Journal of Business and Management Studies
ISSN: 2709-0876
DOI: 10.32996/jbms
Journal Homepage: www.al-kindipublisher.com/index.php/jbms

JBMS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Impact of Energy Prices and Macroeconomic Variables on GDP Prediction UK: Machine Learning Approach

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| ABSTRACT

Gross Domestic Product (GDP) is one of the critical indicators of an economy. This study aims to predict the GDP of the United Kingdom using vital macroeconomic variables from 1990 to 2018 as predictors, which include energy prices, unemployment rate, Real Effective Exchange Rate (REER) inflation and net migration. Several machine learning models, namely Support Vector Regression (SVR), Random Forest (RF) and Gradient Boosting Machines (GBM), were implemented, analysed and compared. The models were trained on both scaled and unscaled data, with hyperparameter tuning applied to optimise performance. The models' performances and accuracy were analysed by employing evaluation metrics Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). As per the findings, after hyperparameter tuning, the SVR model performed best in GDP prediction, followed by GBM. The results of this study underscore the critical role of macroeconomic variables in GDP prediction while highlighting the potential of machine learning models to produce valuable and reliable insight into economic forecasting.

| KEYWORDS

GDP Prediction, Economic Forecasting, Machine Learning, Energy Prices, macroeconomic variables.

| ARTICLE INFORMATION

ACCEPTED: 16 September 2024 **PUBLISHED:** 03 October 2024 **DOI:** 10.32996/jbms.2024.6.5.13

1. Introduction

Gross Domestic Product (GDP) refers to the monetary value of goods and services produced by a country during a specific period. GDP is a significant indicator of the health and performance of an economy (Kubiszewski, et al., 2013). Growing GDP is a clear indicator of growth in businesses, employment, income per capita and the strength of an economy. (Tkacz & Hu, 1999). Accurate forecasting of GDP is a crucial step in formulating functional plans and policies in an economy since it aids in foreseeing any adverse or favourable conditions, helps allocate scarce resources and aids in developing effective strategies to reduce possible downturns (Maccarrone, et al., 2021). However, accurate GDP prediction is a challenging task since numerous factors directly or indirectly influence the direction of GDP growth, such as consumer behaviour, government policies, investment trends and unexpected economic events (Spahiu, et al., 2022). Due to the complexities in accurate GDP forecasting with traditional methods, advanced machine learning techniques are increasingly adopted (IMF, 2024).

Several traditional methods have been utilised in GDP prediction based on statistical and econometric principles. Dynamic Stochastic General Equilibrium Model (DSGE) (Christiano, et al., 2005), Cointegration and Error Correction Models (ECM) (Engle, 2004) and Ordinary Least Square (OLS) regression (Greene, 2012) are few of the dominant statistical forecasting methods applied in the macroeconomic forecasting domain. But, due to the current complex non-linear relationships among micro and macro-economic factors and substantial datasets, economic forecasting has been driven towards machine learning methods in recent years (Yuejiao, et al., 2022).

This study presents a novel approach to GDP prediction in the UK by conducting a comparative analysis of several machine learning models using diverse macroeconomic variables from 1990 to 2018 as predictors. Specifically, this study compares the prediction performance of several machine learning models, namely, Linear Regression (LR), Support Vector Regression (SVR), Random Forest (RF) and Gradient Boosting Machines (GBM). The distinct characteristic of this research lies in the combined usage of energy prices and other macroeconomic variables on the GDP prediction of the UK. While existing literature often addresses the impact of macroeconomic variables on GDP, the inclusion of energy prices as a critical factor combined with other crucial indicators reflects a comprehensive understanding of the significant role of energy prices in economic performance. Additionally, the application of advanced machine learning techniques aids in capturing complex, non-linear relationships between variables, producing more robust predictions. Integrating crucial macroeconomic variables with machine learning advances the methodology of GDP prediction but also offers valuable insight into the impact of energy prices and other economic variables on influencing the economic growth of the UK. Hence, this multifactored analysis addresses the gap in existing research and progresses the knowledge base on economic forecasting in modern, data-driven approaches. The performance of these models is compared with established evaluation indicators, namely, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). By evaluating and comparing the model performance in interpreting the relationship between input features and GDP it is expected to identify the best performing and reliable machine learning model for forecasting. Thereby, it is expected to produce valuable insight into one of the crucial indicators of the UK economy.

This study utilises several crucial macroeconomic variables as inputs to the prediction models due to their significant impact on the economy and its future direction. The variables are energy prices, unemployment rate, Real Effective Exchange Rate (REER), inflation and net migration. As an example, energy prices directly impact production costs and consumer spending (H, et al., 2019), inflation erodes purchasing power and investments (Huillier, et al., 2023), REER impacts international trade (Greene, 2012) while net migration affects the size and demographic trends of the labour market, which eventually influence the GDP (Hall, et al., 2023). These interlinked factors underline the complexity of GDP forecasting and emphasise the need for advanced machine-learning techniques that effectively adopt trends and identify their complicated relationships. In contrast, traditional methods require a predefined model structure for the prediction process.

The remainder of this paper is structured as follows: The literature review section provides a brief comparative review of the currently available related studies; the methodology section details the data collection, preprocessing and configuration of the machine learning models; the results section presents a comparative analysis of the prediction performance of the models. And the discussion section interprets the findings and their implications while addressing limitations and suggestions for future work in relation to the topic.

