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Forecast Recession: A Comparative Study of Economic Forecasting Methods for the COVID-19 Impact

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Abstract

The global economy has faced unprecedented disruptions due to the COVID-19 pandemic, underscoring the critical need for robust and adaptable predictive models. This study evaluates the effectiveness of advanced predictive models in forecasting economic conditions during such crises, focusing on two significantly impacted economies: the United States and Italy. A range of models was utilized in our study, such as XGBoost, Spatial Lag Models (SLM), Random Forest, and Long Short-Term Memory (LSTM) networks. Through rigorous application of time series differencing and feature selection techniques, we aimed to improve model performance and capture the unique economic disruptions caused by COVID-19. This study offers insights into the ongoing improvement and broadening of predictive models to boost their robustness and applicability during global disruptions.

Keywords

COVID-19, Economic Forecasting, XGBoost, Spatial Lag Model, Random Forest, LSTM Networks

1. Introduction

An economic recession generally signifies a substantial downturn in a region's overall economic activity, commonly measured by two successive quarters of decline in its Gross Domestic Product (GDP). Beyond the GDP numbers, the repercussions of a recession are seen in sustained declines in real income, job weakening, reduced retail sales, decreased consumer confidence, and numerous other economic sectors. The comprehensive impact of a recession is profound and multifaceted, affecting both economic stability and societal well-being in complex ways.

COVID-19, a novel coronavirus not previously identified in humans, has delivered a unique and deep shock to the world economy, impacting demand and supply chains across numerous sectors, distinguishing itself from typical downturns often triggered by financial imbalances or shifts in economic policy. The COVID-19 crisis caused simultaneous disruptions in supply due to factory closures and quarantine measures. Additionally, consumer spending dropped while savings rose. In studies by Ludvigson et al. (2020) and Baker et al. (2020), the economic shock induced by the pandemic is similar to that seen during the Great Depression, marked by a swift and substantial rise in unemployment and pervasive economic uncertainty.

Studying post-COVID-19 data is essential for comprehending the peculiar qualities of this disruption compared to prior downturns. Analyzing post-COVID-19 data yields an understanding of how various industries and economies adapt to concurrent supply and demand disturbances. Shaping robust anticipatory frameworks from these examinations provides insights into planning for future global events similar to COVID-19, ensuring preparedness and resilience.

This paper aims to assess the performance of various advanced predictive models in the context of COVID-19, focusing on two significantly impacted economies: the US and Italy. The United States was chosen due to its significant economic and health impacts from the pandemic, making it a critical case study for understanding the broader economic repercussions. Between February 2020 and May 2022, the deaths of one million Americans from COVID-19 led to a considerable decrease in life expectancy and an estimated economic welfare loss of US$3.57 trillion (Silva et al., 2023). On the other hand, as of 2022, 24% of the Italian population was aged 65 and above, compared to 18% in the United States (United Nations Population Division, 2022). This difference may contribute to the increased vulnerability and higher mortality rates during the pandemic. Moreover, Italy's economy is highly integrated into the global market. By 2019, exports of goods and services as a percentage of GDP are 31.6% (World Bank, 2023) and imports of goods and services as a percentage of GDP are 28.3% (Imports of goods and services, 2023). As the pandemic caused factory closures, shipping delays, and decreased global demand, Italy's trade-dependent sectors experienced substantial downturns.

We use a wide variety of predictive models, from straightforward statistical approaches like Spatial Lag Models to machine learning, such as XGBoost and LSTM networks. Each model offers unique strengths: Spatial Lag Models effectively understand spatial dependencies, making them ideal for capturing the geographic spread and regional impacts of COVID-19; XGBoost excels in handling structured data with high accuracy, making it particularly suited for the complex and multifaceted nature of COVID-19 economic data; and LSTM networks are proficient in capturing temporal dependencies in time-series data, making them well-suited for modeling the sequential patterns of economic trends impacted by the pandemic. The importance of these models and the rationale for their evaluation will be discussed in detail in Section 4.

The rest of the paper starts with a review of the related studies, focusing on the economic forecasting methods and the impacts of COVID-19 on macroeconomic variables. Next, we present the data sources, including COVID-19 case data and economic indicators, and the methodology, encompassing statistical and machine learning models such as Spatial Lag Models, XGBoost, Random Forest, and LSTM networks. We then process and critically appraise the results of these predictive models, highlighting key findings such as each model's strengths and limitations in capturing the pandemic's economic impacts. This is followed by a discussion of the main findings and their implications for economic forecasting and policy-making during global crises. Finally, we summarize our study and provide directions for future research to improve the robustness and accuracy of economic predictions in unprecedented situations.

2. Related Works

Our research builds on these foundations by integrating the methodological insights from Ludvigson et al.'s nonlinear modeling, the real-time data utilization from Baker et al., the granular, data-driven approach of Chetty et al., and the scenario-based forecasting techniques of Primiceri and Tambalotti. Specifically, our study aims to analyze the robustness of Gross Domestic Product (GDP) forecasting models under the impact of COVID-19, considering a broad spectrum of economic indicators and their interrelations.

2.1. The Macroeconomic Effects of Costly Disasters

Ludvigson et al. (2020) focus on the macroeconomic implications of COVID-19, drawing comparisons with past natural disasters that were typically local and transient. Unlike these events, COVID-19 induced sustained macroeconomic uncertainty and significant job losses, with effects paralleling the Great Depression. They utilize a Vector Autoregression (VAR) model, analyzing data from NOAA to evaluate the financial and human costs of disasters adjusted to current economic values. This study's nonlinear approach to understanding large-scale disasters provides a crucial methodological insight for our analysis, emphasizing the need for models to capture the outsized impacts of unprecedented global shocks. While their approach provides a solid foundation for understanding large-scale disasters, it opens the door for further exploration into how various predictive models perform under pandemic conditions, which our research aims to address.

2.2. COVID-Induced Economic Uncertainty

Baker et al. (2020) address the surge in macroeconomic uncertainty caused by the pandemic, using innovative measures such as the VIX, the Economic Policy

Uncertainty Index, and various business and forecaster surveys. Their findings on the immediate and severe impacts on GDP, driven by uncertainty, help underline the significant economic fluctuations that models need to account for. This research aligns with our study's focus on the broader economic impacts and the necessity of real-time data to capture rapidly evolving economic conditions. Our study builds on this by incorporating a comparative analysis of different predictive models, enhancing the understanding of how real-time data can be used to navigate such economic volatility.

2.3. The Economic Impacts of COVID-19

Chetty et al. (2024) constructed a detailed public database to analyze the differential impacts of COVID-19 on consumer spending, business revenue, and employment across ZIP codes, industries, and income levels. They found that high-income individuals' reduced spending disproportionately affected small businesses in affluent areas, highlighting the varied economic effects across different sectors and demographics. This study's granular approach to data collection and analysis provides a valuable perspective for our research, especially in considering the localized impacts of global crises and the effectiveness of policy responses like stimulus checks and small business loans. Their granular approach provides critical insights into localized effects. Complementing this, our research evaluates multiple predictive models to assess their reliability and accuracy, thereby extending the application of such granular data to broader predictive analyses.

2.4. Macroeconomic Forecasting in the Time of COVID-19

Primiceri and Tambalotti (2020) explore the challenges of forecasting the economic impact of the pandemic using a novel approach that integrates a specific "COVID shock" into their forecasting models. They developed scenarios to project future economic outcomes, providing insights into the recovery of slow employment and consumption patterns. This work's scenario-based modeling approach is particularly relevant to our study, emphasizing the importance of incorporating a range of potential future states to understand better and anticipate the pandemic's prolonged economic effects. Our study complements this by not only focusing on a single modeling strategy but also providing a comparative evaluation of multiple models, which can offer a more nuanced understanding of their performance and optimization under pandemic conditions.

3. Correlation Analysis between Economic Mobility Data and COVID-19 Case Data

Understanding how economic mobility interacts with COVID-19 case data is important to bring together various impacts of the pandemic on economic activity. These correlations can be used to reveal larger patterns and trends that will, in turn, support public policy-making or economic forecasting. This research was conducted to determine behavioral responses towards COVID-19, the effectiveness of lockdowns, and the vulnerability of different economic activities.

