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A Machine Learning Approach to Predict Economic Freedom Index

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Abstract: *In this study, machine learning methods are used to estimate a nation's economic freedom index. Economic growth and development have been proven to be strongly correlated with the economic freedom index, which measures a nation's economic laws and regulations. This study used a dataset that included the Economic Freedom Index and several economic variables for 162 countries. The data underwent processes such as outlier removal, encoding categorical variables, and filling in missing values. The performance of a machine learning model was enhanced through hyperparameter tuning after it had been trained using a variety of techniques, including decision trees, random forests, and XGBoost. The outcomes demonstrate that the XGBoost algorithm outperformed other models. It had a 92% accuracy rate in predicting a nation's economic freedom index. In order to help policymakers improve a nation's economic laws and regulations, this study illustrates the potential of employing machine learning techniques to anticipate economic freedom.*

Keywords: Economic freedom index (EFI), XGBoost, country, machine learning, economic growth, development and accuracy

I. INTRODUCTION

The ability of people and enterprises to make economic decisions without interference from the government or other entities is referred to as economic freedom. It encompasses a wide range of factors, including, among others, how open a nation is to trade, the manner in which rules are established, and property rights. According to studies, nations with higher levels of economic freedom typically experience better economic results, such as higher rates of economic development, better job creation, and higher living standards. The demand for precise and trustworthy methods to quantify economic freedom is expanding, given how crucial it is and how it may affect economic outcomes.

How ML techniques can be applied to forecast economic indicators has attracted a lot of attention in recent years. The ability to forecast a nation's economic freedom index has grown in importance. Growth and development in the economy have been proven to be strongly correlated with the economic freedom index, which measures a nation's economic laws and regulations. A number of economic indicators have been studied in the past, including corruption (Lima & Delen, 2020), the gross domestic product (Tran et al., 2023), inflation (Akkoç & zgür, 2021), technical efficiency (Adkins et al., 2002), social capital (Berggren & Jordahl, 2006), and economic growth (Grier & Tullock, 1989; Heckelman, 2000).

Since ML approaches can account for intricate, nonlinear interactions between variables, they are effective at forecasting economic indicators. Additionally, ML methods can aid decision-makers in improving a nation's economic regulations and policies. However, it is crucial to understand that ML results should be interpreted cautiously and that ML techniques by themselves cannot take the place of industry knowledge and expertise. The purpose of this study is to explore the viability of using ML approaches for forecasting a country's economic freedom index based on a dataset containing various economic variables (Gwartney et al., 2002; DEPREN & Yang, 2021). The results of the paper's investigation on the effectiveness of other machine learning algorithms, including decision trees, Random forests, and XGBoost,reveal that XGBoost surpasses other models by accurately forecasting a country's economic freedom index. This study adds to the expanding corpus of research that demonstrates how ML techniques could be utilized to aid in economic policy decisions (Meng, 2022; Ozden & Guleryuz, 2022; Cicceri et al., 2020).

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The results of our study show how well different categorization algorithms predict economic index scores and compare how well they do in this regard. Users can view the forecasts and further explore the dataset on the streamlit website we developed. Overall, this work advances our knowledge of the connection between economic freedom and economic success and provides scholars and policymakers with a useful tool.

II. LITERATURE SURVEY

[1] The study offers a machine-learning strategy for forecasting and elucidating the degrees of corruption in various nations. The authors built predictive models from the data they collected from various sources using machine learning algorithms like decision trees and random forests. According to the study, machine learning techniques can be used to accurately forecast corruption levels. The most significant predictors of corruption were found to be economic freedom, income inequality, and government effectiveness. Support Vector Regression, Gradient Boosting Machine, Random Forest, and K-Nearest The machine learning models in the research are trained and tested using data from institutions like the World Bank, the International Monetary Fund, and the United Nations. According to a study, the Gradient Boosting Machine method exceeds the competition in terms of precision and productivity. The study discusses how typical machine learning methods can be applied to economic forecasting and how effectively they can predict GDP numbers.

