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Article

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Predictive analysis of Somalia's economic indicators using advanced machine learning models

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ABSTRACT

Accurate Gross Domestic Product (GDP) prediction is essential for economic planning and policy formulation. This paper evaluates the performance of three machine learning models—Random Forest Regression (RFR), XGBoost, and Prophet—in predicting Somalia's GDP. Historical economic data, including GDP per capita, population, inflation rate, and current account balances, were used in training and testing. Among the models, RFR achieved the best accuracy with the lowest MAE (0.6621%), MSE (1.3220%), RMSE (1.1497%), and R-squared of 0.89. The Diebold-Mariano p-value for RFR (0.042) confirmed its higher predictive accuracy. XGBoost performed well but with slightly higher error, yielding an R-squared of 0.85 and p-value of 0.063. In contrast, Prophet had the highest forecast errors, with an R-squared of 0.78 and p-value of 0.015. For enhanced interpretability, SHapley Additive exPlanations (SHAP) were applied to RFR, identifying lagged current account balance, GDP per capita, and lagged population as key predictors, along with total population and government net lending/borrowing. SHAP plots provided insights into these features' contributions to GDP predictions. This study highlights RFR's effectiveness in economic forecasting and emphasizes the importance of current and lagged economic indicators.

IMPACT STATEMENT

This study presents a critical advancement in economic forecasting for Somalia by comparing the performance of three machine learning models—Random Forest Regression, XGBoost, and Prophet—in predicting Gross Domestic Product (GDP) based on historical economic data. The findings underscore the superior accuracy of the Random Forest Regression model, which yielded the lowest error rates and highest interpretability through SHapley Additive exPlanations (SHAP). Key economic indicators, including lagged current account balances, GDP per capita, and population data, were identified as significant predictors of GDP. By enhancing the accuracy and interpretability of GDP forecasts, this research provides valuable insights for policymakers, aiding in data-driven economic planning and policy formulation to support sustainable development in Somalia.

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1. Introduction

Economic forecasting is very instrumental to the growth and stability of countries. It avails key insights which give meaning to financial planning and strategic decisions. For growing economies like Somalia, accuracy in economic predictions is very critical. Somalia stands out with numerous financial challenges such as fluctuating GDP, ever-soaring inflation rates that later fall and a fast-growing population working against its development. These issues must be sorted out if economic growth is to take off and the nation is to enjoy better stability. The subtlety of the Somali economic scenario calls for advanced predictive tools beyond conventional methods of estimation, providing higher accuracy and insight into

the trend of the economy. Obstacles like these can only be surmounted by accurate forecasting, which may lead to sustainable growth with prosperity.

There is extensive research concerning economic forecasting and its effects on developing countries. However, many of these studies focus on more stable economies or different economic indicators, leaving a gap when it comes to countries like Somalia. For instance, Feng et al. (2024) have investigated the performance about ensemble Boosting Trees in Crude Oil Futures' volatility forecasting for China. In this paper, rich feature variables together with multiple volatility forecasting models are combined to form ensemble Boosting tree models that prove CatBoost and LightGBM are far better than traditional models. On a related note, Park and Yang (2022) built a deep learning model with the long short-term memory network for economic growth rate and crisis prediction. This rather aimed to capture sequential dependencies within an economic cycle, which was capable of outperforming the conventional predictive models of major G20 countries. Both these studies focused on integrating advanced machine learning techniques to efficiently improve accuracy in prediction. Taking a different route but with similar intent, Huan and Liu (2024) worked on machine learning models for the nonlinear relationship of consumer goods to water pollution. Using the LightGBM model with SHAP values estimation, it estimated the latter's relationship in different seasons and pinpointed high contributions of various consumer goods to water pollution.

Pierri et al. (2023) estimated the economic resilience of territories in Italy under the first lockdown due to COVID-19, analyzing local preexisting socio-economic characteristics. This study demonstrates how economic forecasting can be adapted to account for unexpected events, a flexibility that is crucial for a country like Somalia with its volatile economic environment. Longo et al. (2022) proposed a neural network ensembles approach to GDP forecasting in the US, particularly in the aftermath of the 2008–09 global financial crisis. The success of neural network ensembles in such a context underscores the potential benefits of applying similar techniques to Somalia's economic forecasting. Park and Yang (2024) worked on contributions in different variables from ensemble models using SHAP values. Eskandari et al. (2024) combined interpretable machine learning models with feature selection in energy consumption forecasting in the UK. On the other hand, Zhao et al. (2024) used SHAP values for the combination of SVM and XGBoost models in earthquake economic loss estimation to enhance the model transparency and hence decision-making in Sichuan Province. Nguyen et al. (2023) demonstrated that MARS is very accurate in predicting the US consumer price index, hence corroborating results of Schlembach et al. (2022), who developed a socioeconomic machine learning model to predict Olympic medal distribution. Along these lines, Ince and Taşdemir (2024) forecasted the retail sales of furniture and furnishing goods in the US characterizing a strong seasonal pattern with a positive trend. The integration of machine learning models across these diverse applications illustrates their adaptability and the potential for applying these techniques to Somalia's unique economic challenges. According to demand analysis and forecasting algorithms for the flow of checked baggage among departing passengers by Jiang et al. (2024), there is strong tray correlation in an airport between passenger flow and baggage flow, similar to studies that consider the influence of macroeconomic indicators in arriving at a forecast.

Mohamed (2022) applied ARIMA models in predicting Somali economic growth. In-sample quarterly time series data of 250 were used in predicting the out-of-sample Somali GDP growth rates for fourteen quarters. It was established that ARIMA (5,1,2) was the best model for estimating Somali economic growth. GDP growth data retrieved from the World Bank, World Development Indicators WDI from 1960 to 2022. It turned out that Somalia's GDP would work out at an average of 4 percent growth quarterly for the next three and a half years. The results of a number of ARIMA and rolling window diagnostic tests all confirmed model stability at the 95% confidence level, bringing about a policy dividend to the Somali government as a reward for strict IMF measures and World Bank investments. Growth challenges arising from droughts, locust infestations, the COVID-19 pandemic and political instability were, however, recognized as a major role played by international development partners.