3.1. Data Sources

This analysis draws from two primary sources: The COVID-19 Diagnostic Test Results Data (NREVSS, 2023) by the National Respiratory and Enteric Virus Surveillance System (NREVSS). This dataset includes SARS-CoV-2 Nucleic Acid Amplification Test (NAAT) outcomes, covering clinical, public health, and commercial labs. This includes daily counts of individual confirmed positive cases of COVID-19 reported in states. The second source is the Community Mobility Reports from Google Maps (Google LLC, 2024). The second dataset comprises Community Mobility Reports from Google Maps (Google LLC, 2024), detailing geographic movement trends across various categories, including retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential areas.

The Retail and Recreation category reflects the impact of the pandemic on consumer behavior, as it shows visits to places like restaurants and shopping centers. The grocery and pharmacy category also includes various essential service locations, which helps verify whether any shift in passengers' consumer behavior is observed concerning the demand for essential goods or health products. The Parks category captures changes in behavior at public parks and other outdoor spaces, which may help to determine the degree to which the public follows or eases social distancing efforts.

The Transit Stations category provides data on the frequency of public transport usage, which can be used as measured complements of the previous indicators. It gives important information about a change in urban mobility linked to economic activity. The workplace category estimates physical attendance and provides insight into how the pandemic affected workplace economics, leading to remote work. Last, the Residential category shows how long people stay at home, which generally increases when states have stay-at-home orders or if remote work and unemployment are rising.

3.2. Methodology

The analytical process began with standardizing relevant columns such as date and state across both datasets to ensure consistency. The COVID-19 test results were then reorganized to summarize the daily number of new cases reported per state. Similarly, the mobility data was aggregated to capture the total changes in mobility categories per state and day.

Addressing missing data, all columns were converted to numeric types where necessary, and missing values were filled with the mean of the respective columns to avoid any analytical errors due to NaN values.

After cleaning and merging the data frame, we calculated the correlation between new COVID-19 case numbers and various mobility metrics using the correlation coefficient. This is to identify the strength and direction of linear relationships between the variables. The analysis was conducted using the Pearson correlation coefficient, which is ideal for detecting direct correlations between the rise in COVID-19 cases and shifts in mobility patterns.

3.3. Results

The analysis revealed a negative correlation between new COVID-19 cases and workplace mobility. This interesting negative correlation can be seen when comparing the number of new COVID-19 cases with workplace mobility (see Figure 1), which equates to −0.103214. This indicates that higher reported cases of COVID-19 are generally associated with less workplace mobility, which may reflect the adoption of remote work arrangements or shops closing when more people become infected.

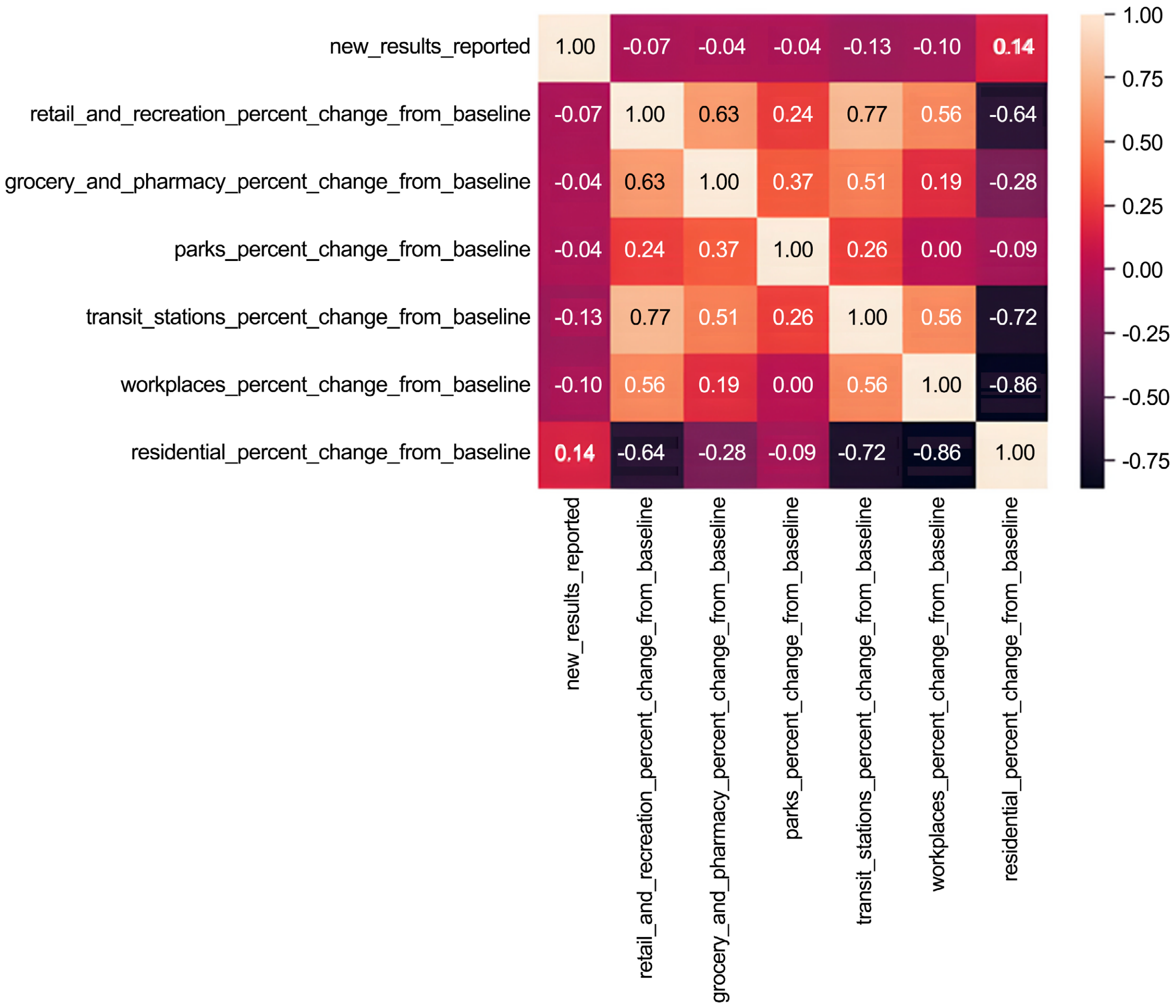

Figure 1. Correlation heatmap between new COVID-19 cases and mobility metrics. Own work.

On the other hand, we observed a weak positive correlation between the number of new cases and changes in residential mobility with a correlation coefficient of 0.137042. This reveals that, generally, when more COVID-19 cases are recorded by ZIP code, the number of people staying at home also increases (perhaps driven by official lock-down orders or a shift to work from home was available).

Different mobility categories such as retail and recreation, grocery pharmacy, parks and transit stations displayed less consistent correlations with new COVID-19 cases or uniformly weaker ones than workplace mobility did (see **Figure 1**), indicative of a combination of patterns affecting public mobility adjustments due to the pandemic effects.

4. Predictive Models

Predictive modeling in economic forecasting involves using historical data to predict future economic trends. In this study, we concentrate on some advanced predictive models to understand the macroeconomic implications of the pandemic for both the United States and Italy. Models compared in this package include XGBoost, Spatial Lag Model (SLM), Random Forests and LSTM Networks. Below, we describe the set of economic indicators employed by each model.

4.1. Data Sources and Preparation

In this study, we developed comprehensive datasets forecasting economic recessions in the United States and Italy by gathering a wide array of economic indicators offering insight into the complex dynamics of downturns.

4.1.1. Key Indicators

The economic indicators used in our study are the following: GDP, Unemployment Rate, Inflation Rate, Producer Price Index (PPI), Home Price Index, Population, Stock Values, Net Export, Saving rate, one-year Treasury Rate, and Corporate yield.