The research suggests applying conventional machine learning methods to forecast gross domestic product in different nations. In their study, the authors examine how various machine learning methods, including linear regression, decision trees, random forests, and the support vector machine, perform when used to forecast GDP. They test the effectiveness of these algorithms using a number of datasets that contain GDP data from different nations. The results show that the SVM method outperforms other algorithms at estimating GDP figures for different countries. At the 8th EAI International Conference on the Nature of Computation and Communication in October 2022, the paper was presented. [2]

[3] The issue of inflation forecasting in Turkey, a developing nation that has had significant inflation rates in recent years, is the main subject of the article by zgür and Akkoç (2021). The authors suggest a strategy for choosing the most important variables for inflationary prediction that is based on predictive machine learning algorithms. They test the effectiveness of different algorithms, such as decision trees, random forests, and artificial neural networks, as well as the propensity of the selected variables to forecast future events. The findings demonstrate that predictive machine learning algorithms may predict inflation more precisely than conventional econometric models, particularly when contrasted with how inflation is currently anticipated. Now, demonstrate the significance of considering factors like social and political circumstances when attempting to forecast inflation in developing nations.

[4] The research looks at the connection between technical prowess and economic independence. The researchers construct indices of economic freedom based on the Economic Freedom of the World index from the Fraser Institute by using data envelopment analysis (DEA) to assess the effectiveness of technology systems. According to the study, nations with greater degrees of freedom in the economy also tend to have more technologically advanced economies. The authors hypothesize that this may be due to the favorable effects of economic freedom on incentives, innovation, and resource usage. However, the authors also assert that there might be additional institutional elements that have an impact on how effectively technology functions and that additional study is required to completely understand this link.

[5] Using panel data analysis for a sample of 101 countries between 1980 and 1995, the short-term relationship between economic freedom and economic growth is investigated. The findings imply that economic freedom and short-term economic growth have a beneficial and statistically significant link. Economic freedom, according to the author, may help the economy thrive since it encourages investment, increases productivity, and makes more efficient use of resources.

[6] The degree to which people trust and work together, which is termed social capital in the article, is examined in connection to economic freedom. According to the authors, economic independence can increase social capital through stimulating economic growth, reducing corruption, and increasing people's opportunities to participate in volunteer organizations. By examining data from many nations regarding economic freedom, social capital, and other crucial variables, they put their theory to the test. Economic freedom is positively correlated with social capital, even after accounting for other factors like wealth, education, and political institutions. The authors draw the conclusion that

encouraging economic freedom may be an effective method to increase social capital and create a more successful and cohesive community.

[7] Every year, the Fraser Institute publishes a report called the Economic Freedom of the World Index. The report's findings are presented in the paper. The index compares the degree of economic freedom among various countries based on five important criteria: the size of the government, the protection of property rights provided by the legal system, the availability of stable currencies, the ability to engage in international trade, and regulations on financing, labor, and business. The research also discusses the relationship between economic freedom and variables including income levels, economic growth, and the proportion of individuals living in poverty.

[8] The study examines the factors that contributed to economic growth in 98 nations between 1951 and 1980. The authors examine how factors including investment, population expansion, governmental spending, and free trade impact economic growth using a regression analysis. They discover economics and investment. They discover that there is a considerable inverse association between financial autonomy and what they consider to be the levels of corruption in a nation. This implies that perceptions of corruption are generally lower in nations with greater economic independence. They discover that there is a considerable inverse correlation between economic freedom and perceived levels of corruption in a nation. This implies that perceptions of corruption are generally lower in nations with greater economic independence. The study also provides details on the aspects of economic freedom that are most strongly associated with a feeling of less corruption. According to the findings, policies that support economic independence may also help to improve public perceptions of corruption.

[9] The study looks at the connection between perceived corruption and economic freedom in various nations. The authors contend that economic freedom is a key factor in determining how much corruption exists in a nation. The study uses statistical analysis to examine its hypotheses using data from 156 different nations. According to the findings, economic freedom and perceptions of Corruption is negatively correlated, meaning that perceptions of corruption are often lower in nations with higher levels of economic freedom. In order to reduce corruption and enhance social and economic outcomes, the article emphasizes the value of economic freedom.

