We are back again! What can artificial intelligence and machine learning models tell us about why countries knock at the door of the IMF?

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Abstract

This paper examines the factors that predict an IMF bailout. In doing so, we use a large dataset from 1993 to 2021 with 6550 observations and 138 features and adopt recent advances in machine learning and artificial intelligence models such as tree-based, boosting and artificial neural network techniques. We find that apart from traditional indicators such as debt and macroeconomic factors; agricultural, energy, health and social factors are strong predictors of an IMF bailout. These factors have hitherto not received much attention in the literature.

Keywords: Artificial intelligence; Machine learning; IMF bailout

JEL Codes: F3; F4

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1 Introduction

The International Monetary Fund (IMF) was set up in 1945 with 44 member countries after the world had experienced two world wars. Countries that experienced balance of payments (BoP) problems could borrow from the IMF to help stabilize their economies. The IMF functions as the international lender of last resort. Over the years, the Fund has provided financial support to countries experiencing macro fundamental problems through bailout mechanisms. According to Iseringhausen et al. (2019), any member country or government that faces financial trouble, whether low-income, middle-income or rich, can go to the IMF for a bailout. Without a bailout from the IMF in recent times, many of these countries would have struggled to keep their economies afloat due to the effects of COVID-19 pandemic and the Russian-Ukraine war. To help overcome BoP challenges and debt crisis, the IMF offers different forms of support such as concessional and non-concessional instruments, surveillance (i.e. policy monitoring and advice), capacity building (in the form of managing public finance and regulatory reforms), and the provision of interest-free loans and other forms of lending facilities.

Several studies situated in the context of emerging markets and developing countries, support a positive picture of the likelihood for a country to seek IMF support (Dicks-Mireaux et al., 2000; Dreher and Walter, 2010; Iseringhausen et al., 2019). However, some countries hesitate seeking an IMF bailout because of IMF conditionalities and the negative effects that some countries have suffered after entering into an IMF program (Bird and Rowlands, 2017; Dreher, 2006). For instance, African countries generally had a bitter experience with the IMF due to the painful structural adjustment programs that were implemented in the 1980s and 1990s. Some of these conditionalities included a freeze on public sector employment and wage increases which led to unrest in the labour front, and a freeze or withdrawal in subsidies on food, water, electricity and agriculture. In addition, the IMF has faced massive criticism based on its institutional structure, its level of transparency, and its impact on maintaining the stability of countries that have utilized an IMF program (Dreher, 2006).

There is extensive literature that examined the determinants of the likelihood of a country seeking an IMF lending program. For instance, studies have focused on weak economic indicators[1] (Bird et al., 2004; Ifrah et al., 2021; Iseringhausen et al., 2019); distorted current account balance (Bird and Rowlands, 2017; Joyce, 1992; Knight and Santaella, 1997); and the mismanagement of fiscal and monetary policy instruments (Bird, 2007) – as the main reasons that force a country to seek an IMF

[1] Namely, high debt service ratio, the BoP deficits, low GDP and declining growth rates.

bailout program. In particular, Joyce (1992) use a logit model and find that countries that seek IMF program normally have higher shares of government expenditure, severe current account deficits and smaller reserves. Similarly, Bird et al. (2004) using a poisson regression model find that repeated users of IMF support have more capital outflows and larger current account deficits. In addition, they also find that these countries normally have lower reserve holdings, investment rates and income per capita.

On the other hand, some studies have argued that the credibility of the IMF support program amidst unresolved adjustment policy problems, structural and BoP problems of most participating countries, as well as non-compliance with the conditionality measures are factors that restrain a country from going to the IMF for support (Goldstein and Montiel, 2017; Przeworski and Vreeland, 2000). For instance, Przeworski and Vreeland (2000) use the Heckman selection model and find that most countries seek the IMF program because of foreign reserves crisis. The study also find that countries that stay in the program experience low economic growth. Earlier studies also find no evidence that the IMF program improved balance of payments (Connors, 1979; Reichmann and Stillson, 1978), even though some studies find some improvements (Bird, 1996). Despite these conflicting evidence, countries repeatedly seek for an IMF bailout. The question therefore remains as to: why do countries seek an IMF bailout?

The world has seen some of the worst global conditions in recent decades. The COVID-19 pandemic, rising global interest rates, record high inflation rates, the strengthening of the US dollar has posed challenges for many economies. Especially for low-income countries in Africa, there has been an intense debate as to whether countries should seek support from the IMF to secure their ailing economies as a result of these global conditions. Due to their poor economic performance, most of these economies have had credit downgrades and are unable to access international capital markets. Despite these challenges, the political will to seek help from the Fund is a major consideration given the perceived negative political capital for incumbent governments; this usually affects the timing with which these countries seek for help. However, forces beyond a country's control may force it to seek an IMF bailout.

Therefore, this study seeks to understand the factors that lead countries to seek support from the IMF. This is important especially for policy makers because knowledge of these existing factors can help them decide the appropriate timing to seek for assistance. Going too late for assistance may worsen the existing economic conditions of the country. This may prolong the time to have an agreement with the Fund or not have the desired agreement or in a worse-case scenario not get an agreement.

Indeed, when the economic conditions are worse, the IMF may impose some strict conditions in a bid to have some stability in the Fund's financial resources. Our study is, therefore, important to help identify the key factors that leads countries to seek for IMF support. Our main contribution lies in the use of new techniques that are better at predicting outcome variables. Specifically, we use machine learning (ML) and artificial intelligence (AI) models such as tree-based, boosting and neural network techniques. The advantages of these models compared to traditional estimation techniques are that: i) whether a country seeks an IMF bailout is probabilistic in nature and is a prediction problem which machine learning and artificial intelligence models are better at compared to traditional econometric methods (see Amini et al., 2021); ii) ML and AI models can detect non-linearities in the dataset without being explicitly programmed to do so (see Amini et al., 2021; Gu et al., 2020). Indeed, many of the variables such as a country's debt-to-GDP ratio, foreign currency reserve, BoP, inflation, interest rate and oil price may change in a non-linear fashion in relation to the probability of seeking IMF support and may also interact in unpredictable ways when a country is in financial distress. Thus, our approach allows us to identify and untangle the complex, high-dimensional, and interactive effects that exist between the features that predict a country seeking IMF support.