GDP is a measure of the production of goods and services, hence the obvious correlation between moderation or stagnation in GDP growth and the health and vitality of the economy. Labor market conditions (unemployment rate) and inflationary pressures (CPI and PPI) are major factors that showcase the dynamics of purchasing power and cost structures. The Home Price Index, in the meantime, best captures consumer housing market well-being and family pursuits, with oblique effects on household wealth and spending.

For Employment and Consumption, larger population sizes feign employment problems. Stock tends to increase by reflecting increased convection. Changes in interest rates, for one-year Treasury bill rate and Corporate yield, are expected to influence both the cost of borrowing and the investment decision itself. Net Exports measure the contribution of trade balance towards GDP, while the Saving Rate shows how confident consumers feel about future spending.

These indicators provide a holistic view of the state of economic activity. They help forecast GDP growth since they track different dimensions of economic strength and momentum.

4.1.2. US Dataset

Our first dataset spans US indicators from January 1984 through October 2023. primarily extracted from World Bank and Federal Reserve Economic Data (FRED) quarterly data on GDP (World Bank, 2022), Unemployment Rate (U.S. Bureau of Labor Statistics, 2024a), Inflation Rate (CPI) (U.S. Bureau of Labor Statistics, 2024b), Producer Price Index (PPI) (U.S. Bureau of Labor Statistics, 2024c), Home Price Index (S&P Dow Jones Indices LLC, 2016), Population (United Nations - World Population Prospects, 2024), Stock Values (World Federation of Exchanges database, 2024), One-Year Treasury Reader (Macrotrends, 2024a), Corporate yield (U.S. Department of the Treasury, 2024), Net Exports (U.S. Bureau of Economic Analysis, 2024), Saving Rate (OECD, 2024), and S&P 500 PE Ratio (Macrotrends, 2024b). Ranging from production levels and labor market health supporting that production to consumers' and businesses' views on prospects and financial market fluctuations, these indicators provide a window into various facets of the US economy (**Table 1**).

Table 1. Descriptive statistics of key economic indicators for the Italy.

	Mean	Standard Deviation	Minimum	Maximum	Observations
date	NaN	NaN	NaN	NaN	153
GDP	12076.589222	5679.501318	3908.054	25029.116	153
Inflation Rate	3.7	2.812519	−1.6	14.5	153
Net Export	−382.357484	261.658414	−1089.677	−20.536	153
One Year Treasury	3.677043	2.963934	0.060909	12.02619	153
Corporate Bond	6.820458	2.281333	2.79	13.26	153
Housing Price	142.528378	62.372154	63.735	312.953	148
PE	22.899256	14.088975	9.0978	120.3907	153
PPI	152.408941	38.621253	99.4	246.453	153
Saving Rate	3.455945	2.070403	−2.65264	7.013946	149
Unemployment Rate	6.007843	1.700369	3.6	14.9	153
Stock Value	1944444444.445312	15545835287757.773438	1110000000000.0472	00000000000.0	144
Population	287410.915033	30665.02546	235456.0	332918.0	153

Figure 2 displays the trends of these economic indicators over the specified period. With periodic downturns, the consistent upward trend in GDP highlights the overall economic growth and the impacts of significant economic events. Fluctuations in inflation and unemployment rates showcase the economy's responsiveness to policy changes and external shocks. The sharp decline in the one-year Treasury rate post-2008 indicates the aggressive monetary policy responses to crises. These trends are crucial for understanding how the economy has evolved and reacted to past recessions, providing a foundation for our forecasting models to predict future downturns, particularly in the post-COVID-19 context.

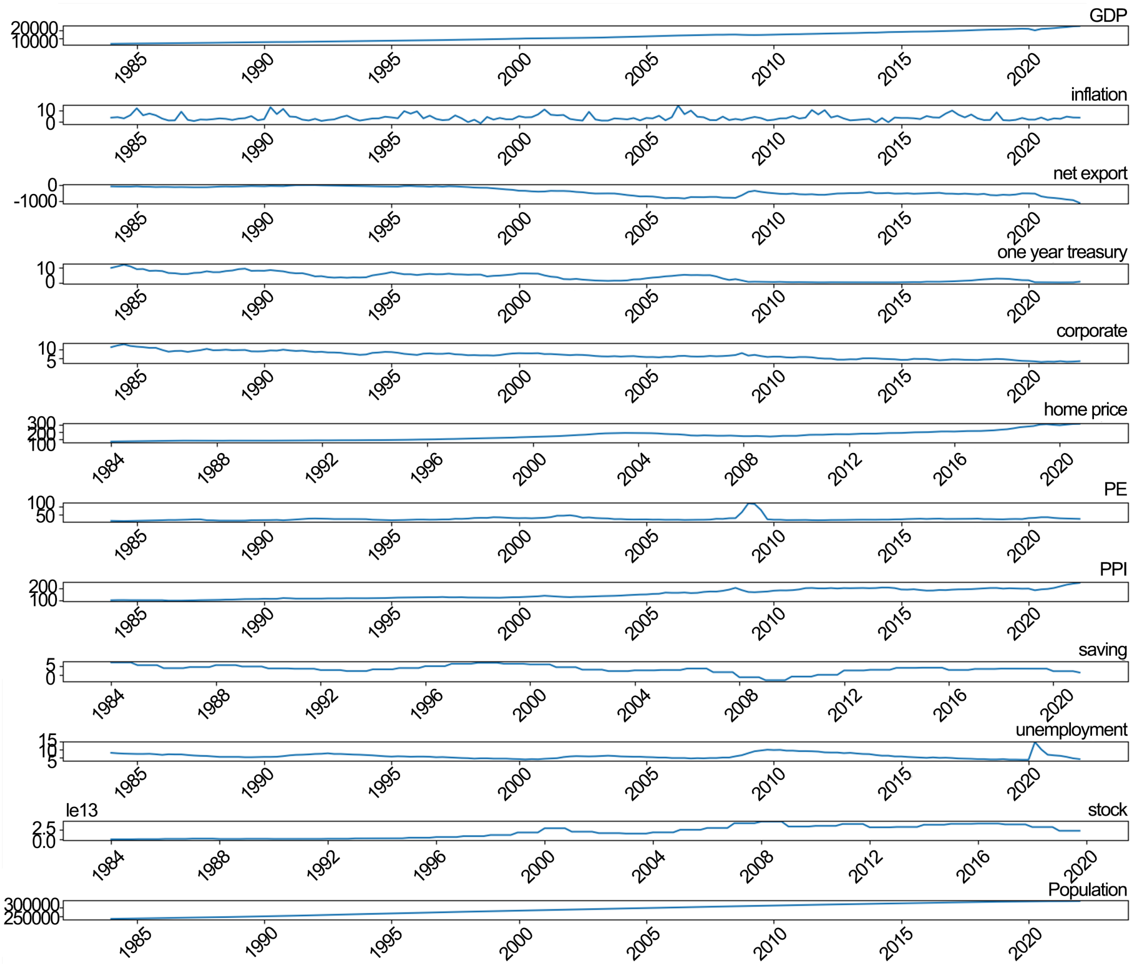

Figure 2. Trends of economic indicators in the United States (1984-2023). Own work.

4.1.3. Italy Dataset

The second dataset provided insight into Italy's economic landscape across multiple dimensions over several decades. From 1960 through 2022, annual statistics such as GDP (Macrotrends, 2024c), Unemployment Rate (International Labour Organization, 2024), CPI (International Monetary Fund, 2024), PPI (Organization for Economic Co-operation and Development, 2024a), Housing Price (Bank for International Settlements, 2024), Population (Italy Population, 2024), Total Value of Stock (Organization for Economic Co-operation and Development, 2024b), Net Export (Macrotrends, 2024d), and Saving Rate (World Bank, 2024) unveiled ebbs and flows in Italy's economy. Though not all the same metrics appeared as in the American data, examining developments over time and between locations enhanced understanding of how macroeconomic forces manifest differently (**Table 2**).

Figure 3 reveals the trends of Italy's economic indicators over the specified period. Interest rates have been low for more than a decade, but high unemployment combined with stable house prices suggests something very different to the economic dynamics in the US. This information is fundamental to our models to improve recession forecasts in a different economic context.

Table 2. Descriptive statistics of key economic indicators for the U.S.