[10] The research suggests a novel way for assessing free trade zones' capacity for scientific and technical innovation using the random forest (RF) weighting method. A free trade zone innovation evaluation model is created using an approach that combines the benefits of the random forest algorithm with weighting analysis. The Greater Bay Area free trade zone in Guangdong, Hong Kong, and Macao is evaluated using the suggested technique for its capacity for innovation. The findings demonstrate that the suggested method may accurately assess how creative free trade zones are and provide important data to decision-makers and other interested parties.

[11] The 2022 article by Ozden and Guleryuz uses enhanced machine learning methods to investigate the connection between economic growth and human resources. The authors model the relationship between several economic and human capital metrics, such as GDP per capita, education spending, and health care spending, using a range of machine learning approaches, including random forests, decision trees, and gradient boosting. A selection of 149 nations from 1995 to 2018 were included in the study. The findings indicate that ML algorithms are a good tool for deciphering the nuanced relationship between human capital and economic development and that some factors, like education, are more crucial than others to forecasting economic progress. Overall, the work advances our understanding of how machine learning techniques can be used in economic analysis and clarifies the variables influencing economic growth.

[12] The study suggests using machine learning to predict economic downturns in Italy. The authors estimate the likelihood that a recession will occur during the next two quarters using a dataset of 148 macroeconomic indicators from 1970 to 2018 and a variety of algorithms for machine learning, including random forests and artificial neural networks. According to their analysis of the performance of the various algorithms, the random forest model exceeds all of them in terms of predicted accuracy. The authors also discuss the most crucial indicators that can be utilized to anticipate recessions, as well as the implications of their research for decision-makers.

[13] This essay examines how the economy has altered as a result of machine learning. Three topics are highlighted: prediction, determining what caused something, and optimizing. It examines the benefits and drawbacks of applying machine learning to economics research, including the requirement for huge datasets, the difficulty in comprehending the findings, and the danger of overfitting. The author also explores the application of machine learning to several

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branches of economics, including labor, macro, and development economics. The report finishes with some suggestions for possible future lines of inquiry.

[14] The notion of using ML in economic forecasting is covered in Paruchuri's (2021) article. The author provides an overview of machine learning techniques and how they apply to economic forecasting. The difficulties of using machine learning for economic forecasting, such as data quality and interpretability, are also covered in the article. According to the author, machine learning can be an effective tool for increasing the precision of economic projections, but it requires careful consideration of the data and algorithms utilized. The study provides a thorough analysis of the applications of machine learning in economic forecasting.

III. OVERVIEW OF DATASET

The dataset utilized in this experiment was the economic index dataset from the Heritage Foundation. It includes information on various countries' rankings and economic freedom metrics. The dataset comprises a number of variables, including property rights, government spending, trade freedom, and business freedom, among others, and covers the years 2013 through 2022.

The classification dataset, the visualization dataset, and the preprocessed data were each given their own portion of the dataset. The models were trained and tested using the preprocessed data; the visualization dataset was used to provide a variety of visuals; and the classification dataset was used to train and test classification models.

The dataset was preprocessed to get rid of outliers and make sure all the features were consistent. There were 178 countries in the preprocessed dataset, along with 27 characteristics. The score, a number from 0 to 100 on a scale used to measure economic performance, was the dependent variable of interest.

Overall, the dataset contains a wealth of interesting data that can be used to create and test models that can forecast economic index scores as well as examine how economic freedom

The remaining sections of the essay are organized as follows: The second section provides an overview of the dataset used, while the third section describes the methodology and classification models employed. The methodology of the study is presented in Section 4, while the findings and their implications are discussed in Sections 5 and 6. Section 7 and Section 8 conclude with conclusions and future research recommendations.

IV. METHODOLOGY

This project used classification algorithms to predict countries' economic index scores based on economic freedom indicators. This project's methodology is as follows: The index's minimum scores defined the range. For analysis, continuous variables were created. Thresholding values ensured only relevant data was included. Label encoding converted index scores to numbers. The country name and ID columns were removed because they were irrelevant to the analysis. One-hot encoding encodes region values. For analysis, x and y were separated into input and output. SMOTE oversampled minorities to balance the dataset. GDP columns were removed since they were irrelevant to the analysis. Chi-squares were used to determine variable associations. Box plots exclude outliers for accurate data. Understanding variable relationships requires a correlation matrix. Only columns with correlations below 0.6 were preserved. To test the model, trainingom:train and test samples were created. The data was cleaned, preprocessed, and prepared for analysis.

