Predicting an Economic Recession Using Machine Learning Techniques

By

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Abstract

A few economic downturns were predicted months in advance. This research has the ability to give the best performing models to assist businesses in navigating prior recession periods. The study address the subject of identifying the most important variables to improve the overall performance of the algorithm that would effectively predict recessions. The primary aim of this study was to improve economic recession prediction using machine learning (ML) techniques by developing an inch-perfect and efficient prediction model in order to avoid greater government deficits, growing inequality, significantly decreased income, and higher unemployment. The study objective was to establish the relevant method for addressing imbalance data with suitable features selection strategy to enhance the performance of the machine learning algorithm developed. Furthermore, artificial neural network(ANN) and Random Forest (RF) were used in predicting economic recession using ML techniques. This study would not have been possible without the publicly available data from the online open source Kaggle, which provided ordinal categorical data for the specific data utilized. The major findings of this study were that the ML algorithm RF performed better at recession prediction than its rival ANN. Due to the fact that two ML algorithms in this research were employed , further ML tools can be used to improve the statistical components of the study.

Keywords: *Recession, machine learning, artificial neural network, random forest, imbalance data, prediction model*

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Declaration

I, Mashaka Molepo (15018425), hereby declare that the dissertation for the Master of Science degree in Applied Mathematics at the University of Venda, hereby submitted by me, has not previously been submitted for a degree at this or any other university, and that it is my own work in design and execution and that all reference material contained therein has been duly acknowledged..

Mashaka Molepo

15018425

23 April 2021

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Dedication

This work is dedicated to my late grandparents.

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In this field which has expanded and assessed my perception of the principles of science, I would like to express my sincere appreciation to my supervisors Dr Wilbert Chagwiza and Mr Tlou Kubjana. I appreciate your patience and always available when needed, because of your assistance this study was achievable. This project would not have been accomplished without the publicly accessible data from online open source Kaggle.

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Chapter 1

INTRODUCTION

1.1. Background of the Study

Down the years, abundant in crude countries such as Algeria, Libya and Gabon and mineral-rich Botswana had flourished in the midst of some of the top economies since the twenty-first century, while Zimbabwe and the Democratic Republic of Congo, possibly among the developed countries in the world, have plunged into the category of the poverty-stricken countries in the world, the primary reason being a widespread government corruption [11]. Due to the misery of the Covid-19 pandemic which brought the world to an economic halt, hopes for economic success in 2020 have also been lost.

The Covid-19 disease outbreak began in December 2019 in Wuhan, China, and has since spread around the world [12]. Only at time of the very first draft of this press release, nearly 200,000 cases of the virus had been identified around the world. The number has increased to over 150 million as of those infected, including over 3 million deaths and over 80 million recoveries. In the early stages of the pandemic, China enforced strict curfews, causing demand to fall and output to be disrupted. Labor markets, in particular, had been impacted, affecting businesses all over the world. Thousands of people have lost their jobs nearly everyday, and many companies have closed their doors [13].

South Africa's economy declined by 7%, that is the worst result since the South African Reserve Bank (SARB) began gathering data in 1912, according to the SARB [3]. Moreover, since the second quarter of 2020, when hard lockout constraints were imposed, the economy had improved, but it has been one of the toughest years in line with economic growth. The GDP plummeted by 11,9%, which was more than 5 times the 1.5%t decline that accompanied the global financial crisis (GFC). Due to the lockout restrictions, there was also less investment, with real GDP growth falling by 8.9%. Household consumption expenditures, in particular, grew at a slower pace in the fourth quarter, possibly as a result of many people being forced to stay at home as per national lockdown regulations.

In addition to the pandemic, policymakers need to work together to rectify economic and trade tensions that could jeopardize a possible recovery from the Covid-19 downturn. The employment sector has been one of the sectors which was hit very hard. Following the global financial

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crisis, government debt and deficits are set to increase more globally than during 2006-2010 [1]. The International Monetary Fund (IMF) managing director Kristalina Georgieva [14], revealed that it has been projected that one-third of the 189 IMF member countries will indeed impacted by Covid-19 [2]. The prediction of certain measures of interest, such as Gross Domestic Product (GDP), was still one of the most important economic difficulties [15].

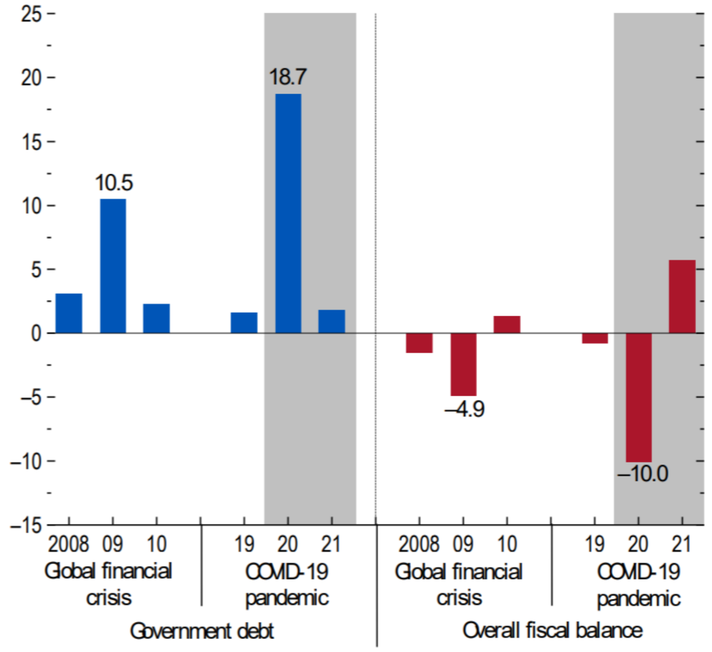

Figure 1.1: The Government Debt and Overall Fiscal Balance shifts [1]

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The National Bureau of Economic Research (NBER) business cycle dating committee describes a recession as a major economic downward trajectory that is generally observable in terms of production, employment, real income and other indicators, lasting more than a few months [16]. The financial market can help in learning the magnitude of a recession. According to studies conducted by [17], the NBER updated the notion of a business cycle in 2001. The following is how they describe a business cycle: "... a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years ..." [17]. To date, twelve African countries have joined this international forum for governments and central bank governors: Benin, Burkina Faso, Côte d'Ivoire, Egypt, Ethiopia, Ghana , Guinea, Morocco, Rwanda, Senegal, Togo and Tunisia [18].

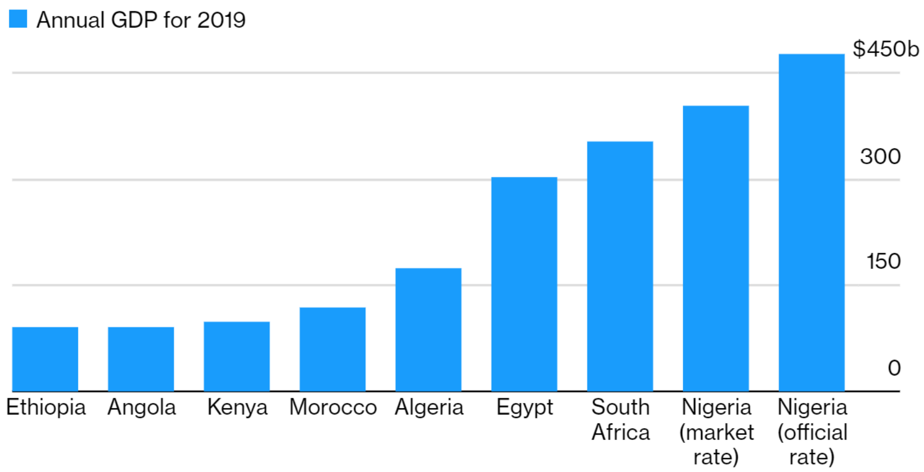

Figure 1.2: Annual GDP in some region of Africa [2]

Financial institutions, private economists, shareholders, and business industry expects all eager to find out which indicators can be relied on to predict recessions and economic turmoil. One of the most popular used indicators, according to study by [3], was the maturity yield curve, that appear to be correlated with a higher probability of a time of economic decline or significantly reduced economic growth when it was slightly negative [19]. Strategy Analytics within IRI company recently revealed that the seriousness of the 2020 Corona Virus induction recession measured by real GDP changes occurring will indeed be unparalleled with the Great Depression [20]. The Great Depression was the most massive financial crisis in the history of the rest of the developed world, it began following the October 1929 stock market mishap, which spooked Wall Street and swept millions of shareholders out [21].

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Based on the degree of shock they have brought to the global economy, [22] highlighted two similarities between the Great Recession and the Covid-19 crises. Firstly, both instances, uncertainty has escalated, implying a gloom-ridden and long-term impact on actual activity. Secondly, [22] highlighted that in terms of the magnitude of the perceived supply-and-demand shocks, the Great Recession was by far closest comparable occurrence in recent decades to the Covid-19 pandemic. [22] also noticed that when the study for the other G7 countries was repeated at the same time, similar results emerge. Furthermore, GDP growth in 2020Q1 was projected to be especially low in France, Italy, and the United Kingdom, moderate in Japan, and intermediate in Germany.

It had been well established that the accuracy of econometric model forecasts suffers during times of recession and even during periods of rapid recovery. This trend can be attributed to a number of factors. To begin with, econometric models are designed to detect the average behavior of variables, whereas severe downturns and rapid turnarounds are called tail events [22]. Specific models, such as quantile regressions, may be used to capitalize on the tail actions, however their output with macro data appears to be inadequate given the small info presented [23].

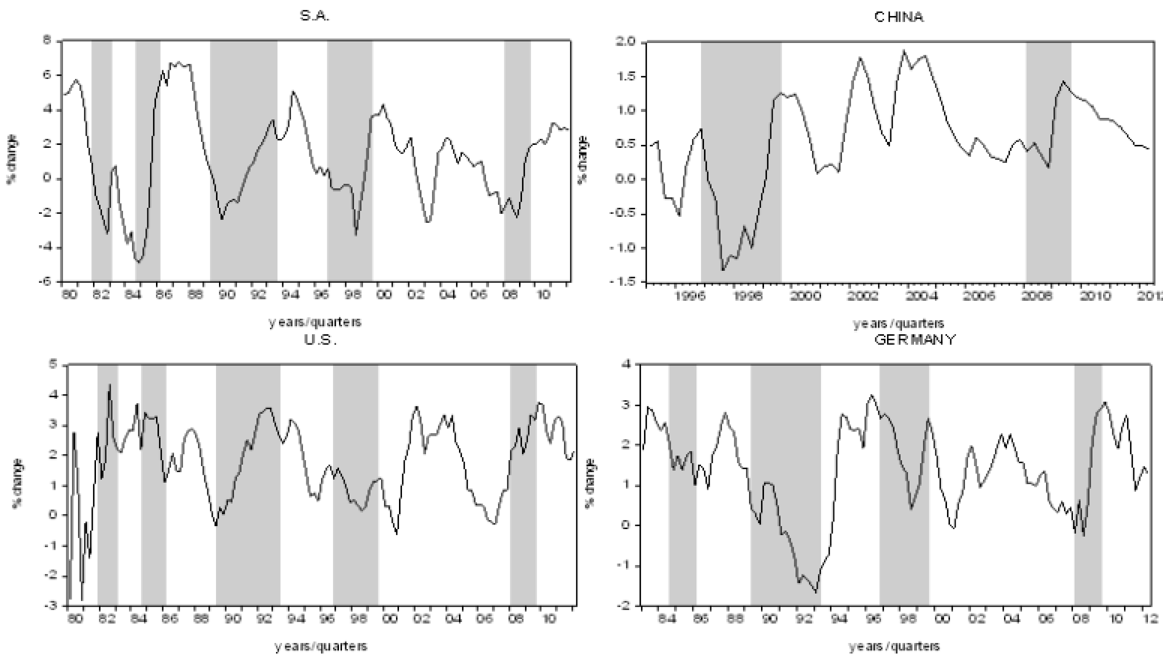

Figure 1.3: Term Structures OfInterest Rates And S.A. Business Recessions [3]

The immense uncertainties in the existence of Covid-19 have long-term economic turmoil [24]. Even if the scale and length of a recession as depression are generally not agreed, most analyst agree that recession has a significant decrease in economic activity after two consecutive quarters of decrease in real GDP in one country [25]. Shareholders and

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lawmakers encounter a major obstacle in correctly predicting economic cycle expansions and declines, notably the impending recession. Business people, shareholders, lenders, accountants, and other partners are all interested in developing a model that can recognise financial turmoil. Although developing a model with soaring predictive ability has been challenging, it was within reach to foresee not only the likelihood of an organization backsliding, but also, more importantly, to take specific steps to avoid more massive repercussions [26]. Most analysts largely agree that recession was when the real GDP downward trend exceeds 10%. Upon improving the prediction of recession using ML techniques, this study has addressed the problem of class imbalance with reference to the data of this study which potentially improve the prediction.

Covid-19 has been a highly devastating issue because it was so recent that almost no one was resistant to it, spreads easily and sometimes spreads before signs become visible. As there was no vaccine available, these factors make Covid-19 a deadly pandemic, with the extensive consequences for all regions of the world. According to [19], as banking industry expand, both macro depth and macro liquidity rise at the same time. However, if macro depth rises speedily unlike liquidity, a change was probable to happen, impacting the sector as a whole. The downturn in global markets has consumed a turbulent world with a controversial degree of liquidity [27].

This framework can be interpreted in a range of forms, one of which was focused on financial industry enthusiasm. Shareholders would bumped up stock prices when they are optimistic about future market and gain potential [27]. In order to counteract these impacts, Central banks have taken measures to guarantee that liquidity was preserved and to alleviate economic shocks. To ensure bank liquidity, Japan and China have taken similar measures with the People's Bank of China (PBOC) and the Bank of Japan (BoJ) offering $240 billion and $43 billion.

According to economists, a recent state of emergency in Japan could cause a double-dip recession if tighter regulations fail to curtail outbreaks or are extended. Tokyo which account for nearly one-third of the economy, are due to enter a state of emergency on Sunday 25th April 2021, just over a month since the capital's previous emergency was removed. This has shattered expectations for a fast economic rebound driven by improved exports and a resurgence in household consumption.

Europe has fully committed a €1.7 billion bailout plan to reduce the financial consequences of Covid-19 on the euro region, with investments across all Member States , the United Kingdom, as well as nations outside the European Union [28]. On the other side, France, Spain and Italy have respectively pledged EUR 345 billion, EUR 200 billion and EUR 25

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billion to help finance businesses [28]. In order to mitigate the effects of Covid-19, the Bank of England lowered its interest rate to 0.1%. In the United Kingdom, Chancellor Rishi Sunak stated a €330 billion plan of urgent government loans to assist those who are in monetary strain. An extra £20 billion of fiscal funding has also been given in an effort to save UK companies [29].

Europe's relief package includes:

- The Coronavirus Business Interruption Loan scheme [29] provided financing of up to 5 million pounds for small to medium-sized businesses via the British Business Bank.
- Support allocation with £ 25,000 for retail, hospitality, leisure companies.
- Micro enterprises incentive support with £ 10,000.
- 1-year non-remunerated business expenses holiday for all retail, hospitality, leisure and nursery companies in England.
- The Bank of England 's new borrowing site to assist in liquidity between many large companies, aiding them overcome the instability of coronavirus revenue by loan payments.
- The Bank of England 's new borrowing site to assist in liquidity between many large companies, aiding them overcome the instability of coronavirus revenue by loan payments.
- A Statutory Sick Pay [29] stimulus plan for Small and medium-sized enterprises (SMEs).
- Postponement of VAT and salary tax charges.
- Coronavirus employment protection scheme .
- The time to pay system of the Her Majesty's Revenue and Customs (HMRC).

In an effort to mitigate the damage of the virus to the US economy, the US Federal Reserve has reportedly lowered interest rates by 0.5 per cent and also improve the economy by buying $125 billion in bonds [30]. Moreover, Trump's administration succeeded to negotiate a $2 trillion 'virus-aid package'-CARES Act [31]. The relief package includes

- $500 billion in credit and access to credit distributed by the US treasury to small and large enterprises.
- $377 billion in government loans to small companies, $10 billion in case of emergencies financial aid.