	Mean	Standard Deviation	Minimum	Maximum	Observations
date	NaN	NaN	NaN	NaN	63
GDP	1034.400483	798.453927	40.385288	2408.655349	63
CPI	5.68285	5.461145	−0.137708	21.064168	63
Unemployment Rate	9.867938	1.823628	6.08	12.68	32
Housing Price	45.295062	36.84957	1.428325	101.36725	63
Government Bonds	7.689855	5.373831	0.811233	20.215	43
Population	56537785.666667	2635848.091982	50199700.0	60789140.0	63
Net Export	1243644897.454412	5141582978.397923	−9177950000.0	15543775000.0	63
PPI	88.911978	15.207903	61.868197	124.975	32
Saving Rate	15.517979	8.81733	−5.34025	30.588261	60
Stock Value	56.716145	47.757496	3.966525	164.124432	63

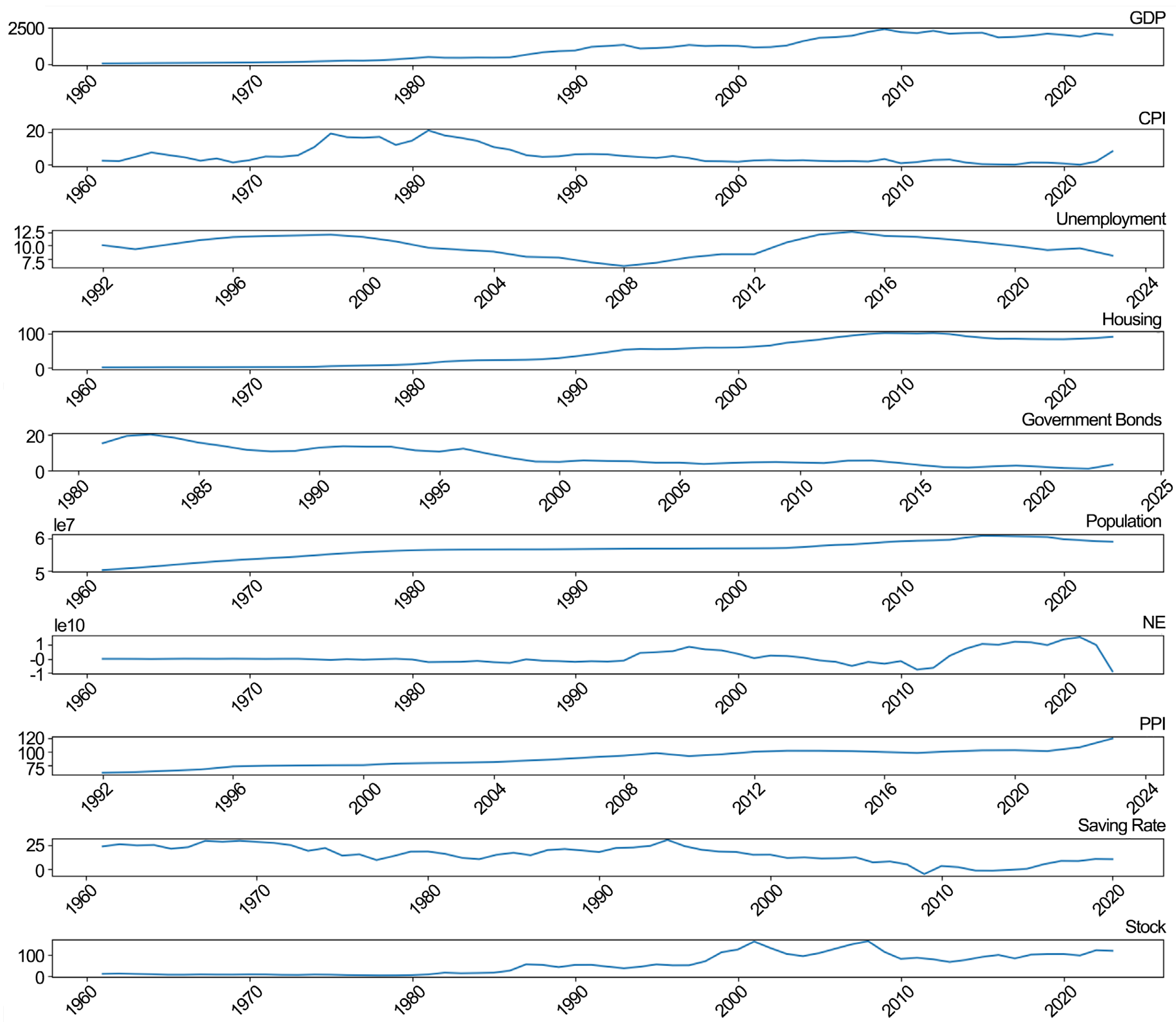

Figure 3. Trends of economic indicators in Italy (1960-2022). Own work.

4.2. Predictive Modeling Approaches

We used XGBoost, Spatial Lag Model (SLM), Random Forests, and LSTM Networks on these datasets.

4.2.1. XGBoost

XGBoost (Extreme Gradient Boosting) utilizes gradient-boosted decision trees, optimized for speed and performance. A decision tree is a straightforward model that takes a data set and breaks it down into branches using certain conditions. At the end of each branch are predictions. However, the problem with a single decision tree is that it is not powerful. XGBoost solves this by sequentially building an ensemble of decision trees, whereby new trees correct more horizontal lines than previous ones. After repeating this method for many trees, we have a powerful and accurate model: gradient boosting. XGBoost is good for working with big data sets, as it can effectively identify dependencies between variables and model interactions. Given XGBoost's capability of handling large data and capturing intricate patterns in forecasting GDP, it is a useful tool to predict economic performance during unprecedented conditions, possibly due to COVID-19-like events.

4.2.2. Spatial Lag Model (SLM)

The Spatial Lag Model (SLM) is a regression model that incorporates spatial dependencies between some data points. More plainly, it considers how the value of a variable in one location might be influenced by the values of the same variable in nearby locations. This is especially useful for all economic data, which is often impacted by geographical factors. For example, one region's economic activity may depend on neighboring areas' economic situation. These spatial autocorrelations are incorporated and accounted for in SLM predictions, enabling it to identify spillover effects and enhance its comprehension of regional economic interactions. By incorporating spatial dependencies, we can provide more accurate and insightful GDP forecasts.

4.2.3. Random Forest

Random Forest is an ensemble learning technique that builds multiple decision trees and merges them for more accurate results. Unlike a single decision tree that may tend to overfit, overfitting is greatly minimized in random forests as it averages the prediction of each tree. Each tree in this forest is trained on a random subset of the data, thus adding more randomness to the process. Hence, Random Forest is extremely robust and applicable to many datasets. As such, it is adept at dealing with relatively complex and diverse data structures, making it suitable for GDP forecasting. The unpredictable economic environment caused by the pandemic further supports random forests as a reliable choice.

4.2.4. LSTM Networks

Long Short-Term Memory (LSTM) networks are a recurrent neural network (RNN) type that handles sequence data, such as time series. LSTMs are explicitly designed to avoid the long-term dependency problem. Unlike traditional neural networks, which process data in a single pass, LSTMs have loops that allow information to persist. Using this technique in time series forecasting is especially useful since future values at some point in time depend upon patterns observed over time. In the case of GDP forecasting, LSTM networks are especially useful for their ability to incorporate and learn from the temporal dynamics and trends inherent in economic data, providing accurate and insightful predictions even in the face of abrupt changes like those experienced during the COVID-19 pandemic.

4.2.5. Overcoming the Limitations of Tree-Based Models

XGBoost and Random Forests, as tree-based models, are highly effective in addressing various machine-learning problems. Nonetheless, the inherent design of tree-based methods causes these models to face challenges with trend extrapolation.

Tree-based models partition data into branches and leaves based on the values of input features. Each leaf node predicts using the average target value (for regression) or the majority class (for classification) of the training samples within that leaf. The limitation arises from the localized nature of these models, as predictions are based on the training set observations that fill the leaves. When a new instance features values outside the training data's range, the model applies the prediction from the nearest leaf node. This means the model cannot correctly learn trends or patterns outside the training data or extrapolate.

