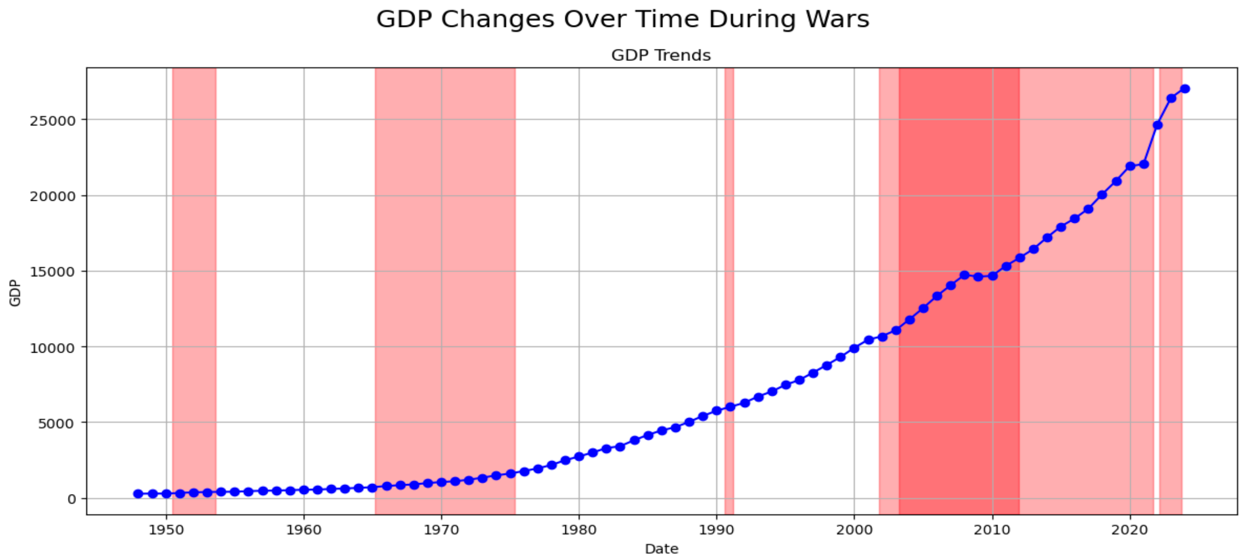
2. Figure 2 below shows the volatility of GDP growth across different quarters over multiple decades, with periods of war highlighted in light red shade. There is no consistent pattern; some war periods correspond with economic expansion, others with contraction.

Figure 2



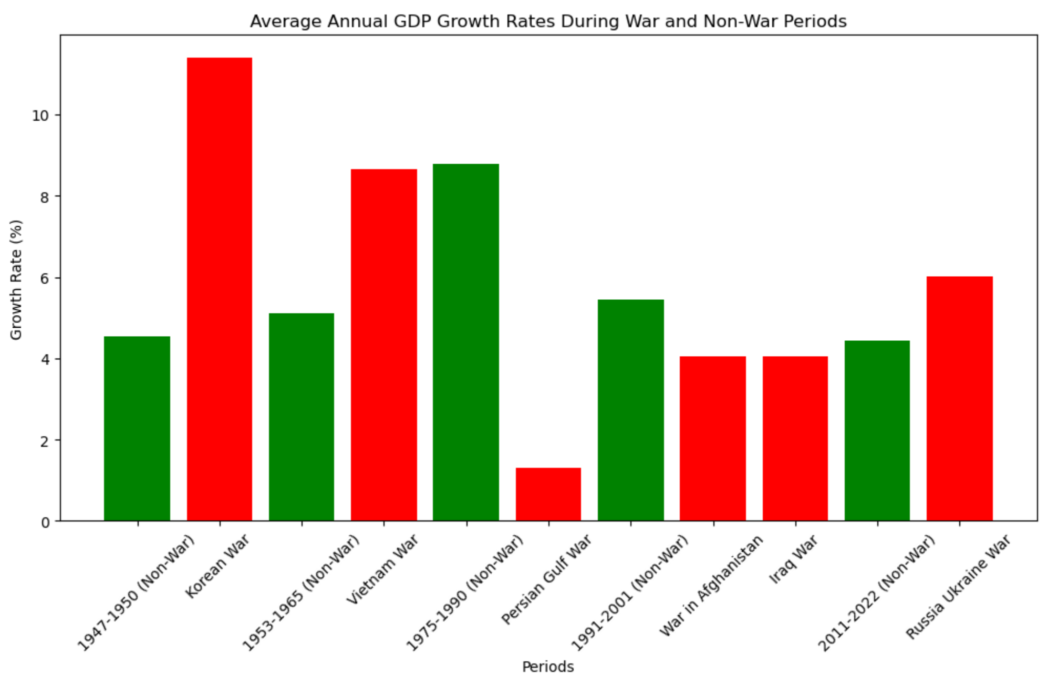
3. Figure 3 shows the overall trend of GDP during wars with periods of war highlighted in light red shade. The overall graph shows an upward trend in GDP growth.

Figure 3



4. The bar chart in Figure 4 shows that war periods (red bars) generally correspond with higher annualized GDP growth rates than non-war periods (green bars), suggesting a wartime economic boost. Non-war periods show a consistent baseline growth rate, while war periods like the Korean War display notable peaks in growth. However, the Persian Gulf War is an anomaly with lower growth than surrounding non-war periods. The recent "Russia Ukraine War" period exhibits a heightened growth rate, aligning with the historical pattern of war-time economic upsurge.

Figure 4:

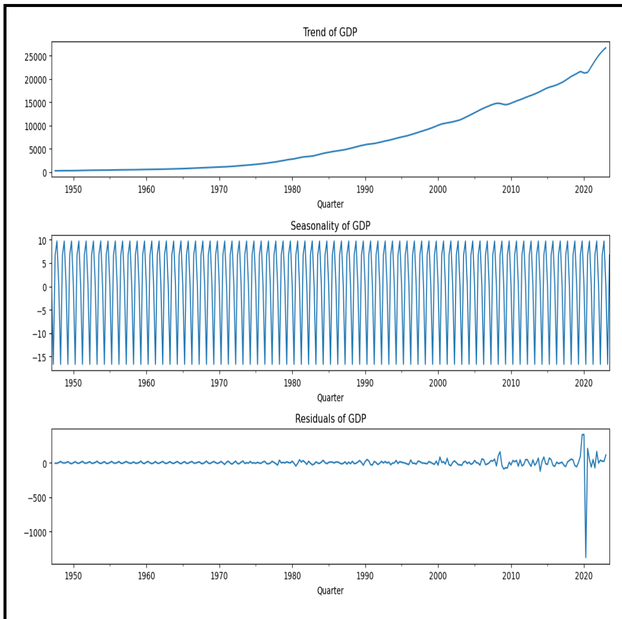


Supervised Deep Learning Modelling

1. Analysis of target variable ‘GDP’ before modeling

I applied trend-seasonality-residual analysis plot and Augmented Dicky Fuller test as shown in figure 5, and from there it can be concluded that the target variable of prediction ‘GDP’ is highly nonlinear and non-stationary.