- Feature Selection: We selected the most relevant features to train the classification models. This was done using the Recursive Feature Elimination (RFE) technique, which ranks the features based on their importance.
- Property Rights: Property Rights define private or public entities' legal ownership of resources.
- Judicial Effectiveness: An effective judiciary safeguards its citizens' rights from infringement.
- Government Integrity: Government transparency demonstrates that the government has a duty to the public.
- Tax Burden: A tax burden is a measurement of the tax load on the government.
- Government Spending: The money the government spends on the purchase of goods and the provision of services is referred to as government spending.
- Fiscal Health: Fiscal health refers to a government's capacity to organize, oversee, and finance essential investments and services.

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Business freedom is the capacity to launch, run, and shut down a business, which illustrates the effectiveness of government regulation.

- Labor Freedom: The labor freedom component is a quantitative indicator that looks at many facets of a nation's legal and regulatory environment governing the labor market.
- Monetary Freedom: the degree to which prices are stable over time and the extent to which governments intervene to set those prices
- Trade Freedom: Trade freedom is a proxy for the ease with which goods and services can be imported and exported around the world, taking into account both tariff and non-tariff barriers.
- Investment Freedom: A number of investment limitations are evaluated by the Investment freedom index.
- Financial Freedom: Financial freedom is the state of having sufficient cash on hand, investments, and savings to finance the activities you wish to pursue in life.

4.1 Model Selection: It experimented with several classification models, including Logistic Regression, K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Gradient Boosting, XGBoost, Support Vector Machines (SVM), and Artificial Neural Networks (ANN).

A) **Logistic Regression**: Logistic regression is a linear algorithm used for binary classification. It tries to draw a line that separates the two classes by finding the best set of weights for each feature. It works by transforming the output of the linear function through a sigmoid function to get a probability value that can be thresholded to make a binary prediction.

Parameters used:

● penalty: l2 : L2 regularization penalizes the sum of squares of the weights

● solver: ‘newton-cg’ : Algorithm to use in the optimization problem. ‘newton-cg’ for multiclass problems. Newton methods use an exact Hessian matrix

● max_iter: 100: Maximum number of iterations taken for the solvers to converge.

B) Decision Tree: A decision tree is a non-linear algorithm that works by recursively splitting the data into subsets based on the most important features. It creates a tree-like model of decisions and their possible consequences. It can be used for both classification and regression problems.

Parameters used:

● random_state=0: Controls the randomness of the estimator.

● criterion='entropy': The function to measure the quality of a split

● min_samples_leaf=1 : the minimum number of samples required to be at a leaf node.

● max_depth=8: The maximum depth of the tree.

● min_samples_split=2 : The minimum number of samples required to split an internal node

C) Random Forest: A random forest is an ensemble algorithm that combines multiple decision trees to make a more robust and accurate prediction. It works by randomly selecting a subset of features and data points and building decision tree from each subset.

Parameters used:

● n_estimators=100 : The number of trees in the forest

● criterion='gini'

● max_depth=8

● min_samples_split=2

● min_samples_leaf=1

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D) Support Vector Machine (SVM): SVM is a linear or non-linear algorithm used for both binary and multi-class classification problems. It tries to find the best hyperplane that separates the classes by the largest margin. It works by transforming the data into a high-dimensional space where a linear boundary can be found.

Parameters used:

● 'C': 1: Regularization parameter. The strength of the regularization is inversely proportional to C.

● 'kernel': 'linear' : Specifies the kernel type to be used in the algorithm

E) Naive Bayes: Naive Bayes is a probabilistic algorithm used for classification problems. It works by calculating the probability of each feature for each class and multiplying them to get the probability of the entire feature set for each class. The class with the highest probability is chosen as the predicted class.

Parameters used:

● priors=None : Prior probabilities of the classes If specified, the priors are not adjusted according to the data.

● var_smoothing=1e-09: A portion of the largest variance of all features that is added to variances for calculation stability

F) Gradient Boosting: Gradient boosting is an ensemble algorithm that combines multiple weak models (usually decision trees) to make a strong model. It works by iteratively training new models to correct the errors of the previous models. The final prediction is made by aggregating the predictions of all the models.

