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Economic Recession Forecasts Using Econometric Models and Machine Learning Models based on the Evidence from the COVID-19 Pandemic

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Abstract

This paper analyses economic recession and delineates its fundamental characteristics. With a particular focus on the United States and Italy, this paper studies the profound impact of the COVID-19 pandemic on the economy. Also, the paper include the analysis of COVID-19 Community Mobility Reports for the year 2020. Methodologically, this paper employs a multifaceted approach, incorporating techniques from econometrics such as the Vector Autoregressive (VAR) model. Furthermore, it integrates machine learning models and deep learning models, all of which are crucial in comprehending the intricate dynamics of economic recessions and their interplay with external shocks, notably the COVID-19 pandemic. In the pursuit of model selection, the paper assesses the predictive performance using established metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) . The results indicate that, in the analysis of data from the United States and Italy, the Random Forest Regression method exhibits relatively small errors, showing the best overall performance. When measuring errors in the United States data using RMSE, the Gradient Boosted Regression method performs the best. In addition, Ordinary Linear Regression is not consistently the least effective method; in some cases, it even outperforms machine learning or deep learning approaches. For instance, when assessing Italian data using the RMSE method, Linear Regression yields the smallest error.

Keywords

Economic Recession; COVID-19; VAR Model; Machine Learning; Forecasting; Mean Absolute Error; Root Mean Squared Error.

1. Introduction

Since March 2020, the global community has been grappling with the devastating impact of the COVID-19 pandemic on both public health and economies. An economic recession refers to a prolonged decline in economic activity within a country or a broader region. It is characterized by a decrease in gross domestic product (GDP), a contraction in industrial production, reduced consumer spending, rising unemployment rates, and declining business investment. Recessions often result in reduced consumer confidence, lower corporate profits, and overall economic uncertainty. However, they are considered to be a normal part of the economic cycle, though their duration can vary widely. The impact of COVID-19 on society as a whole is mainly as follows.

Supply Chain Disruptions: The pandemic disrupted global supply chains, causing shortages of essential goods and components. Factory closures and transportation restrictions hindered the production and distribution of goods, leading to supply shortages and price fluctuations.

Business Closures and Unemployment: Many businesses, particularly those in sectors like hospitality, travel, and retail, were forced to shut down temporarily or permanently due to lockdowns and reduced consumer demand. This may resulted in a surge in unemployment.

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Decline in Consumer Spending: Fear of infection, coupled with income uncertainty, caused consumers to cut back on discretionary spending. This reduction in consumer demand led to a decline in sales for many businesses, further contributing to economic contraction.

Financial Market Volatility: The uncertainty surrounding the pandemic led to significant volatility in financial markets. Stock markets experienced sharp declines, and investors sought safe-haven assets, such as gold and government bonds.

In conclusion, the COVID-19 pandemic had far-reaching effects on the global economy, causing recessions in many countries. Governments and central banks responded with unprecedented fiscal and monetary measures to mitigate the economic impact and facilitate recovery.

The remaining sections of this article are structured as follows: Firstly, an introduction to the study based on Google COVID-19 Community Mobility Reports for the United States in 2020 will be provided, offering a detailed elucidation of the correlation between economic mobility and Covid-19 data. Subsequently, predictive models will be established based on various methodologies, including Vector Autoregressive (VAR) models, linear regression models, machine learning, and deep learning techniques to forecast the GDP of both the United States and Italy within the context of economic recession. Finally, a predictive assessment will be conducted, utilizing metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to comparatively evaluate the performance of each forecasting model, ultimately identifying the most optimal model.

2. Study based on Google COVID-19 Community Mobility Reports of US in 2020

Correlating economic mobility data with COVID-19 data is essential to uncover the complex relationship between public health and economic dynamics. This analysis provides insights into how mobility patterns impact virus transmission and how pandemic-induced changes influence economic behaviors. Understanding these correlations helps shape targeted policies and anticipate economic trends during and after the crisis.

2.1. Backgrounds of the Pandemic in US, 2020

The pandemic triggered a rapid economic contraction, leading to skyrocketing unemployment rates and a sharp decline in economic activity. Businesses across industries, particularly in sectors like hospitality, travel, and retail, faced severe revenue losses as consumer demand plummeted. The uncertainty surrounding the virus further prompted a reduction in consumer and business investment.