Figure 5



Augmented Dicky Fuller Test

```
ADF Statistic: 8.099528374671129
p-value: 1.0
Critical Values:
        1%: -3.452
        5%: -2.871
        10%: -2.572
The series is likely non-stationary.
```

2. Experimental set up for Modeling

The primary objective of having deep learning models such as LSTM, GRU, and 1D CNN in this project is to predict GDP of the country under three distinct scenarios: 1. No involvement of the US in war (hypothetical peace), 2. America’s involvement only during global war periods and 3. Country’s always involved in war (hypothetical conflict). This prediction is achieved through multivariate time series analysis, incorporating various other factors like Consumer Price Index (CPI), Unemployment Rate (UNRATE), Personal Savings, Inflation Rate, Gross Domestic Product (GDP), Personal Consumption Expenditures (PCE), Gross Savings, Gross Saving as a Percentage of Gross National Income, Gross Domestic Investment, Net Saving as a Percentage of Gross National Income, military spending and Federal Funds Rate (FED FUNDS). LSTM / GRU prove advantageous in this scenario due to their capacity to preserve and utilize past data over prolonged durations, which is essential for preventing the loss of crucial information vital to making precise predictions. LSTM / GRU, with their unique architecture featuring cell states and gating mechanisms, excel in remembering and leveraging long-term dependencies. This capability ensures that vital historical data, like past economic trends, is not lost but is instead used effectively for making more accurate and reliable GDP prediction, capturing the complex

dynamics of economic indicators over time. A sliding window approach has been employed on the input sequence with defined timesteps so that the model can effectively capture temporal interdependencies among the macroeconomic features. Windows of 5 years (20 quarters) as time steps determined using hyperparameter tuning have been chosen to predict the target label at the end of each window. Having at least this amount of data within each window is crucial for the model to discern and learn patterns in the multivariate time series data.
In addition to LSTM and GRU, I experimented with 1D CNN due to its proficiency in extracting local and temporal features from multivariate time series data. This capability enables it to identify key patterns, such as short-term economic fluctuations. As the size of the dataset is small, a simple set up is done with one hidden layer to prevent overfitting.

Example Set Up (Features Window Size = 20 Quarters determined through hyperparameter tuning)

LSTM	**GRU**	**1D CNN**
LSTM Model Structure: (Sequential) (LSTM): LSTM(input_shape=(window, features), units=num_nodes,, activation=activation, kernel_initializer=init_mode) (Dropout): Dropout(rate=drop_out) (Dense): Dense(units=1)	GRU Model Structure: (Sequential) (GRU): GRU(input_shape=(window, features), units=num_nodes,, activation=activation, kernel_initializer=init_mode) (Dropout): Dropout(rate=drop_out) (Dense): Dense(units=1)	CNN Model Structure: (Sequential) (Conv1D_1): Conv1D(input_shape=(window, features), filters=num_nodes, kernel_size=kernel_size, activation=activation, kernel_initializer=init_mode) (Dropout): Dropout(rate=drop_out) (Flatten): Flatten() (Dense): Dense(units=1)

3. Hyperparameter Tuning And Model Selection

1. To perform robust time series analysis, 90% of total data records (307) were allocated to the training set, ensuring substantial data for learning economic indicator patterns impacting GDP. The model trains on this historical data in chronological order for accurate future predictions. The data is further split, with 10% of the training data forming a validation set for hyperparameter tuning and performance assessment without bias. The final 10% is a test set, chronologically following the training set to evaluate the model's real-world predictive capabilities and avoid data leakage. This structure maintains chronological integrity vital for time series prediction.

2. To facilitate the training of multiple models, I developed custom functions (model_training.py). This modularized function streamlines the process, enabling me to efficiently read the data and fit various models using straightforward commands. This approach significantly enhances the conciseness of my code and minimizes repetitive tasks. This efficient setup not only optimizes my workflow but also ensures that I can focus on analysis and improvement without being hindered by technical redundancies.

3. Models (LSTM/GRU) were fitted to the training set and the defined search space for the Gridsearch instance was the following:

```
param_grid = {
    'num_nodes': [8, 16, 24, 32],
    'learning_rate': [0.0001, 0.001, 0.01],
    'batch_size': [1, 4],
    'activation': ['relu', 'tanh', 'sigmoid'],
    'drop_out': [0.1, 0.2, 0.6, 0.8],
    'init_mode': ['glorot_uniform', 'uniform', 'normal', 'glorot_normal'],
    'optimizer': ['SGD', 'Adam']
 }
```

The LSTM and GRU models are quite a bit slower and applying all parameters in the grid takes a long time so a very simple set of two/three configurations has been set up to explore. Results are shown in below three tables:

Table 1

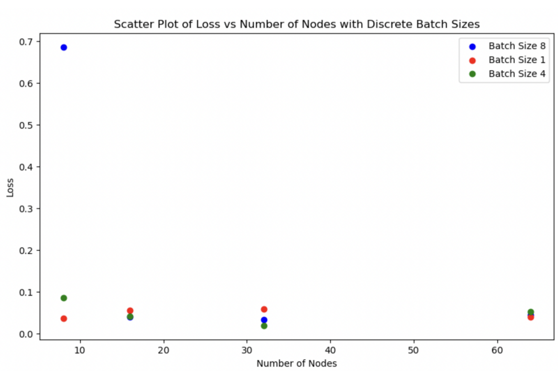
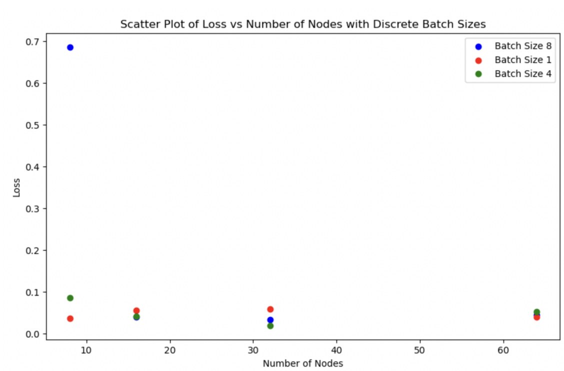
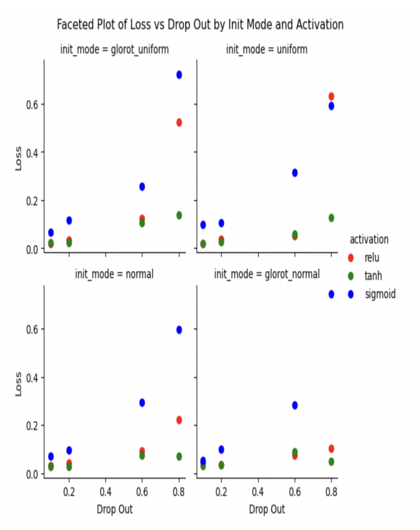
Hyperparameter Tuning On num of nodes and batch size	**Hyperparameter Tuning on Learning rate and Optimizer**
	

Table 2

<table>
<tr><th>Hyperparameter Tuning On Dropout, Activation and Weight Initialization</th><th>Hyperparameter Tuning On Learning_rate and Optimizer</th></tr>
<tr><td>


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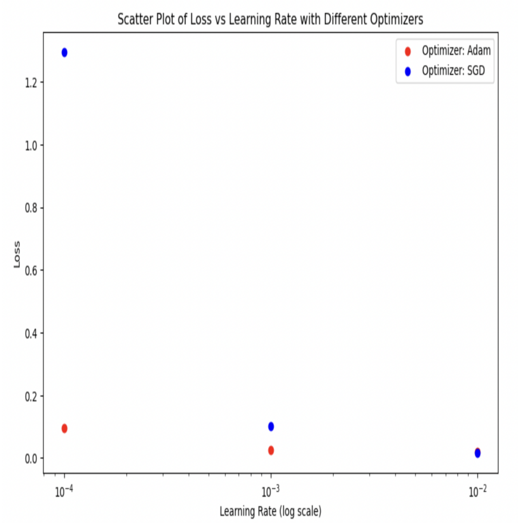

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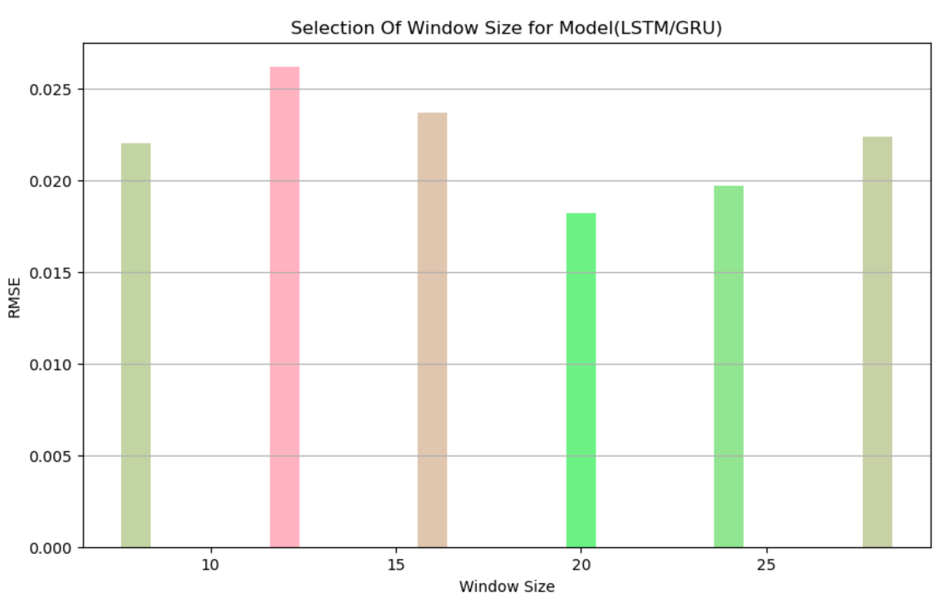
Table 3:

<table>
<tr><th>Hyperparameter Tuning To Determine Length Of Sliding Window On Input Sequence</th></tr>
<tr><td>


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</table>

4. Model 1D CNN was fitted to the training set and the defined search space for the Gridsearch instance was the following:

```
param_grid = {
    'num_nodes': [8, 16, 24, 32],
    'learning_rate': [0.0001, 0.001, 0.01],
    'batch_size': [1, 4],
    'activation': ['relu', 'tanh'],
    'drop_out': [0.1, 0.2, 0.6, 0.8],
    'init_mode': ['glorot_uniform',  'glorot_normal'],
   'optimizer': ['SGD', 'Adam'],
   'kernel_size':[2,3,5]


}
```

Table 4:

Hyperparameter Tuning On Number Of Nodes And Batch Size

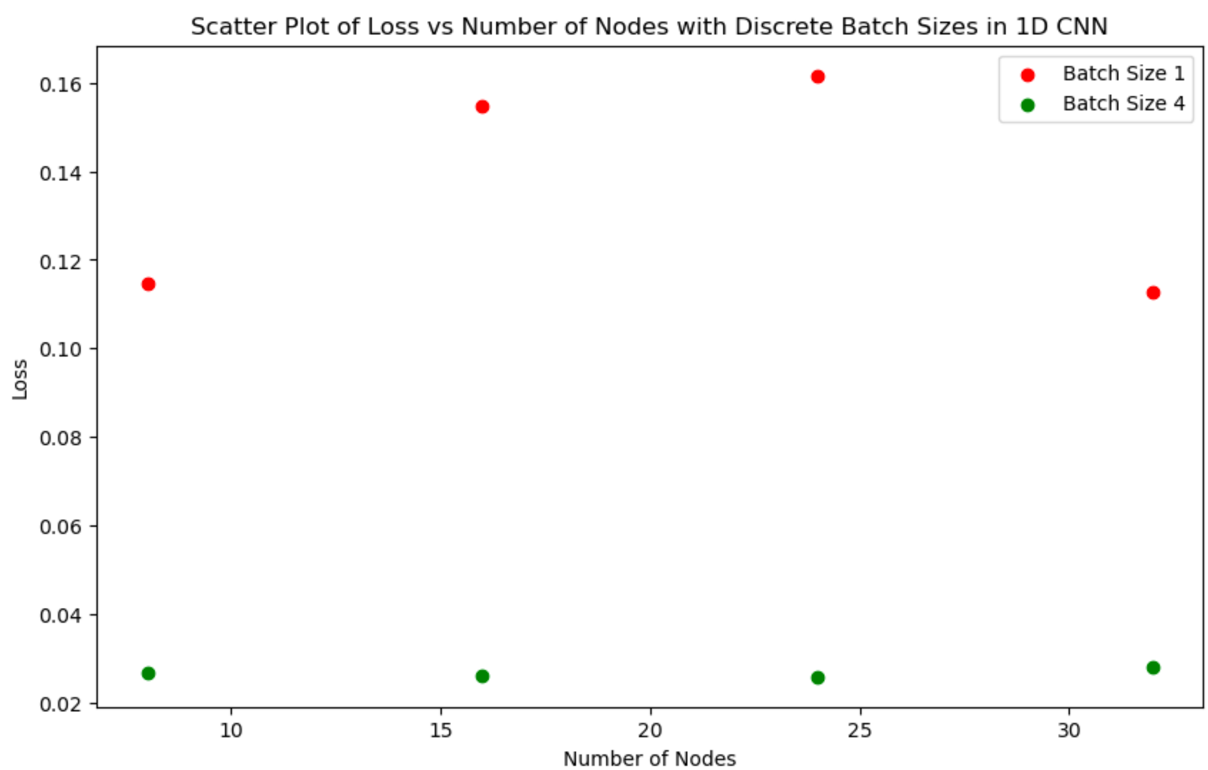


Table 5

Hyperparameter Tuning On learning_rate, optimizer and activation Function

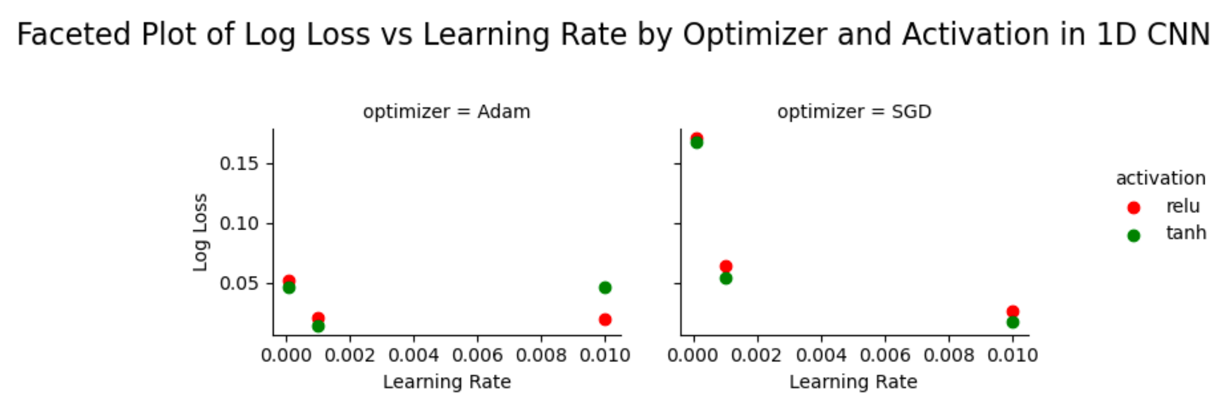


Table 6

Hyperparameter on kernel_size, drop_out and weight initialization

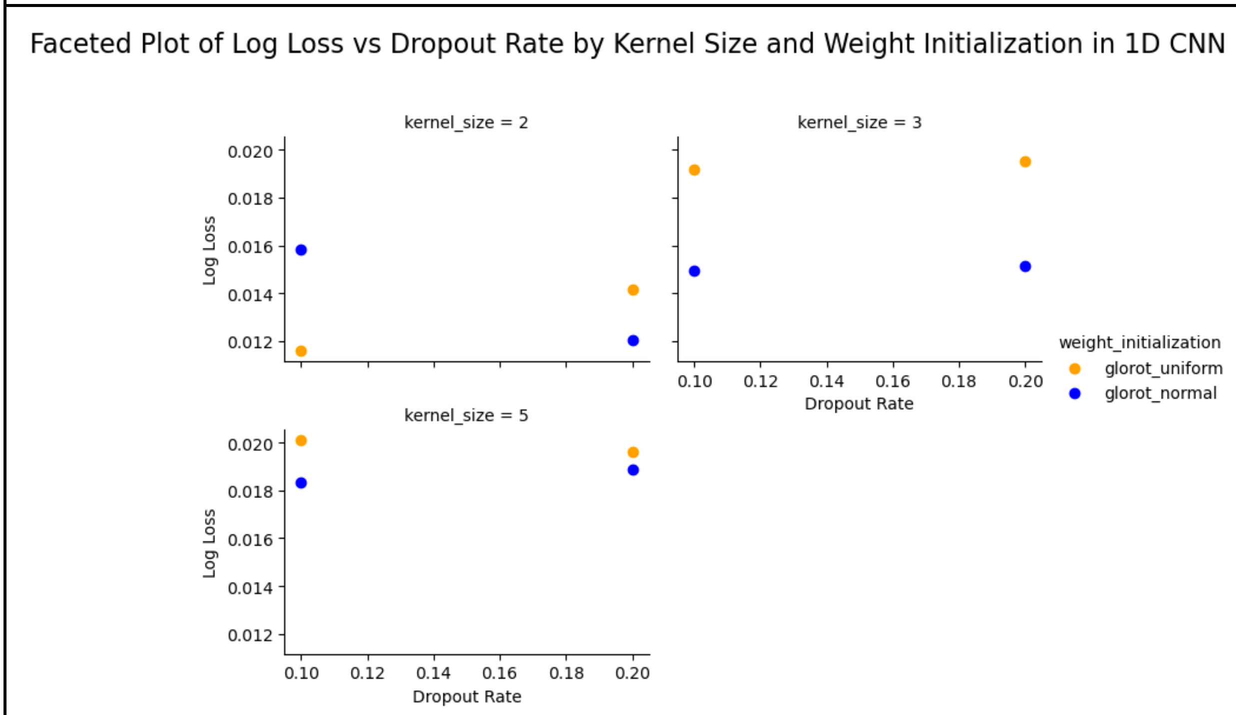