The remainder of the paper is structured as follows. Section 2 describes the dataset and presents the methodology used in this study. Section 3 presents and discusses the empirical findings. Section 4 concludes.

2 Data and Methodology

2.1 Data

The data for the different types of programs accessed by IMF member countries was obtained from the IMF. The sample period is from 1993 to 2021. We obtained the other features (variables) from the World Development Indicators (WDI) and Bertelsmann Stiftung over the same time period.[2] Given that the number of years that a country seeks an IMF bailout represents a small proportion of the sample, we use sample overweighting and underweighting approaches in an attempt to improve the predictability of our algorithms. Specifically, we used the Synthetic Minority Over-sampling Technique (SMOTE) which allows us to overweight the minority class (IMF bailouts). We also explore underweighting techniques such as the RandomUnderSampler from imblearn.

[2]The detailed sources of the data and the list of countries are reported in Table A1 and Table A2 in the Appendix, respectively.

2.1.1 Train/Validation/Test data split

We split the data into train, validation and test sets to enable us judge the performance of our machine learning models on unseen or test data. We employ a Train/Validation/Test ratio split of 60/20/20. In addition, we perform Cross Validation using the K-Folds method and a K of 10 on the training data. Consequently, the training data is split into 10. The artificial intelligence/machine learning models trained or learnt on 9(K-1) folds of the data and evaluated performance on 1. Thus, instead of 1 performance metric, we had K or 10 metrics. High cross validation scores are an indication that our models will perform well on unseen data, are stable and have low variance.

2.1.2 Data pre-processing

We perform outlier treatment for all the variables in our data set. We first of all compute the interquartile range (IQR). The first quartile is represented by the 25th percentile and the third quartile is represented by the 75th percentile. We remove values that are 1.5 times outside this range. We also treated for missing values in the data set using the median filler.

2.2 Machine learning algorithms

We adopt various machine learning algorithms to predict the factors that explain why countries seek an IMF Bailout. The algorithms include Logistic Regressions, Bagging, Random Forest, AdaBoost, Gradient Boost, XGBoost and Artificial Neural Networks.

Our model selection is based on the models that have the highest Recall score, the models that are consistent based on the other evaluation metrics (mainly Precision and the F1 scores), and finally based on models that have the least over-fitting. Machine learning models are known to quickly overfit the data. The consequence of overfitting are that the machine learning models perform extremely well on the training data but have lower performance on unseen data or test data.

2.2.1 Hyper-parameter tuning

We select the final models for our prediction after tuning the models. Tuning is important to boost the predictability of our models. Hyper-parameter tuning represents the process of trying to improve the performance of our machine learning models by searching for the best parameters. These parameters cannot be learned from the data and are specified by the programmer. We tune parameters such as the learning rate, the number of estimators, the tree depth, max features, maximum sample size, gamma, scale pos weight, the number of neurons and dropout rates.

2.2.2 Model performance evaluation

We use the confusion matrix to help us evaluate the performance of our algorithms. The confusion matrix gives us the number of True Positives[3], True Negatives[4], False Positives[5] and False Negatives[6]. Based on the metrics from the confusion matrix, we compute the Accuracy ratio, the Recall Score, the Precision Score and the F1 Score. We measure the performance of our models using the Accuracy, Recall, Precision and F1 Score. We do not rely on the Accuracy Score because the data set is imbalanced.

The Recall score tells us the percentage of actual IMF bailouts that we are able to predict. Recall is defined as:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{1}$$

The Precision Score on the other hand tells us what percentage of our predictions of countries going to the IMF are actually correct. Precision is defined as:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{2}$$

Finally, we examine the F1 Score which is a harmonic mean of Precision and Recall. The F1 score is defined as:

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The F1 score ranges between zero and one. A value of one represents perfect recall and prediction.

[3]This represents our prediction of those who would take an IMF bailout and actually did.
[4]This represents our prediction of countries who would not take an IMF bailout and indeed they did not seek a bailout.
[5]This represents our prediction of countries those who would seek a bailout but they did not.
[6]This represents our prediction of those who would not seek a bailout but actually did.