In response to the economic turmoil caused by the pandemic, the US government enacted a series of measures aimed at stabilizing the economy and mitigating the hardships faced by individuals and businesses. The COVID-19 pandemic has resulted in an unprecedented economic crisis for the US, necessitating swift and comprehensive government intervention to stabilize the economy. The multifaceted response, encompassing fiscal and monetary measures, shows the government's determination to pave the way for recovery in the post-pandemic era.

2.2. Community Mobility Data

Amidst the global response to COVID-19, public health authorities highlighted the potential utility of aggregated, anonymized insights similar to those used in Google Maps, to aid in critical decision-making to combat the pandemic[1]. These insights culminated in the creation of Community Mobility Reports, designed to offer valuable perspectives on shifts in response to policies aimed at addressing the challenges posed by COVID-19. These reports specifically tracked trends in movement over time based on geographic locations and encompassed various

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categories of places, including retail and recreational areas, grocery stores and pharmacies, parks, transit stations, workplaces, and residential zones.

The data for these reports was amassed from users who had chosen to enable Location History settings on their devices. Google leveraged its extensive user base to compile this data in an aggregated and anonymous manner. The reports depicted changes in mobility patterns by showcasing percentage increases or decreases compared to a baseline period, before the pandemic. These insights allowed public health officials and policymakers to discern whether people were adhering to social distancing measures and stay-at-home directives, thereby enabling them to evaluate the effectiveness of the implemented policies.

The data of these Community Mobility Reports provided valuable indicators of economic activity and the movement of people, reflecting the changes in consumer behavior, workforce dynamics, and overall economic sentiment. By observing fluctuations in mobility trends within various categories such as workplaces, retail, and recreation, it was possible to gain insights into the impact of lockdowns, remote work practices, and changes in spending patterns.This data not only facilitated public health decision-making but also shed light on the intricate relationship between mobility, economic behaviors, and policy efficacy.

2.3. Correlation between Economic Mobility and Covid-19 Data

The scatter plot in Figure 1 illustrates the relationship between certain economic indicators and the number of new cases. According to Figure 1, there appears to be some linear correlation between COVID-19 cases in the United States and these indicators. However, further analysis requires the calculation of linear correlation coefficients.

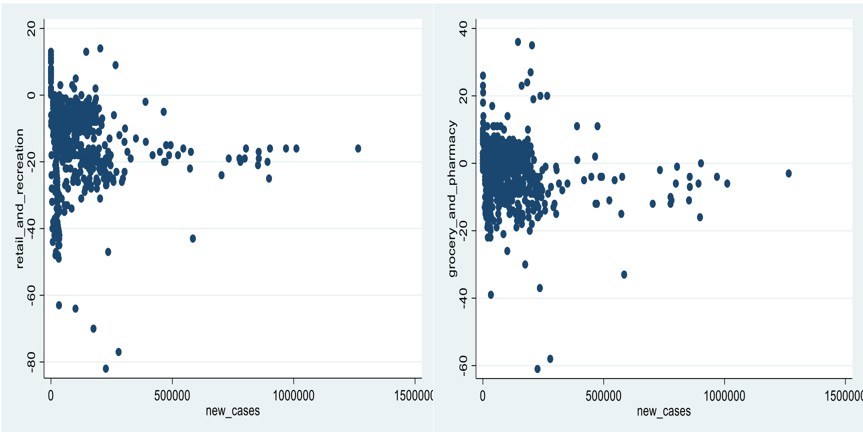

Figure 1. Relationship between COVID-19 cases and economic indicators in the United States

Next, calculate the Pearson Correlation Coefficients, and the results are shown in Figure 2 below:

	new_ca~s	retail~n	grocer~y	parks	transi~s	workpl~s	reside~l
new_cases	1.0000						
retail_and~n	-0.1217*	1.0000					
	0.0001						
grocery_an~y	-0.1488*	0.7918*	1.0000				
	0.0000	0.0000					
parks	-0.3372*	0.4446*	0.4537*	1.0000			
	0.0000	0.0000	0.0000				
transit_st~s	-0.1367*	0.8314*	0.6298*	0.5395*	1.0000		
	0.0000	0.0000	0.0000	0.0000			
workplaces	0.0180	0.5046*	0.2972*	0.1514*	0.7438*	1.0000	
	0.5742	0.0000	0.0000	0.0000	0.0000		
residential	0.0707	-0.7099*	-0.4664*	-0.4417*	-0.8969*	-0.8707*	1.0000
	0.0273	0.0000	0.0000	0.0000	0.0000	0.0000	