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- $100 billion for health
- $45 billion to be allocated to the Disaster Relief Fund
- $29 billion in credit, debt insurance, excise taxes and gasoline tax deductions
- $25 billion in food aid
- $17 billion for the postponement of ongoing transactions.
- $17 billion for national defense
- $14 billion for agriculture.
- $1,200 to be offered to any adult American with a salary of just under $75,000

The US extreme recession that happened in 1981 was widely viewed as a consequence of a severe financial crisis, while the recent recession that began at the end of 2007 received much of its strength as a result of the September 2008 financial crisis [32]. The rebound from the recent recession was also noteworthy for taking longer than most other post-World War II recovery. By June 2012, 3 years after the recession's peak was declared, metrics such as revenue, industrial productivity, and unemployment were performing well below their comparable values in prior periods of rising. As it stand, Covid-19 was compared to the great recession.

Economists polled by IHS Markit predict that actual, or inflation-adjusted, GDP would be 6.7 percent stronger in the fourth quarter of 2021 than it was for the previous year. Additionally, some analysts, particularly former Treasury Secretary and Obama White House economic advisor Lawrence Summers, are concerned about the volume of money being pumped into the economy Given the prospect of solid economic expansion for the year, the main question for analysts, companies, policymakers, and average citizens was what comes next.

When North Korea invaded South Korea in June 1950, the United States was still in the middle of a rapid rebound from a contraction that ended in 1949, and ramping up for the war effort quickly threw the economy into overdrive. GDP was 13.4% higher in the fourth quarter of 1950 than it had been the previous year. Inflation surged, only to plummet again. However, the global climate has changed dramatically. Manufacturing was no longer as essential in the United States as it once was. Services, which contributed for roughly 40% of GDP in the 1950s, today contribute for roughly 60% of it. Several of the repercussions of the Covid-19 crisis were indeed peculiar, like the manner in which it impacted utilities such as travel and restaurant expenditure while having a much lighter impact on the industry.

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In the midst of the global Covid-19 pandemic that have ravaged world economies, predicting the risk of a financial downturn was more valuable than before. The spread of the Covid-19 in South African shores found a fragile economy that had undergone two successive quarters of an economic downturn. Then as component of the Covid-19 pandemic, the global recession intensified, resulting in many people being unemployed and losing income for long stretches of time, some are even living in abject poverty. The R500bn Covid-19 relief package does not demonstrate a well-built economic stimulus distribution, but focuses instead on short-term aid.

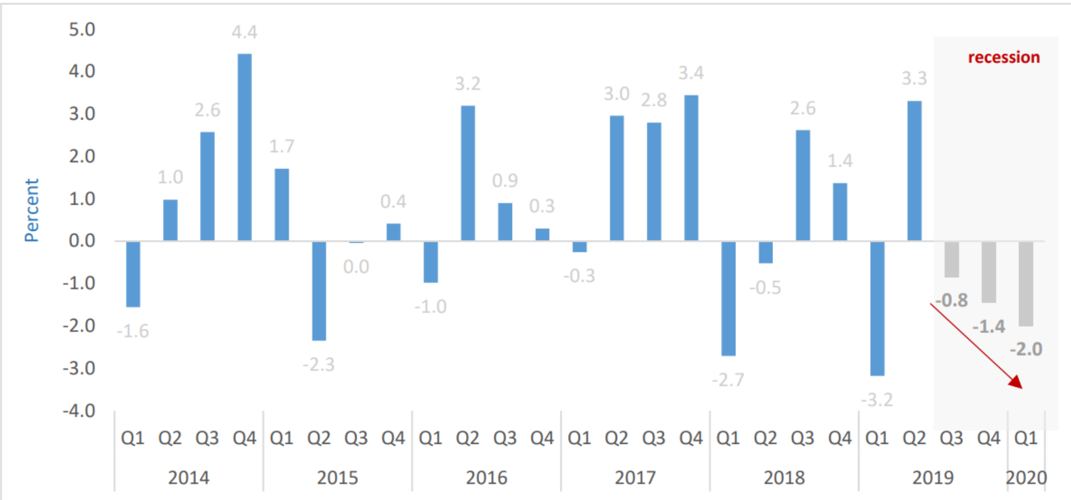

Figure 1.4: South Africa's Fiscal Balance shifts [4]

The South African fiscal relief package of R500 billion from global financial institutions such as the World Bank, International Monetary Fund, the BRICS New Development Bank and the African Development Bank includes the following measures:

- R200 billion under the loan guarantee scheme.
- Approximately R100 billion in job generation programs.
- R70 billion in case of emergency tax measures.
- Support for deprived families with a surplus of R50 billion.
- Above R40 billion towards salary security via Insurance Fund for Unemployment (UIF).
- Above R30 billion towards health and other front line programs.
- R20 billion for local government to effectively help in the matters relating to COVID-19.

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South African Finance Minister Tito Mboweni indicated that the budget shortfall for 2020/2021 is forecast to rise to 6.8% of GDP during 2020 budget speech. Significant Inflation rates by sector during the first quarter of 2020 were: mining (21.5%; manufacturing (8.5%); energy, water and gas (5.6%); and infrastructure (4.7%) with agriculture sector being the only business sector with substantial gains was +27.8% [4]. Based on 151 episodes of global systemic banking crises from 1970 to 2017, the database of Laeven and Valencia stipulated that in a financial recession, the total overall production loss is about 20% over the course of the crisis, which lasts on average two years [6].

Prior to the Covid-19 skerge the PricewaterhouseCoopers (pwc) did studies on trends in the South African banking market in which they revealed that looking back in time, there has been four major regular participants throughout the South African banking sector which have benefited greatly being Barclays Africa, Standard Bank, Nedbank and FirstRand. That being said, there are industry dynamics that might have an effect on the banking environment and also the competitiveness of these companies, including: (i)the arrival of digital advancement with relatively low models (e.g., Discovery) from nearby financial services competitors; (ii)non-financial services companies (e.g., the South African Post Office) are establishing business and sector-specific banks that are tightly integrated with wider distribution networks; and lastly (iii)the four banking institutions are undergoing transformations to meet changing consumer, legislative, and technological demands [33].

Multiple financial services providers have been expanding their portfolios in recently by incorporating fully digitized banking services to provide improved customer experiences at lower costs [33]. Since the Covid-19 pandemic arrived on South African shores, there has been a burst of activity as the banking sector moves closer to being a "marketplace without boundaries," [33].

The provision of bank borrowings to the financial sector was usually part of a country's government response to bank crisis, directly in response to financial crises. During global banking crises, comprehensive liquidity relief was widely available. When faced with a recession, both rich and poor countries, as well as middle-income countries, have relies largely on liquidity assistance. [6] revealed that the broader range of measures used by high-income countries during a downturn, including the structured implementation of reserve bank exchange facilities during the global economic meltdown. Moreover, have also found out that, on average, low and middle-income countries depend on liquidity provision as a stabilization mechanism for far too long unlike high-income countries prior to actually adopting bank restructuring and recapitalization interventions [6].

Financial services crises are usually accompanied by spikes in private-sector credit and are

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correlated with considerably higher productivity losses than "normal" downturns, larger contractions in bank credit, worse reductions in asset values, and increases in budget deficits [6]. Government agencies commonly utilized partial or absolute support on any or all bank liabilities to mitigate cash shortages and relieve funding strains on these institutions throughout the early stages of financial crises, sometimes in conjunction with liquidity assistance. They usually buy time for law makers to implement more detailed settlement and adjustment strategies.

Financial cycles typically hit their apex before a recession occurs, according to studies by the Economic Cycle Research Institute (ECRI). Since well before the 1980s, there has always been a connection among the composite economic period model and economic crisis in the United States and the United Kingdom [34]. Simultaneous period, United States' deep recession in the early 2000s did not align with an economic cycle high point: although the market crashed and share prices plunged, the economic expansion continued as assessed by debt and house values, just to recover some couple of years elapsed, causing the Great Recession [35]. The figure below the shaded area represent recessions.

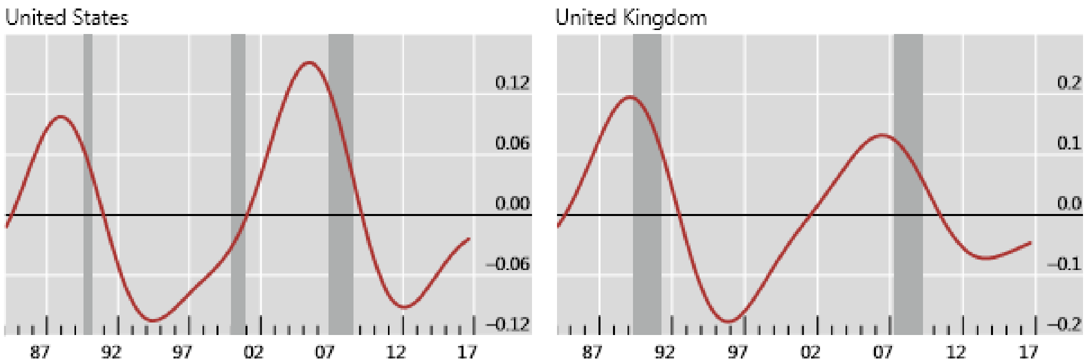

Figure 1.5: Financial cycle betweeen USA and UK [5]

A prior by study by [35] identified two main elements of the business cycle. For starters, financial cycle spikes are often associated with financial meltdown or big economic strain. The self-reinforcing relationship between financial distress, asset values, and risk-taking can overwhelm capital reserves through expansions, making them more vulnerable and laying the groundwork of future recessions [35]. As a consequence, the market could suffer and the banking sector may be increasingly strained. Second, the financial cycle, which has increased in amplitude for about the last four decades and more, 8 would be much broader than that of the business cycle. From the beginning of the 1980s, business cycles have remained for almost a decade, and financial period have lasted over a decade [35].

Furthermore, [35] emphasize that policy system cycles may have been a component as to why economic cycle amplitude has increased since the early 1980s. To begin with, banking sector was liberalized at that time. This reform, in the absence of adequate prudential

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protections, probably gave more space for the self-reinforcing connections at the core of the financial period to carry through. Secondly, inflation-targeted financial systems had become standard at the very same time. The position of monetary and debt cluster had been steadily diminished by central banks as their thinking has evolved. This implied if prices stayed low, even as economic disparities developed, financial institutions had little incentive to intensify policies [35]. Finally, beginning in the 1990s, the arrival of China, Cuba, Laos, North Korea, and Vietnam into the world economy, combined with foreign commodity market development and technology advances, increased world demand and intensified economic rivalry.

In July 2009, months after the Queen of England's visit to the London School of Economics, the British Academy replied to the Queen about why no one had noticed the imminent credit crisis. In their three-page long letter they mention that numerous observers predicted the recession but no one would have predicted the precise shape it would develop, as well as the timing of its occurrence and intensity [36]. In such cases, it was critical to predict not just the magnitude of the problem but also its timing. Finally, while there were many reasons for the inability to predict the magnitude, full length, and intensity of the downturn and to avoid it, it was mostly a fault of the collective imagination of many intelligent individuals, in the country and abroad in considering the dangers to the entire structure [36].

Studies by [6] revealed that in many instances, the length of a recession is set at 5 years, beginning with a year into the recession. Furthermore, over half of the occurrences that was record in high-income countries had long-lasting economic turmoil that lasted 5 years or longer [6]. Since several recessions in high-income countries coincided with the global economic meltdown, the severity of the recessions may be a significant component in understanding these discrepancies in length.

Monetary policy serves a crucial role in resolving downturns and improving turnarounds in several cases. Nevertheless, its impact was diminished in the aftermath of an economic meltdown. Fiscal stimulation tends to be particularly effective during downturns triggered by economic meltdown. Monetary easing was also correlated with greater turnarounds; however, the effect of stimulus measures on growth intensity was observed to be lower in countries with higher rates of government debt [5]. Downturns caused by economic collapses have become more serious and long-lasting than downturns caused by other shocks and recovery from such downturns have generally been sluggish, owing to poor household consumption and tight credit constraints.

On March 31, 2021, the World Bank published a report on Sub-Saharan Africa's economic rebound after the global economic downturn and as per the World Bank's biannual financial

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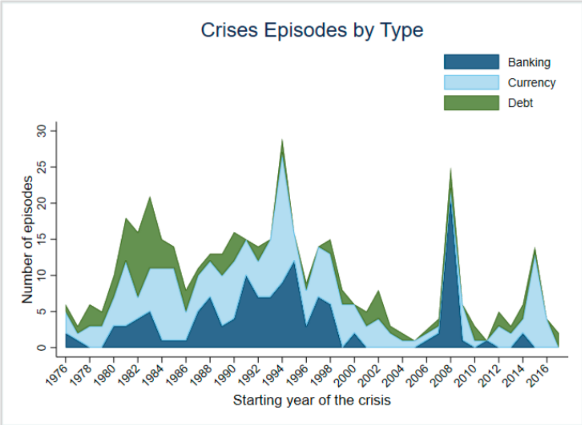

Figure 1.6: Crises episodes by type [6]

evaluation for the region, economic activity in Sub-Saharan Africa declined by 2.0% in 2020, bringing it closer to the interval of the projection in April 2020, and expectations for recuperation are improving despite efforts to prevent surge of the deadly virus and accelerate vaccine roll-outs. In 2021, the region's increase was projected to range between 2.3 and 3.4 %, relying on domestic and foreign policies. A new wave of Covid-19 outbreaks was weighing down growth projections for 2021, with regular outbreaks roughly 40% greater than the first wave.

The actual GDP growth rate for 2022 was expected to be 3.1% and by the end of 2021, operation in several nations in the region would have been far below pre-Covid-19 estimates, raising the risk of long-term effects of the virus outbreak on standard of living. According to the World Bank, recovery in Sub-Saharan Africa is likely to be unstable. Non-resource-intensive financial systems such as Côte d'Ivoire and Kenya, and also mining-dependent financial systems such as Botswana and Guinea, are estimated to expand significantly in 2021, thanks to a turnaround in private spending and investment as credibility strengthens and commodities expand.

The Southern and Eastern Africa sub-region's growth collapse was expected to be -3.0% in 2020, with the sub-region's main economies, South Africa and Angola, driving the decline. The sub-region's economy was projected to expand by 2.6% in 2021 and 4.0% in 2022, except Angola and South Africa. The Western and Central Africa sub-region's growth collapsed by 1.1% in 2020, lower than the 1.1% expected in October 2020, owing to a less extreme collapse in Nigeria, the sub-region's biggest market, in the second quarter of the year. The Western and Central Africa sub-region's actual GDP was expected to rise by 2.1% in 2021 and 3.0% in 2022.

In an integrated global economy, the Covid-19 outbreak disrupted both supply and demand. On the supply side, diseases decrease labor supply and output, whereas lock-downs, company

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closures, and social isolation often trigger supply shortages; on the demand side, increase in unemployment and lost income and deteriorated economic conditions. The global volatility threshold variable was statistically significant in 15 of 19 advanced economies and four of 14 emerging economies, according to [7] research. Unrestricted global volatility can have a number of consequences for economic development as such higher preventative investments, reduced or postponed investment, and a greater cost of capital are among them [37].

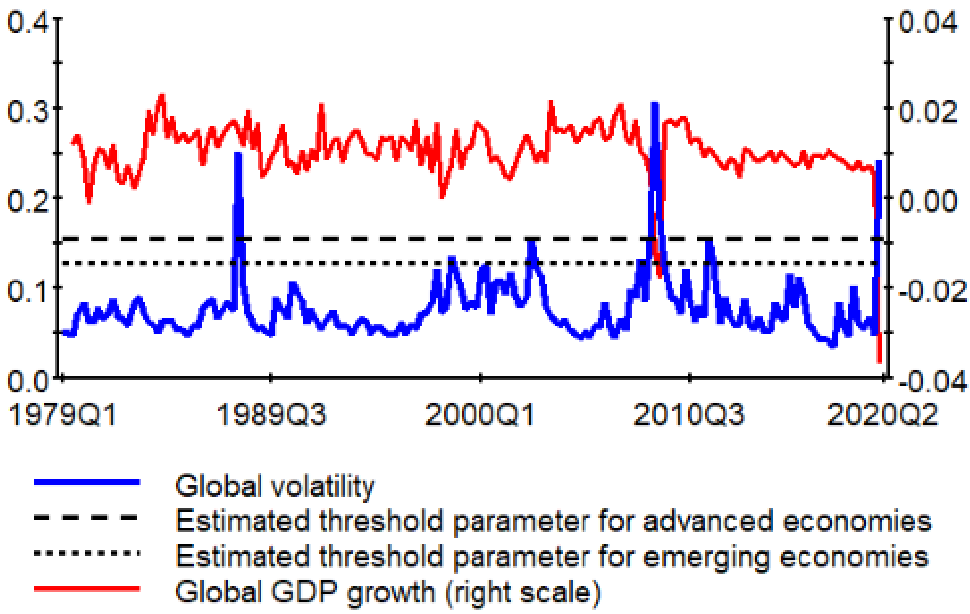

Figure 1.7: Global volatility and GDP growth [7]

According to [37] report, the pandemic would likely reduce real world GDP by 3% points compared to the level of global economic activity which would have occurred in the absence of the outbreak. Furthermore, the United States and the United Kingdom are very likely to suffer severe and longer-lasting consequences, while China's result has a greater than 50% probability of being good.