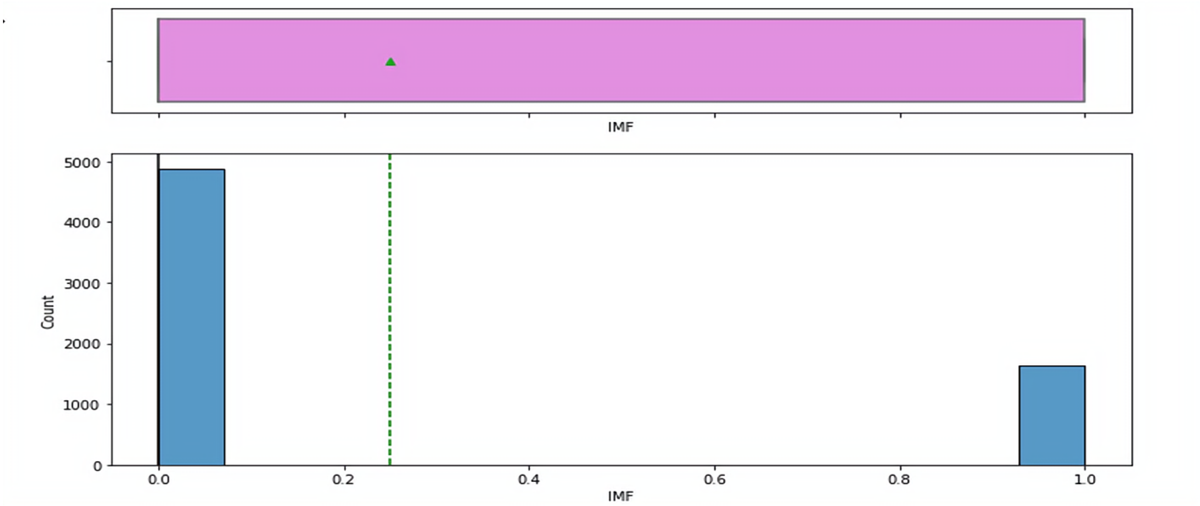
2.2.3 Feature importances

Finally, we examine the feature importances that the machine learning algorithms suggest are important for predicting a country seeking an IMF bailout. The feature importances are a ranking of the features (independent variables) that the machine learning algorithms identify as explaining an IMF bailout. Due to the fact that the algorithms provide a ranking of the features, we are able to determine most important factors that explain why countries seek an IMF bailout.

3 Results and Discussion

In this section, we present the results from our empirical experiments. We first present information on the characteristics of the data at our disposal. This is followed by results from our model building. We then present results from our hyperparameter tuning which is aimed at improving model by searching for the best parameters. Finally, we present and discuss the results from the feature importances.

Figure 1: Programme vs. Non-programme years



3.1 Data characteristics

Figure 1 shows that for the entire data (6550 observations and 138 features), 25% of country years represented years in which countries were in an IMF programme. On the other hand, 75% of country years (4880 observations) represented years in which countries were not in an IMF programme. Consequently, we have a clear class imbalance in our dataset. This provides strong support for our use of class imbalance techniques.

Table 1 shows the data we have in the training, validation and training data set. The class distribution on the training, validation and test data are also quite similar and similar to the overall distribution of 75%/25% in the overall data.

Table 1: Training, validation and test data characteristics

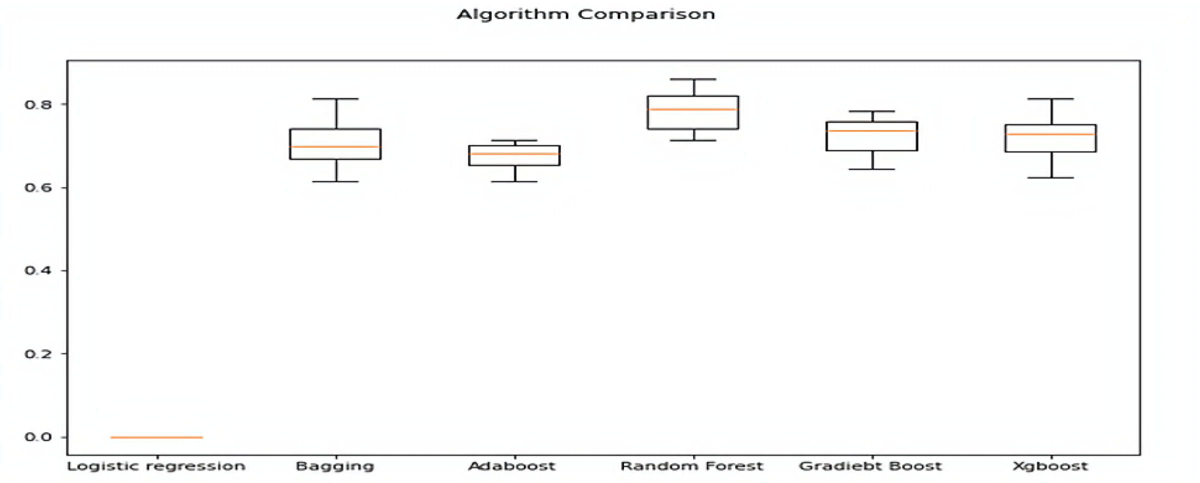
	Training Data	Validation Data	Test Data
Shape (Rows/Columns)	3906/138	1302/138	1302/138
Class (0/1)	(0.742/0.258)	(0.758/0.242)	(0.765/0.235)

Note: Class 0 represents non-IMF programme years; class 1 denotes IMF programme years.

3.2 Model building

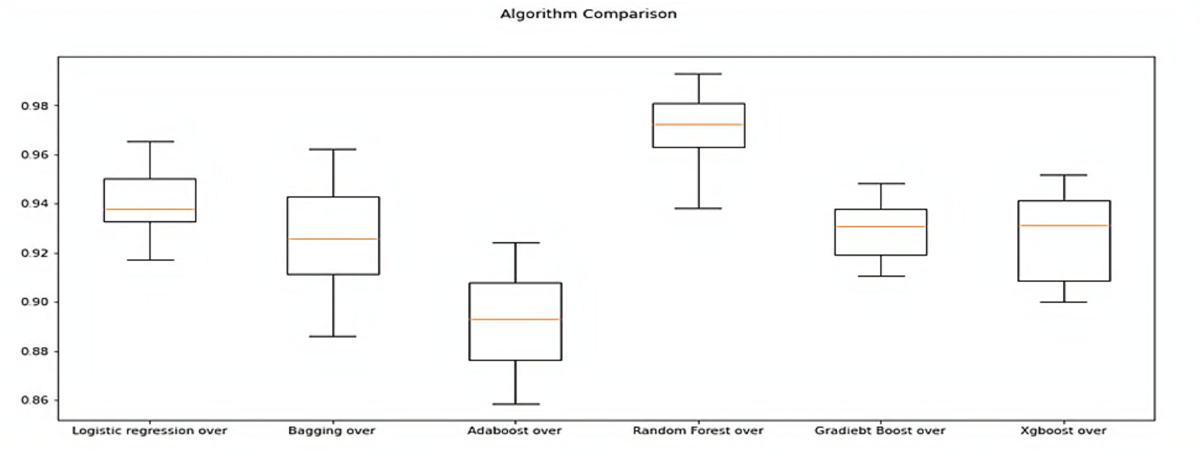
Figure 2 presents results from using the original data. The original data does not include a treatment for class imbalance. We see that Random Forest produces the highest cross validation (CV) score whilst Ada Boost produces the lowest CV score. The performance across the models are similar but mostly below a CV of 80%.