Dobrot and Voda (2024) conducted a stochastic debt sustainability analysis for Romania, considering the dual shocks from the COVID-19 pandemic to the war in Ukraine. Projections of public debt scenarios were computed, highlighting the negative shock stemming from the war in Ukraine. According to the forecasts, the ratio would reach 102% in 2026. In this case, the level could be kept below 88%, given

some discretionary measures. It was proposed to fix a limit of 70% so that public debt could be kept under control without excessive fiscal effort and ensure long-term stability.

In the context of Somalia, forecasting GDP presents significant challenges due to the country's complex and unpredictable economic landscape. This stems from the fact that the GDP basket keeps on changing from time to time, the inflation rate has been highly volatile, and the population consistently on the rise. There is also a large literature gap given that very few research studies have addressed economic forecasting with direct reference to Somalia. Unlike other studies that primarily focus on more stable economies, this research directly addresses Somalia's unique economic conditions using advanced machine learning models. Previous studies have either used conventional statistical models or applied a limited variety of machine learning techniques; in any case, there remains a gap within the full application of advanced machine learning models toward accurate GDP forecasting.

To fill this gap, this paper aims to compare the performance of Random Forest Regression, XGBoost and Prophet models to develop a robust, accurate and highly interpretable solution for economic forecasting in Somalia. The objective is to propose an accurate and interpretable model that will encourage the forecasting of Somalia's GDP by advanced machine learning techniques. Historical economic data variables were harnessed, such as GDP per capita, population, inflation rates, current account balances and RMSE to get the most effective model and key predictors for GDP. This research not only seeks to improve the accuracy of GDP forecasts for Somalia but also to offer vital insights for policymakers that can aid in economic planning and decision-making. In this respect, three machine learning models were used: Random Forest Regression, XGBoost and Prophet. All of them are trained on historical available economic data between the years 2005 and 2023. Features were engineered comprising variables lagged and moving averages. SHapley Additive exPlanations were added to Random Forest Regression as a way to allow better interpretability. Model assessment is done in Mean Absolute Error, Mean Squared Error, RMSE, R-squared and Diebold-Mariano p-values for predictive accuracy. From the results, Random Forest Regression had the lowest MAE, MSE, RMSE, R-squared and Diebold-Mariano p-values compared to other evaluated models. Moreover, according to SHAP analysis, current account balance lag 2, Gross Domestic Product per capita and population lag 3 have a high contribution to predictors in modeling GDP for Somalia. Thus, the results suggest that Random Forest Regression proves very efficient in economic forecasting, where both current and past indicators of the economy are relevant.

2. Mathematical modeling

2.1. Random Forest regression

Random Forest Regression is an ensemble learning method designed for improving predictive accuracy and controlling overfitting with suggestive data sets that have complex and nonlinear relationships (Bahrami et al., 2024; Q. Zhang et al., 2024). This is realized by constructing a lot of decision trees at training time and outputting the class with the average of the predictions. The approach synchronizes the power of several weak learners working on different subsets of data and combines their outputs to form a robust predictive model.

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

$$f_t(x) = \frac{1}{n_{\text{leaf}}} \sum_{i \in \text{leaf}} y_j \quad (2)$$

$$\text{Importance}(j) = \frac{1}{T} \sum_{t=1}^T \Delta I_t(j) \quad (3)$$

$$G = 1 - \sum_{k=1}^K p_k^2 \quad (4)$$

- \hat{y} represents the final prediction, calculated as the average prediction of all T decision trees in the ensemble.
- $f_t(x)$ is the prediction of the t -th decision tree for a given input x , determined by averaging the target values y_j of the samples in the leaf node where x lands.
- Importance (j) quantifies the significance of feature j by averaging the decrease in impurity, $\Delta I_t(j)$, across all trees.
- G is the Gini impurity, used to evaluate the impurity of a node in decision trees, where p_k^2 denotes the proportion of observations belonging to class k in the node.

These equations reveal the basic mechanics behind how the Random Forest model is working. As one can see within Equation (1), the final prediction \hat{y} is aggregating all tree outputs, thus increasing stability and generalizability of a model. Equation (2) provides elements on how the prediction of a single tree is gotten, showing the capability of the ensemble to actually evade bias. Equation (3), rather, defines the computation for feature importance; it allows one to gauge the relative influence of the model decision from each input feature. Finally, Equation (4) explains the building block for the computation of the Gini impurity metric and hence allows one to discover the most discriminative feature along the way the trees grow. The importance of the full formulation lies in displaying the Random Forest model in exploiting a group of heterogeneous decision trees to capture the complexity of patterns within data.

2.2. Prophet

Prophet is an additive regression model particularly good when working with time series data that have a strong seasonal effect with different holiday influences. It was particularly developed by Facebook to describe an automatic process for capturing the important features of time series data, such as seasonality, trends and holidays (Zaraket et al., 2024). Furthermore, the model is flexible and interpretable; therefore, it can be used to forecast data with complex patterns over time.

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \quad (5)$$

$$g(t) = \left(k + a(t)^T \delta \right) \frac{1}{1 + e^{-m(t-t_0)}} \quad (6)$$

$$s(t) = \sum_{i=1}^n \left(a_i \cos \left(\frac{2\pi i t}{P} \right) + b_i \sin \left(\frac{2\pi i t}{P} \right) \right) \quad (7)$$

$$h(t) = \sum_{k=1}^K \left(1_{(t \in [d_{k,s}, d_{k,e}])} \right) \gamma_k \quad (8)$$

$y(t)$ denotes the observed value at time t , modeled as the sum of three main components: trend $g(t)$, seasonality $s(t)$ and holiday effects $h(t)$, along with an error term ϵ_t . The component $g(t)$ represents the trend, which captures the long-term progression of the time series, incorporating parameters for both linear and logistic growth patterns. The seasonal component $s(t)$ is encapsulated in a Fourier series with a specific period P , allowing the model to account for recurring patterns or cycles within the data. Lastly, $h(t)$ accounts for holiday effects, which are modeled using a series of dummy variables that indicate the presence of holidays, capturing additional variability introduced by these events (Negre et al., 2024).