To address this limitation in our study, we applied differencing to the economic indicators before feeding them into the XGBoost and Random Forest models. Differencing is a statistical method that converts a time series into a stationary format by computing the differences between consecutive data points. This transformation helped mitigate the overfitting issue by ensuring the models focused on the underlying patterns in the data rather than the trends. This approach effectively reduces the noise associated with non-stationary data, allowing the models to generalize better on unseen data.

4.2.6. Feature Selection and Model Training

For XGBoost, we first applied time series differencing to stabilize the series' mean and reduce trends and seasonality (see **Figure 4**). By correlation matrix, we selected corporate Bound and home price for the US dataset, which correlate with differenced GDP greater than 0.5. For the Italy dataset, we selected CPI, unemployment rate, population, net export, and total stock value by the threshold of 0.1. The dataset was then split into training and testing sets with a 70:30 ratio without shuffling to maintain the temporal order. The XGBoost model was fine-tuned using Grid Search CV to optimize hyperparameters. The final model is defined by parameters "max_depth = 3", "learning_rate = 0.1", and "n_estimators = 50" for the US dataset and "max_depth = 3", "learning_rate = 0.05", and "n_estimators = 50" for the Italy dataset.

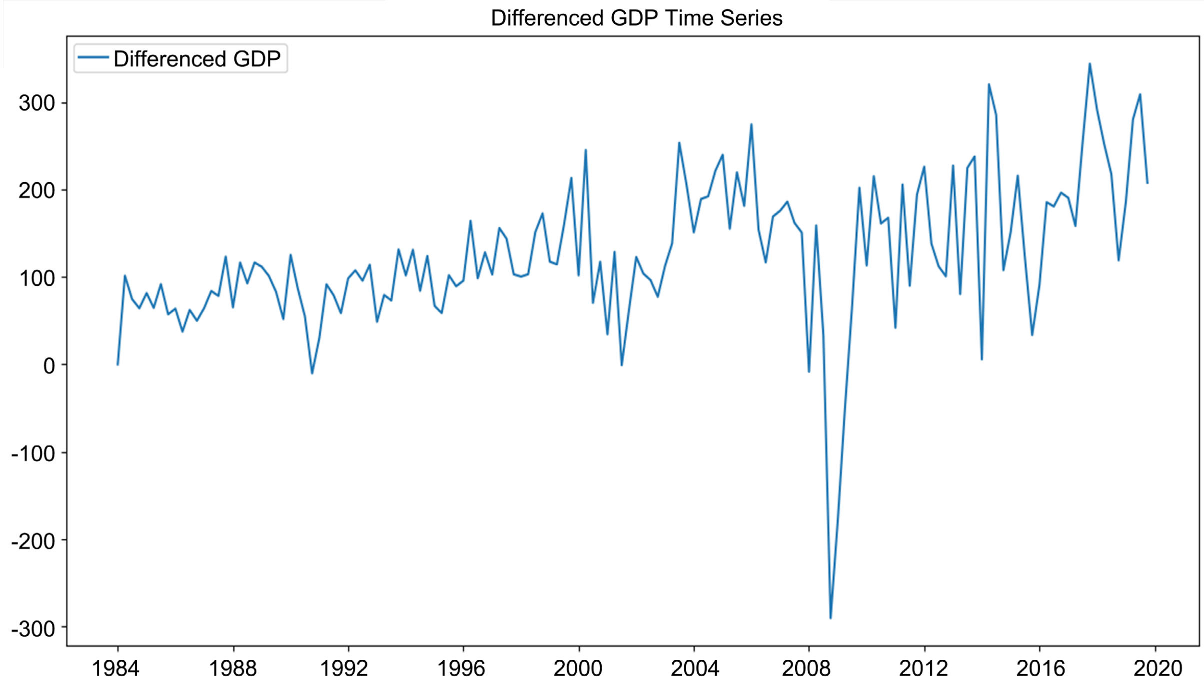

Figure 4. Differenced GDP time series for the United States. Own work.

For Spatial Lag Model (SLM), feature selection was based on the correlation of each feature with GDP. Features with an absolute correlation greater than 0.5 were selected. The selected features for the US dataset were net export, one-year treasury bound, corporate bond, home price, PPI, stock value, and population. We selected CPI, house price, government bonds, population, PPI, saving rate, and stock value for the Italy dataset. This method is appropriate as it ensures that only features with a strong linear relationship with GDP are included, which is crucial for regression models like SLM.

For Random Forest, like XGBoost, the process started with time series differencing to stabilize the series' mean and reduce trends and seasonality (see **Figure 4**). Based on the trained model, we selected the top four most important features by feature importance. For the US dataset, the features selected were corporate bonds, S&P 500 PE Ratio, population, and unemployment rate. For the Italy dataset, we selected the saving rate, stock value, CPI, and unemployment rate. The model for both countries is trained with "n_estimators = 100".

For LSTM Networks, feature selection was based on lagged correlations with GDP, identifying GDP, Population, PPI, Home Price, and Stock as the most relevant features over three lags for the US and Italy. This method captures the temporal dependencies and ensures that the model can learn from past values to predict future GDP. The selected features were lagged to create a supervised learning dataset. The data was normalized using MinMaxScaler to improve the efficiency of the neural network training. The final dataset included lagged values for the selected features, and the target variable, GDP (t + 1), shifted by a one-time step into the future. The LSTM model was then trained on this prepared dataset, optimizing its performance for time series forecasting.

5. Prediction Results of US

5.1. Evaluation of the XGBoost Model

The XGBoost model's performance in predicting U.S. GDP demonstrated a mixed outcome, as evaluated by the Root Mean Squared Error (RMSE) of 87.90 for the test set. The predictive accuracy showed moderate performance, with the model managing to capture some economic trends but still displaying room for improvement, particularly in periods with heightened economic volatility post-2020 (**Figure 5**).

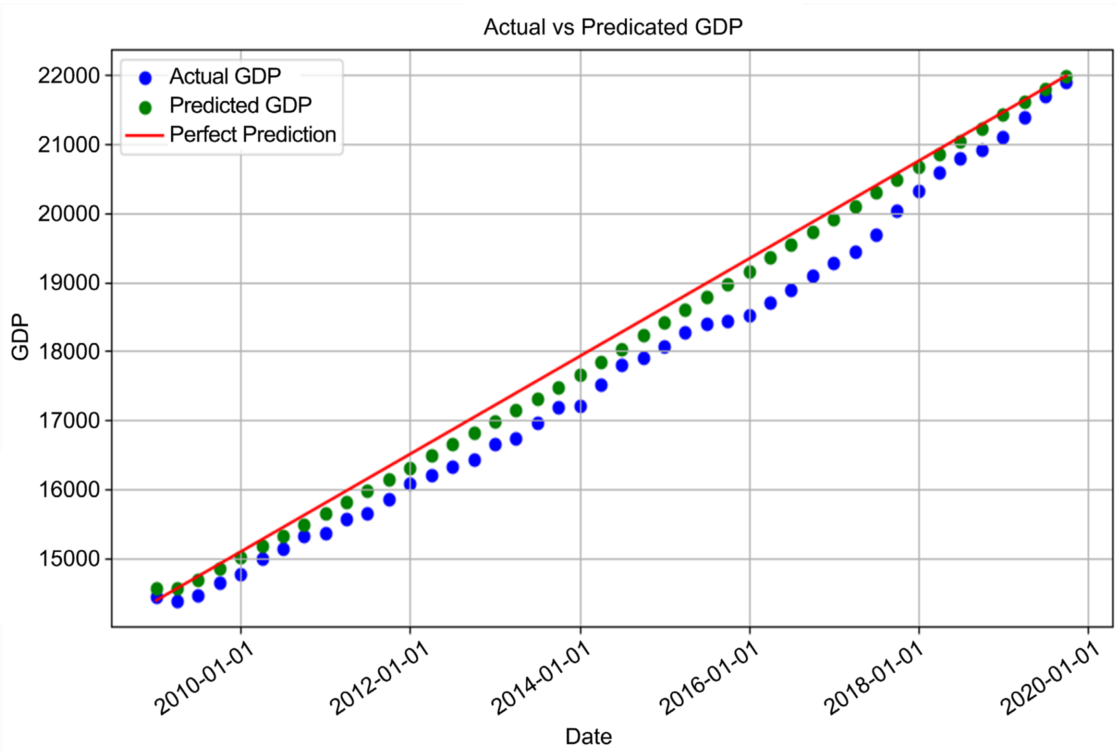

Figure 5. Actual vs. predicted GDP values using XGBoost model for the U.S. own work.

