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Predicting Ethiopian gross domestic product using machine learning model

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Abstract

The Gross Domestic Product (GDP) is an extensive indicator that reflects all of a country's economic activity over a certain time period. It calculates the total monetary value of all commodities and services produced within the country's borders. We employed a variety of algorithms and models to forecast Ethiopia's GDP using machine learning, including linear regression, Lasso regression, ridge regression, decision tree regression, random forest regression, gradient boosting regression, support vector machine regression, and neural network regression. Three phases comprise our investigation. First, we collect a dataset consisting of several economic statistics from the National Bank of Ethiopia. The gathered dataset is then preprocessed to ensure machine learning models can use it. Ultimately, we partition the dataset, designating 80% of it for model training and the remaining 20% for performance assessment. We employ a 5-fold cross-validation approach and consider evaluation metrics, including R-squared, mean absolute error, root mean square error, and mean squared error, to assess the efficacy of the model. Among all the models, Ridge Regression performs the best, achieving the lowest root mean squared error of 27,231,241,464.13, the highest R-squared value of 0.9950, a mean squared error of 1.06e+20, and a mean absolute error of 21,552,080,423.90. These results indicate that the model captures 99.5% of the variability in the data. Consequently, using the test dataset, the Ridge Regression model accurately forecasts Ethiopia's GDP.

Keywords: Gross Domestic Product; Ethiopia Economy; Machine Learning; Predictive model evaluation; Regression algorithm; Macroeconomic indicators

Introduction

Gross Domestic Product (GDP) measures the total monetary value of all goods and services produced within a nation's borders over a specific period of time. It serves as a key indicator of economic activity, calculated through the expenditure approach, which combines the spending of households, corporations, and the government (Egbunike and Okerekeoti, 2018). Gross Domestic Product (GDP) measures a nation's total production of goods and services over a period, providing a comprehensive assessment of its economic state. Comparing GDP over time requires adjusting for inflation. It's typically calculated annually but can be done weekly (Bekaert et al., 2006). Ethiopia, a developing nation, heavily relies on agriculture, which contributes 43% to its GDP and employs 83% of the population. Despite past growth challenges, the country has seen strong economic growth recently (Abdi et al., 2020). Ethiopia's GDP in 2022 was $126.78 billion, comprising about 0.06% of the global economy.

Despite efforts to bolster the economy, some initiatives have faced challenges, potentially influenced by economic instability elsewhere (Agu et al., 2022). Ethiopia focuses on industrialization for economic growth, establishing parks and economic zones to attract investments and enhance manufacturing. These efforts have drawn foreign investment and generated jobs, as noted by the World Bank (2019). Ethiopia modernizes agriculture to boost productivity and alleviate poverty. Initiatives include promoting irrigation, offering farmer support, and investing in research. These efforts have led to higher food production and improved livelihoods (Rohne, 2022). Ethiopia invests heavily in infrastructure, building roads, railways, and energy projects to boost connectivity and spur economic growth. These efforts have bolstered trade, job creation, and private sector investment (Clapham, 2018). Ethiopia taps into tourism for economic growth, highlighting its cultural and natural attractions to attract international visitors. This strategy has led to steady tourism growth, creating jobs, and boosting foreign exchange earnings (Degarege and Lovelock, 2021).

Machine learning applies computational algorithms to turn data into practical models, stemming from statistics and artificial intelligence communities (Edgar and Manz, 2017). Machine learning, a key part of AI systems, is vital for solving diverse industry challenges (Elisaye et al., 2023). Machine learning captures complex economic relationships, handling numerous variables and detecting nonlinear patterns often missed by traditional statistics. It excels at processing high-dimensional datasets, enhancing GDP prediction accuracy through techniques like dimensionality reduction and feature selection (Huang et al., 2005). Predictive modelling uses historical and current data to forecast future events, employing techniques like machine learning and data mining. It falls under AI, with machine learning handling structured data and deep learning managing unstructured data like text, voice, and images (Spratling, 2017).

Existing literature mainly centers on predicting Ethiopia's GDP using traditional statistical methods (Abdurhman et al., 2024), Traditional statistical models typically employ linear relationships between predictors and the target variable. However, GDP is influenced by a broad array of factors that may not adhere to linear patterns. In contrast, our machine learning models are adept at handling nonlinearities and interactions, resulting in more precise predictions, especially in intricate scenarios. Traditional statistical models often hinge on specific assumptions, such as the normality of residuals or the independence of observations, which may not always hold in real-world economic data. Breaching these assumptions can yield biassed estimates and unreliable predictions. Conversely, our machine learning models, particularly those rooted in empirical data learning, exhibit greater resilience to assumption violations and can adapt to various data distributions and patterns. While traditional statistical models may perform adequately with smaller datasets, they may struggle to generalize to new data or discern subtle relationships in their absence. On the other hand, our machine learning models can harness extensive datasets to unveil concealed patterns and generate more accurate predictions, contingent on the data's high quality and representation of the underlying population. The utilization of traditional statistical models presents challenges for policymakers endeavoring to make informed decisions and devise effective economic policies (Abdulhafedh, 2017).

This research identifies a gap in utilizing machine learning models for GDP prediction in Ethiopia. These models can handle diverse data, offering policymakers more accurate GDP forecasts by analyzing various factors like economic indicators, government policies, infrastructure, and socio-economic aspects. Addressing this gap empowers policymakers to make informed decisions, allocate resources effectively, and design evidence-based policies for economic development and stability in Ethiopia. Our research aims to forecast Ethiopia's GDP using economic indicators and financial variables, exploring if machine learning can improve prediction accuracy alongside traditional methods. We utilize a range of machine learning models, including linear regression, Lasso regression, ridge regression, decision tree regression, random forest regression, gradient boosting regression, support vector machine regression, and neural network regression, to assess their effectiveness and compare their performance. By evaluating these models, we seek insights into their effectiveness in GDP prediction, paving the way for advanced forecasting methodologies in Ethiopia.

The key contributions of this study include creation of a predictive framework; improved prediction accuracy; contribution to data-driven policy making; identification of key predictive features; and customization for developing economies.

Methods and techniques

Proposed study design

To predict Ethiopia's GDP utilizing machine learning, we have implemented a research design that encompasses the steps depicted in Figure 1.