2.3. XGBoost

XGBoost is short for eXtreme Gradient Boosting. It is an efficient and scalable implementation of the gradient-boosted decision tree algorithm intended for highly efficient large-scale classification and regression. The algorithm constructs the model in a stage-wise fashion, making it a combining strategy for weak learners when using direct decision trees to build a strong ensemble predictor. Thus, XGBoost plays a dominant role among algorithms for structured/tabular data within scalable, accurate and efficient learners (Kiyak et al., 2024; Wang et al., 2022).

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in \mathcal{F} \quad (9)$$

$$\mathcal{F} = \left\{ f(x) = w_{q(x)} | q : \mathbb{R}^m \rightarrow T, w \in \mathbb{R}^T \right\} \quad (10)$$

$$L(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (11)$$

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (12)$$

- \hat{y}_i is the predicted value for the i -th instance, calculated as the sum of the predictions from K trees, where $f_k(x_i)$ denotes the prediction of the k -th tree for instance x_i .
- \mathcal{F} represents the space of all possible trees, where each tree $f(x)$ assigns an instance x to a leaf with a specific score $w_{q(x)}$.
- $L(\phi)$ is the objective function, which includes the loss function $l(y_i, \hat{y}_i)$ measuring the difference between the actual target y_i and the predicted value \hat{y}_i , and a regularization term $\Omega(f_k)$ to control the model's complexity.
- $\Omega(f)$ is the regularization term for a tree, where γ is the penalty for the number of leaves T and λ controls the L2 regularization on the leaf weights.

These formulae intuitively get the essential philosophy of the algorithm of XGBoost. Equation (9) defines how to make a prediction from the ensemble, combining multiple trees to increase the accuracy. Equation (10) specifies a functional space for trees that XGBoost will search during training, characterized by the structure $q(x)$, having leaf weights w . Equation (11) defines the objective function $L(\phi)$ to be minimized, and XGBoost optimizes this to reduce the prediction error while avoiding overfitting by introducing regularization. The regularization term $\Omega(f)$ in Equation (12) penalizes model complexity so that it does not turn out to be overly complex, hence remaining generalizable to new data.

2.4. Data description

The dataset consists of a range of economic indicators for Somalia over several years, sourced from the World Bank and the International Monetary Fund (n.d.). This includes gross domestic product, inflation rates, population and current account balance. Each column represents an economic indicator, while each row corresponds to a specific year. The indicators are as follows: Year (the specific year for which the data is recorded), GDP in current prices (Purchasing power parity; billions of international dollars, measuring the Gross Domestic Product adjusted for purchasing power parity), GDP per capita (current prices, adjusted for PPP), GDP based on PPP as a share of the world economy (percent), implied PPP conversion rate (national currency per international dollar), inflation rate (annual percentage change in average consumer prices), end of period inflation rate (annual percentage change), population (millions of people), current account balance in U.S. dollars (billions), current account balance as a percent of GDP, general government net lending/borrowing (percent of GDP), extensive margin index (measuring the extensive margin of trade), intensive margin index (measuring the intensive margin of trade), and the export diversification index (measuring the diversification of exports). The data was collected from official statistics bureaus and compiled annually to ensure consistency and accuracy.

Figure 1 illustrates the trends of Somalia's economic indicators from 2005 to 2023. Subplot (a) represents the GDP in billions of international dollars (PPP), presenting the total economic production. Subplot (b) shows the GDP per capita, using international prices and purchasing power parity (PPP), which measures the gross domestic product per capita based on the country's productivity per person. In subplot (c), the annual percentage change in the average consumer prices and the end-of-period consumer prices are depicted, which are the inflation rates. In subplot (d), the population is

