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Forecasting Trade Balance Dynamics: A Machine Learning Approach. A Case Study of Zimbabwe

BY

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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS OF THE BACHELOR OF SCIENCE HONOURS DEGREE IN STATISTICS AND FINANCIAL MATHEMATICS.

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APPROVAL FORM

This is to certify, that this research project is the result of my own research work and has not been copied or extracted from past sources without acknowledgement. I hereby declare that no part of it has been presented for another degree in this University or elsewhere.

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Supervisor`s Declaration

I hereby declare that the preparation and presentation of this project are per the guidelines on projects laid down by Bindura University of Education, Zimbabwe.

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DEDICATION

I dedicate this project to my family members, Mr and Mrs Manjengwa, for their unwavering love and support.

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I would like to begin by thanking God for his continual guidance and protection while I studied at Bindura University's Department of Science Education. Reflecting on the highs and lows, I know obstacles made me stronger and gave me wisdom that I hopefully will be able to pass on to others one day. I owe a special gratitude to my supervisor, Dr. T.W. Mapuwei. His calm discussions and great encouragement helped me stay on track on the original focus of my research and throughout the process. Through his experience, I would learn how to narrow ideas which hopefully improved the overall quality of my work. I would like to also give a special thank you to Nokutenda, Emmanuel, and Nyasha for always being there during my most challenging times, this meant a lot to my mood when I needed it the very most. Lloyd was also important in this journey his quick comments, thoughtful edits, and late-night chats helped me cross the finishing line of my dissertation journey. Most of all, I am so grateful to my parents, Mr. and Mrs. Manjengwa. Their love, quiet faith and gentle encouragement has always inspired me to keep going. This achievement would not have been possible without their consistent encouragement and counsel.

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ABSTRACT

This study employed a quantitative inquiry of the plan that sought to model Zimbabwe's exchange urgency using a 15-year time-series dataset from January 2010 to December 2024. We obtained monthly exchange urgency data from national statistics agencies as they have a comprehensive check outline to capture economic cycles and seasonal variations. Our study examined the forecasting accuracy of classical and machine learning techniques such as (SARIMA), Long Short-Term Memory (LSTM) networks, Feedforward Neural Networks (FFNN), Back Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost). We properly planned the data set by making it stationary using normalisation and differencing. The models were trained and tested using time-based partitioning. Our preferred evaluation tools were Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as this allows us to compare the forecasting performance of each show. We concluded that deep learning models, and many particularly LSTM, may lessen the required models on economic forecasting projects where cyclical and seasonal factors must be considered. We recommend that economic planners and lawmakers adopt LST models to improve accuracy of exchange of plans and macroeconomic modelling. We further propose that future models combine hybrid and actual cases.

ABBREVIATIONS

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
SVM	Support Vector Machine
Xgboost	Extreme Gradient Boosting
LSTM	Long Short-Term Memory
FFNN	Feedforward Neural Network
RBZ	Reserve Bank of Zimbabwe

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Chapter 1

1.0 Introduction

Machine Learning is a part of AI that makes it possible for computers to learn from given sets of data, experience or examples. Beginning in the 1950s, artificial intelligence (AI) has grown into a multidisciplinary field with applications in almost every sphere of life. To find patterns and regularities in data, MA is an application of AI (Kulkarni & More, 2016). Thus, there are uses for machine learning in every business world. Macroeconomic variable forecasting is one such application, which is a helpful tool for all nations. It is noteworthy that machine learning and artificial intelligence have significant effects on international trade and macroeconomics.Trefler & Goldfarb (2018). Thus, Machine Learning has several applications in the economic sector. One such application is the forecasting of macroeconomic variables, a useful instrument for all countries. Notably, (AI) and Machine Learning have far-reaching consequences for global macroeconomics and trade, Goldfarb and Trefler (2018).

In a rapidly evolving global economy, the ability to forecast trade flows is essential for the growth and resilience of the nation in the economy. The policymakers require good data to develop good economic policy, while businesses need to know in order to weather market fluctuations as well as optimise their effectiveness. The SADC Free Trade Area (FTA) has been one of the predominant regional trade arrangements, whose aim is to liberalise intra-regional trade and enhance economic cooperation among members such as Zimbabwe.

Nevertheless, despite all these initiatives, the trade balance for Zimbabwe has continued to decline, citing a need for improved analytical approaches in order to better understand trade dynamics. Traditional statistical analysis methods are generally stumped by the complexity that forms part of trade data, particularly in a country like Zimbabwe whose external factors like forces of global market fluctuations, policy swings, and socio-economic influences have significant impacts (Chiripanhura & Mavhunga, 2021). In this context, Machine Learning provides a compelling option with advanced analytical power that can detect hidden patterns and provide dependable predictions from historical data (Zhang et al., 2021).This research aims to utilize sophisticated analytical methods, that is, machine learning to improve trade forecasting accuracy and make evidence-based recommendations that can guide Zimbabwe towards economic recovery and growth. Through the use of evidence from Zim Trade, the study aims to determine the major determinants of trade activities and create models that enhance the predictive power of trade forecasts. Ultimately, this project aims to contribute to scholarly discussion of trade analysis and equip policymakers and businesses with the capacity to deal with the complexity of international trade.

1.1. Background of Study

The economic history of Zimbabwe is marked by periods of hyperinflation, particularly from 2008 to 2009, when inflation reached astronomical levels, rendering the Zimbabwean dollar practically worthless (Chiripanhura & Mavhunga, 2021). This led use of a multi-currency regime, with the United State currency being the most widely used currency in formal for business operations. They reliance on foreign currency has had a direct impact on the country's trade performance. While Zimbabwe remains rich in natural resources, including gold, platinum, and agricultural products like tobacco, it faces significant challenges in transforming these resources into sustained export growth.

Imports, on the other hand, are critical for meeting domestic demand for products such as fuel, machinery, and foodstuffs, but Zimbabwe's ability to finance these imports is often constrained by a shortage of foreign currency (ZIMSTAT, 2020). The result has been recurring trade deficits, with imports consistently outpacing exports. For example, between 2017 and 2019, Zimbabwe's trade deficit averaged $2.5 billion annually, as the country struggled to boost its export capacity while continuing to rely on essential imports (Zhou, 2020).

Traditional forecasting methods, including econometric models used for forecasting, such as (ARIMA), have been used to analyses and predict trade trends. These models rely on historical data and linear relationships between variables such as GDP, exchange rates, and inflation (Mlambo, 2019). However, Zimbabwe's trade dynamics are complex, involving non-linear interactions between global market conditions, commodity prices, local economic policies, and external shocks like geopolitical tensions or pandemics. As a result, the methods use frequently predicting full spectrum of factors affecting Zimbabwe's trade performance.

It is hardly necessary to restate that the export-led growth hypothesis dominates Zimbabwe, but this does not negate the significance of Moyo and Mapfumo (2015) and

Pindiriri et al. (2014). This research is very to support trade growth hypothesis (e.g., Mafusire, 2001); exports or Cts encourage growth but use Artificial Neural Networks (ANNs) to model and forecast imports and exports. To date, this method has not been applied to Zimbabwe's export and import analysis. In the instance of Zimbabwe, this study is the first of its kind. Despite numerous trade policy reforms since independence, Zimbabwe's economy has had difficulty taking off (Bonga et al., 2015). After a protracted period of poor policy decisions and international isolation, Zimbabwe's thriving economy fell apart.

The country attained lower-middle-income status in 1982, just two years after gaining independence, with a GDP per capital of US$1205 and a expected life span of 61.4 years. In 2016, with a gross domestic product per capita of US$878.20 and an expected life span of 57 years, it dropped to low-income status. Comparing 2002–2012 to the 1990s, overall exports continued to decline in both volume and value. From a peak of roughly US$2.6 billion in 1997 to roughly US$1.3 billion in 2006, for instance, export revenues decreased 49%. The import bill grew quickly during that time, from US$2.2 billion in 1996 to roughly US$2.7 billion in 2006. According to the Zimbabwean government (2012), the trade balance has been negative since 2002Zimbabwe's exports dropped from US$3.6 billion in 2011 to US$2.8 billion in 2016, a 5.7% yearly decline. In 2016, the trade deficit was US$2.4 billion, while imports totaled US$5.2 billion. The current account deficit fell from 4.2% of GDP in 2016 to 4% in 2017 as exports rose. It is anticipated that export incentive programs, which were first introduced in 2016, will drop to 3.8% of GDP in 2018 due to the government's intentions to impose additional import restrictions and controls. Merchandise imports mainly finished goods, fuel, and electricity continue to surpass exports, the supply of much-needed foreign exchange is under strain: Because agricultural and mining account for 85% of our foreign currency eearnings, export diversification is essential. Machine learning, contrast, offers a more sophisticated approach to trade forecasting by leveraging large datasets and advanced algorithms to identify hidden patterns and relationships. Unlike traditional models, which require pre-defined equations and assumptions, Machine Learning (ML) can learn from using data and continuously improve its accuracy as more information becomes available. This adaptability makes Machine Learning particularly valuable in Zimbabwe’s context, where economic and trade conditions are highly volatile.

A real-life example that highlights Zimbabwe's trade challenges is the country's dependence on tobacco exports. Tobacco is Zimbabwe's top export commodity, accounting for nearly 20% of total export earnings in 2019 (Zim Trade, 2020). However, fluctuations in global demand for tobacco, coupled with changing consumer preferences and increasing global regulations on tobacco use, have made it difficult for Zimbabwe to maintain consistent export revenues. In 2020, the COVID-19 pandemic reduced worldwide supply chains, resulting in a decline of tobacco exports as logistics costs soared and demand dropped in key markets such as China and Europe (Zhou, 2020).

1.2 Statement of the Problem

The Zimbabwean economy has been characterised by a sequence of complex issues like hyperinflation, currency instability, and over-reliance on a narrow range of export commodities. Documentation issues have driven significant trade deficits with these trading patterns in trade where imports significantly exceed their exports. Thus, there have been chronic trade deficits stifling economic growth and development, largely due to heavy dependence on critical imports such as petroleum products, foodstuffs, and machinery. Eventually, the country is increasingly susceptible to exogenous shocks affecting its trade sector, such as market fluctuations, geopolitical military conflict, and consumer consumption changes. Although commerce is the backbone of the Zimbabwean economy, traditional methods of modelling trade flows using econometric models may not reflect the complexity of the trade situation. For the most part, the models rely on historical data as well as linear interdependencies between some economic activity and so they do not represent or capture the more complex and non-linear interdependencies of the trade market. This creates an alignment for greater mechanisms of analytics with some level of assurance that they can provide accurate and credible forecasting trade. Machine learning is considered one of the preferable solutions to the above challenges, which uses more advanced algorithms, data-driven approaches, offers an end-to-end solution. Provided the model evolves, so long as there is enough data, machine learning solutions offer reliable and consistent insights in real-time. Machine Learning can use specific algorithms to process large data sets and identify complex patterns to better predict export and imports overall trends. As such with machine learning increasing in terms of scope, creating more efficiencies for predictive analytics based on machine learning should not be a consideration.

The first stage of the challenges is going to be presented in this study, the lack of reliable forecasting models of Zimbabwe's export and import behaviour, negatively influencing trade and economic planning as well as informed policymaking. Through this study, an attempt is made to investigate the potential for applying machine learning to trade history data to develop more accurate forecasting models, identify determinants of trade performance, and evaluate the impact of external shocks of trade sequence. Through the solution of the aforementioned problem, this research hopes to development strategies that enhance trade performance and economic resilience in our country.

1.3 Research Objectives:

The purpose of the study to develop a machine leaning framework for forecasting export and import trends in Zimbabwe by using Artificial Neural Networks and Supporting vector Regression with the following objectives

1. To analyses Zimbabwe trade balance trends over period 2010 -2024
2. To assess the performance of Machine learning models (ANN and SVM) against traditional econometric models.
3. To forecast Zimbabwean trade balance over period of 2024 – 2030
4. To determine whether Zimbabwe has trade deficit or surplus

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1.3.2 Research Questions:

These research questions are designed to guide the investigation into export and import trends using machine learning techniques, providing a comprehensive framework for analysis.

1. How can machine learning models be used to accurately analyses Zimbabwe's trade balance trends?
2. How can machine learning techniques be effectively applied to forecast export and import trends in Zimbabwe?
3. How does the predictive performance of machine learning models compare to traditional econometric models in forecasting trade trends?

4. What insights can machine learning-generated forecasts provide regarding future market opportunities and risks for Zimbabwe's trade sector?

1.4 Significance of the Study

The research is significant to the list of stakeholders: government, researchers, business consultants, trade associations, chamber of commerce, financial institutions, investors and all other businesses in the nation. All concur that investment is key to economic development. The research recommendations will have a profound contribution to the Ministry of Industry and Commerce in crafting policies to inform government undertakings to trade policies that restore and economic growth rates in the Zimbabwe economy. For several years, business partners have been inclined towards the Western countries. Recently, though, the government's been really pushing to trade more with Asian countries, and like, especially China. You can totally tell because there's been a ton of projects that China's been working on. It's like, they're everywhere, you know? It's a big deal for the People's Republic of China, for sure. The study will also assist the trader whose mandate is to harmonies trade customs in the country, in developing policies that will enhance rather than suppress trade between member nations. One recalls the recent row between South Africa and Zimbabwe on the payment of border tolls, where the import tax is to be raised by 20%. This formed a lengthy and unjustified quagmire between the two countries. It was a deadlock that would hardly have arisen had decision-makers been well advised on the likely outcomes of their actions, diplomatically and economically.

In addition, accurate prediction of trade and better understanding of trade dynamics are central to building Zimbabwe's economic resilience. Given the country's history of economic volatility, the ability to predict changes in the flows of trade can help mitigate the adverse effects of external shocks, such as changes in commodity prices and global demand. This study aims to aid in policies that bring about economic stability, reduce trade imbalances, and promote sustainable growth in Zimbabwe. The study bridges the gap in literature on applications of machine learning in economic and trade analysis, particularly in developing countries. The study offers proof of the efficacy of machine learning techniques in precise trade pattern prediction and can serve as identity for future studies as well as spur future research into new methods of economic analysis.

This can create a move towards evidence-based methods in trade policy and economic planning.

The research will provide important data to existing empirical studies on trade balance effects on GDP growth as it will focus on Zimbabwe as a specific example. The research provides important findings that may be helpful in determining policy decisions. The research will enhance current knowledge by carrying out a thorough analysis of the subject matter in terms of Zimbabwe's economic condition despite the very diverse opinions concerning this issue.

This study extends beyond scholarly contribution; it attempts to provide lessons applicable to improving trade forecasting, informing policy intervention, and ultimately driving Zimbabwe economic growth and stability. Through the application of machine learning, the research aims to build platforms for more sustainable and informed trade practices in an increasingly interconnected and complex global marketplace.

The study will also be useful to the importers and exporters (individuals or companies) because it will enable them to understand the manner in which their activities create the growth of gross domestic products. In a way, it may enhance levels of patriotism among entrepreneurs, as the profit motive may be a greater concern to them.

1.6. Limitations of the Study

The study aims to provide valuable detailed into applying machine learning for forecasting export and import trends in Zimbabwe. Several limitations may affect the research findings and their generalizability. Acknowledging these limitations is crucial for contextualizing the results and understanding the scope of the study. The following are the key limitations:

1.6.1 Data Availability and Quality

The accuracy and reliability of machine learning models deeply depend on the quality of data and completeness of data used for analysis. In Zimbabwe, there may be challenges related to:

- **Incomplete Data:** Historical trade data may be incomplete or missing, particularly for certain periods or specific commodities. This could impact on the robustness of the analysis and the models developed.
- **Limited Access to Real-time Data:** The lack of access to timely and comprehensive trade data may hinder the ability to capture the most current trends and patterns, which is critical for effective forecasting.

1.6.2 Model Complexity and Interpretability

Machine learning models, especially complex algorithms like neural networks and ensemble methods, can sometimes function as "black boxes." This complexity may lead to:

- **Reduced Interpretability:** While these models may provide accurate forecasts, their intricate nature can make it challenging to understand the underlying factors influencing predictions. This could hinder the ability to derive actionable insights for policymakers and stakeholders.

- **Overfitting Risk:** Complex models may overfit the training data, capturing noise rather than genuine patterns, which can result in poor performance when applied to unseen data.

1.6.3Economic and Political Instability.

Zimbabwe's economic landscape is characterised by volatility, which can affect trade dynamics and complicate forecasting efforts. Factors contributing to this instability include:

- **Policy Changes:** Frequent changes in government policies, trade regulations, and economic strategies can lead to unpredictable shifts in trade patterns that may not be adequately captured by historical data.
- **External Shocks:** Events such as global economic downturns, changes in commodity prices, or geopolitical tensions can significantly influence trade flows and may not be anticipated in the modeling process.

1.6.4.Generalization of Findings

The findings of this study may be specific to Zimbabwe and its unique economic and trade context. As such:

- **Limited Applicability to Other Contexts:** The insights derived from this research may not be directly transferable to other countries or regions with different economic structures, trade dynamics, or political environments.
- **Focus on Specific Commodities:** The study may primarily focus on certain key export and import commodities, which could limit the broader applicability of the findings across diverse sectors of the economy.

1.6.5 Resource Constraints

Researching machine learning applications in trade analysis can be resource-intensive. Limitations in terms of:

- **Time and Funding:** Limited time and financial resources may restrict the depth of analysis, the complexity of models employed, and the range of data sources considered.
- **Technical Expertise:** While the research team may possess foundational knowledge of machine learning, the complexity of advanced techniques may necessitate additional training or collaboration with experts, which could impact the study's timeline and execution.

1.6.6 Ethical Considerations

The use of machine learning in trade analysis raises ethical considerations, particularly concerning:

- **Data Privacy:** Ensuring that the data used complies with privacy regulations and ethical standards is crucial. Any breach of data privacy could compromise the integrity of the study and its findings.
- **Bias in Data and Algorithms:** Machine learning models can inadvertently perpetuate biases present in the training data, leading to skewed results. It is essential to remain vigilant about potential biases and take steps to mitigate their impact.

1.7.Delimitations

The research on machine learning's application in Zimbabwe's export and import trends is defined by specific delimitations set by the researcher. Geographical Scope: The study is specifically focused on Zimbabwe and its trade dynamics. While global trade trends and international factors will be considered, the analysis will primarily concentrate on Zimbabwe's export and import activities, excluding other countries or regions. This focus is intended to provide a detailed understanding of Zimbabwe's unique economic context and trade challenges.

Time Frame: The analysis will utilize historical trade data from a specified time frame, which will be defined in the methodology chapter. For instance, the study may examine trade data over the past five years to identify trends and patterns. This time frame allows for a comprehensive analysis of changes in trade dynamics while ensuring that the data remains relevant to current economic conditions.

Data Sources: The research will rely on specific data sources, including historical trade data obtained from Zim Trade, ZIMSTAT, and other relevant government agencies. Secondary data from academic journals, reports, and statistical databases will also be utilized. The study will not include primary data collection methods, such as surveys or interviews, due to resource constraints and the focus on quantitative analysis.

Machine learning offers a variety of techniques for data analysis, This study will focus on selected algorithms that are deemed most appropriate for forecasting trade trends. Techniques such as (ANN), (SVM), and time series forecasting methods will be employed. Other machine learning algorithms or hybrid approaches will not be covered, as the aim is to maintain a focused analysis on the chosen methods.

Policy Context: The research will not delve into the political context or specific policy decisions made by the Zimbabwean government, though these factors may indirectly influence trade dynamics. The focus will be on economic variables and their relationships with export and import trends, allowing for a more data-driven analysis without extensive political commentary.

Outcome Measures: The primary outcome measures for this study will be the accuracy and reliability of the machine learning models in forecasting trade trends. Other potential impacts of trade policies or broader economic changes will not be quantitatively assessed within the scope of this research.

1.8 Definition of Terms

This section provides definitions of key terms used throughout the study, ensuring clarity and understanding for the readers. These terms are integral to the research on applying machine learning to forecast and analyze export and import trends in Zimbabwe. Artificial Intelligence (AI), according to Yeo et al (2000) AI refers to intelligence displayed by machines. AI is the opposite of natural intelligence , which refers to the intelligence exhibited by humans and other animals. AI is essentially implemented using an intelligent agent that is any representation of device and or algorithm that studies its environment and suggests or implements an action to successfully achieve a stated goal. AI systems learn by examining patterns in provided data. In 2016, Goodfellow et al. Machine learning is an approach used in artificial intelligence (AI), which is the study of algorithms that enables computer programs to automatically get better with time. (Mithell 1997**)** Learning by machines Additionally, machine learning can be separated into three primary categories: reinforcement learning, unsupervised learning, and supervised learning. The use of machine learning on datasets with the goal of precisely forecasting future outputs (known as predictors in statistical literature) and outputs of interest (known as dependent variables in statistical literature) is known as supervised learning.

Friedman and associates (2009). The system is trained using labelled data in supervised machine learning. Each data point is categorised by labels, such as "Bananas" or "Avocado," into one or more groups. The system then learns the structure of this data, which is referred to as training data, and uses it to assess new or test data and appropriately classify it. Learning without labels is called unsupervised practice. The Royal Society (2017). The process by which an agent learns how to maximize a predetermined reward signal is known as reinforcement learning. Barto and Sutton (2018). The practice of reinforcement is not covered in further detail in this paper because there aren't many actuarial problems that can be linked to this kind of learning, and Parody (2016) offers guidance on how to apply it in the insurance industry..

Prediction

Forecasting is the process of estimating future values based on historical values and other pertinent data, according to Hyndman and Athanasopoulos (2018). Forecasting helps businesses and policymakers make well-informed decisions by predicting changes in import and export volumes. For efficient resource allocation and economic planning, accurate forecasting is necessary.

Export

An export is a good or service produced in one country and sold to another. Exports are vital for a country's economy as they generate revenue and contribute to economic growth. In Zimbabwe, key exports include agricultural products (such as tobacco and cotton), minerals (like gold and platinum), and manufactured goods.

Import

An import is a good or service purchased from another country and brought into the domestic market. Imports are crucial for providing essential goods and services that may not be available or produced in sufficient quantities within a country. Zimbabwe mainly depends on imports for a range of products, such as food, machinery, and fuel.

Balance of trade. A country's trade balance is the difference in its trade balance over a specific time period. The trade balance is positive (trade surplus) when exports exceed imports, and negative (trade deficit) when imports exceed exports. The trade balance of a country is a crucial indicator of its economic health.

1.9 Organisation of Study

The problem identified, the research questions to be addressed, and pertinent background information are introduced in the first chapter. The necessary theoretical and empirical frameworks proposed by other researchers, along with their research findings where the problem was discussed and analyzed, are provided in the next chapter. Research methodology will contain descriptions of the methods used to investigate the problem. The main areas are the research design, sample design, and the research instruments used in conducting the research. Chapter 4 deals with data analysis and it will be 19 focused on the presenting collected information, analysis, and discussion of results. The last chapter consists of the conclusions and recommendations based on the research findings

1.10 Chapter Summary

This chapter 1 introduces the study, focusing on the use and effectiveness of machine learning to forecast trade dynamics (export and import)trends in Zimbabwe. It highlights the importance of trade for Zimbabwe's economy, particularly in light of its historical economic challenges. Traditional forecasting methods are inadequate in capturing complex trade dynamics, necessitating more advanced approaches like machine learning. This study is organized as follows: Chapter one - Introduction- gives a brief information of the topic and explains the author's motivation for choosing this topic, Chapter 2- Literature review- summaries the most important pieces of literature on the topic and provides additional background for understanding the proposed topic and the feasibility of proposed methodologies, Chapter 3- Methodologies description- provides background on the used machine learning methods, including, but not limited to, runtime analysis, hyper-parameters and discussion of some of their drawbacks, Chapter 4 Dataset Description- describes the uniqueness of the data. Data manipulation- follows up on the previous chapter to explain the techniques used to cleanse and transform of the data. Chapter 5 Results Comparison- compares results from the gravity equation and the three machine learning techniques against each other not only in terms of numerical accuracy, but also in terms of ease of interpret-ability and it also highlights certain limitations of the techniques used, and finally, Chapter 5 Conclusion- summaries the most important results from this thesis and suggests areas for further research.

CHAPTER 2 : LITERATURE REVIEW

2.0 Introduction

The aim of this study was to investigate causal relationship between imports, exports and economic growth in Zimbabwe. The study will be guided by the following specific objectives: to examine the effect of imports on economic growth and to investigate the effect of exports on economic growth. Economic growth key indicator is inflation rate, GDP, human development index, poverty rate and also others.

2.1 Review of Theories

Using data from 1975 to 2002, Narayan et al. (2008) used ARIMA models to forecast Fiji's imports and exports. They discovered that imports would exceed exports between 2003 and 2020, and that current account deficits would average F$934.4 million during that time. Using data from July 1998 to July 2009, Khan (2011) examined Bangladesh's total imports using the SARIMA, Holt-Winters, and VAR models. They came to the conclusion that the VAR model performs better than the other models at predicting Bangladesh's total imports. Using data from 1947 to 2013, Farooqi (2014) used the ARIMA approach to analyze Pakistan's trade balance and discovered that the SARIMA (2, 2, 2) and SARIMA (1, 2, 2) models were appropriate for predicting Pakistan's yearly imports and exports, respectively. Using a data set spanning the years 1989 to 2014. She discovered that while both models produced results that were essentially identical, more research should look into the ANNs technique because of its superior forecasting capabilities. Using data from 1993 to 2016, Baxter and Rising, these two 2018 people, went all the way with the ANN approach to forecast what Australia's export air cargo would be. And believe it or not? They thought it's really good at forecasting the amount of things we're we get export out of every year. They tried different numbers from like, a long time ago, 1968 to 2017. Then Alam, another chap in 2019, took the same ANN idea and mixed it with a thing called SARIMA, which is basically the cool cousin of ANNs, and tried to predict the Saudi Kingdom's yearly trade stuff. It turns out that the ANN and these ARIMA models (basically, the high-faulting' versions of forecasting future trade) are actually quite accurate in estimating how much the nation will buy and sell within a year. So yes, ANNs and ARIMA can be useful tools for being aware of what's going on with export and import in Saudi.

