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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Outline of Presentation

- Background
- Study objectives
- Why machine Learning and artificial intelligence?
- Methodology
- Findings
- Conclusion and policy recommendations

Background

- The IMF was established in 1944 to help promote;
  - international monetary cooperation,
  - international trade and growth,
  - reduce exchange rate restrictions and controls and
  - provide financial support to countries facing balance of payment challenges.

- The IMF functions as the international lender of last resort.

Background

- Without a bailout from the IMF, countries like Argentina, Sri Lanka, Pakistan and Ghana may have struggled to keep their economies afloat.

- The IMF World Economic Outlook (2020) revealed that the IMF was lending to 33 countries that were at high risk of debt distress.
  - Out of the 33 countries, an estimated amount of UD$ 11.3 billion, was given to 28 of these countries

Background

- Some of the factors that have been identified by the prior literature as to why countries seek a bailout include;
  - high debt service ratio,
  - balance of payment deficits,
  - low GDP and declining growth rates (Ifrah et al., 2021; Iseringhausen et al., 2019)
  - poor macroeconomic conditions (inflation and interest rates, etc.)
  - distorted current account balance (Joyce, 1992; Knight & Santaella 1997; Bird & Rowlands, 2017); and
  - the mismanagement of fiscal and monetary policy instruments (Bird, 2007)

Background

- IMF bailouts can have a positive effect;
  - Corsetti, Guimaraes, & Roubini, 2006;
  - Dicks-Mireaux et al., 2000;
  - Dreher & Walter, 2010;
  - Iseringhausen et al. 2019;
  - Ifrah et al., 2021

Background

- Bailouts could also have a negative effect;
  - Bandow & Vasquez, 1994;
  - Dreher, 2006;
  - Bird & Rowlands, 2017;
  - Marchesi & Sabani 2007;
  - Unigovskaya & Mercer-Blackman, 2000

- African countries for example had a bitter experience with the IMF due to the painful SAPs that were implemented in the 1980s and 1990s.

Background

- In recent times, especially in low-income countries such as Africa, there has been an intense debate as to whether countries should seek support from the IMF due to:
  - the effects of the COVID-19 pandemic,
  - Russian/Ukraine war
  - credit downgrades and
  - inability to access international capital markets.

- A number of factors including political will are some of the key considerations as to whether a country would seek a bailout.

- However, forces beyond a country's control may force it to seek an IMF bailout.

Objective

- This paper seeks to examine the features that explain why a country would seek an IMF bailout.

Why Machine Learning (ML) and Artificial Intelligence?

- The advantage of ML & AI models compared to traditional estimation techniques are that;
  - 1) whether a country seeks an IMF bailout or not is probabilistic in nature and is a prediction problem which ML & AI models are better at compared to traditional econometric methods (see Amini, Elmore, Öztekin, & Strauss, 2021).
  - In particular, Amini, Elmore, Öztekin, & Strauss (2021) find that their ML models perform better than standard econometric techniques that include non-linear terms as well as interactions.

Why Machine Learning?

- 2) ML & AI models can detect non-linearities in the dataset without being explicitly programmed to do so (see for example Amini, Elmore, Öztekin, & Strauss, 2021, Gu et al., 2020)

- Thus, our approach helps us to identify and untangle the complex, high dimensional, and interactive effects that exists between the features that predict a country seeking for IMF support.

Overview of IMF Programs

- The IMF provides various forms of support to its member countries.
  - The Policy Coordination Instrument (PCI)
  - The Policy Support Instrument (PSI)
  - The Rapid Credit Facility (RCF)
  - The Rapid Financing Instrument (RFI)
  - The Exogenous Shocks Facility (ESF)
  - The Resilience and Sustainability Facility (RSF)
  - The Standby Credit Facility (SCF)
  - The Standby Arrangement (SBA)
  - The Extended Fund Facility (EFF)
  - The Extended Credit Facility (ECF)
  - The Precautionary and Liquidity Line (PLL)
  - The Flexible Credit Facility (FCL)

NON-MONETARY

Overview of IMF Programs

- **The Policy Coordination Instrument (PCI)**
  - The PCI is available to developing and developed countries who do not need financial support but are open to the IMF's policy support
  - The PCI has a duration of 6 months to 4 years.
- **The Policy Support Instrument (PSI)**
  - Open to low-income countries who do not want to access financial resources from the IMF but seek support and endorsement of their economic and financial policies.
  - The duration of a PSI is usually between 1 to 5 years.

EMERGENCY FUNDING

Overview of IMF Programs

- **The Rapid Credit Facility (RCF)**
  - The RCF provides quick and concessionary (zero interest) financial support to *low-income countries* due to issues such as natural disasters, commodity price shocks and domestic problems.
  - The RCF is usually a one off arrangement with a repayment period of 5.5 years to 10 years.
- **The Rapid Financing Instrument (RFI)**
  - The RFI is similar to the RCF, however, unlike the RCF it is open to *all member countries*.
  - Facilities under this program must be paid within 3.25 to 5 years.

Overview of IMF Programs

- **The Exogenous Shocks Facility (ESF)**
  - The ESF provides concessionary financing to countries who face a sudden and exogenous shock.
  - The program has a duration of 1 to 2 years with a repayment period of 5.25 years to 10 years.

PANDEMICS AND CLIMATE CHANGE

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Dr. Richard B. Bateyo, FIoBS

Overview of IMF Programs

- **The Resilience and Sustainability Facility (RSF)**
  - The RSF provides low and middle-income countries support to deal with pandemics and issues related to climate change
  - The minimum duration for a facility is 18 months.
  - Countries have a 10.5 year grace period, however, the loan must be paid within 20 years.

BOP Support for Low Income Countries

Dr. Richard B. Bateyo, FIoBS

Overview of IMF Programs

- **The Standby Credit Facility (SCF)**
  - The SCF is dedicated to *low-income-countries* who are facing short-term balance of payment challenges and shocks or crisis.
  - The duration is usually between 12 and 36 months.
  - Countries have a four-year grace period, however, the loan must be paid within 8 years.
- **Standby-Arrangement (SBA)**
  - Provides support to *emerging and advanced economies* who are facing challenges with external financing challenges
  - The usual duration for this facility is 12-24 months with repayment period of 3.25 - 5 years.

Overview of IMF Programs

- **The Extended Fund Facility (EFF)**
  - Medium-term support
  - 3-4 years with a repayment period of 4.5 – 10 years.

- **The Extended Credit Facility (ECF)**
  - Long-term support for LICs
  - 3 – 5 years with a repayment period of 5.25 - 10 years.

ECONOMIES WITH STRONG FUNDAMENTALS

Overview of IMF Programs

- **The Precautionary and Liquidity Line (PLL)**
  - The PLL provides flexible liquidity support to countries with good economic fundamentals to help them deal with shocks such as regional and global stress.
  - The duration is usually six months, one year or two years.

- **The Flexible Credit Facility (FCL)**
  - The FCL is designed for countries with very strong economic fundamentals and policy frameworks who are facing a liquidity challenge.
  - The FCL was designed to take away the stigma of accessing IMF resources.
  - The FCL is for one or two years with a repayment period of 3.25 - 5 years.

Methodology - Data

- The data for the different types of programs accessed by IMF member countries was obtained from the IMF.
- The data was from 1993 to 2021.
- We obtained the other features/independent variables from the World Development Indicators and the Bertelsmann Stiftung over the same time period.

Methodology - Sample

- Given that the number of years that a country seeks an IMF bailout represents a small proportion of the sample (25%) we employed the following techniques;
  - Sample overweighting
  - Sample underweighting

- In particular, we used the Synthetic Minority Oversampling Technique (SMOTE) which allows us to overweight the minority class (IMF Bailouts).

- We also explored underweighting techniques such as the RandomUnderSampler from imblearn.

Methodology – Train/Val/Test

- We split the data into train and test sets to enable us judge the performance of our machine learning models on unseen or test data.
- We employed a Train/Val/Test ratio split of 60/20/20.
- In addition, we performed Cross Validation using the K-Folds method and a K of 10.
- Consequently, the training data was split into 10. The ML models trained or learned on 9 (K-1) folds of the data and evaluated performance on 1.

Methodology - Train/Val/Test

- 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.

Methodology – Model Evaluation

- We used the confusion matrix to help us evaluate the performance of our algorithms.
- **Confusion Matrix**
  - The confusion matrix gives us the number of True Positives, True Negatives, False Positives and False Negatives.
- ***True Positive Rate***
  - This represents our prediction of those who would take an IMF Bailout and actually did.
- ***True Negative Rate***
  - This represents our prediction of countries who would not take an IMF Bailout and indeed they did not seek a bailout.

Methodology - Model Evaluation

- **False Positive Rate**
  - This represents our prediction of countries those who would seek a bailout but they did not.
- **False Negative Rate**
  - This represents our prediction of those who would not seek a bailout but actually did.

Methodology - Model Evaluation

- Based on the metrics from the confusion matrix, we computed
  - The Accuracy ratio,
  - The Recall Score,
  - The Precision Score and
  - The F1 Score.

- We measured the performance of our models using the Recall, Precision and F1 Score.

- We do not rely on the Accuracy Score because the data set is imbalanced.

Methodology - Model Evaluation

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

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

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

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Methodology - Model Evaluation

- Finally, we examined the F1 Score which is a harmonic mean of Precision and Recall.

- The F1 score is defined as

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

- The F1 score ranges between zero and 1. A value of one represents perfect recall and prediction.

Methodology - Algorithms

- We employed various Machine Learning Algorithms to predict the factors that explain why countries seek an IMF Bailout.

- The Algorithms include
  - Logistic Regressions,
  - Random Forest Regressors,
  - AdaBoost Regressors,
  - Gradient Boost Regressors,
  - XGBoost Regressors,
  - Artificial Neural Networks

Methodology – Model Tuning

- We selected the final models for our prediction after tuning the models.

- Tuning is important to boost the predictability of our models.

Methodology – Feature Importance

- We examine the feature importances that the ML algorithms suggest are important for predicting a bailout.
- The feature importances are a ranking of the features that the ML algorithms identify as explaining a bailout.
- Due to the fact that the algorithms provide a ranking of the features, we are able to determine the most important factors that predict a bailout.

RESULTS

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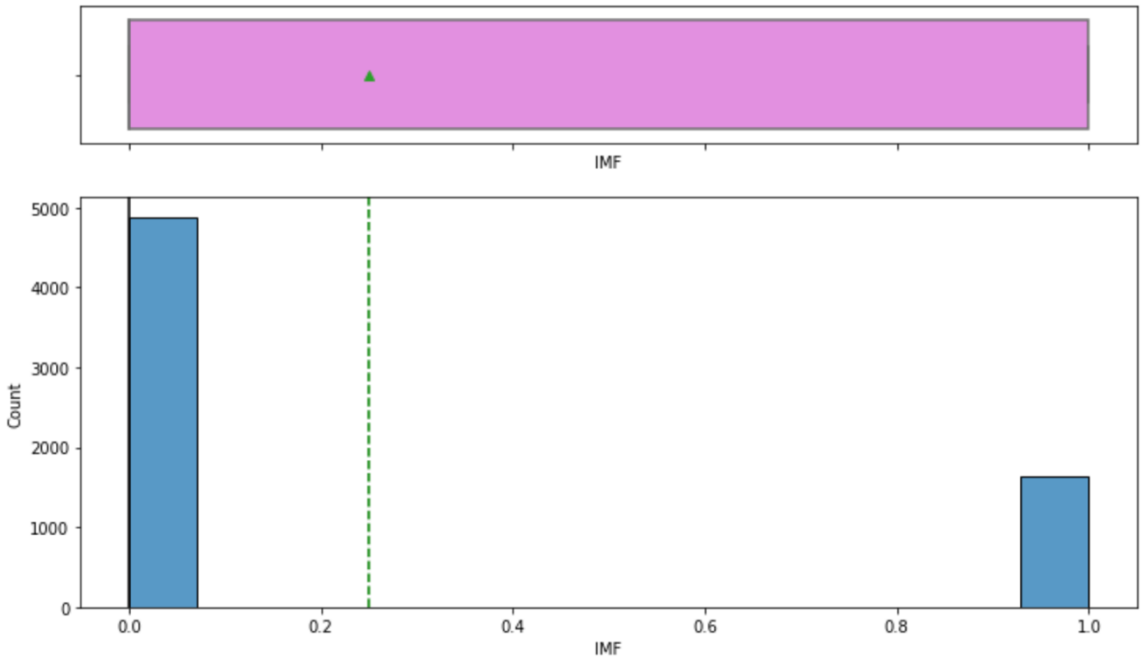
Programme vs Non-Programme Years



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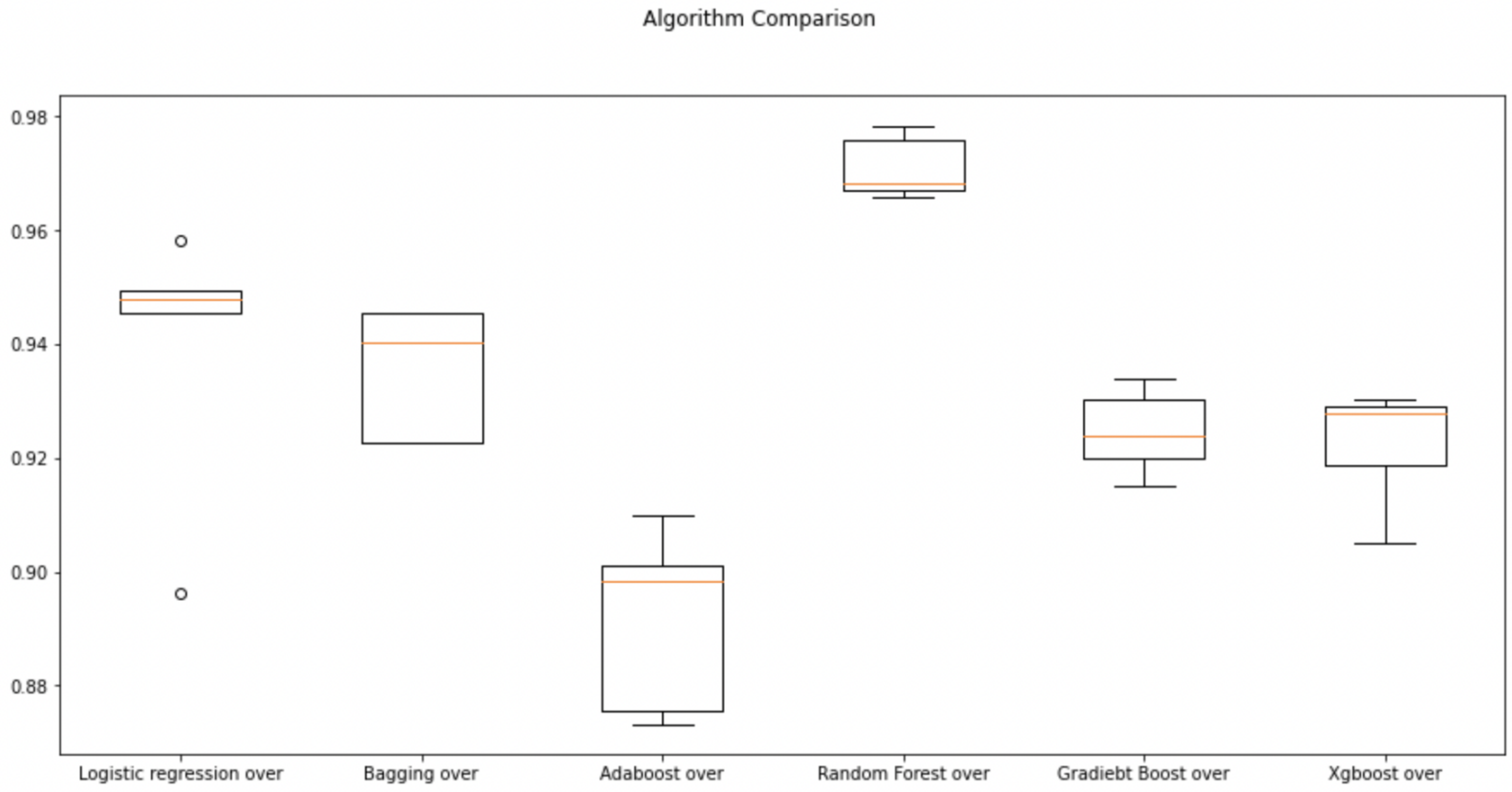
Training, Validation and Test Data Characteristics

	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)

Model building

Oversampled Data -Algorithm Comparison



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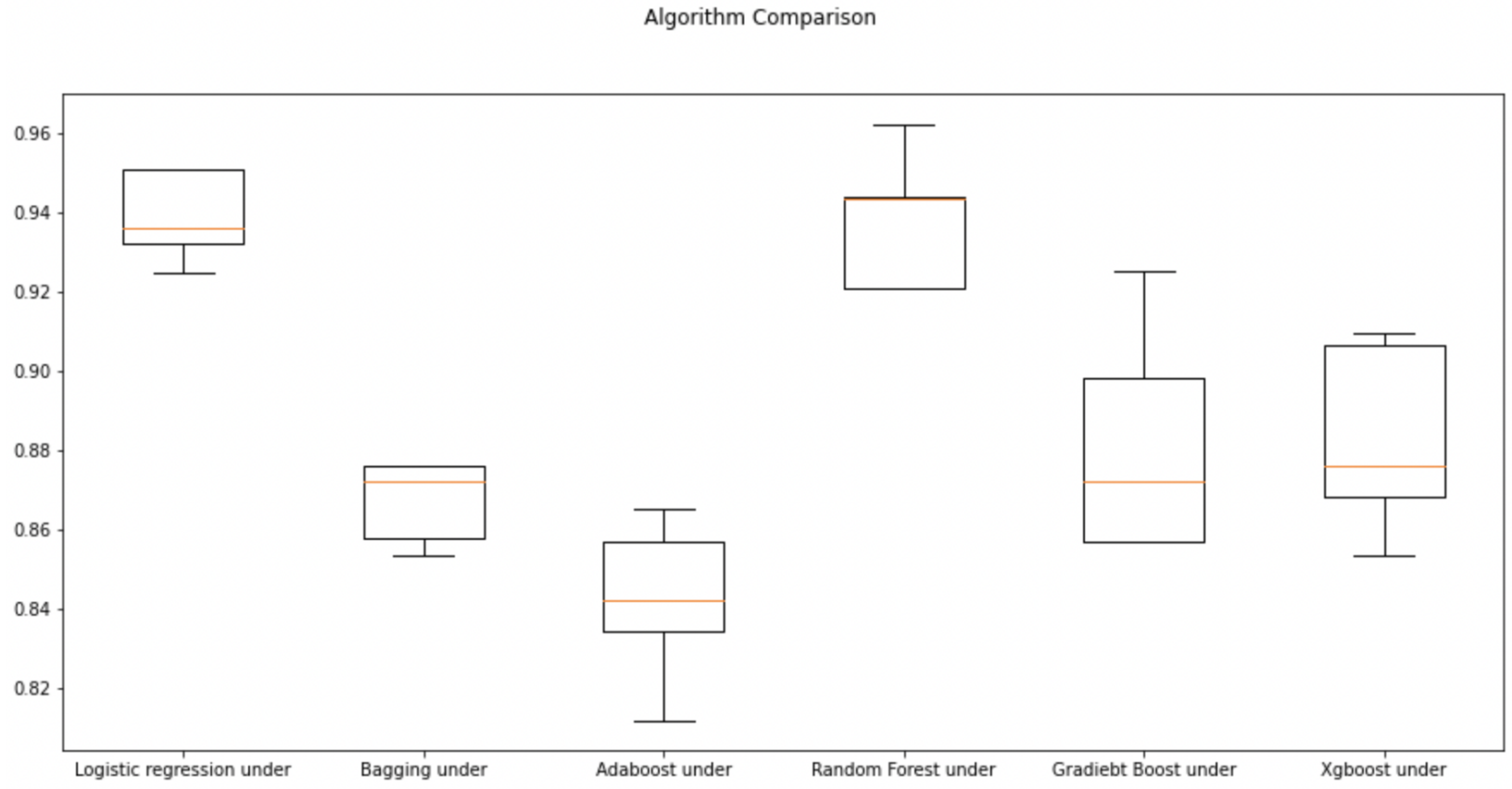
Undersampled Data -Algorithm Comparison



Hyper parameter tuning

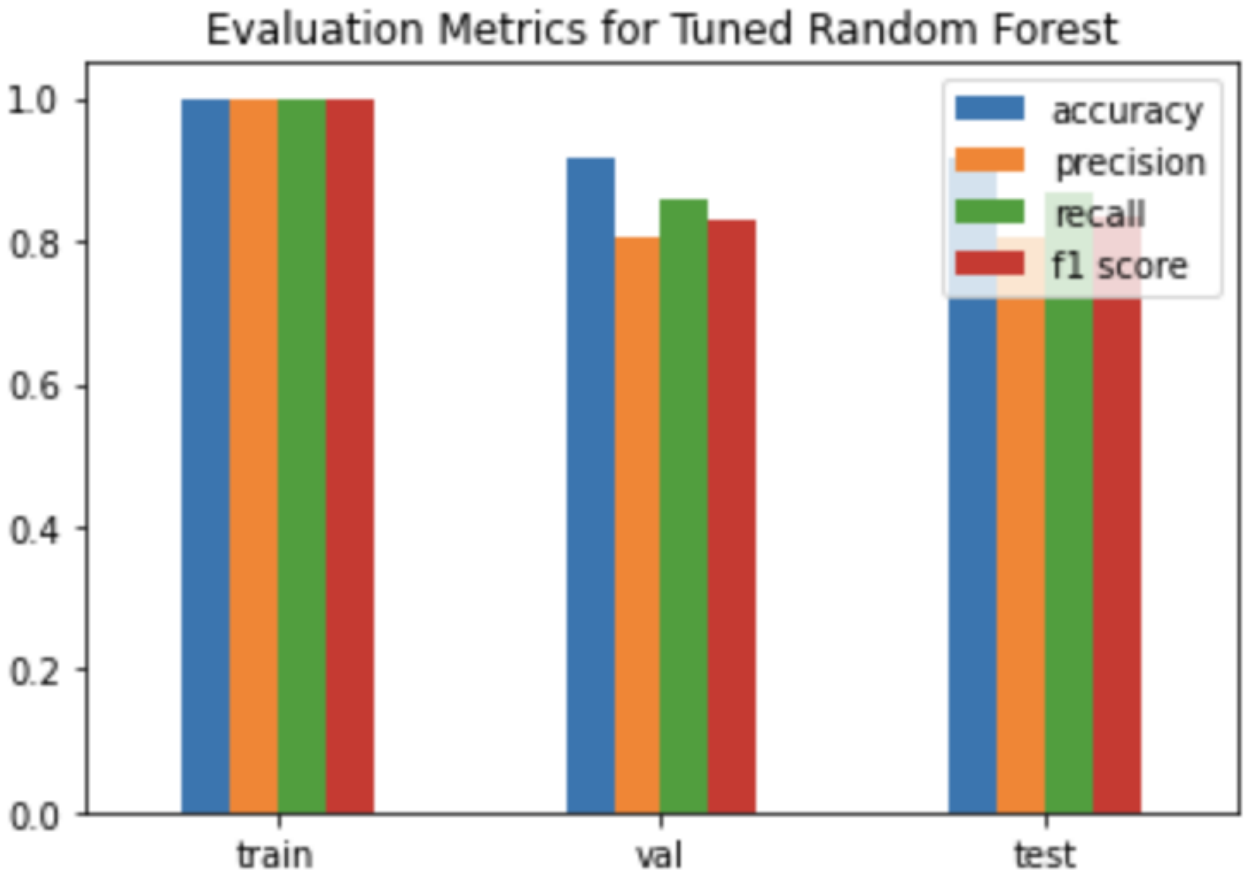
Hyper-Parameter Tuning

- Random Forest – Overweighted Sample

- The purpose of hyper-parameter tuning is to see if we can squeeze out a little bit more performance after over-sampling and under-sampling.

Hyper Parameter	Optimal
N Estimators	200
Max Samples	0.6
Minimum sample leaves	1
Max features	Sqrt Root

Random Forest - Performance



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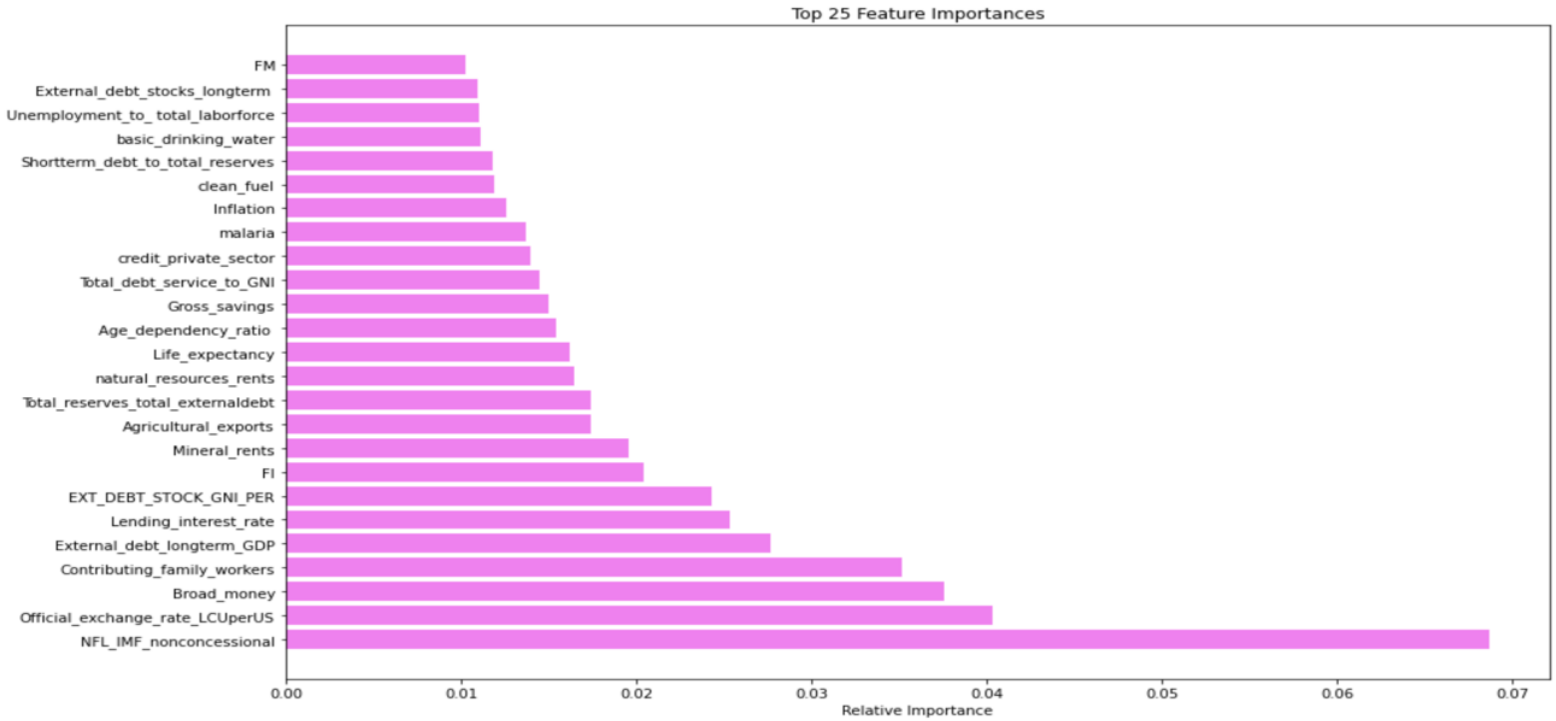
Findings - Feature Importances



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Feature Importances

Variables from Feature Importance	Non-Program	Program
Financial Development		
Broad_money	High	Low
FI	High	Low
Gross_savings	High	Low
FM	High	Low
Credit_private_sector	High	Low
ATM	High	Low
Financial Market Volatility		
VIX	Low	High
Macro Factors		
External_debt_longterm_GDP	Low	High
Unemployment_to_ total_laborforce	Low	High
Personal_remittances_received_GDP	Low	High
Grants	Low	High
Corruption_score	Low	High
government_consumption_expenditure	High	Low

Feature Importances

Variables from Feature Importance	Non-Program	Program
Agricultural and Service Factors		
Arable_land	Low	High
Agricultural_land	Low	High
Agricultural_exports	Low	High
ICT_imports	High	Low
Energy Factors		
clean_fuel	High	Low
CO2_emissions	High	Low
Renewable_electricity	Low	High
natural_resources_rents	Low	High
Trade Tax Factors		
International_trade tax	Low	High
Import duties	Low	High

Feature Importances

Variables from Feature Importance	Non-Program	Program
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
Social Factors		
least_basic_sanitation	High	Low
basic_drinking_water	High	Low
power_consumption	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

Conclusion and Recommendations

- 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 debt, unemployment, tax policy etc.
- We also uncover new factors such as the structure of the structure of the economy (agragrian), health related factors, financial market volatility, social factors.
- 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.

Conclusion and Recommendations

- It also provides 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.

- The key limitation of our study is that these factors may not be ‘causal’ factors per se.