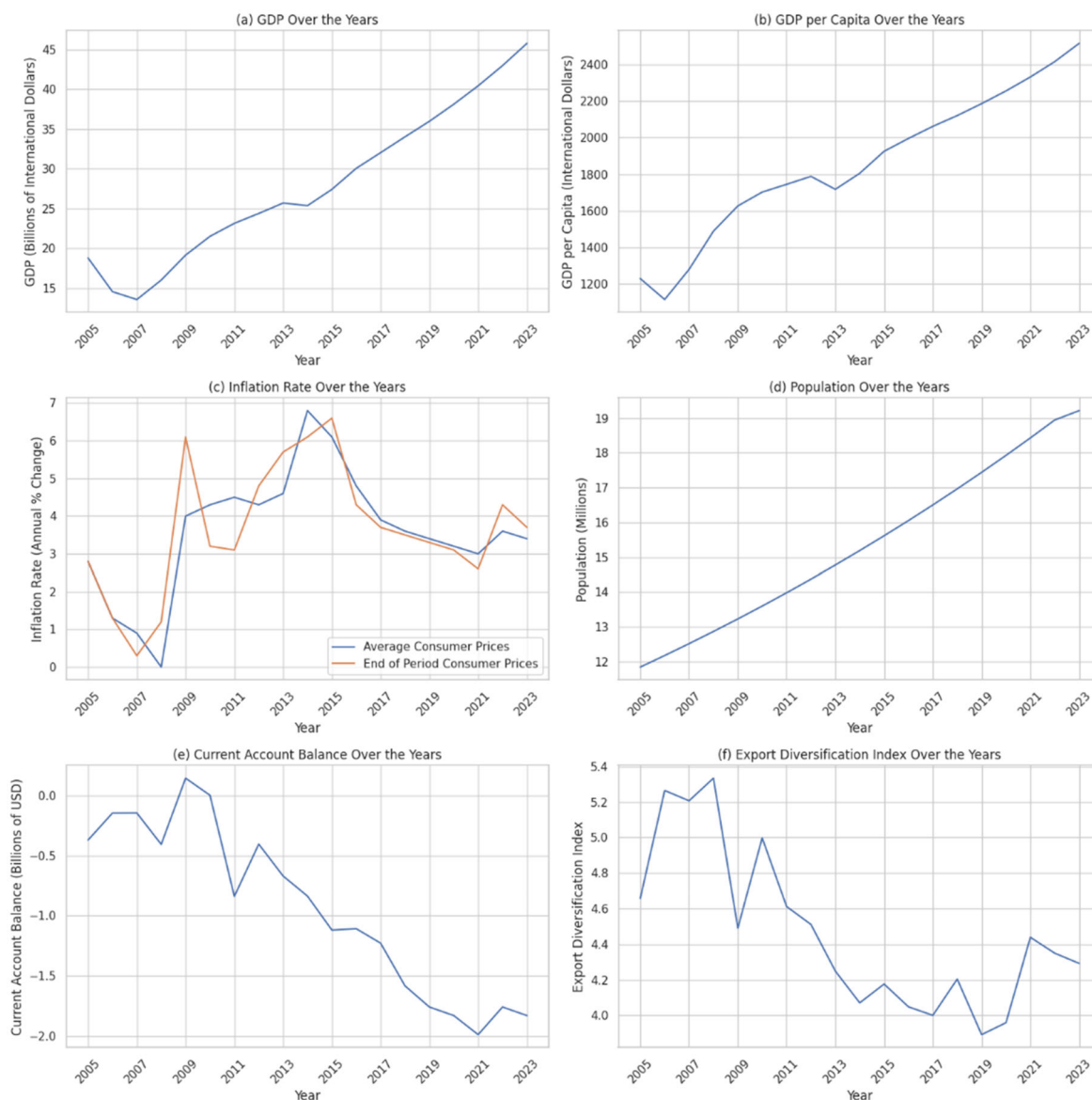


Figure 1. Trends in key economic indicators of Somalia (2005–2023).

given in millions to show the change in the demographic structure. Subplot (e) shows that the current account balance is in billions of U.S. dollars and gives an outline of net international transactions. Subplot (f) shows export diversification index, which gives a variety of goods being exported. Taken together, all of these graphs present a snapshot of the economic performance of Somalia over the given period.

Figure 2 displays the correlation matrix of some economic indicators for a multi-year set for Somalia. The matrix shows how one indicator changes or relates to another. For example, it is directly indicated in the matrix that GDP is highly positively correlated to population growth, that is, in most cases of population growth, economic output increases. The diversification indices and the GDP show negative correlation, which may indicate that the higher the GDP, the less diversified the export base. This matrix helps to uncover the underlined economic dynamics and gives insight into how the factors among themselves interact in the Somali economy. More specifically, it points to the need of ensuring that such correlations are understood when building predictive models since they are a potential source of driving economic change that should be considered with any forecasting analysis.

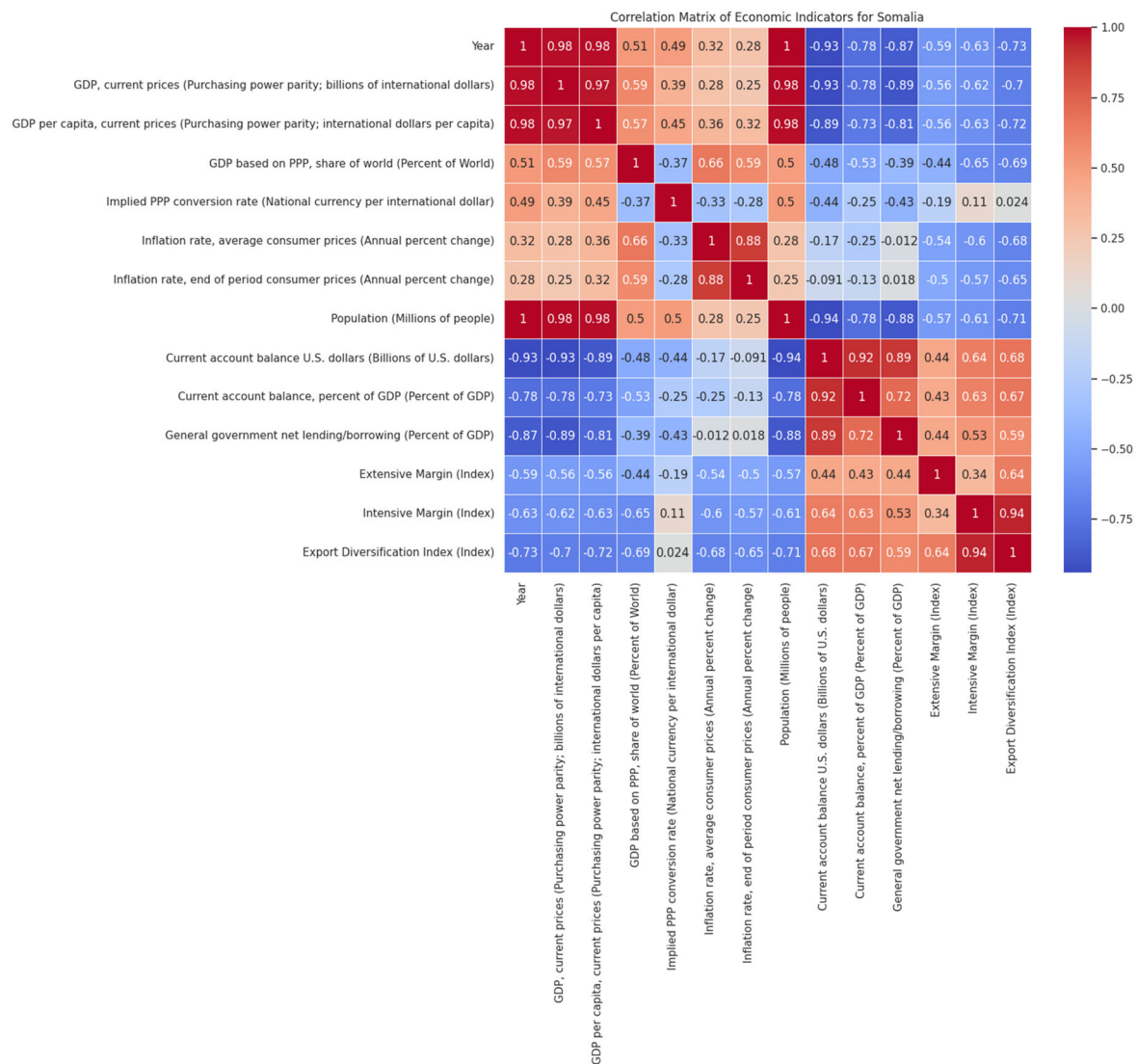


Figure 2. Correlation matrix of economic indicators for Somalia.