2.2 The H-O Theory or Eli Heckscher and Bertil Ohlin Theory

Eli Heckscher and Bertil Ohlin developed this tidy idea that is called the Heckscher-Ohlin theory, which is basically an elegant way of explaining how countries export and import from each other. Basically, it's just the fact that countries have different amounts of things, like laborers, land, and machines, and because of that they are good at making certain things. This theory holds that if a given country has more of something than another, they can then produce it less expensively and better, which is their "comparative advantage." It's much like you and your friend working on a project and you know you're that much more mathematically inclined, so you'll handle all the math part while your friend handles what they're better at. When a country has a relatively abundant resource, it can produce goods more efficiently. The Heckscher-Ohlin theory states that trade enables each nation to specialize. In exchange for goods, it is less equipped to produce; each nation exports the product it is best suited to produce.

2.3 Trade Promotions

Trade encourages the use of a greater (Romer, 1987) and better (Aghion and Howitt, 1992; Serletis, 1992) range of capital equipment and intermediate products. According to Broda et al. (2006), imported varieties contribute 15% of productivity growth in a typical country worldwide, with the effects being more pronounced in developing nations. For the much-needed knowledge spillovers between nations, trade is essential (Grossman and Helpman, 1991). International trade is essential to a country's economic development and growth (Smith, 1776; Marshall, 1890). Economic growth is fuelled by international trade (Nurkse, 1961). Exports are crucial in Zimbabwe because, as demonstrated by Mafusire (2001), Ogbokor (2005), and others, they significantly and favorably impact economic growth.As demonstrated by Mafusire (2001), Ogbokor (2005), et al. Puruweti (2016) exports are extremely important in Zimbabwe because they significantly and favorably impact economic growth. On the other hand, research by Pindiriri et al. (2014) has demonstrated that Zimbabwe's economic growth is significantly and favorably impacted by the import of capital goods and intermediate inputs. This demonstrates beyond a reasonable doubt that both trade balances are crucial for Zimbabwe. It implies that Zimbabwe cannot experience any significant growth in the absence of international trade.

2.4 Artificial Neural Network Models

The simplified model of biological neurons serves as the foundation for artificial neural network models. This has made it possible for them to mimic the composition and operation of biological neurons. Similar to biological neurons, artificial neurons are also occasionally referred to as the perceptron model. Their usage is depicted in the diagram below.

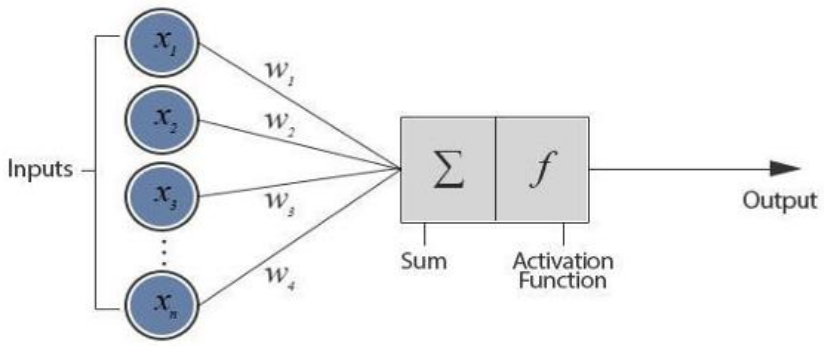

Figure: 2.1 The Perceptron Model (Pitts, McCulloth, 1943)

The basic typical perceptron model will have a variety of inputs, as the above diagram illustrates. Every input is weighed separately. Each of the perceptron model weights is multiplied by an input, which either raises or lowers the initial input signal. are then added up from each input, and the summation is passed through.

2.5 Learning of a neural network

Learning is the process of connecting various events with their outcomes (Buffet 2015). According to his argument, learning thus turns into a likely attempt to support the cause-and-effect principle. Machine learning (neural networks) has an advantage over biological neurons (humans) in that it can handle, assimilate, and act upon vast amounts of data. Another advantage is that, in contrast to human neurons, the accuracy and processing time are significantly faster and more dependable. It has been observed that the data and figures produced by stock exchanges typically exhibit a trend and sequential pattern that can be readily recognized by a neural network after it has been trained.

2.6 Supervised Learning

According to Makridakis and Anderson (2014), the learning algorithm that is categorized as supervised learning adheres to a pattern that requires that the network's intended output be known and provided for. Accuracy is a crucial desired outcome in the complex process of training the inputs to produce the outputs. The degree of error margin will be decreased by regularly updating the weights.

2.7 Unsupervised learning

In unsupervised learning, the network is supposed to analyze the pattern in the input; it is the neural network's responsibility to produce the output without outside assistance, claim Makridakis and Anderson (2014). Typically linked to data mining, this kind of learning paradigm is intricate. Due to its capacity to forecast an output based on the calculations of other comparable outputs it has learned from, this form is adopted by many algorithms.

2.8 Prediction techniques used

The significance of a stock's price has garnered a lot of attention from investors in recent years (Okan et al, 2009). The desire to analyze, predict, and plan investment portfolios is what motivates this focus. Profitability, dividend accumulation, and an initial return (ROI) are the goals of any investment. In light of this, making predictions is crucial and worthwhile in any market. Accurate computational prediction models are necessary because factors such as trading volumes, turnovers, exchange capitalization, share price fluctuations, and market indices become the deciding factors in any investment decision. Trading volume and price volatility are positively correlated, as is primarily shown in economic and financial literature. In contrast to the volume growth rates that were previously generated. Utilizing the Standard and (poor S&P) index from the daily aggregate data, the evaluations were conducted using a linear distributed lag and VAR model.

2.9 Time series forecasting

According to Jennings and Kulahci (2008), time series forecasting treats a system as a "black box" and looks for the variables influencing its behaviour. They contend that while time series predictions analyse patterns and generate a forecast, the factors influencing behaviour are not readily apparent and simple. Treating a system as a "black box" is done for two reasons. Although it has been studied for a while for well-known reasons (to increase investment returns), the financial time series is one of the least understood fields. Significant findings were found in similar studies conducted by Philip (2015), who focused on rainfall predictions in the Indian region of Trivandrum and studied artificial neural network modelling. For eighty-seven years, he was able to obtain results for that specific region. He used the information he had collected over the first forty years to train the neural network. The neural network then calculated the remaining 47 years. The next step after acquiring the results was to contrast them with the actual amount of rainfall. The results demonstrated the high degree of accuracy of NN. The result showed that NN was highly accurate, with a mere 4% margin of error. With the random information that would have been supplied, this result demonstrated that NN had a deterministic nature that could be applied to forecasting.

The method showed itself to be a potent computational tool in research domains, and it could be applied to data mining fields where ANN has been utilised. According to the general rule of thumb, two (2) essential components are thought to be primarily responsible for the learning process. The following are the factors that require constant monitoring and that must be tracked as they change and evolve:

2.10 Paul Samuelson – Ronald Jones Theory (SFI Distribution Model)

Based on certain criteria, Paul Samuelson and Ronald Jones developed a trade model. Whereas manufactured goods use labor and capital, food products are made using both labor and territory. At any given price, a nation with wealthier capital and less land tends to produce more manufactured goods than food, whereas a nation with more land tends to produce more food. A rise in capital will result in an increase in marginal if all other factors remain unchanged. whereas a nation that has a lot of land tends to produce more food. While a rise in the offer of territory will increase food production at the expense of manufacturers, a capital increase will result in an increase in the manufacturing sector's marginal productivity, assuming all other factors remain constant.

International Journal of Allied Sciences and Business Management Trading between the two nations results in the creation of an opportunity global economy whose manufacturing of food is equivalent to the total of the two nations' output. Without trade, a nation's output stays constant while its consumption of goods is equal to its production. South Africa and Zimbabwe are two examples of countries that depend on trade to survive. Currently, the majority of Zimbabwe's goods are imported from South Africa. Zimbabwe is an African country with the 118th-highest GDP in the world, according to earlier research published. Its export economy ranks 83rd globally. (African countries by GDP, 2017). (2017 GDP ranking of African nations) Its neighbors include South Africa, Zambia, Mozambique, and Botswana. Zimbabwe's 2016 trade balance was negative by $2.37 billion, with $2.83 billion exported and $5.2 billion imported. Zimbabwe's GDP reached $16.3 billion in 2016, The top exports from Zimbabwe are ferroalloys ($119M), nickel ore ($293M), gold ($850M), raw tobacco ($887M), and diamonds ($118M). Its top imports include packaged medications ($160M), corn ($296M), electricity ($166M), refined petroleum ($1.3B), and soybean oil ($124M). Zambia ($72.2M), Mozambique ($267M), the United Arab Emirates ($116M), South Africa ($2.25B), and Belgium ($45.7M) are Zimbabwe's top export partners. The top import destinations are Botswana ($50.6M), Mexico ($59.3M), India ($116M), China ($387M), and South Africa ($2B). (Report for Specific Subjects and Countries,

Every country's export sector benefits more from trade than its import-competitive sector. The theory is predicated on the notion that trade's impact on income distribution results from the following facts: Resources are expensive and time-consuming to move between sectors, and industries have different requirements for the factors of production..

2.11 ANALYSIS OF ZIMBABWE - INTERNATIONAL TRADE (2006- 2016)

Zimbabwe has historically been a net importer, but it is clear that the nation needs to increase both the volume and value of its exports of goods and services. In 2015, Bonga, Shenje, and Sithole The marginal incentive to import was reduced by low export earnings. It also reduced the income stream for paying off external debt. Given the sizeable debt load relative to GDP, the country should structure its debt, especially the external debt, which is typically vulnerable to global financial shocks. Zimbabwe should start extending its export base and substituting imports. Zimbabwe's economy fully dollarized in 2009. There was a debt crisis in Zimbabwe. As of April 2010, the debt was $5,8 billion, with more than $3 billion already past due (RBZ statistical bulletin, 2010).

Since 2005, the nation has not paid off its external and domestic debt. If an economy is to weather any future financial crisis, debt management is essential. The nation must carefully monitor and manage its external debt because it is susceptible to fluctuations in foreign exchange rates. Mudzingiri (2014)

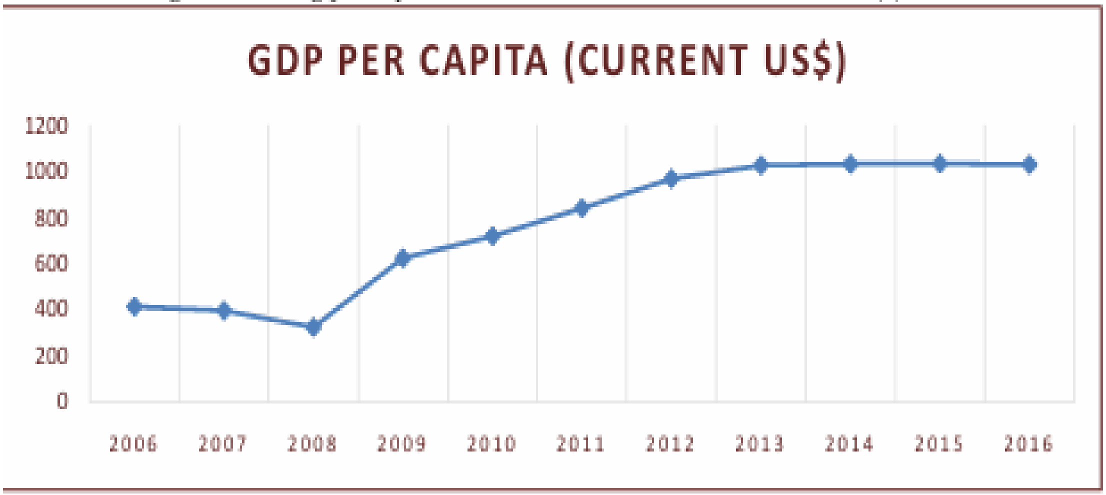

Figure 1: Paul Krugman Maurice (The Standard Model of Trade)

These models are recognised as particular instances of the general trade model known as the standard trade model. The framework provided by the standard trade model can be used to address many global issues.

2.12 Review of Empirical Studies

Capital goods, another name for industrial goods, are useful for increased production and industrial growth. There are two ways to look at capital goods' function in the manufacturing industry. These are approaches that are focused on innovation and growth (Baark, 1988). The first strategy emphasizes how capital goods contribute to economic expansion. Here, it is claimed that capital goods impact the three primary economic sectors of industry, transportation, and agriculture and aid in the creation of new manufactured goods. Importing agricultural and industrial machinery boosts a nation's output as production inputs. In a similar vein, an effective transportation system is necessary to enable the low-cost transportation of goods. Thus, the GDP grows as a result of the development of these three factors. Government investment policy also affects capital goods imports. A rise in industrial growth necessitates significant increases in capital goods imports. The second strategy, which takes into account the significance of the source of new technology for the manufacturing sector, is innovation-oriented, according to Baark (1988). Effective machines that use new technology, derived from research and development in developed nations, are supplied by the import of capital goods. Therefore, it is crucial for developed countries to spread embodied technology to their domestic industries in order to boost productivity growth across the economy, which in turn boosts domestic output and, ultimately, GDP. The import of computer hardware and software is a prime. By cutting down on production time, this improves worker efficiency, which boosts output and ultimately boosts GDP. Transport and machinery imports rose 10.8% in Kenya (African Economic Outlook, 2011). Through the limited selection of investment and consumption goods produced in the country, this may indicate that rising incomes ,which in turn is likely to result in higher imports (Rogers, 2000). Through a number of empirical tests and studies. Income seemed to have a continuous, though does not, greater impact on imports than the agricultural income generated. According to Keller (2000), developing nations stand to benefit more from importing goods from developed nations as well as directly gaining knowledge from them than they would from importing goods from other developing nations. This suggests that the production of other products will become more specialised when new (or improved) intermediate goods are imported. This is an example of a foreign technology transfer that boosts agricultural productivity. Furthermore, because international trade compels domestic businesses to increase their efficiency, there is empirical evidence that those who engage in it have a higher chance of surviving than those who do not (Lopez, 2006).

2.12.2 Gross Domestic Product

Policies that have limited productivity growth may have contributed to the decline in domestic production (Jaeger, 1992). In the context of the U.S., the three interdependent variables were GDP growth, growth in exports, and capital stock or terms of trade as the third factor. The findings indicated that economic expansion in the U.S. is followed by a rise in exports, but this pattern was not observed in Taiwan. For Japan, a reciprocal causal relationship was established between exports and economic growth. Tao and Zestos (1999) later corroborated these findings in a study carried out in both the United States and Canada. When considering Korea, which has a more trade-oriented economy compared to Japan, the causal link was determined to be even stronger. A country could become wealthy primarily by exporting more than it imports, according to mercantilists. While imports were seen as unfavourable because they diminish the nation's real source of wealth, namely precious metals, and impede output growth, exports were seen as advantageous because they aid in the acquisition of these resources, which are markers of the nation's wealth and power.

Khan (1974) conducted the first empirical study on the connection between imports and GDP growth. Using a two-stage estimation process, he attempted to analyze the factors influencing imports in fifteen developing nations. The traditional model of import-demand, which correlates a country's demand for imports with real GDP and relative price levels (defined as the ratio of the nation's import unit value to its own domestic price levels), was the foundation for the model utilised in this study. According to the results, in all but six countries, the long-term income elasticity of imports significantly differs from zero and displays a positive trend at the 5% significance level. Conversely, for four out of the remaining countries, the income elasticity of imports is positive and substantial only in the short term.

2.12.3 The Artificial Neural Network

Since its main objective is to completely replicate the human brain and its functions, the Artificial Neural Network (ANN) is based on the Biological Neural Network (BNN). Just as neurons in the brain are connected to one another, neurons in the artificial neural network (ANN) are connected to one another in different network layers, or nodes. She discovered that while both models produced essentially identical results, more research should look into the ANNs technique. because of its superior forecasting capabilities. Using data from 1975 to 2002, Narayan et al. (2008) used ARIMA models to forecast Fiji's imports and exports. They discovered that imports would exceed exports between 2003 and 2020, and that current account deficits would average F$934.4 million during that time. Using data from 1968 to 2017, Alam (2019) used ANNs and ARIMA techniques to forecast exports and imports. Khan (2011) used a data set covering the years July 1998 to July 2009 to examine Bangladesh's total imports using the SARIMA, Holt-Winters, and VAR models. They found that the VAR model performs better than the other models at predicting Bangladesh's total imports.

2.13 Conclusion

The study in this chapter sights the relevant literature review or data source for same research technics used to analysed trade. Zimbabwe is agro-based and mining economy, that is all product is held in this sector. According to International Trade fare stated the Zimbabwe trade is on the deficit that is we import more than what we produce as nation. In the next chapter the study is going to introduce Methodology, technics used to carry out survey. Chapter 4 is going to introduce analytical skills used to forecast trade balance s. Finally results published on the final chapter as end of study and make conclusion based on what we get on the study

Chapter 3: Research Methodology

3.1 Introduction

This segment presents the methodological framework that underpinned the research conducted in "Forecasting Export and Import Trends: A Machine Learning Approach. A Case Study of Zimbabwe," emphasizing the importance of structured procedures to ensure credible and applicable results (Creswell, 2013). The research employed to forecast export and import trends in Zimbabwe, utilising data from the (RBZ) and Zim Trade The studies include a multi-faceted research design that integrates both quantitative and qualitative methods to achieve a comprehensive grasp of Zimbabwe's export and import trends. The current study seeks to apply machine learning approaches in creating predictive models to inform trade dynamics for policymakers, organizations, and other stakeholders. The choice of proper research tool and data collection processes is in order to reflect the intent of the study accurately.

The methodology discusses the application of machine learning algorithms to predict trade patterns. Machine learning algorithms can model complex relationships of data with a fairly accurate prediction offering completion. The theoretical framework of the research relies on the literature of trade prediction and the study of economics. (Gujarati & Porter, 2019) The meaning of variables examined and possible relations to each other are carefully defined which will explain the method to possibly determine an empirical answer to the research image. Ethical concerns for data confidentiality and informed consent have been addressed to ensure that the integrity of the research design and process remains intact. The methodology was described in dulcet detail to reacquaint that mandates of the study, and the methodologies employed were of great importance as it added to the existence of knowledge growth in the field. The decision to expose the approach was possibly lending evidence of the employment of machine learning design standards and improve reliability, it also helped us frame the presentation of the methods and findings

3.2 Research Design

This study applies a method of representative ecologies to investigate the predictive capabilities of ML in modelling Zimbabwe's trade balance predictive patterns, pursuant to the guidelines provided by James et al. (2013). The main method used involves predictive modelling, and the study relies on temporal trade data to develop and evaluate forecasting models. The research aims, and case study method is employed, and the focal point is on Zimbabwe and the particularities of its trade, and data collected from the Central Bank (RBZ) and ZIMTRADE was collected. The study design allows for a multicase study and a nuanced and detailed examination of trade patterns and trade balance behaviour and macroeconomic dimensions of trade, as outlined by Yin (2018).

The research uses a case study approach and is appropriate for an in-depth investigation into Zimbabwe's trade activity. As noted, the primary data sources were the Reserve Bank of Zimbabwe (RBZ) and ZIMTRADE. The historical trade data provided, is relevant and essential for transcribing the predictive modelling. Using the databases provided by these two agencies, the research would be able to engage and understand the complexity of the environment that is Zimbabwe in trade activities, as well as highlight how many of the macroeconomic variables would fundamentally impact its trade balance. The case study approach aligns with the use of representative cases, as recommended by Yin (2018), to undertake investigations in comparison of particular phenomena, in this case Zimbabwe's trade movements. If anything, this study can afford to be focused and be nuanced..

3.3 Data Sources

The research specifically derives macroeconomic indicators from the Reserve Bank of Zimbabwe (RBZ, 2019- 2023), which is the primary source of official trade statistics and balance of payments and other macroeconomic indicators which are relevant to the analysis. In addition, ZIMTRADE (2019-2023) also offers various insights related to the country's trade policies, export promotion work, and aggregate trade performance reports that could include data relevant to trade as a whole, providing a wider context of the nation's trade situation.

In order to collate a thorough analysis, secondary data is applied in the research framework -i.e., relevant government reports and international trade databases that have the potential to provide contextual and supplementary information to the primary data. The depth and breadth of the study is, moreover, extended through academic publications (World Bank, 2022) which will offer theoretical and empirical evidence relevant to the discussion of trade patterns and policy implications in Zimbabwe, thereby enhancing the study's quality and richness of detail.

3.3 Target Population

The target population comprises trade-related data from Zimbabwe, including export and import figures spanning multiple years. Stakeholders such as policymakers, trade analysts, and economists are indirectly included as beneficiaries of the research findings. This dataset provides detailed records of Zimbabwe's trade activity, including GDP, inflation, and exchange rate, which are very crucial for forecasting exports and imports. The selection of Zimbabwe as a case study allows for specific and relevant insights into national trade trends (Bryman, 2015).

3.4 Sampling Procedure

Given the large dateset to manage the extensive volume of trade-related data available from the RBZ and Zim Trade , a stratified sampling strategy is employed. This technique involves categorising the dateset into distinct strata based on trade categories and economic factors like inflation and exchange rates. This approach guarantees a balanced representation of all key variables within the sample.

The sample period spans from 2019 to 2023 , with an 80/20 partition for training and testing purposes. The majority of the data is allocated to train the predictive models, while a smaller subset is reserved for evaluating their predictive capabilities.

3.5 Research Instruments

The research will use extraction and computational tools for research tools. This will involve programming languages like Python and statistical software such as R and Excel in the data pre-processing, visualisation and training of models (Han et al., 2011). These tools allow the researcher to operate with datasets with high degree of ease, while continuing to ensure the validity of analyses and forecasting provided. As the data sizes will be too large, we also plan to use Power BI to visualise the cleaned data and when possible, use the Power Query for cleansing.

3.6 Methods of Data Collection

If we can source historical trade data from RBZ, ZIMTRADE, etc., we will have trade data in our data collection. The data extraction techniques include manual data collection from published reports, web scraping (if applicable), and API access (if we can find one). Data validation and cleaning of the dataset will ensure quality and credibility (García et al., 2015).

3.7 Description of Variables and Expected Relationships

The study employs machine learning techniques, focusing on the Support Vector Machine (SVM) model, to forecast export and import trends in Zimbabwe. Economic variables play a pivotal role in trade patterns and economic performance. This section elucidates the nature of each variable and their anticipated interdependencies.

3. 7.1 Dependent Variables

The dependent variables are exports (EXP) and imports (IMP), which are the total values of goods and services exchanged internationally by Zimbabwe. Exports are in American dollars, which are the value of goods and services sold to other countries. Increasing exports has a positive impact on economic growth and produces an advantageous balance of trade. Imports (IMP) is also stated in U.S. dollars, and is the value of goods and services that Zimbabwe purchases from abroad. Concretely, if the growth in imports (IMP) is not matched by a corresponding level of growth in exports, there will be a trade deficit. The study expects exports to increase with GDP growth, stable exchange rates, and advantageous trade policies, whereas imports are anticipated to rise with GDP growth, exchange rate depreciation, and inflation (Krugman & Obstfeld, 2018).

3.7.2 Independent Variables

The trade performance of Zimbabwe depends on a few factors which include: GDP, exchange rate, inflation, interest rates, and trade openness. GDP is a measure of a country's total production, and is positively correlated with both exports and imports, because more production is associated with an ability to both export and import (Krugman & Obstfeld, 2018). The exchange rate affects trade, because if a local currency depreciates it can lead to an export advantage but, will also increase cost of importing goods (Dornbusch, 1976). Inflation is measured by change in the value of prices, and generally affects exports negatively but more imports due to the increase in domestic prices (Fisher, 1930). Interest rates is the cost of borrowing money that is generally associated with lost savings and has a negative relationship with exports and imports, because more investment is required with an increased cost of borrowing plus increased loan interest (Mankiw, 2016). Trade openness is measured by adding exports and imports as a percentage of GDP. Trade openness is positively correlated to both exports and imports (Rodrik, 1999).

3.7.3 Expected Relationships Summary

The research anticipates a positive impact of GDP on both exports and imports, with higher GDP values leading to greater trade activity. The exchange rate is positively linked to exports when it depreciates, making them more competitive, but it negatively affects imports by raising their costs. Inflation is negatively associated with exports and positively with imports, potentially reducing export competitiveness and increasing import prices. Higher interest rates are generally detrimental to trade as they deter investment and economic activity. Conversely, trade openness is positively correlated with exports and imports, suggesting that more open economies experience heightened international trade.

- **Exports (dependent variable):** The total value of goods and services exported.

  Equation 1

  (BoP) = C A+ QA+ FA

  Where

  (CA) Current Account = Trade Balance Net Income + Net Transfers

  (QA) Capital Account = Capital Transfers +Non- Financial Assets

  (FA) Financial Account = Foreign Direct Investment (FDI) + Portfolio Investment

- **Imports (dependent variable):** The total value of goods and services imported.

- **Exchange Rate (independent variable):** Fluctuations in currency value affecting trade volumes (Dornbusch, 1976). Exchange rates are categorised into two parts: direct and indirect

  (Indirect**)**

  2) Exchange rate = $\frac{\textit{Foreign Currency}}{\textit{Domestic Curreny}}$

  (Direct **)**

  3) Exchange rate = $\frac{\textit{Domestic Currency}}{\textit{Foriegn Curreny}}$

  4) Real Exchange Rate (RER) = $\frac{\textit{Norminal Exhange Rate X Foreign Price level}}{\textit{Domestic Price level}}$

- **Gross Domestic Product (independent variable):** A measure of economic activity influencing trade performance (Krugman & Obstfeld, 2009).