Figure 2: Model predictions using the original data



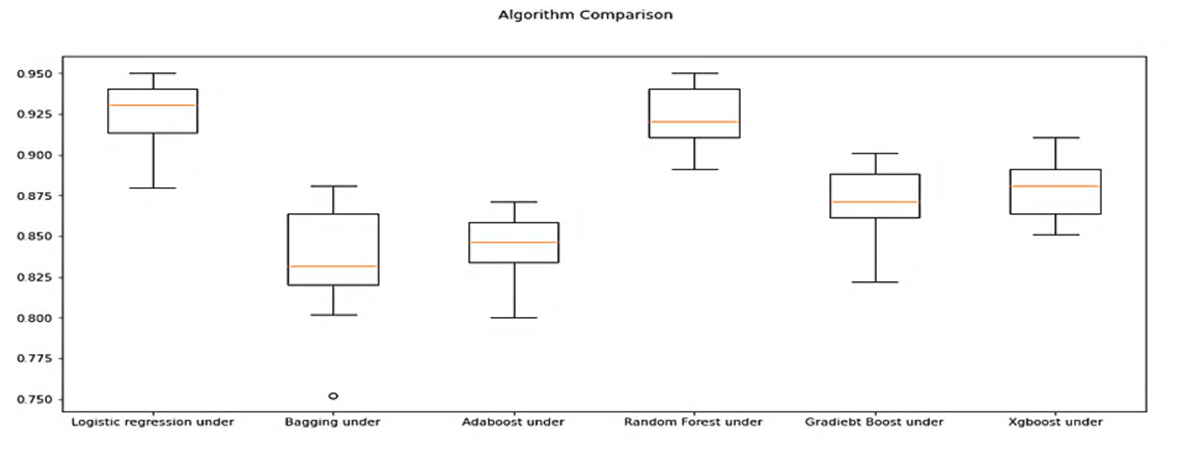
Using the Synthetic Minority Oversampling Technique (SMOTE) to balance the data by increasing the size of the minority class (IMF programme years), in Figure 3 we see an improved performance (higher CV scores) compared to the original data. Here as well, Random Forest has the highest CV score whilst Adaboost has the lowest CV score. Most of the CV scores are above 90%.

Figure 3: Model predictions using the over-sampled data



Using the Random UnderSampler from imblearn to balance the data by decreasing the size of the majority class (non-IMF programme years), in Figure 4 we see an improved performance (higher CV scores) compared to the original data. Logistic Regression has the highest CV score whilst Adaboost has the lowest CV score. However, we observe that the performance using over-sampling is better than using under-sampling. Consequently, we performing hyper-parameter tuning using the over-sampled data.

Figure 4: Model predictions using the under-sampled data



3.3 Hyper-parameter tuning: best parameters

Table 2 shows the best parameters for our machine learning algorithms. These parameters are the ones we used in estimating our algorithms. Figure 5 shows the evaluation metrics after running these models. We settle on the Random Forest because it has some of the highest evaluation metrics and is stable and consistent across both the validation and test data. The feature importances are therefore based on the Random Forest.

Table 2: Hyper-parameter tuning: best parameters

Model	Logistic Regression	Ada Boost	Random Forest	Gradient Boost	XGBoost
C	0.1				
Penalty	l1				
Solver	Liblinear				
Learning rate		0.2		0.2	0.1
N Estimators		200	200	125	150
Max Depth		3			
Minimum Sample Leave			1		
Max Samples			0.6		
Max Features			Square Root	0.7	
Sub-Samples				0.7	0.8
Scale POS Weight					10
Gamma					3

3.4 Features importances

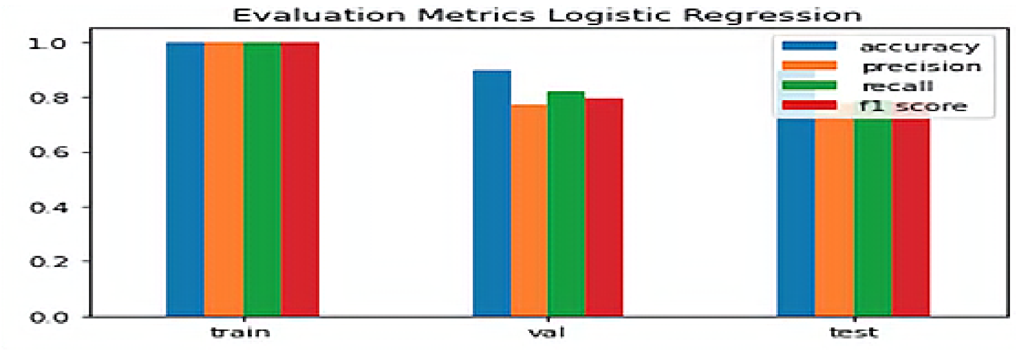
Figure 6 below shows the feature importances based on the Random Forest classifier. Figure 6 displays the top 25 factors that predict an IMF bailout. Taking an IMF non concessionary loans is the biggest factor predicting an IMF bailout. This is followed by exchange rate movements, broad money, contributing family workers, and long-term external debt to GDP.

To help us explain the feature importances, we group the top features into various categories and examine whether the feature is high or low in a programme and non-programme year.

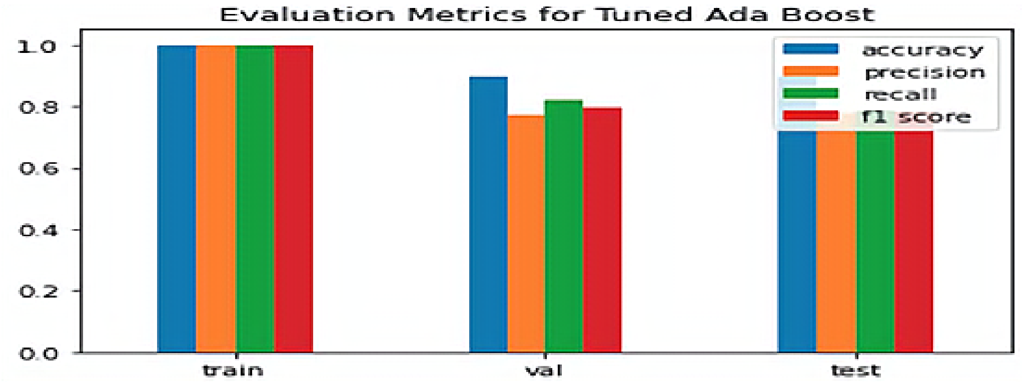
From Tables 3 and 4 we see that IMF bailouts are associated with low financial development. In addition, financial market volatility, represented by the Chicago Board Options Exchange Volatility Index (VIX), is a strong predictor of an IMF bailout or programme. In terms of macro factors, as expected, high debts and low reserves predict an IMF bailout. Interestingly, accessing IMF loans (both concessional and non-concessional) are strong predictors of a bailout. This suggests that some countries become regular “customers" of the IMF. Furthermore, high inflation and interest rates are associated with a higher likelihood of a bailout. High unemployment is also associated with IMF bailouts. In addition, countries that rely heavily on grants and remittances are more likely to need an IMF bailout. Corruption, low government expenditures and high income inequality are also associated with a higher likelihood of an IMF bailout.

Figure 5: Evaluation metrics after hyper-parameter tuning

Panel A: Logistic regression



Panel B: Ada Boost



Panel C: Random Forest

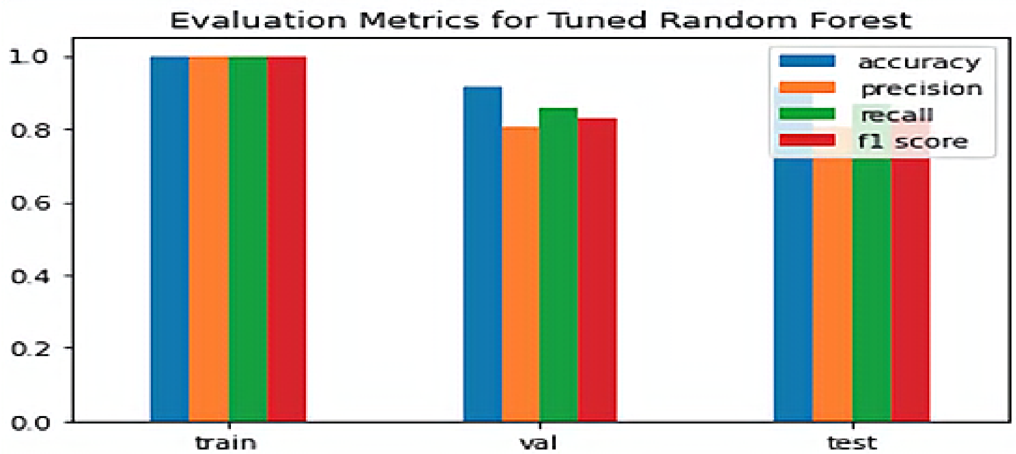
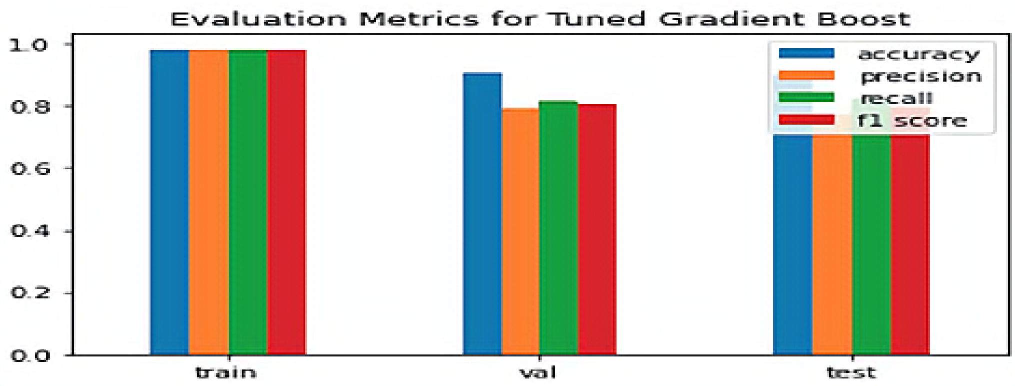
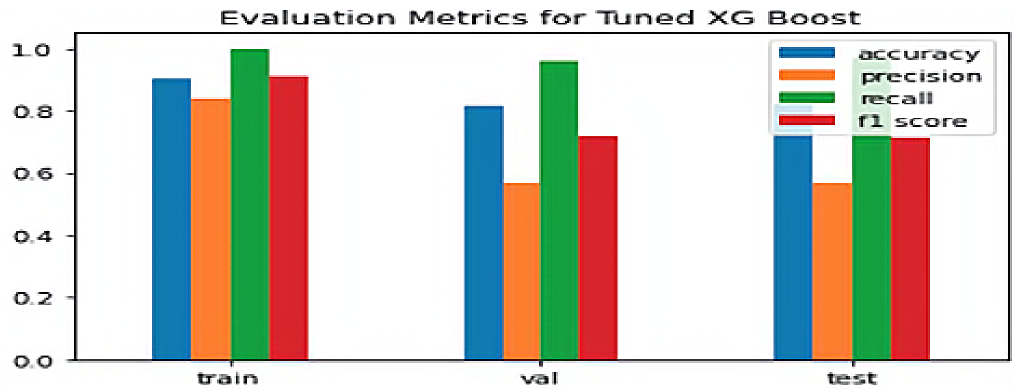


Figure 5: continued

Panel D: Gradient Boost



Panel E: XGBoost



Panel F: Artificial Neural Network

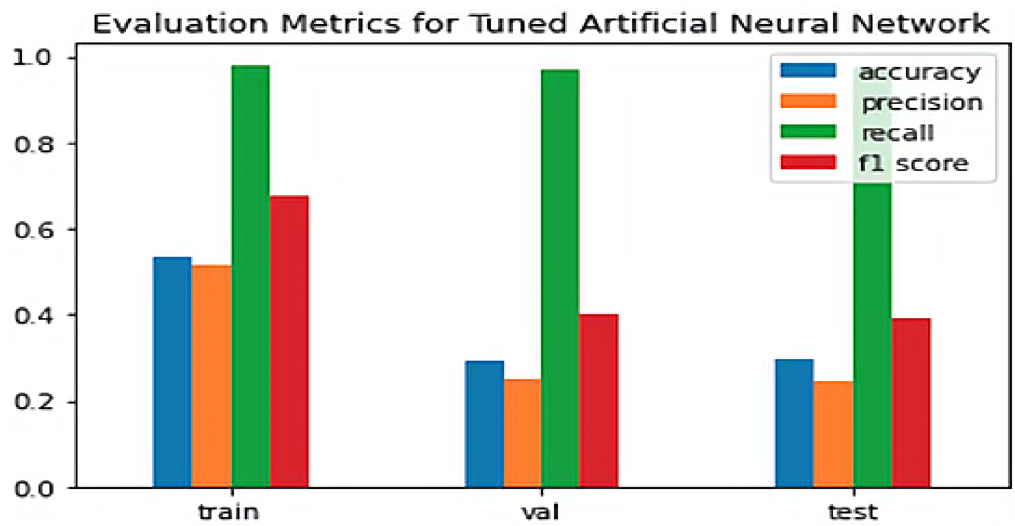


Figure 6: Features importances

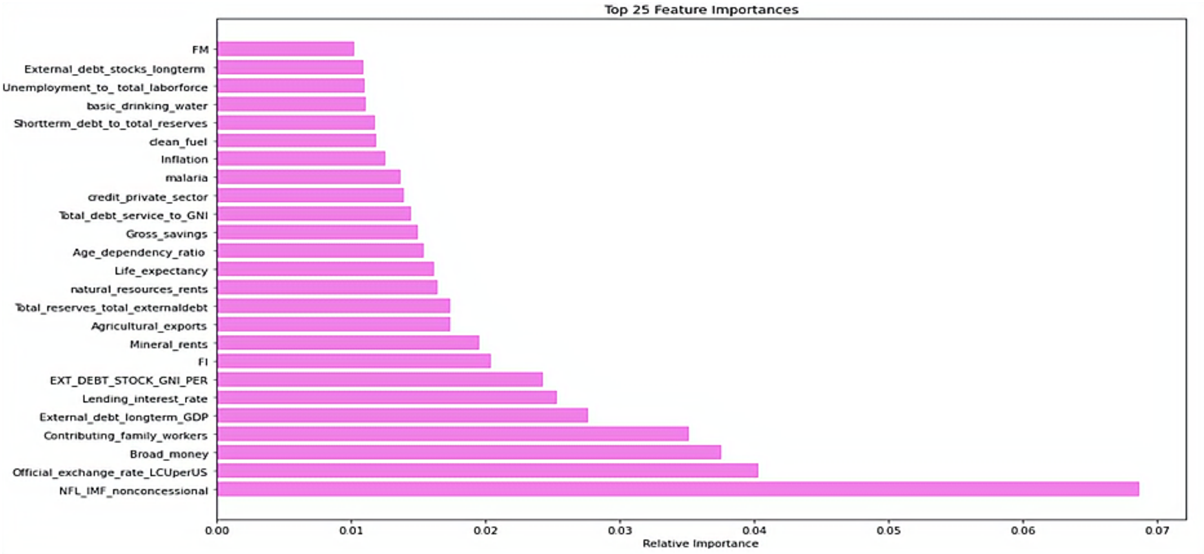


Table 3: Predictors of an IMF bailout (financial development and financial market volatility)

Variables from Feature Importances	Non-programme year	Programme year
Panel A: Financial development factors		
Broad money	High	Low
Financial institutions	High	Low
Gross savings	High	Low
Financial markets	High	Low
Credit private sector	High	Low
ATM	High	Low
Panel B: Financial market volatility and stability		
VIX	Low	High

Note: Broad money is the sum of currency outside banks expressed as a percentage of GDP; Financial institutions represent financial institutions in terms of depth, access and efficiency; Gross savings denote the gross savings of a nation's income less consumption plus net transfer as a percentage of GDP; Financial markets stand for financial market in terms of depth, access and efficiency; Credit private sector denotes the domestic credit to private sector as a percentage of GDP; ATM represents the number of ATMs per 100,000 adults; VIX represents the Chicago Board Options Exchange (CBOE) Volatility Index.

From Table 5, we find that agricultural, energy and trade factors are associated with an IMF Bailout. In particular, high levels of agriculture and low information and communications technology (ICT) exports are predictive of a bailout. Low energy consumption and high natural resource rents are also found to be predictive of a bailout. Energy consumption is an indicator of economic activities and thus we observe low energy consumption in bailout years. In addition, the association between high natural resources and a bailout is suggestive of a natural resource curse. In terms of trade factors, high levels of international trade taxes and import duties are shown to be predictive factors of a bailout or IMF programme.

Table 4: Predictors of an IMF bailout (debt, macro factors and government quality)

Variables from Feature Importances	Non-programme year	Programme year
Panel A: Debt indicators		
NFL IMF nonconcessional	Low	High
NFL IMF concessional	Low	High
External debt long term GDP	Low	High
Total debt service to GNI	Low	High
Panel B: Macro indicators		
Inflation	Low	High
Lending interest rate	Low	High
Panel C: Government quality indicators		
Unemployment to total labor force	Low	High
Personal remittances received GDP	Low	High
Grants	Low	High
Corruption score	Low	High
Government consumption expenditure	High	Low
Gini index	Low	High

Note: NFL IMF nonconcessional represents net financial flows, IMF non-concessional in current USD; NFL IMF concessional represents net financial flows, IMF concessional in current USD; External debt long term GDP denotes external debt stocks with maturity exceeding a year; Total debt service to GNI represents total debt service as a percentage of gross national income (GNI). Inflation is measured as the percentage change in the consumer price index; Lending interest rate denotes the lending rates of banks as a percentage; Unemployment to total labor force stands for unemployment as a percentage of the total labor force; Personal remittances received GDP denotes personal remittances received as a percentage of GDP; Grants is measured as grants received as a percentage of revenue; Corruption score represents the control of corruption; Government consumption expenditure represents general government final consumption expressed as a percentage of GDP; Gini index represents the Gini coefficient, a measure of inequality.

Table 5: Predictors of an IMF bailout (agricultural, energy and trade factors)

Variables from Feature Importances	Non-programme year	Programme year
Panel A: Agricultural and service factors		
Arable land	Low	High
Agricultural land	Low	High
Agricultural exports	Low	High
ICT imports	High	Low
Panel B: Energy factors		
Clean fuel	High	Low
CO2 emissions	High	Low
Renewable electricity	Low	High
Natural resources rents	Low	High
Power consumption	High	Low
Panel C: Trade factors		
International trade tax	Low	High
Import duties	Low	High

Note: Arable land denotes arable land as a percentage of land area; Agricultural land denotes agricultural land as a percentage of land area; Agricultural exports represent agricultural raw materials exports as a percentage of merchandise export; ICT imports represents ICT goods imports as a percentage of total goods import; Clean fuel denotes the percentage of the population with access to clean fuel; CO2 emissions denotes CO2 emissions measured in kilogram per PPP $ of GDP; Renewable electricity represents renewable electricity output as a percentage of total electricity output; Natural resource rents denotes total natural resources rents as a percentage of GDP; Power consumption represents electric power consumption in kWh per capita; International trade tax denotes taxes on international trade expressed as a percentage of revenue; Import duties represents customs and other import duties as a percentage of tax revenue.

From Table 6, we observe that the quality of healthcare is a strong predictor of a bailout. For instance, the levels of tuberculosis, HIV, and malaria are all associated with a bailout. Furthermore, the life expectancy is found to be a strong predictor of a bailout. In addition, sanitation, the quality of drinking water, the number of women in parliament and high age dependency are found to be associated with a bailout.

4 Conclusion

Using a large data set (6550 observations and 138 features) and employing recent advances in machine learning and artificial intelligence, we contribute to the debate as to the factors that predict the likelihood of a country needing an IMF bailout. Our study uncovers many factors that can predict why a country seeks an IMF Bailout. These factors include traditional factors such as high levels of external debt, unemployment, financial market volatility, foreign exchange reserves, tax policy and so on. We also uncover new factors such as the structure of the economy (agragrian), energy factors, trade factors, health related factors, and social factors. Though these factors have not been employed in the extant literature, we find that they are useful at least in a predictive sense in identifying countries that are likely to need an IMF bailout.

Table 6: Predictors of an IMF bailout (health and social factors)

Variables from Feature Importances	Non-programme year	Programme year
Panel A: Health factors		
Tuberculosis	Low	High
Incidence of HIV	Low	High
Malaria	Low	High
Fertility rate	Low	High
Private health expenditure	Low	High
Life expectancy	High	Low
Panel B: Social factors		
Least basic sanitation	High	Low
Basic drinking water	High	Low
Managed drinking water	High	Low
Women in parliament	High	Low
Employers female	High	Low
Age dependency ratio	Low	High
EW welfare regime	High	Low
Individuals internet	High	Low
Contributing family workers	Low	High

Note: Tuberculosis represents the incidence of tuberculosis per 100,000 people; Incidence of HIV denotes the total incidence of HIV per 1,000 uninfected population; Malaria represents the incidence of malaria per 1,000 population at risk; Fertility rate denotes the total fertility rate measured in births per woman; Private health expenditure represents the domestic private health expenditure expressed as a percentage of current health expenditure; Life expectancy represents life expectancy at birth measured in number of years; Least basic sanitation is the percentage of the population using at least basic sanitation services; Basic drinking water is the percentage of the population using at least basic drinking water services; Managed drinking water represents the percentage of the population using safely managed drinking water services.; Women in parliament represents the proportion of seats held by women in national parliaments; Employers female denotes female employers as a percentage of female employment; Age dependency ratio is the age dependency ratio expressed as a percentage of working-age population; EW welfare regime refers to welfare regime, the extent to which social safety nets provide compensation for social risk; Individuals internet represent individuals using the internet as a percentage of population; Contributing family workers denotes the total contributing family workers expressed as a percentage of total employment.

Overall, our findings suggest that low financial development, high financial market volatility, high levels of debt, poor government quality (e.g. corruption, unemployment, income inequality), high levels of agriculture, services such as ICT imports, poor health services quality, and social factors such as poor sanitation, access to clean water, and gender diversity are strong predictors of a bailout. In addition, accessing previous funds from the IMF (whether concessionary or not) is found to be a strong predictor of a bailout. This suggests that countries become “regular" customers of the IMF. Our work contributes to the financial fragility literature as it provides a way of identifying countries that are vulnerable and may need an IMF bailout. It also provides development financial institutions (DFIs) and countries with a framework to monitor the financial health of countries and pointers or levers to improve their financial resilience and reduce the probability of financial distress or needing an IMF bailout.

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Appendix

Table A1: Variables from Features importances and sources

Variables from Feature Importance	Source
Panel A: Financial development	
Broad money	World Development Indicators
FI (Financial Institutions)	IMF
Gross savings	World Development Indicators
FM (Financial Markets)	IMF
Credit private sector	World Development Indicators
ATM	World Development Indicators
Panel B: Financial market volatility and stability	
VIX	Yahoo Finance
Panel C: Debt indicators	
NFL IMF nonconcessional	World Development Indicators
NFL IMF concessional	World Development Indicators
External debt longterm GDP	World Development Indicators
Total debt service to GNI	World Development Indicators
Panel D: Macro indicators	
Inflation	World Development Indicators
Lending interest rate	World Development Indicators
Panel E: Government quality	
Unemployment to total laborforce	World Development Indicators
Personal remittances received GDP	World Development Indicators
Grants	World Development Indicators
Corruption score	World Governance Indicators
Government consumption_expenditure	World Development Indicators
Gini Index	World Development Indicators
Panel F: Agricultural and service factors	
Arable land	World Development Indicators
Agricultural land	World Development Indicators
Agricultural exports	World Development Indicators
ICT imports	World Development Indicators
Panel G: Energy factors	
Clean fuel	World Development Indicators
CO2 emissions	World Development Indicators
Renewable electricity	World Development Indicators
Natural resources rents	World Development Indicators
Power consumption	World Development Indicators
Panel H: Trade factors	
International trade tax	World Development Indicators
Import duties	World Development Indicators

Table A1: continued

Variables from Feature Importance	Source
Panel I: Health factors	
Tuberculosis	World Development Indicators
Incidence of HIV	World Development Indicators
Malaria	World Development Indicators
Fertility rate	World Development Indicators
Private health expenditure	World Development Indicators
Life expectancy	World Development Indicators
Panel J: Social factors	
Least basic sanitation	World Development Indicators
Basic drinking water	World Development Indicators
Managed drinking water	World Development Indicators
Women in parliament	World Development Indicators
Employers female	World Development Indicators
Age dependency ratio	World Development Indicators
EW welfare regime	Bertelsmann Stiftung's Transformation Index (BTI)
Individuals internet	World Development Indicators
Contributing family workers	World Development Indicators

Table A2: List of Countries

Afghanistan	Canada	Gabon	Kosovo	New Caledonia	Solomon Islands	Venezuela, RB
Albania	Cayman Islands	Gambia, The	Kuwait	New Zealand	Somalia	Vietnam
Algeria	Central African Republic	Georgia	Kyrgyz Republic	Nicaragua	South Africa	Virgin Islands (U.S.)
American Samoa	Chad	Germany	Lao PDR	Niger	South Sudan	West Bank and Gaza
Andorra	Channel Islands	Ghana	Latvia	Nigeria	Spain	Yemen, Rep.
Angola	Chile	Gibraltar	Lebanon	North Macedonia	Sri Lanka	Zambia
Antigua and Barbuda	China	Greece	Lesotho	Northern Mariana Islands	St. Kitts and Nevis	Zimbabwe
Argentina	Colombia	Greenland	Liberia	Norway	St. Lucia	
Armenia	Comoros	Grenada	Libya	Oman	St. Martin (French part)	
Aruba	Congo, Dem. Rep.	Guam	Liechtenstein	Pakistan	St. Vincent and the Grenadines	
Australia	Congo, Rep.	Guatemala	Lithuania	Palau	Sudan	
Austria	Costa Rica	Guinea	Luxembourg	Panama	Suriname	
Azerbaijan	Cote d'Ivoire	Guinea-Bissau	Macao SAR, China	Papua New Guinea	Sweden	
Bahamas, The	Croatia	Guyana	Madagascar	Paraguay	Switzerland	
Bahrain	Cuba	Haiti	Malawi	Peru	Syrian Arab Republic	
Bangladesh	Curacao	Honduras	Malaysia	Philippines	Tajikistan	
Barbados	Cyprus	Hong Kong SAR, China	Maldives	Poland	Tanzania	
Belarus	Czech Republic	Hungary	Mali	Portugal	Thailand	
Belgium	Denmark	Iceland	Malta	Puerto Rico	Timor-Leste	
Belize	Djibouti	India	Marshall Islands	Qatar	Togo	
Benin	Dominica	Indonesia	Mauritania	Romania	Tonga	
Bermuda	Dominican Republic	Iran, Islamic Rep.	Mauritius	Russian Federation	Trinidad and Tobago	
Bhutan	Ecuador	Iraq	Mexico	Rwanda	Tunisia	
Bolivia	Egypt, Arab Rep.	Ireland	Micronesia, Fed. Sts.	Samoa	Turkey	
Bosnia and Herzegovina	El Salvador	Isle of Man	Moldova	San Marino	Turkmenistan	
Botswana	Equatorial Guinea	Israel	Monaco	Sao Tome and Principe	Turks and Caicos Islands	
Brazil	Eritrea	Italy	Mongolia	Saudi Arabia	Tuvalu	
British Virgin Islands	Estonia	Jamaica	Montenegro	Senegal	Uganda	
Brunei Darussalam	Eswatini	Japan	Morocco	Serbia	Ukraine	
Bulgaria	Ethiopia	Jordan	Mozambique	Seychelles	United Arab Emirates	
Burkina Faso	Faroe Islands	Kazakhstan	Myanmar	Sierra Leone	United Kingdom	
Burundi	Fiji	Kenya	Namibia	Singapore	United States	
Cabo Verde	Finland	Kiribati	Nauru	Sint Maarten (Dutch part)	Uruguay	
Cambodia	France	Korea, Dem. People's Rep.	Nepal	Slovak Republic	Uzbekistan	
Cameroon	French Polynesia	Korea, Rep.	Netherlands	Slovenia	Vanuatu	