Figure 2. Pearson Correlation Coefficients results

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In the provided results, an asterisk (*) signifies statistical significance at α=0.01. The numerical value below each result represents the P-value obtained from the correlation test. A smaller P-value indicates greater significance. Based on the outcomes of the correlation analysis, at a significance level of 0.05, it is evident that new cases display a significant positive correlation with all variables, except for workplace change. Specifically, the correlation coefficient between workplace change and new cases is a mere 0.018, indicating a weak association. This observation is further supported by the insignificance of the correlation, with a P-value of 0.5742, signifying a lack of statistical significance. Furthermore, the absolute value of the correlation coefficient between all economic mobility variables and new cases remains below 0.6, indicating a correlation level below the moderate threshold. Similarly, calculate Spearman Correlation Coefficients to reflect the correlation between the indicators. The results are shown in Figure 3.

	new_ca~s	retail~n	grocer~y	parks	transi~s	workpl~s	reside~l
new_cases	1.0000						
retail_and~n	-0.0866*	1.0000					
grocery_an~y	-0.1305*	0.8110*	1.0000				
parks	-0.2497*	0.4344*	0.5068*	1.0000			
transit_st~s	-0.0438	0.7987*	0.6584*	0.5605*	1.0000		
workplaces	0.0961*	0.3809*	0.2369*	0.1426*	0.6941*	1.0000	
residential	0.0012	-0.6107*	-0.4469*	-0.4277*	-0.8856*	-0.8866*	1.0000

Figure 3. Spearman Correlation Coefficients results

In the provided results, an asterisk (*) signifies statistical significance at α=0.05. The Spearman correlation coefficient analysis reveals significant correlations between new cases and the variables of retail, grocery, parks, and workplaces. Notably, the correlations with retail, grocery, and parks are negative, a pattern visually confirmed by the scatter plot representations. Conversely, the correlation coefficient between new cases and residential is a mere 0.0012, indicating an exceedingly weak and statistically insignificant association. This observation is further emphasized by the absence of discernible patterns evident in the scatter plot, signifying a lack of regularity between the two variables.

3. Predictive Model

Establish predictive model for the US Gross Domestic Product (GDP) is significant important, as it offers invaluable economic insights to decision-makers, investors, businesses, and researchers. Such a model plays a pivotal role in the formulation of economic policies, strategic planning for business investments, risk management and impacting the global economy. Given the substantial influence of the US economy on the global stage, precise GDP forecasts have the capacity to unveil international trade dynamics, trends in commodity prices, and shifts within the global marketplace. This is especially crucial for nations deeply interconnected with the US through trade relationships.

3.1. Data

The data for this analysis was sourced from two reputable platforms: Fred and Stooq[2]. The analysis encompassed a dataset spanning from the first quarter of 1980 (1980Q1) to the fourth quarter of 2022 (2022Q4). The datasets for Italy and the United States differ in some aspects. The dependent variable in this analysis is the Gross Domestic Product (GDP), while the independent variables encompass various economic indicators. Besides, the collected data

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takes into account the impact of COVID-19 on the economic landscape. The specific variables selected and their description are shown in Table 1. The sample size for the United States dataset comprised 172 observations.

Table 1. Variable declaration table - United States

Variable name	Types of variables
GDP	dependent variable
Spread	explanatory variable
unemployment_rate	explanatory variable
PPI	explanatory variable
Housing_price	explanatory variable
net_exports	explanatory variable
P/E_ratio	explanatory variable
Population	explanatory variable
total_stock	explanatory variable
10-year_treasury_rate	explanatory variable
saving_rate	explanatory variable
Inflation_Rate	explanatory variable

3.2. Models

First, it is necessary to briefly introduce and explain the specific forecasting models used in this paper. These models include econometric models, machine learning models, and deep learning models.

1) Vector Autoregression (VAR) Model:

The Vector Autoregression (VAR) model is a multivariate time series model that captures the relationships among multiple variables over time. It considers each variable as a linear combination of its lagged values and the lagged values of other variables in the system. VAR models are widely used in econometrics and finance to analyze the dynamic interactions and responses of variables to shocks or changes in the system[3]. The order of the VAR model determines the number of lagged terms considered for each variable, allowing it to capture both short-term and long-term dependencies in the data.

2) Linear regression model

Linear regression model is a statistical method used to model the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the variables, where changes in the independent variables are associated with proportional changes in the dependent variable. The model aims to find the best-fitting line that minimizes the sum of squared differences between the observed and predicted values. This allows for the prediction of the dependent variable based on the values of the independent variables.

3) Support Vector Machine Regression:

Support Vector Machine Regression (SVR) is a machine learning algorithm used for regression tasks. SVR aims to find a hyperplane that best fits the data while maintaining a specified margin of error (epsilon)[4]. It maps the input data into a higher-dimensional space and finds the hyperplane that maximizes the margin while allowing data points to lie within the margin. SVR can handle non-linear relationships between features and target variables by utilizing kernel functions. It is particularly necessary for dealing with complex data patterns and outliers.

4) Random Forest Regression:

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Random Forest Regression is an ensemble learning algorithm that combines multiple decision trees to make accurate predictions. Each decision tree is built using a random subset of the data and features, and the final prediction is an average or weighted average of the predictions from individual trees. This approach reduces overfitting and improves generalization. Random Forest Regression is effective in handling non-linearity, interactions between features, and noisy data. It's known for its robustness and ability to provide feature importance rankings.

5) Gradient Boosted Regression:

Gradient Boosted Regression is another ensemble technique that combines multiple weak learners, typically decision trees, to create a strong predictive model. It builds trees sequentially, with each subsequent tree aiming to correct the errors of the previous ones. This process is guided by the gradient of the loss function, hence the name "gradient boosted." Gradient Boosted Regression is powerful in capturing complex relationships in the data and is often used for tasks that require high predictive accuracy.

6) K-Nearest Neighbors Regression:

Nearest Neighbors Regression is a non-parametric algorithm used for both classification and regression tasks. It predicts the target value for a given data point by averaging the target values of its k-nearest neighbors. The "k" value is a hyperparameter that determines the number of neighbors considered. K-Nearest Neighbors Regression is capable of handling various data distributions and complexities.

7) Long Short-Term Memory (LSTM):

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to capture long-range dependencies in sequential data[5]. LSTMs are particularly effective in time series analysis and natural language processing. Unlike traditional RNNs, LSTMs mitigate the vanishing gradient problem through gated cells that control the flow of information. They can learn from both short-term and long-term patterns in data and are adept at handling sequences with varying time lags and complex temporal relationships.

3.3. Model Predictions

Figure 4. Variable value trend chart

Initially, a VAR model was established for predictive analysis. An inspection of the time series data was conducted to observe the trends exhibited by each variable over time. Figure 4 illustrates the numerical trends of various economic variables over time. It was evident in Figure 4 that variables such as GDP, PPI, Housing Price, and Population displayed discernible

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monotonic increasing trends. However, other variables, including spread and inflation date, exhibited random fluctuations devoid of any discernible trends over time.

In order to show which variables have predictive significance for GDP, Granger causality tests as well as cointegration tests are very necessary. Finally, the model passed a series of tests.

Because the number of samples in the training sample is 166, which is a relatively large sample, BIC was chosen as the indicator to judge the lagging order. In the above output, the BIC drops to lowest at lag 3, then increases at lag 4 and then continuously drops further. Here go with the lag 3 model.

```
Results for equation GDP
=========================================================================================
                           coefficient       std. error           t-stat            prob
-----------------------------------------------------------------------------------------
const                      1995.021786      5074.879895            0.393           0.694
L1.GDP                       -0.982007         0.124416           -7.893           0.000
L1.unemployment rate      18916.679623      9204.776140            2.055           0.040
L1.PPI                     3901.904790      2049.844227            1.904           0.057
L1.Housing price           6622.064684      2790.237206            2.373           0.018
L1.net exports               -1.099917         0.610926           -1.800           0.072
L1.saving rate            -2876.109651      5314.029504           -0.541           0.588
L2.GDP                       -0.963247         0.175997           -5.473           0.000
L2.unemployment rate      10477.186362     11328.471878            0.925           0.355
L2.PPI                       60.995778      2072.539395            0.029           0.977
L2.Housing price           5269.722905      2756.298640            1.912           0.056
L2.net exports               -1.208164         0.565236           -2.137           0.033
L2.saving rate           -12074.391052      7122.179261           -1.695           0.090
L3.GDP                       -0.857626         0.127547           -6.724           0.000
L3.unemployment rate       -803.184257      9583.957464           -0.084           0.933
L3.PPI                     1738.229116      2248.848960            0.773           0.440
L3.Housing price           6688.234145      2867.467444            2.332           0.020
L3.net exports               -0.535839         0.613464           -0.873           0.382
L3.saving rate           -16030.816681      5083.706289           -3.153           0.002
=========================================================================================
```

Figure 5. VAR model results

Figure 5 shows part of the training results in the VAR model with GDP as the dependent variable.

Table 2. DW test results

Variable	DW
GDP	1.81
unemployment rate	1.96
PPI	2.12
Housing price	1.91
net exports	1.99
saving rate	1.95

Table 2 shows the results of the DW sequence correlation test. The closer it is to the value 2, then there is no significant serial correlation. Then, doing the forecast.

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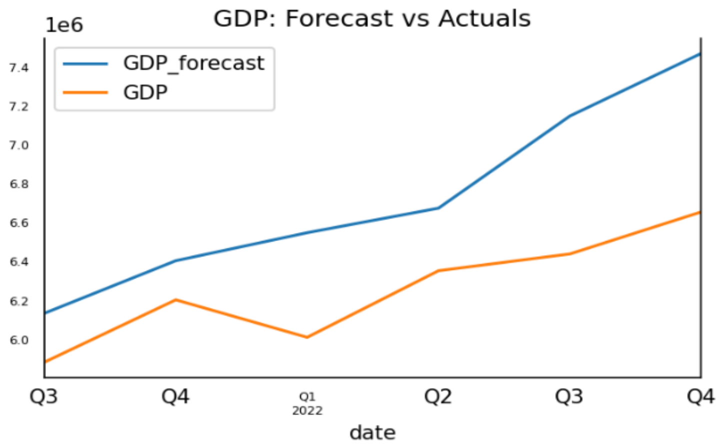

Figure 6. Prediction effect of VAR model

Figure 6 shows the predicted and actual GDP results. The above results are the predicted values of the VAR model for each variable and the graphical representation of the GDP forecasts, respectively. It can be seen that for the test set data, the predicted value of the model is slightly higher than the real GDP value, and the prediction effect is average.

Then, make the evaluation. Prediction error, goodness-of-fit and other indicators are used to evaluate the accuracy of model prediction. Below are the results of the indicators forecast for GDP, including MAPE, MAE, MPE, RMSE, corr and minmax. The forecast accuracy of GDP is presented in the Table 3.

Table 3. VAR model prediction error

MAPE	0.0746
ME	472298.9
MPE	0.0746
RMSE	526105.1
CORR	0.9263
MINMAX	0.0684

From the perspective of MAPE, MPE, and corr, the predictive effect of the model is okay, but if ME or MAE is used as the evaluation standard, The error is relatively large, and the prediction effect is average.

Table 4. MAE values predicted by each model - United States

Model type	MAE value
Linear Regression	40657.6705
Support Vector Machine Regression	1270199.574
Random Forest Regression	39863.7317
Gradient Boosted Regression	55572.1307
K-Nearest Neighbors Regression	87153.0486
LSTM	49811.2217

Subsequently, both machine learning and deep learning methodologies were employed for forecasting.A standardized practice was applied in configuring hyperparameters for both approaches. Specifically, the training-to-testing data split ratio was set at 80% for the training

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set and 20% for the testing set. Additionally, the Long Short-Term Memory (LSTM) model underwent rigorous training over the course of 100 epochs.This uniformity in hyperparameter settings across the various machine learning approaches ensures a consistent and equitable evaluation framework. The predictive performance was assessed using two widely accepted error metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics serve as indicators of the model's accuracy and effectiveness in forecasting. The Test MAE results are displayed in the Table 4.