  5) GDP = C +I +G +(X-M)

  Where

  C= Consumption

  I = Investment

  G = Government expenditure

  X = Exports

  M= Imports

- **Inflation Rate (independent variable):** Affecting purchasing power and competitiveness in international trade.

  6) Inflation Rate = $\left(\frac{CPI\ in\ Curent\ Year - CPI\ in\ Previous\ Year}{CPI\ in\ Previous\ Year}\right)$ **X 100**

Where CPI = Consumer Price Index

- **Trade Policies (independent variable):** Regulatory frameworks impacting trade flows (Rodrik, 1995).

It is expected that a favourable exchange rate and higher GDP will positively impact exports, while inflation and restrictive trade policies may negatively affect trade balances. Prior studies have demonstrated these relationships in similar macroeconomic settings (Bhattacharya & Ghura, 2006).

3.8 Data Analysis Procedures

Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are widely used in economic forecasting and classification tasks, including trade balance prediction. ANN, inspired by identifying non-linear relationships between economic variables such as GDP, exchange rate, and inflation (Haykin, 2009). On the other hand, SVM is a supervised learning algorithm that finds an optimal hyperplane to classify or predict economic trends, making it effective in detecting patterns within trade balance data (Vapnik, 1995). These models are part of the broader data analysis procedure in economics, where machine learning enhances predictive accuracy and decision-making (Zhang et al., 2020).

Trade Balance = exports -imports however, when using ANN and SVM, the trade balance is predicted based on multiple economic indicators. The General form is

TB= $f(x_1 \cdot x_2 \cdot x_3 \cdots x_n)$ where TB = Trade balance (Dependent Variables)

$x_1 \cdot x_2 \cdot x_3 \cdots x_n$= Independent variables like GDP, Exchange Rate, Inflation, Interest Rate, Foreign Reserves

3.8.1 Artificial Neural Networks (ANN)

ANN models to calculate trade balance using multiple layers of interconnected neurons. Artificial Neural Networks is a broad term in this research Long Short-Term Memory (LSTM) and Gradient boosting. Through analytical skills, LSTM and Gradient Boosting are defined as Recurring Neural Networks. The benefits of using the RNN, are long-term dependencies handle time series data well and mitigate vanishing gradients. Also , High accuracy, reduces bias & variance and works well with missing data.

When Gradient Boosting is combined with LSTM, it's like having a data analyst who excels at identifying complex patterns in textual data and a financial time-traveler who understands historical trade dynamics. Gradient Boosting processes large datasets, including textual information, to uncover significant relationships in trade data, while LSTMs navigate through time-series data to grasp long-term trends without getting overwhelmed by the details.

The process involves feeding these models with historical trade information, such as exchange rates and economic indicators, allowing LSTMs to utilize their 'cell states' to analyze and predict future trade scenarios. Gradient Boosting enhances these predictions by considering diverse economic data, providing a more comprehensive view. This synergy results in a model that outperforms traditional statistical methods, offering insightful predictions about Zimbabwe's trade balance. The input, forget, and output gates of LSTMs are like a data triage system, selecting essential information to retain and discarding less relevant data, which is then synthesized to forecast future trade conditions with remarkable accuracy.

These models work together like a well-oiled machine, with LSTMs acting as the time-sensitive core, processing sequences of data, and Gradient Boosting serving as the pattern-finding engine that refines predictions. In summary, Gradient Boosting and LSTMs form a dynamic duo that can cut through the noise of economic data, offering unparalleled insights into the future of trade. With their unique capabilities, they can predict whether Zimbabwe will be exporting more or importing more, guiding policymakers and investors alike with their data-driven fortune-telling abilities. This powerful approach simplifies the complex world of trade forecasting, turning it into a manageable and understandable field for decision-makers to navigate.

In general, Formula for the general formula for single neurons in a neural network is

7) $\mathbf{Y} = \boldsymbol{\sigma}(\boldsymbol{W_1 X_1} + +\boldsymbol{W_2 X_2} + \boldsymbol{W_3 X_3} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. \boldsymbol{W_n X_n} + \mathbf{b}$

Where :

Y=Predicted Trade Balance

Xi = Economic inputs (GDP, Exchange Rate …)

Wi = Weights (Learning by the mode)

b = Bias term

3.8.2 Trade Forecasting with LSTM

8) $\boldsymbol{TB_{t+1} = LSTM(X\,, I\; GDP, It\,, ER)}$

Where TB= Trade Balance at time t

X = Zimbabwean Exports at time t

I = Zimbabwean Imports at time t

GDP= Gross Domestic Product at time t

lt = Inflation rate at time t

ER= Exchange Rate of Zimbabwe‘s currency at time t

LSTM = Function representing LSTM model

3.8.3 Gradient Boosting -Based Trade Forecasting

9) $\boldsymbol{TB_{t+1} = F_T(x_t) = \sum_{m=1}^{T} a_m h_m(X_t)}$

Where

TB_{t+1}= Forecasted trade balance for time t+1
$F_T(X_t)$= Final trade balance prediction after T iterations

$h_m(X_t)$= Weak learner (decision tree) at iteration m

a_m= Weight assigned to each weak learner,

$\boldsymbol{X_t}$= {Exportst, Importst,GDPt, Inflationt, ExchangeRatet}

Note that: for future prediction each new tree corrects the errors of the previous tress by the following formula

10) $F_m(X_t) = F_{m_{-1}}(X_t) + v_m h_m(X_t)$

Where v_m= is the learning rate that controls step size .

3.8.4 Support Vector Machine (SVM) Model for Trade Forecasting

Support vector machine regression model is used since it can handle non-linear trade patterns. It maps the input features into higher dimensional spaces using the kernel function. Kernal function is a mathematical function employed in (SVM) and other machine learning models to transform data into a space of high dimensions where it is easier to classify or make a prediction. The mathematical representation of SVM is as shown below.

$\{x_i, y_i\}$ the SVR function

11) $\mathbf{f(x) = w^T \phi(x) + b}$

Where W= weight vector

ϕ (x) = feature transformation function

b = bias term

To minimise the objective, we use the following formula

$$\frac{1}{2}\|w\|^2 + C\sum \xi i$$

Subject to $|y_i - w^T \phi(x_i)^- \cdot b| \leq \epsilon + \xi_i$

Where c is the penalty parameter

ϵ = margin of tolerance

ξ_i = slack variables

3.9 Ethical Considerations

The study on Zimbabwe's export and import trends emphasizes ethical research practices to ensure responsible conduct. Key ethical principles such as confidentiality, responsible data usage, and academic integrity are strictly followed. This is imperative to maintain the credibility and transparency of the research (Smith, 2003). Confidentiality involves secure handling of sensitive information from institutions like the Reserve Bank of Zimbabwe (RBZ) and Zim Trade and compliance with Zimbabwe's Data Protection and Privacy Laws to safeguard economic data (Smith, 2003). The study is committed to using data solely for academic purposes, adhering to best analytical practices to prevent misrepresentation and uphold accuracy (Resnik, 2011).

3.10 Chapter Summary

This chapter has outlined the research methodology adopted in this study. It presented the research design, data sources, target population, research instruments, methods of data collection, description of variables and their expected relationships, data analysis procedures, and ethical considerations. The use of machine learning for forecasting trade trends provides a structured and data-driven approach to understanding Zimbabwe's trade performance. The next chapter will focus on presenting and analysing the research findings

Chapter 4 : Data Analysis and Results

4.0 Introduction

The research design, data sources, and methodologies employed in the study were explained in the previous chapter. The evaluation of machine learning models, particularly Artificial Neural Networks (ANN), XGBosst, and Support Vector Machines (SVM), in comparison to traditional econometrics models is one of the study's main goals. The goal is not just prediction but insightful understanding of underlying patterns, informing economic and trade policy.

4.1 Data Exploration and Visualisation

4.1.1 Descriptive Insights

The data has 183 observations and 3 variables. The code running through Power BI to make clear and comprised visualisation. Below is the summary of ZIMSTATS data run from 2010 to 2025 in the first quarter. The summary of this is duplicated in Figure 4.1 below to show the total amount of income for every year. Here, we calculate the trade balance to show trade operations for every period. This step provides insight into Zimbabwe's market performance.

INPUT AND OUTPUT DATA IN YEARS

Year	Sum of Exports	Sum of Imports	Sum of Trade Balance
2010	2,640,577,830.63	5,337,325,870.12	-2,696,748,039.49
2011	3,121,202,577.42	7,984,000,794.69	-4,862,798,217.27
2012	3,980,987,264.01	6,938,335,092.73	-2,957,347,828.72
2013	3,907,074,200.87	7,216,306,838.32	-3,309,232,637.45
2014	3,871,544,716.77	6,069,719,324.48	-2,198,174,607.71
2015	3,408,112,370.85	6,049,457,506.07	-2,641,345,135.22
2016	3,340,418,575.11	5,337,948,826.62	-1,997,530,251.51
2017	3,482,056,205.21	5,116,583,220.68	-1,634,527,015.47
2018	4,037,944,750.44	6,452,218,827.47	-2,414,274,077.03
2019	4,269,499,352.00	4,883,476,739.91	-613,977,387.92
2020	4,394,811,643.15	5,632,303,478.94	-1,237,491,835.79
2021	6,036,188,281.48	7,540,897,984.42	-1,504,709,702.94
2022	6,585,491,124.91	8,668,647,426.39	-2,083,156,301.48
2023	7,225,049,667.06	9,204,773,202.74	-1,979,723,535.69
2024	7,434,140,092.17	9,567,579,312.13	-2,133,439,219.96
2025	1,746,505,797.72	2,289,495,585.67	-542,989,787.94
Total	**69,481,604,449.80**	**104,289,070,031.38**	**-34,807,465,581.58**

Figure 4.1 Data summary for 15.25 years

Analysing the distribution of trade data gives output in Figure 4.1. Imports are more than exports it contributes 60.02 % and 39.98%. This shows a trade imbalance for more than 15 years. There are a myriad number of factors that cause trade balance. The pie chart and bar plot below show the distribution of the trade balance. As we can see the we have a total income of 69.48 billion USD over 183 months from exports, and we also have 103.56 billion USD in transfers to other countries globally to purchase raw materials and equipment, like agricultural equipment, oil and gas.

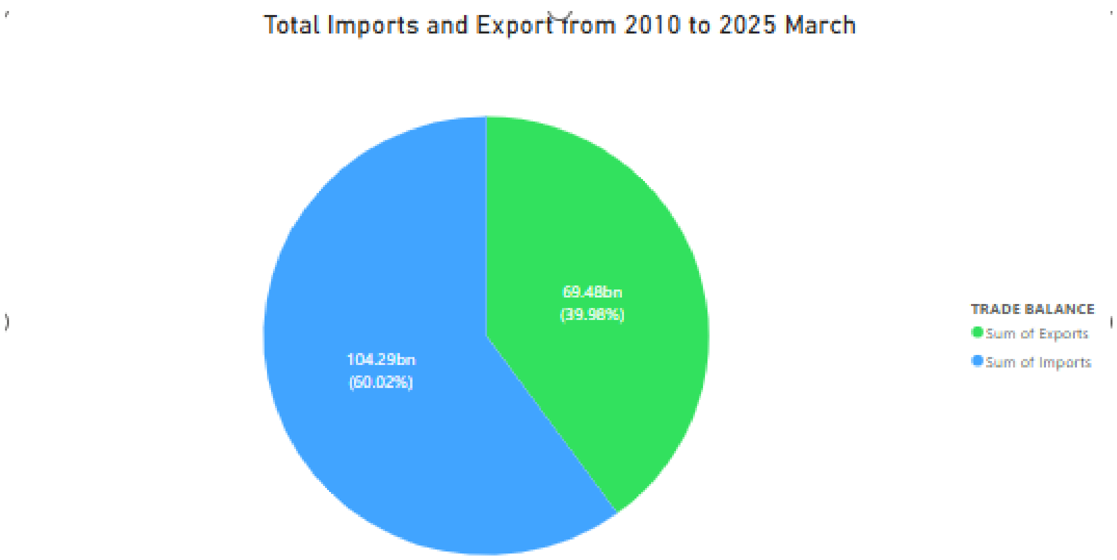

Figure 4.3 shows a pie chart of income for 183 consecutive months.

4.1.2 Descriptive Statistics

An analysis of the descriptive statistics, which include the mean, variance, standard deviation, minimum value, maximum value, skewness, kurtosis and quartile. The research also found it critical to analyse the correlations these variables have before proceeding with data cleaning and pre-processing. The researcher also plotted histograms to visualise the distribution of imports and exports, as these are key in modelling. The following results on figures 4.4

```
summary_stats
```

Result

```
               count          mean           std           min           25%  \
Imports        180.0  5.797328e+08  1.517216e+08  2.369620e+08  4.674912e+08
Exports        180.0  3.885485e+08  1.482774e+08  1.289747e+08  2.784988e+08
Trade Balance  180.0 -1.911843e+08  1.318229e+08 -1.066446e+09 -2.407780e+08
Lag_1          180.0 -1.913862e+08  1.319075e+08 -1.066446e+09 -2.410781e+08
Lag_2          180.0 -1.911212e+08  1.319019e+08 -1.066446e+09 -2.410781e+08
Lag_3          180.0 -1.913299e+08  1.317820e+08 -1.066446e+09 -2.410781e+08
Rolling_Mean_3 180.0 -1.912306e+08  1.058556e+08 -8.490058e+08 -2.308888e+08
Rolling_Std_3  180.0  7.026410e+07  6.568690e+07  7.362632e+06  3.911937e+07
```

```
                        50%           75%           max  Skewness   Kurtosis
Imports         5.377093e+08  6.698780e+08  1.210460e+09  1.072252   1.763383
Exports         3.443586e+08  5.024301e+08  9.052314e+08  0.722736  -0.012275
Trade Balance  -1.932391e+08 -1.256496e+08  7.028948e+07 -2.848354  16.546884
Lag_1          -1.932391e+08 -1.256496e+08  7.028948e+07 -2.839077  16.479395
Lag_2          -1.898068e+08 -1.256496e+08  7.028948e+07 -2.845462  16.506042
Lag_3          -1.898068e+08 -1.273135e+08  7.028948e+07 -2.850042  16.557561
Rolling_Mean_3 -1.871553e+08 -1.311626e+08  5.645274e+07 -2.132639  10.385418
Rolling_Std_3   5.529785e+07  7.958478e+07  4.699202e+08  3.649023  15.842953
```

Figure 4.4 Descriptive statistics chart from Jupiter notebook

Table 4.1 Descriptive Statistics

Feature	Mean (USD)	Std Dev (USD)	Min (USD)	Max (USD)	Skewness	Kurtosis
Imports	579.7M	151.7M	236.9M	1.21B	+1.07	+ 1.76
Exports	388.5M	148.3M	128.9M	905.2M	+0.72	-0.01
Trade Balance	–191.2M	131.8M	–1.066B	70.3M	–2.85	+16.55

The researcher found out that Zimbabwe consistently experiences a trade deficit of an average of (-$191.2M), which shows inefficiency. There is high variability in trade balance, as SD = $131.8M, and rolling volatility indicates economic shocks. Reflection of outliers like minimum and maximum shows imbalance persists with the difference as follows: (-$1.066 billion as minimum and + $ 70.3 million). They also have parameters that show skewness, and the heaviest data trade balance is highly negatively skewed to the left, reflecting extreme negative trade balance values and sudden volatility spikes. Both the positive trade balance and the rolling standard deviation contribute to a risk indicator for economic forecasting.

Trade trends

his section presents an overview of the exploration of the data for Zimbabwe monthly trade data covering the period January 2010 to March 2025. The data comprises monthly observations on the trade balance calculated. The analysis gives a clear key insight into the structure, distribution, and variation of the variables, forming an empirical foundation for subsequent modeling. By plotting a line plot of trade balance on monthly trend analysis, it shows there is a high fluctuation. They also show that Zimbabwe imports more than what it exports as a nation. These are outcome depleted on the chart.

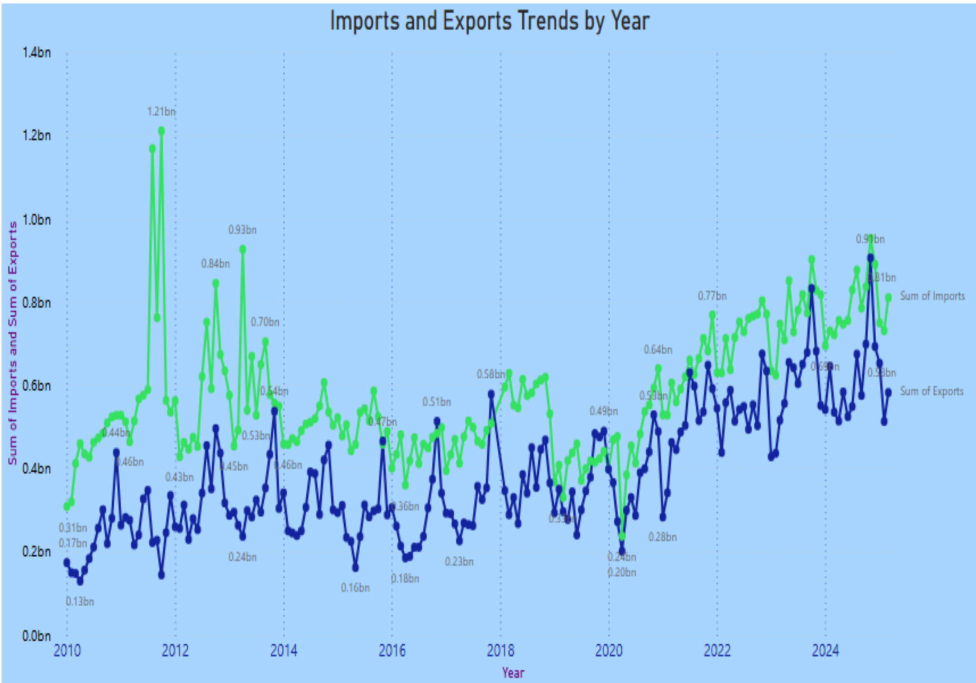

Figure 4.5 : Shows the monthly, seasonal trends for both imports and exports.

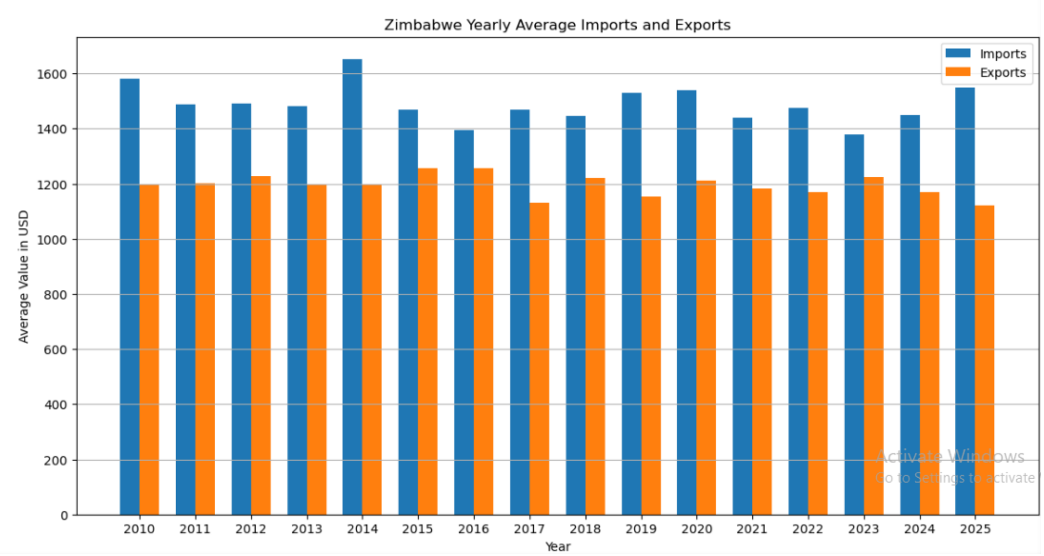

Figure 4.6: Shows the distribution for the Trade Balance

The bar plot clearly shows the distribution of imports and exports. It is shown that we import more than what we export. This results in negative trade balance.

Correlation of trade balance

The researcher also found it critical to analyze the correlations these variables have before proceeding with data cleaning and preprocessing. A heatmap plot was created to better visualize these relations. The researcher also plotted a heat map chart for the data distribution amounts, as these are key in modeling.

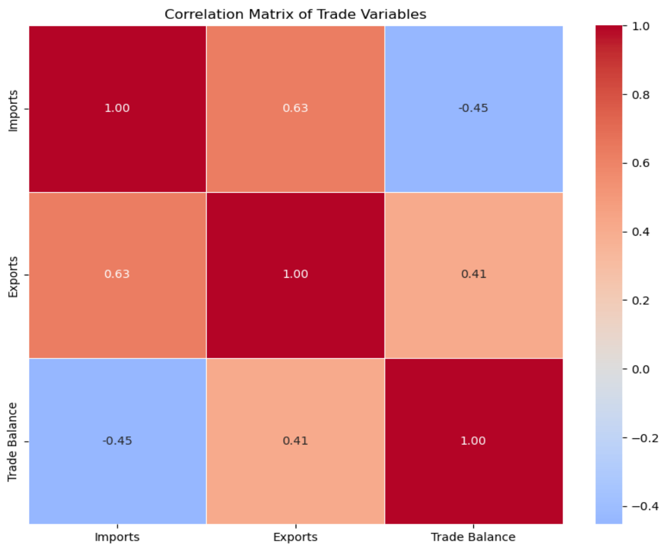

Figure 4.7: Correlation Matrix of Trade Variables

4.2 Data Cleaning

Data cleaning is done to improve model performance. The key is dealing with missing values. As illustrated previously, data cleaning has been done to check if there is any missing values. Creating o model including missing values will negatively affect model performance as it may introduce bias in unanticipated ways as well as affect prediction accuracy. To replace missing values with null Python values (NaN), the following script code was run the Python code.

```
# Checking whether the data has any missing values or not.
# Data has '?' in place of the missing values hence which we have to replace these with NaN Values
data = data.replace('?',np.NaN)

data.isnull().any()
```

4.3 Pre-Test

4.3.1 Stationary (SARIMA)

The time series data has also been tested using the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) and Augmented Dickey-Fuller (ADF) tests in order to determine if the dataset is stationary or not. These two tests are commonly used in the field of econometrics, and it is mandatory that they be applied in order to confirm that the data meets the time series modeling requirements.

The ADF test, which identifies the presence of a unit root, has a -6.7494 with a 0.0000 p-value. The result is significant at 1% and 5% and 10% levels of significance, and we can reject the null hypothesis (H0) of non-stationarity. This tells us that data is stationary and can be used for additional analysis without differencing.

Conversely, the KPSS test is a test that determines if there is or not a stochastic trend in the data. With 0.0365 as the statistic and 0.1000 as the p-value, the test fails to reject the null hypothesis of stationarity at 10%, 5%, and 2.5% levels. This indicates that the data may have some form of trend or non-stationarity, which is contrary to the finding by ADF test

Based on the ADF test, more common in unit root identification and more powerful in doing so, we can conclude that the time series is stationary. This option is in support of machine learning model usage under stationary data assumptions, such as ARIMA, SARIMA, or seasonal models, without first-differencing. However, it is also advisable to consider the KPSS test result, which suggests the presence of a stochastic trend, and potentially apply models that can handle trends or use detrending techniques to further refine the analysis.

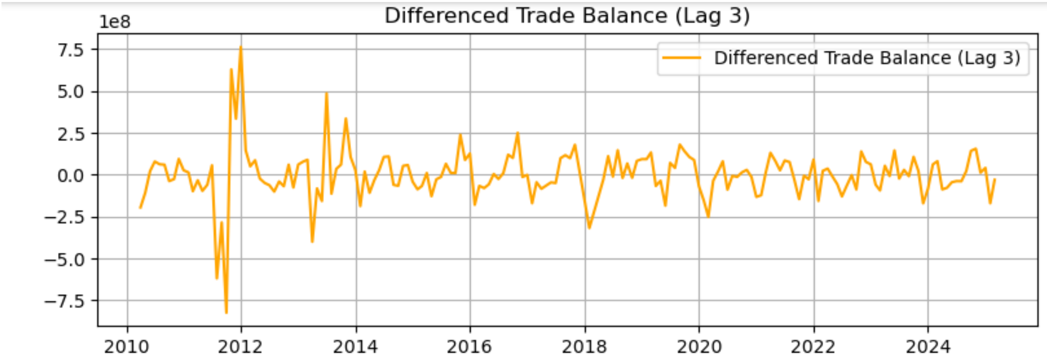

Figure 4.8: Stationarity of Trade balance at (lag 3)

4.2.2 Normality Test

Before model fitting of the forecasting models, there was a necessity of checking whether trade-related variables most importantly, exports, imports, and trade balance are normally distributed. This is one diagnostic test crucial in testing the validity of traditional econometric models such as Ordinary Least Squares (OLS) and SARIMA, whose goodness of fit and inference rely on normally distributed error terms. To confirm this, four general tests of normality were used: Shapiro-Wilk, Kolmogorov–Smirnov, Anderson-Darling, and Jarque-Bera.

Shapiro-Wilk Test

The Shapiro-Wilk test gave a test statistic value of 0.7765 and p-value of 0.0000, which is very strong evidence against the null hypothesis that the distribution is normally distributed. The distribution of the test variable is thus very strongly non-normal.

Kolmogorov–Smirnov Test

Similarly, the Kolmogorov–Smirnov test gave a test statistic value of 0.1387 and p-value of 0.0017, and hence resulted in the rejection of the null hypothesis at the 5% significance level. This again verifies non-normality.