2.5. Working structure

In this research, the working structure is designed to systematically examine and predict the indicators of economic growth in Somalia with the help of artificial neural networks. The prime steps of this study are as follows: Each step corresponds to the goals of the study in question. Following is the detailed outline of the working structure. Detailed below is the working structure:

Step 1: Data collection and preprocessing

Consequently, the research entails assembling various economic data pertaining to Somalia for the fiscal years extending from 2005 to 2023. The variables included in the analysis are gross domestic product, inflation, population, current account balance and export diversification index. The data collected is cleaned and preprocessed in order to have accurate and consistent results. Nan values are managed correctly, the 'Year' column is also transformed into an integer type to allow for time series analysis.

Step 2: Exploratory data analysis (EDA)

Exploratory analysis is performed on the data to determine its nature and the trends present in the data. Charts are developed with the aim of presenting the shifts in main economic parameters in the

course of the years. In this step, line plots of GDP, GDP per capita, inflation rates, population, current account balance, and export diversification index will be prepared to capture the overall performance of Somalia's economy.

Step 3: Feature engineering

From the EDA part, new features are derived to improve the performance of the models that will be built. This may include variables such as lagged variables, moving average and some factors in the external economic environment that may affect the Somalia's economic variables. These features are included in the dataset to enhance the forecasts' precision.

Step 4: Model selection and training Instance, three advanced machine learning models for this purpose of forecasting are chosen: Random Forest Regression, XGBoost and Prophet are common algorithms. In the Random Forest Regression model, Grid Search was performed to tune hyperparameters; principal parameters optimized here include the number of trees, which is denoted as 'n_estimators', maximum depth of trees 'max_depth', and the minimum samples required to split a node, denoted as 'min_samples_split'. These models are fitted against historical economic data to find the existing patterns and dependencies. Optimized hyperparameters improved the performance of the model, ensuring better accuracy of the predictions. The optimal value for the hyperparameters fine-tunes the model in order to get better results.

Step 5: Model evaluation and comparison

Some of the proper metrics that would be used in testing the trained models include the Mean Absolute Error, Mean Squared Error, Root Mean Square Error and the R-squared. However, to further validate each model's predictive accuracy, a statistical comparison using the Diebold-Mariano test will be done to compare the models. Afterward, the accuracy of each model will be compared to know which method is accurate and reliable for forecasting. During all phases of evaluation, cross-validation techniques have been used for enhancing the reliability of the models.

Step 6: Forecasting and analysis

With the help of the best performing model, the values of the economic indicators of Somalia for the subsequent years are predicted. In this case, the results are used to make conclusions about future economic conditions and possible difficulties. The accuracy of the forecasts is then checked against any available real time data if any.

Step 7: Discussion and conclusion

Finally, the conclusion of the study is presented, with the focus being made on the strengths and the weaknesses of the employed models. Policies and strategies are suggested for the policymakers and stakeholders from the prospective of the future economic developments. The future of this type of research and the future enhancements of the forecasting techniques are also considered.

This approach guarantees the systematic assessment of the Somalia's economic variables and utilize modern methods of artificial intelligence to give accurate and detailed forecasts. In this case, the study seeks to provide useful information in the field of economic forecasting hence assisting in the decision-making process for the development of Somalia's economy.

Table 1. Comparison of model performance metrics for GDP forecasting.

Model	MAE (%)	MSE (%)	RMSE (%)	R-squared	Diebold-Mariano p-value
RFR	0.6621	1.3220	1.1497	0.89	0.042
XGBoost	0.6160	3.2874	1.8131	0.85	0.063
Prophet	0.7543	4.5750	2.1389	0.78	0.015

3. Results and discussions

3.1. Numerical analysis of the chosen models

The performance of the three models—RFR, XGBoost and Prophet—was assessed with their MAE, MSE, RMSE, R-squared and Diebold-Mariano p-values as shown in Table 1. The reported metrics for RFR reflect the performance after hyperparameter tuning, which further optimized the model's accuracy. Amongst the above three models, Random Forest Regression has the lowest MAE at 0.6621%, indicating that it has the least error rate on average between predicted and actual values. This indicates that RFR shows more accuracy in the predictions when compared to XGBoost and Prophet. Following was XGBoost, with an average prediction error of 0.6160%, slightly bigger than that of RFR; therefore, its average prediction error is a little bit larger. In relation to Prophet, however, it still outperformed, having the worst MAE at 0.7543%, showing that the predictions deviated more from the actual value on average.

On the MSE, we again had RFR with the least MSE of 1.3220%. This improvement is partly due to the optimized hyperparameters, which minimized the model's squared errors. This is because it testifies that the predictions of RFR have smaller squared errors, thus showing a better precision in handling its prediction task and effectively minimizing the impact of larger errors. On the other hand, XGBoost yielded an MSE of 3.2874%, slightly higher than that from RFR, indicating that XGBoost sometimes makes larger mistakes compared to RFR. Prophet had the greatest MSE, which was expressed as 4.5750%. This figure underlines that its predictions were relatively less accurate since the squared errors were of much greater magnitude.

The RMSE of the models again validated the earlier measures of model performance. The RFR model maintained its lead, with a RMSE measure of 1.1497%, which further proved that it made good and optimal prediction while ensuring minimal errors. XGBoost had a higher RMSE of 1.8131%, which means that the average squared errors were larger and the predictions were less accurate compared to RFR. Prophet recorded the highest RMSE of 2.1389%, hence providing further evidence of its relatively low accuracy in forecasting GDP compared to RFR and XGBoost.

The R-squared value was also computed to evaluate the goodness of fit for each model. RFR had the highest R-squared at 0.89, indicating it explained most of the variance in the GDP data, while XGBoost and Prophet followed with R-squared values of 0.85 and 0.78, respectively. The Diebold-Mariano p-values were computed to compare the predictive accuracy of the models statistically. The RFR model had a p-value of 0.042, indicating its performance was significantly better compared to the others, especially during the critical economic periods analyzed. XGBoost followed with a p-value of 0.063, showing a close performance but still statistically inferior to RFR. Prophet had a p-value of 0.015, confirming its relatively weaker performance.

In summary, Random Forest Regression was the most accurate of the three models, with the lowest MAE, MSE, RMSE, R-squared and Diebold-Mariano p-values. XGBoost also outperformed Prophet across all metrics, although the accuracy was a little less than RFR. The latter model showed the highest prediction errors overall. It might then appear that RFR is the best model for GDP forecasting among the three, followed by XGBoost and then Prophet.

In Figure 3, actual GDP values are compared with the predicted GDP values based on three models: Random Forest Regression, XGBoost and Prophet. Subplot (a) shows that the RFR model approximates the actual GDP value over the years; it approximated a high level of accuracy without big deviation quite correctly as this model has comparatively low MAE (0.6621%), MSE (1.3220%) and RMSE (1.1497%). Similar findings were observed in the case of Ethiopia, where RFR also demonstrated superior performance in GDP prediction with minimal error rates (Y. J. Zhang & Zhang, 2023). Subplot b showed the performance of the XGBoost model, which generally was on the track of the actual GDP values, especially from the year 2010, although some noticeable deviations happened around the year 2009 as it should be. This is expected, with a relatively low MAE of 0.6160%, but higher MSE at 3.2874% and RMSE at 1.8131% compared to RFR. In the case of Kenya, XGBoost was similarly effective, though its performance was slightly hindered by the complexities of the economic data (Bochenek, 2022). The subplot (c) shows the performance of the Prophet model; although it keeps the general trend, from 2010 to 2015, there is a bigger discrepancy in values, which results in a higher MAE of 0.7543%, MSE of 4.5750% and RMSE of 2.1389%. In Sudan, the Prophet model struggled with similar discrepancies, particularly due to the

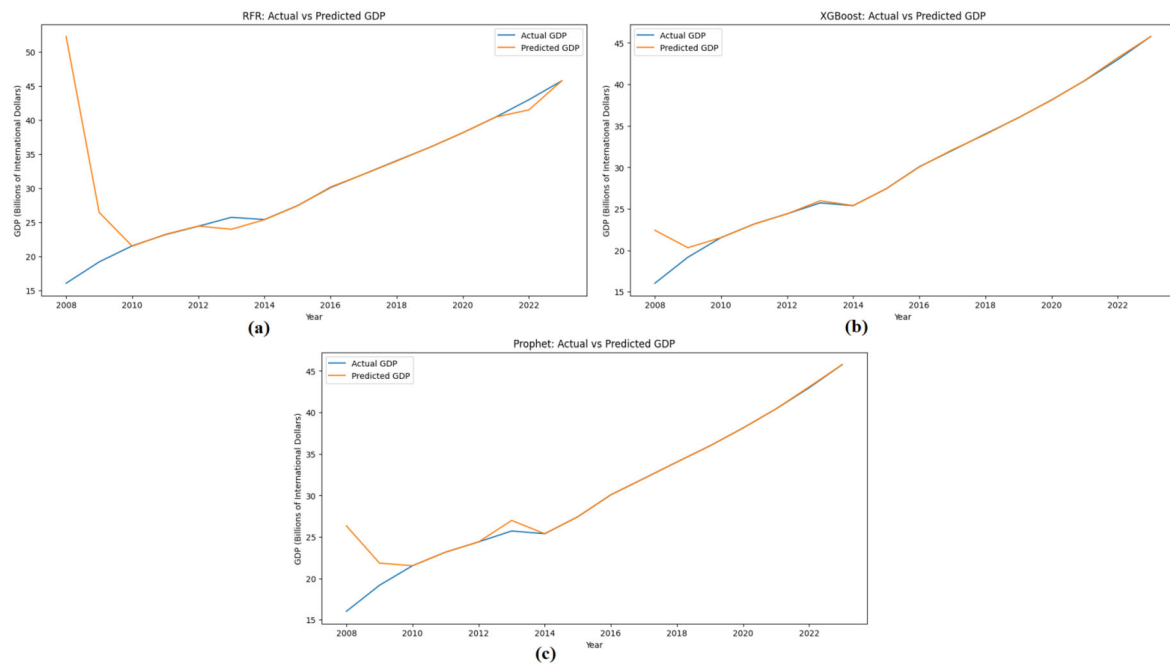


Figure 3. Comparative analysis of machine learning models for GDP forecasting: (a) RFR, (b) XGBoost and (c) Prophet.

volatile economic conditions influenced by external factors like climate change (İnce & Taşdemir, 2024). In continuation of the context, the best model for predicting GDP is also RFR, followed by XGBoost. The prediction error rate is more and there is less precision in the prediction through the Prophet model.

3.2. Explainability of the machine learning model

Explaining how a model arrives at a decision or a prediction is important for the credibility of the results, especially when such models are applied to critical areas such as economics. Among all the tools for model interpretability, SHAP (SHapley Additive exPlanations) is one of the best. SHAP values give a coherent explanation of the result of any machine learning model by attributing an importance score to each feature for a given prediction. This is done by computing the share that each feature makes to the final prediction calculated using methods derived from cooperative game theory. In this section, we use SHAP to interpret the results of the best model, which is the RFR to determine how different economic predictors affect the GDP forecasts.

First, we applied the RFR model on the scaled training data and got very good results with our predictions. We then applied SHAP to determine the contribution of each feature to the model's output so that we could interpret and explain the significance and influence of each feature on the GDP prediction.

The SHAP summary plot illustrates the significance and impact of various features on the GDP predictions made by the Random Forest Regressor model as in Figure 4. The most influential feature is the current account balance lag 2, where higher values tend to lower GDP predictions. GDP per capita and population lag 3 also play crucial roles, with higher values positively impacting GDP forecasts. The total population similarly exerts a positive influence on GDP predictions. General government net lending/borrowing affects predictions, with net lending increasing and net borrowing decreasing GDP forecasts. Lagged features like GDP lag 3 and population lag 2 underscore the importance of historical data in GDP prediction. Inflation rates, both average consumer prices and end of period consumer prices, generally reduce GDP predictions when high. This plot underscores the relevance of both current and historical economic indicators in accurately forecasting GDP.