2. Literature Review

GDP is a comprehensive measure that measures the total value of goods and services produced in an economy. It is considered as a representation of the wealth of an economy by investors, regulators and academics, which they utilise as a tool in the decision-making process (Provost & Fawcett, 2013). The GDP of an economy can be measured based on the market value by using the equation below. Where the price of product n is P and the quantity purchased is represented in Q. Here, it is assumed that only one year's worth of production is considered. This measurement is known as nominal GDP (Bhandari & Frankel, 2017).

$$GDP = (P1 * Q1) + (P2 * Q2) +.... (Pn+1 * Qn+1) +(Pn.Qn)$$

But changes in nominal GDP do not always represent the actual state of the economy (Ulrich, 2004) Therefore, real GDP is calculated after adjusting the inflation and comparing the current year with base-line GDP. The real GDP is represented by the equation below, where 'PB,n' is the base year price, product – 'n' and 'Qc,n' for the amount of n goods purchased in a given year (Sa'adah & Wibowo, 2020).

$$\text{Real GDP} = (PB,1 * QC,1) + (PB,2 * QC,2) +.... + (PB,n+1 * QC,n+1) + (PB,n * QC,n)$$

GDP is a strong indicator of the growth or decline of an economy (Provost & Fawcett, 2013). Therefore, countries tend to maximise GDP during fiscal planning to achieve better economic growth (Divya & Rama Devi, 2014). Prediction of the economic status of a country is highly valuable for the performance of organizations, policymakers, as well as public welfare and living quality. However, it is a complex task to predict GDP as it involves complicated calculations, and the official data are primarily released to the public after one-quarter delay (Yoon, 2021). Hence, there is a substantial need for proper GDP prediction with currently available data.

GDP forecasting methods can be categorized as quantitative forecasting and qualitative forecasting. Qualitative forecasting mainly focusses on experts' judgements and opinions. It is mainly used when historical data is unavailable. Business and consumer survey data (Claveria, 2021), Delphi method (Hsu, 2007) panel consensus forecasting (Armstrong, 2001) are some of the commonly used qualitative methods in economic forecasting.

Interms of quantitative methods, traditionally statistical and econometric models have been used for GDP predictions. Most commonly used models are namely, Autoregressive Moving Average (ARIMA), Vector Autoregression (VAR), Structural Equation Modeling (SEM) and Partial Least Squares (PLS). ARIMA model (Box & Jenkins, 1976) predicts GDP by analyzing past data trends through combination of autoregressive (AR) terms, Differencing (I) to achieve stationarity and Moving average (MA) to represent past forecast error. The VAR model (Sims & A, 1980) measures the linear interdependencies among several time series variables to produce comprehensive macroeconomic forecasting. And SEM provides insight into the structural dynamics of GDP by combining factor analysis and multiple regression (Bollen, 1989). PLS is another statistical model (Wold, 1985) that simultaneously decompose the predictor variables and response variables to find linear connections also known as laten variables that heighten the covariance between the predictors and the response allowing the derived variables to be relevant for predicting the response variable. These traditional methods produce a strong framework for GDP forecasting, although they tend to portray limitations in handling large datasets and non-linear relationships.

During recent times a considerable number of studies are leaning towards machine learning methods for macro and micro econometric forecasting (Granger & Engle, 1987). Artificial Neural Networks (ANN) are particularly common among econometric forecasting as they are able to model complex non-linear relationships by following the human brain neural structure (Zhang & Yu, 1998). As for an example (Shams, et al., 2024) use PC-LSTM-RNN model to capture the long-term dependencies among variables. Bayesian Vector Autoregression (BVAR) is another commonly used model (Yoo, 2023), (Sílvia, et al., 2019). Additionally, XGboost algorithm also portray promising results in prior studies as it can handle large datasets and improve prediction accuracy through advanced regularization techniques and scalable implementation of gradient boosting (Chu & Qureshi, 2023), (Bharathi & Navaprakash, 2024).

This paper addresses notable gaps in previous studies that employ machine learning for GDP prediction by incorporating a substantial set of macroeconomic variables in relation to UK. These variables are often analyzed in isolation rather than combined (Ali Shah, et al., 2013). Prior studies have frequently focused on limited set of input variables or utilize traditional econometric models that face difficulties in capturing complex, non-linear relationships of econometric data (Stock, et al., 2002), (Andreas, et al., 2008), (Teräsvirta, 2005). This study leverages the abilities of advanced machine learning models such as linear regression, SVR, random forest and GBM to uncover intricate patterns among the variables while providing comparative analysis on the models' performance. Further, by using UK specific data it is expected to address the contextual gap to identify how the variables represent unique economic conditions of UK, which is something that generalized studies inadequately address (Li, et al., 2021). Thus, this paper contributes to the current literature by producing robust, data driven insight into the inter connections and impacts between economic indicators and GDP in the UK context, with the aid of state of the are machine learning techniques.