Parameters used:

● n_estimators=100 ● learning_rate=1.0 ● max_depth=1

● random_state=0

G) Extreme Gradient Boosting (XGBoost) : XGBoost is a more advanced version of gradient boosting that uses a different optimization algorithm and regularization techniques. It is one of the most popular algorithms for structured data problems because of its speed and accuracy.

Parameters used:

● booster = 'gbtree' : Which booster to use.

● eval_metric = "error"

● eta = 0.3 : Step size shrinkage used in update to prevent overfitting.

● gamma = 0 : Minimum loss reduction required to make a further partition on a leaf node of the tree.

● max_depth = 6 : Maximum depth of a tree.

● min_child_weight=1 : Minimum sum of instance weight (hessian) needed in a Child.

H) Artificial Neural Network (ANN): ANN is a non-linear algorithm inspired by the structure and function of the human brain. It consists of layers of interconnected nodes that transform the input data into output predictions. It is a powerful algorithm used for a wide range of problems, including classification and regression.

Parameters used:

● batch_size = 128

● epochs = 1000

● activation='relu'

● Optimizer = 'Adam'

● Loss = 'Binary Cross Entropy'

● No of hidden layers= 3

● 2 Dropout layers (0.25)

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4.2 Model Training and Testing

A common practice in machine learning is to split the data into training and testing datasets. While the testing dataset is intended to evaluate the model's performance on untrained data, the training dataset is used to teach the model to make precise predictions. We can prevent overfitting, which happens when the model memorizes the training data and performs poorly on fresh data, by utilizing a separate testing dataset.

We assess the performance of several models on the testing dataset after fitting them to the training dataset. This assessment enables us to choose the model that best fits the current issue. To assess the effectiveness of multiple models, we frequently utilize a variety of metrics, including accuracy, precision, recall, and F1-score. The final model is selected based on how well it performs on the testing dataset.

4.3 Model Optimization

The parameters of an algorithm known as hyperparameters are those that are predetermined rather than learned from the data. The process of optimizing these hyperparameters to boost the model's performance is known as fine-tuning. To identify the best settings, this procedure entails choosing a range of potential values for each hyperparameter and then evaluating various combinations of these values.

We applied methods including grid search, random search, and Bayesian optimization to fine-tune the parameters of the best-performing model. Testing every conceivable set of hyperparameter combinations within a given range is the task of grid search. A subset of hyperparameters is tested using a random selection of them from a given range. The hyperparameter space is modeled using prior experiments, and the most promising regions are chosen for further investigation.

We reassessed the model's performance after tweaking it to be sure it had improved. Multiple iterations of this procedure can be carried out until the ideal hyperparameters are identified.

4.4 Model Deployment

We created and optimized the best-performing model, then used Streamlit, a Python package for creating interactive web apps, to deploy it on a web application. Users can input economic freedom metrics into this web application, and the program then gives forecasts for a country's economic index score. To design and develop a user-friendly interface for the online application, we employed Streamlit. Users can interact with the model by submitting inputs through the user interface once it has been placed on the web application. The model-based processing of the inputs by the program results in the generation of the relevant predictions, which are subsequently displayed to the user on the web interface.

In this project, we used indicators of economic freedom to forecast how each country would score on the economic index. The most crucial features for predicting the economic index score were then determined using feature selection techniques after preprocessing the data first. In the following step, we trained and assessed a variety of classification models, including logistic regression, decision trees, random forests, SVM, naive Bayes, gradient boosting, and XGBoost. We chose the top-performing model and adjusted its hyperparameters to further enhance its performance after evaluating the performance of each model using a testing dataset. At Last, we implemented the top-performing model on a Streamlit online application that lets users enter economic freedom metrics and get forecasts for a country's economic index score. Overall, this project shows how machine learning algorithms can accurately anticipate economic index scores based on measurements of economic freedom and offers a useful tool for researchers and policymakers to use when making decisions.

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V. COMPARATIVE ANALYSIS RESULTS

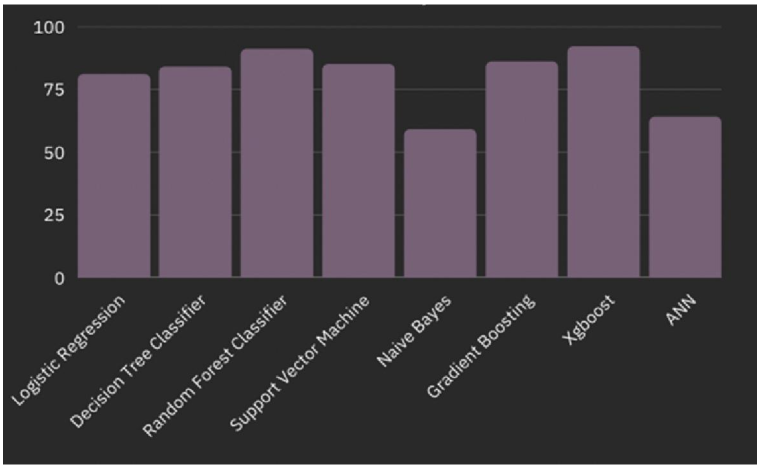

Figure 1 : Bar chart on accuracy of all machine learning models

Table 1. Stacked bar chart of precision, recall, and F-Score for all machine models used

Model	Accuracy	Precision	Recall	F-score
Decsion Tree	84	86	86	86
Random Forest	81	82	83	82
Support Vector machine	85	83	83	83
Naive Bayes	59	58	59	57
Gradient Boosting	86	88	87	88
XGBoost	92	93	94	94
ANN	64	63	65	65

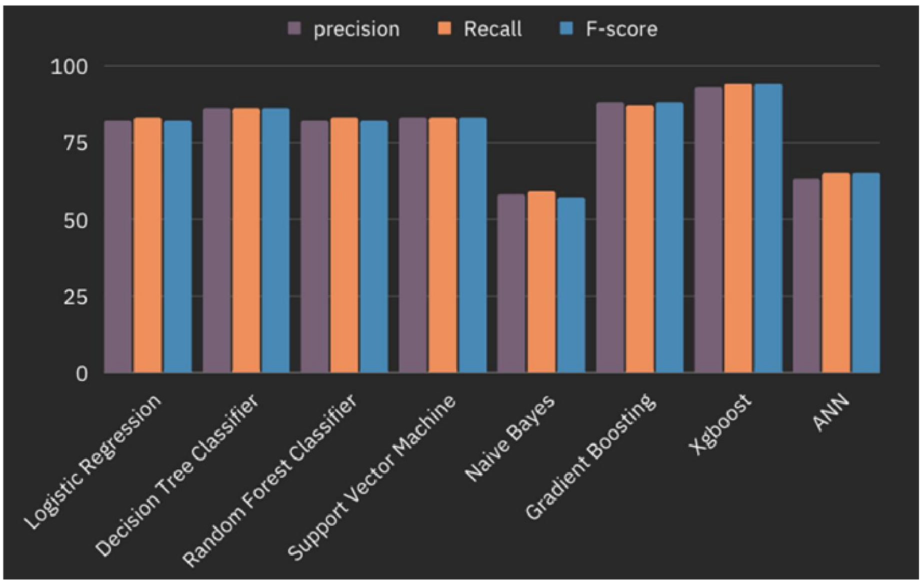

Figure 2 : Stacked barchart for all machine learning models used vs. precision, recall, and F-score

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VI. RESULT FOR XGBOOST

The XGBoost model's performance was additionally enhanced by tweaking its hyperparameters, making it the model with the best performance. Based on these findings, the XGBoost model was put into a web application so that users could quickly access it.

In conclusion, XGBoost was the best model for forecasting the economic index scores of various countries based on their economic freedom metrics, according to the analysis of the eight models. The model was adjusted to enhance performance, and for user friendliness, it was put into a web application.