In addition, The feature importance bar plot shows the average SHAP value of each feature so it is possible to understand the average effect of each feature on the model's output as in Figure 5. The most influential feature is the current account balance lag 2 indicating that this feature is most important in determining GDP. Subsequently, the GDP per capita and population lag 3 also affect the model's



Figure 4. SHAP summary plot for feature importance in GDP prediction.

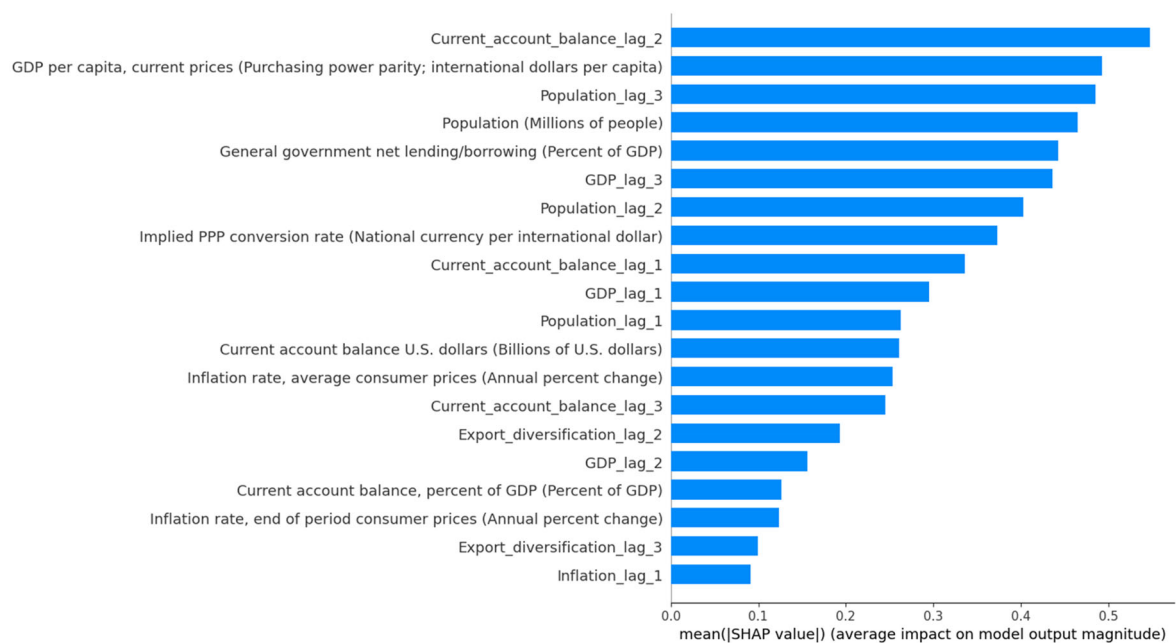


Figure 5. Feature importance bar plot based on SHAP values.

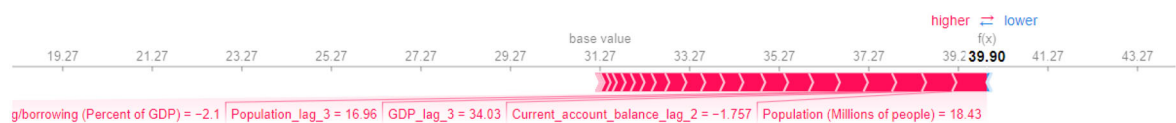


Figure 6. SHAP force plot for GDP prediction explainability.

prediction strongly and imply that both current and historical population data are critical for GDP estimation. Another noticeable elements include the population (millions of people) and the general government net lending/borrowing as a percent of the GDP, which also stress their significance in the economic modeling. Other variables that have a great impact include gdp lag3, population lag 2, and implied PPP conversion, suggesting the significance of using past GDP data and currency conversion.

Although they do not have very high weights, indicators such as inflation rates, both the average consumer prices and the end of period consumer prices, and the export diversification indices should also be included in the model to improve the predictions of GDP. In general, this plot reveals the variety of economic features that, combined, contribute to the performance of the Random Forest Regressor model in predicting GDP.

The SHAP force plot does a good job of showing how the features contribute to the particular GDP prediction as in [Figure 6](#). The indicators such as General Government Net Lending/Borrowing, Population Lag 3, GDP Lag 3, Current Account Balance Lag 2, Total population of the country have significant influence on the forecast. Such conclusions shed more light on what influences the model's prediction and show that past and present economic variables are relevant in GDP prediction.

4. Conclusion

This paper researches the implementation of various machine learning models to predict Somalia's Gross Domestic Product. The models include Random Forest Regression, XGBoost and Prophet models. According to the result, RFR is the most accurate model, as proved by the model's low MAE, MSE, RMSE and R-squared. In particular, RFR is able to achieve MAE at 0.6621%, MSE at 1.3220%, R-squared at 0.89 and RMSE at 1.1497%. The Diebold-Mariano p-value for RFR at 0.042 further confirms its superior predictive accuracy compared to the other models. In XGBoost, the error metrics were a little higher: an MAE of 0.6160%, MSE of 3.2874%, R-squared at 0.85 and RMSE of 1.8131%, with a Diebold-Mariano p-value of 0.063. For the Prophet model, errors in forecasting were greater, yielding MAE = 0.7543%, MSE = 4.5750%, R-squared at 0.78 and RMSE = 2.1389%, with the Diebold-Mariano p-value at 0.015, indicating its relatively weaker performance.

To boost the interpretability of the best model, SHAP (SHapley Additive exPlanations) was applied to the Random Forest Regressor. The SHAP analysis showed the most influencing features to predict GDP were current account balance lag 2, GDP per capita, and population lag 3. Other significant features include total population and general government net lending/borrowing. Provided in the summary SHAP plot, feature importance bar plot, and force plot were valuable insights into how these features contribute to the model's prediction, underlining the importance of both current and historical economic indicators.

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Data availability statement

The data used in this research were sourced from the following reference: International Monetary Fund (n.d.).