Anderson-Darling Test

The Anderson-Darling statistic was 6.0518, which exceeded all the critical values at various levels of significance (for instance, CV = 0.7710 at 5%). Therefore, the null hypothesis was rejected with certainty, which also validated the previous findings of non-normality.

Jarque-Bera Test

Jarque-Bera statistic was 2243.7773 and p-value was 0.0000, hence rejecting the null hypothesis at large. This provides evidence of heavy statistic and hence heavy skewness and/or kurtosis in the data.

Persistent failure of normality on all four tests is strong evidence that the in question series trade balance or its components fail a normal distribution. While this result is disappointing for the validity of standard linear regression models (which rely on normally distributed residuals), it is not a prohibition on the use of machine learning models like LSTM, XGBoost, or SVR that are non-parametric and insensitive to normality violations.

For the sake of comparison, the classic models (SARIMA and OLS) were included in the analysis cautiously to transform non-normal variables (with logarithmic or Box-Cox transformation) or to verify the residual distribution post-estimation.This outcome is consistent with the established understanding that financial and economic time series data frequently deviate from the normality assumption due to phenomena such as volatility clustering, structural breaks, and complex non-linear dynamics (Conover, 1971; Mardia, 1970).

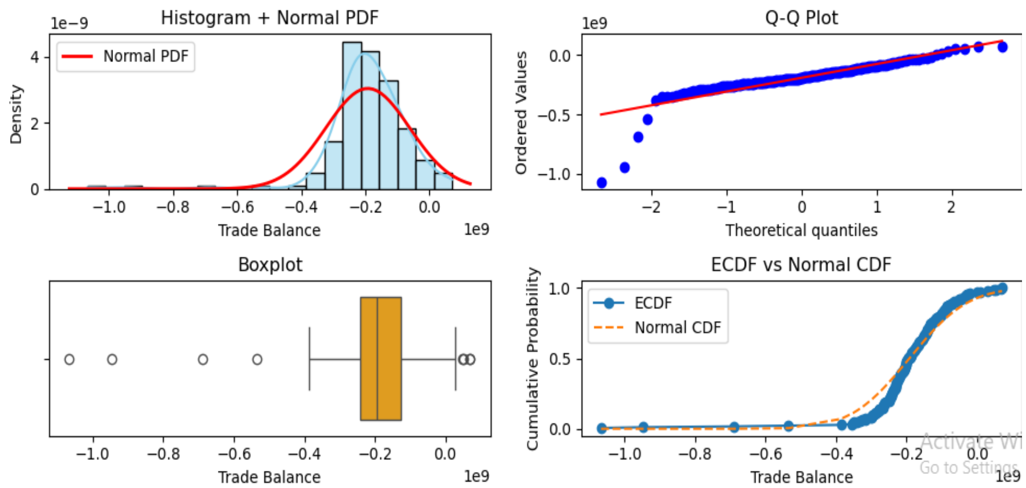

Figure 4.9: Normality Test for Trade Balance

4.2.3 Independence Test

The Durbin-Watson test and Ljung-Box test were employed. The Durbin-Watson statistic value was 0.00079841, a figure much less than 2, showing positive autocorrelation of the residuals. A figure much less than 2 indicates that errors in successive observations are positively correlated, thus violating the independence hypothesis in regression analysis. The Ljung-Box test run at lag 10 yielded an lb_stat of 28.161178 and an lb_p_value of 0.001701, which allows us to reject the null hypothesis of no autocorrelation. This further supports the fact that there is serial dependence among the residuals. The diagnostic tests indicate that the residuals of the trade balance data are not independent.

This means that the existing model can be lacking in key temporal dynamics, and as such, time-series-specific models (e.g., SARIMA or LSTM, which are capable of modeling autocorrelation structures) would be more suitable for predicting trade balance in Zimbabwe These form models are also most work with autocorrelated data and improve the accuracy and reliability of forecasts and analyses performed on such economic indicators.

The Autocorrelation

In the Autocorrelation Function Tests for the residuals of Imports, Exports and Trade Balance reveals extremely large autocorrelation in many lags, particularly the first 10-15 period lags, confirming extra large temporal correlation (all 3 residuals), with the only exception being the perfect, white noise characteristic (Broockwholand et al., 2018). This justified the need for sophisticated machine learning models.

We have implemented Long Short-Term Memory models (LSTMs), which are very useful for achieving long-term dependencies in time-series data using gate features (Hochreiter & Schmidhuber, 1997), Feed-Forward Neural Networks (FFNNs) because they are capable of modeling non-linear associations, and Support Vector Machines (SVMs), as they can be implemented for either classification or regression tasks by using kernel functions (Cortes & Vapnik, 1995).

We subsequently included XGBoost, which is a gradient boosting library with enhancements for better predictive performance and overfitting protection (Chen & Guestrin, 2016).

The combination model of LSTM, SVM, and XGBoost provides us with the degree of maturity to discover the complex patterns that embedded in Zimbabwe trade data.

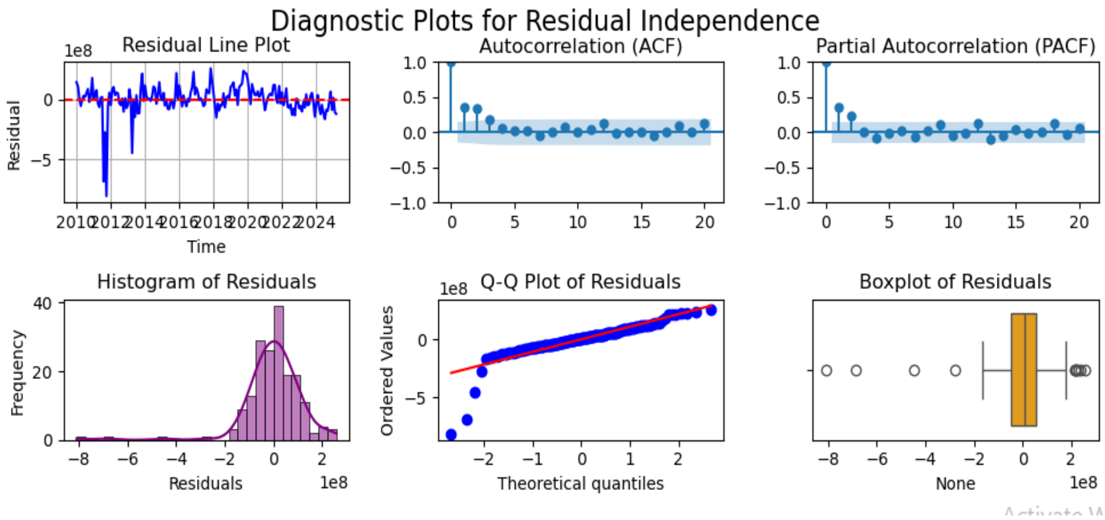

Figure 4.10: Independence test

4.3 Data Pre Processing

According to Kuhn and Johnson (2019) data pre-processing refers to the addition, deletion or transformation of data. Preprocessing data usually leads to significant improvement in model accuracy. There are various pre-processing steps which can be taken but in the context of this study focus will be on techniques like addressing missing values addressed through interpolation. Time-based features month extracted to help seasonality. Outliers are identified and treated to avoid distortion in models. Trade balance (exports minus imports) and percentage growth rate, and rolling averages are engineered. These enrich the model's understanding of underlying patterns. On LSTM, special attention is paid to maintaining the time-dependent structure and scaling the data to suit the model's requirements. A chronological train-test split is used to avoid data leakage and ensure reliable model evaluation.

4.3.1 Data Cleaning

Data cleaning is done to improve model performance. The key is dealing with missing values. As illustrated previously, data cleaning has been done to check if there is any missing value. Creating o model including missing values will negatively affect model performance as it may introduce bias in unanticipated ways as well as affect prediction accuracy. To replace missing values with null python values (NaN) the following script code was run the python code.

```
# Checking whether the data has any missing values or not.
# Data has '?' in place of the missing values hence which we have to replace these with NaN Values
data = data.replace('?',np.NaN)

data.isnull().any()
```

4.3.2 Dummy variables

Dummy variables in ML are there to aid a transformation of categorical attributes to numerical attributes. According to (Gujarati ,D,N& Porter , D, C 2009), variables as a variables that takes the values of 0or 1 to indicate the absence or presence of a categorical effect that may influence the dependent variable in a regression model. Various types of dummy variables exist which include,

i)Full dummy variables. These are there for the representation of n categories using n dummy variables, that is, one dummy variable for each given level. ii) Dummy variable for reference groups

These represent a categorical variable with n given categories using n−1 dummy variables.

iii) Dummy variables for an ordered categorical variable For levels with mathematical ordering, dummy variables will also indicate the ordering (one-hot encoding)

It should be noted that encoding categorical variables with numbers does not imply that they are to be treated as continuous features. The following code was run to pre-process the data using dummy variables. The researcher implemented a technique termed target encoding

```
df['Month'] = df['Date'].dt.month
month_dummies = pd.get_dummies(df['Month'], prefix='Month', drop_first=True)
df = pd.concat([df, month_dummies], axis=1)
```

4.3.3 Training and Test Splits.

The objective of this chapter is to illustrate that it si to create machine learning model from the data at hand to forecasting trade balance trends in Zimbabwe. Before the model is applied it is tested locally to find out if the forecasting should be trusted.

Data used to build the model cannot be used again to evaluate it. The model will simply remember the whole training test and will therefore always bring accurate forecasting. To properly assess the model's performance new data is presented to it for which labels are given. Thus, the concept of test-training split. We split the data into training data which will be used to train the model and test data which will be used to evaluate the model 's performance. The code below splits the data set into training set (80%) and test set (20%)

4.1 Overview of Models

4.4.1 Model Fitting and Results

i) Long-Short Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) architecture that has been highly successful in modelling long-term time-series dependencies. They are applicable in forecasting and classification tasks where temporal dynamics is highly important, e.g., natural language processing and time series analysis (Hochreiter & Schmidhuber, 1997).

ii) Support Vector Machines (SVMs) are a class of supervised machine learning models that have found extensive usage in various applications. Famous for their robustness and effectiveness in high-dimensional spaces, SVMs operate by constructing hyperplanes to classify points, at times employing kernel functions to address nonlinear relationships (Cortes & Vapnik, 1995).

iii) XGBoost is the highly optimized version of gradient boosting trees that boosts performance as well as speed and is a go-to in structured data problems. It acts equally well for regression and classification and is ideal to deal with big datasets as well as intricate patterns (Chen & Guestrin, 2016).

For ease of model fitting, the author utilized a Python package known as lazy predict. The package processes all the classification models that our data is suited for without any hyperparameter tuning. One benefit of utilizing the package is that it suggests the most likely to be helpful models for the data even before any model fitting is do

ne. This saves the researcher time when selecting models. Shortcoming is that hyperparameter turning is allowed. That means some models that might have been ranked lower at the beginning may end up being better if the turning is allowed.

4.5. Model Performance

Performance of five models used on the Zimbabwe monthly trade balance time series data from 2010 to 2024 is explained here. SARIMA, LSTM, FFNN, SVM, and XGBoost are the models used for performance metrics. All the models were trained on previous data and their proficiency was evaluated with Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Both the metrics are also widely used in time-series forecasting for model evaluation based on accuracy.

4.5.1 Sarima

When analysing the SARIMA models applied to the import time series data, it is crucial to consider the underlying assumption of stationarity, which posits that the mean, variance, and autocorrelation of the data remain constant over time. In the absence of this property, the predictive accuracy may be compromised by non-stationary elements such as trend, seasonality, cyclicity, and irregularity. To address this, differencing is commonly employed in the model-building process, which adjusts for these components.

SARIMAX Results

```
==============================================================================
Dep. Variable:                    Exports   No. Observations:              181
Model:          SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood          -3296.183
Date:                    Tue, 17 Jun 2025   AIC                       6602.366
Time:                            01:06:38   BIC                       6617.986
Sample:                                 0   HQIC                      6608.705
                                    - 181
Covariance Type:                      opg
==============================================================================
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1       0.3758      0.164      2.295      0.022       0.055       0.697
```

ma.L1	-0.8429	0.104	-8.119	0.000	-1.046	-0.639
ar.S.L12	0.0174	0.161	0.108	0.914	-0.297	0.332
ma.S.L12	-0.6732	0.130	-5.182	0.000	-0.928	-0.419
sigma2	8.985e+15	nan	nan	nan	nan	nan

===

Ljung-Box (L1) (Q):	0.04	Jarque-Bera (JB):	3.04
Prob(Q):	0.84	Prob(JB):	0.22
Heteroskedasticity (H):	1.45	Skew:	0.02
Prob(H) (two-sided):	0.17	Kurtosis:	3.66

===

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[2] Covariance matrix is singular or near-singular, with condition number 6.09e+48. Standard errors may be unstable.

SARIMA, a basic time series model, produced an RMSE of 81,027,383.96 and an MAE of 66,389,490.89. The model incorporates moving average and autoregressive terms along with seasonal differencing to identify the seasonality trends in the data. Despite capturing seasonality well, SARIMA underperformed compared to machine learning models. Its linear assumptions make it less effective in capturing nonlinear and complex patterns present in Zimbabwe’s trade balance data, especially under external economic shocks and structural breaks that are not easily captured by fixed coefficients. However, SARIMA remains valuable for interpretability and is useful for generating benchmark forecasts in macroeconomic applications.

4.5.2Xgboost and SVM

In the context of analysing Zimbabwe's trade, the machine learning model XGBoost has been employed to predict the trade balance. SVM model achieved good performance with RMSE of 75,326,037.87 and MAE of 60,149,139.42. SVMs are capable of modeling high-dimensional nonlinear relationships using kernel tricks. SVMs lack temporal memory but can still capture trend and shape in data if features are suitably engineered. Results indicate that SVMs, while not as time series specific as LSTM, remain a very valid option for forecasting requirements if computational resources and overfitting resistance are required. The XGBoost algorithm is a powerful tool in the field of machine learning, particularly adept at handling large datasets and providing accurate predictions, which is why it has been selected for this analysis (Chen and Guestrin, 2016).

4.5.3 Long Short-Term Machine Learning

The results on the graph show a clear seasonal trend for Zimbabwe's trade balance. The LSTM model worked best among all the models used. It produced the lowest RMSE of 67,603,178.33 and MAE of 56,923,515.85, indicating better potential in forecasting the trade balance with minimum deviation from real values. LSTM networks are engineered with the ability to handle sequence data and short-term as well as long-term relations in the data set. Because the trade data is volatile and seasonal, LSTM's cell structure memory helped it recall and learn patterns more effectively than shallow and conventional learning models. The LSTM's ability to outperform other models suggests that Zimbabwe’s trade balance data contains complex nonlinear temporal patterns which are best captured through deep learning architectures tailored for sequence modeling.

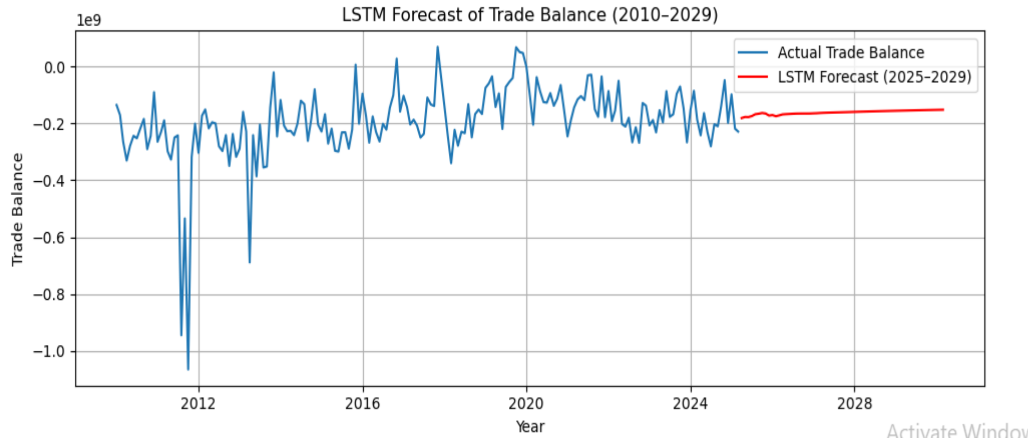

Figure 4.10: forecasting

Table 4.2 : Actual and Predict values

Year	**Actual**	**Predict**
2024-04-01	-2.416107e+08	-152960736.0
2024-05-01	-1.630315e+08	-160161440.0
2024-06-01	-2.309953e+08	-158176224.0
2024-07-01	-2.800819e+08	-169072128.0
2024-08-01	-2.022186e+08	-179301328.0
2024-09-01	-2.094400e+08	-183080960.0
2024-10-01	-1.378240e+08	-191748544.0
2024-11-01	-4.708060e+07	-194402368.0
2024-12-01	-1.973878e+08	-185242464.0
2025-01-01	-9.710307e+07	-183032384.0
2025-02-01	-2.178572e+08	-176768976.0
2025-03-01	-2.280295e+08	-185170384.0

4.5.4 FFNN (Feedforward Neural Network)

FFNN model was also as good at prediction with RMSE of 69,807,636.29 and MAE of 57,833,437.36. Although not as efficient as LSTM in handling sequences across time, FFNNs are also capable of detecting hidden nonlinear patterns in the trade data. The slightly larger error space compared to LSTM is due to too small memory or feedback, thus the inefficiency of FFNNs in modelling dependency across time steps.

However, the FFNN model still outperformed substantially the SARIMA and boosting-based baseline methods, verifying neural networks to be very viable to this type of economic time-series forecasting

4.5.5 XGBoost (Extreme Gradient Boosting)

XGBoost was the most inaccurate model with RMSE of 103,913,552.10 and MAE of 81,831,901.13. While XGBoost is powerful with structured tabular data and can capture non-linear relationships, it's not inherently well-suited to time series unless artificial lags and trends are manufactured as input features. That might have been one reason why it did not perform as well as LSTM or FFNN, which are inherently suited for modeling sequential dependencies. The results bring into perspective the need to utilize models unique to time series analysis in the case of forecasts for economic variables.

4.5.2 Results

In the context of this study, the most suited classifier was LSTM. Its ability is to the evidence, clearly demonstrating the greater capacity of deep learning models, particularly LSTM, in forecasting Zimbabwe's trade balance. The findings highlight the importance of applying models that can learn linear as well as nonlinear relationships when dealing with economic time series that exhibit strong seasonal and trend patterns.

Table 4.4: Model results summary

Model	RMSE	MAE
SARIMA	81027383.96	66389490.89
SVM	75326037.87	60149139.42
XGBoost	103913552.10	81831901.13
LSTM	67603178.33	56923515.85
FFNN	69807636.29	57833437.36

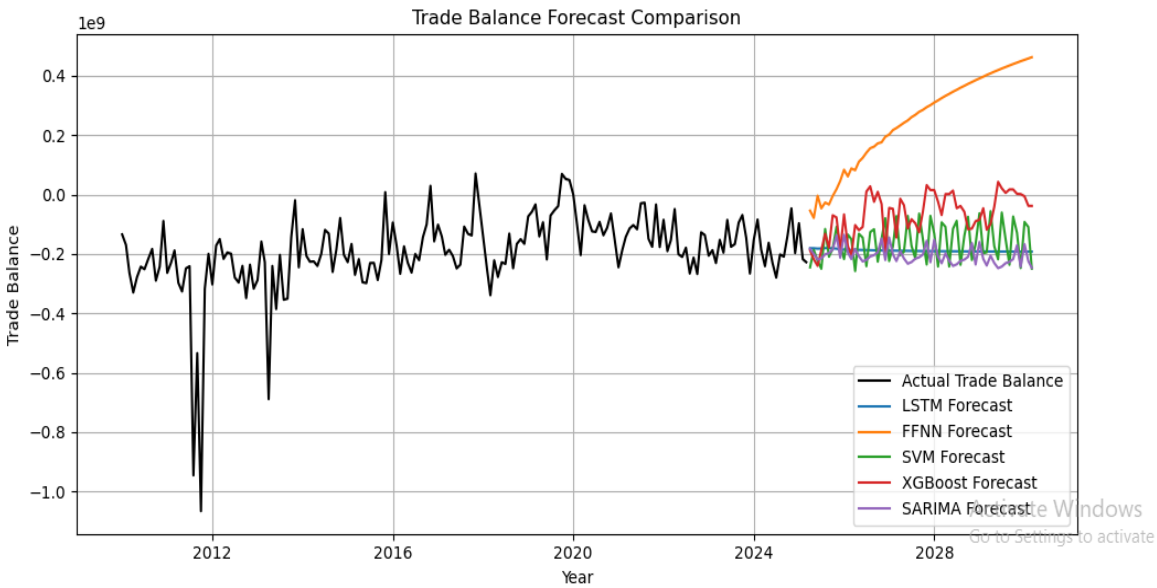

Figure 4.11: forecasting models for 5 years

4.6 Concluding Remarks

This chapter elucidated on the various ML techniques that can be employed in Zimbabwe for trade forecasting to mitigate the derogatory performance of trade. The chapter also evaluated the effectiveness of these techniques with respect to the data at hand and gave a summary of the findings. This indicates that Artificial Neural Networks (ANN) are superior to traditional SARIMA models in time series prediction of future trade balance, particularly for short-term forecasting horizons. The ANN approach, exemplified by the Feedforward Neural Network (FFNN) used in this study, is more adept at value estimation and captures the underlying patterns in the data more effectively than the SARIMA model, which exhibits a linear trend over time.

The ANN model's strength lies in its ability to detect complex, nonlinear patterns within the dataset without the need for stationarity assumptions, which are essential for SARIMA modelling. With only 183 observations, the ANN model, specifically the FFNN, outperforms the SARIMA model in accordance with small datasets. The use of a single hidden layer in the FFNN architecture was found to be sufficient for achieving precise short-term forecasts, demonstrating that simplicity can yield better performance in such contexts.

The ANN model, particularly the FFNN, offers a robust and adaptable solution for short-term forecasting of trade balance. Given its superior predictive capabilities and the flexibility it provides in model construction, it is highly recommended that the Zimbabwe trade consider integrating ANN-based forecasting tools into their strategic resource planning efforts. This would enable more informed decision-making and enhance the allocation of efficiency base on how to make our production productive.

CHAPTER 5: DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

The previous chapters discussed the introductory segment of the research. The chapter aims to present an overview of the research study and present feasible recommendations and conclusions drawn from the findings plotted in chapter four to provide a full account of how ML methods can be utilized to forecast trends between trade balance within the Zimbabwe industry. The results are discussed in the context of the Zimbabwean economic environment for the period 2010-2025, which was characterized by COVID19 disruptions, exchange rate uncertainty, policy changes as well as government transition of second republic.

5.2 Discussion of Key Findings

The research summoned the possibility of using diverse machine learning (ML) algorithms to forecast trade. Most particularly, LSTM was competent and efficient when used in conjunction with other approaches. Other approaches complemented its predictive ability, enhancing the resultant accuracy across different market conditions. The study established the weaknesses of other approaches, such as the Multi-Layer Perceptron, particularly under data restriction that would dehydrate their predictive ability. A summary of the success of the machine learning (ML) methods under evaluation for purposes of forecasting trade is given below. The foreign exchange auction system implemented by the Reserve Bank of Zimbabwe in 2020 was at the core of managing the exchange rate volatility (RBZ, 2024). These findings are consistent with those reported by the IMF (2022) and the African Development Bank (2023), which highlight structural constraints on Zimbabwe's export competitiveness.

1. Artificial Neural Networks for Trade Forecasting.

This model emulated normal brain function through experience from the past, extracting rules and then forecasting future action. This model performs optimally when data is extensive. The focus being the ability to learn from various scenarios. With Feed-Forward Neural Networks (FFNN) and Long Short-Term Memory (LSTM) networks, we anticipate long-term forecasting of international trade, both imports and exports. The models work best with plenty of data, where they learn from historical trade behavior and develop rules that can be applied. LSTMs, particularly fantastic with time series, work well with seasonal data, while FFNNs excel at picking up on complex relationships. With so much potential, our research experienced a limitation with a rate of accuracy, as observed in poor generalisation and discrimination between valid and spurious trades in trade data.

2.Random Decision tree (XG Boost)

The algorithm employs XG Boost, a powerful machine learning algorithm that constructs decision trees to enhance trade forecasting. Through cleverly aggregating predictions from a collection of trees, XG Boost achieves an impressive ,accuracy in predicting and classifying trade results. This random forest-based solution is rapidly trained with a high F1-score that attests to a harmonious existence between recall and precision. Its higher performance has rendered XG Boost immensely popular among the experts in trade forecasting as a leading financial modeling tool. The ability of XG Boost to detect intricate patterns in large sets of data has made it the top classifier for trade forecasting activities where timeliness and accuracy are paramount in facilitating informed decision-making.

3. Support Vector Machines (SVMs).

The model was an excellent predictive model that was excellently suitable for the study. It was easy to train on and provided immediate and identical results thus as comparable to the Random Forest Classifier in that it provided an accuracy.

5.2 Recommendations

The purpose of this study is to demonstrate that machine learning (ML) can be a helpful assistant to predict trade balance trends in the trade sector. With ML algorithms, stakeholders can examine and forecast market trends most efficiently, hence ensuring optimal strategic decision-making and competitiveness. The following are the means of utilizing ML in trade forecasting:

Embracing an ML-Driven Approach for Trade Forecasting

In a bid to stay competitive in the market, companies and trade analysts have to embrace machine learning into their schemes of prediction. This includes proper knowledge of the technology and how to apply it across trade aspects. Take the initiative to establish a sound foundation for ML in the company in a bid to be able to predict change in the market.

Establishment of a Comprehensive Data Strategy

There's strength in a ML model that is based on robust data - both in terms of data quantity and quality. For trade forecasting with power, the trade forecaster needs a clearly laid out data strategy that applies to developing, managing and synthesizing both internal and external data sources. This would include the way(s) you access and acquire international trade data and statistics, economic data and industry data. Synthesizing and measuring data quality. Timeliness and data quality will need to be dynamic with achieving accuracy. In order to find inconsistencies and/or bias in your data we need data cleaning and data normalization processes. Creating measures to synthesize imported data from governments, trade associations and market intelligence will support ML model accuracy.