5.2. Evaluation of Spatial Lag Model (SLM)

The Spatial Lag Model resulted in an RMSE of 2424.97. The model's coefficients are corporate (−3.80), PE (−2.25), population (5.92), and PPI (−6.22), highlighting their relative importance in the model.

The Predicted vs. Actual Values plot (**Figure 6**) illustrates that the model underestimates GDP for higher actual values, as seen by clustering points below the perfect prediction line (red line). This underprediction is strongest after 2020, showing that the model struggles to adapt to the new COVID-19-induced economic disruptions.

This can be seen even more clearly in the Residual Plot (**Figure 7**). As the predicted values rise, the spread of residuals also increases. This pattern, by nature of the high GDP responses, insinuates a possibility for heteroscedasticity, which is when the variance of the errors changes for different levels of GDP, meaning the model is less reliable for high levels of GDP.

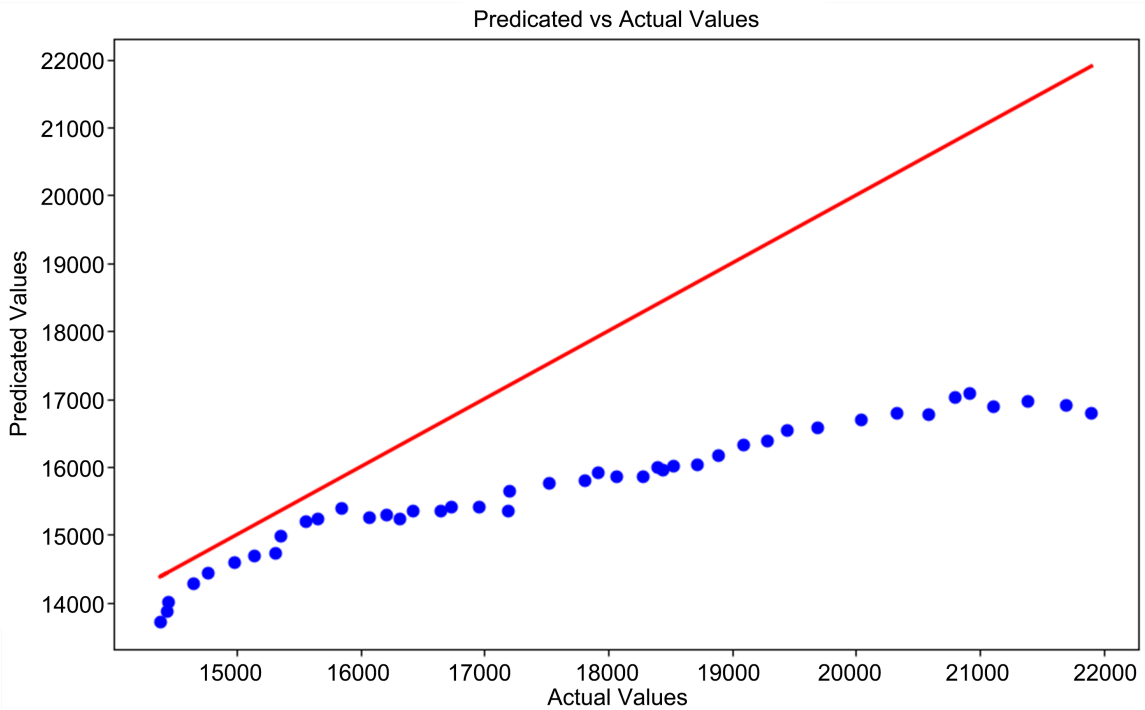

Figure 6. Predicted vs. actual values for U.S. GDP using the Spatial Lag Model (SLM). Own work.

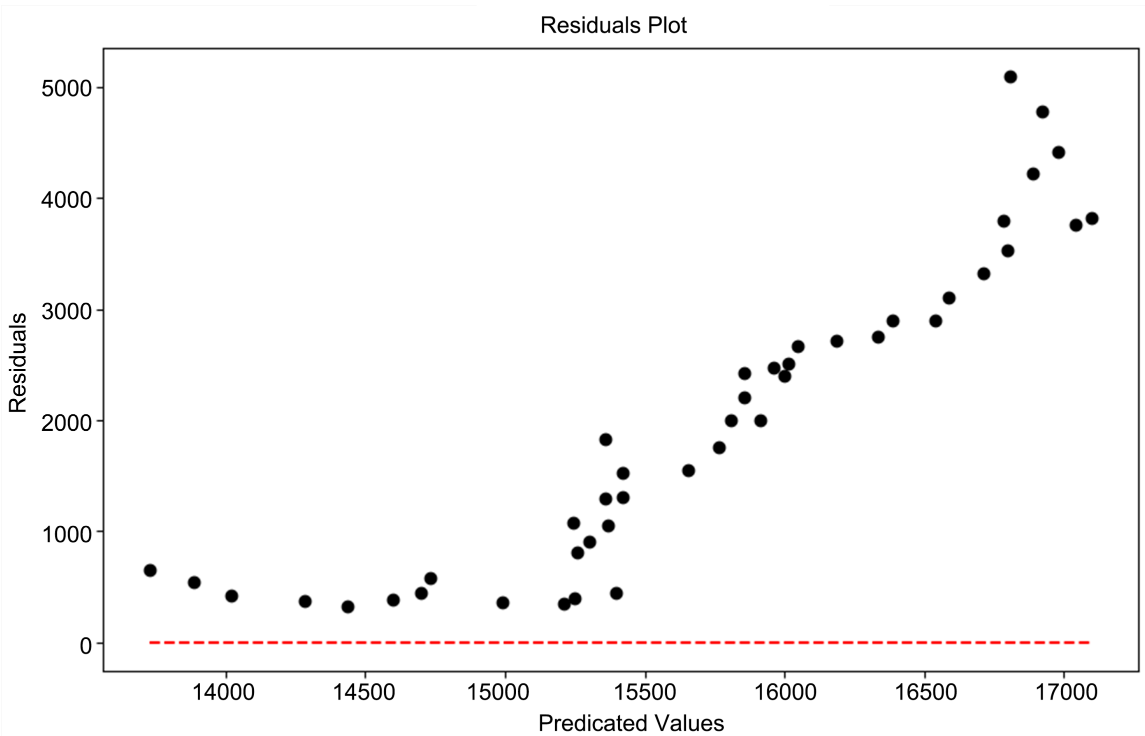

Figure 7. Residual plot for Spatial Lag Model on U.S. GDP. Own work.

Despite these challenges, the SLM offers valuable insights into the spatial dependencies on GDP. Therefore, it is useful for capturing the geographic spread and regional impacts of economic phenomena like COVID-19.

5.3. Evaluation of Random Forest

The Random Forest model's performance in predicting U.S. GDP faced significant challenges, shown by an RMSE of 113.83. The learning curve (Figure 8) shows the rapid drop in RMSE for the training and test set in the first epochs as the model is learning. Nonetheless, the test RMSE exceeds the training RMSE by a large margin, indicating overfitting despite the model optimization with time series differencing. The large discrepancy in training and test RMSE indicates that the model has difficulty generalizing on unseen data.