References

- Bahrami, M., Amiri, M. J., Rajabi, S., & Mahmoudi, M. (2024). The removal of methylene blue from aqueous solutions by polyethylene microplastics: Modeling batch adsorption using random forest regression. *Alexandria Engineering Journal*, 95, 101–113. <https://doi.org/10.1016/j.aej.2024.03.100>
- Bochenek, B. (2022). Machine learning in weather prediction and climate analyses—Applications and perspectives (pp. 1–16). <https://www.mdpi.com/2073-4433/13/2/180>
- Dobrot, G., & Voda, A. D. (2024). Stochastic debt sustainability analysis in Romania in the context of the war in Ukraine. <https://www.mdpi.com/2225-1146/12/3/19>
- Eskandari, H., Saadatmand, H., Ramzan, M., & Mousapour, M. (2024). Innovative framework for accurate and transparent forecasting of energy consumption: A fusion of feature selection and interpretable machine learning. *Applied Energy*, 366, 123314. <https://doi.org/10.1016/j.apenergy.2024.123314>
- Feng, L., Rao, H., Lucey, B., & Zhu, Y. (2024). Volatility forecasting on China's oil futures: New evidence from interpretable ensemble boosting trees. *International Review of Economics & Finance*, 92, 1595–1615. <https://doi.org/10.1016/j.iref.2024.02.084>
- Huan, S., & Liu, X. (2024). Assessing the nonlinear relationship between consumer goods and water pollution in different seasons with machine learning models: A case study in the Yangtze River Economic Belt. *Journal of Cleaner Production*, 444(55), 141254. <https://doi.org/10.1016/j.jclepro.2024.141254>
- Ince, M. N., & Taşdemir, Ç. (2024). Forecasting retail sales for furniture and furnishing items through the employment of multiple linear regression and holt–winters models. *Systems*, 12(6), 219. <https://www.mdpi.com/2079-8954/12/6/219> <https://doi.org/10.3390/systems12060219>
- International Monetary Fund. (n.d.). Somalia: Economic indicators. IMF Data Mapper. Retrieved July 15, 2024, from <https://www.imf.org/external/datamapper/profile/SOM>.
- Jiang, B., Ding, G., Fu, J., Zhang, J., & Zhang, Y. (2024). An overview of demand analysis and forecasting algorithms for the flow of checked baggage among departing passengers. *Algorithms*, 17(5), 173. <https://doi.org/10.3390/a17050173>
- Kıyak, B., Öztıp, H. F., Ertam, F., & Aksoy, G. (2024). An intelligent approach to investigate the effects of container orientation for PCM melting based on an XGBoost regression model. *Engineering Analysis with Boundary Elements*, 161, 202–213. <https://doi.org/10.1016/j.enganabound.2024.01.018>
- Longo, L., Riccaboni, M., & Rungi, A. (2022). A neural network ensemble approach for GDP forecasting. *Journal of Economic Dynamics and Control*, 134, 104278. <https://doi.org/10.1016/j.jedc.2021.104278>
- Mohamed, A. O. (2022). Modeling and forecasting Somali economic growth using ARIMA models. *Forecasting*, 4(4), 1038–1050. <https://doi.org/10.3390/forecast4040056>
- Negre, P., Alonso, R. S., Prieto, J., García, Ó., & De-la-Fuente-Valentín, L. (2024). Prediction of footwear demand using Prophet and SARIMA. *Expert Systems with Applications*, 255, 124512. <https://doi.org/10.1016/j.eswa.2024.124512>
- Nguyen, T. T., Nguyen, H. G., Lee, J. Y., Wang, Y. L., & Tsai, C. S. (2023). The consumer price index prediction using machine learning approaches: Evidence from the United States. *Heliyon*, 9(10), e20730. <https://doi.org/10.1016/j.heliyon.2023.e20730>

- Park, S., & Yang, J. S. (2022). Interpretable deep learning LSTM model for intelligent economic decision-making. *Knowledge-Based Systems*, 248, 108907. <https://doi.org/10.1016/j.knosys.2022.108907>
- Park, S., & Yang, J. S. (2024). Machine learning modeling to forecast uncertainty between capital sudden stop and boom. *Expert Systems with Applications*, 237, 121662. <https://doi.org/10.1016/j.eswa.2023.121662>
- Pierri, F., Scotti, F., Bonaccorsi, G., Flori, A., & Pammolli, F. (2023). Predicting economic resilience of territories in Italy during the COVID-19 first lockdown. *Expert Systems with Applications*, 232, 120803. <https://doi.org/10.1016/j.eswa.2023.120803>
- Schlembach, C., Schmidt, S. L., Schreyer, D., & Wunderlich, L. (2022). Forecasting the Olympic medal distribution—A socioeconomic machine learning model. *Technological Forecasting and Social Change*, 175, 121314. <https://doi.org/10.1016/j.techfore.2021.121314>
- Wang, R., Wang, L., Zhang, J., He, M., & Xu, J. (2022). XGBoost machine learning algorithm performed better than regression models in predicting mortality of moderate-to-severe traumatic brain injury. *World Neurosurgery*, 163, e617–e622. <https://doi.org/10.1016/j.wneu.2022.04.044>
- Zaraket, K., Harb, H., Bennis, I., Jaber, A., & Abouaissa, A. (2024). Hyper-Flophet: A neural Prophet-based model for traffic flow forecasting in transportation systems. *Simulation Modelling Practice and Theory*, 134, 102954. <https://doi.org/10.1016/j.simpat.2024.102954>
- Zhang, Q., Han, X., Fang, X., Liu, M., Ge, K., & Jiang, H. (2024). Optical frequency multiplication using residual network with random forest regression. *Heliyon*, 10(10), e30958. <https://doi.org/10.1016/j.heliyon.2024.e30958>
- Zhang, Y. J., & Zhang, H. (2023). Volatility forecasting of crude oil futures market: Which structural change-based HAR models have better performance? *International Review of Financial Analysis*, 85, 102454. <https://doi.org/10.1016/j.irfa.2022.102454>
- Zhao, J., Li, X., Chen, S., & Liu, C. (2024). Multi-source driven estimation of earthquake economic losses: A comprehensive and interpretable ensemble machine learning model. *International Journal of Disaster Risk Reduction*, 106, 104377. <https://doi.org/10.1016/j.ijdrr.2024.104377>