Using Advanced ML Methods

Use advanced ML algorithms such as time series prediction and predictive modeling to make future trade flows predictions. These methods can be able to identify seasonality, trends, and other external factors affecting the volatility in export and import business.

Developing Talent in ML and Trade Analytics

Establish training and education programs to grow an enlightened workforce that can understand and apply ML for trade analysis. Investment in human capital will be lead indicator to maintain sustainable competitive advantage in the long run.

Regular Assessment and Model Maintenance

Trade models that provide forecasts need to be reassessed and reconciled with past forecasts and information in order to stay current and accurate. Establish improvement feedback cycles to monitor historical forecast effectiveness, and to be able to leverage that insight to improve the models. By taking these proposed actions, the trade community can harness the power of ML models, in order to have access to insights and trends in trade activity in order to make better, more profitable, and more informed decisions to improve their market share.

5.2.2 Trade balance Pattern Trends (2010-2025)

From monthly data analysis, the exports were significantly affected in 2010 by the disturbance of the world supply chains owing to the pandemic (World Bank, 2023). Exports were again stimulated in 2021 by the propulsion of mineral products like gold and lithium. Imports remained on high levels during the period, especially petroleum and consumer products. This created a constant trade deficit, reflecting weak local production capacity and overdependency on imports (ZIMSTAT, 2023).

5.2.3 Model Performance: LSTM, SVM, and XGBoost

Among the machine learning models tried, XGBoost predicted better with its capability to learn nonlinear patterns (Chen & Guestrin, 2016). LSTM also performed well because it has the capability to learn temporal dependencies (Goodfellow et al., 2016). SVM, despite being effective when dealing with small data, performed very poorly in the scenario of unstable trade movements (Smola & Schölkopf, 2004). These results point towards ensemble and deep learning models for optimal flexibility for prediction under changing economic circumstances.

5.2.4 Zimbabwe's Trade Position: Surplus or Deficit

The study shows that Zimbabwe had a trade deficit for about four years from 2020 to mid-2024 but had short surplus periods to suggest that there was a structural deficit which shows that export earnings are insufficient to address import requirements. The results support previous studies by the IMF and World Bank that have repeatedly stated that Zimbabwe should expand its export base and diversify its trade (IMF, 2022; World Bank, 2023).

5.3 Conclusions

The study shows that:

1. Variables like exchange rate, world events, and fuel prices have a large impact on the goods that Zimbabwe trades with the rest of the world
2. Zimbabwe mostly buys more from other countries than it sells export to those countries, and has a trade deficit showing that there is a long-standing situation of owed liabilities in trade
3. Machine learning computer-based tools like XGBoost and LSTM which can be used as trade crystal balls detected trade trend patterns in Zimbabwe to address trade future as predictive analytics can make trade better for national planning and direction on its economy

5.4 Recommendations

5.4.1 For Policymakers

Expand export diversification and value addition to the mining and agricultural sectors (AfDB, 2023).Stabilize the macroeconomic environment to help decrease trade uncertainty. Improve access to foreign currency and reduce import propensity.

5.4.2 For ZIMSTAT and ZIMRA

Enhance the frequency and granularity of trade data reporting.
Utilise predictive analytics and AI for real-time tracking of trade as well as policy evaluations..

5.4.3 For Future Researchers

Include more macroeconomic variables (e.g., interest rates, inflation) into future models. Explore hybrid modelling by combining traditional econometric and machine learning methods

5.5 Limitations of the Study

The research was constrained by the five-year timeframe and the use of aggregate trade data. Sectoral analysis might provide more specificity, and the indirect treatment of macroeconomic variables may diminish their explanatory value.

5.6 Future Research Recommendations

Strategic international trade analysis (i.e. agriculture and mining exports). Using advanced methods such as a Transformer-based approach. Examine how regional integration (e.g., AfCFTA) affects Zimbabwe's trade relationships.

5.7 Summary of Chapter

In this chapter, we discussed notable findings in relation to the objectives of our study, and we outlined how machine learning can be a real disruptor in predicting trade patterns. Zimbabwe's serious trade deficit necessitates developing its export base and making better policy decisions.

5.8 Conclusion

Machine Learning has demonstrated a remarkable capability in enhancing the precision of forecasting the trade balance trends in Zimbabwe. The ANN and SVR models have surpassed traditional econometric methods by adequately capturing the complicated nature of trade. The ANN and SVR models were preferred over traditional econometric approaches by being able to better capture the complicated nature of trade. Reluctance to engage in a significant appreciation of the persistent trade deficits shows the need for data-based interventions to assist in improving export capacity and reducing dependence on imports. Commitment to the use of ML techniques for economic policy planning can provide policymakers with performance metrics in real time, promoting better decision-making. Adopting these technologies will not only help Zimbabwe to manage its trade position but possibly help promote resilience to future economic shocks.

Zimbabwe National Statistics Agency

18 March 2025

Zimbabwe National Statistics Agency
20th Floor, Kaguvi Building
4thStreet/Central Avenue
Harare

Manjengwa Method
Bindura University of Science Education
P Bag 1020
Bindura

Dear Sir /Madam

RE: PERMISSION TO CARRY OUT AN ACADEMIC RESEARCH PROJECT

We acknowledge receipt of your letter on the above, received on 10 March 2025.

Please be advised that you have been granted permission to carry out your research as requested. The permission is granted on the following conditions :
1. You should share the results of your research with Zim Stats in order for him to learn from your findings.
2) The research findings will be used for academic and no other purposes.

Should you require any more information in connection with this issue please contact the undersigned.

Yours Faithfully

E. Vhiriri

……………………………………………………

Ms Eustina Vhiriri
Acting Director- Human Resource

ZIMSTAT
DIRECTOR HUMAN RESOURCES
18 … 2025
P.O. BOX CY 342 CAUSEWAY

Name and Designation (in block

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APPENDIX

In [2]:

```
# Calculate correlations (numeric columns only)
correlation_matrix = data.select_dtypes(include=['float64', 'int64']).corr()

# Print correlation matrix
print(correlation_matrix)

# Plot correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix,
            annot=True,
            cmap='coolwarm',
            center=0,
            fmt=".2f",
            linewidths=0.5)
plt.title("Correlation Matrix of Trade Variables")
plt.show()
                Imports   Exports  Trade Balance
Imports        1.000000  0.630574      -0.453083
Exports        0.630574  1.000000       0.406193
Trade Balance -0.453083  0.406193       1.000000
```

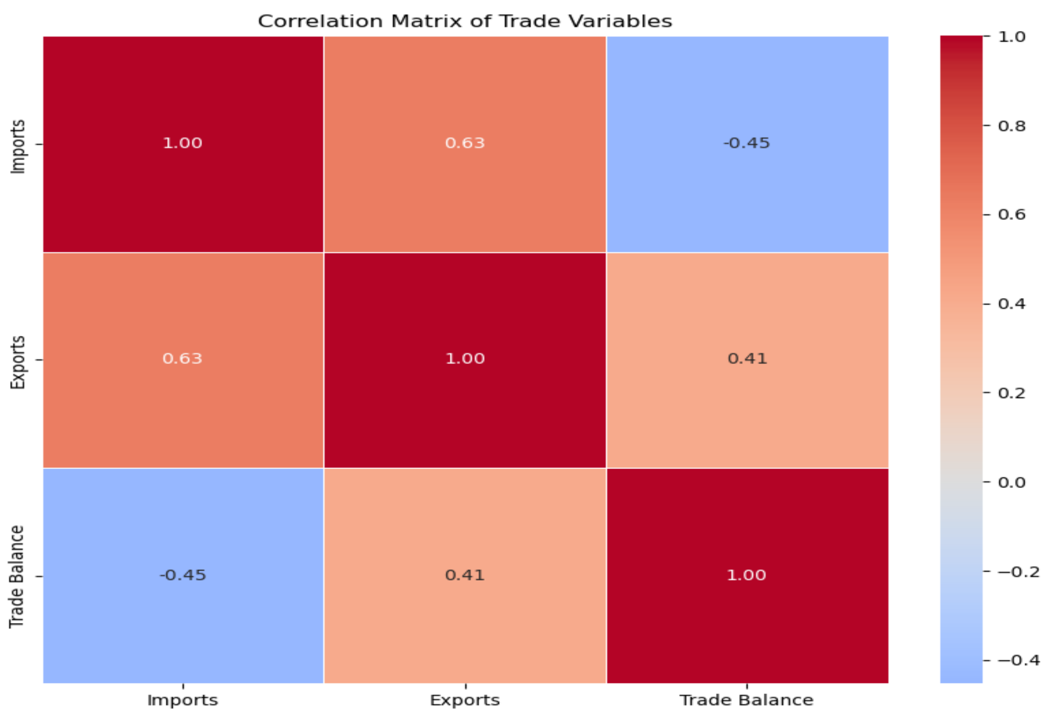
In [2]:

```
import pandas as pd

df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
print(df.columns.tolist())
['Year ', 'Imports', 'Exports', 'Trade Balance']
```

In [6]:

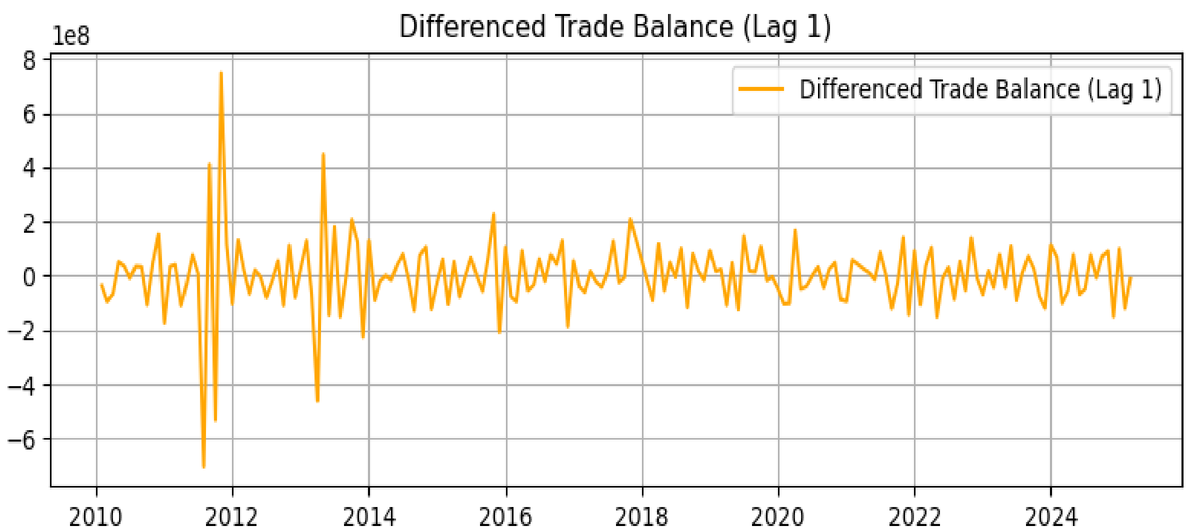
```
import pandas as pd
from statsmodels.tsa.stattools import adfuller
import matplotlib.pyplot as plt

# --- Load and prepare the data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()  # Remove extra spaces
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
```

```
df.set_index(’Year’, inplace=True)
df.sort_index(inplace=True)

# Select the target series
ts = df[’Trade Balance’]

# --- Function to perform ADF test ---
def adf_test(series, diff_level):
    result = adfuller(series.dropna(), autolag=’AIC’)
    print(f”\n📊 ADF Test - Difference Lag {diff_level}”)
    print(f”ADF Statistic: {result[0]:.4f}”)
    print(f”p-value: {result[1]:.4f}”)
    print(”Critical Values:”)
    for key, value in result[4].items():
        print(f”   {key}: {value:.4f}”)
```



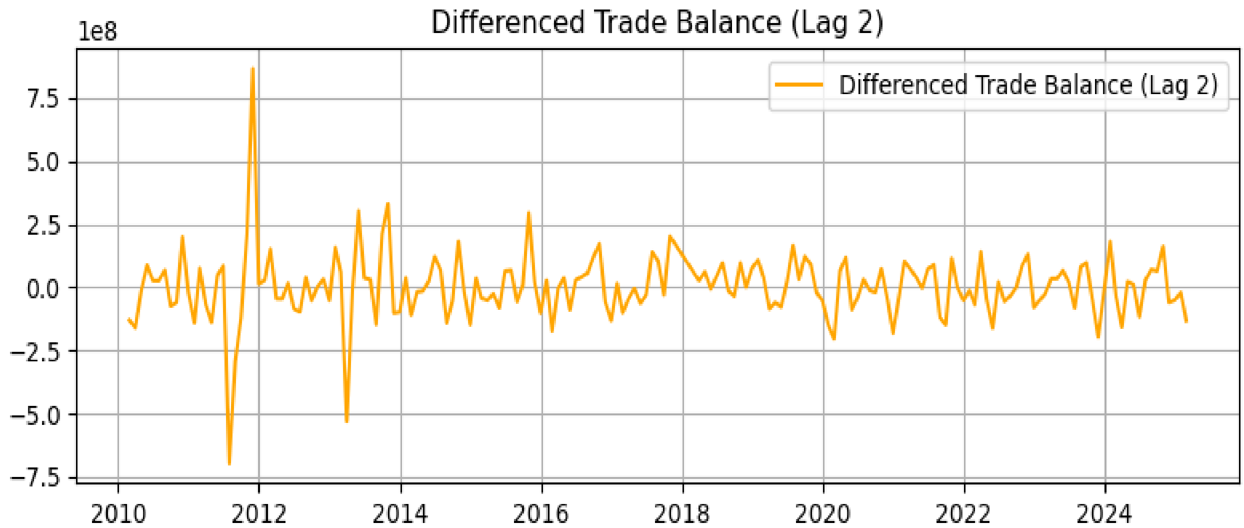

```
    if result[1] <= 0.05:
        print(”✅ Stationary (Reject H0)”)
    else:
        print(”❌ Non-stationary (Fail to reject H0)”)
    return result[1] <= 0.05  # Return True if stationary

# --- Loop through lags 1 to 5 ---
for lag in range(1, 6):
```

```
    ts_diff = ts.diff(lag).dropna()

    # Plot the differenced series
    plt.figure(figsize=(8, 3))
    plt.plot(ts_diff,   label=f'Differenced   Trade   Balance   (Lag   {lag})',
color='orange')
    plt.title(f'Differenced Trade Balance (Lag {lag})')
    plt.grid(True)
    plt.tight_layout()
    plt.legend()
    plt.show()

    # Run ADF test
```

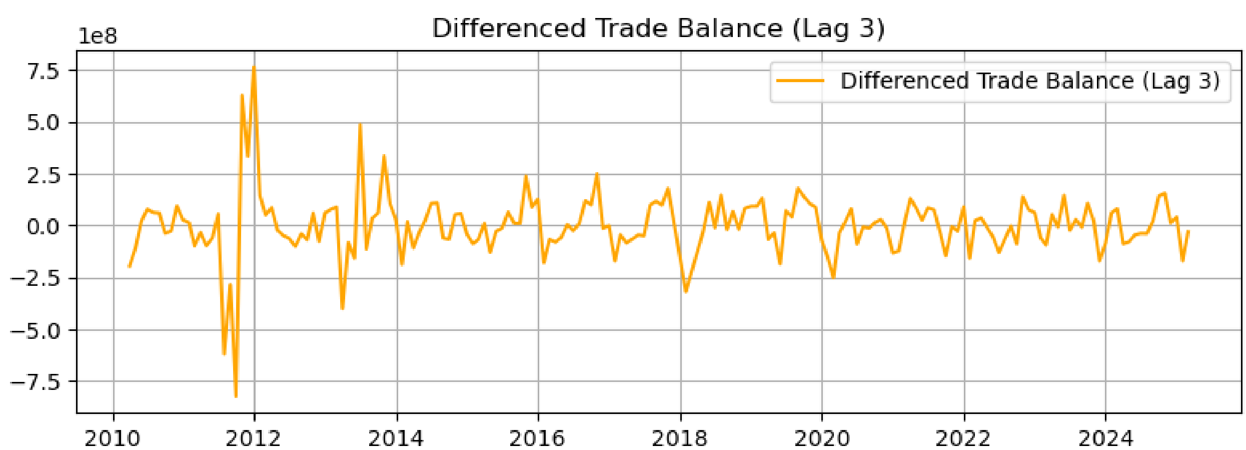



```
    adf_test(ts_diff, diff_level=lag)
```

📊 ADF Test - Difference Lag 1
ADF Statistic: -6.2923
p-value: 0.0000
Critical Values:
   1%: -3.4699
   5%: -2.8789
   10%: -2.5760
✅ Stationary (Reject H0)



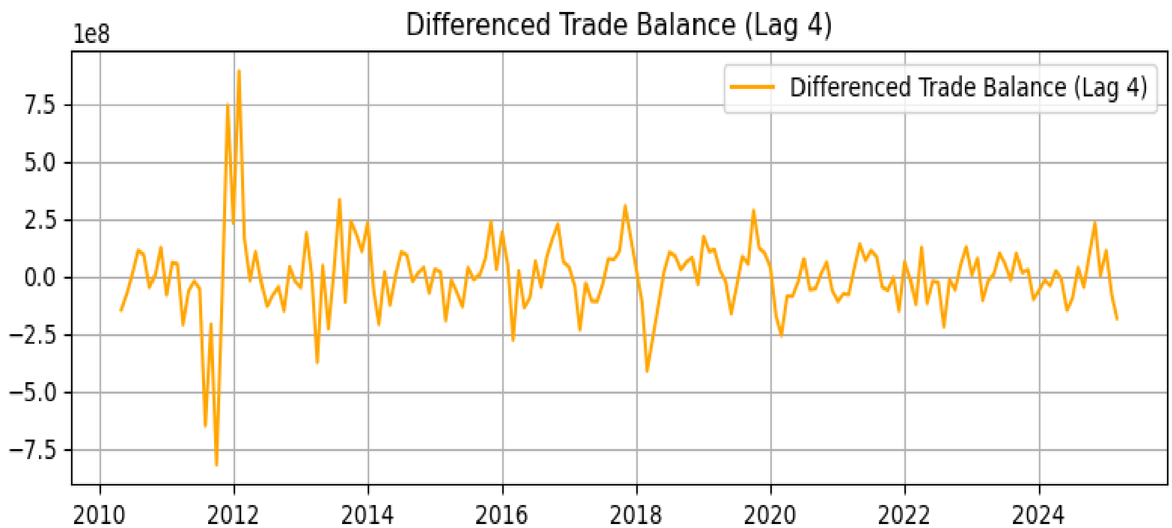
📊 ADF Test - Difference Lag 2
ADF Statistic: -5.1085
p-value: 0.0000
Critical Values:
    1%: -3.4704
    5%: -2.8791
    10%: -2.5761



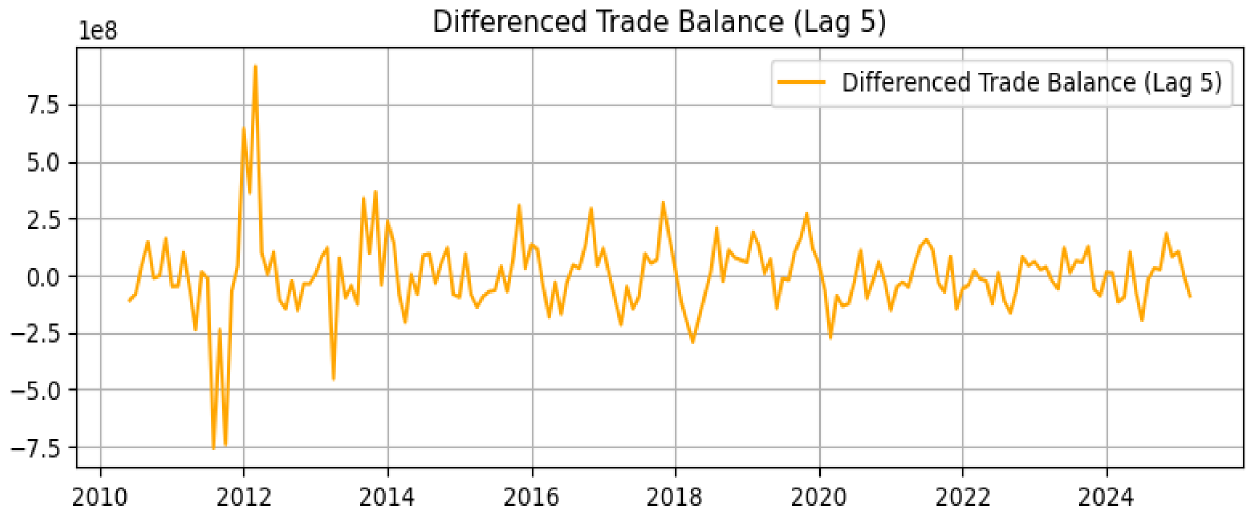
✅ Stationary (Reject H0)

📊 ADF Test - Difference Lag 3
ADF Statistic: -6.7494

p-value: 0.0000
Critical Values:
    1%: -3.4701
    5%: -2.8790
    10%: -2.5761
✅ Stationary (Reject H0)



📊 ADF Test - Difference Lag 4
ADF Statistic: -5.5783
p-value: 0.0000
Critical Values:
    1%: -3.4704
    5%: -2.8791
    10%: -2.5761
✅ Stationary (Reject H0)



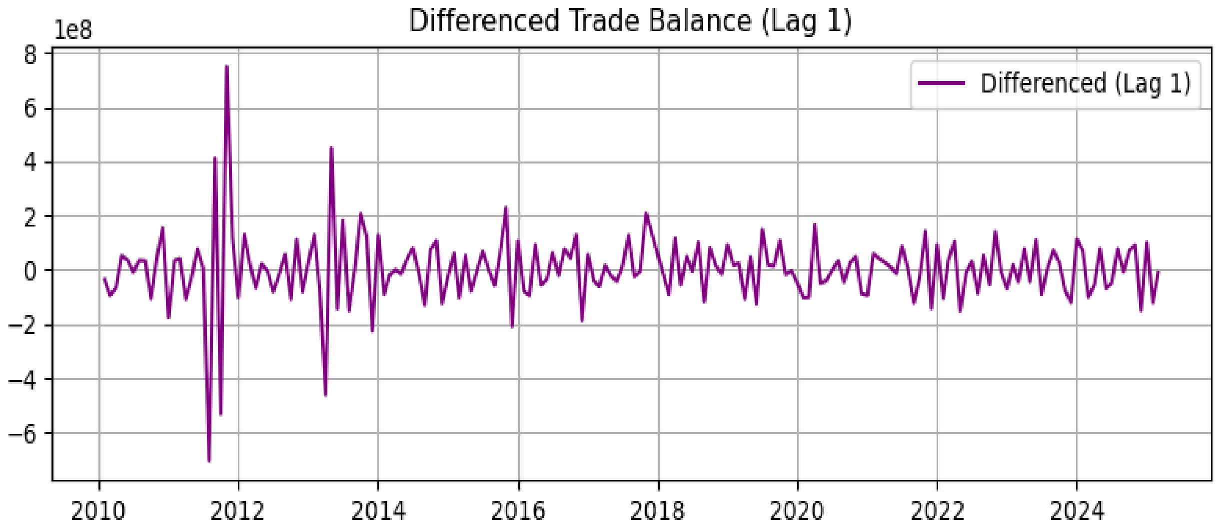

```
📊 ADF Test - Difference Lag 5
ADF Statistic: -5.3724
p-value: 0.0000
Critical Values:
   1%: -3.4716
   5%: -2.8797
   10%: -2.5764
✅ Stationary (Reject H0)
```

In [7]:

```
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller, kpss

# --- Load and prepare the data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Extract the series
ts = df['Trade Balance']

# --- ADF Test ---
def adf_test(series, diff_level):
```