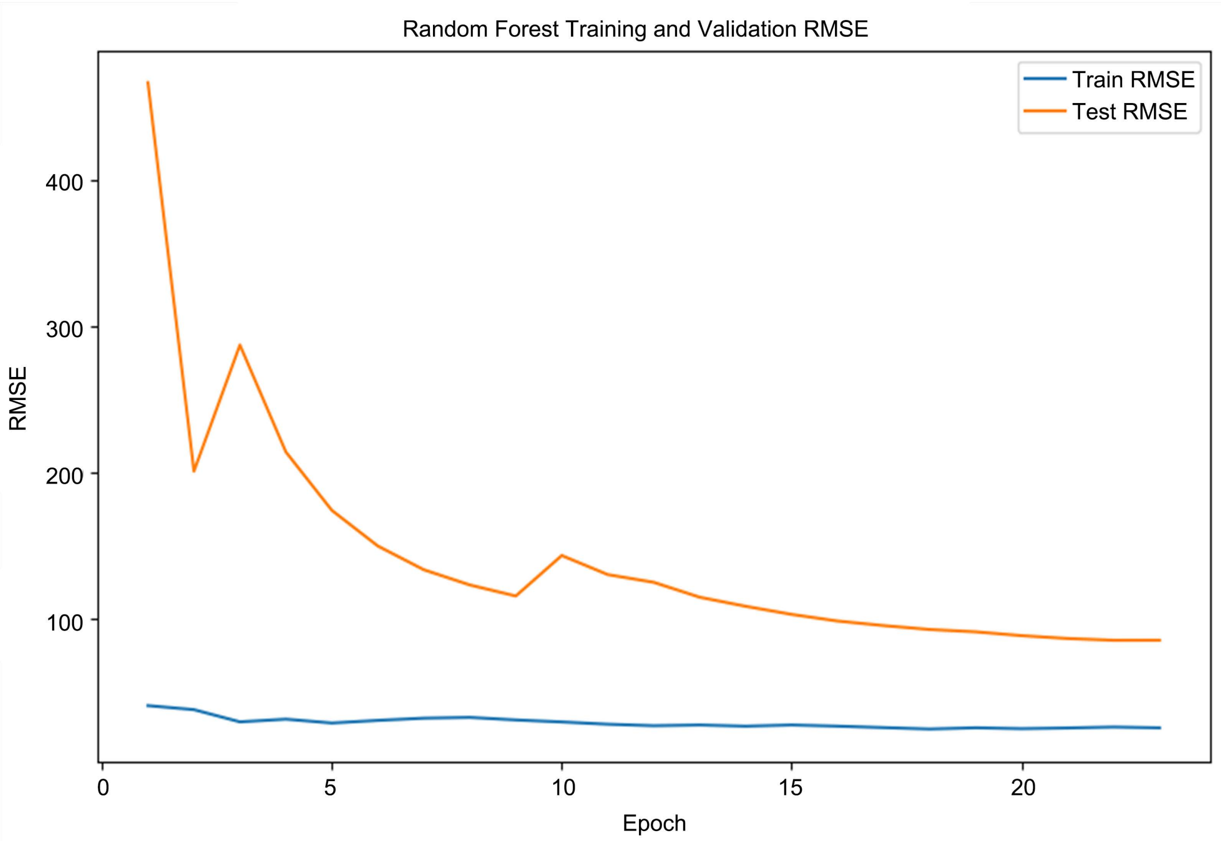

Figure 8. Learning curve of random forest model for U.S. GDP prediction. Own work.

5.4. Evaluation of LSTM Networks

The LSTM network showed excellent performance, as demonstrated by the low RMSE values of 0.659. The learning curves (Figure 9) indicated effective learning with rapid convergence, suggesting the model's ability to generalize well to new data. The extremely low test RMSE further highlights the LSTM's precision in modeling and predicting the sequential trends of the GDP, making it a valuable tool for forecasting economic outcomes over time.

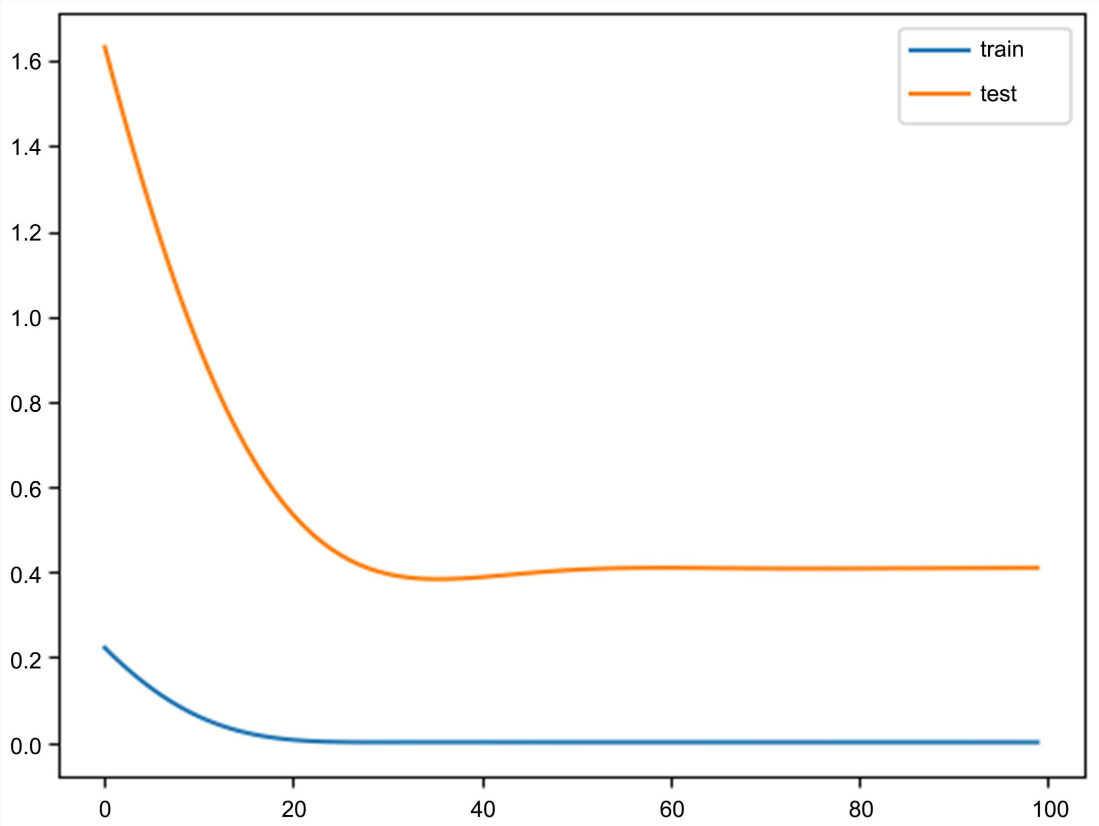

Figure 9. Learning curve of long-short term memory network for U.S. GDP prediction. Own work.

6. Prediction Results of Italy

6.1. Evaluation of Models

Various predictive models were evaluated for their ability to accurately forecast economic conditions in Italy, revealing distinct strengths and weaknesses. The XGBoost model exhibited significant discrepancies, with an RMSE of 160.67. This mirrors the model's performance on U.S. data, where the RMSE was 87.90, indicating that XGBoost struggled more with the Italy data. Similarly, the Spatial Lag Model (SLM) faced notable limitations, reflected in an RMSE of 256.78. However, this performance is better than SLM's performance with the US data, where the RMSE was 2424.97, making the SLM much more adequate for the Italy data than the US data. The random forest model maintained a steady performance between the two datasets, achieving an RMSE of 161.39 for Italy.

Most notably, the LSTM model learned the signals in different datasets with stunning accuracy, attaining an RMSE of 0.181 for Italy. This performance significantly surpasses the other models, highlighting the potential and power of the LSTM model. Its performance on the U.S. data, which also showcased superior accuracy, further reinforces its strength. The learning curve (**Figure 10**) suggests that the LSTM model is highly effective in predicting Italy's GDP, particularly in capturing complex temporal dependencies and trends affected by external shocks like the COVID-19 pandemic.