The machine learning models used in this study are LR, SVR, RF and GBM specifically for the UK economy. Linear regression model was selected due to its straightforward implementation and the model's ability to provide clear insight into relationships between GDP and the predictors, serving as a baseline model for comparing more complex models (ref). SVR was employed in the study as it can easily handle non-linear relationships between variables with kernel functions making it ideal for identifying non-linear relationships between complex economic data. And the RF model was employed to capture the complex interactions among several different variables without the need for explicit specifications, which make it suitable for multi-faceted GDP prediction (ref). similarly, GBM was utilized as it can capture complex patterns but with greater accuracy as it can sequentially correct errors from previous iterations using the boosting technique. Further, it can provide insight into the importance of different predictors in GDP prediction providing valuable insight into the prediction process (ref).

3. Materials and Methods

3.1 Data Acquisition and Extraction

Data for this study was acquired from the Office of National Statistics (ONS) UK and the World Bank for the years 1990-2018, ensuring accurate and consistent coverage of the key economic indicators relevant to GDP prediction. The GDP data was sourced as gross domestic product in chained volume measures, seasonally adjusted in million pounds (£m). Energy price data were obtained through the consumer price index (CPI for fuel components, with real prices based on the year 2010) and the energy price data consists of – solid fuels, gas, electricity, liquid fuels, domestic fuels, motor and oil. Also, the unemployment rate covering individuals aged 16 and over was seasonally adjusted and provided as a percentage. And Inflation metrics were derived from the Consumer Price Index including owner occupiers' housing costs (CPIH) annual rates for all items with 2015 as base year. Net migration values were included to account for the demographic influence on the growth or decline of GDP. Additionally, REER data was sourced from World Bank data base that offers insight into the UK's trade competitiveness in an international scale. After extraction from different sources the data was compiled into a single dataset for easy handling. And the dataset was examined for missing values, errors, skewness and consistency.

The following figure is a visual representation of UK GDP from 1990 to 2018. According to the graph the GDP trend for UK shows a general upward trend stipulating economic growth. however, there is a noticeable dip around 2008-2009 due to the global financial crisis during that period, followed by recovery period and continuous growth (ref). This indicates the overall resilience and long-term expansion of the UK economy over a span of nearly three decades.

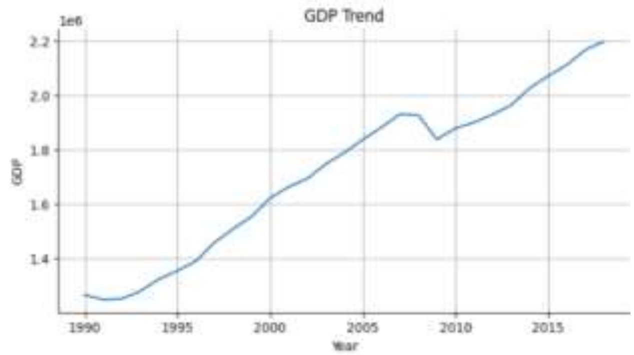

Figure 1 UK GDP trend (1990-2018)

3.2 Data Preprocessing

3.2.1 Correlation Analysis

As a part of the preprocessing correlation analysis was conducted on the dataset to help identify the relationship between variables and their impact on GDP. According to the correlation matrix GDP is positively correlated with net migration (0.91) indicating higher net migration association with increased GDP, likely due to the inflow of labor and growth in consumers contributing to the economy. Similarly, all energy prices present a strong correlation with GDP reflecting significant role energy sector plays in UK economy through high demand for energy, increased industrial and economic activity, influence of global energy markets and the impact of UK government's Energy Price Guarantee scheme that is aimed at managing the impact of rising energy costs on households while maintaining economic stability (Waddams, 2023). 4

Contrastingly, GDP shows a strong negative correlation with unemployment rate (-0.66), highlighting the economic growth impact on job creation resulting in lower unemployment. And the moderate negative correlation between REER and inflation indicates the growth in GDP is linked with enhancing export competitiveness resulting weaker REER and lower inflation that supports the economic stability.

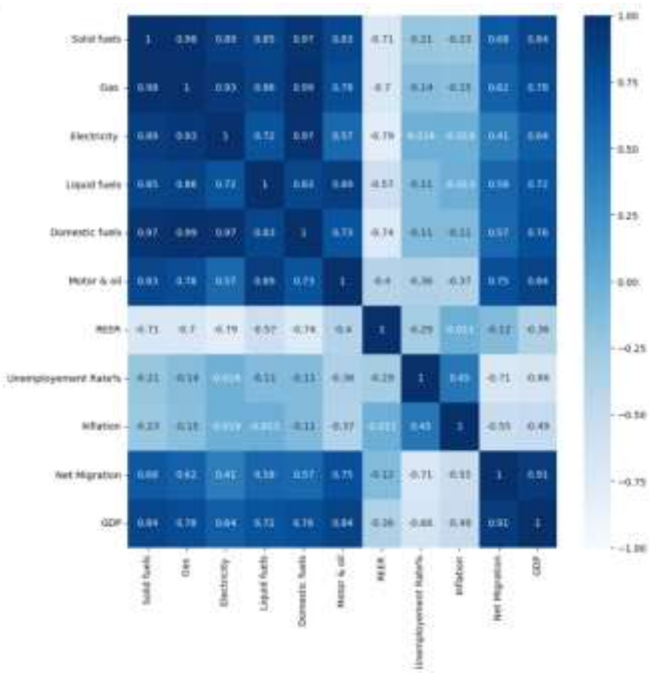

Figure 2 Correlation matrix

3.2.2 Statistical analysis and splitting

Descriptive statistical analysis was conducted on the dataset, since it consists of a wide range of economic indicators over 29 observations. According to the analysis the features disclose significant variabilities. As for an example, energy prices show substantial fluctuations in price levels, especially in gas prices where the mean value is 79.59 with standard deviation of 27.86, reflecting notable changes in energy prices over time. And the mean of unemployment rate stands at 6.64% with a standard deviation of 1.77% exhibiting varying employment conditions over the years. Similarly net migration exhibits high fluctuating migration patterns. Although, inflation shows moderate variability with a mean of 2.58% and standard deviation of 1.67%.

	Solid fuels	Gas	Electricity	Liquid fuels	Domestic fuels	Motor & oil	REER	Unemployement Rate%	Inflation	Net Migration	GDP
count	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	29.000000	2.900000e+01
mean	77.531034	79.586207	91.134483	69.217241	84.765517	81.600000	114.767870	6.641379	2.579310	174758.620690	1.717661e+06
std	19.962663	27.857878	19.301781	29.307045	23.406276	16.714942	11.671087	1.769890	1.666772	96383.406683	2.989216e+05
min	58.300000	51.100000	65.500000	32.000000	59.700000	56.600000	97.302362	4.200000	0.400000	-13000.000000	1.248461e+06
25%	59.900000	56.100000	73.200000	44.200000	65.500000	69.300000	103.398585	5.200000	1.600000	77000.000000	1.458467e+06
50%	65.100000	62.200000	86.200000	56.700000	71.700000	83.800000	113.762294	6.200000	2.300000	185000.000000	1.788931e+06
75%	102.600000	108.500000	105.000000	80.600000	107.600000	89.800000	126.182395	8.000000	2.600000	252000.000000	1.929229e+06
max	105.500000	128.700000	129.500000	125.700000	123.600000	112.700000	130.435556	10.400000	8.000000	329000.000000	2.197841e+06

Figure 3 Descriptive statistical analysis

These variations underline the importance of ensuring that training and testing data represent overall data distribution. Hence, random splitting was employed to avoid biases and ensure the model can generalise well to new, unseen data. The dataset was split using the 'train_test_split' function of 'sklearn.model_selection', and the dataset was split allocating 80% of the data for training and 20% for testing.

3.2.3 Data Scaling

As the features in the dataset are individual observations and in different scales the dataset was normalized using the 'MinMaxScaler' to ensure the features are comparable, consistent and equally contribute to the machine learning models. This scaler transforms each feature to a scale between 0 and 1. The formula for MinMaxScaler is as follows:

$$X_{Scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

X- original feature value X_{min}, X_{max} - minimum and maximum value

3.2 Modelling

For this study, the application of 4 different machine learning models were explored and compared on diverse economic indicators. The models selected for this study are Linear Regression, Support Vector Regression, Random Forest, and Gradient Boosting Machines. Each model was trained with both scaled and unscaled data to assess the impact of data normalization on model performance. Further, hyperparameter tuning was performed for all models besides linear regression in an attempt to optimize the prediction accuracy of each model.

3.2.1 Linear Regression

Linear regression is one of the most widely used statistical models in macroeconomic prediction analysis (Elliott, et al., 2008). Here, the model was trained on both scaled and unscaled independent variables (macroeconomic variables) to find the relationship with dependent variable (GDP) by fitting a linear equation to the observations. Mathematical expression of the model:

$$GDP = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

$$GDP = \beta_0 + \beta_1(Solid\ Fuels) + \beta_2(Unemployement\ Rate) + \cdots + \beta_n(Net\ Migration) + \in$$

β_0 - intercept, $\beta_1, \beta_2 \ldots \beta_n$ – coefficient of each independent variable $\in$ - error term.

3.2.2 Support Vector Regression (SVR)

SVR is a machine learning model that is mainly used for classification related tasks. It is an extension of Support Vector Machines (SVM) model. SVR model applies principles of SVM to regression related problems (Peters, 2001), to enable the model to capture non-linear relationships among variables. By mapping energy prices and other economic variables into a high-dimensional space using Kernal function, SVR is able to model complex interactions between GDP and economic indicators. Due to the ability of handling non-linear relationships SVR can be identified as a robust choice for economic forecasting where high-level complexities are common (Xiang-rong, et al., 2010).

SVR model was trained on both scaled and unscaled data. Both models were trained with radial basis function (RBF) kernel. Additionally, hyperparameter tuning was applied using GridSearchCV to find the best hyperparameters for the SVR model. The regularization parameter grid includes – C :(1, 10, 100), the kernel Coefficient γ('Scale', 'auto'), the epsilon-tube width $\in$ (0.01, 0.1, 0.2) and the kernel type ('rbf', 'linear'). The best was selected based on cross validation.

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + b$$

$K(x_i, x)$ – kernel function, α_i, α_i^* - Lagrange multipliers x_i - support vectors, b – bias term

3.2.3 Random Forest

Random forest is an ensemble learning method that combines several decision trees to enhance predictive accuracy and control over-fitting (Yoon, 2021). Every tree in the random forest model is built on a random subset of the dataset, and the final prediction is achieved by averaging the outputs of all the trees. This approach enhances the model's robustness and accuracy by reducing variance and capturing a broader range of data patterns, which makes random forest well-suited for GDP prediction based on diverse economic indicators (Breiman, 2001). Mathematical representation of the model:

$$\hat{f}(x) = \frac{1}{T}\sum_{t=1}^{T} f_t(x)$$

$\hat{f}(x)$ – Final prediction, T – total number of trees $f_t(x)$ – prediction from the t^{th} tree.

The model was trained on both scaled and unscaled data using 100 trees. Similar to previous model GridSearchCV was used to find the best hyperparameters for the Random Forest model. The parameter grid includes different values for the number of estimators, maximum depth, minimum samples required to split an internal node and minimum samples required to be at a leaf node. The best suited model was selected based on cross validation.

3.2.4 Gradient Boosting

Gradient Boosting is considered a powerful ensemble technique that creates models sequentially, with every new model correcting the errors of the previous model. This model increases accuracy by focusing on the residuals and efficiently minimizing the prediction error. This method is primarily effective in capturing intricate patterns and interactions among the data. Making it highly suitable for economic forecasting (Yoon, 2021). The interactive nature of GBM ensure the model consistently improve while providing precise and reliable GDP prediction (Friedman, 2001).

Similar training methods were followed for GBM. Additionally, in hyperparameter tuning different values were included in the parameter grid as – learning rate: (0.1, 0.01), number of estimators, maximum depth, subsample, minimum samples required to split an internal node, minimum samples required to be at a leaf node, and maximum features. The best model was selected based on cross validation outcome.

$$\hat{f}(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$$

$\hat{f}(x)$ – Final prediction, M – Total boosting iterations, γ_m- weight applied to the m^th^ weak learner, *$h_m(x)$ – m^{th} weak learner (E.g.- a decision tree)*

4. Results and Discussion

4.1 Performance Evaluation

The Models' performance in predicting GDP of UK was evaluated with evaluations metrics. Such as, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). These metrics provide a comprehensive overview of the models' prediction accuracy and error characteristics, allowing detailed evaluation of the models in determining which model produces reliable forecasts based on the given economic indicators.

RMSE is a commonly used metric that measures the square root of the average squared difference between predictions and the actual values. It is vital in understanding the absolute fit of the model to the data. In this study, GDP is measured in large numbers, and RMSE helps quantify the predictions deviation from the actual values. Hence, lower RMSE indicates the model's robustness against large errors. And MAE provides the average absolute difference between the predicted values and the actual values in the same units as the output variables, allowing easy interpretation. In the current context, MAE helps determine how close the predicted values are to the actual GDP values without the influence of outliers. While MAPE calculates the prediction accuracy as a percentage, which is valuable in economic forecasting where the GDP can change in large scale over time. MAPE thus helps normalize the errors and provide a clear understanding of the models' performances in predicting the relative changes of GDP.

4.1.1 Linear Regression

Performance of LR model was evaluated using both scaled and unscaled data. The evaluation metrics remained similar with slight differences for both scenarios, which demonstrated an RMSE – 65, 566.79, MAE – 52,648.15, MAPE – 0.0272. According to the results, scaling hardly impacted the performance of the linear regression model. Although, consistency across the metrics indicate that the model is robust to the input feature scaling and maintain stable prediction accuracy and error rate regardless of input feature scaling. Which implies that the simple structure and the straightforward approach can effectively capture the linear relationship between the GDP and economic indicators. The scatter plot clearly depicts the close alignment predicted values have with actual GDP values.

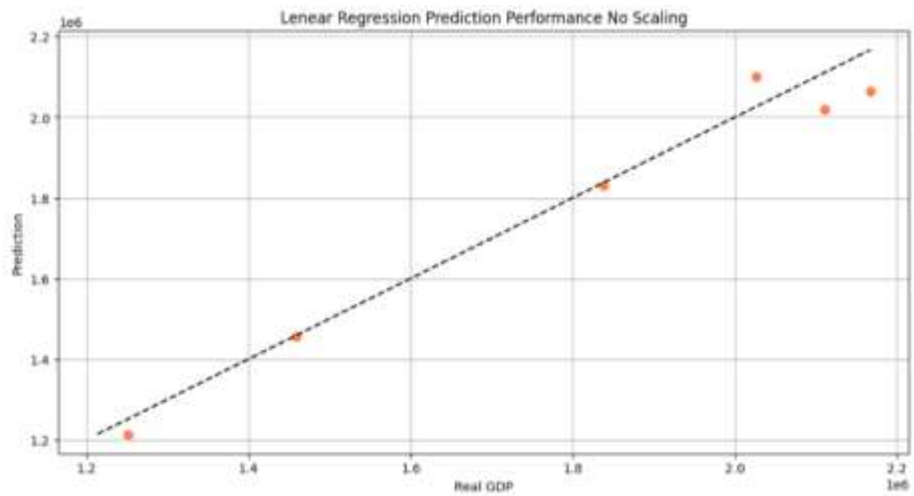

Figure 4 Lenear regression prediction performance

4.1.2 Support Vector Regression (SVR)

Performance of SVR was assessed with both scaled and unscaled data, followed by hyperparameter tuning. According to the evaluation metrics, unlike LR scaling had significantly improved the performance of SVR model. Although, hyperparameter tuning somewhat increased RMSE, but positively influenced MAE and MAPE compared to the scaled SVR model without hyper parameter tuning. Which indicates that hyperparameter tuning enhances the model's ability in capturing overall trend and reduce relative error regardless of the increase in RMSE, which makes it highly effective in GDP prediction. As presented through the scatter plots scaling present a notable improvement in model performance, and the tunned model showcase even tighter clustering. Meaning that hyperparameter tuning lead to balanced and more accurate model even though it does not always reduce all error metrics.

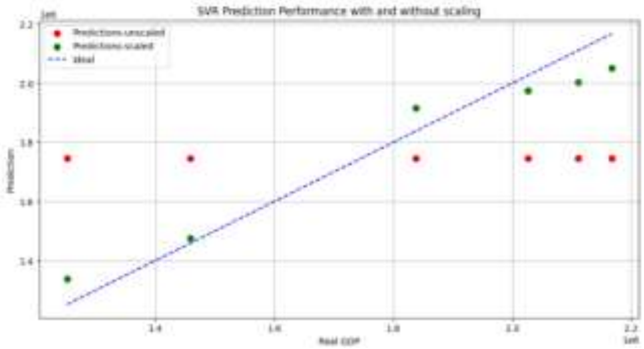

Figure 6 SVR performance with and without scaling

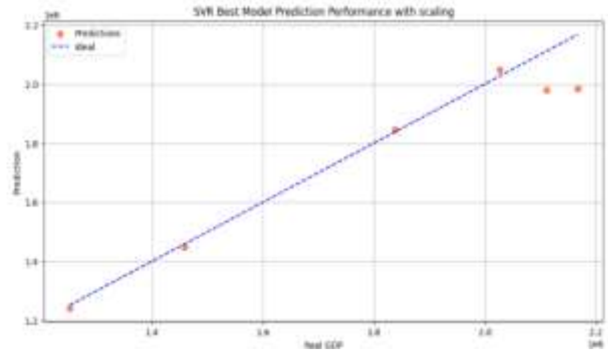

Figure 5 SVR best model performance

4.1.3 Random Forest (RF)

Performance of RF model was also evaluated on both scaled and unscaled data, also with hyperparameter tuning. The model with unscaled data performed slightly better than SVR with unscaled data, although scaling slightly worsens the performance of the model. Further, hyperparameter tuning did not show improvement compared to the original version of the model. Meaning, the tuning produced a best version of the model with similar characteristics to the original without enhancing the prediction accuracy. Which indicates that this model's performance with regards to the dataset is not sensitive to scaling nor hyperparameter tuning. As depicted by the scatter plot both scaled and unscaled versions of the model follow the general trend of the actual data but significantly deviate for some GDP values, which reflect the model's slight incompetence in predicting the GDP values.

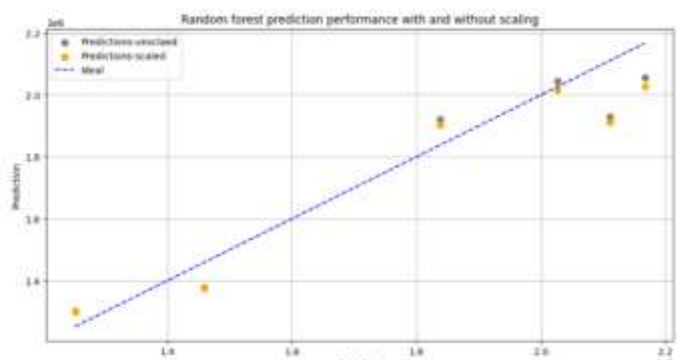

Figure 8 RF performance with and without scaling

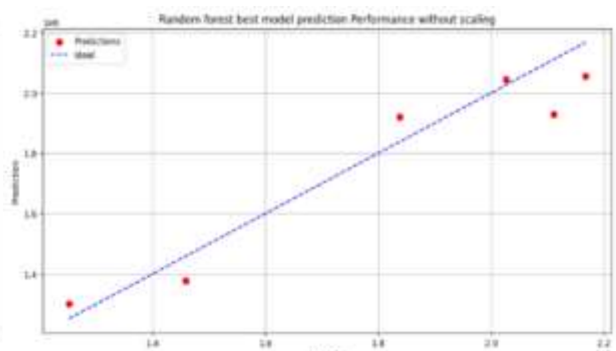

Figure 7 RF best model performance

4.1.4 Gradient Boosting (GBM)

Similar to previous models GBM performance was also evaluated based on scaled, unscaled data and hyperparameter tuning. Without scaling GBM gained RMSE -80,677.47, MAE -68, 176.69, MAPE- 0.0358. For this model data scaling resulted in slightly higher error rates. And interestingly, hyperparameter tuning worsens the performance of the original model although it produced better overall performance compared to the scaled version. This suggests that the default GBM model fits better with the dataset and scaling does not impact positively to this model.

Further, the feature importance analysis of GBM model indicated that 'Net Migration' and 'Solid Fuels' as the most significant features of the prediction model, indicating their strong influence on the predictions. While 'REER' and 'Unemployment rate' display minimal impact on the model's performance.

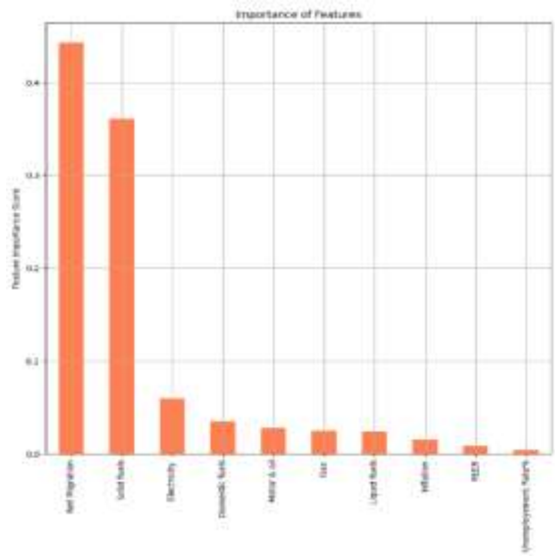

Figure 9 GBM feature importance

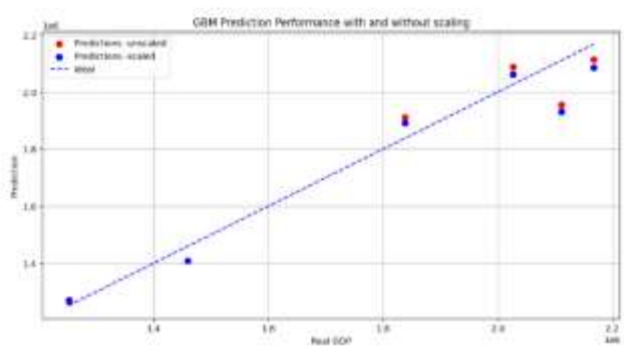

Figure 10 GBM performance with and without scaling

Figure 11 GBM best model performance

4.2 Discussion

In summary, LR model showed consistent results with slight changes in both scaled and unscaled versions of the dataset. Indicating the irrelevance in scaling for the model's performance. On the contrary, SVR displayed a noticeable improvement with scaling by reducing RMSE from 347,604 to 82,920 and MAPE from 0.191 to 0.042. and hyperparameter tuning of the SVR model showed overall best performance even though it slightly increased RMSE. In terms of the RF model, the model seemed to perform well with unscaled data. Scaling did not improve the model's performance; even though the tunned version of the model displayed overall better performance compared to the scaled version it did not make a significant impact on the original model. Finally, the GBM model showcased best performance without scaling. Same as the RF model scaling and hyperparameter tunning did not impact positively for the GBM model.

Out of all evaluated models, SVR best model with scaling can be identified as the overall best performing model. Even though it reached a slightly high RMSE of 93362.0634, other two metrics remined low with MAE – 68,807.03 and MAE – 0.0294 – lowest of all models indicating superior prediction accuracy compared to other models. In comparison, GBM without scaling also demonstrated strong performance in all metrics, especially in minimizing large error. Given the importance of reducing the relative errors in economic forecasting, the SVR hyperparameter tunned model can be considered as the overall best model for GDP prediction.

according to the simple error metrices, linear regression seemed to produce better performance although, SVR best model demonstrated superior performance by achieving significantly lower error rates. Which penalized large errors more heavily compared to other models. Which indicates SVR hyperparameter tunned model with scaling as the most suitable model for accurate GDP prediction, as it accurately captured the complexities and nuances of the dataset that LR model fail to identify. Therefore, regardless of the LR's strength in simple error metrices SVR best model's capabilities in reducing large errors underscores its advantages as the best performing model of this study while the RF model ranked at last despite demonstrating strong performance.

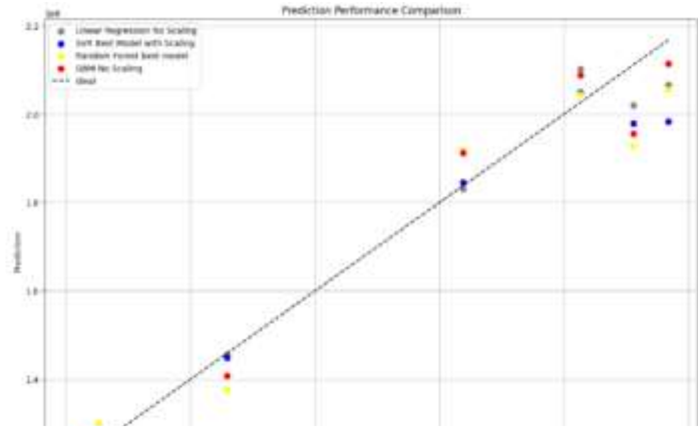

Figure 12 Performance comparison of all models

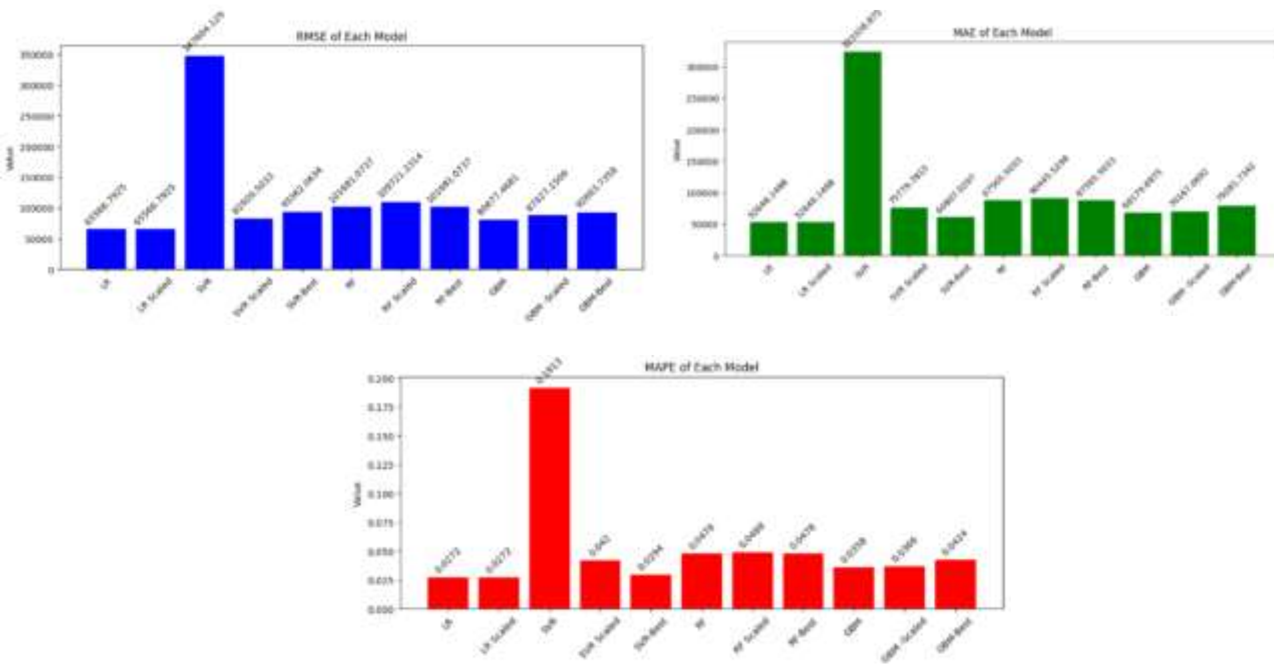

Figure 13 RMSE, MAE and MAPE of all models

5. Conclusion

This study contributes to the current literature in GDP prediction by employing two regression models as linear regression – a statistical learning model, support vector regression – a kernel-based model and two tree-based models as random forest and gradient boosting machines. The study was conducted by focusing on several key macroeconomic variables that have either been addressed independently or overlooked in prior studies. By incorporating both diverse and critical indicators of UK this study provides more comprehensive and comparative analysis on the application of machine learning models in GDP forecasting, thus addressing gaps in existing literature and offering novel insights into the complex dynamics of economic forecasting.

Out of the evaluated models, hyperparameter tuned SVR emerged as the top performing model in terms of minimum production error, particularly in relation to MAE and MAPE. Even though linear regression model showed considerably good performance in simple error metrics, GBM's ability to minimize large errors underscored the advantage in capturing complex economic relationships making it the next best model in GDP prediction. The RF model also demonstrated robust performance in terms of handling diverse inputs. Analysis of these models emphasize the importance of appropriate model selection based on the characteristics of input features and requirements of the relevant economic forecasting.

Findings of this study present significant implications for economic forecasting, strategy and policy creation, as the ability to accurately forecast GDP with machine learning allows economist, analysts, industrialists, investors and other interested parties to foresee economic trends with much clarity. This study demonstrated that incorporating diverse economic indicators, specifically energy prices, net migration, unemployment rate, REER and inflation into prediction models can enhance the prediction accuracy of GDP forecasting, which is an important element in timely, worthwhile strategies and interferences. In terms of policymaking, accurate GDP prediction enables informed decision, capitalizing on positive economic trends and even making way for timely and effective policies to reduce the impact of economic downturns. Regarding the current study, it was recognized that 'Net Migration' and 'Solid Fuels' as critical factors in UK GDP prediction. Policy makers can equip this information to tailor immigration policies to optimize economic growth. According to the correlation analysis net migration positively correlates with GDP (0.91), therefore policies can be implemented to attract skilled workers to boost economic productivity. Similarly, as the findings suggest energy prices substantially influence GDP; policies can be implemented to prioritize renewable energy sources to buffer against energy price shocks. Which is something the UK has already focused on through investments in renewable energy and strategic energy reserves (Hassan, et al., 2024). In terms of businesses, accurate GDP prediction is valuable in strategic planning as it help identify economic trends that can be exploited and invested. Further, it aids in establishing contingency plans to mitigate the negative impacts of the forecasted risks.

This study was limited to data from 1990 -2018, which may not fully capture the long-term trends and anomalies. The recent economic impact of COVID-19 pandemic was intentionally excluded to maintain the consistency in the dataset by focusing a period with more stable economic conditions. And data before 1990 were not included in the study due to inconsistency and unavailability of data. These exclusions were intended to avoid highly variable economic effects distorting the underlying trends and relationships of the analysis. Further, this study primarily focusses on five macroeconomic indicators. While these are significant indicators potential influential variables such as sector specific performances, technological advancements and government spending were not considered, which could possibly positively influence the comprehensiveness of the models. And this study was conducted only based on UK economic data with only four models with their inherent assumptions and limitations.

Therefore, future studies can be conducted to incorporate a broader set of economic indicators to further improve accuracy and robustness of prediction models.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

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