According to the International Monetary Fund, the United States and Japan will not regain production amounts to the level before the outbreak until the second half of the year 2021. The euro zone and the United Kingdom, now in crisis, and won't meet that threshold until sometime in 2022. According to the Guardian's article Uneven recovery from Covid19 recession could hit poorer countries hard, the Chinese economy was in a category by itself, and it was predicted to be 10% bigger by the end of 2021 than it was during the end of 2019. From the other side of the trajectory, many developed and developing economies may take longer to re-bounce to levels the were before the outbreak.

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1.2. Problem Statement

A handful of economic recessions were predicted months ahead of time. Therefore, in order to eliminate these increasing repercussions through recessionary periods, better predictive models need to be developed to help businesses and governments to create better laws that support millions of people prior these periods since the state of the economy is an important factor in policy development. This study has the potential to provide the best performing models to help businesses navigate prior recession periods. We address the problem of selecting the most relevant features to improve the overall performance of the algorithm that would effectively carry out recession prediction. This is a concern since the previous research has demonstrated that these methods has shown bias outputs on the class ratio not being uniform. Traditionally, the proposed machine learning algorithms have been used widely for pattern recognition, but hardly any research was being done in finance particularly recession prediction. Considering that the use of recession prediction in ML, particularly in finance, was a new approach in the frame, there are very few papers in this context of refers.

1.3. Aims and Objectives

The intentions of this study and its steps to follow are outlined below.

1.3.1 Aims

- The primary aim of this study was to improve the prediction of economic recession using machine learning techniques.
- To develop an efficient model in order to refrain from enhanced government deficits, increasing inequality, considerably lower income and continually increased unemployment.

1.3.2 Objectives

i. To establish the relevant method for addressing imbalance data.

ii. To develop relevant features to improve the accuracy of the model.

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iii. To establish suitable features selection strategy to enhance the performance of the machine learning algorithm developed; and

iv. To predict economic recession using ANN and RF.

1.4. Research Questions

(a) Which of the chosen oversampling techniques for classification would be more effective when dealing with imbalanced data?

(b) How features developed improves the overall prediction accuracy of the model?

(c) How do feature selection strategies improve the overall performance of the machine learning developed?

(d) Which machine learning algorithm amongst RF and ANN would effectively carry out recession prediction?

1.5. Significance of the Study

This study seeks to make contribution to the existing body of knowledge by implementing the top performing model in predicting economic recession using artificial neural network (ANN) and Random Forest (RF) with already existing methods for addressing class imbalance and suitable feature selection.

1.6. Limitation of the study

A large number of trees in a prediction algorithm made it inefficient and slow. This can be improved by adding new algorithms that are more encompassing in enhancing prediction.ANN has been known to have unexplained network functioning, which has added to the challenge of demonstrating the problem of the network because it is hardware reliant.

1.7. Dissertation Outline

In what follows, Chapter 2 discusses the recent literature related to the study, feature selection methods, machine learning techniques selected, class imbalance techniques and evaluation

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methods. Chapter 3 presents the methodology with emphasis on the selected machine learning algorithms that are going to be used in this study. Chapter 4 presents the thesis plan of work. Chapter 5 wraps up the proposal with the conclusion.

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Chapter 2
LITERATURE REVIEW

2.1. Introduction

As previously highlighted, most analysts largely agree that recession was when the real GDP downward trend exceeds 10% [15]. This was well established that even in recessionary periods the market conditions of companies are characterized by poor revenue growth. The annual GDP collapse due to Corona Virus pandemic was expected to be higher than the standard recessions ever since second world war [20]. Tin Kam Ho developed the very first method for random decision forests [38], with the primary emphasis on measuring variable significance by possible combination and utilizing inaccuracy out of bag as an approximation of inaccuracy in generalization [39].

The father of economics, Adam Smith, outlined three reasons for poor profitability[6] (a) Labor-market rivalry that leads to increased wages and hence lower revenue; (b) Capital market rivalry results in the increase in capital goods rates; (c) Rivalry in markets goods and services pressure capitalists to trade at lower rates, which also reduces profits. A recent study by [40] looked at 153 recessions in 63 countries between 1992 and 2014, and discovered that economists across both the public and private sectors overlooked the significant proportion.

The stock market was an important economic organization that facilitates financial development and performance. It allows businesses and governments to collect long-term money, allowing them to fund new ventures and extend operational capabilities [41]. Studies by [42] highlighted that the efficiency with which the stock market executes its asset distribution determines an economy's overall growth rate. Several stock markets, particularly in developing countries, encounter challenges that have severe repercussions, such as (i) liquidity problems, (ii) a lack of functions, and (iii) a lack of a very well advanced institutional investors.

An essential part of economic growth has been stock markets since they provide a platform for listed companies to collect long-term equity as well as a place for investors to invest. When the stock market accumulate capital, it often assigns a greater portion of the funds to companies that have reasonably high expectations, as shown by their rewards and financing decisions [41]. Thus, this enables funds to be directed through the drive of supply-and-demand to companies that rapidly increase in performance, thus increasing economic growth

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and expansion.

Stock market liquidity tends to mitigate the downside risk and expense of participating in long-term ventures. Furthermore, a study by [43] noted that early investors could trade their stake in a firm rapidly and effortlessly in a liquid market, shareholders won't be unable to lay hands on their assets for the period of their initial investment. A very well advance stock market was projected to potentially increase savings by broadening the range of financial collateral arrangements available to depositors, allowing them to expand their investments and reduce risks while still efficiently distributing funds to profitable units. As a result, the economic growth rate will be accelerated.

Economic development, according to [44], was undeniably essential and cuts through disciplines, influencing all aspects of society directly and indirectly. Furthermore, banking policy on interest and inflation rates aid in the development of the economy and, more importantly, serve as vehicles for economic growth. However, identifying the crucial opportunities for growth and explaining the wide variance in cross-country economic performance and reliability was one of the most difficult tasks for growth economists. Neither modernist nor endogenous growth models are capable of clarifying the concepts of uneven development and enduring global inequality [45].

The study of [46] forecasted systemic economic collapse without understanding the economy's "real" model, using as much knowledge as possible from traditional macroeconomic variables such as debt, GDP, wages, consumption, credit, interest rates, monetary aggregates, asset prices, proxy for sentiment, commodity prices, house prices, external imbalances. According to his report, [46] concluded that there was high demand to employ machine learning software to provide valuable insights to people in management of the financial sustainability about when and where they should step change their approach, collect more intelligence, and use their resources wisely.

Research results by [47] found that the effect of growth and inflation on relative prediction outcomes varies depending on the stage of economic development. As a result, as shown by the NBER business cycle dating committee, the condition variable represents the value of one throughout financial crises and null amid expansions [48]. In the paper by [48] outlined that the economic models outperform the auto-regressive benchmark as ratios are a measure that are larger than one. Furthermore, only a few instances of unconditional equivalent predictive output tests failing have been discovered. The economic models are generally poor than the auto-regressive benchmark in situations where the projections are statistically distinguishable from one another [48].

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Upward Phase	Duration in Months
April 1983 – June 1984	15
April 1986 – February 1989	35
June 1993 – November 1996	42
September 1999 – November 2007	99
September 2009 – September 2010	13

Figure 2.1: South African Business Cycles since 1980 : Upwards Phase [8]

Downward Phase	Duration in Months
September 1981 – March 1983	19
July 1984 – March 1986	21
March 1989 – May 1993	51
December 1996 – August 1999	33
December 2007 – August 2009	21

Figure 2.2: South African Business Cycles since 1980 : Downwards Phase [8]

The upward phases of the business cycle reflect times of rapid growth , while the downward phases reflect business cycle sections reflecting times of rapid downturn in the South African economy. The duration of months the fluctuations persisted through both scenarios indicates the length of both downward and upward shifts [8]. Times of contraction in South Africa has been seen in each of these downward stages. Most economists and analysts argued that somehow lowering of the yield curve in 1988 and 1989 signaled an impending recession in the United States, but studies by [49] looked into the data meaning of the term structure of interest rates. Their research was broken down into the following distinct three topics: First, whether the yield curve contains any additional details not yet available in other economic figures; second, whether the yield curve counts as one of the main indicators of economic activity; and third, whether the yield curve is valuable for monetary policy objectives [49]. In conclusion, [49] reported that increasing inflation rates, beyond 4% in South Africa, are detrimental to GDP growth. In order to prevent a significant negative impact on productivity, policymakers should maintain inflation within the goal range, ideally under 5% [8].

2.2. Handling Class Imbalance

The African country recession data sets display high imbalance with 92.81% of the samples being classified in "0" or "No Recession" and 7.82% of the samples in the "1" or "Recession". The above mentioned machine learning models chosen for this study are most effective for class imbalance data [50]. The algorithms for machine learning mostly result in bias output based on the class ratio not being uniform, so this over-sampling approaches focusing on

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class imbalance will be used to overcome this problem [50].

2.2.1 Synthetic Minority Oversampling Techniques

This technique was found to be a state-of-the-art and tends to work quite well in diverse application, more especially in addressing over-fitting issues [51]. The major drawback with Synthetic Minority Oversampling Techniques (SMOTE) was that it dismisses information which may be useful [51]. Imbalanced classification entails building statistical models on classification data sets of extreme imbalanced data. The difficulty of dealing with imbalanced data sets was that too many machine learning algorithms would neglect, and hence behave poorly on the minority samples, despite the fact that performance on the sample was usually the most essential. SMOTE involves selecting samples in the feature space that are similar together, distinguishing them by drawing a line between them, and again defining them by inserting a new sample across the line.

The SMOTE data pre-processing strategy was a forerunner in the scientific field for imbalanced classification. Many modifications and substitutes have been suggested since its release to increase its success in various scenarios but SMOTE is still regarded as among the most prominent data pre-processing algorithms in machine learning and data mining due to its success and impact [52] [53]. The sampling methods are narrowly classified into two categories: under-sampling and oversampling. Under-sampling techniques are well known for providing a portable balanced training range while also lowering the cost of the learning level. According to the findings of the [54] analysis, the SMOTE algorithm produces an infinite number of synthetic minority cases in order to change the classifier learning bias against the minority class [55] .

However, it still has certain unintended consequences. First, it raises the classifier's variability, and second, it generates twisted temporal probabilities and it can also eliminate several valuable examples for the classifier's modeling [56]. However, using random oversampling simply leads to a greater weight or expense for the minority cases. As a result, accurate modeling of such clusters of minority data even by classification algorithm which also be difficult in the context of overlapping [57] [52].

2.2.2 Adaptive Synthetic

In this study we will also use Adaptive Synthetic (ADASYN) oversampling technique in addressing the issue of imbalanced data. When certain forms of data distribution greatly

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overpower the instance space in comparison to other data distributions, imbalanced learning takes place. The ADASYN method achieves learning regarding the distribution of data (specifically imbalanced data sets) in two ways: (a) decreasing the bias introduced by the imbalanced data set, and (b) optimally changing the classifiers decision boundary more towards the complicated sample [58].

The fundamental principle behind ADASYN is using a weighted variance for distinct minority class instances based on their level of complexity in training, with more synthetic data produced for minority class instances that are more hard to implement than minority class instances that are troublesome to implement. The ADASYN method increases training with regard to data distributions in two ways: (1) it reduces the bias created by imbalanced data, and (2) it iteratively transitions the class analysis boundary through challenging cases [55].

The most recent research methodologies for dealing with imbalanced learning abnormalities can be divided into five primary categories:

(a) Sampling techniques - the purpose of this approach was to create different oversampling and/or under-sampling strategies to account for imbalanced distributions in the initial data sets. Looking into study by [59], sampling techniques incorporate probabilistic projections, pruning, and data pre-processing were investigated for decision tree learning. Moreover, the analysis revealed that pruning could assist because it increases the generalization of the decision tree classifier.

(b) Synthetic data generation - through artificially constructing data samples this technique attempts to compensate for imbalances in the initial data sets.

(c) Cost sensitive learning (CSL) - Rather than using sampling techniques or synthetic data generation approaches to create balanced data distributions, CSL uses an unique tactic: It employs a cost-matrix for various types of errors, for example, to promote learning from imbalanced datasets. [60] has suggested two straightforward solutions to the problem of class imbalance. One distinguishing advantage of their methods was that they don't have to modify the classifiers centrally, making them simple to enforce.

(d) Active learning - traditionally, active learning methods are used to solve problems involving unlabeled training results. [61] assessed the efficiency of acquisition functions and uncertainty estimation approaches for active learning with Convolutional Neural Networks (CNNs) on image classification tasks in his research. He also demonstrated that ensemble-based uncertainties reliably outperform other approaches of uncertainty estimation and contribute to state-of-the-art active learning performance on MNIST and CIFAR-10.

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(e) Kernel-based methods - kernel-based approaches have been utilized to investigate the imbalanced learning issues. [62] suggested a weighted online sequential extreme learning machine with kernels (WOSELMK) for class imbalance learning (CIL). WOS-ELMK outperformed competitive online sequential classification algorithms in classification performance on 17 imbalanced binary class datasets.

2.3. Feature engineering techniques and preprocessing

In the field of machine learning, feature engineering was a critical method. In the real world, data is complex, because it must be cleaned before being fed into a machine learning algorithm or doing simple analytics. As a result, analysts expend the majority of their time processing data. The main purpose of feature engineering was to enhance accuracy as well as to translate raw data into features or columns.

2.3.1 Outliers and Missing values

Lost information in a data was considered one of the major issues with data mining technique and this issue can be amplified when vast data was incomplete in the existence of imbalanced data [63]. The data for this study has no missing values.

2.3.2 Data Split

Cross-validation was a great approach for using all of the specific instances accessible as training and testing observations [64]. It emulates use of certain training and testing data by learning the algorithm subsets multiple times with just a fraction of 1 / K of training instance remaining out because of testing purposes [64]. The data will be divided into 75% training and 15% test sample utilizing the python SK-learn library. Moreover, in this study we will utilize stratified k-fold cross-validation with imbalanced data to maintain train class distribution and testing set within each analysis and the validation sample will be 15%.

"Fold" describes the number of subsets leading from this instances [65]. We will be using stratified split train-tests also known as stratified k-fold cross-validation on these classification tasks, because we have a serious class imbalance [65]. This method of data re-sampling to evaluate the generalization performance of prediction and to improve the classification accuracy [66]. The classifier was constructed utilizing k-1 subsets that also constitute the training data set.

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2.4. Modelling

The analysis applied in the study was executed utilizing Python with libraries including matplotlib, pandas, numpy, Sci-Kit Learn. To minimize the variable size in this study filter and wrapper was also applied to reduce some redundant variables.

2.5. Feature Selection Process

2.5.1 Filtering

Filters resemble strategies that select features prior to actually implementing classification to a machine learning algorithm [67]. A filter method decrease the size of features independently on a classification model. One common drawback of these strategy was their univariate aspect. To consider making the selection, filtering techniques are focused on the

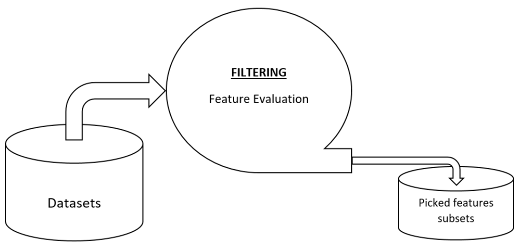

Figure 2.3: Filter Framework

application of an analysis criterion independent of a final classifier, including dependency, distance, graph-based learning or consistency measurements over the input data [68]. In addition, as they have several other benefits, such as scalability or high velocity, the final classification most often results in low accuracy [68].

2.5.2 Wrapping

A wrapper algorithm explores the function space to score subsets according to their predictive value, maximizing the subsequent evaluation approach used for classification by the corresponding subset [69]. On a modelling algorithm, which was taken as a black box evaluator, wrappers consider feature subsets by the quality of the performance [70]. Thus, a wrapper would then assess subsets with regards to the the performance of the classifier for binary classification [69]. For each subset, the assessment was repeated, noting that feature subsets are also biased towards the modelling algorithm on which they were assessed. Wrappers are relatively slow in identifying sufficiently good subsets than filters since they rely solely on

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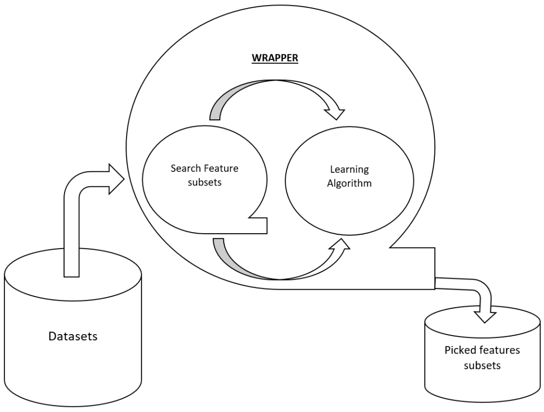

Figure 2.4: Wrapper Framework

modelling algorithm's resource requirements [70].

2.6. Economic recession prediction models

2.6.1 Recession prediction statistical models

2.6.1.1 Probit model

The probit model has been known as linear regression model that changes the details found in key indicators into likelihood of a recession at a given period of time.

$$Pr(Recession|Y_{t-k}) = R(\alpha_0 + \alpha_1 TS_{t-k} + \alpha_2 CS_{t-k} + \alpha_3 SP500_{t-k} + \alpha_4 CLI_{t-k}) \quad (2.1)$$

Whereby TS is the term spread, R is the normal cumulative distribution function, CS is change in the corporate spread, SP500 is the SP 500 return, and CLI is the composite index of leading indicators. For predicting a downturn k months onward the approach is projected utilizing lagged knowledge as $Pr(Y_{t-k}) = TS_{t-k} + \alpha_2 CS_{t-k}, SP500_{t-k}, CLI_{t-k}$. Unless the likelihood is below 50 percent, then the formula signifies growth so a growth was much more probable than that of a contraction; if the likelihood is higher than 50 percent, a recession was much more probable.

2.6.1.2 Neftçi's sequential probability model

Neftçi's sequential probability model is a non-linear approach that makes some implication about an overthrow of the information collection process of the composite index of leading indicators data which could then be used to suggest a breakthrough in economic performance. Numerous observations are expected in using this approach to predict downturns. To use this

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approach to predict downturns, the expected likelihood of a peak is relative to the one which was before confidence level, which is supposed to enable a limited likelihood.

2.6.1.3 Stock and Watson's experimental recession indexes

Stock and Watson's experimental recession index is a complex econometric time series model designed to predict the likelihood of a downturn, it is calculated in two phases by [71]. Firstly, market variations are perceived thru the multi-equation variable approach and within the second phase, regarded as the pattern recognition step, [71] utilise approximate model to produce C_{t+k} predictions during the first phase.

2.6.1.4 Simple rules of thumb using the composite index of leading indicators

The composite index approach was developed in the twentieth century as a way of offering an overview of the economic sequence that had a prevailing connection with the economic cycles [72]. Drops in the composite index of leading indicators are meant to provide an early notice of an economic downturn, and can also offer useful insights as an indicator of a potential downturn [72]. K-month rule-of-thumb model: If $(CLI_t < 0, ..., CLI_{t-k} < 0)$ then an indication of a downturn is provided. The study of [73] whom many regard as the father of the leading indicators, advocated that a limited amount of key indicators 66 could be utilized to generate a valuable quantitative index which would give early indications for evolving business activity.

2.6.2 Recession prediction using machine learning models

According to the study by [71], random forest has higher level out-of-performance prediction accuracy, with neural network just almost equivalently perfect as random forest in out-of-performance samples. In-light of this, accuracy predictions obtained from cross-validation of k-folds in time series settings are optimistically biased. Moreover, based on research by [74] cross-validation of k-folds suggests that the predictability of tree methods tends to dominate that of neural networks.

Along with their ability to tackle background noise and high-dimensional predictive analytic, it has been discovered that random forest and Naive Bayesian perform best in predicting financial crisis. A number of studies have attempted to use different algorithms such as the Bayesian, random forest, static and dynamic probit model for predicting and evaluating probability of occurrence in recession and its fiasco [15]. Random forests is an approach of conducting different deep decision trees, learned on various sections of the very same learning set, again with goal of minimizing the variance [51]. However, close attention in this study will be rooted on two machine learning algorithms, namely ANN [75] and random forest [63].

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ANN has facilitated advancement in a wide range of technologies, from computer vision to language processing to voice recognition and speech recognition [76]. More and more massive training data sets and highly complicated systems have really been essential to these outcomes. For instance, the neural network included in [77] had 11 million parameters, which increased to nearly 67 million for bidirectional Recurrent neural networks and 116 million for [78]s recent forward only Gated Recurrent Unit (GRU) systems. However, its use in finance was limited.

By separating 16 variables from 103 indicator variables [79] succeeded in acquiring the most efficient variables to be included in particular times of economic crises, such indicator variables can already be analyzed as a crisis anticipation detectors. In the daily Istanbul Stock Exchange (ISE) National 100 Index, [80] tried to establish two approaches as well as compare their performance outcomes in predicting the direction of movement. Ten technical indicators or features have been picked as input variables for the presented models. Analyses demonstrate that ANN model average performance (75.74%) was reported to be largely better than the SVM model (71.52%).

To predict recession in the US financial industry, [81] utilized extreme gradient boosting. They demonstrated that incomes kept, the pre-tax return on assertions and the overall risk-based capital. In his study, [82] attempted to predict the financial crisis under less advanced nations utilizing data from the 1980-2004 periods, applying ANN model. Through forecasting the quarterly gross domestic product (GDP) growth rate for the euro area, [83] explore the implementation of random forests in economics. They then use RF algorithm through creating a Monte Carlo simulation to allow a forecast of GDP growth and they discover that RF provides better performance, but the linear model shows much better performance.

Empirical studies by [84] revealed that the random forest method outperformed the ANN, the study analyzed the random forest and SVM forecasting efficiency with the ANN, discriminant analysis and logit model to forecast Indian stock market changes based on financial indicators. The study of [85] applied the machine learning approach based on learning vector quantization (LVQ) with the Markov dynamic factor switching approach for the ongoing downturn in real-time. The predictive value of the yield curve in estimating downturns was calculated by using the probit model. A steeper yield curve indicates faster real output growth, while a flatter yield curve indicates slower real output growth, according to AB's observations [3].

According to [86], investigated boosting to increase the out-of-sample efficiency of logit models in forecasting economic downturns, the results revealed that every indicator's predictive value continued to change over time, contributing to the inference that each economic

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cycle introduces unusual behaviour in the results. [87] evaluated static and dynamic probit method on predicting both in and out of sample economic downturns 1-6 quarters ahead, with the prior generating higher performance on 1 to 4 quarter time periods, whereas the other produced "at least" comparable output for longer time periods.

Following the findings of the study by [88], examines Canadian GDP growth rates and finds that the ANN algorithm is stronger than a linear algorithm throughout the year of projection period but not over the quarterly projection period. Furthermore, due to the non-linear effect of macroeconomic variables, they are also important in the end, according to the [88]. During a recession, [89] look at monthly projection of manufacturing relationship between inflation and unemployment rate in developed economies. They uncovered that their auto-regressive neural network does not outperform the standard auto-regressive algorithm by a significant margin.

[90] examines GDP statistics for South Africa, Nigeria, and Kenya independently and finds that the ANN algorithm outperforms systemic econometric algorithms and ARIMA algorithms in most of the requirements regarded. Their key argument seems to be that emerging economies are “vulnerable to potentially disruptive influences from stock prices, external pressures, and even production and trade pressures” [90]. According to [91]’s research, decision trees, neural networks, and help vector machine algorithms are all extremely vulnerable to class imbalance. As a result of the large scale of the records, there is a high likelihood of class imbalance. Furthermore, the possible consequences of class imbalance on machine learning are extreme due to the complex problems embedded in such results.

ANNs have been introduced as a advanced approach for grasping neural data capturing in the mind. According to [92]’s research, neural networks can acquire a specific connection between various spatial state variables. They demonstrate that both design process and the training method used have an effect on neural processing characteristics. In order to decipher something individuals dream of, [93] used deep learning models and discovered that decrypted attributes from dream fMRI data were significantly associated with those identified with dream-related object classes.

[94] introduces representational distance learning (RDL) as a stochastic gradient descent approach that moves the conceptual field of a learner model to estimate the conceptual field of a target model in order to improve the performance of ANNs. [95], on the other hand, looked at chunking, which was a concept that refers to the aggregation of objects while doing a cognitive assignment, which leads to improved task efficiency. [96] demonstrate that neuronal response to sensory stimuli can be developed utilizing end-to-end trainable recurrent neural networks, which was an interesting issue in neuro-science: how are neural

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interpretations to sensory feedback biologically structured?

Research results by [97] show that the SVM exceeds the other classification methods, and the random forest method exceeds the ANN, discriminant analysis and logit model used in this study. [97] differentiate random forest and SVM's model performance with ANN, discriminant analysis and logit model to predict the motion of Indian stock index influenced by economic variable indicators. The effectiveness of relevant financial key indicators for forecasting economic downturn was studied by [81] using a boosted regression tree technique. Their outcomes revealed that the paramount indicators are the short-term interest rate and term spread.

The study of [98] re-examined the word spread as a prominent predictor within that scope of the probit analysis, he considered the phrase spread to become the absolute great recession indicator relative to several other key economic measures and financial variables. The Receiver Operating Characteristics (ROC) curve curve indicates the proportion of false negatives that one will have to exchange for an extra percent of true positive, [99] lately had used ROC curve to determine the potential of different leading measures to identify the downturn [99]. A system of 100 percent accuracy will direct a ROC curve to the upper left corner.

According to [100]'s findings, models constructed for AUC-ROC exhibit a significant result in performance; additionally, the use of area under precision recall curve (AUC-PR) as an estimate of SDP model performance. Moreover, [101] used to test models on strongly biased data distributions and as such the ROC curve produces positive outcomes; thus, the PR curve was regarded for analysis of such situations. [102] discovered that precision was extremely unpredictable and that in some situations, in order to achieve high recall, we sacrifice precision, while [103] identified precision-recall (PR) as a good accuracy assessor for immensely distorted data distributions. [104] have recorded precision for a much more accurate representation of actual results.

2.7. Machine Learning Techniques

2.7.1 Artificial Neural Network (ANN)

An Artificial Neural Network also known as Neural Network (NN) has been described by [105]. as "a system composed of several basic processing elements running in parallel, the role of which was determined by network configuration, link strengths, and the processing performed at computational elements or nodes". The ANN algorithm provides better

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techniques than conventional methods. Artificial neural network has been a deep learning approach imitating neurons or receptors of the sensory organ and layout of the brain [75].

The NN method was composed of three layers: an input layer which retrieve the actual data that was sent to the system, a hidden layer which their work was dictated by inputs, weight, and the interaction among them. When a hidden element must be configured, weights across input and hidden variables are used. Latsly, an output layer which effectively function on hidden unit operation and weight, as well as the relationship between hidden units and output [106].

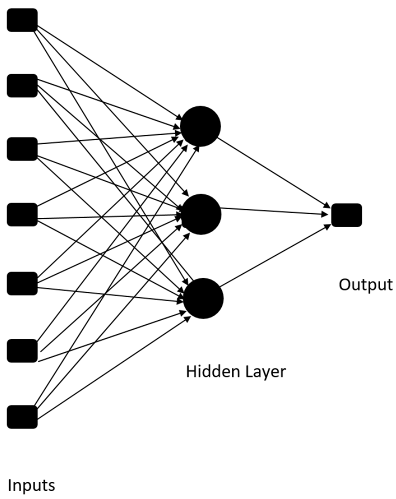

Figure 2.5: Overview of Neural Network

The performance of a network will be obtained by the following equation:

$$\Psi_k = \sum_{i=1}^{n} \phi_{ki} x_i \tag{2.2}$$

whereby the input variables and weights of the network are $(x_1, x_2, ..., x_k)$ and $(\phi_1, \phi_2, ..., \phi_k)$ respectively. Signals are transmitted to the output layer from the input neurons, and weight could increase or decrease the correlation.
The output of the network will be obtained by the following equation:

$$Y_k = \alpha(\phi_{ki} + \beta_k) \tag{2.3}$$

whereby the bias and activation function of the network are β_k and α respectively.

The output neuron's value was a weighted sum of the hidden neurons' values, which was compatible with some methods in the study by [90], but other techniques in the study by [107] include a sigmoid mapping of this linear combination. Validation entails splitting the data set into a training set for tuning the parameters that reduce the loss function and a

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validation set for evaluating the algorithm's output.

In the analysis by [108], when discussing if the linear or ANN algorithm must be recommended, he concluded that the ANN model's generalizability had been assured by validation. The claim that the ANN algorithm outperforms the pooled OLS algorithms on both the training and validation sets is more than sufficient to suggest that the ANN algorithm method was better in terms of MSE. The efficiency of any algorithm, as well as neural network training, was constrained by one of 3 components: arithmetic bandwidth, memory bandwidth, or latency.

2.7.2 Random Forest (RF)

In classification, RF has been defined as an ensemble learning technique consisting of numerous decision trees [63] and yield the class which would be the mode of outcome of the class by specific trees [51]. This approach ensures that even the proportions of the data are numerically equal to the previous data [51]. Using this algorithm to generate a bootstrap sample, then a good approach will be sampling the initial data set with substitute for the specific input data.

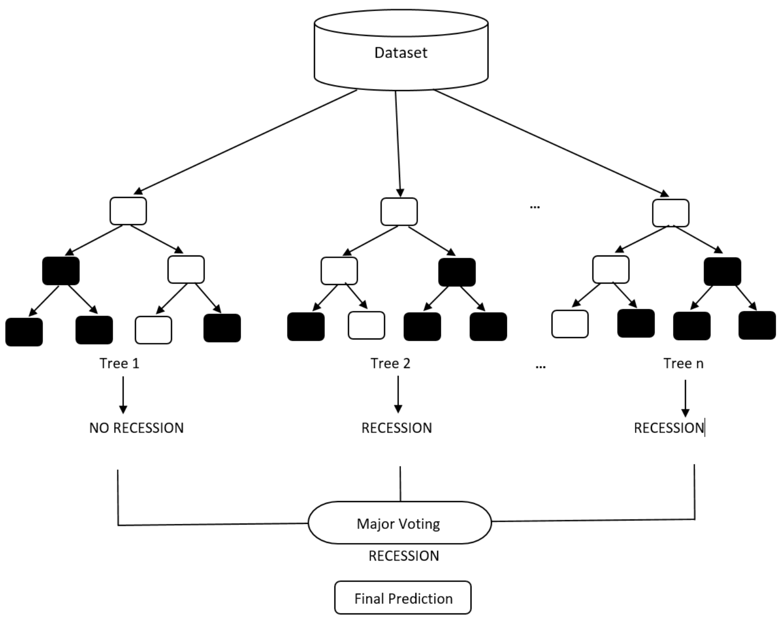

Figure 2.6: Overview of Random Forest

Given the input sample:

$$\mathcal{R}_n = \{(x_k, y_k)\}_{k=1}^{n} \tag{2.4}$$

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In which the amount of decision trees was $\mathcal{R}_n = (D_1, D_2, D_3, ..., D_n)$. Training on numerous trees on a single training set will mostly leads to a better performance of the model to tightly aligned bootstrapping trees. The final class will be predicted with regards to the maximum voting from $\mathcal{R}_n$ classifier. In this study we will use stratified k-fold cross-validation for optimal amount of trees. It is worth noting that $(x_1, x_2, x_3, ..., x_n)$ is the amount of features in the sample.

The major difference among random forest and bagging seems to be that random forest only regard a subset of predictors on separation. The forest error rate depends on the strength of each specific forest trees, as well as the correlation in the middle of any two forest trees. Increasing the correlation has a direct proportionality on the forest error rate. Moreover, increasing the strength of the specific trees has an indirect proportionality on the forest error rate.

The advantage of random forest has been that it produces several trees on data subset and merges all trees output. Thus it minimizes the risk of over-fitting in decision trees and then also lowers the variance and thus increase the accuracy. However, the setbacks are that the predictive accuracy was mostly inferior to gradient-boosted trees over complicated tasks and that random forest has less describable than one decision tree [109].

Random Forest uses pooled segments of both the learning sample and the subspace, resulting in increased unpredictability and decreased variance. A variety of random forest variations have been developed that comply with various problem scenarios. Random Survival Forests is an ensemble tree approach for the interpretation to set of data that use a range of models. The study of [110] suggested increasing decision trees with bootstrap data sets relying on a slicing principle optimizing the logrank statistic upon slicing.

Multivariate random forests interpretations expands use of random forests to much more than one output, predicting the impact of covariates across a sample. [111] suggested that utilizing the concept of decision trees to solve regression issues with multivariate feedback. Enriched Random Forest are interpreted by shifting random sampling such that fewer descriptive data sets would be less effective when taken, the likelihood of trees with more effective feature to be included in the forest improve.

If the amount of possible features is high and the proportion of genuinely insightful features is minimal, a dilemma occurs as random forest classification efficiency decreases significantly. In their analysis, [112] indicated that determining how insightful each independent variables use certain pre-filtering techniques, including t-tests, to measure approximately how effectively a predictor will distinguish two categories. Quantile regression forest provide a non-parametric and precise means of calculating constrained distributions for elevated re-

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sponse variable.

2.8. Chapter Summary

Section 2.1 of this chapter provides an introduction to the literature review. Section 2.2 describes how we deal with class imbalances using SMOTE and ADASYN. Sections 2.3 and 2.5 address feature engineering methods and pre-processing, while sections 2.4 and 2.5 represent modeling and feature selection. Section 2.6 addresses economic recession prediction models, and Section 2.7 concludes with machine learning techniques.

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Chapter 3
METHODOLOGY

3.1. Introduction

The chapter entails broad description of the machine learning that will be applied in this study and a more in-depth outline of the data pre-processing stage and concluding with the evaluation technique that will be used.

3.2. Classification

Supervised learning was a part of machine learning algorithm that utilizes a specified set of data which was identified as a training data set to acquire information. The training data set contains input data and output data. Then a supervised learning algorithm produces the model that can draw conclusions of the output data for a testing data set which is used to verify the performance of the proposed model. Classification may be divided into two distinguishable aspects – binary and multi-class classification. In this analysis, huge concentration was on binary classification in which only two classes are evaluated and this regards whether there was a recession or no recession, while multi-class classification includes classifying an object to one of several classes [113]. Binary classification was a two-class estimation dilemma in which the results are classified as either positive or negative. For recession prediction, binary classification entails mapping all occurrences of a dataset involving recession and non-recession components to recession or non recession.

Classification issues with a vast number of features pose a major challenge to the proper construction of final versions. First, since most learning methods consider the whole feature space when building the model, it was more tough to locate a true optimal solution.

3.3. Datasets

The recession data set that used was African country data and was publicly accessible at online open source Kaggle, as such no consent was required. The data set has 49 variables with a total of 486 samples. In this study, GDP is our recession indicator, so if GDP goes below zero, it was defined as recession and if GDP is above zero, it was defined as non-recession. Our target variable was growthbucket with binary values 0 and 1, which

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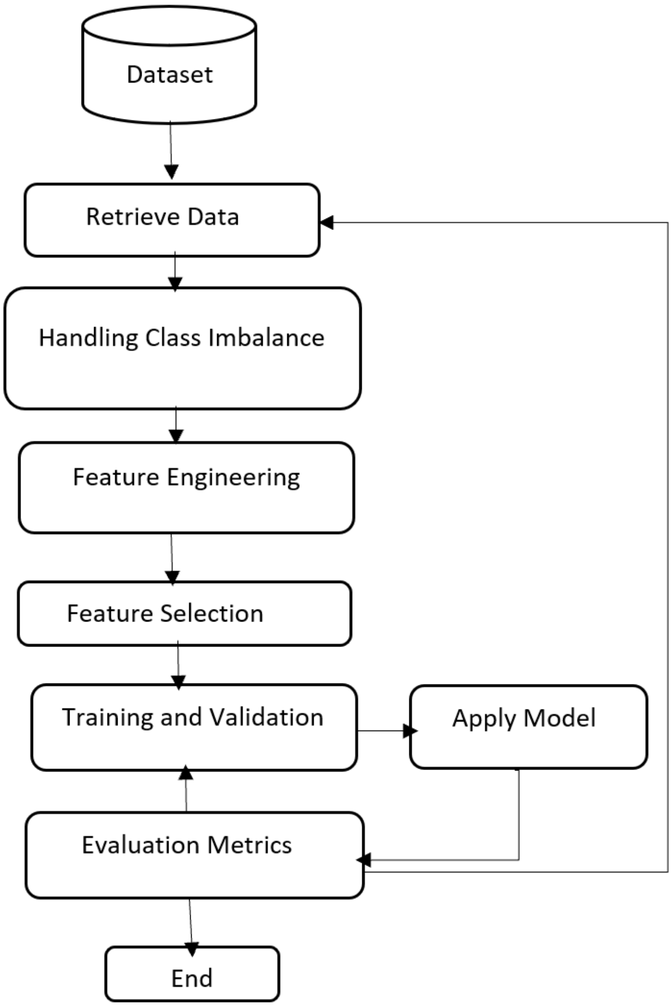

Figure 3.1: Supervised Learning Framework

signifies"1" = Recession and "0" = No Recession, in this context "Recession" means less than 0% growth. The data covered 27 African countries including: Morocco, South Africa, Tanzania, Rwanda, Eswatini, Togo, Burkina Faso, Angola, Tunisia, Nigeria, Kenya, Burundi, Benin, Namibia, Central African Republic, Sudan, Gabon, Niger, Sierra Leone, Lesotho, Mauritania, Senegal, Mauritius, Botswana, Cameroon, Zimbabwe and Mozambique. The above countries continued to live through unstable financial crisis [15].

In this study, focus was on countries that had ground of contributing to critical analysis of the economic recession since the 27 countries of focus have transitioned in and out of recession. Moreover, since recession is broadly viewed as a global economic recession, the set of data for this study was Penn World productivity, which includes a relatively high level of revenue, inputs, outputs and productivity for more than 180 countries, Bank of Canada index commodity indices and World Bank GDP growth data set.

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Energy, metals and minerals, forestry, agriculture and fish are among many indicators of economic recession in this study under year-on-year percentage change annual bank of Canada commodity price index. In addition, the price level indicators are imports, exports, capital stocks, capital formation, household consumption and consumption by the government. Moreover, the shares indicators include household consumption, gross capital formation, government consumption, merchandise exports, merchandise imports, residual trade and GDP statistical discrepancy at current purchasing power parities (PPPs).

3.4. Feature Selection

The key use of feature selection has been that: (a) it can train algorithm faster, (b) It simplifies the process of the ML algorithm and helps to make its interpretation uncomplicated, (c) identifying the most essential features which contribute the highest possible performance in ML [114]. In addition, the likelihood of over-fitting often raises the size of the feature space, therefore, feature extraction is an effective approach to preventing over-fitting [114]. Correlation matrix with heat-map is a common approach for visualisation features as such it will be used in this study as to effortlessly understand than reading tabular data [115].

3.5. Data Imbalance Problem

The data sample for this study represents non-recession overshadows the entire data. Therefore, oversampling techniques which includes ADASYN and SMOTE will be used to overcome this problem. Synthetic over-sampling approaches tackle this issue by producing samples of the synthetic minority class to equalize the dispersion between the majority class which includes about 92.81% of the sample and minority class which includes about 7.87% data samples.

3.6. Machine Learning Algorithms

In this study, the baseline model was acquired by using features identified from a heat-map correlation matrix which is the comparative analysis of measured values between each pair of dimensions. Therefore, construction of those models with regards to the wrapper and filter features identified using SMOTE and ADASYN sampling approaches. The interpretation of data to be presented in this study was also apply cross-validation specifically stratified k-fold cross validation. Furthermore, compared the performance of the above selected machine

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learning techniques using F1-Score, gini coefficient and ROC curve.

3.7. Evaluation metrices based on threshold

The evaluation metrices based on threshold used in this study are recall, precision, f1- score and cohen's kappa. All these evaluation metrics have a threshold level, beyond which positive instances are estimated and negative instances are estimated. It makes no difference how near an estimate will be to the standard for these metrics; what matters is whether it was higher or lower than the threshold.

3.7.1 Recall

A successful prediction model should have a high Recall as well as a high Precision. The recall is calculated as follows:

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{3.1}$$

Recall checks out of all the times, how many times that actual class was positively classified or recollected. For maximum recall which was one, we should have no false positives. Moreover, for minimum recall the is no false negatives.

3.7.2 Precision

Precision was defined as the degree of conformity between individual outcomes acquired within specified limits. Precision was determined by the concentration of random errors and had no relationship to the actual or given value of the evaluation. The precision is calculated as follows:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{3.2}$$

Figure 3.2: High precision and Low accuracy

Precision is typically calculated as the standard deviation of test outcomes. A high variance indicates less accuracy. More specifically, precision is described in greater description by

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[116] as: (i)repeatability, which is where the fewest variations are permitted, and (ii) reproducibility, which is when the precision of the technique as performed in different fields is considered.

3.7.3 F1 Score

The F1 score was used to measure a test's accuracy, and it balances the use of precision and recall. The F1 score can provide a more realistic measure of a test's performance by using both precision and recall [117].

The F1 score is calculated as follows:

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{3.3}$$

The F1-score, on a data set, was a measure of the accuracy of a model. It was an approach that combines model precision and recall, and has been described as the harmonic mean of model precision and recall [117]. The F1-score was effective in which false positive or false negative costs differ or if a huge class imbalance exists [117].

3.7.4 Cohen's kappa

Cohen's Kappa(also known as kappa) was first adopted by J. A. Cohen in the discipline of psychology as a benchmark of consensus in the middle of the pair judges, and was eventually included in the study as a determinant of performance in classifying [118]. More importantly, Kappa has been adopted in the classification as a benchmark of agreement between the measured and the actual and predicted subsets during data analysis. The Cohen's Kappa is

$$\zeta = \frac{Accuracy - \rho}{1 - \rho} \tag{3.4}$$

where ρ is the hypothetical probability of chance agreement, given by

$$\rho = \sum\nolimits_{i=1}^{n} \frac{K_{\mathrm{i}} x K_{\mathrm{j}}}{m^2} \tag{3.5}$$

For i = 1, . . . , m and j = 1, . . . , n. Moreover, K encompasses the actual and predicted subsets of the testing data. The integration of Kappa analysis into machine learning, especially financial data analysis, was still a recent research venture. Kappa can be insufficient under various conditions, especially where the distribution of data was unbalanced. If the distributions of the target classes are not similar, the optimal Cohen's kappa output will be smaller. However,

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when dealing with unbalanced data, Cohen's kappa seems to be more effective than overall accuracy. In terms of predicted precision of a single prediction, little can be said about Cohen's kappa.

3.8. Evaluation matrices based on probabilistic of errors

The evaluation metrices based on probabilistic of errors used in this study are accuracy and RMSE.

3.8.1 Accuracy

Accuracy is the proportion of exactly categorized instances in the test sample. Accuracy is given by

$$\rho = \sum_{i=1}^{n} \frac{K_{\mathrm{ii}}}{m^2} \tag{3.6}$$

Accuracy represents the reliability of an evaluation, while precision represents the repeatability of an evaluation. Precision without accuracy was completely ludicrous, but precision it doesn't in any way suggest accuracy.

Figure 3.3: High accuracy and Low precision

In essence, accuracy analyzes the diagonals of the confusion matrix since it does not encompasses whether the off-diagonal components contribute to the inaccuracies.

3.8.2 Root Mean Squared Error (RMSE)

The Root Mean Square Error (RMSE) was a classical way of evaluating a model's error in estimating quantitative results. RMSE's primary goal is to serve as a classifier for trained models and evaluating their accuracy. High RMSE results imply a large disparity among accuracy and predictions, indicating poor output [119]. When displaying the RMSE, the implicit premise was that the errors are unbiased and adopt a normal distribution. As a result, using the RMSE provides a more clear overview of the error distribution [120].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(PredictedValue_{\mathrm{i}} - ActualValue_{\mathrm{i}})^2}{n}} \tag{3.7}$$

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$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{3.8}$$

whereby

$\hat{y}_i = \hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are the predicted values of the features.

$y_i = y_1, y_2 \ldots, y_n$are the actual values of the features.

n is number of measurements.

i is the variable.

In comparison to the mean absolute error (MAE), empirical studies by [1] showed that the RMSE is the best statistics metric for a performance measure as well as a representation of the error distribution [120].

3.9. Evaluation metrices based on Ranking

The evaluation metrices based on ranking used in this study are gini coefficient, Kolmogorov-Smirnov (K-S) test, Matthews correlation coefficient and ROC curve. The metrics are only affected by the order in which the cases are presented, not by the actual expected values, therefore it makes no difference if expected values lies between various intervals as long as the order was maintained [121]. The ROC curve represents the true positive rate (TPR) as a function of false positive rate (FPR) , while the Accuracy-Recall curve represents precision as a function of recall.

3.9.1 Gini Coefficient

Gini coefficient (gini) was a recognized metric of inequality, it evaluates the distribution of inequality which can consider a value of 0 to 1, with 0 accounting for a totally equal distribution and 1 accounting for a totally unequal distribution [9]. Gini coefficient is how the model exceeds random predictions with regards to the ROC curve and can be calculated using the lorentz curve, which was a visual display of probability distribution showing relative frequencies.

The Gini Coefficient is

$$G = \frac{A}{A + B} \tag{3.9}$$

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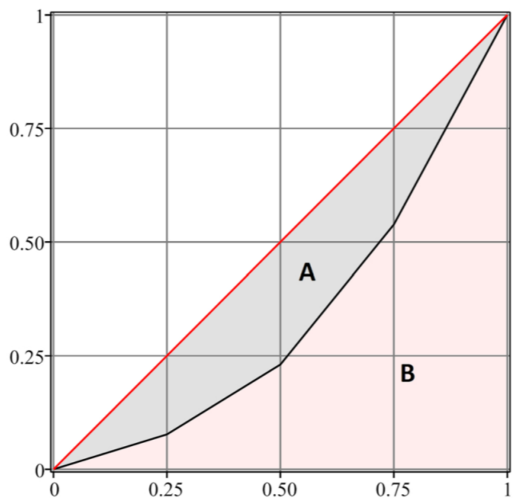

Figure 3.4: The discrete Lorentz curve [9]

G is therefore equivalent to 2A and 1 2B, because A + B = 0.5.

Then, the area under the Lorentz curve is

$$B = \frac{1}{2}\sum_{i=1}^{m}(D_i - D_{i-1})(P_i - P_{i-1}) \tag{3.10}$$

The system was split into equally sized components m. The attribute $k_i \geq 0$ is identified for each component i, with $k_1 \geq k_2 \geq \ldots \geq k_m$ as the calculated values. The limitation of gini is that the decision thresholds are not explicitly represented in the ROC summarise test performance over regions of the ROC space rarely operate and also is not sensitive to sample size change [9].

3.9.2 Kolmogorov-Smirnov (K-S) test

The KS Test was an effective instrument for rapidly distinguishing samples from various distributions. The cumulative distribution function (CDF), which was firmly established as an essential component of the KS test. Evaluating the test statistic utilizing empirical cumulative distribution functions was potentially the most difficult part, but the simplified version was to mathematically validate the more effective performance. Mapping out the CDF, F(k) for K random variable where k contains a set of potential values for the probability distribution K. The CDF of K was then identified as:

$$F(k) = P(K \leq k) \tag{3.11}$$

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The empiric CDF, only one observation of the KS test, is intended to equate the theoretical CDF along with empiric CDF as described [122].

$$Fs(k) = Ps(K \leq k) = \frac{1}{s}\sum_{l=1}^{s}(K_l \leq k) \tag{3.12}$$

A small sample of K-S test for any specified F(k) could tested then be analyzed as

$$Ds = \max_{k} |Fs(k) - F(k)| \tag{3.13}$$

The Kolmogorov-Smirnov test has many benefits, including non-parametricity and generalisation, and those are outweighed by limitations in establishing adequate proof to refute the null hypothesis.

3.9.3 Matthews correlation coefficient

Matthews correlation coefficient(MCC) determine the efficiency of the predictor as the ϕ-coefficient assess the relationship acquired by the interpolation of the Pearson correlation coefficient for binary variables [118]. The binary variables for MCC is ϕ= γ(X,Y) in which $X = (x_1, x_2, ..., x_m)^l$ and $Y = (y_1, y_2, ..., y_m)^l$ are m-dimensional vectors and are represented in this kind of form.

$$X_i = \begin{cases} 1 & \text{if recession} \\ 0 & \text{otherwise no recession} \end{cases} \tag{3.14}$$

$$Y_i = \begin{cases} 1 & \text{if recession} \\ 0 & \text{otherwise no recession} \end{cases} \tag{3.15}$$

The Pearson correlation coefficient for binary variables γ(X,Y) is given by

$$\gamma(X, Y) = \frac{\sum_{i=1}^{m}(X_i - \overline{\mathbb{X}})(Y_i - \overline{\mathbb{Y}})}{\sqrt{\sum_{i=1}^{m}(X_i - \overline{\mathbb{X}})^2} + \sqrt{\sum_{i=1}^{m}(Y_i - \overline{\mathbb{Y}})^2}} \tag{3.16}$$

Furthermore, MCC for binary classification is

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(FP + TN)(TP + FN)(FN + TN)}} \tag{3.17}$$

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3.9.4 Receiver Operating Characteristic (ROC) curve

Receiver Operating Characteristic (ROC) curve was a visual graph showing the analytical capacity of a binary classification method, as its discriminatory cutoff is diverse [10]. The ROC curves are obtained through defining the true positive rate (TPR) at different threshold environments against the false positive rate (FPR) [10]. We use the AUROC statistic to analyze the results, which is the region under the ROC curve, with AUROC = 1 for a perfect recession classifier and AUROC =0.5 for a reversible recession classifier. AUC between 0 and 0.5 on the ROC curve indicates that it rates a random positive example greater than a random negative example.

The highest probable ROC curve, was with an AUC of 1.0, rates all positives over all negatives. However, if you have a "right" classifier with an AUC of 1.0, one should be cautious because it most definitely means a there was a flaw in the model. AUC between 0.5 and 1.0 on the ROC curve indicates that it rates a random positive example higher than a random negative example more than half of the time. The AUC values for real-world binary classifications are usually in this range. AUC of 0.5 for the ROC curve indicates that it rates a random positive example greater than a random negative. As a result, the resulting classification model was essentially useless, as its statistical potential is no greater than random guess.

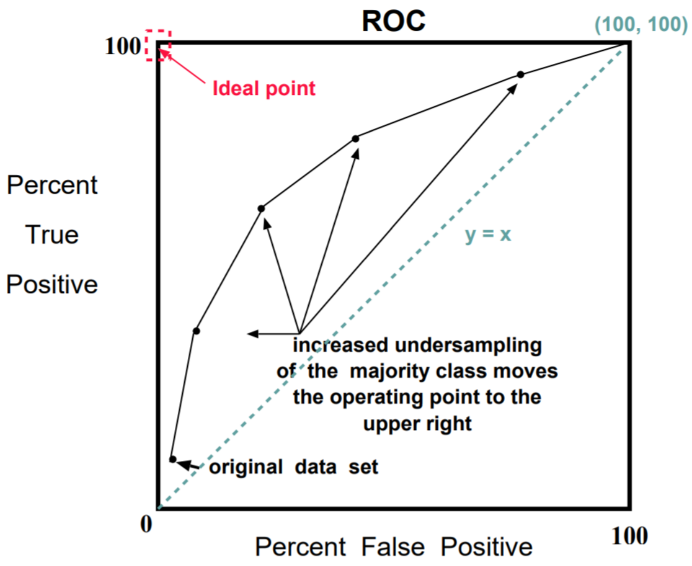

Figure 3.5: Visual interpretation of ROC curve [10]

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		Predicted value	
		Recession	No Recession
Actual Value	Recession	$TruePositive$	$FalseNegative$
	No Recession	$FalsePositive$	$TrueNegative$

Table 3.1: Actual and Predicted values

Crucial performance-classification components

$$Accuracy = \frac{TruePositives + TrueNegatives}{Positives + Negatives}$$

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

$$Sensitivity = \frac{TruePositives}{TruePositives + FalseNegatives}$$

$$Specificity = \frac{TrueNegatives}{TrueNegatives + FalsePositives}$$

Specificity indicates the amount of negatives properly described this will give the likelihood of a negative test implying that there would not be any recession happening, while sensitivity indicates the amount of positives described correctly. This will give the likelihood of a positive test that a recession will take place. Sensitivity does not really bring the false positives into consideration. The ROC curve, that provides a tradeoff between two variables, was used to determine how a model's output varies over the TPR and FPR.

3.10. Chapter Summary

Section 3.1 of this chapter provides an introduction to the methodology. Section 3.2 provides an overview of the classification workflow for this study, while Section 3.3 highlight the type of data sets that was used in this study. Sections 3.4 and 3.5 address feature selection methods and data imbalance problem. Section 3.6 provides an in-depth description of ML algorithms used in this study. Section 3.7 provides the evaluation matrices based on threshold, while sections 3.8 and 2.9 provides evaluation matrices based on probabilistic of errors and ranking respectively.

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Chapter 4
RESULTS ANALYSIS

4.1. Introduction

When data sets include data from classes of varying probability of incidence, the output of a machine learning algorithm may be negatively impacted. This issue is exacerbated as certain groups are characterized by a large number of samples and others are represented by a small number. This was the case with our data, which had a significant class imbalance, so we had to start by addressing the problem by selecting the best subsets for our study. In this analysis, we used cross-validation to validate our models, and to prevent fitting problems, both techniques used a test set to evaluate model performance. The major obstacle in the finance industry that is to develop machine learning approaches for intelligently leveraging information and extracting valuable insights.

In this study we have successfully developed two model that have improved the performance from the baseline model we had. In terms of accuracy, it yields sufficient results for the intended purpose. Furthermore, it captures close to the point of occurrence and makes accuracy adjustments explicit balanced with the use and effort. In terms of relevance, the data is relevant to the intended intent, and there is a quality assurance and feedback mechanism in place. Furthermore, it is reliable because the collection process is consistent. In terms of data validity, it can be used for definition and compatibility with other data. Moreover, the data used in this analysis contains no missing, invalid, or incomplete data.

4.2. Statistical characteristics of data

The section below provides insights on the statistical characteristics of data. The table below show the first ten features description on how the standard deviation, minimum, maximum, mean, count and quarterlies are distributed. This table highlight the high class imbalance and skewness that exist in the data.
The African country recession data sets display high imbalance with 92.81% of the samples being classified in "0" or "No Recession" and 7.82% of the samples in the "1" or "Recession". The study by [50] support our findings that algorithms for machine learning mostly result

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	pop	emp	emp_to_pop_ratio	hc	ccon	cda	cn	ck	ctfp	cwtfp
count	486.000000	486.000000	486.000000	486.000000	486.000000	486.000000	4.860000e+02	486.000000	486.000000	486.000000
mean	20.185755	7.121089	0.357865	1.777389	64361.006942	80885.988722	2.442244e+05	0.004583	0.454419	0.453431
std	30.037490	9.921471	0.080541	0.446339	129634.856793	156740.416624	4.725163e+05	0.008210	0.206562	0.203056
min	1.061468	0.243000	0.198212	1.069451	2781.259277	2984.366943	5.790397e+03	0.000124	0.098622	0.107790
25%	3.830730	1.048750	0.297922	1.445886	9117.209716	11081.697755	2.429231e+04	0.000514	0.301179	0.295615
50%	10.868272	4.184000	0.368841	1.689902	17471.495120	22228.022460	6.432356e+04	0.001355	0.400647	0.405870
75%	24.220695	8.517560	0.416717	2.117452	58016.873047	69676.791020	1.886244e+05	0.003227	0.616736	0.603459
max	190.886307	65.156548	0.555433	2.885300	758455.187500	896604.812500	2.886312e+06	0.041835	0.998187	1.031707

Table 4.1: Data description

in bias output based on the class ratio not being uniform, so this over-sampling approaches focusing on class imbalance will be used to overcome this problem. As seen in figure 4.2 imbalanced data distribution, the ratio is 1:10 which is high bias for our data. The imbalance

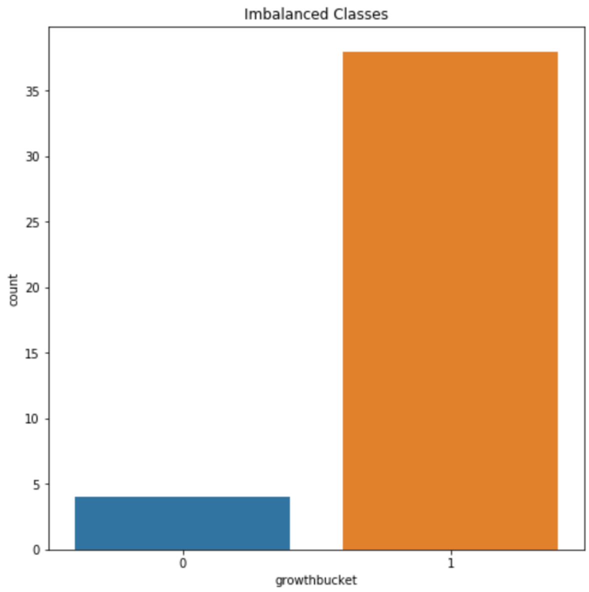

Figure 4.1: Imbalanced Data distribution

class problem as shown in the figure above was successfully solved using undersampling technique. The ratio is now 1:1 which is an equal number of classes. Oversampling will be highlighted in terms of correlation matrix.

This study support the study by [51] emphasises that the difficulty of dealing with imbalanced data sets was that too many machine learning algorithms would neglect, and hence behave poorly on the minority samples, despite the fact that performance on the sample was usually the most essential. Therefore, SMOTE was used in selecting samples in the feature spaces that are similar together as such distinguishing them by drawing a line between them by inserting a new sample across the line. Furthermore, the study encapsulate the analysis done by [56] which stipulate that the SMOTE algorithm produces an infinite number of synthetic minority cases in order to change the classifier learning bias against the minority class.

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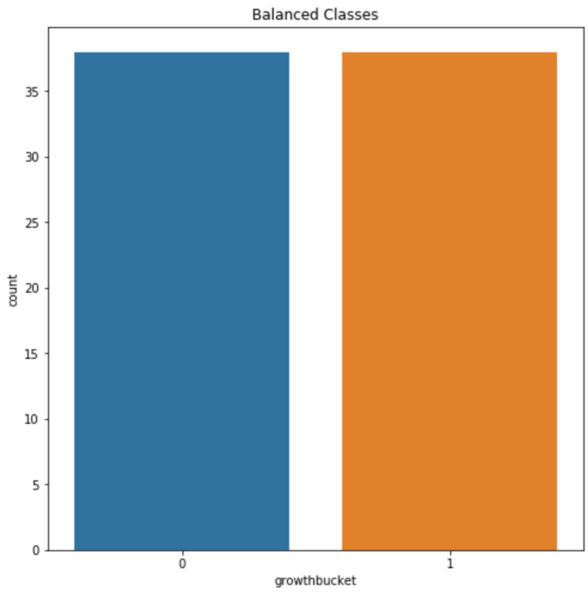

Figure 4.2: Balanced Data distribution

4.3. Feature selections strategy

In terms of feature significance, a correlation matrix was included in the assessment so that filtering and wrapping processes could be performed. The matrix highlights positions where there is a strong correlation between features and positions where there is a low correlation. The correlation matrix figure above encompassed the oversampling technique and as its shown in the figure the position of high correlation is centralized around the diagonal i.e area of green. This high correlation was utilized in obtaining feature importance of datasets.

4.4. Machine learning models

4.4.1 Random forest

In this model we have used (388,49) , (388,) for the training set and (98, 49), (98,) for the testing set. The table below shows the confusion matrix for RF that has true positive of 115 and true negative of 2, while the false negative of 1 and false positive of 4.

		Predicted value	
		Recession	No Recession
Actual Value	Recession	2	4
	No Recession	1	115

Table 4.2: RF Confusion Matrix

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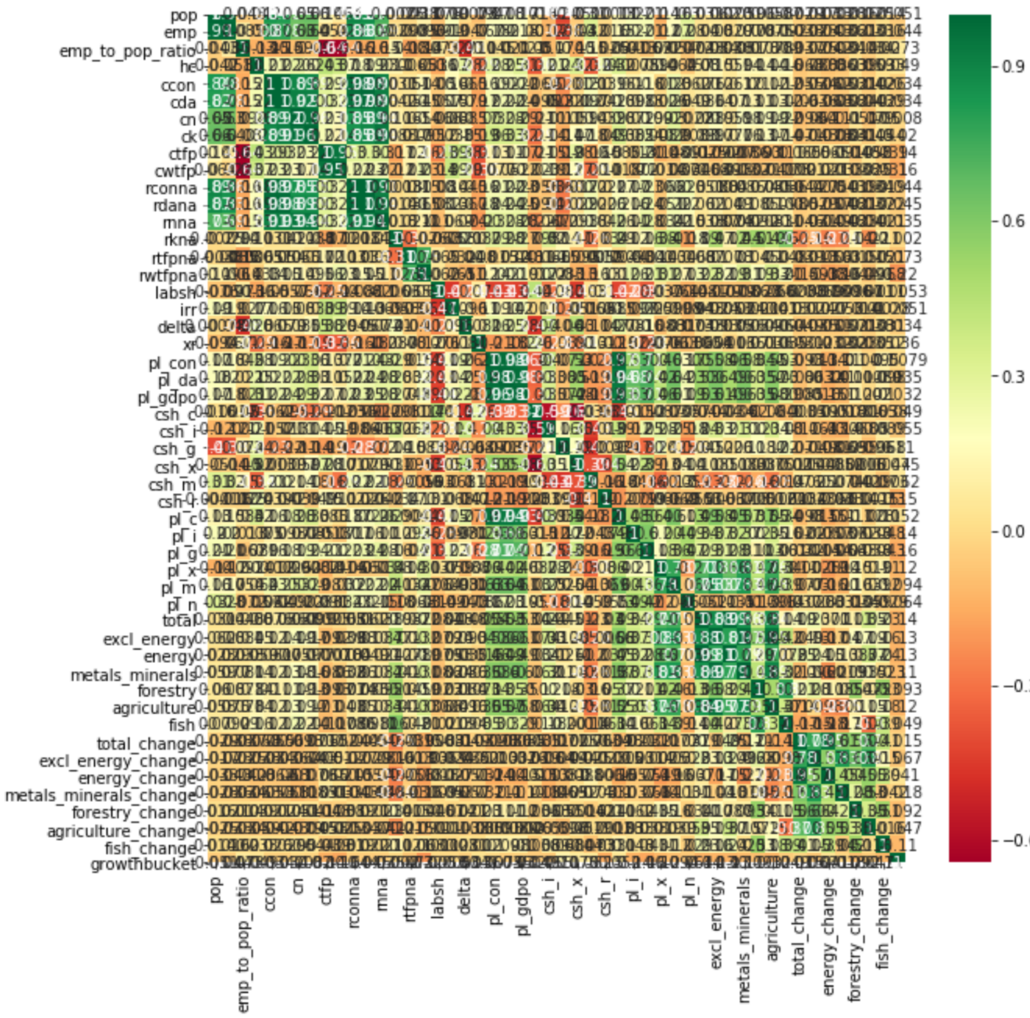

Figure 4.3: Correlation of the data

Precision, which can be used as a quality indicator for the Rf model, was found to be 0.67 , while recall was found to be 0.33 which can be regarded as a measure of quantity. This algorithm returns more important data than trivial ones, while at the same time returns the minority of relevant results. This outcome is supported by the study of [104] who has recorded precision for a much more accurate representation of actual results. In this analysis, the macro average for RF was found to be 0.82 for precision and 0.66 for recall, giving each prediction a comparable weight when measuring loss, but in our case where our data was imbalanced and certain predictions were more important (based on their proportion), we used 'weighted' average.

The the harmonic mean of the model's precision and recall which is F1 Score is 0.44. Furthermore, macro average for this matrices was found to be 0.71 with weighted average of 0.95. This model has a good F1-Score approximation of about 0.7, but it does not support the [116] analysis that indicates precision is inversely proportional to accuracy, since the accuracy for this model is 0.96. In terms of Cohen's Kappa which was found to be 0.43,

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Evaluation metrices based on threshold					
	Recall	Precision	F1 Score	Cohen's Kappa	Specificity
RF	0.33	0.67	0.44	0.43	0.99
macro average	0.82	0.66	0.71		
weighted average	0.95	0.96	0.95		

Table 4.3: Threshold for RF

the distributions of the target classes were not balanced, therefore the optimal Cohen's kappa output was smaller of which this result is supported by the study of [118].

Evaluation metrices based on probabilistic errors		
	Accuracy	RMSE
RF	0.96	0.20

Table 4.4: Probabilistic errors for RF

In this analysis, we obtained a low RMSE of 0.20 and an accuracy of 0.96, implying adequate accuracy dispersion. This study backs up [119]'s findings that low RMSE results indicate a significant discrepancy between accuracy and precision, suggesting high performance.

In this study, we have achieved an MCC of 0.45 which is a strong positive relationship

Evaluation metrices based on ranking	
	MCC
RF Value	0.45

Table 4.5: Ranking for RF

for the RF model. The line with no discrimination is a diagonal line running from the bottom left to the top right point. The points above the line of no prejudice reflect correct classification, while the points below represent incorrect classification. In this analysis for RF ROC curve, all of our points are over the line of no prejudice, indicating that we achieved positive outcomes.

In our study we have seen an increased accuracy and in turn lower variance this results correspond with the study of [109] that random forest produces several trees on data subset

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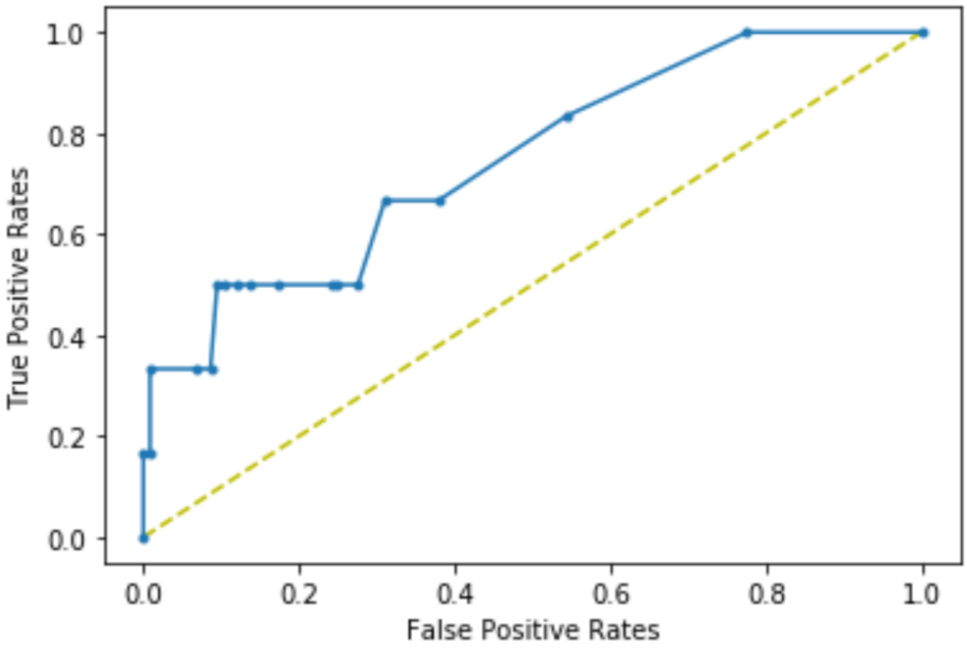

Figure 4.4: RF ROC curve

and merges all trees output and as a results it minimizes the risk of over-fitting in decision trees and then also lowers the variance and thus increase the accuracy. Furthermore, we have seen an increase in performance when we applied feature selection processes. The filter method decrease the size of features independently on a classification model, while the wrapper method assessed subsets with regards to the the performance of the classifier for binary classification. The result from this study supported findings by [112] that if the amount of possible features is low and the proportion of genuinely insightful features is maximal, a dilemma occurs as random forest classification efficiency increases significantly.

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4.4.2 Artificial Neural Network

In this model we have used (388,49) , (388,) for the training set and (98, 49), (98,) for the testing set. The table below shows the confusion matrix for RF that has true positive of 104 and true negative of 4, while the false negative of 2 and false positive of 12.

		Predicted value	
		Recession	No Recession
Actual Value	Recession	4	2
	No Recession	12	104

Table 4.6: ANN Confusion Matrix

Evaluation metrices based on threshold					
	Recall	Precision	F1 Score	Cohen's Kappa	Specificity
ANN	0.67	0.25	0.35	0.31	0.89
Macro average	0.78	0.62	0.65		
Weighted average	0.89	0.95	0.91		

Table 4.7: Thresholds for ANN

Table 4.6, it can be observed that the quantity measure, recall, was approximately three times higher than the precision quality. Precision was found to be 0.25, while recall was found to be 0.67. This imply that the model's degree of conformity between individual outcomes acquired within specified limits is quite low. This results are supported by study of [102] that precision is extremely unpredictable and that in some situations, in order to achieve high recall, we sacrifice precision. Moreover, the concentration of the random error in this model is poor as compared to the RF model above. As a result, the macro average of recall in this model is greater than that of precision. On the contrary, it was noticed that the weighted average of precision is 0.95, which is significantly higher than the weighted average of recall and F1 Score. Based on these findings, it is possible to infer that the RF model outperforms the ANN model.

We obtained a low RMSE of 0.20 and an accuracy of 0.89 for RF, indicating sufficient accuracy dispersion. This results also supports [119]'s findings that low RMSE results mean

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Evaluation metrices based on probabilistic errors		
	Accuracy	RMSE
ANN	0.89	0.33

Table 4.8: Probabilistic errors for ANN

a major difference between accuracy and precision, implying high efficiency.

Evaluation metrices based on ranking	
	MCC
ANN Values	0.33

Table 4.9: Ranking for ANN

In this analysis, we obtained an MCC of 0.45, indicating a clear positive association for the RF model. The line of no discrimination is a vertical line that runs from the bottom left to the top right edge, and the points above it represent correct classification, while the points below represent incorrect classification. AUC between 0.5 and 1.0 on the ROC curve indicates that it rates a random positive example higher than a random negative example more than half of the time which real-world binary classifications are usually in this range.

In this analysis for ANN ROC curve, all of our points are over the line of no preju-

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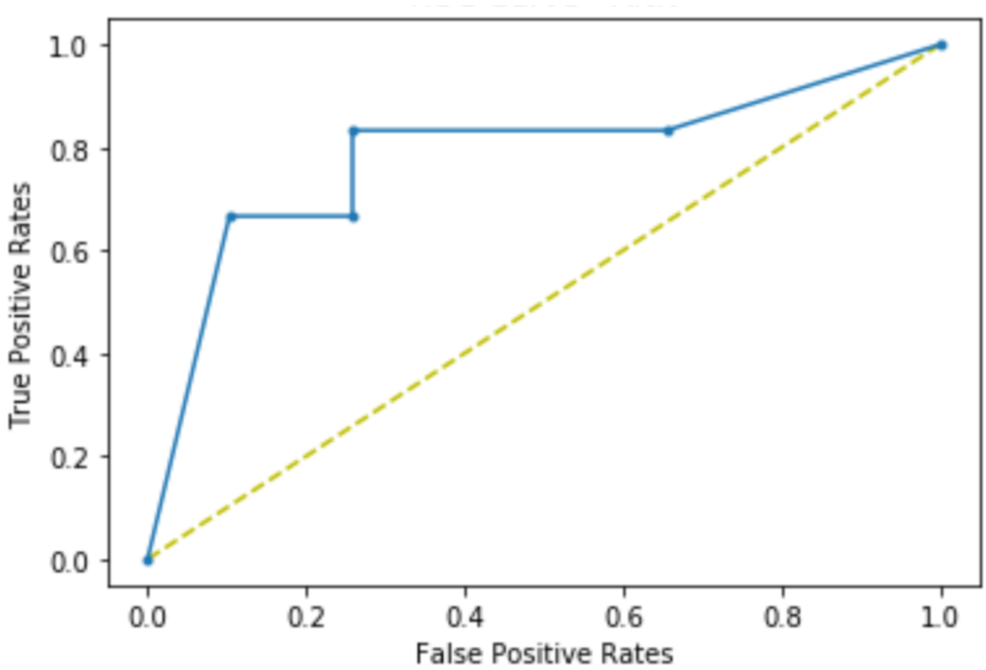

Figure 4.5: ANN ROC curve

dice, indicating that we achieved positive outcomes. This supervised learning model for classification group performed poorly as compared to the RF model, since the amount of accurate predictions for RF is higher than for ANN, making RF a better prediction model for our study. Furthermore, this ROC curve result makes use of [101] knowledge, as such the ROC curve produces positive outcomes; thus, the PR curve was regarded for analysis of such scenarios.

4.5. Chapter Summary

Section 4.1 of this chapter provides an introduction to the results analysis. Sections 4.2 and 4.3 details statistical characteristics of data and feature selection strategy. Lastly, Section 4.4 addresses machine learning models with emphasis on random forest and ANN.

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Chapter 5
SUMMARY, CONCLUSION AND RECOMMENDATION

5.1. Summary

To remove these growing ramifications during recessionary times, the study discuss the issue of selecting the most relevant features to improve the overall performance of the algorithm that would effectively predict recessions. Machine learning algorithms have been commonly used for pattern recognition, but little research has being conducted in finance, especially in recession. The primary aim of this study was to improve the prediction of economic recession using machine learning techniques.Furthermore, two develop an efficient model in order to refrain from enhanced government deficits, increasing inequality, considerably lower income and continually increased unemployment. This supported by establishing the relevant method for addressing imbalance data, developing relevant features to improve the accuracy of the model, establishing suitable features selection strategy to enhance the performance of the machine learning algorithm developed; and predict economic recession using ANN and RF.

5.2. Conclusion

When looking into analysis of the evaluation metrics of the two models, it was discovered that the RF outperforms the ANN. The features which are the most important were delta, ctfp, pln, pli, rtfpna rtwfpna, cda, ccon. Wrappers were relatively slower than filters in identifying the great subsets which supported the study by [70]. The size of the features were decreased to ten features as shown by their distribution below. In terms of the RF we obtain the Cohen's Kappa of 0.43 and MCC of 0.45 which are slightly better as compared to ANN model which achieved the Cohen's Kappa of 0.31 and MCC of 0.33. Moreover, in term of RMSE, ANN appeared to have performed better than RF. The proposed methodologies reached accuracy of 96% for RF and accuracy of 89% for ANN. ANN model performed poorly as compared to the RF model, since the amount of accurate predictions for RF was higher than for ANN, making RF a better prediction model for our study. In conclusion, the ML algorithm RF

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performed better at recession prediction than its rival ANN.

5.3. Recommendations

Future analysis with economic recession using ML techniques should include the incorporation of other approaches into the analysis, and feature selection should include additional performance metrics and visualization techniques. A large number of trees in a prediction algorithm made it inefficient and slow. This can be improved by adding new algorithms that are more encompassing in enhancing prediction.

5.4. Area of Further Research

ANN is hardware dependent and it has a reputation for incomprehensible network behavior, which has made it more difficult to verify the network's problem. This could be a subject for future research, and while it was not the primary focus of this study, it had a significant impact on identifying the flaws in some areas. In this research, we were able to successfully create two models that outperformed the baseline model. Nonetheless, due to the fact that two ML algorithms in this research were employed , further ML tools can be used to improve the statistical components of the study.

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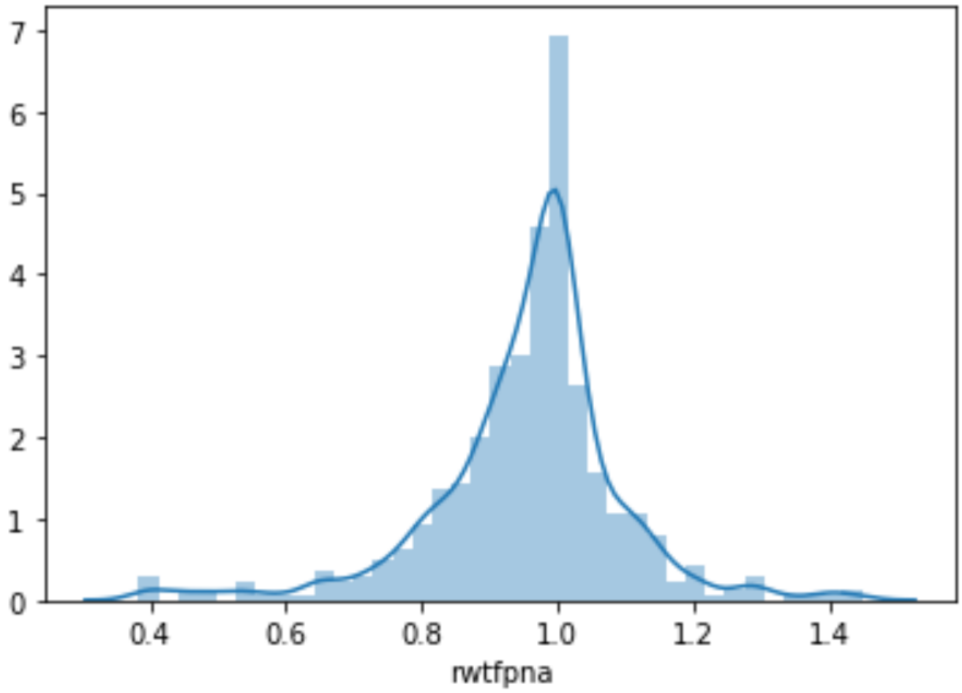
Appendix A

APPENDICES

A.1. The welfare-relevant TFP at constant national prices (2011=1)



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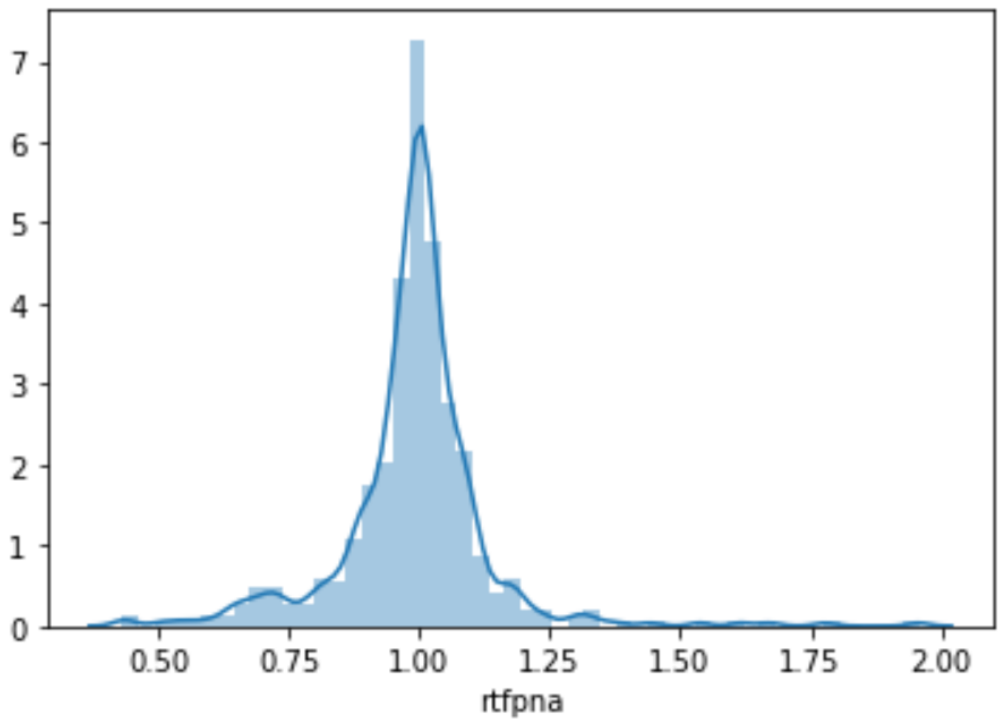
A.2. The TFP at constant national prices (2011=1)



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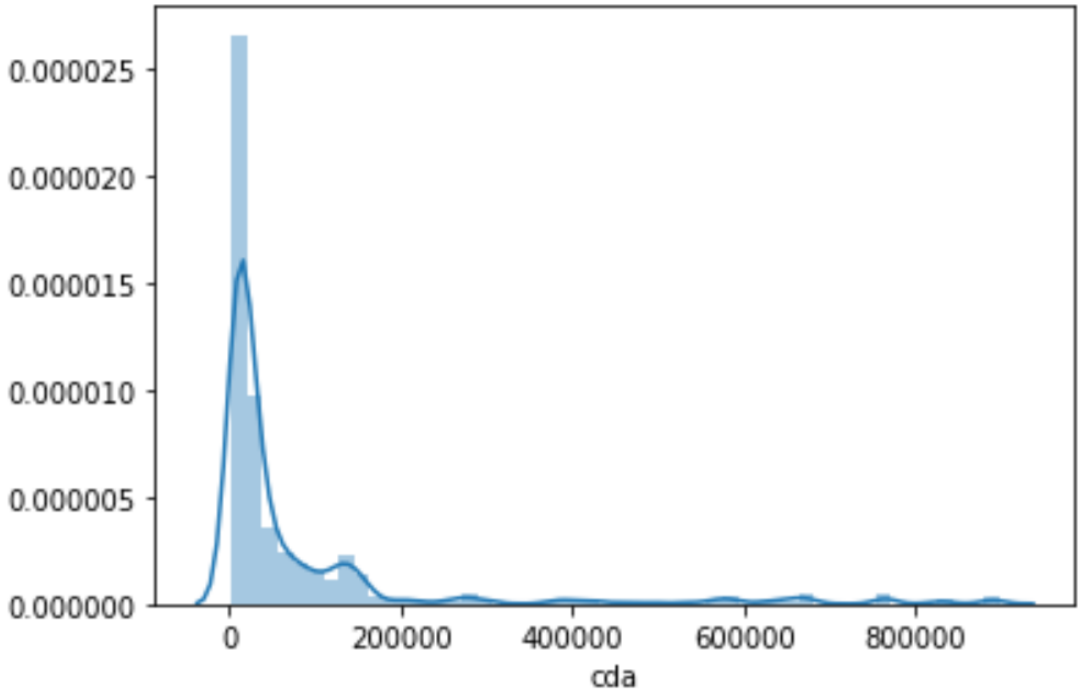
A.3. The real domestic absorption, (real consumption plus investment), at current PPPs (in mil. 2011US$)



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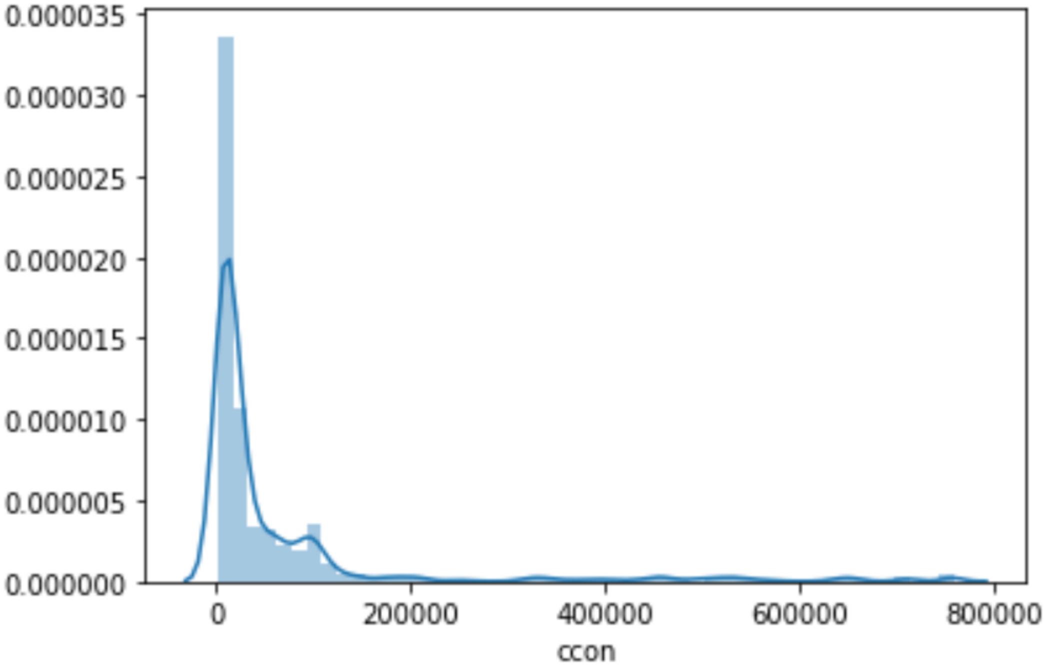
A.4. The real consumption of households and government, at current PPPs (in mil. 2011US$)



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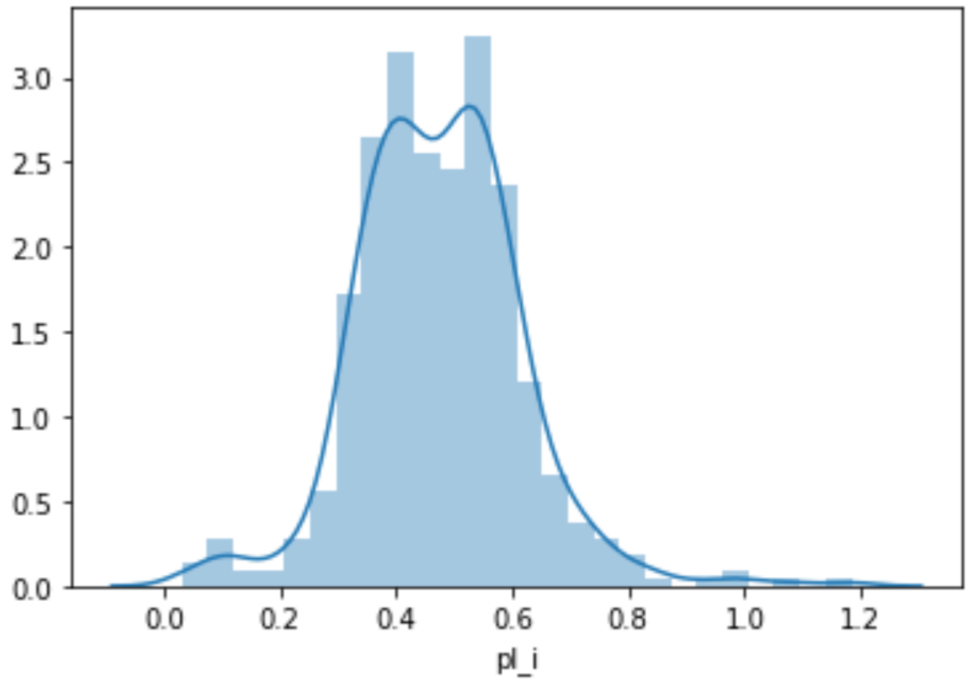
A.5. The price level of capital formation, price level of USA GDPo in 2011=1



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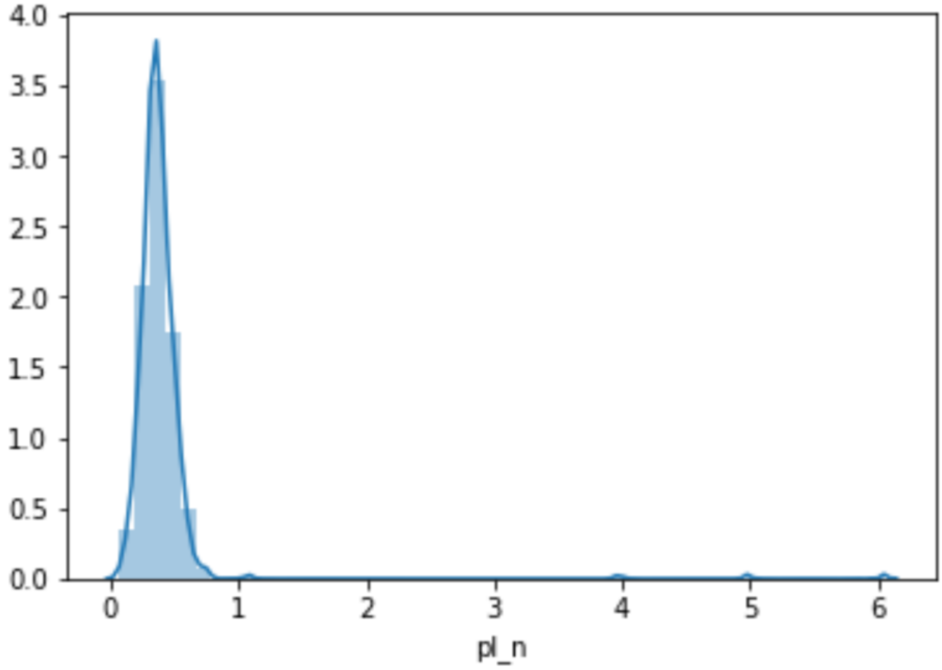
A.6. The price level of the capital stock, price level of USA in 2011=1



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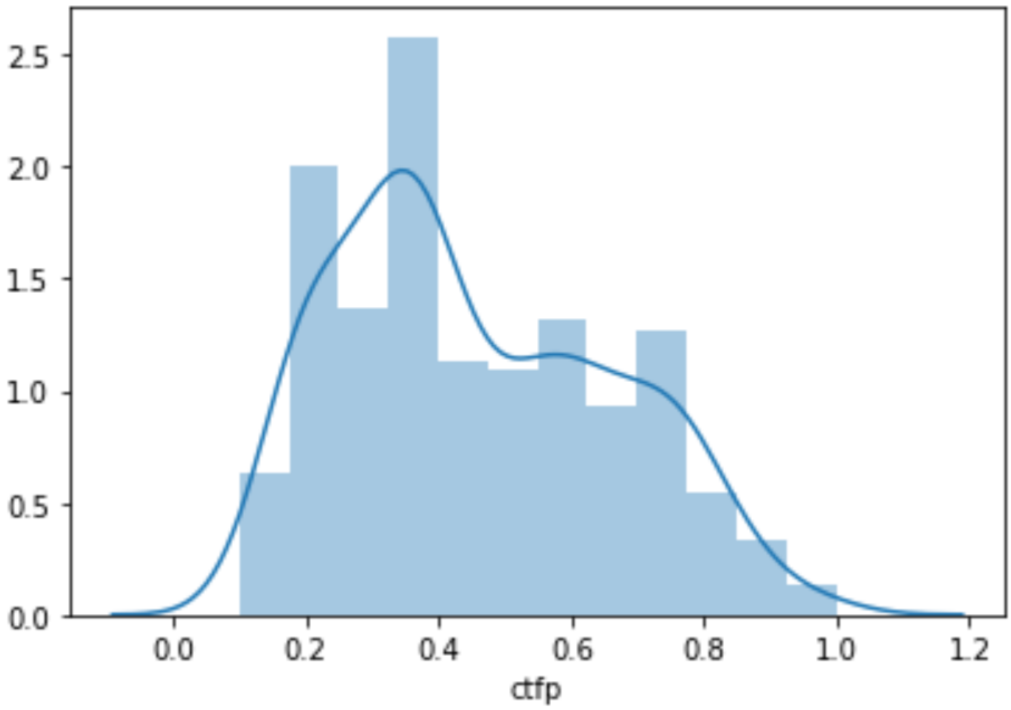
A.7. The TFP level at current PPPs (USA=1)



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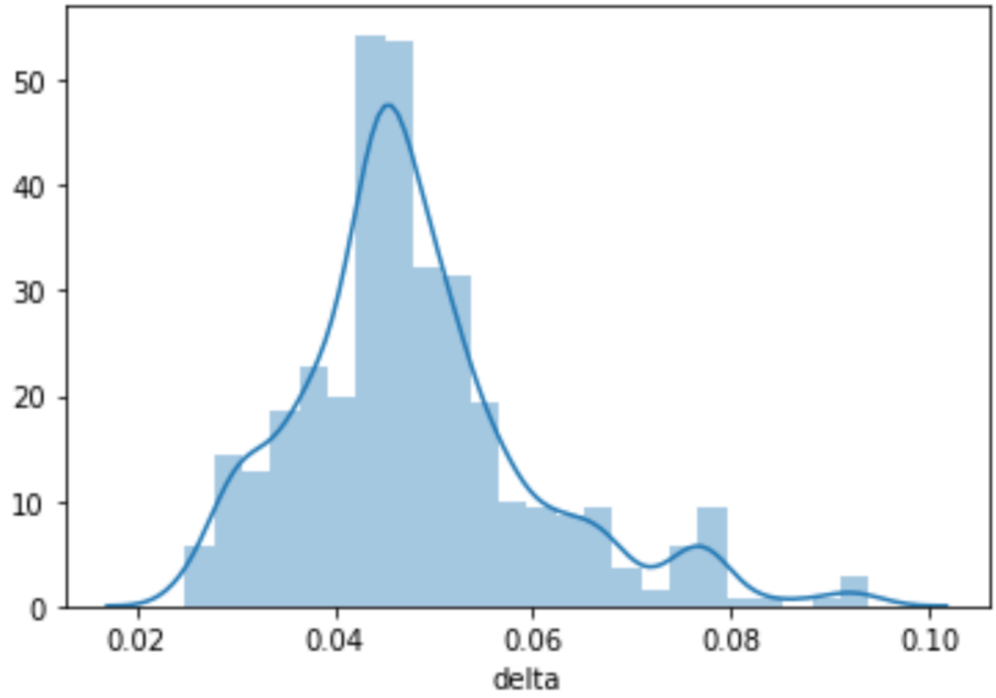
A.8. The average depreciation rate of the capital stock



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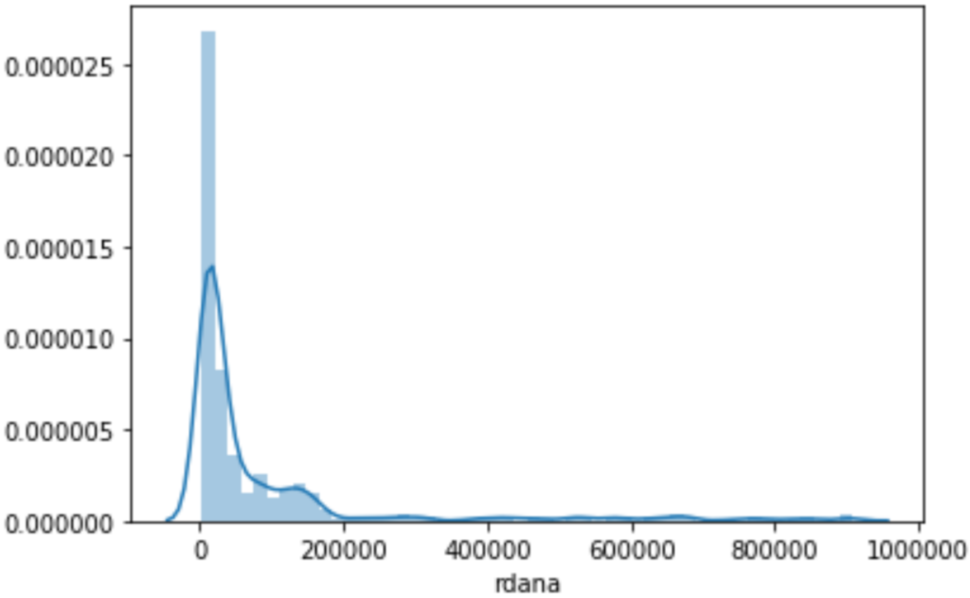
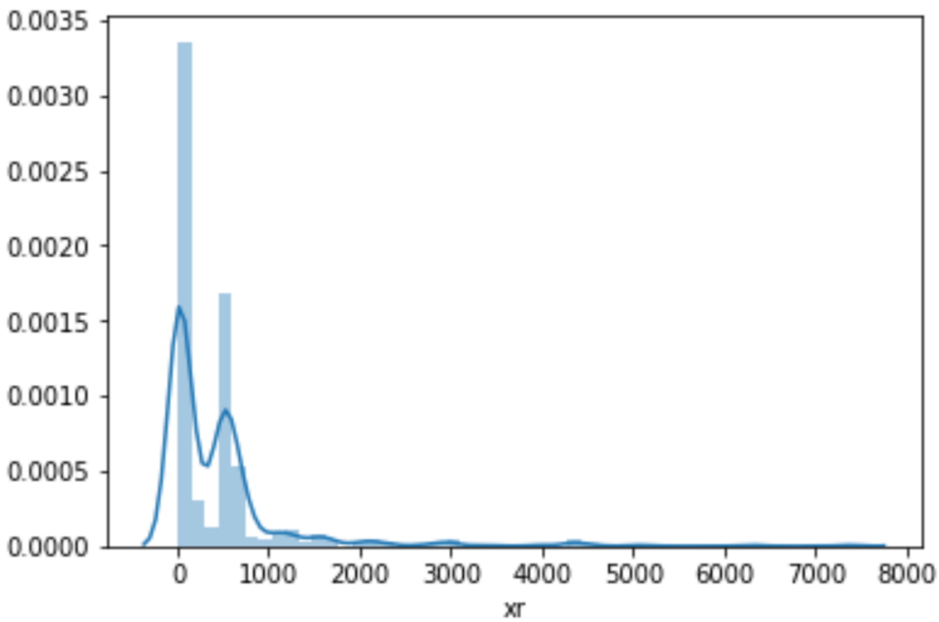
A.9. The real domestic absorption at constant 2011 national prices (in mil. 2011US$)



A.10. The exchange rate, national currency/USD (market+estimated)



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