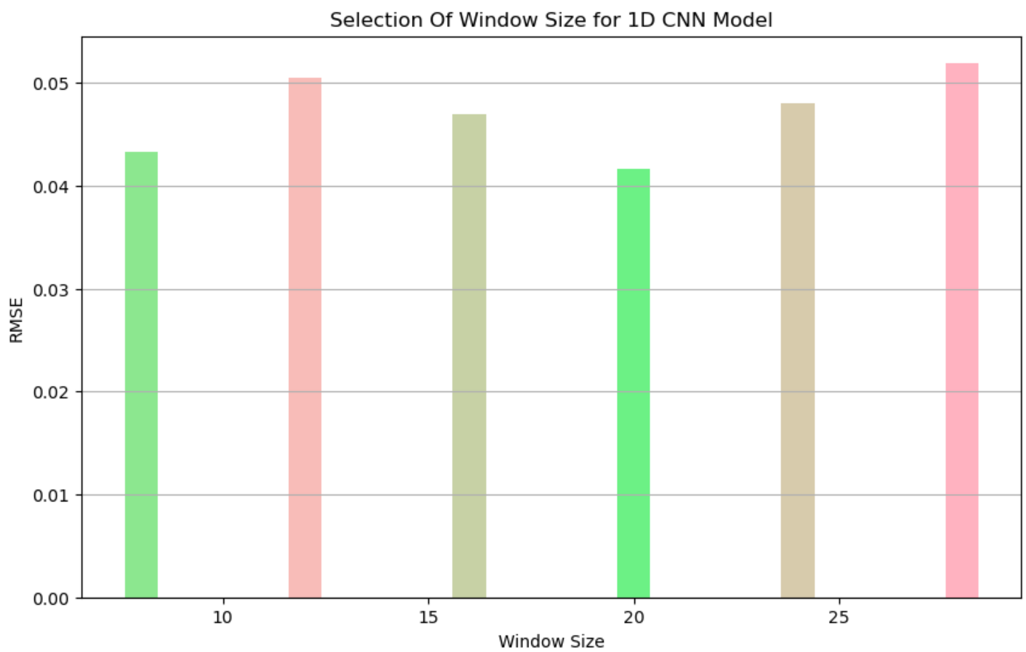


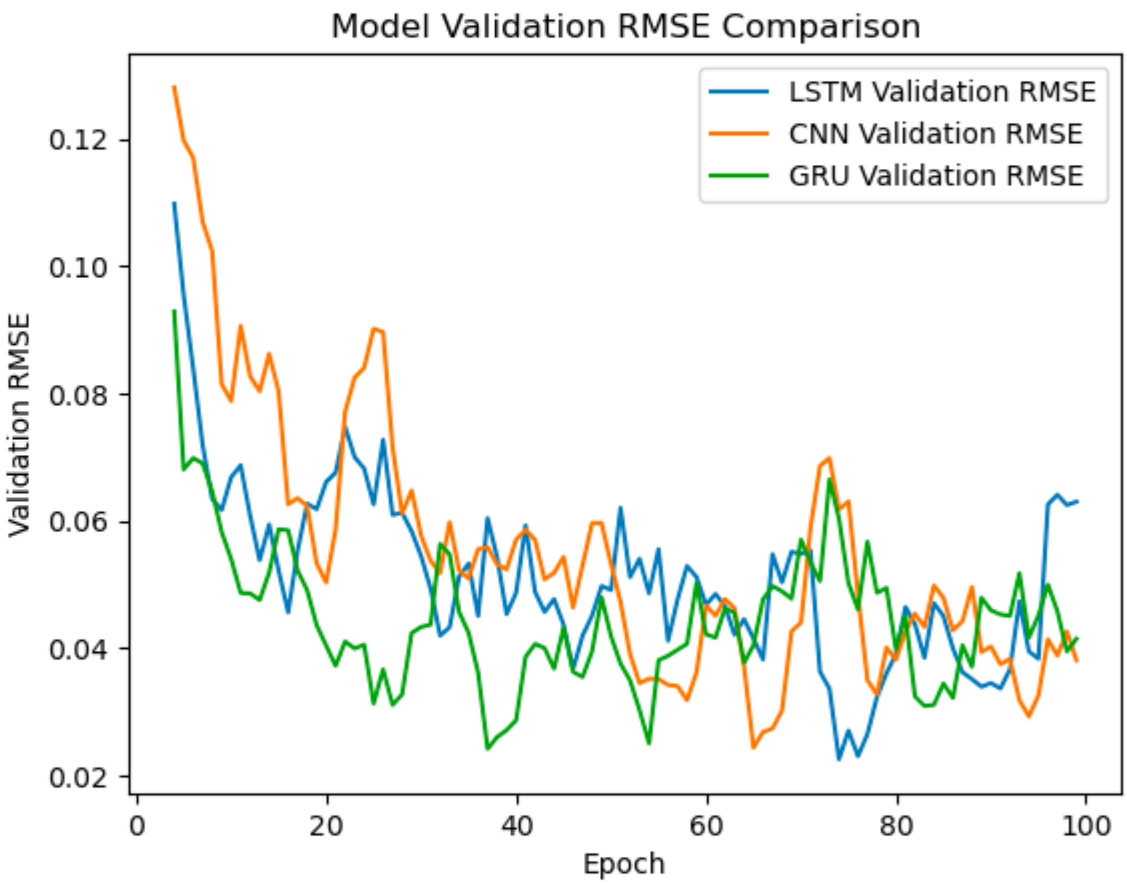
Table 7

Hyperparameter Tuning To Determine Length Of Sliding Window On Input Sequence



6. Based on the graphs above, I inferred the trend of each variation of parameter, which tends to decrease loss and then chose the hyperparameters for optimal training loss.

7. Once I obtained the optimal parameters for models through hyperparameter tuning, as discussed previously, I proceeded to train models for 100 epochs using these optimal settings. By employing early stopping with a patience of 10 epochs (concludes training after waiting for 10 epochs and see that if the validation loss is still increasing, this takes care of noise in validation RMSE score), it was determined that the sweet spot for models (LSTM/GRU) is 46 epochs whereas for CNN it is 50 epochs. Among all models, GRU exhibited the best performance, as shown in the results below.



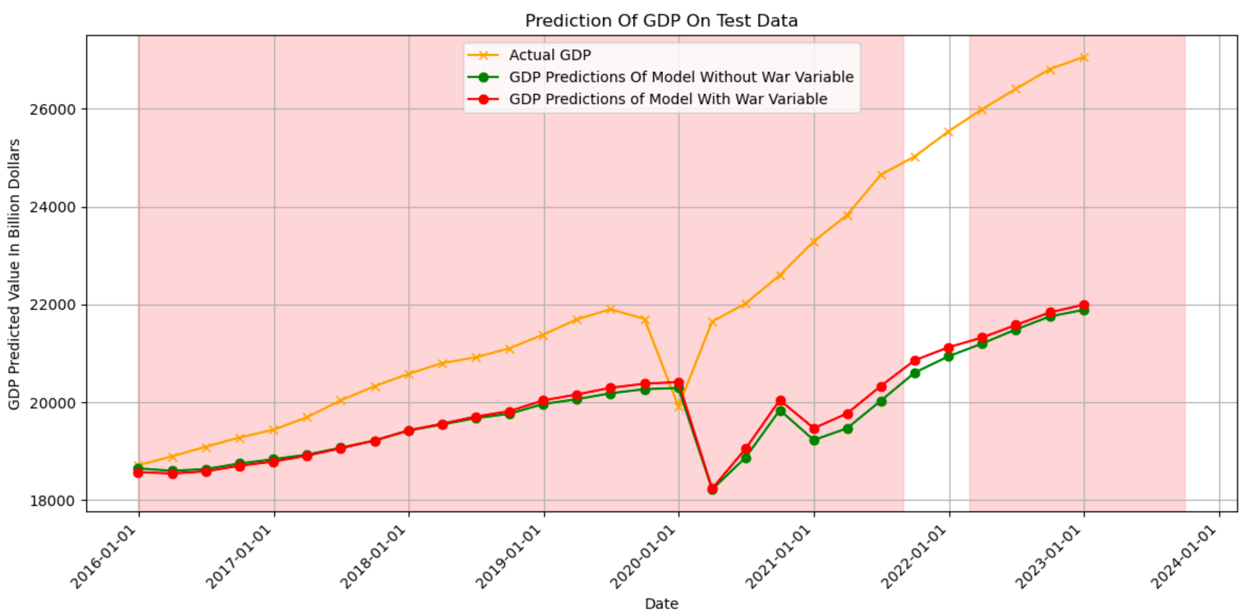
Rank	Model	Specifications	Validation RMSE
1.	GRU	window_size=20 quarters, features=12, epoch=46, hidden layers=1, num_nodes=24, batch_size=4, learning_rate=.001, optimizer='Adam',dropout rate=0.1, activation='tanh, init_mode='glorot_uniform'	0.046
2.	LSTM	window_size=20 quarters, features=12, epoch=46, hidden layers=1, num_nodes=24, batch_size=4, learning_rate=.001, optimizer='Adam',dropout rate=0.1, activation='tanh, init_mode='glorot_uniform'	0.052
3.	1D CNN	window_size = 20 quarters, features=12, epoch=50, hidden layers=1, num_nodes=24, batch_size=4, learning_rate=.001, optimizer='Adam',dropout rate=0.1, activation='tanh, init_mode='glorot_normal'', kernel_size=2	0.056

Evaluation Of Rank1 Model By Adding New Feature ‘War’

Comparative Analysis Between New Model With War And Old Model Without War

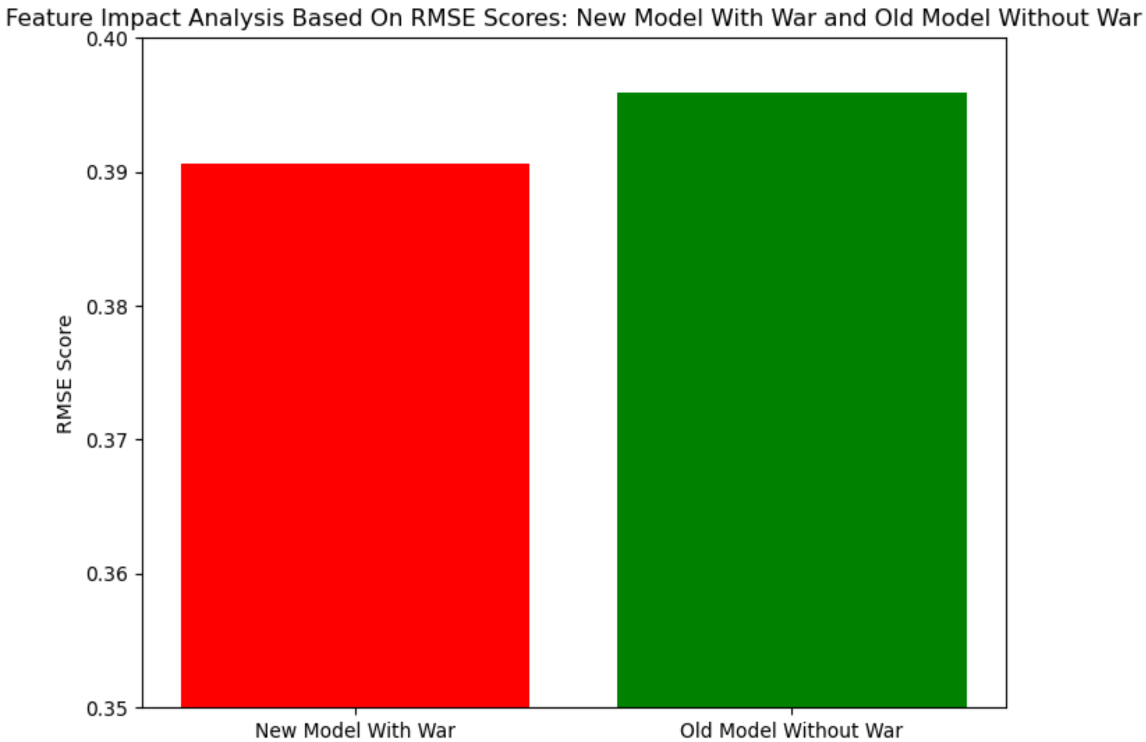
1. A new feature named ‘war’ has been added to the rank 1 model, which takes a boolean value. It is set to '1' during times of American involvement in global wars, including the Korean War (1950-06-25 to 1953-07-27), Vietnam War (1965-03-08 to 1975-04-30), Persian Gulf War (1990-08-02 to 1991-02-28), War in Afghanistan (2001-10-07 to 2021-08-30), Iraq War (2003-03-20 to 2011-12-18), and the Russia-Ukraine War (2022-02-24 to an assumed end of 2023-12-31). It is set to '0' during periods when the country is not engaged in wars. The model, now with 13 features instead of the previous 12, has been retrained and evaluated on unseen test data for prediction using a custom function (model_evaluation.py). The resulting line chart plots GDP predictions over time due to US engagement in global wars, with a red line and light red shading the periods of war. Despite some fluctuations, the model predicts an overall increasing trend in GDP during times of war as presented in figure 6.

Figure 6



2. To evaluate feature impact analysis as shown in figure 7, two iterations of the Rank 1 Model were compared: one trained with 12 features and another trained with an additional 13th feature i.e ‘War’. The performance of both models was evaluated on unseen test data, with the test RMSE score serving as the metric for comparison. The objective was to ascertain which model more accurately predicts the country's GDP. The model trained with 13 features, which includes the 'war' variable, demonstrated superior predictive performance. This outcome indicates that the inclusion of the 'war' feature improves GDP prediction, leading to the conclusion that America's involvement in global conflicts has a notable impact on GDP.

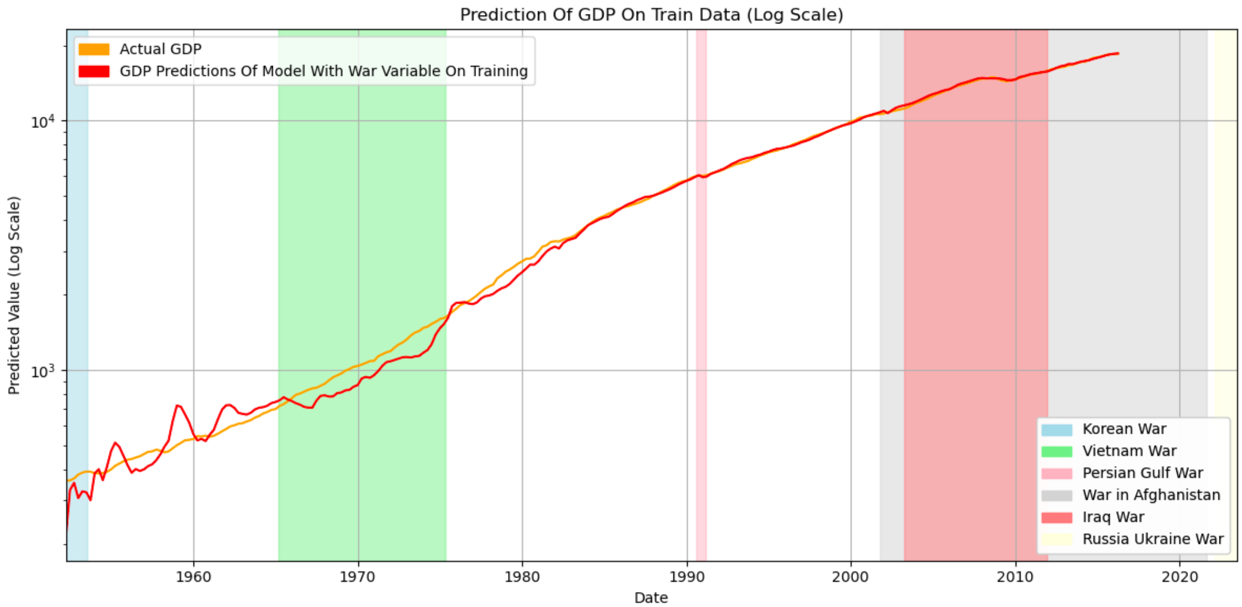
Figure 7



Failure Analysis

Predictions of models hinges heavily on the quality and completeness of the underlying data. During historical periods such as the Korean and Vietnam Wars, economic indicators like unemployment rates, federal funds rates, military spending, and inflation rates play pivotal roles in shaping a country's economic landscape. I have plotted model prediction on GDP against historical data contained in the training set and observed that the model failed to predict GDP impact during the Korean War and Vietnam War as shown in figure 8. The root cause of this failure is due to lack of comprehensive data present in the official website on economic indicators (UNRATE, Fed Funds, Military Spending and Inflation Rate) during that period in the training phase. If the dataset a model is trained on lacks this crucial information the model's ability to generate reliable prediction is significantly undermined. So, I think that the absence of detailed, accurate historical economic data impedes the model's learning process, resulting in predictive discrepancies.

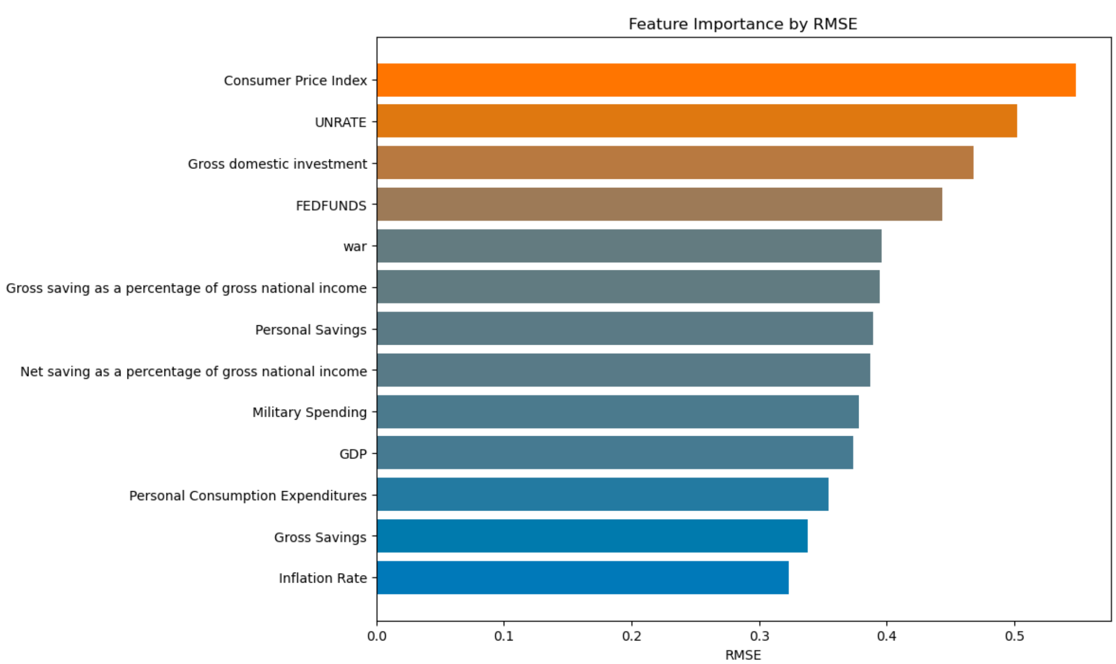
Figure 8



Feature Importance

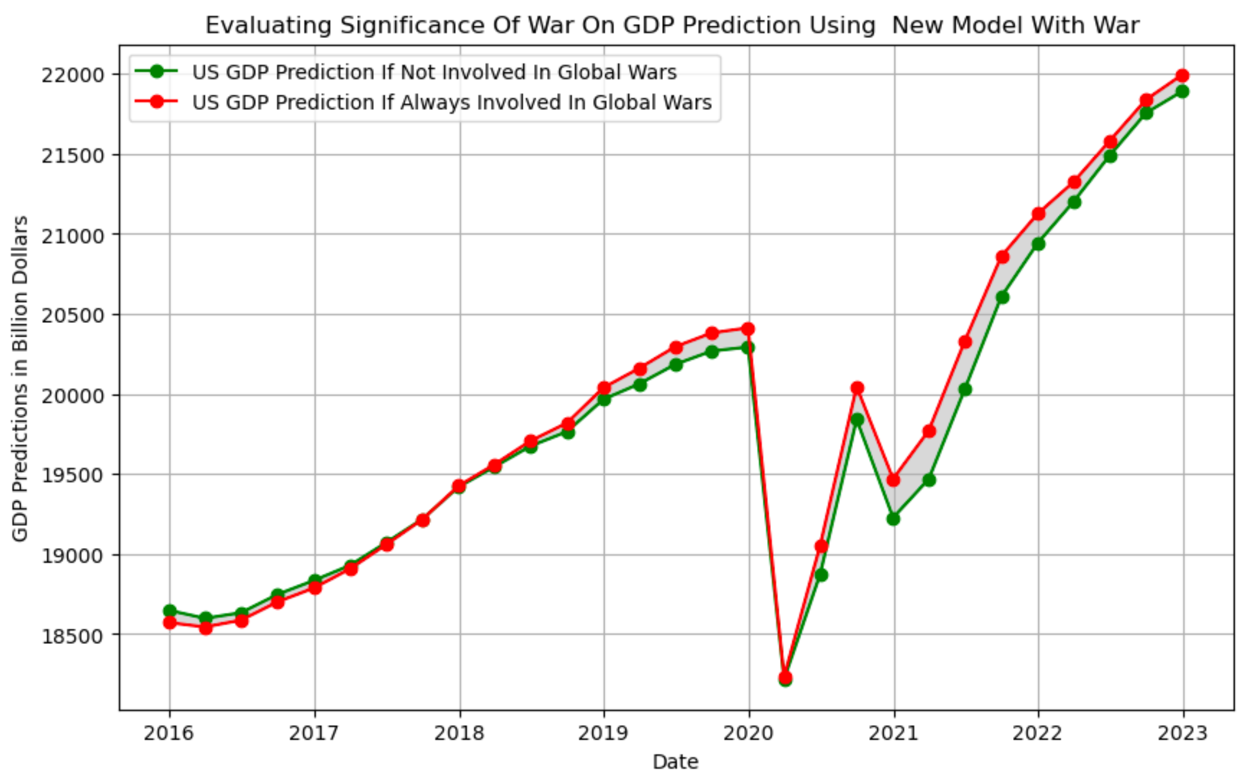
To determine the relative importance of features in the model as shown in figure 9, each feature was omitted one at a time during training while keeping all other features constant. The impact of each feature on model predictions was measured using the test RMSE (Root Mean Square Error) score. Features resulting in the highest increase in the RMSE score when removed were considered the most significant, indicating that the absence of these variables leads to poorer model predictions on unseen test data. This method ranks features by their contribution to the model's predictive accuracy, with a higher RMSE score signifying greater importance. These have been captured in a horizontal bar chart. Here it can be seen from the graph that 'war' plays an important role in the model's prediction (US GDP) being 5th important variable among all.

Figure 9



The final trained model has been applied to two hypothetical scenarios as presented in figure 10 for inference: 1. America is perpetually engaged in war, achieved by setting the 'war' variable to '1' for all instances regardless of the country's actual involvement in conflicts, and 2. America is never engaged in war, this time by setting the 'war' variable to '0' in all instances, again irrespective of actual war engagements. The purpose of this simulation is to assess which scenario would theoretically benefit the country's GDP the most. Based on the graph generated from the model's predictions under these two scenarios, it has been observed that the model suggests the country's GDP would benefit more if the country were to remain in a state of constant war engagement. However, this is a simplified projection and actual economic outcomes of war involve complex factors beyond the scope of the model.

Figure 10



Conclusion

The analysis and deep learning models employed in this study suggest a generally positive impact between America's involvement in global conflicts and its GDP growth. This is aligned with article 1 in literature review which states that there is a boost in GDP due to governmental spending on military activities. This research was conducted using a selected set of macroeconomic variables to predict GDP. It is important to note that the GDP is influenced by a multitude of macroeconomic factors. The inclusion of additional variables could potentially alter the model's predictions. More data and more sophisticated analytical techniques may be required for enhanced predictive accuracy. However, our findings are promising and indicate that wartime activities can have a beneficial economic impact.

Statement Of Work

Name	Task
Sairindhri Bhattacharya	Individual Contributor to the whole project

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