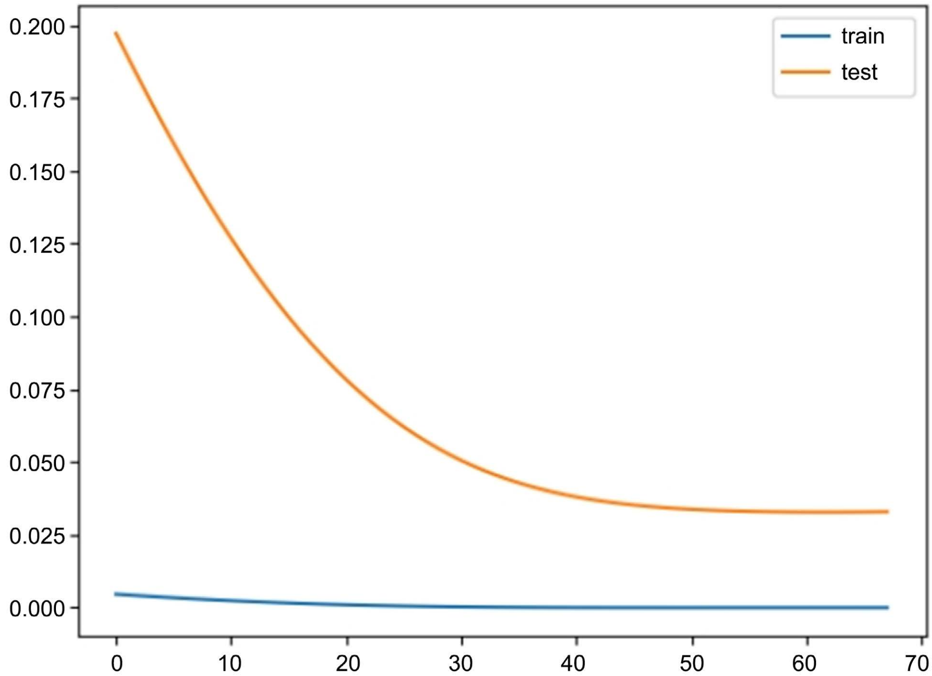

Figure 10. Learning curve of long-short term memory network for Italy GDP prediction. Own work.

6.2. Final Model Selection

Considering all factors, such as performance, interpretability, and computational efficiency, we have chosen the Long-Short-Term Memory (LSTM) network as the final model for GDP prediction in the context of COVID-19's economic impact.

LSTM networks are designed to capture long-term dependencies in sequential data, making them well-suited for time series forecasting, particularly for GDP, where trends and patterns often span long periods. The LSTM model's superior performance in both the U.S. and Italy datasets supports this. Additionally, the final RMSE for Italy's GDP prediction using LSTM was significantly lower than that of other models, showcasing its reliability.

While LSTM is selected as the final model for its outstanding performance and robustness, we recognize the importance of model interpretability and computational efficiency.

XGBoost provides more interpretability than LSTM while performing better than Random Forest and SLM. A tree-based structure allows for a clear understanding of feature importance and decision paths. Despite its limitations in handling trends and temporal dependencies, XGBoost's performance could be significantly enhanced by applying different detrending methods. Combining XGBoost with robust detrending methods can offer a balance between performance and interpretability, making it a viable alternative for scenarios where understanding the model's decisions is as important as the accuracy of the predictions.

6.3. Applying the Methodology to Other Crises

The methodology and findings from this study, especially the evaluation of various predictive models, can be extended to forecast economic impacts during other global crises.

Long-Short-Term Memory networks, as demonstrated in this study, can effectively predict the economic impact of pandemics by capturing the prolonged effects on various economic sectors. We believe its ability to handle long-term dependencies in sequential data was a significant factor in its superior performance in our study. This attribute makes LSTM networks ideal for modeling the the sequential nature of financial indicators like stock prices, interest rates, market indices, and tracking recovery trends following unprecedented natural disasters.

XGBoost and Random Forest models struggles with trend extrapolation, which can be mitigated by combining it with robust detrending methods. This combination enhances its performance for long-term forecasts, providing insights to forecasting the impact of unprecedented natural disasters with decision tree-based models.

For Spatial Lag Models, future researchers can consider incorporating regional data, which leverage the strength of SLMs in understanding geographical impacts. SLMs can be effective in modeling the economic impact of regional disasters such as earthquakes, floods, or hurricanes, and localized events like city-wide strikes or localized outbreaks of disease.

7. Further Research

7.1. Limitations of the Analysis

First, despite the effort detrending the datasets with time series differencing and fine-tuning the hyperparameters, XGBoost and Random Forest show signs of overfitting. This indicates an inherent limitation of tree-based models in extrapolating trends beyond the scope of the training data.

Second, the analysis predominantly utilized quantitative data, which may overlook qualitative factors such as political stability, public sentiment, or unquantifiable policy impacts, which can significantly influence economic outcomes. Moreover, although effective in incorporating spatial dependencies, the spatial lag models may not fully account for global interconnectedness and external economic influences between countries not included in this study.

Third, the study only focused on two major economies: the United States and Italy. While COVID-19 significantly impacted these countries and provided valuable insights, the findings may not be generalizable to other regions with different economic structures, policies, and pandemic responses. Expanding the scope to include a broader range of economies would provide a more comprehensive understanding of the global economic impact of the pandemic.

Last, the datasets were limited to pre-defined economic indicators, which may not encompass all relevant variables that affect economic performance. For instance, the rapid technological changes and digital transformation, which have accelerated during the pandemic, are not directly measured in the economic indicators used.

7.2. Suggestions for Further Research

7.2.1. Integration of Real-Time and High-Frequency Data

Real-time and high-frequency data has been recognized for its potential to enhance economic forecasting during periods of significant uncertainty (Primiceri & Tambalotti, 2020). Such data could include high-frequency transaction details, labor market activities, and consumer behavior metrics. This approach enables a more nuanced and immediate analysis of economic shifts, providing a dynamic perspective crucial during rapidly evolving situations such as a global pandemic.

7.2.2. Inclusion of Qualitative Factors and Broader Economic Indicators

Integrating qualitative assessments, such as policy shifts, political events, and public health responses, can provide deeper insights into the socio-economic drivers of change. Baker et al. (2020) noted that non-quantitative factors, such as policy decisions and public sentiment, profoundly influenced macroeconomic uncertainty during the COVID-19 pandemic. Furthermore, expanding the variable set to include measures of technological adoption, digital economy penetration, and healthcare system resilience could yield a more comprehensive understanding of their roles in economic resilience and recovery.

7.2.3. Cross-Country Comparative Analyses and Hybrid Approaches

Extending the comparative approach to include a more diverse array of countries that vary in economic structures and policy responses would enrich the understanding of different economic impacts and recovery patterns. This broader scope could help formulate generalized economic models capable of predicting outcomes across different global contexts, drawing on the comparative method used to analyze the economic impacts in the U.S. and Italy.

Building on the current use of models like XGBoost and LSTM, future studies could explore hybrid models that combine elements of machine learning and traditional econometric methods. Such hybrid models could better capture complex, nonlinear interactions between multiple economic factors, potentially offering a balance between predictive power and interpretability, overcoming the limitations of tree-based models like XGBoost and Random Forest of this study.

8. Conclusion

While the COVID-19 pandemic has presented profound economic challenges, it has also offered unique insights into the dynamics of global economic interdependence and the critical role of adaptive, data-driven policy-making.

In this paper, we applied a range of advanced predictive models, including XGBoost, Spatial Lag Models (SLM), Random Forest, and Long Short-Term Memory (LSTM) networks, to quarterly economic data from the U.S. (1984-2023) and annual data from Italy (1960-2022). Each model was carefully tuned. Differencing was applied to the time series data to stabilize the mean and reduce trends and seasonality, significantly enhancing the models' performance.

Our findings highlight the strengths and limitations of each model predicting GDP under COVID-19-induced shocks. The LSTM model emerged as the most accurate, capturing temporal dependencies and complex patterns in the data, making it ideal for forecasting economic conditions during the pandemic. The XGBoost model showed promise when combined with advanced detrending methods to address its limitations in trend extrapolation.

Despite the significant findings, the study also revealed important limitations. Even after detrending the datasets, tree-based models like XGBoost and Random Forest exhibited signs of overfitting, especially with post-2020 data. Additionally, future research should include a broader range of economies and incorporate a wider array of indicators, including sector-specific data and qualitative factors, to provide a more comprehensive understanding of the global economic impacts of the pandemic.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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