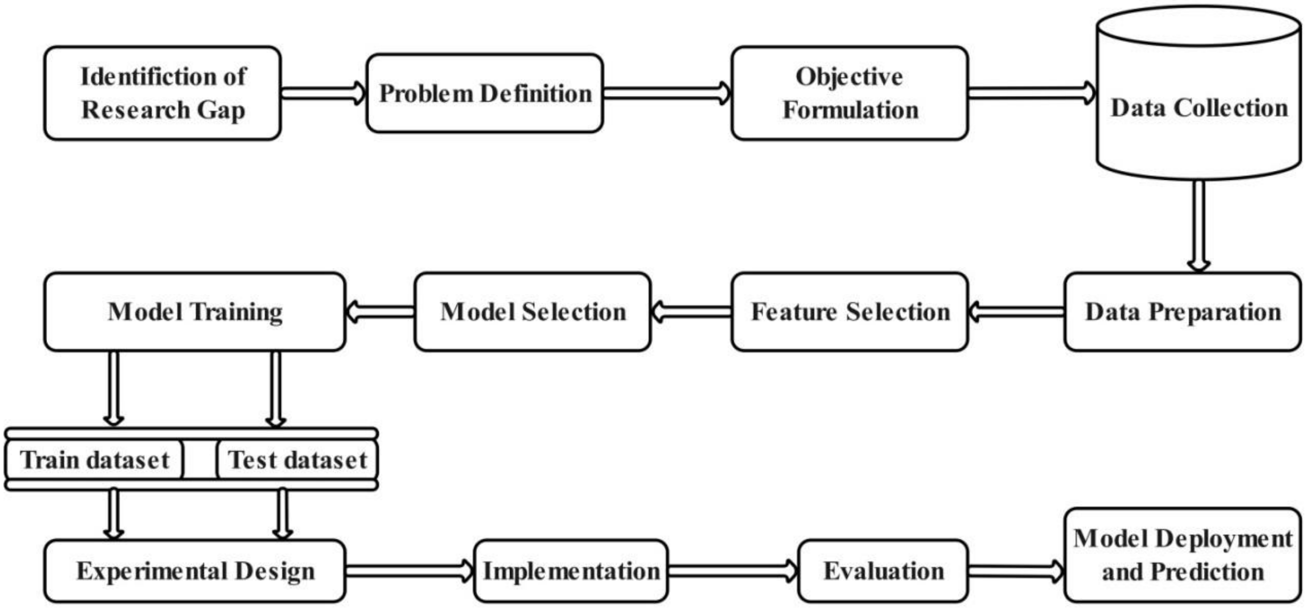

Figure 1: Diagram illustrating the experimental flow of the suggested approach.

Data source

The National Bank of Ethiopia (NBE), being Ethiopia's central bank, serves as a valuable resource for gathering data to study the country's GDP. It is really important in the collection and management of economic data across different sectors and indicators. By obtaining data from the NBE, we have a comprehensive dataset consisting of 21 rows and 12 columns. The dataset is structured on an annual frequency basis for training machine learning models. The dataset we gathered is centered on the real gross domestic product (RGDP) for the base year 2015, without considering the GDP deflator. This is because the GDP deflator is useful for measuring changes in the overall price level and inflation rate. Real GDP is typically preferred for predicting GDP because it provides a more accurate measure of economic growth and is better suited for analyzing economic trends and making forecasts. This dataset includes important economic variables such as government expenditure, net export, personal consumption expenditure, investment, wages and salaries, population, foreign exchange reserve, general inflation rate, foreign direct investment, export rate, and real gross domestic product. This extensive and reliable data serves as a foundation for understanding the factors that influence Ethiopian GDP.

Tools and software libraries for experimental work

We employed Python as our programming language, which interacts with several libraries included in the Anaconda distribution. Additionally, we utilized Jupyter Notebook as our interactive computing

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environment. The following popular Python libraries were utilized in this study: Scikit-learn, Pandas and NumPy, Matplotlib, Seaborn, XGBoost, and Statsmodels.

Data preparation

After collecting data from the National Bank of Ethiopia (NBE) to forecast Ethiopia's GDP using a machine learning model, the subsequent stage entails data preparation for the experimental process. During this phase, we conducted data cleaning, encompassing the handling of missing values, outliers, inconsistencies, and noise. We also integrated various datasets, involving tasks such as feature concatenation and data aggregation, selected pertinent features, scaled and normalized the features, managed categorical variables, and transformed the data while addressing multicollinearity. To execute these tasks, we utilized a combination of Python libraries, including Pandas, NumPy, and Scikit-learn. These libraries are highly versatile and provide extensive capabilities for data cleaning and manipulation. They offer a wide range of functions and methods that effectively handle various data cleaning tasks.

Feature selection

We have selected key factors that significantly impact Ethiopia's GDP dynamics. These factors include government expenditure, net export, personnel consumption expenditure, investment, wage and salary, population, foreign exchange reserve, general inflation rate, foreign direct investment, and exchange rate. These variables have a strong influence on GDP, supported by substantial scientific evidence. For instance, research by Alesina and Perotti (1999) indicates that increased government expenditure positively affects GDP growth, particularly during economic downturns. Similarly, Romer and Romer (2010) highlight the role of net exports in driving GDP fluctuations, especially during economic expansions or contractions. Personnel consumption expenditure, emphasized by Mankiw and Weil (1989), and investment, as highlighted by Barro (1991) and Jorgenson (1963) are also significant determinants of GDP growth. Additionally, studies by Blanchard and Katz (1999) underscore the impact of wage and salary increase and population growth on GDP dynamics, respectively. Moreover, foreign exchange reserves can influence GDP through their effects on exchange rates and external trade, as supported by research by Ranciere and Jeanne (2006). The general inflation rate, according to Fischer (1979), and Taylor (1979) can either promote or hinder GDP growth, depending on its level. Foreign direct investment (FDI) is another important driver of GDP, as indicated by research by Alfaro et al. (2004) and Blomström (2002). Exchange rate fluctuations analyzed by Obstfeld and Rogoff (1996) and Bahmani-Oskooee and Brooks (1999) also play a crucial role in shaping GDP dynamics, affecting trade competitiveness and capital flows.

Machine learning models selection for the study

In our study aimed at predicting the Gross Domestic Product (GDP) of Ethiopia, we relied on a dataset comprising quantitative or numerical data. This type of data is particularly advantageous for regret machine learning, as it enables us to apply various regression models. In our analysis, pivotal roles are played by various models, such as linear regression, decision tree regression, Lasso regression, ridge regression, and random forest regression.

Linear regression is a method of statistics utilized to describe the correlation between several independent variables and a dependent variable. A typical equation for a basic linear regression equation (Montgomery et al., 2021) is as follows:

$$Y = \beta_0 + \beta_i * X_i + \varepsilon_i \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_}(1)$$

Where:

- Y is the dependent variable (in this example, GDP).
- X denotes the independent variable (such as economic indicators).
- β_0 serves as the y-intercept, signifying the value of Y when X is zero.
- β_i is represents the slope, depicting the alteration in Y for a one-unit change in X.
- ε_i signifies the error term, which accommodates the variability in Y that remains unexplained by the regression model.

Decision tree regression: Unlike linear regression, decision tree regression is not predicated on a linear connection between both dependent and independent features (Hastie et al., 2009).

$$Y = \frac{1}{N}\sum_{i=1}^{N} y_i \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_}(2)$$

Where:

- Y is the predicted target value for instance *X*.
- N is the number of training instances that fall into the same leaf node as *X*.
- y_i are the target values of the training instances in the same leaf node.

Lasso regression: It is a regression approach that involves choosing variables and normalizing them at the same time. It is also known as the Least Absolute Shrinkage and Selection Operator. This strategy is useful, especially when working with datasets with a large number of characteristics, because it effectively reduces the influence of unimportant factors (Friedman et al., 2010).

$$\mathrm{Y} = \beta_0 + \Sigma(\beta_i * X_i) + \varepsilon \quad \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_}(3)$$

Where:

- Y denotes a dependent variable's forecasted value.

- β_0 is the y-intercept
- $\Sigma(\beta_i * X_i)$ represents the sum of the product of the coefficients (βi) and the corresponding independent variables (Xi)
- ε represents the error term

Ridge regression**:** It was created to address the problem of convergence in linear regression models. Its main objective is to minimize the sum of squared coefficients as well as the sum of squared residuals, which show the difference between the values that were predicted and the actual values (Fox, 2015).

The formula can be depicted as:

$$mimimize\ J(\beta) = \sum_{i=1}^{N}(y_i - X_i\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j^2 \text{ \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(4)}$$

Where:

The parameter λ in Ridge Regression governs the degree of shrinkage applied to the coefficients, striking a balance between diminishing residuals and minimizing the magnitude of coefficients. Increased values of λ intensify regularization and shrinkage. Ridge Regression incorporates a normalization term to mitigate the impact of multicollinearity, stabilizing the model by pulling coefficient values towards, though not precisely to, zero. This achieves a compromise between model complexity and the influence of correlated variables.

- N is the number of observations.
- p is the number of predictors (features).
- y_i is the observed target value for the i^{th} observation.
- X_i is the vector of predictor variables for the i^{th} observation.
- β is the vector of regression coefficients to be estimated.
- λ is the regularization parameter, also known as the tuning parameter or penalty term.
- The term $\sum_{i=1}^{N}(y_i - X_i\beta)^2$ represents the residual sum of squares, which measures the difference between the observed target values and the values predicted by the linear model.
- The term $\lambda\sum_{j=1}^{p}\beta_j^2$ is the regularization term, where β_j represents the j^{th} regression coefficient.

Random Forest Regression creates multiple decision trees and aggregates their forecasts toward additional precise and strong predictions (Breiman, 2001).

$$\text{Y} = \frac{1}{T}\sum_{t=1}^{T} f_t(X) \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(5)}$$

Where:

- Y is the predicted output (target value) for the input instance X.
- T is the total number of trees in the forest.
- $f_t(X)$is the predicted output of the t^{th} tree for the input instance X.

Gradient Boosting: a machine learning algorithm that associates a collaborative of feeble pupils, typically decision trees, towards a robust prognostic method. It is a boosting algorithm that iteratively builds the model by minimizing a loss function through gradient descent (Friedman, 2001).

$$F(x) = \beta_0 + \Sigma(\gamma * h(x)) \quad (6)$$

Where:

- F(x) reflects the desired variable's projected value.
- β_0 is the initial prediction or the y-intercept
- $\Sigma(\gamma * h(x))$ represents the sum of the contributions from individual weak learners (h(x)) weighted by their respective learning rates (γ)

Neural network regression: involves employing an artificial neural network to forecast the relationship between input data and a continuous target variable in machine learning. This method consists of interconnected layers of nodes (neurons) that analyze and transform incoming data to generate predictions (Goodfellow et al., 2016).

$$Y = f(W * X + b \quad (7)$$

Where:

- Y denotes the target variable's expected value.
- f(.) is the function of activation that causes the representation to be nonlinear.
- W denotes the weight matrix that governs the fragility of neural connections.
- X denotes the input characteristics.
- b denotes a prejudice term

Support vector machine Regression: a machine learning algorithm employing support vector machines to approximate the association between input features and a continuous target variable. The primary objective is to identify a hyperplane that optimally accommodates the data by simultaneously minimizing prediction errors (Cristianini and Shawe-Taylor, 2000).

$$Y = \Sigma(\alpha_i * K(X_i, X)) + b \quad (8)$$

Where:

Y signifies the anticipated value of the target variable.

$\Sigma(\alpha i * K(Xi, X))$ represents the sum of the product of the coefficients (αi) and the kernel function (K) applied to the support vectors (Xi) and the input variable (X); b denotes the bias term.

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Experimentation results

Coding data for experimentation

Coding data for experimentation involves systematically assigning labels or codes to collected data. In our study, we encountered a feature with a lengthy string name that was not suitable for experimentation or graph plotting. To address this, we have provided a list of collected data features and their corresponding codes:

Table 1. Features and its codes

Features	Code
Years	Year
Government Expenditure	GE
Net Export	NE
Personal Consumption Expenditure	PCE
Investment	Inv
Wages and Salaries	WS
Population	POP
Foreign Exchange Reserve	FER
General inflation Rate	GIR
Foreign Direct Investment	FDI
Export Rate	ER
Real Gross Domestic Product	RGDP

Feature scaling

In order to ensure optimal performance of our machine learning model, we employed the technique of feature scaling using the Standard Scaler. This process involved transforming our features to a standard scale, where the mean is centered at 0 and the standard deviation is set to 1. By performing this scaling, we aimed to eliminate any potential bias caused by varying scales or units in our features. This allows the model to effectively compare and weigh the impact of each feature on the prediction of GDP, ensuring that no single feature dominates the learning process. The standardized features provide a level playing field for the model, enabling it to make more accurate and reliable predictions based on the scaled feature values.

Correlating features

In this study, we examined the correlation among various features. The presence of correlated features enhances the accuracy of the machine learning model's predictions. Moreover, these correlated features offer supplementary insights and enable the model to grasp intricate patterns within the data. The figure presented below illustrates the correlation among various features in our feature-scaled data.

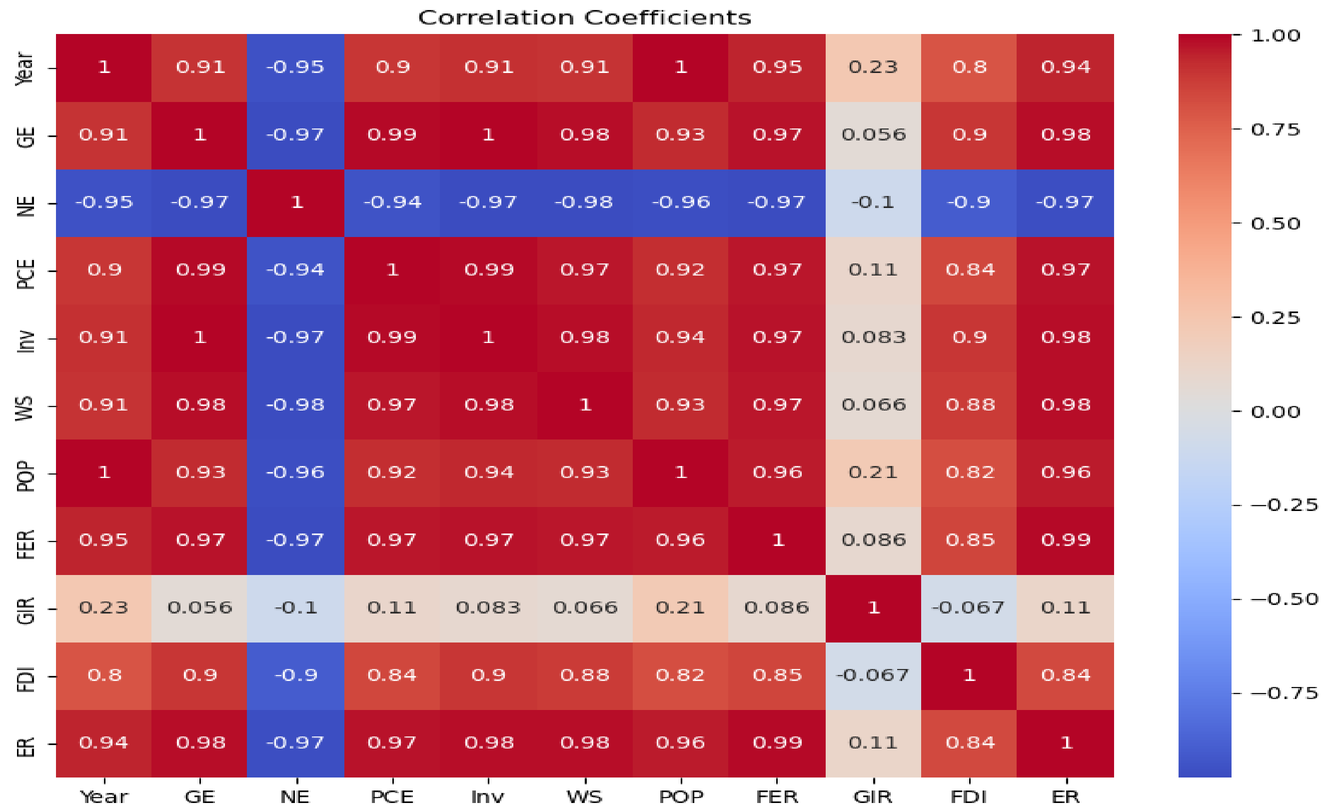

Figure 2. Correlation coefficient of features

Splitting training and testing data

In order to ensure reliable and accurate machine learning results, the collected data for experimentation has undergone a random split into two distinct sets: training and testing. The training dataset encompasses 80% of the collected data, while the unallocated fraction is set aside exclusively for evaluating the effectiveness of the lmachine learning system. The primary purpose of the training data is to help improve the performance of the machine learning system. In contrast, the testing data is critical in determining the efficacy of the trained machine learning model. The dataset utilized in this study was sourced from the National Bank of Ethiopia, ensuring both its credibility and appropriateness for analysis. The provided information presents a sample dataset that has been organized using the Pandas library. This dataset is displayed in Table 2.

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Table 2. Summary statistics of input features:

	GE	NE	PCE	Inv	WS	POP	FER	GIR	FDI	ER
count	2.100000e+01	2.100000e+01	2.100000e+01	2.100000e+01	21.000000	2.100000e+01	2.100000e+01	21.000000	2.100000e+01	21.000000
Mean	1.392048e+11	-1.323200e+11	5.900524e+11	2.947190e+11	10.945400	8.783298e+07	3.768095e+10	12.165974	1.156048e+09	15.269405
std	1.493066e+11	1.267893e+11	6.621609e+11	3.323755e+11	1.987174	1.522378e+07	3.319868e+10	13.735518	1.359333e+09	7.426839
min	1.710000e+10	-3.500000e+11	4.300000e+10	1.700000e+10	8.792894	6.507758e+07	2.830000e+09	-10.773386	7.000000e+07	8.142600
25%	2.460000e+10	-2.710000e+11	7.680000e+10	3.190000e+10	9.465111	7.530103e+07	9.980000e+09	7.321393	2.550000e+08	8.651800
50%	4.690000e+10	-8.280000e+10	2.910000e+11	1.190000e+11	10.047310	8.675558e+07	2.710000e+10	10.393734	4.650000e+08	12.890900
75%	2.310000e+11	-2.410000e+10	9.010000e+11	5.090000e+11	12.329750	9.974677e+07	6.640000e+10	15.300000	1.860000e+09	20.095600
max	4.800000e+11	-7.680000e+09	2.360000e+12	1.040000e+12	14.900360	1.141206e+08	1.080000e+11	55.241315	4.140000e+09	31.342700

Results

a) Linear Regression Model (LRM)

Upon training the linear regression model with the relevant data, noteworthy results were obtained. The Root Mean Square Error (RMSE) for this model was computed to be 90,966,944,633.33. Additionally, the Mean Squared Error (MSE) was found to be 1.75e+21, while the Mean Absolute Error (MAE) was determined to be 35,053,781,191.96. These parameters provide details on the model's accuracy and performance. Furthermore, the coefficient of determination (R^2) was computed to be 0.9931, showing that the model clarifies approximately 99.31% of the changeability in the data. This indicates that the linear regression model adequately matches the observed data. To present the results in a more intuitive manner, a visual representation in the form of a plot graph was generated. This graph depicts the predicted GDP values and compares them with the actual GDP values. We may acquire a better grasp of the regression analysis results by looking at this graph.

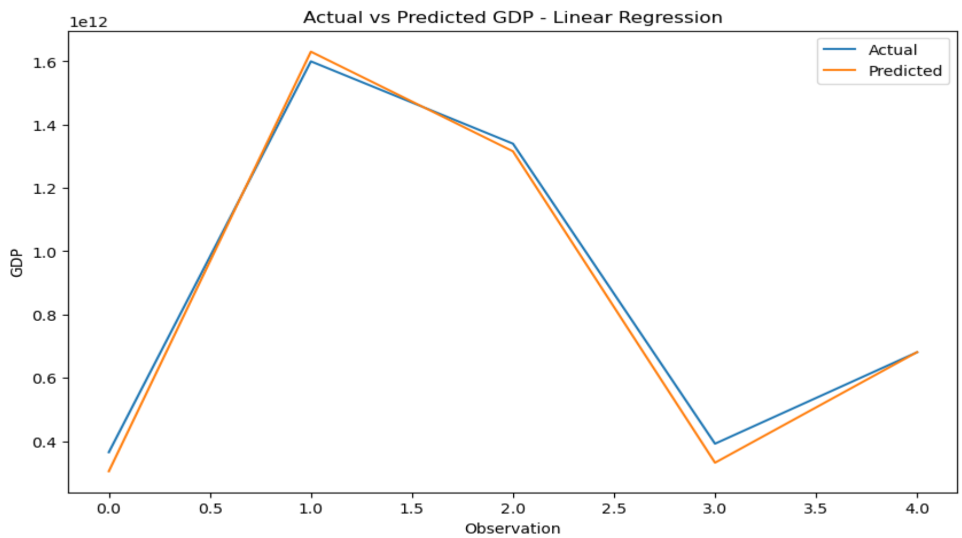

Figure 3. Linear regression: Actual GDP vs. Predicted GDP.

b) Decision Tree Regression Model (DTRM)

After training the Decision Tree Regression Model, we discovered significant results. The Root Mean Square Error (RMSE) of the model was computed and found to be 129,125,102,590.12. The Mean Squared Error (MSE) was discovered to be 8.10e+21, while the Mean Absolute Error (MAE) was assessed to be 73,600,000,000.00. These metrics offer valuable information about the accuracy and performance of the model. Furthermore, the coefficient of determination (R2) was calculated to be 0.9682, indicating that the model accounts for approximately 96.82% of the observed erraticism. This shows that the Decision Tree

Regression Model fits the observed data quite well. A plot graph was created to graphically illustrate the results. This graph compares the anticipated GDP numbers to the actual GDP values. We may acquire a full grasp of the regression analysis's conclusion by analyzing its graphic depiction.

However, when compared to other trained models, the performance of the Decision Tree Regression Model may not fulfil the unique needs of our study. It is critical to analyze the model's outcomes in light of our study goals. The graph illustrating the anticipated GDP values and their comparison with the actual GDP values will aid in understanding the regression analysis result.

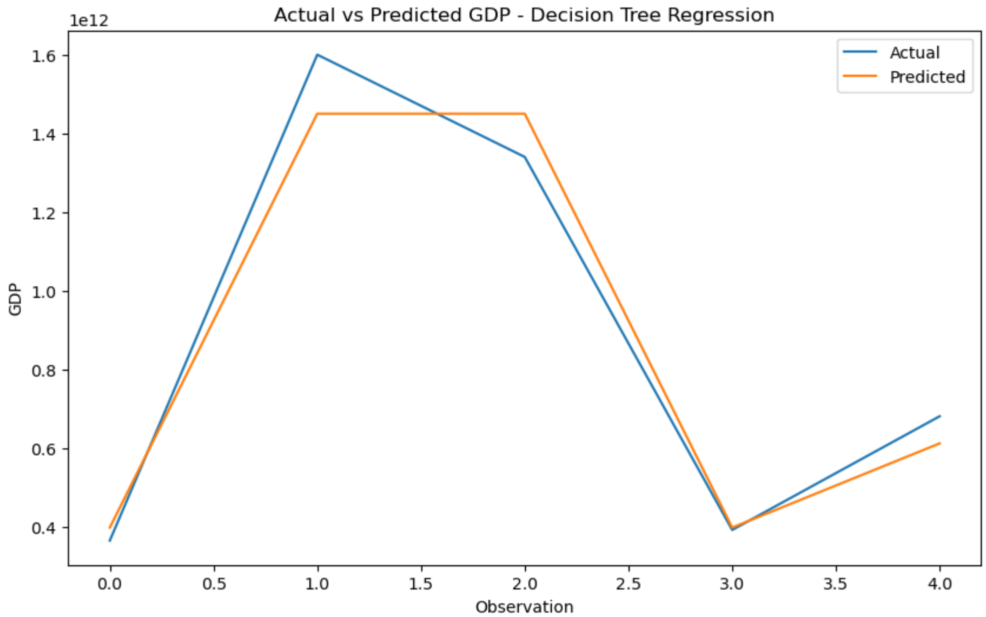

Figure 4. Decision tree regression model: Actual GDP vs. Predicted GDP.

c) Lasso Regression Model (LaRM)

We discovered some intriguing results after training the Lasso Regression Model (LRM).

Based on the performance measures of the model, it seems that the Root Mean Square Error (RMSE) is quite high at 43,185,938,276.79. This indicates that there is a significant difference between the predicted values and the actual values. Similarly, the Mean Squared Error (MSE) is extremely large at 3.57e+21, indicating a substantial amount of error in the model's predictions. The Mean Absolute Error (MAE) of 45,438,841,909.11 also suggests a considerable deviation between the predicted and actual values. These metrics provide information about a model's precision and effectiveness. Furthermore, the coefficient of determination (R2) was calculated to be 0.9860; consequently, the model describes approximately 98.60% of the variance in the data. This shows that the lasso regression model is a good match for the given data. A plot graph was created to graphically illustrate the results. This graph depicts expected GDP numbers and compares them to actual GDP levels. We may acquire a better grasp of the regression analysis results by looking at this graph.

However, when compared to other trained models, the lasso regression model's performance may not fulfil the unique needs of our study. It is vital to evaluate the model's results in light of our study aims. The graph representing anticipated GDP and its comparison with actual GDP values will assist in comprehending the regression analysis result.

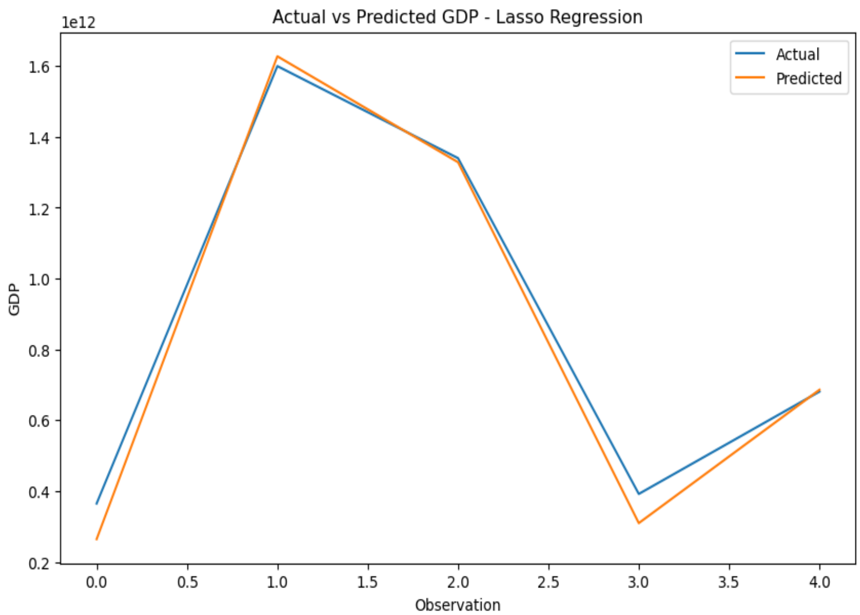

Figure 5**.** Lasso regression model: Actual GDP vs. Predicted GDP.

d) Ridge Regression Model (RRM)

Upon training the Ridge Regression Model (LRM), we obtained noteworthy results. The model's performance metrics were evaluated, revealing that the Root Mean Square Error had a value of 29,831,371,464.13. The Mean Squared Error (MSE) was calculated as 1.06e+20, while the Mean Absolute Error (MAE) was determined to be 22,652,080,435.94. These metrics give useful information about the model's precision and effectiveness. Furthermore, the coefficient of determination (R^2) was computed to be 0.9950, signifying that the model clarifies approximately 99.76% of the variance in the data. This high value suggests that the Ridge regression model fits the observed data exceptionally well. To visually represent the results, a plot graph was generated. This graph illustrates the predicted GDP values in comparison to the actual GDP values. By examining this visual representation, we can gain a comprehensive understanding of the regression analysis outcome. The performance of the Ridge regression model may not meet our study's specific requirements when compared to other trained models. It is crucial to evaluate the model's results within the context of our research objectives. The graph depicting the predicted GDP values and their comparison with the actual GDP values will provide further clarity in interpreting the regression analysis outcome.

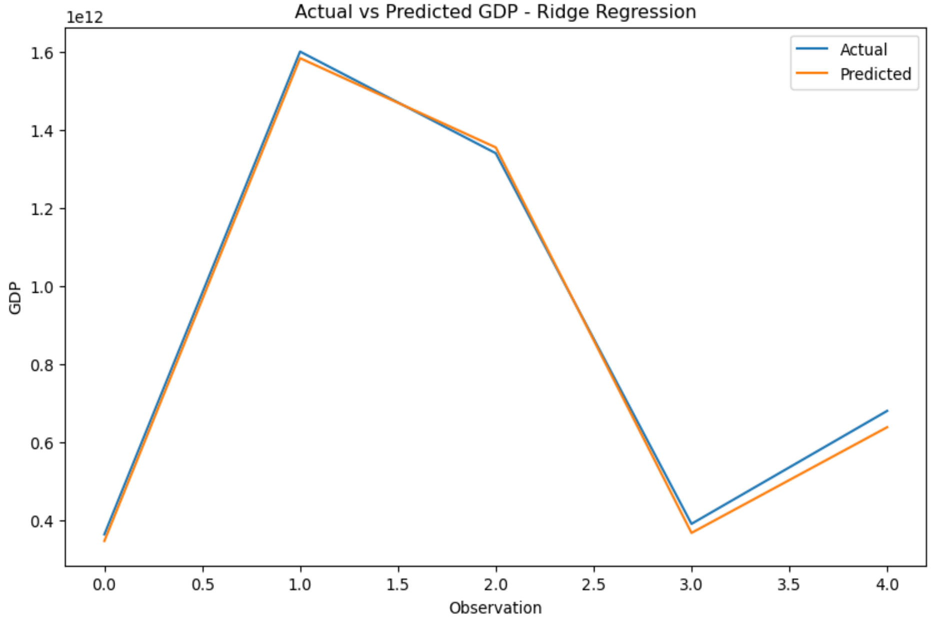

Figure 6. Ride regression model: Actual GDP vs. Predicted GDP.

e) Random Forest Regression Model (RFRM)

After training the Random Forest Regression model, we obtained interesting results. The model's performance was evaluated, and the Root Mean Square Error (RMSE) was determined to be 72,226,603,524.21. The Mean Squared Error (MSE) was 2.84e+21, while the Mean Absolute Error (MAE) was 48,578,000,000.00. These metrics provide valuable insights into the accuracy and performance of the model. Furthermore, the coefficient of determination (R2) was calculated to be 0.9888, which means that the model fits about 98.88% of the actual variance. This specifies that the RFR model adequately matches the observed data. A plot graph was created to display the results visually. This graph compares expected GDP values to actual GDP numbers. We may acquire a thorough grasp of the regression analysis's conclusion by analyzing its graphic depiction. However, when contrasted with other trained models, the results of the Random Forest Regression model may not fulfil the unique objectives of our study. It is critical to evaluate the model's outcomes in the context of our study aims. The graph illustrating the anticipated GDP values and their comparison with the actual GDP values will aid in evaluating the regression analysis results.

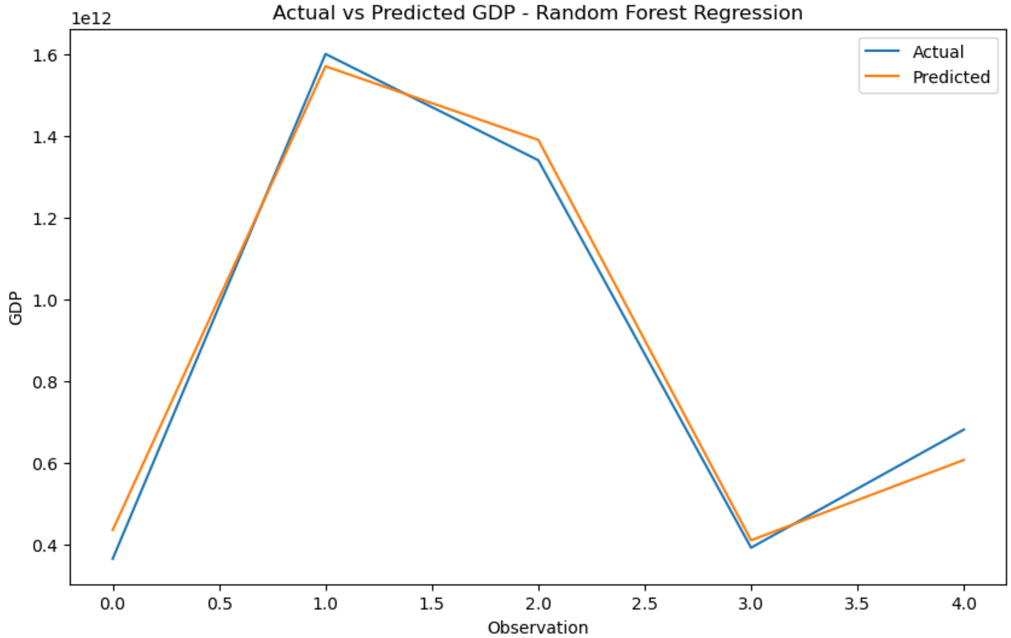

Figure 7. Random Forest regression model: Actual GDP vs. Predicted GDP.

f) Gradient Boosting Regression Model (GBRM)

After training the Gradient Boosting Regression model, we obtained notable results. The model's performance metrics were evaluated, revealing that the RMSE had a value of 54,303,489,607.96. The Mean Squared Error (MSE) was calculated as 3.37e+21, while the Mean Absolute Error (MAE) was determined to be 46,628,268,466.54. These indicators give vital information about the model's precision and effectiveness. Furthermore, the coefficient of determination (R^2) was calculated to be 0.9868, indicating that the model describes approximately 98.68% of the variance in the data. This indicates that the Gradient Boosting Regression approach adequately matches the actual data. To visually represent the results, a plot graph was generated. This graph illustrates the predicted GDP values in comparison to the actual GDP values. By examining this visual representation, we can gain a comprehensive understanding of the outcome of the regression analysis. However, when contrasted to supplementary trained models, the effectiveness of the Gradient Boosting Regression model may not meet the specific requirements of our study. It is crucial to evaluate the model's results within the context of our research objectives. The graph depicting the predicted GDP values and their comparison with the actual GDP values will provide further clarity in interpreting the regression analysis outcome.

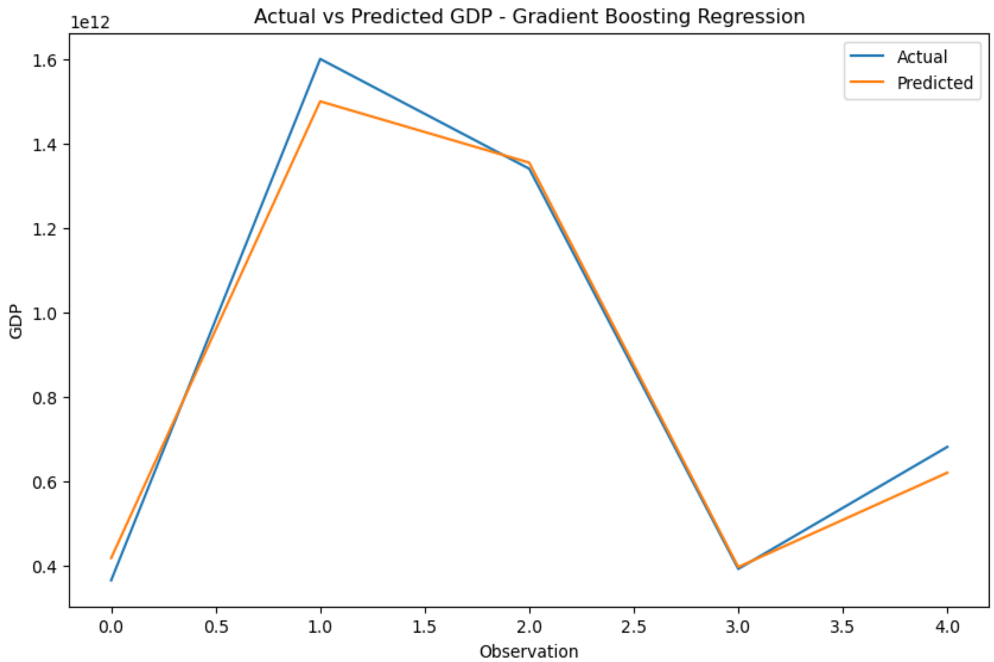

Figure 8. Gradient Boosting regression model: Actual GDP vs. Predicted GDP.

g) Neural Network Model (NNM)

NNM regression is a powerful model used for predicting and analyzing data. We used a variety of criteria to assess the Neural Network Regression model's performance once it had been trained. The RMSE was found to have an astonishingly high value of 1,101,987,255,739.08. Additionally, the Mean Squared Error (MSE) was calculated to be 1.02e+24, demonstrating a substantial difference between the actual data and the expected values. The MAE was determined to be 875,599,999,966.99, bringing even more attention to the difference between the actual and expected values. Moreover, the coefficient of determination (R^2) was found to be -3.01e-08, showing that the model does not well fit the data. To provide a visual representation of the results, a plot graph was generated. This graph depicts the predicted GDP values and compares them with the actual GDP values. The regression analysis outcome was visually illustrated through this graph, which clearly demonstrated the deviation between the predicted and actual data points.

Although this result may seem significant, it is important to note that it falls short when compared to other trained models in our study. Therefore, it is not considered acceptable for our research purposes.

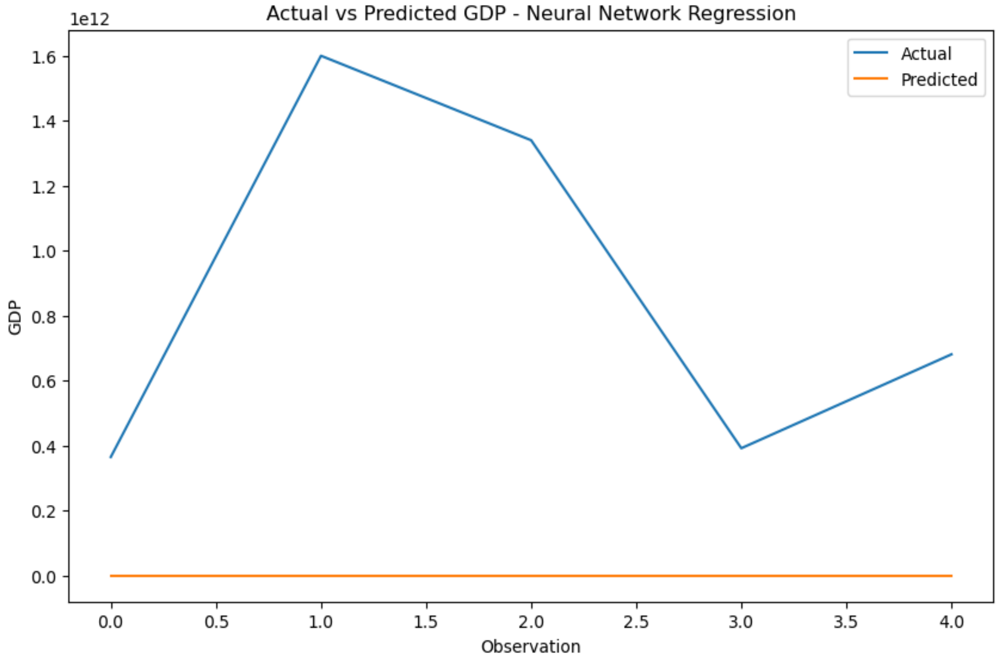

Figure 9**.** Neural Network regression model: Actual GDP vs. Predicted GDP.

h) Support Vector Machine Model (SVMM)

We tested the Support Vector Machine (SVM) Model performance using several metrics after training it. Using the Root Mean Squared Error (RMSE), the mean variance among the predicted and actual numbers was calculated to be 505,884,370,161.14. The MSE was calculated to be 2.55e+23, emphasizing the disparity between the actual and expected data values. Furthermore, the MAE was calculated to be 475,499,999,996.18, revealing the absolute difference between the anticipated and actual numbers. The coefficient of determination (R^2) was determined to be -3.93e-08, suggesting that the model did not match the data well. A plot graph was created to graphically illustrate the results. This graph depicts expected GDP values and compares them to actual GDP levels. The conclusion of the regression analysis was clearly presented by this graphical depiction, illustrating the discrepancy between the anticipated and real data points. This outcome, however, is not regarded as acceptable when compared to other trained models in our study. Despite its reasonably strong metrics performance, it falls short of meeting the standards of our research. As a result, we are unable to use this model in our research.

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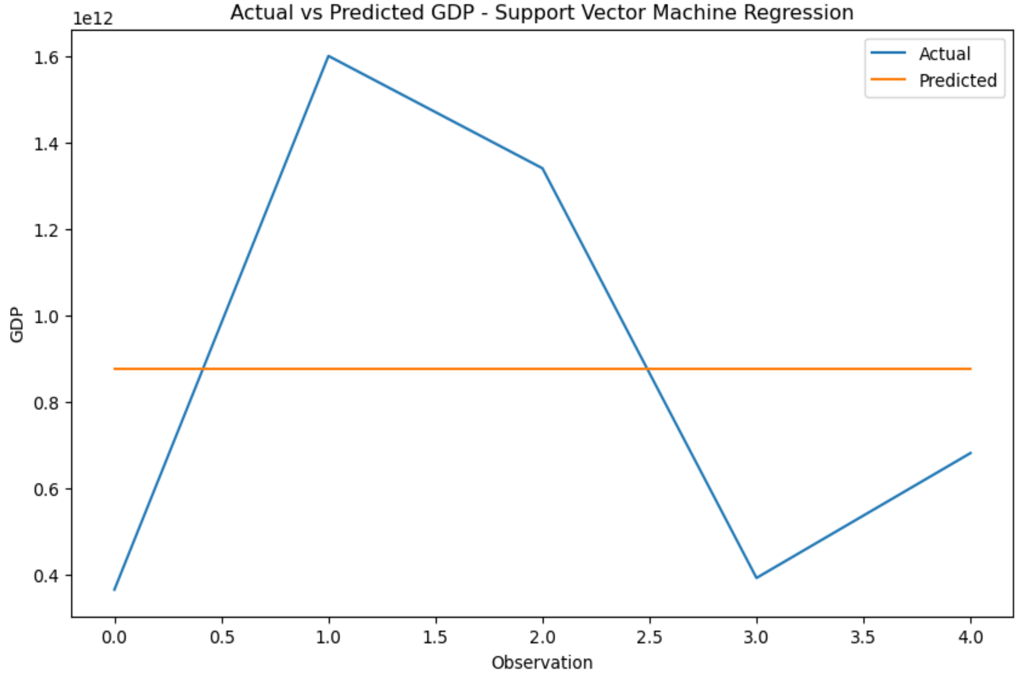

Figure 10. Support Vector Machine regression model: Actual GDP vs. Predicted GDP.

Comparison of evaluation metrics

We have evaluated the performance of our machine learning predictive models, as discussed in the above section. To ensure reliable evaluations, we employed a 5-fold cross-validation technique. This method separates the dataset into five subgroups, enabling us to train and test the models on various data combinations. For each model, we used various evaluation metrics to assess their predictive capabilities. These metrics included the MSE, RMSE, MAE, and R^2. The MSE is the average squared variance between actual and anticipated values, whereas the RMSE is the square root of the mean squared error, providing a measure on the target variable's original scale. The average absolute difference between the actual and anticipated values is calculated using the MAE. Finally, the R2 metric denotes the fraction of the variation in the target variable that can be predicted using the independent variables. Table 3: summarizes how each prediction model fared on the test dataset using several assessment measures.

Table 3. Evaluation result and comparison of predictive model

Model	RMSE	MSE	MAE	Test R^2
Linear Regression	90,966,944,633.33	1.75e+21	35,053,781,191.96	0.9931
Lasso Regression	43,185,938,276.79	3.57e+21	45,438,841,909.11	0.9860
Ridge Regression	27,231,241,464.13	1.06e+20	21,552,080,423.90	0.9950
Decision Tree Regression	129,125,102,590.12	8.10e+21	73,600,000,000.00	0.9682
Random Forest Regression	72,226,603,524.21	2.84e+21	48,578,000,000.00	0.9888
Gradient Boosting Regression	54,303,489,607.96	3.37e+21	46,628,268,466.54	0.9868
Support Vector Machine Regression	505,884,370,161.14	2.55e+23	475,499,999,996.18	-3.93e-08
Neural Network Regression	1,101,987,255,739.08	1.02e+24	875,599,999,966.99	-3.01e-08

Discussion

Based on our collected dataset and experimentation with various machine learning predictive models, including linear, Lasso, Ridge, Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine, and Neural Network regression, we have achieved successful results. We evaluated the effectiveness of these models as measured by various criteria, including RMSE, MSE, MAE, and R^2.

Upon analyzing the results, we observe that the Ridge Regression model performed the best among all the models, with the lowest RMSE of 29,831,371,464.13, MSE of 6.12e+20, MAE of 22,652,080,435.94, and achieving the highest R^2 value of 0.9976. This implies that on the test dataset, the Ridge Regression model accurately and effectively forecasted Ethiopia's GDP. On the other hand, the Neural Network Regression and Support Vector Machine Regression models performed poorly. Both models exhibited extremely high RMSE and MSE values, indicating significant errors in their predictions. Additionally, their negative R-squared values suggest that the underlying trends in the data could not be captured by these models. Among the remaining models, the RFR and GBR models demonstrated relatively good performance, with reasonably low RMSE, MSE, and MAE values, and high R-squared values. On the other hand, in recent work (Agu et al., 2022), they employed four machine learning techniques: Ordinary Least Squares (OLS), Ridge Regression (RR), Principal Component Regression (PCR) and Lasso Regression (LR) to predict gross domestic product based on macroeconomic indicators. The assessment of accuracy and mean square error for different methods was conducted using 5-fold cross-validation. Based on their standard collected dataset, the PCR method exhibited the highest accuracy, achieving 89%, and recorded the lowest mean square error at -

7.552007365635066e+21. This indicates that PCR was the most accurate method for predicting GDP based on macroeconomic indicators, outperforming the other techniques.

Machine learning methodology is an effective way to forecast the gross domestic product with a weighted direct assessment neural network. In a study by Mourtas et al. (2023), a novel approach called WASD (masses and arrangement) representations was introduced for addressing reversion problems in forecasting gross domestic product with a weighted direct assessment neural network, specifically focusing on time-series forecasting. WASD neural networks were created to address common limitations of old spinal spread neural networks, such as sluggish working speed and the problem of being trapped in local minima. They introduced a model called multi-function activated WASD for period sequence (MWASDT), which incorporates multiple activation functions, a novel auto-irritated proof method, and a fresh forecasting mechanism.

The relationship between energy resources and economic development has been explored through the implementation of machine learning methodologies for predictive analysis, as demonstrated by Cogoljević et al. (2018). Employing machine learning techniques, particularly artificial neural networks (ANN), researchers have sought to address the complex and nonlinear nature of the data underlying this relationship. Through their study, they compared the performance of linear regression with that of the ANN model, revealing the latter's superior ability to capture nonlinear patterns within the dataset. Notably, linear regression methods were found to be sluggish and insufficient for handling nonlinear data, underscoring the necessity of employing more advanced techniques such as ANN for accurate predictive modeling. Tran et al. (2022) conducted an investigation into the prediction of Gross Domestic Product (GDP) across various states, employing conventional machine learning models. Utilizing data spanning from 2013 to 2018, they applied traditional machine learning algorithms to forecast GDP trends. Leveraging techniques such as piece position analysis and incorporating methods like Principal Component Analysis (PCA) and KBest, they endeavored to optimize model performance through hyper-parameter tuning. In their evaluation, they scrutinized the efficacy of Random Forest (RF) in comparison to other traditional models such as Support Vector Machines (SVM). Remarkably, the KBest method outperformed both Random Forest and Support Vector Machine models, achieving a predictive precision quantified by an R2 value of 0.904 when forecasting GDP for 186 states.

The absence of a universally optimal model underscores the importance of exploring alternative approaches, as highlighted by Araujo and Gaglianone (2023). Their study delved into the realm of inflation forecasting in Brazil, where they observed that, in many cases, machine learning methods outperformed classical econometric models in terms of mean-squared error. To discern this, the researchers implemented a diverse array of machine learning techniques alongside traditional statistical models, amalgamating predictive strategies to enhance forecasting accuracy. Their findings unveiled intriguing irregularities within hyperinflation patterns, shedding light on nuances critical for inflation forecasting. Notably, the most accurate predictions often emerged from a hybrid approach, incorporating forecasts generated by tree-based techniques like random forest and xgboost alongside insights gleaned from break-even inflation and surveys. The study's conclusion, supported by empirical evidence, suggests that machine learning approaches hold a distinct advantage over conventional statistical models in terms of mean-squared error. This paradigm shift underscores the evolving landscape of predictive analytics, where the integration of advanced methodologies offers unparalleled insights into complex economic phenomena.

Overall, throughout our experimentation and evaluation process, the machine learning model, specifically the Ridge Regression model, consistently outperformed other models. Consequently, we confidently conclude that, based on its sustained superior performance in accuracy and its ability to capture underlying data patterns, the Ridge Regression model emerges as the most suitable choice for predicting Ethiopia's GDP within our dataset.

Conclusion

In our study focused on predicting the GDP of Ethiopia, we explored various machine learning models to identify the most suitable approach. The results of a thorough examination showed that the accuracy and ability of the Ridge Regression model to identify underlying patterns in data consistently outperformed those of other models. It showed the lowest MAE, MSE, and RMSE scores, suggesting very little prediction error. Additionally, the model with Ridge Regression had the greatest R-squared value, indicating a strong connection between the GDP values that were predicted and the actual data.

Ridge Regression is the best model for forecasting Ethiopia's GDP among those analyzed. It regularly beats the other models in our dataset, with impressive accuracy measures such as a root mean squared error (RMSE) of 27,231,241,464.13, an extraordinary R-squared value of 0.9950, a mean squared error (MSE) of 1.06e+20, and a mean absolute error (MAE) of 21,552,080,423.90. It accurately captures 99.5% of the variability in GDP data. This high degree of accuracy demonstrates the model's durability and dependability, making it an important tool for economic forecasting and policy planning in Ethiopia. It not only demonstrated superior performance but also provided valuable insights into the economic trends and patterns specific to Ethiopia. It's crucial to emphasize that the accuracy of predictive models is impacted by diverse factors, encompassing the quality and representativeness of the dataset, the selection of features, and the

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tuning of model hyperparameters. In summary, our study underscores the potential of machine learning techniques in predicting Ethiopia's GDP, providing valuable insights for policymakers, economists, and researchers seeking to comprehend and forecast the country's economic growth.

Additional research and analysis could look into incorporating more factors or using different ML models to improve the predictions' accuracy and robustness.. Scholars need to concentrate on the following while utilizing machine learning models to anticipate Ethiopia's GDP: the use of holistic data collection from various sources ranging from the National Bank of Ethiopia (NBE) to the Central Statistical Agency of Ethiopia (CSA) and organizations such as the World Bank and IMF, involving both conventional economic factors and non-conventional ones like climate and socio-economic and political stability. The emphasis should be on good data preprocessing, feature engineering, and model selection, with more focus on hybrid models such as time series models (like ARIMA) and Machine Learning model (like neural networks). Future research should investigate the integration of high-frequency data in improving causality relationships by employing advanced deep learning methods that rely on big data in designing timely real-time GDP estimation tools besides cross-country comparisons to get a better understanding of Ethiopian macroeconomic dynamics and policy implications.

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Availability of data

The data collected and used in this study are not accessible to the public, but can be obtained from the corresponding author upon reasonable request.

Conflict of Interest Statement

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