Best-performing model: XGBoost

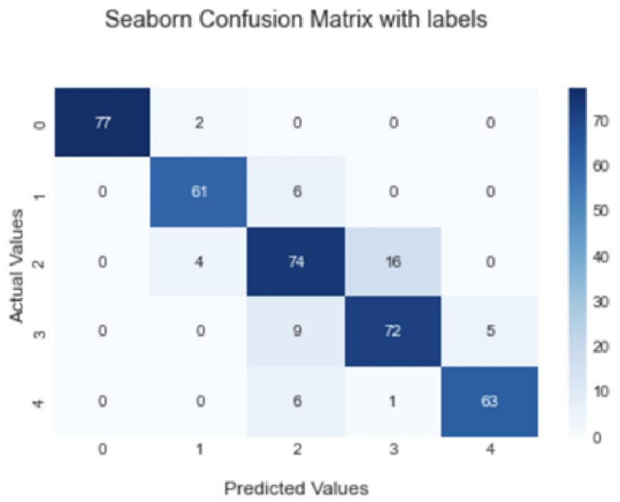

Figure 3: Confusion matrix

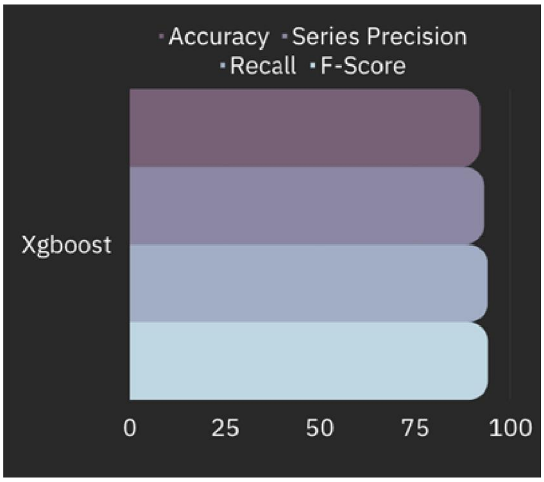

Figure 4 : F- Score

Accuracy	92%
Precision	93%
Recall	94%
F- score	94%

Table 2. Result of XGBoost

Formula,

Accuracy = (TP+TN)/(TP+TN+FP+FN)

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F1-Score = 2*((Precision*Recall)/(Precision*Recall))

After all the calculations, the predictions of all the metrics in the classification report exceeded more than 92%, making it one of the best model to predict the economic freedom index of the country

VII. CONCLUSION

In the end, determining a nation's level of economic independence is a challenging and comprehensive undertaking that necessitates careful evaluation of numerous elements. It is not a perfect or comprehensive assessment, but the index presented here is a valuable tool that takes into consideration a number of significant elements and provides a pretty accurate indication of how economic freedom varies from nation to nation. The results should be viewed cautiously because there might be other significant factors that the index has missed.

Realizing that economic freedom is a broad notion with many components is crucial. Government regulations, property rights, the rule of law, and trade policy are a few of these components. It's possible that a single indicator will fall short of capturing the complexity of economic freedom and the differences between national economies. You might not receive a complete or accurate picture of a nation's economic freedom if you merely look at an index.

Additionally, it's crucial to keep in mind that even little variations in an index score between nations may not always indicate significant variations in their levels of economic freedom. Economic freedom's functioning in the real world can alter significantly despite slight changes in the index score.

It's crucial to conduct thorough research that considers numerous elements and dimensions in order to get a more accurate image of a nation's economic freedom. You must examine a wide range of indicators, conduct extensive study, and comprehend how each country's economic situation differs in order to accomplish this.

VIII. FUTURE ENHANCEMENTS

The Economic Freedom Index (EFI), which gauges the degree of economic freedom in various nations, is discussed in the statement. The 12 economic freedoms that make up the EFI are considered crucial for economic expansion and development. Property rights, freedom from corruption, and freedom from government spending are some of these liberties.

We can learn a lot about how economic policies impact economic growth and prosperity from the historical data collected by the EFI. Businesses, scholars, and other people can learn more about the economic elements that contribute to success by examining the EFI of various nations over time.

The EFI can be a helpful tool for policymakers to assess the success of their economic policies and pinpoint areas where they might be improved. Based on the degree of economic freedom in various nations, the EFI can assist firms in making wise judgments about where to invest and operate.

Overall, anyone who wishes to understand more about the relationship between economic freedom, growth, and prosperity will greatly benefit from the EFI and the historical data it contains.

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