The analysis revealed that among the employed methodologies, Random Forest Regression demonstrated the most superior performance. Figure 7 representations of the prediction errors, providing a more intuitive means to observe and compare the magnitude of errors.

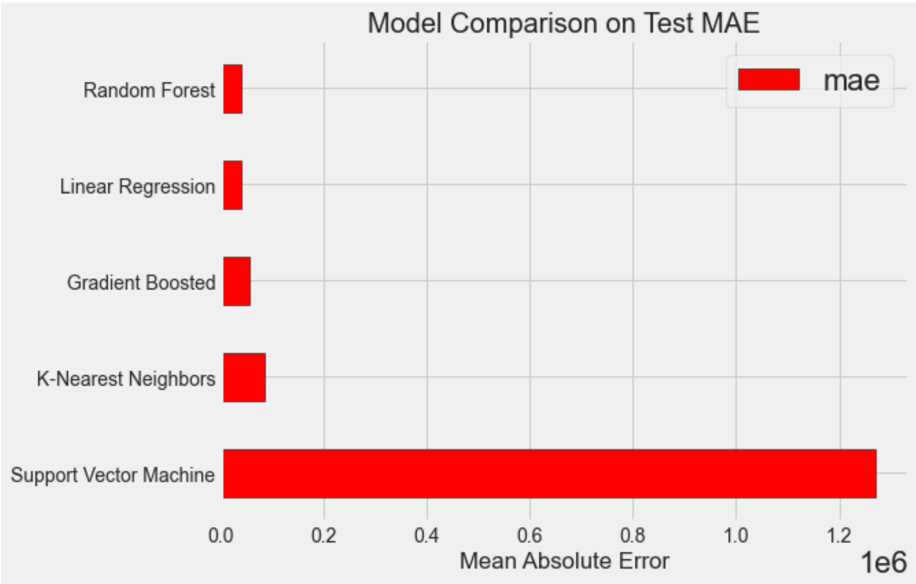

Figure 7. Test MAE comparison diagram - United States

Similarly, Test RMSE results can be utilized to gauge prediction errors, enabling a comparison of the performance among various models. Among the methodologies employed, Gradient Boosting Regression exhibited notably superior performance in the analysis. The Test RMSE results are displayed in the Table 5.

Table 5. RMSE values predicted by each model - United States

Model type	RMSE value
Linear Regression	79392.407
Support Vector Machine Regression	1590959.388
Random Forest Regression	81618.4247
Gradient Boosted Regression	78993.7937
K-Nearest Neighbors Regression	114589.8399
LSTM	280358.76

4. Model Predictions of Italy

4.1. Data

The data for the analysis of Italy was sourced from two platforms: Fred and Stooq. This analysis encompasses a dataset spanning from the first quarter of 1996 (1996Q1) to the fourth quarter

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of 2022 (2022Q4). The Italian dataset encompassed 108 observations. The specific variables selected and their description are shown in Table 6.

Table 6. Variable declaration table - Italy

variable name	types of variables
GDP	dependent variable
Treasury_Bills	explanatory variable
unemployment_rate	explanatory variable
PPI	explanatory variable
Housing_price	explanatory variable
net_exports	explanatory variable
Share_growth	explanatory variable
Population	explanatory variable
total_stock	explanatory variable
Bond_Yields	explanatory variable
saving_rate	explanatory variable
Inflation_Rate	explanatory variable

4.2. Models Predictions

Similar to the economic forecasting section for the United States, a similar methodology was employed for forecasting the Italian economy. This mainly entailed the utilization of machine learning and deep learning models.

In this section, the predictive performance was assessed using two widely accepted error metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These metrics serve as robust indicators of the model's accuracy and effectiveness in forecasting. The Test MAE results are presented in the Table 7. A smaller value indicates a smaller prediction error associated with the respective model, thus reflecting better predictive performance for the model.

Table 7. MAE values predicted by each model - Italy

Model type	MAE value
Linear Regression	14095.7474
Support Vector Machine Regression	36608.1379
Random Forest Regression	13911.104
Gradient Boosted Regression	15289.3386
K-Nearest Neighbors Regression	16259.4073
LSTM	29276.4689

The analysis revealed that Random Forest Regression demonstrated superior performance in this context. Figure 8 representations of the prediction errors, providing a more intuitive means to observe and compare the magnitude of errors.

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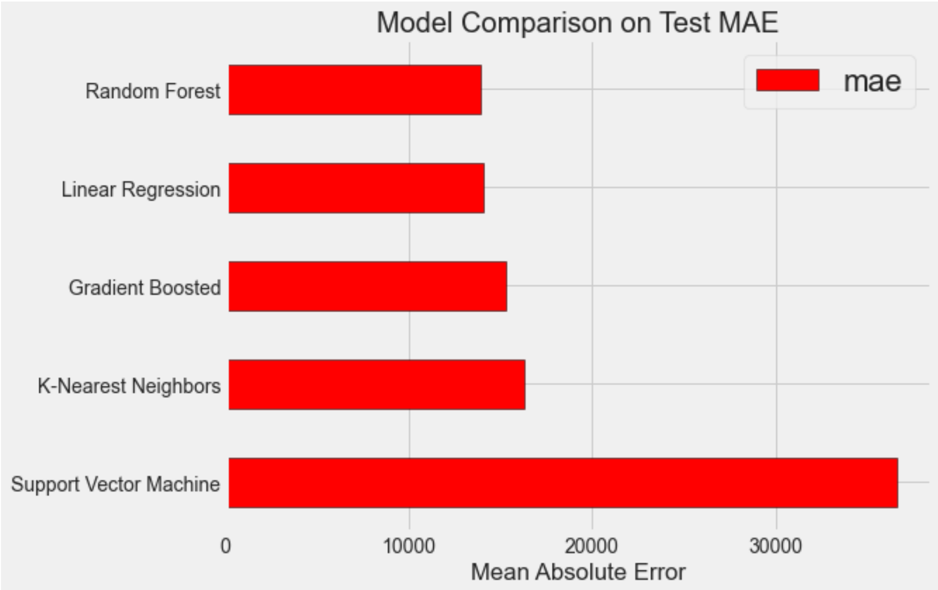

Figure 8. Test MAE comparison diagram - Italy

Test RMSE results can be utilized to gauge prediction errors, enabling a comparison of the performance among various models. Among the methodologies employed, Linear Regression exhibited notably superior performance in the analysis. The Test RMSE results are displayed in the Table 8.

Table 8. RMSE values predicted by each model - Italy

Model type	RMSE value
Linear Regression	16529.3084
Support Vector Machine Regression	45228.7515
Random Forest Regression	18511.4644
Gradient Boosted Regression	19695.8427
K-Nearest Neighbors Regression	18484.4589
LSTM	33542.87

The analysis indicated that Linear Regression exhibited superior performance in this context.

5. Limitations of Models

While the predictive models employed in this study demonstrate notable effectiveness, further research is needed. Also, it is imperative to acknowledge certain small limitations:

1) In several instances, machine learning techniques do not exhibit superior performance when compared to the conventional linear regression approach. The overall efficacy of linear regression remains commendable.

2) The determination of hyperparameters necessitates a tailored approach based on specific contextual nuances, with meticulous consideration to mitigate potential issues associated with overfitting.

3) Given the constraints posed by a relatively confined dataset, machine learning models may not consistently yield optimal performance.

These identified constraints will be subject to closer scrutiny in future research endeavors.

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6. Conclusion

The COVID-19 pandemic has had a huge impact on economic development. This paper employs various machine learning and econometric methods to forecast economic recessions. Through the modeling analysis and the comparative analysis of prediction errors, it was determined that when analyzing data from both the United States and Italy, the Random Forest Regression method displays relatively small errors, indicating its superior overall performance.

When assessing errors in the United States data using the RMSE metric, the Gradient Boosted Regression method emerges as the top performer. Ordinary Linear Regression doesn't consistently rank as the least effective method; in certain scenarios, it even surpasses the performance of machine learning or deep learning approaches. Notably, when evaluating Italian data with the RMSE method, Linear Regression yields the smallest error, stating its unexpected effectiveness. In summary, various models, especially machine learning models, have an important impact on GDP forecasting in the context of recessions.

Acknowledgments

Professor Erik S. Yan.

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