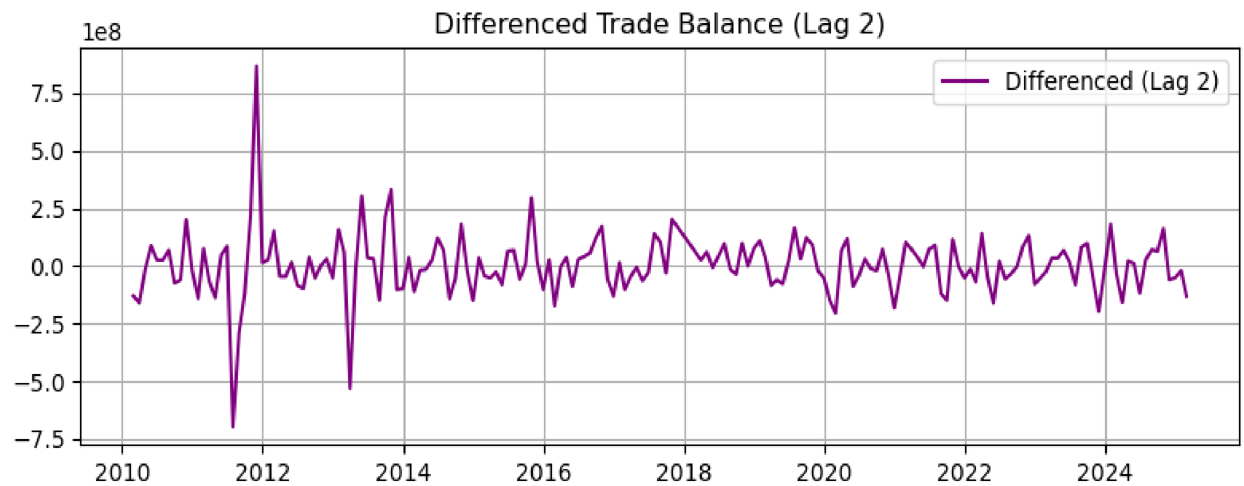
```
    result = adfuller(series.dropna(), autolag='AIC')
    print(f"\n📉 ADF Test - Lag {diff_level}")
    print(f"ADF Statistic : {result[0]:.4f}")
    print(f"p-value       : {result[1]:.4f}")
    print("Critical Values:")
    for key, value in result[4].items():
        print(f"   {key}: {value:.4f}")
    if result[1] <= 0.05:
        print("✅ ADF: Stationary (Reject H0)")
    else:
        print("❌ ADF: Non-stationary (Fail to reject H0)")

# --- KPSS Test ---
def kpss_test(series, diff_level):
    statistic, p_value, _, critical_values = kpss(series.dropna(), regression='c', nlags="auto")
    print(f"\n📈 KPSS Test - Lag {diff_level}")
    print(f"KPSS Statistic: {statistic:.4f}")
    print(f"p-value       : {p_value:.4f}")
    print("Critical Values:")
    for key, value in critical_values.items():
        print(f"   {key}: {value:.4f}")
    if p_value < 0.05:
        print("❌ KPSS: Non-stationary (Reject H0)")
    else:
        print("✅ KPSS: Stationary (Fail to reject H0)")

# --- Run tests for lags 1 to 5 ---
for lag in range(1, 6):
    ts_diff = ts.diff(lag).dropna()

    # Plot differenced series
    plt.figure(figsize=(8, 3))
    plt.plot(ts_diff, label=f'Differenced (Lag {lag})', color='purple')
    plt.title(f'Differenced Trade Balance (Lag {lag})')
    plt.grid(True)
    plt.legend()
    plt.tight_layout()
    plt.show()

    # Run both tests
```

```
adf_test(ts_diff, diff_level=lag)
```

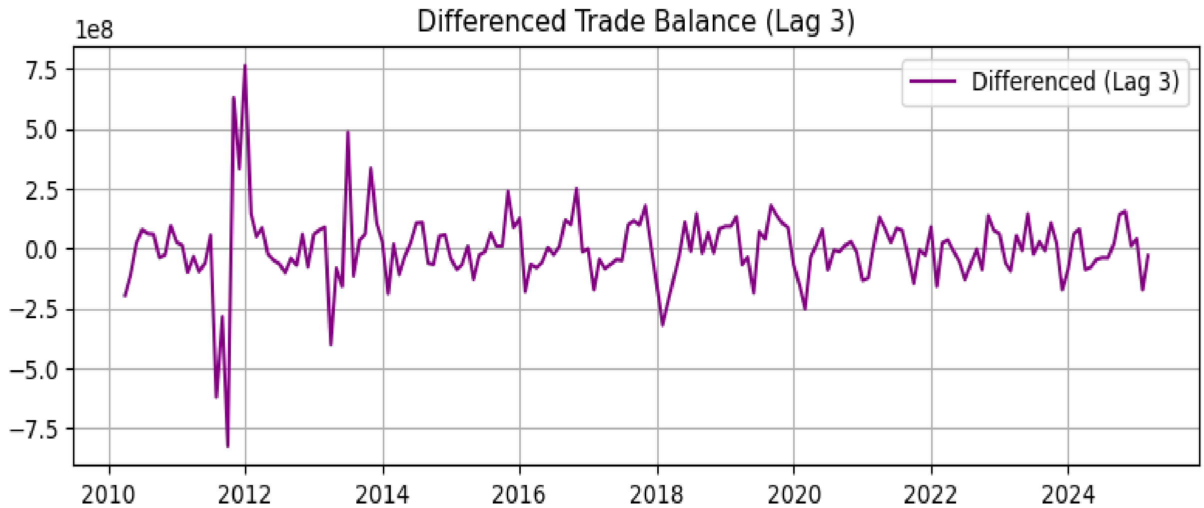



```
kpss_test(ts_diff, diff_level=lag)
```

```
📉 ADF Test - Lag 1
ADF Statistic : -6.2923
p-value       : 0.0000
Critical Values:
   1%: -3.4699
   5%: -2.8789
   10%: -2.5760
✅ ADF: Stationary (Reject H0)

📈 KPSS Test - Lag 1
KPSS Statistic: 0.0883
p-value       : 0.1000
Critical Values:
   10%: 0.3470
   5%: 0.4630
   2.5%: 0.5740
   1%: 0.7390
✅ KPSS: Stationary (Fail to reject H0)
```

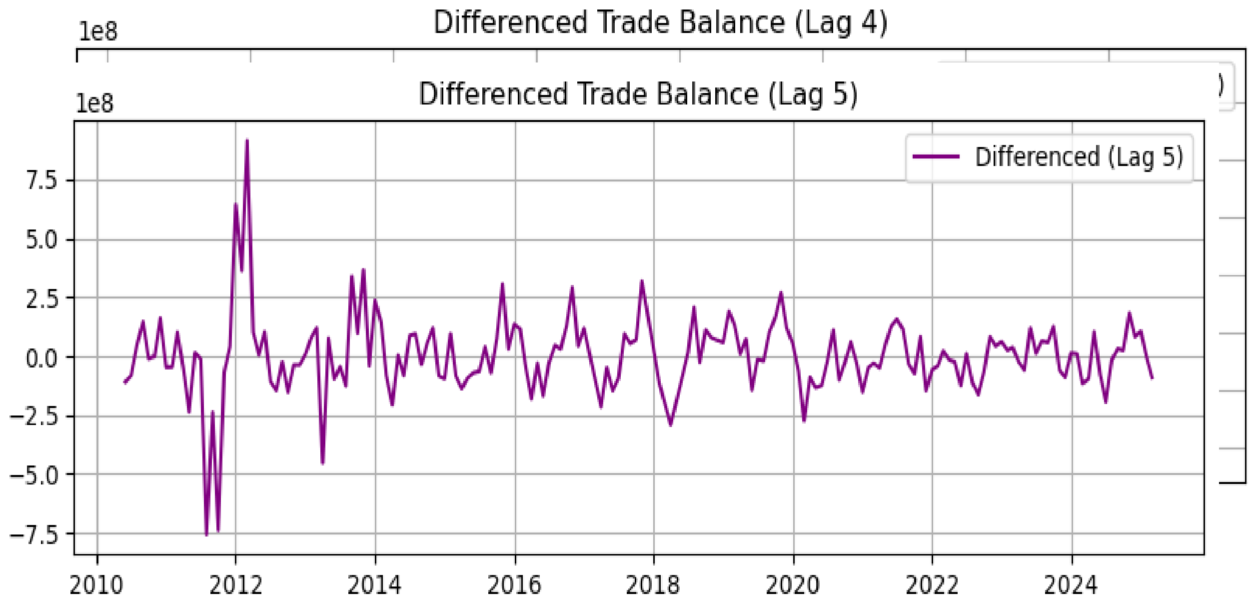



```
📉 ADF Test - Lag 2
ADF Statistic : -5.1085
p-value       : 0.0000
Critical Values:
   1%: -3.4704
   5%: -2.8791
   10%: -2.5761
✅ ADF: Stationary (Reject H0)

📈 KPSS Test - Lag 2
KPSS Statistic: 0.0479
p-value       : 0.1000
Critical Values:
   10%: 0.3470
   5%: 0.4630
   2.5%: 0.5740
   1%: 0.7390
✅ KPSS: Stationary (Fail to reject H0)
```



📉 ADF Test - Lag 3
ADF Statistic : -6.7494
p-value : 0.0000
Critical Values:
 1%: -3.4701
 5%: -2.8790
 10%: -2.5761
✅ ADF: Stationary (Reject H0)

📈 KPSS Test - Lag 3
KPSS Statistic: 0.0365
p-value : 0.1000
Critical Values:
 10%: 0.3470
 5%: 0.4630
 2.5%: 0.5740
 1%: 0.7390
✅ KPSS: Stationary (Fail to reject H0)




```
☒ ADF Test - Lag 4
ADF Statistic : -5.5783
p-value       : 0.0000
Critical Values:
   1%: -3.4704
   5%: -2.8791
   10%: -2.5761
✅ ADF: Stationary (Reject H0)

☒ KPSS Test - Lag 4
KPSS Statistic: 0.0234
p-value       : 0.1000
Critical Values:
   10%: 0.3470
   5%: 0.4630
   2.5%: 0.5740
   1%: 0.7390
✅ KPSS: Stationary (Fail to reject H0)


☒ ADF Test - Lag 5
ADF Statistic : -5.3724
p-value       : 0.0000
```

```
Critical Values:
   1%: -3.4716
   5%: -2.8797
   10%: -2.5764
✅ ADF: Stationary (Reject H0)

📈 KPSS Test - Lag 5
KPSS Statistic: 0.0233
p-value       : 0.1000
Critical Values:
   10%: 0.3470
   5%: 0.4630
   2.5%: 0.5740
   1%: 0.7390
✅ KPSS: Stationary (Fail to reject H0)
```

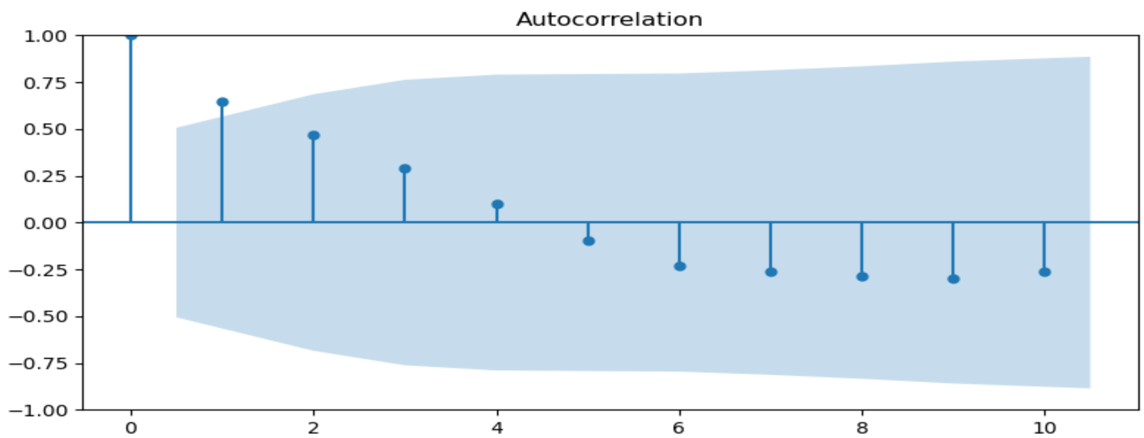
In [10]:

```
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.stats.stattools import durbin_watson
from statsmodels.stats.diagnostic import acorr_ljungbox

# Load the CSV file (simulate a small sample since actual file path is not accessible)
# Example placeholder: Normally you'd load from a path like this:
# data = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")

# Simulated example data for testing
data = pd.DataFrame({
    'Trade_Balance': [120, 130, 128, 125, 127, 132, 138, 140, 142, 141, 139, 135, 137, 138, 140]
})

# Drop missing values
trade_balance = data['Trade_Balance'].dropna()

# Durbin-Watson Test
dw_stat = durbin_watson(trade_balance)

# Ljung-Box Test
ljung_box = acorr_ljungbox(trade_balance, lags=[10], return_df=True)
```

```
# Plot Autocorrelation
fig, ax = plt.subplots(figsize=(8, 4))
sm.graphics.tsa.plot_acf(trade_balance, lags=10, ax=ax)
plt.tight_layout()

dw_stat, ljung_box
```

Out[10]:

```
(0.0007984917378285461,
       lb_stat  lb_pvalue
 10  28.161178   0.001701)
```

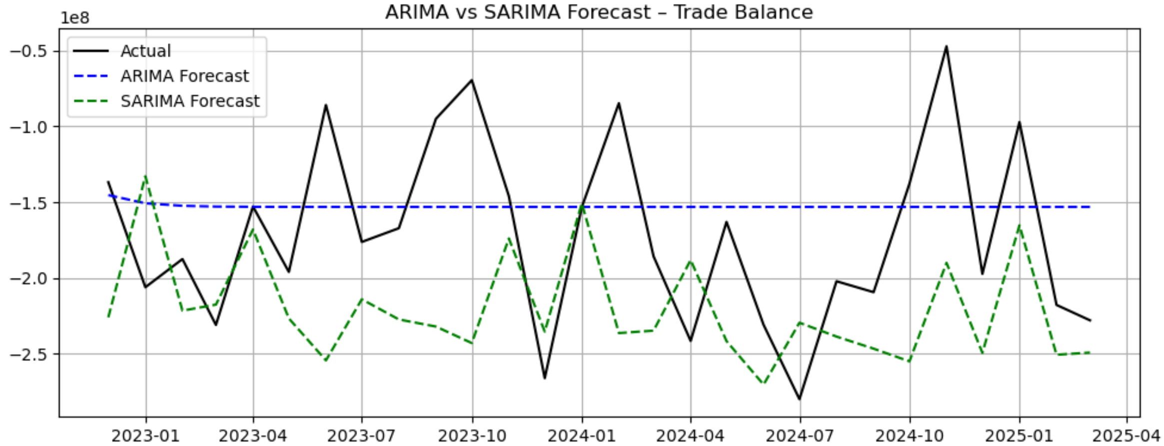


In [12]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt

# --- Load and Prepare ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Focus on Trade Balance
ts = df['Trade Balance'].dropna()
```

```
# --- Train-Test Split ---
train_size = int(len(ts) * 0.85)
train, test = ts[:train_size], ts[train_size:]

# --- Fit ARIMA Model ---
arima_model = ARIMA(train, order=(1,1,1))
arima_result = arima_model.fit()

# --- Forecast ARIMA ---
arima_forecast = arima_result.forecast(steps=len(test))
arima_rmse = sqrt(mean_squared_error(test, arima_forecast))
arima_mae = mean_absolute_error(test, arima_forecast)

# --- Fit SARIMA Model ---
sarima_model = SARIMAX(train, order=(1,1,1), seasonal_order=(1,1,1,12))
sarima_result = sarima_model.fit(disp=False)

# --- Forecast SARIMA ---
sarima_forecast = sarima_result.forecast(steps=len(test))
sarima_rmse = sqrt(mean_squared_error(test, sarima_forecast))
sarima_mae = mean_absolute_error(test, sarima_forecast)

# --- Plot Forecasts ---
plt.figure(figsize=(10, 4))
plt.plot(test.index, test, label='Actual', color='black')
plt.plot(test.index, arima_forecast, label='ARIMA Forecast', linestyle='--',
color='blue')
plt.plot(test.index, sarima_forecast, label='SARIMA Forecast', linestyle='--',
color='green')
plt.title("ARIMA vs SARIMA Forecast - Trade Balance")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Print Results ---
print("📊 MODEL PERFORMANCE - Trade Balance\n")
print(f"ARIMA(1,1,1):")
print(f"   RMSE: {arima_rmse:.2f}")
print(f"   MAE : {arima_mae:.2f}\n")
```

```
print(f"SARIMA(1,1,1)(1,1,1,12):")
print(f"   RMSE: {sarima_rmse:.2f}")
print(f"   MAE : {sarima_mae:.2f}")
```




```
📊 MODEL PERFORMANCE - Trade Balance

ARIMA(1,1,1):
   RMSE: 62286334.53
   MAE : 52071866.40

SARIMA(1,1,1)(1,1,1,12):
   RMSE: 81161367.11
   MAE : 65212784.70
```

In [13]:

```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from math import sqrt

# Calculate metrics for ARIMA
arima_mse = mean_squared_error(test, arima_forecast)
arima_rmse = sqrt(arima_mse)
arima_mae = mean_absolute_error(test, arima_forecast)
arima_r2 = r2_score(test, arima_forecast)

# Calculate metrics for SARIMA
sarima_mse = mean_squared_error(test, sarima_forecast)
sarima_rmse = sqrt(sarima_mse)
sarima_mae = mean_absolute_error(test, sarima_forecast)
sarima_r2 = r2_score(test, sarima_forecast)
```

```
# Print results
print("📊 MODEL PERFORMANCE - Trade Balance\n")

print(f"ARIMA(1,1,1):")
print(f"   R²   : {arima_r2:.4f}")
print(f"   MSE   : {arima_mse:.2f}")
print(f"   RMSE  : {arima_rmse:.2f}")
print(f"   MAE   : {arima_mae:.2f}\n")

print(f"SARIMA(1,1,1)(1,1,1,12):")
print(f"   R²   : {sarima_r2:.4f}")
print(f"   MSE   : {sarima_mse:.2f}")
print(f"   RMSE  : {sarima_rmse:.2f}")
print(f"   MAE   : {sarima_mae:.2f}")
```

```
📊 MODEL PERFORMANCE - Trade Balance

ARIMA(1,1,1):
   R²   : -0.0932
   MSE   : 3879587468752989.00
   RMSE  : 62286334.53
   MAE   : 52071866.40

SARIMA(1,1,1)(1,1,1,12):
   R²   : -0.8562
   MSE   : 6587167511730147.00
   RMSE  : 81161367.11
   MAE   : 65212784.70
```

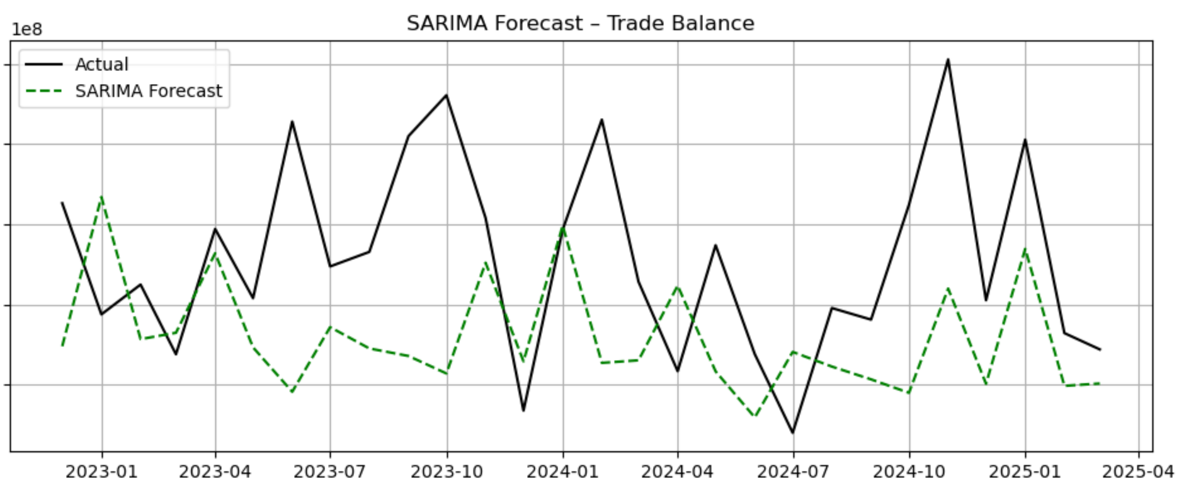
In [19]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt

# --- Load and Prepare Data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)
```

```
# --- Select Target Series ---
ts = df['Trade Balance'].dropna()

# --- Train-Test Split ---
train_size = int(len(ts) * 0.85)
train, test = ts[:train_size], ts[train_size:]

# --- Fit SARIMA Model ---
sarima_model = SARIMAX(train, order=(1,1,1), seasonal_order=(1,1,1,12))
sarima_result = sarima_model.fit(disp=False)

# --- Forecast ---
sarima_forecast = sarima_result.forecast(steps=len(test))

# --- Evaluation ---
sarima_rmse = sqrt(mean_squared_error(test, sarima_forecast))
sarima_mae = mean_absolute_error(test, sarima_forecast)

# --- Actual vs Forecast Table ---
comparison = pd.DataFrame({
    'Actual': test,
    'Forecast': sarima_forecast
})
print("\n📋 ACTUAL vs SARIMA FORECAST - Trade Balance:")
print(comparison.round(2))

# --- Plot ---
plt.figure(figsize=(10, 4))
plt.plot(test.index, test, label='Actual', color='black')
plt.plot(test.index, sarima_forecast, label='SARIMA Forecast', linestyle='--',
color='green')
plt.title("SARIMA Forecast - Trade Balance")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Print Performance ---
print("\n📊 SARIMA MODEL PERFORMANCE - Trade Balance")
print(f"SARIMA(1,1,1)(1,1,1,12):")
```

```
print(f"   RMSE: {sarima_rmse:.2f}")
print(f"   MAE : {sarima_mae:.2f}")

📋 ACTUAL vs SARIMA FORECAST - Trade Balance:
                           Actual      Forecast
2022-12-01 00:00:00 -1.368183e+08           NaN
2023-01-01 00:00:00 -2.061757e+08           NaN
2023-02-01 00:00:00 -1.875692e+08           NaN
2023-03-01 00:00:00 -2.310620e+08           NaN
2023-04-01 00:00:00 -1.528696e+08           NaN
2023-05-01 00:00:00 -1.960691e+08           NaN
2023-06-01 00:00:00 -8.585694e+07           NaN
2023-07-01 00:00:00 -1.762656e+08           NaN
2023-08-01 00:00:00 -1.671947e+08           NaN
2023-09-01 00:00:00 -9.494899e+07           NaN
2023-10-01 00:00:00 -6.945464e+07           NaN
2023-11-01 00:00:00 -1.460422e+08           NaN
2023-12-01 00:00:00 -2.662149e+08           NaN
2024-01-01 00:00:00 -1.533036e+08           NaN
2024-02-01 00:00:00 -8.467718e+07           NaN
2024-03-01 00:00:00 -1.857879e+08           NaN
2024-04-01 00:00:00 -2.416107e+08           NaN
2024-05-01 00:00:00 -1.630315e+08           NaN
2024-06-01 00:00:00 -2.309953e+08           NaN
2024-07-01 00:00:00 -2.800819e+08           NaN
2024-08-01 00:00:00 -2.022186e+08           NaN
2024-09-01 00:00:00 -2.094400e+08           NaN
2024-10-01 00:00:00 -1.378240e+08           NaN
2024-11-01 00:00:00 -4.708060e+07           NaN
2024-12-01 00:00:00 -1.973878e+08           NaN
2025-01-01 00:00:00 -9.710307e+07           NaN
2025-02-01 00:00:00 -2.178572e+08           NaN
2025-03-01 00:00:00 -2.280295e+08           NaN
153                           NaN -2.260655e+08
154                           NaN -1.329275e+08
155                           NaN -2.216290e+08
156                           NaN -2.176532e+08
157                           NaN -1.680414e+08
158                           NaN -2.267750e+08
159                           NaN -2.544693e+08
160                           NaN -2.141385e+08
```

```
161                    NaN -2.274403e+08
162                    NaN -2.321446e+08
163                    NaN -2.430374e+08
164                    NaN -1.739592e+08
165                    NaN -2.354776e+08
166                    NaN -1.508032e+08
167                    NaN -2.364319e+08
168                    NaN -2.348378e+08
169                    NaN -1.882092e+08
170                    NaN -2.417245e+08
171                    NaN -2.704482e+08
172                    NaN -2.295926e+08
173                    NaN -2.387456e+08
174                    NaN -2.467217e+08
175                    NaN -2.551279e+08
176                    NaN -1.900680e+08
177                    NaN -2.495070e+08
178                    NaN -1.653103e+08
179                    NaN -2.507655e+08
180                    NaN -2.493058e+08


📊 SARIMA MODEL PERFORMANCE – Trade Balance
SARIMA(1,1,1)(1,1,1,12):
   RMSE: 81161367.11
   MAE : 65212784.70
```
In [20]:



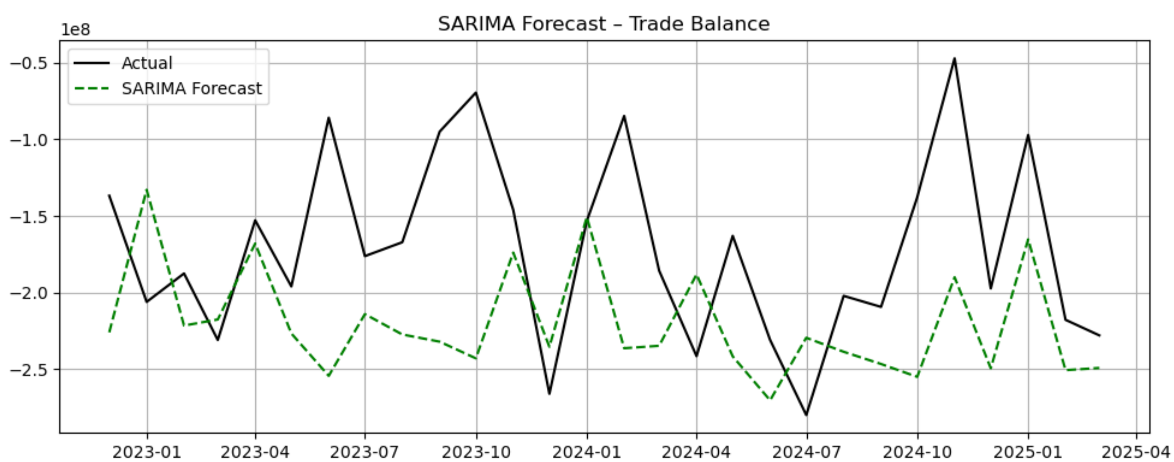

```
import pandas as pd
```

```
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt

# --- Load and Prepare Data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# --- Target Series (Trade Balance) ---
ts = df['Trade Balance'].dropna()

# --- Train-Test Split ---
train_size = int(len(ts) * 0.85)
train, test = ts[:train_size], ts[train_size:]

# --- Fit SARIMA Model ---
model = SARIMAX(train, order=(1,1,1), seasonal_order=(1,1,1,12))
results = model.fit(disp=False)

# --- Forecast ---
forecast = results.forecast(steps=len(test))

# --- Actual vs Forecast Table ---
comparison = pd.DataFrame({
    'Actual': test,
    'SARIMA Forecast': forecast
})
print("\n📋 ACTUAL vs SARIMA FORECAST - Trade Balance:")
print(comparison.round(2))

# --- Plot ---
plt.figure(figsize=(10, 4))
plt.plot(test.index, test, label='Actual', color='black')
plt.plot(test.index, forecast, label='SARIMA Forecast', linestyle='--',
color='green')
plt.title("SARIMA Forecast - Trade Balance")
plt.legend()
```

```
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Print Model Accuracy ---
rmse = sqrt(mean_squared_error(test, forecast))
mae = mean_absolute_error(test, forecast)
print("\n📊 SARIMA MODEL PERFORMANCE - Trade Balance")
print(f"RMSE: {rmse:.2f}")
print(f"MAE : {mae:.2f}")
```

```
📋 ACTUAL vs SARIMA FORECAST - Trade Balance:
                           Actual  SARIMA Forecast
2022-12-01 00:00:00 -1.368183e+08              NaN
2023-01-01 00:00:00 -2.061757e+08              NaN
2023-02-01 00:00:00 -1.875692e+08              NaN
2023-03-01 00:00:00 -2.310620e+08              NaN
2023-04-01 00:00:00 -1.528696e+08              NaN
2023-05-01 00:00:00 -1.960691e+08              NaN
2023-06-01 00:00:00 -8.585694e+07              NaN
2023-07-01 00:00:00 -1.762656e+08              NaN
2023-08-01 00:00:00 -1.671947e+08              NaN
2023-09-01 00:00:00 -9.494899e+07              NaN
2023-10-01 00:00:00 -6.945464e+07              NaN
2023-11-01 00:00:00 -1.460422e+08              NaN
2023-12-01 00:00:00 -2.662149e+08              NaN
2024-01-01 00:00:00 -1.533036e+08              NaN
2024-02-01 00:00:00 -8.467718e+07              NaN
2024-03-01 00:00:00 -1.857879e+08              NaN
2024-04-01 00:00:00 -2.416107e+08              NaN
2024-05-01 00:00:00 -1.630315e+08              NaN
2024-06-01 00:00:00 -2.309953e+08              NaN
2024-07-01 00:00:00 -2.800819e+08              NaN
2024-08-01 00:00:00 -2.022186e+08              NaN
2024-09-01 00:00:00 -2.094400e+08              NaN
2024-10-01 00:00:00 -1.378240e+08              NaN
2024-11-01 00:00:00 -4.708060e+07              NaN
2024-12-01 00:00:00 -1.973878e+08              NaN
2025-01-01 00:00:00 -9.710307e+07              NaN
2025-02-01 00:00:00 -2.178572e+08              NaN
2025-03-01 00:00:00 -2.280295e+08              NaN
```

153	NaN	−2.260655e+08
154	NaN	−1.329275e+08
155	NaN	−2.216290e+08
156	NaN	−2.176532e+08
157	NaN	−1.680414e+08
158	NaN	−2.267750e+08
159	NaN	−2.544693e+08
160	NaN	−2.141385e+08
161	NaN	−2.274403e+08
162	NaN	−2.321446e+08
163	NaN	−2.430374e+08
164	NaN	−1.739592e+08
165	NaN	−2.354776e+08
166	NaN	−1.508032e+08
167	NaN	−2.364319e+08
168	NaN	−2.348378e+08
169	NaN	−1.882092e+08
170	NaN	−2.417245e+08
171	NaN	−2.704482e+08
172	NaN	−2.295926e+08
173	NaN	−2.387456e+08
174	NaN	−2.467217e+08
175	NaN	−2.551279e+08
176	NaN	−1.900680e+08
177	NaN	−2.495070e+08
178	NaN	−1.653103e+08
179	NaN	−2.507655e+08
180	NaN	−2.493058e+08



```
📊 SARIMA MODEL PERFORMANCE - Trade Balance
RMSE: 81161367.11
MAE : 65212784.70
```

In [26]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from math import sqrt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# --- Load and prepare data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Use 'Trade Balance' series
ts = df['Trade Balance'].dropna().values.reshape(-1, 1)

# --- Scale data ---
scaler = MinMaxScaler(feature_range=(0, 1))
ts_scaled = scaler.fit_transform(ts)

# --- Train-test split ---
train_size = int(len(ts_scaled) * 0.85)
train, test = ts_scaled[:train_size], ts_scaled[train_size:]

# --- Prepare data for LSTM ---
def create_dataset(data, look_back=12):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i+look_back, 0])
        y.append(data[i+look_back, 0])
    return np.array(X), np.array(y)

look_back = 12
X_train, y_train = create_dataset(train, look_back)
```

```
X_test, y_test = create_dataset(test, look_back)

# Reshape input to [samples, time steps, features] for LSTM
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# --- Build LSTM Model ---
model = Sequential([
    LSTM(50, activation='relu', input_shape=(look_back, 1)),
    Dense(1)
])
model.compile(optimizer='adam', loss='mse')

# --- Train Model ---
model.fit(X_train, y_train, epochs=50, batch_size=16, verbose=0)

# --- Forecast ---
y_pred_scaled = model.predict(X_test)

# --- Inverse scale back to original values ---
y_pred = scaler.inverse_transform(y_pred_scaled)
y_true = scaler.inverse_transform(y_test.reshape(-1,1))

# --- Calculate RMSE ---
rmse = sqrt(mean_squared_error(y_true, y_pred))
print(f"Test RMSE: {rmse:.2f}\n")

# --- Create forecast vs actual table ---
test_dates = df.index[train_size + look_back : train_size + look_back +
len(y_pred)]

results_df = pd.DataFrame({
    'Date': test_dates,
    'Actual': y_true.flatten(),
    'Forecast': y_pred.flatten()
}).set_index('Date')

print("Forecast vs Actual Values:")
print(results_df.round(2))
1/1 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 247ms/step
Test RMSE: 72831740.11
```

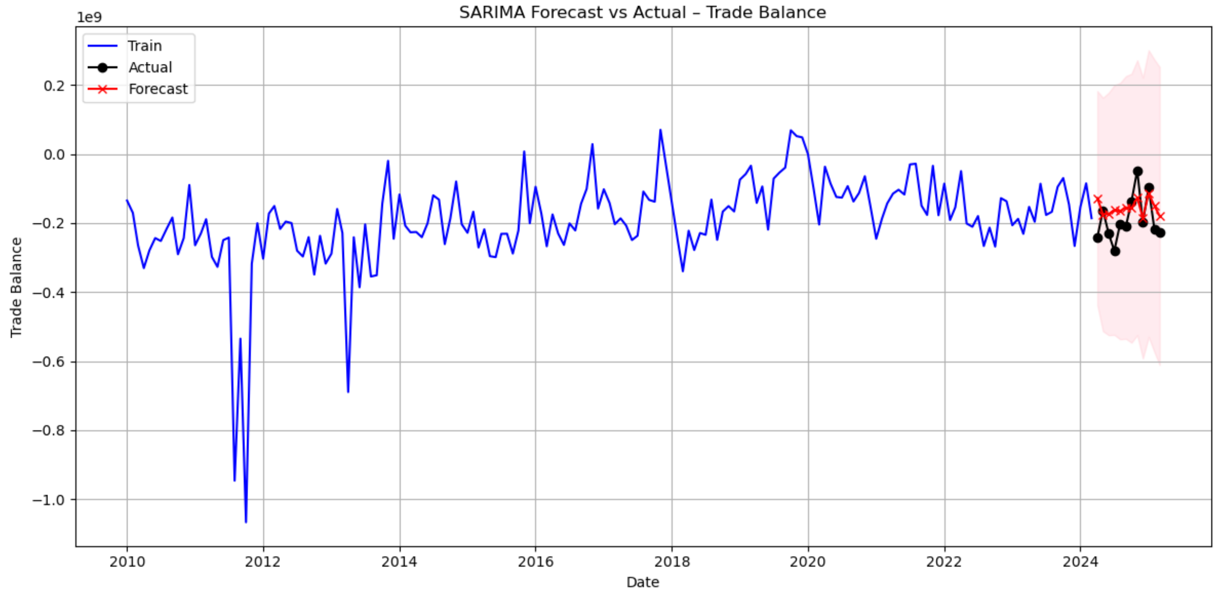
```
Forecast vs Actual Values:
                  Actual     Forecast
Date
2023-10-01 -2.662149e+08 -142845568.0
2023-11-01 -1.533036e+08 -158605312.0
2023-12-01 -8.467718e+07 -154953056.0
2024-01-01 -1.857879e+08 -144195376.0
2024-02-01 -2.416107e+08 -146788352.0
2024-03-01 -1.630315e+08 -158341680.0
2024-04-01 -2.309953e+08 -156546864.0
2024-05-01 -2.800819e+08 -168469648.0
2024-06-01 -2.022186e+08 -182017408.0
2024-07-01 -2.094400e+08 -184224528.0
2024-08-01 -1.378240e+08 -190087952.0
2024-09-01 -4.708060e+07 -186862544.0
2024-10-01 -1.973878e+08 -170166848.0
2024-11-01 -9.710307e+07 -170795408.0
2024-12-01 -2.178572e+08 -160999568.0
2025-01-01 -2.280295e+08 -171260000.0
```

In [32]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error, mean_absolute_error

# --- 1. Load & Prepare Data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Focus on Trade Balance
ts = df['Trade Balance'].dropna()

# --- 2. Split Data (Train/Test) ---
test_size = 12
train = ts[:-test_size]
test = ts[-test_size:]
```

```
# --- 3. Fit SARIMA Model ---
model = SARIMAX(train, order=(1,1,1), seasonal_order=(1,1,1,12))
result = model.fit(disp=False)

# --- 4. Forecast ---
forecast = result.get_forecast(steps=test_size)
forecast_mean = forecast.predicted_mean
conf_int = forecast.conf_int()

# --- 5. Model Performance ---
mse = mean_squared_error(test, forecast_mean)
rmse = np.sqrt(mse)
mae = mean_absolute_error(test, forecast_mean)
mape = np.mean(np.abs((test - forecast_mean) / test)) * 100

# --- 6. Print Metrics ---
print("📊 SARIMA Model Performance - Trade Balance (Last 12 Months)")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape:.2f}%\n")

# --- 7. Actual vs Forecast Table ---
comparison = pd.DataFrame({
    'Actual': test,
    'Forecast': forecast_mean
})
print(comparison.round(2))

# --- 8. Plot Actual vs Forecast ---
plt.figure(figsize=(12,6))
plt.plot(train.index, train, label='Train', color='blue')
plt.plot(test.index, test, label='Actual', color='black', marker='o')
plt.plot(test.index, forecast_mean, label='Forecast', color='red', marker='x')
plt.fill_between(test.index,      conf_int.iloc[:,0],      conf_int.iloc[:,1],
color='pink', alpha=0.3)
plt.title("SARIMA Forecast vs Actual - Trade Balance")
plt.xlabel("Date")
plt.ylabel("Trade Balance")
plt.legend()
```

```
plt.grid(True)
plt.tight_layout()
plt.show()
📊 SARIMA Model Performance - Trade Balance (Last 12 Months)
Mean Squared Error (MSE): 4072369719684321.50
Root Mean Squared Error (RMSE): 63815121.40
Mean Absolute Error (MAE): 53158003.71
Mean Absolute Percentage Error (MAPE): nan%

                          Actual      Forecast
2024-04-01 00:00:00 -2.416107e+08          NaN
2024-05-01 00:00:00 -1.630315e+08          NaN
2024-06-01 00:00:00 -2.309953e+08          NaN
2024-07-01 00:00:00 -2.800819e+08          NaN
2024-08-01 00:00:00 -2.022186e+08          NaN
2024-09-01 00:00:00 -2.094400e+08          NaN
2024-10-01 00:00:00 -1.378240e+08          NaN
2024-11-01 00:00:00 -4.708060e+07          NaN
2024-12-01 00:00:00 -1.973878e+08          NaN
2025-01-01 00:00:00 -9.710307e+07          NaN
2025-02-01 00:00:00 -2.178572e+08          NaN
2025-03-01 00:00:00 -2.280295e+08          NaN
169                           NaN -1.275686e+08
170                           NaN -1.748479e+08
171                           NaN -1.733965e+08
172                           NaN -1.620902e+08
173                           NaN -1.651880e+08
174                           NaN -1.546429e+08
175                           NaN -1.567036e+08
176                           NaN -1.264710e+08
177                           NaN -1.850375e+08
178                           NaN -1.143434e+08
179                           NaN -1.498800e+08
180                           NaN -1.792481e+08
```

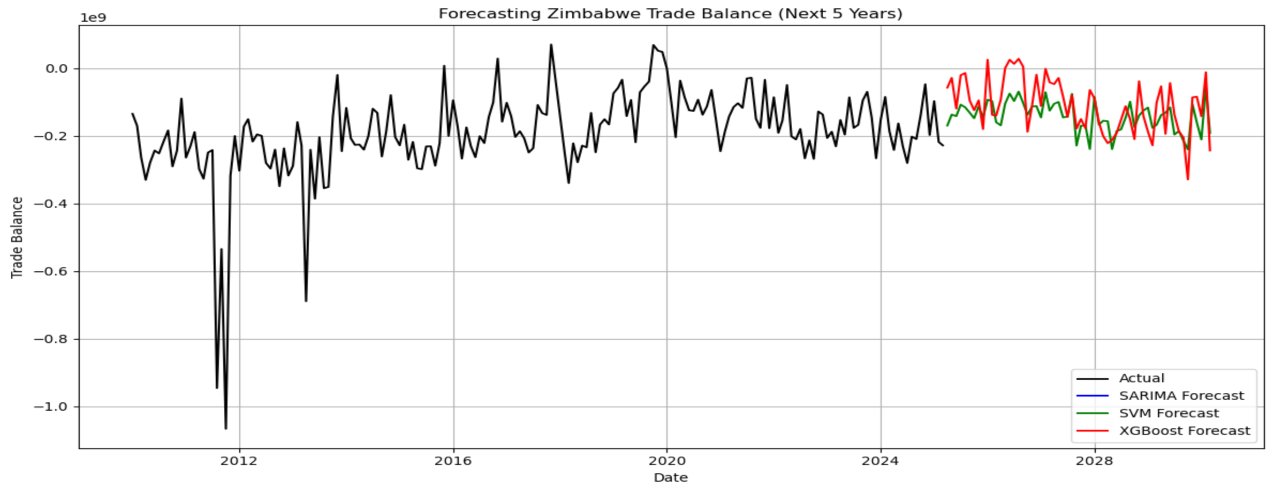


In [35]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.svm import SVR
from xgboost import XGBRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt

# --- Load Data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')  # e.g. Jan-10
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Use Trade Balance
ts = df['Trade Balance'].dropna()

# --- Forecasting 5 Years Ahead (60 Months) ---
forecast_horizon = 60

# --- SARIMA ---
```

```
sarima_model = SARIMAX(ts, order=(1,1,1), seasonal_order=(1,1,1,12))
sarima_result = sarima_model.fit(disp=False)
sarima_forecast = sarima_result.forecast(steps=forecast_horizon)

# --- Preprocessing for ML Models (SVM, XGBoost) ---
scaler = MinMaxScaler()
scaled_series = scaler.fit_transform(ts.values.reshape(-1, 1))

def create_sequences(data, look_back=12):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i+look_back, 0])
        y.append(data[i+look_back, 0])
    return np.array(X), np.array(y)

look_back = 12
X, y = create_sequences(scaled_series, look_back)
X_train, y_train = X[:-forecast_horizon], y[:-forecast_horizon]
X_test = X[-forecast_horizon:]

# --- SVM Model ---
svm_model = SVR(kernel='rbf')
svm_model.fit(X_train, y_train)
svm_forecast = svm_model.predict(X_test)
svm_forecast = scaler.inverse_transform(svm_forecast.reshape(-1, 1))

# --- XGBoost Model ---
xgb_model = XGBRegressor(n_estimators=100)
xgb_model.fit(X_train, y_train)
xgb_forecast = xgb_model.predict(X_test)
xgb_forecast = scaler.inverse_transform(xgb_forecast.reshape(-1, 1))

# --- Future Date Range ---
last_date = ts.index[-1]
future_dates   =   pd.date_range(start=last_date   +   pd.DateOffset(months=1),
periods=forecast_horizon, freq='MS')

# --- Combine Forecasts ---
forecast_df = pd.DataFrame({
    'SARIMA': sarima_forecast,
    'SVM': svm_forecast.flatten(),
```

```
    'XGBoost': xgb_forecast.flatten()
}, index=future_dates)

# --- Plot Results ---
plt.figure(figsize=(12, 6))
plt.plot(ts.index, ts.values, label='Actual', color='black')
plt.plot(forecast_df.index, forecast_df['SARIMA'], label='SARIMA Forecast',
color='blue')
plt.plot(forecast_df.index, forecast_df['SVM'], label='SVM Forecast',
color='green')
plt.plot(forecast_df.index, forecast_df['XGBoost'], label='XGBoost Forecast',
color='red')
plt.title("Forecasting Zimbabwe Trade Balance (Next 5 Years)")
plt.xlabel("Date")
plt.ylabel("Trade Balance")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Print Table of Forecasts ---
print("\n📊 Forecast Table - First 12 Months:\n")
print(forecast_df.round(2).head(12))

# --- Optional: Model Accuracy on last 12 actuals ---
print("\n📈 Model Performance (on last 12 known points):")
test_data = ts[-forecast_horizon:]
common_length = min(len(test_data), forecast_horizon)
for model_name, pred in zip(['SARIMA', 'SVM', 'XGBoost'], [sarima_forecast,
svm_forecast.flatten(), xgb_forecast.flatten()]):
    pred = pred[:common_length]
    actual = test_data[-common_length:]
    rmse = sqrt(mean_squared_error(actual, pred))
    mae = mean_absolute_error(actual, pred)
    print(f"{model_name}: RMSE = {rmse:.2f}, MAE = {mae:.2f}")
```



📊 Forecast Table - First 12 Months:

	SARIMA	SVM	XGBoost
2025-04-01	NaN	-1.692912e+08	-57217772.0
2025-05-01	NaN	-1.368108e+08	-28246736.0
2025-06-01	NaN	-1.417848e+08	-119337448.0
2025-07-01	NaN	-1.074584e+08	-20575142.0
2025-08-01	NaN	-1.154487e+08	-13835107.0
2025-09-01	NaN	-1.314303e+08	-95567952.0
2025-10-01	NaN	-1.478294e+08	-123890032.0
2025-11-01	NaN	-1.125589e+08	-94725280.0
2025-12-01	NaN	-1.454842e+08	-179894112.0
2026-01-01	NaN	-9.300000e+07	25323256.0
2026-02-01	NaN	-9.736183e+07	-137762128.0
2026-03-01	NaN	-1.596874e+08	-140001968.0

📈 Model Performance (on last 12 known points):
SARIMA: RMSE = 81027383.96, MAE = 66389490.89
SVM: RMSE = 75326037.87, MAE = 60149139.42
XGBoost: RMSE = 103913552.10, MAE = 81831901.13

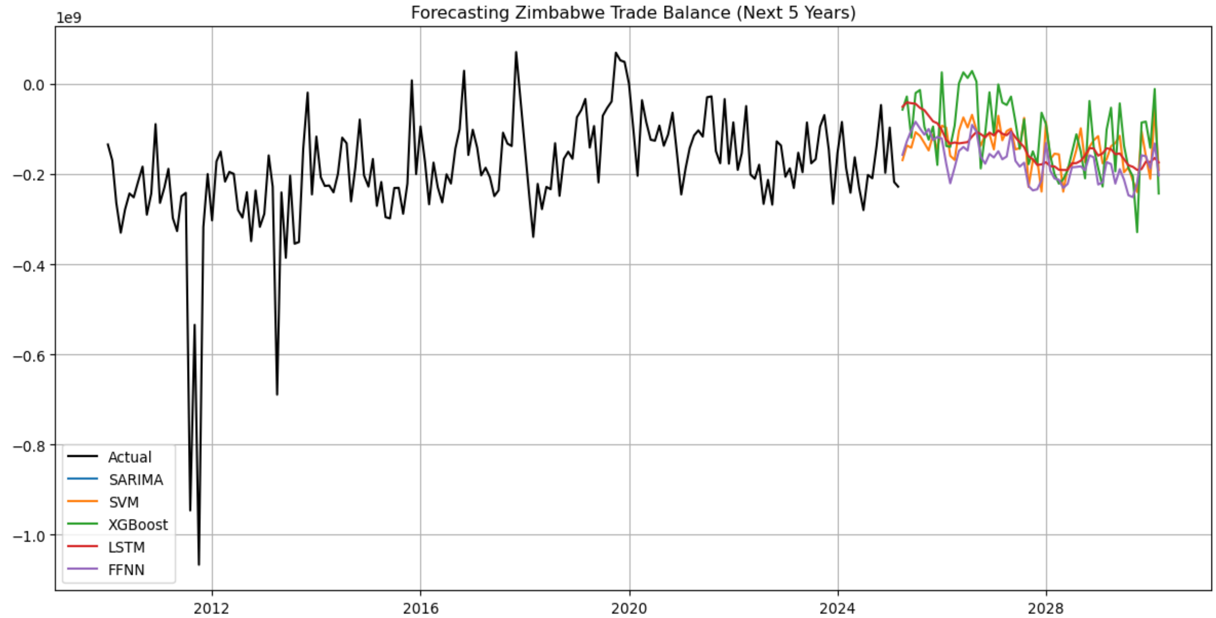
In [36]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

```
from sklearn.svm import SVR
from xgboost import XGBRegressor
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM

# --- Load Data ---
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')  # Example: Jan-10
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)
ts = df['Trade Balance'].dropna()

# --- Forecast Parameters ---
forecast_horizon = 60  # 5 years (monthly)
look_back = 12  # past 12 months input

# --- Preprocessing ---
scaler = MinMaxScaler()
scaled_series = scaler.fit_transform(ts.values.reshape(-1, 1))

def create_sequences(data, look_back=12):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i+look_back, 0])
        y.append(data[i+look_back, 0])
    return np.array(X), np.array(y)

X, y = create_sequences(scaled_series, look_back)
X_train, y_train = X[:-forecast_horizon], y[:-forecast_horizon]
X_forecast = X[-forecast_horizon:]

# --- SARIMA ---
sarima_model = SARIMAX(ts, order=(1,1,1), seasonal_order=(1,1,1,12))
sarima_result = sarima_model.fit(disp=False)
sarima_forecast = sarima_result.forecast(steps=forecast_horizon)

# --- SVM ---
svm = SVR()
svm.fit(X_train, y_train)
svm_pred = scaler.inverse_transform(svm.predict(X_forecast).reshape(-1, 1))
```

```
# --- XGBoost ---
xgb = XGBRegressor()
xgb.fit(X_train, y_train)
xgb_pred = scaler.inverse_transform(xgb.predict(X_forecast).reshape(-1, 1))

# --- LSTM ---
X_train_lstm = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
model_lstm = Sequential()
model_lstm.add(LSTM(50, activation='relu', input_shape=(look_back, 1)))
model_lstm.add(Dense(1))
model_lstm.compile(optimizer='adam', loss='mse')
model_lstm.fit(X_train_lstm, y_train, epochs=20, verbose=0)
X_forecast_lstm          =          X_forecast.reshape((X_forecast.shape[0],
X_forecast.shape[1], 1))
lstm_pred = scaler.inverse_transform(model_lstm.predict(X_forecast_lstm))

# --- FFNN ---
model_ffnn = Sequential()
model_ffnn.add(Dense(64, activation='relu', input_shape=(look_back,)))
model_ffnn.add(Dense(32, activation='relu'))
model_ffnn.add(Dense(1))
model_ffnn.compile(optimizer='adam', loss='mse')
model_ffnn.fit(X_train, y_train, epochs=50, verbose=0)
ffnn_pred = scaler.inverse_transform(model_ffnn.predict(X_forecast))

# --- Future Dates ---
last_date = ts.index[-1]
future_dates    =    pd.date_range(last_date    +    pd.DateOffset(months=1),
periods=forecast_horizon, freq='MS')

# --- Forecast DataFrame ---
forecast_df = pd.DataFrame({
    'SARIMA': sarima_forecast,
    'SVM': svm_pred.flatten(),
    'XGBoost': xgb_pred.flatten(),
    'LSTM': lstm_pred.flatten(),
    'FFNN': ffnn_pred.flatten()
}, index=future_dates)

# --- Plot ---
```

```
plt.figure(figsize=(12, 6))
plt.plot(ts.index, ts.values, label='Actual', color='black')
for col in forecast_df.columns:
    plt.plot(forecast_df.index, forecast_df[col], label=col)
plt.title("Forecasting Zimbabwe Trade Balance (Next 5 Years)")
plt.legend()
plt.grid()
plt.tight_layout()
plt.show()

# --- Forecast Table (First 12 months) ---
print("\n📊 Forecast Table - First 12 Months:\n")
print(forecast_df.head(12).round(2))

# --- Model Performance on Last 60 Months (if available) ---
actual_tail = ts[-forecast_horizon:]
print("\n📈 Model Performance on Last 60 Known Points:")
for model_name in forecast_df.columns:
    try:
        pred = forecast_df[model_name][:len(actual_tail)]
        rmse = np.sqrt(mean_squared_error(actual_tail, pred))
        mae = mean_absolute_error(actual_tail, pred)
        print(f"{model_name}: RMSE = {rmse:.2f}, MAE = {mae:.2f}")
    except:
        print(f"{model_name}: Not enough actual data for evaluation.")
2/2 ━━━━━━━━━━━━━━━━━━━━ 1s 330ms/step
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 95ms/step
```




```
📊 Forecast Table - First 12 Months:

            SARIMA           SVM      XGBoost         LSTM         FFNN
2025-04-01     NaN -1.692912e+08  -57217772.0  -50883524.0 -157617920.0
2025-05-01     NaN -1.368108e+08  -28246736.0  -41200016.0 -127600352.0
2025-06-01     NaN -1.417848e+08 -119337448.0  -43066052.0 -103268816.0
2025-07-01     NaN -1.074584e+08  -20575142.0  -44313412.0  -84228936.0
2025-08-01     NaN -1.154487e+08  -13835107.0  -53389764.0  -99072904.0
2025-09-01     NaN -1.314303e+08  -95567952.0  -58658444.0 -112829008.0
2025-10-01     NaN -1.478294e+08 -123890032.0  -70891960.0 -100333152.0
2025-11-01     NaN -1.125589e+08  -94725280.0  -83358352.0 -124680728.0
2025-12-01     NaN -1.454842e+08 -179894112.0  -87619104.0 -117733096.0
2026-01-01     NaN -9.300000e+07   25323256.0 -102363344.0 -121426608.0
2026-02-01     NaN -9.736183e+07 -137762128.0 -124763256.0 -177397488.0
2026-03-01     NaN -1.596874e+08 -140001968.0 -132726608.0 -220652496.0

📈 Model Performance on Last 60 Known Points:
SARIMA: Not enough actual data for evaluation.
SVM: RMSE = 75326037.87, MAE = 60149139.42
XGBoost: RMSE = 103913552.10, MAE = 81831901.13
LSTM: RMSE = 67603178.33, MAE = 56923515.85
FFNN: RMSE = 69807636.29, MAE = 57833437.36
```

In [37]:

```
import pandas as pd
```

```
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Load and prepare data
df = pd.read_csv("C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv")
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

ts = df['Exports'].dropna()

# Fit SARIMA model
model = SARIMAX(ts, order=(1,1,1), seasonal_order=(1,1,1,12))
results = model.fit(disp=False)

# Print model summary (coefficients, statistics)
print(results.summary())
                                     SARIMAX Results
==============================================================================
============
Dep. Variable:                                   Exports    No. Observations:
181
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood              -
3296.183
Date:                        Tue, 17 Jun 2025   AIC                          6602.366
Time:                                01:06:38   BIC                          6617.986
Sample:                                     0   HQIC                         6608.705
                                        - 181
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.3758      0.164      2.295      0.022       0.055       0.697
ma.L1         -0.8429      0.104     -8.119      0.000      -1.046      -0.639
ar.S.L12       0.0174      0.161      0.108      0.914      -0.297       0.332
ma.S.L12      -0.6732      0.130     -5.182      0.000      -0.928      -0.419
sigma2      8.985e+15        nan        nan        nan         nan         nan
==============================================================================
=====
Ljung-Box (L1) (Q):                   0.04   Jarque-Bera (JB):                 3.04
Prob(Q):                              0.84   Prob(JB):                         0.22
```

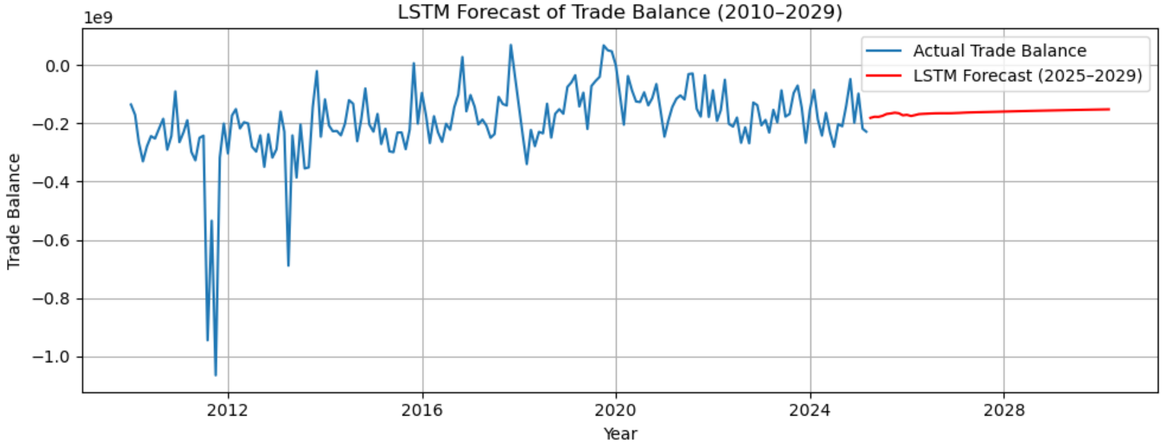
```
Heteroskedasticity (H):               1.45   Skew:                             0.02
Prob(H) (two-sided):                  0.17   Kurtosis:                         3.66
===================================================================================
=====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.09e+48. Standard errors may be unstable.
```

In [44]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM

# Load dataset
file_path = "C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv"
df = pd.read_csv(file_path)
df.columns = df.columns.str.strip()

# Convert Year to datetime and set index
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y', errors='coerce')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Focus on Trade Balance column
ts = df['Trade Balance'].dropna()

# Scale data
scaler = MinMaxScaler()
ts_scaled = scaler.fit_transform(ts.values.reshape(-1, 1))

# Create sequences
def create_sequences(data, seq_length=12):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i + seq_length])
        y.append(data[i + seq_length])
```

```
    return np.array(X), np.array(y)

seq_length = 12
X, y = create_sequences(ts_scaled, seq_length)

# Use all for training
X_train, y_train = X, y

# LSTM Model
model = Sequential([
    LSTM(50, activation='relu', input_shape=(seq_length, 1)),
    Dense(1)
])
model.compile(optimizer='adam', loss='mse')
model.fit(X_train, y_train, epochs=50, verbose=0)

# Forecast next 60 months
forecast_input = ts_scaled[-seq_length:]
forecast = []

for _ in range(60):  # 5 years
    input_reshaped = forecast_input.reshape((1, seq_length, 1))
    pred = model.predict(input_reshaped, verbose=0)
    forecast.append(pred[0, 0])
    forecast_input = np.append(forecast_input[1:], pred)

# Inverse scale
forecast = scaler.inverse_transform(np.array(forecast).reshape(-1, 1))

# Create forecast dates
last_date = ts.index[-1]
forecast_dates  =  pd.date_range(start=last_date  +  pd.DateOffset(months=1),
periods=60, freq='MS')

# Plot
plt.figure(figsize=(10, 4))
plt.plot(ts.index, ts.values, label='Actual Trade Balance')
plt.plot(forecast_dates,   forecast,   label='LSTM   Forecast   (2025–2029)',
color='red')
plt.title('LSTM Forecast of Trade Balance (2010–2029)')
plt.xlabel('Year')
```

```python
plt.ylabel('Trade Balance')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [7]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
import xgboost as xgb

from keras.models import Sequential
from keras.layers import Dense, LSTM

import statsmodels.api as sm
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Load dataset
file_path = "C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv"
df = pd.read_csv(file_path)
df.columns = df.columns.str.strip()

df['Year'] = pd.to_datetime(df['Year'], format='%b-%y', errors='coerce')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)
```

```
ts = df['Trade Balance'].dropna()

# Scale data
scaler = MinMaxScaler()
ts_scaled = scaler.fit_transform(ts.values.reshape(-1, 1))

# Create sequences for NN/SVM/XGB
def create_sequences(data, seq_length=12):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 12
X_seq, y_seq = create_sequences(ts_scaled, seq_length)

# Reshape for LSTM
X_lstm = X_seq.reshape((X_seq.shape[0], X_seq.shape[1], 1))

# Train-test split index for last 60 months test
train_size = len(ts) - 60

X_train_lstm = X_lstm[:train_size - seq_length]
y_train_lstm = y_seq[:train_size - seq_length]

# -- LSTM Model --
model_lstm = Sequential([
    LSTM(50, input_shape=(seq_length, 1)),
    Dense(1)
])
model_lstm.compile(optimizer='adam', loss='mse')

print("Training LSTM...")
model_lstm.fit(X_train_lstm, y_train_lstm, epochs=20, verbose=1)
print("LSTM training done.")

# Forecast 60 months recursively
forecast_input = ts_scaled[-seq_length:].copy()
forecast_lstm = []
```

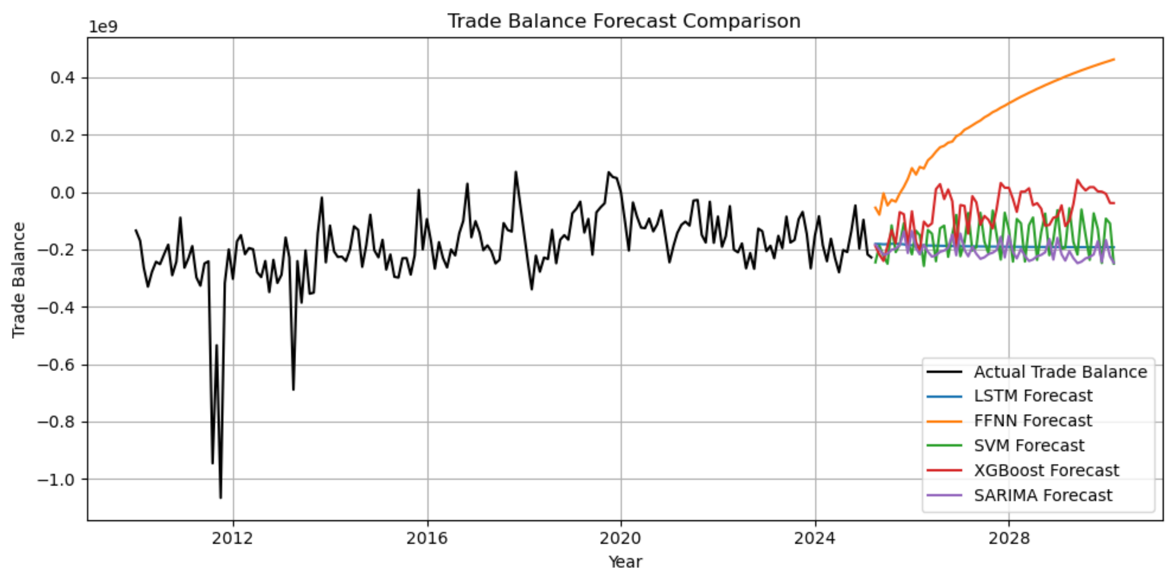
```
print("Forecasting LSTM...")
for _ in range(60):
    input_reshaped = forecast_input.reshape((1, seq_length, 1))
    pred = model_lstm.predict(input_reshaped, verbose=0)
    forecast_lstm.append(pred[0,0])
    forecast_input = np.append(forecast_input[1:], pred)
print("LSTM Forecast done.")

forecast_lstm  =  scaler.inverse_transform(np.array(forecast_lstm).reshape(-1,
1))

# -- FFNN Model --
X_ffnn = X_seq.reshape((X_seq.shape[0], X_seq.shape[1]))
X_train_ffnn = X_ffnn[:train_size - seq_length]
y_train_ffnn = y_seq[:train_size - seq_length].ravel()

model_ffnn = MLPRegressor(hidden_layer_sizes=(50,), max_iter=500)
print("Training FFNN...")
model_ffnn.fit(X_train_ffnn, y_train_ffnn)
print("FFNN training done.")

forecast_input_ffnn = ts_scaled[-seq_length:].flatten()
forecast_ffnn = []

print("Forecasting FFNN...")
for _ in range(60):
    pred = model_ffnn.predict(forecast_input_ffnn.reshape(1, -1))[0]
    forecast_ffnn.append(pred)
    forecast_input_ffnn = np.append(forecast_input_ffnn[1:], pred)
print("FFNN Forecast done.")

forecast_ffnn  =  scaler.inverse_transform(np.array(forecast_ffnn).reshape(-1,
1))

# -- SVM Model --
model_svm = SVR(kernel='rbf')
print("Training SVM...")
model_svm.fit(X_train_ffnn, y_train_ffnn)
print("SVM training done.")
```

```python
forecast_input_svm = ts_scaled[-seq_length:].flatten()
forecast_svm = []

print("Forecasting SVM...")
for _ in range(60):
    pred = model_svm.predict(forecast_input_svm.reshape(1, -1))[0]
    forecast_svm.append(pred)
    forecast_input_svm = np.append(forecast_input_svm[1:], pred)
print("SVM Forecast done.")

forecast_svm = scaler.inverse_transform(np.array(forecast_svm).reshape(-1, 1))

# -- XGBoost Model --
model_xgb = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100)
print("Training XGBoost...")
model_xgb.fit(X_train_ffnn, y_train_ffnn)
print("XGBoost training done.")

forecast_input_xgb = ts_scaled[-seq_length:].flatten()
forecast_xgb = []

print("Forecasting XGBoost...")
for _ in range(60):
    pred = model_xgb.predict(forecast_input_xgb.reshape(1, -1))[0]
    forecast_xgb.append(pred)
    forecast_input_xgb = np.append(forecast_input_xgb[1:], pred)
print("XGBoost Forecast done.")

forecast_xgb = scaler.inverse_transform(np.array(forecast_xgb).reshape(-1, 1))

# -- SARIMA Model --
print("Fitting SARIMA...")
model_sarima = SARIMAX(ts, order=(1,1,1), seasonal_order=(1,1,1,12))
results_sarima = model_sarima.fit(disp=False)
forecast_sarima = results_sarima.forecast(steps=60)
print("SARIMA Forecast done.")

# Plot
forecast_dates = pd.date_range(start=ts.index[-1] + pd.DateOffset(months=1),
periods=60, freq='MS')
```

```
plt.figure(figsize=(10,5))
plt.plot(ts.index, ts.values, label='Actual Trade Balance', color='black')

plt.plot(forecast_dates, forecast_lstm, label='LSTM Forecast')
plt.plot(forecast_dates, forecast_ffnn, label='FFNN Forecast')
plt.plot(forecast_dates, forecast_svm, label='SVM Forecast')
plt.plot(forecast_dates, forecast_xgb, label='XGBoost Forecast')
plt.plot(forecast_dates, forecast_sarima, label='SARIMA Forecast')

plt.title('Trade Balance Forecast Comparison')
plt.xlabel('Year')
plt.ylabel('Trade Balance')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
Training LSTM...
Epoch 1/20
C:\Users\METHOD\AppData\Roaming\Python\Python312\site-packages\keras\src\layers\rnn\rnn.py:199: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
4/4 ━━━━━━━━━━━━━━━━━━━━ 3s 21ms/step - loss: 0.4876
Epoch 2/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.2836
Epoch 3/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.1358
Epoch 4/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0368
Epoch 5/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0194
Epoch 6/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 18ms/step - loss: 0.0424
Epoch 7/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0269
Epoch 8/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0119
Epoch 9/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 0.0195
Epoch 10/20
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0186
Epoch 11/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0199
Epoch 12/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0188
Epoch 13/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 0.0140
Epoch 14/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step - loss: 0.0127
Epoch 15/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - loss: 0.0147
Epoch 16/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0124
Epoch 17/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - loss: 0.0121
Epoch 18/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.0183
Epoch 19/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - loss: 0.0171
Epoch 20/20
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.0152
LSTM training done.
Forecasting LSTM...
LSTM Forecast done.
Training FFNN...
FFNN training done.
Forecasting FFNN...
FFNN Forecast done.
Training SVM...
SVM training done.
Forecasting SVM...
SVM Forecast done.
Training XGBoost...
XGBoost training done.
Forecasting XGBoost...
XGBoost Forecast done.
Fitting SARIMA...
C:\ProgramData\anaconda3\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
```

```
  self._init_dates(dates, freq)
C:\ProgramData\anaconda3\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\ProgramData\anaconda3\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: ValueWarning: No supported
index is available. Prediction results will be given with an integer index
beginning at `start`.
  return get_prediction_index(
C:\ProgramData\anaconda3\Lib\site-
packages\statsmodels\tsa\base\tsa_model.py:836: FutureWarning: No supported
index is available. In the next version, calling this method in a model without
a supported index will result in an exception.
  return get_prediction_index(
SARIMA Forecast done.
```



In [10]:

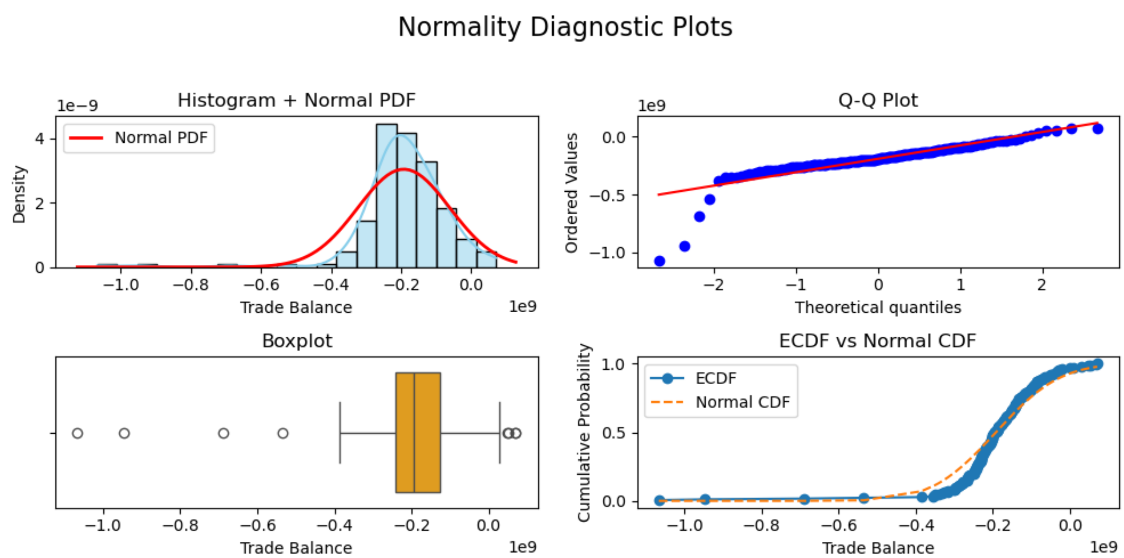
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import shapiro, kstest, anderson, jarque_bera, norm, probplot

# Load dataset
file_path = "C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv"
```

```
df = pd.read_csv(file_path)
df.columns = df.columns.str.strip()

# Extract and clean series
data = df['Trade Balance'].dropna()

print("\n================ NORMALITY TESTS ================\n")

# 1. Shapiro-Wilk Test
stat, p = shapiro(data)
print("Shapiro-Wilk Test:")
print(f"Statistic = {stat:.4f}, p-value = {p:.4f}")
print("=>",  "Normally  distributed\n"  if  p  >  0.05  else  "Not  normally
distributed\n")

# 2. Kolmogorov–Smirnov Test (Standardized)
data_std = (data - data.mean()) / data.std()
stat, p = kstest(data_std, 'norm')
print("Kolmogorov–Smirnov Test:")
print(f"Statistic = {stat:.4f}, p-value = {p:.4f}")
print("=>",  "Normally  distributed\n"  if  p  >  0.05  else  "Not  normally
distributed\n")

# 3. Anderson-Darling Test
result = anderson(data, dist='norm')
print("Anderson-Darling Test:")
print(f"Statistic = {result.statistic:.4f}")
for i in range(len(result.critical_values)):
    sl, cv = result.significance_level[i], result.critical_values[i]
    print(f"  At {sl}% significance level: Critical Value = {cv:.4f}")
    if result.statistic < cv:
        print("  => Normally distributed at", sl, "% level\n")
        break
else:
    print("  => Not normally distributed\n")

# 4. Jarque-Bera Test
stat, p = jarque_bera(data)
print("Jarque-Bera Test:")
print(f"Statistic = {stat:.4f}, p-value = {p:.4f}")
```

```
print("=>", "Normally distributed\n" if p > 0.05 else "Not normally distributed\n")

# ==================== PLOTS ======================

plt.figure(figsize=(10, 5))

# 1. Histogram with KDE + Normal Curve
plt.subplot(2, 2, 1)
sns.histplot(data, bins=20, kde=True, stat="density", color='skyblue')
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
p = norm.pdf(x, data.mean(), data.std())
plt.plot(x, p, 'r', linewidth=2, label='Normal PDF')
plt.title("Histogram + Normal PDF")
plt.xlabel("Trade Balance")
plt.ylabel("Density")
plt.legend()

# 2. Q-Q Plot
plt.subplot(2, 2, 2)
probplot(data, dist="norm", plot=plt)
plt.title("Q-Q Plot")

# 3. Boxplot
plt.subplot(2, 2, 3)
sns.boxplot(x=data, color='orange')
plt.title("Boxplot")

# 4. ECDF vs Normal CDF
plt.subplot(2, 2, 4)
data_sorted = np.sort(data)
ecdf = np.arange(1, len(data_sorted)+1) / len(data_sorted)
normal_cdf = norm.cdf(data_sorted, loc=data.mean(), scale=data.std())
plt.plot(data_sorted, ecdf, label='ECDF', marker='o')
plt.plot(data_sorted, normal_cdf, label='Normal CDF', linestyle='--')
plt.title("ECDF vs Normal CDF")
plt.xlabel("Trade Balance")
plt.ylabel("Cumulative Probability")
plt.legend()
```

```
plt.suptitle("Normality Diagnostic Plots", fontsize=16)
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```

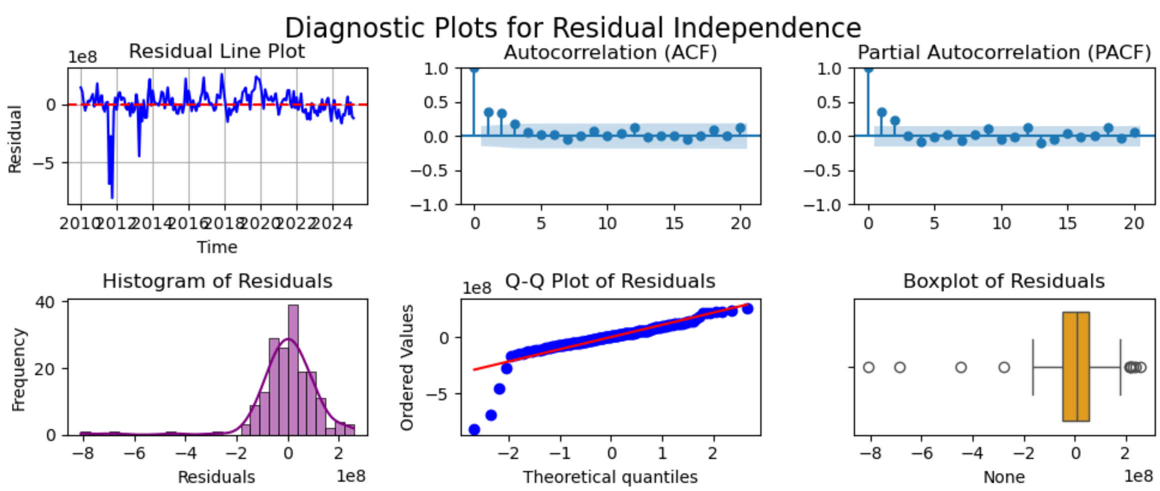
```
================ NORMALITY TESTS ================

Shapiro-Wilk Test:
Statistic = 0.7765, p-value = 0.0000
=> Not normally distributed

Kolmogorov-Smirnov Test:
Statistic = 0.1387, p-value = 0.0017
=> Not normally distributed

Anderson-Darling Test:
Statistic = 6.0518
  At 15.0% significance level: Critical Value = 0.5640
  At 10.0% significance level: Critical Value = 0.6420
  At 5.0% significance level: Critical Value = 0.7710
  At 2.5% significance level: Critical Value = 0.8990
  At 1.0% significance level: Critical Value = 1.0690
  => Not normally distributed

Jarque-Bera Test:
Statistic = 2243.7773, p-value = 0.0000
=> Not normally distributed
```



In [14]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import probplot
import statsmodels.api as sm
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# ======== Load Data & Model ==========
file_path = "C:/Users/METHOD/OneDrive/Desktop/ZimStats.csv"
df = pd.read_csv(file_path)
df.columns = df.columns.str.strip()
df['Year'] = pd.to_datetime(df['Year'], format='%b-%y', errors='coerce')
df.set_index('Year', inplace=True)
df.sort_index(inplace=True)

# Simple regression model for demonstration
df = df.dropna()
y = df['Trade Balance']
X = sm.add_constant(np.arange(len(y)))  # Time trend
model = sm.OLS(y, X).fit()
residuals = model.resid

# ======== PLOTS START HERE ==========

plt.figure(figsize=(10, 4))

# 1. Residual Line Plot
plt.subplot(2, 3, 1)
plt.plot(residuals, label='Residuals', color='blue')
plt.axhline(0, linestyle='--', color='red')
plt.title("Residual Line Plot")
plt.xlabel("Time")
plt.ylabel("Residual")
plt.grid(True)

# 2. ACF Plot
plt.subplot(2, 3, 2)
plot_acf(residuals, lags=20, ax=plt.gca())
plt.title("Autocorrelation (ACF)")
```

```
# 3. PACF Plot
plt.subplot(2, 3, 3)
plot_pacf(residuals, lags=20, ax=plt.gca())
plt.title("Partial Autocorrelation (PACF)")

# 4. Histogram
plt.subplot(2, 3, 4)
sns.histplot(residuals, kde=True, color='purple')
plt.title("Histogram of Residuals")
plt.xlabel("Residuals")
plt.ylabel("Frequency")

# 5. Q-Q Plot
plt.subplot(2, 3, 5)
probplot(residuals, dist="norm", plot=plt)
plt.title("Q-Q Plot of Residuals")

# 6. Boxplot
plt.subplot(2, 3, 6)
sns.boxplot(x=residuals, color='orange')
plt.title("Boxplot of Residuals")

plt.tight_layout()
plt.suptitle("Diagnostic Plots for Residual Independence", fontsize=16, y=1.02)
plt.show()
```



In [ ]: