A Machine Learning Approach for Accurate Valuation of Imports in Uganda

A Thesis by

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DEDICATION

DECLARATION

I, Paul Sentongo, declare that this thesis titled **"A Machine Learning Approach for Accurate Valuation of Imports in Uganda"** is my original work.
It has not been submitted for any degree or examination in any other university or institution. All sources used in the research have been properly acknowledged through citations and references.

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ACKNOWLEDGMENTS

ABSTRACT

Accurate import valuation is crucial for revenue generation and promoting fair trade practices among countries. Traditional valuation methods are often hindered by inconsistency and vulnerability to fraud, resulting in revenue losses estimated at $4.9 billion between 2006 and 2015.

This research presents a machine-learning approach designed to enhance the precision and efficiency of import item valuation within Uganda's customs framework. Using Uganda's historical trade data from 2005 to 2023, we developed and validated predictive models that included Random Forests, XGBoost, and Artificial Neural Networks (ANN). Key variables, such as the country of origin and unit price, were analyzed to train the predictive models. The Random Forest model achieved excellent performance, registering 95% accuracy and outperforming conventional methods. This demonstrates the transformative potential of machine learning.

The research findings showcase the potential of machine learning to mitigate revenue leakage, reduce valuation fraud, minimize valuation disputes, and ensure compliance with international trade regulations.

Looking at the bigger picture, this study offers a framework for developing countries facing similar challenges. Recommendations include institutionalizing machine learning-powered valuation systems, upgrading data infrastructure, and integrating AI expertise within customs operations to ensure sustainable improvements.

In conclusion, this research combines technological innovation with policy action, introducing artificial intelligence as a strong pillar for economic resilience in the international trade network.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

In this study, research has been conducted into the application of machine learning methods for accurately valuing import items within Uganda's customs framework. Customs can be defined as the official department that administers and collects the duties levied by a government on imported goods. We narrowed this down to define customs duties as the tax levied on goods imported or exported within Uganda at different ad valorem rates. and the East African Community Customs Management Act 2004 (EACCMA) is the legal framework for customs in Uganda and the entire East African region.

The valuation of imported goods, also known as customs valuation, refers to the task of assigning a monetary value to imported goods for taxation purposes. Customs duties are the backbone of Uganda's economy, with a contribution to tax revenue estimated at 30% (URA, 2022).

The World Trade Organization (WTO) is an international organization that monitors and regulates international trade among its member countries. Its primary goals are to improve global trade by lowering barriers, adopting clear regulations, and ensuring equitable treatment of all member countries, where Uganda is also a member.

As part of these goals, the WTO has established specific agreements to harmonize and standardize customs practices, notably about the customs valuation of imported products.

Among the agreements, there falls the WTO Valuation Agreement, officially known as the Agreement on Implementation of Article VII of the General Agreement on Tariffs and Trade (GATT) 1994 (The Agreement on Customs Valuation, n.d.), which replaced the GATT Valuation Code during the Uruguay Round discussions that founded the WTO in 1994.

The agreement is critical to harmonizing customs processes around the world. Before this agreement, customs valuation systems differed greatly between countries, causing ambiguity and challenges for multinational businesses. The WTO agreement established a standardized set of procedures for estimating the customs value of imported products. This has resulted in a more standard and predictable environment for international trade, with customs valuations conducted fairly and transparently.

This Agreement establishes a customs valuation system based principally on the transaction value of imported goods as the main method among the rest, as they are all explained further below.

- **Transaction value method:** This is the primary and most widely used method, based on the price payable for the goods when they are sold for export to the country of import. This method includes adjustments for certain costs, such as transport and insurance.
- **Transaction value of identical goods:** If the transaction value cannot be determined, this method is used to assess the customs value based on the price of identical goods exported to the same country at the same time.
- **Transaction value of similar goods:** If identical goods are not available, this method uses the value of similar goods. Goods are considered similar if they have similar characteristics and material composition and can perform the same functions.
- **Deductive method:** This method is used when the value of imported goods cannot be determined using the previous methods. It is based on the unit price at which the imported goods or identical or similar goods are sold on the domestic market, less certain margins and costs.
- **Calculated method:** This method uses the production cost of imported goods, including the costs of materials, manufacturing, and other expenses, plus a margin for profit and overheads. It is applied when the previous methods cannot be used.
- **Method of last resort:** If none of the above methods can be used to determine the customs value, this method is used. It is based on reasonable criteria compatible with the principles and general provisions of the WTO Agreement and on available data.

These methods were primarily developed to ensure that customs valuation is determined transparently and consistently, minimizing conflicts and promoting a fair trading environment for all those involved in international trade.

Despite these benefits, customs experience difficulties and complications when determining the customs value of goods. Since items and transactions vary, each circumstance necessitates a unique interpretation of the WTO standards. This means the customs framework traverses a complexity of local and international trade rules, which can be time-consuming and expensive. Furthermore, there is a risk of under- or over-valuation, which results in financial penalties or delays in the release of products.

Technology and digitization are playing an increasingly important role in the modernization of customs operations, providing answers to some of the issues related to customs valuation and the classification of goods. Automated customs systems improve transaction traceability and speed up import document verification, lowering the risk of fraud and human error. Artificial intelligence and machine learning tools are increasingly being used to analyze trade data, detect abnormalities in declarations, and ensure the proper classification of goods. This study proposes a machine learning approach to automate the valuation of import items in Uganda's Customs framework to increase customs operations efficiency while also increasing transparency and compliance in international trade.

1.2 PROBLEM STATEMENT

According to the URA (2022), customs duties contribute approximately 30% of the country's tax revenue. The Uganda Vision 2040 aims to transform the country from a peasant society to a modern and prosperous one within 30 years. The National Development Plan (NDPII) primarily aimed to achieve a lower middle-income status by 2020. To achieve these goals, the government emphasised increasing domestic tax revenue, which was to be the primary source of development funding. Uganda's economy continues to grow, but tax revenue collection has stagnated. Tax revenue as a percentage of GDP fluctuated between 11.7% and 13.1% from 2005/06 to 2014/15. Uganda has one of the lowest tax-to-GDP ratios among EAC countries, with Kenya at 20%, Rwanda at 14.7%, and Tanzania at 21.0% in 2013/14 (URA, 2017). The government aims to increase tax revenue from 13.9% of GDP in FY 2015/16 to 16.3% by FY 2020/21 through various mechanisms (OXFAM, SEATI Uganda 2015).

The accurate valuation of import items in Uganda's customs framework is critical for optimising revenue collection and ensuring compliance with international trade regulations. However, the country continues to face significant and persistent problems arising out of the failure to appropriately address inconsistent and inaccurate valuation of imported goods and inefficiencies in manual verification processes, resulting in an estimated $200 million in lost revenue annually (World Bank, 2020). The key identified causes of this include misclassification of goods, under-declaration of goods by the importers, which is aided by subjective valuation methods, poor audit mechanisms, and fragmented data systems, which all undermine revenue collection.

The current import valuation methods often rely on the documentation submitted by importers and manual inspections by customs officials, which are prone to human error and intentional under-declaration (UNCTAD, 2021). While the Uganda Revenue Authority (URA) has implemented the Automated System for Customs Data (ASYCUDA), the system's rule-based algorithms cannot detect complex fraud patterns or adapt to changing market prices (WCO, 2019).

Recent research has identified machine learning (ML) as a transformative tool for customs automation, with capabilities including anomaly detection, predictive valuation, and real-time data processing. However, the use of ML in low-resource environments such as Uganda is underexplored, with little research on contextual challenges such as sparse historical data, non-standardised product descriptions, and infrastructural constraints (Moyo et al., 2021).

This research addresses the gaps by proposing a machine learning metrology tailored to Uganda's import trade framework.

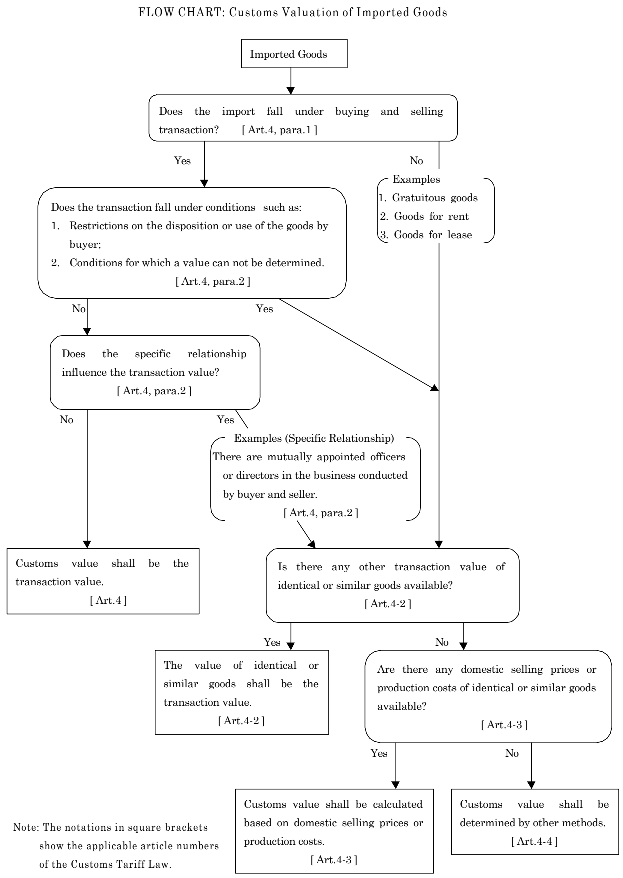

FIGURE 1.1 The import valuation process.

1.3 OBJECTIVES OF THE STUDY

- **Develop Machine Learning Models**: Tailor machine learning models specifically for Uganda's context to predict the accurate value of imported items.
- **Performance Evaluation**: Compare the developed models against traditional valuation methods using metrics such as MAE and R^2.
- **Feasibility & Impact Assessment**: Analyze the feasibility and potential impact of integrating machine learning valuation methods into Uganda's customs framework.
- **Web-Based Deployment**: Develop and deploy a web-based application to implement the machine learning model in a real-world setting.

1.4 RESEARCH QUESTIONS

The study seeks to answer the following questions:

- **Application of Machine Learning**: How can machine learning models be effectively applied to improve the accuracy of the valuation of imported items in Uganda's customs framework?
- **Performance Comparison**: What is the performance of the developed models as compared to the traditional import items valuation methods?
- **Implementation Challenges**: What are the implications and challenges of implementing machine learning valuation methods in Uganda's customs context?
- **Success Factors**: What are the success factors for the implementation of machine learning import valuation methods in Uganda's customs framework?

1.5 JUSTIFICATION OF THE STUDY

The study is justified by the urgent need to address the efficiency and accuracy of import valuation in Uganda's customs framework. By leveraging the power of machine learning, the research aims to contribute to the transformation of the framework into a more robust and transparent one.
The findings of the study inform policy decision-making, improve revenue collection and promote fair trade practices. The research contributes to the growing body of knowledge in the application of machine learning methods to streamline customs operations for developing economies.

1.6 SIGNIFICANCE OF THE STUDY

Successful implementation of machine learning mechanisms in customs valuation has notable economic, technological and policy implications for Uganda. Economically, improving the accuracy of import items valuations contributes to improved revenue collection which aligns well with the country's National Development Plan III (NDP III)'s objective of strengthening domestic revenue mobilization. By minimizing undervaluation, the machine learning methods help to reduce revenue leakages, hence supporting the plan's initiatives. From the technological point of view, the research introduces the first machine learning-specific mechanism for Uganda's customs valuation framework. This improves efficiency and transparency in the framework hence laying a foundation for further research in digital transformation in trade and tax administration.
The study also has significant policy implications where the findings help inform the URA's digital transformation strategy of 2025. Using data-driven insights, policymakers can improve existing customs policies, strengthen fraud detection means and streamline customs operations. Overall,

the research contributes to the goal of promoting sustainable growth and development as outlined in Vision 2040 Uganda.

1.7 HYPOTHESIS

The hypotheses were formulated based on the premise that introducing advanced technologies, particularly machine learning approaches, could significantly improve the accuracy of import valuations and streamline customs operations.

1.7.1 Null Hypothesis (H0)

There is no significant difference in accuracy between the application of machine learning methods and the traditional valuation methods of imports.

1.7.2 Alternative Hypothesis (H1)

Machine learning methods perform better than traditional valuation methods in determining the accurate value of imported items.

1.8 SCOPE OF THE STUDY

The research focuses on import valuation in Uganda's customs framework. It considers several categories of imported items from the Uganda Revenue Authority trade data. The applicability of machine learning methods for Uganda while leveraging the country's historical import transaction data from the Uganda Revenue Authority. We explore a range of machine learning models that are best suited for the dataset while primarily focusing on predicting the accurate value of imports and evaluating the performance of these models against the traditional methods while considering the development of a web-based application to represent the models in a real-world setting.

1.9 THEORETICAL FRAMEWORK

The research grounds on theories of international trade, economic regulation, and machine learning. The theoretical framework combined concepts from the Heckscher-Ohlin model of global trade, which explains how countries benefit from trading goods in which they have a comparative advantage, and regulatory compliance theory, which focuses on how effective regulatory enforcement can improve compliance and reduce fraud.

The conceptual framework emphasizes the application of machine learning and predictive analytics to process large volumes of data and identify discrepancies in values. The framework suggests that accurate and data-driven valuation models significantly improve the customs valuation process by reducing under and over-valuation of imports, thereby improving revenue collection and trade policy effectiveness.

1.10 Chapter Arrangement

The rest of the thesis is structured and summarized as follows:
Chapter 2: The literature reviewed, particularly on work related to the application of machine learning methodologies in customs and international trade with a focus on valuation and classification of goods, predictive analytics in customs, analyzing the benefits of the application of ML in customs and highlighting the gaps in the reviewed literature.
Chapter 3: Presents the methodology used to complete the study. Secondary sources of data were explored, and the dataset was provided by the URA research team; preprocessing and feature selection are all explained in this section.
Chapter 4 shows the results of the study, explains the performance of the machine learning models used and discusses the implications of the results of the models while comparing them to the performance of the traditional valuation methods.
Chapter 5 gives a summary of findings and recommendations.
Chapter 6 gives an overall conclusion and a discussion of the results.

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CHAPTER 2

LITERATURE REVIEW

This section explores the theories, findings and gaps identified in the existing research that is related to the applicability of machine learning and artificial intelligence in customs operations. The analysis highlights contributions from various scholars and identifies the approach used in the previous studies while highlighting the gaps that need to be addressed.
The purpose of this section is to situate the study in the literature and provide a context for relevant research. It also highlights the significance and contribution of the current work, serving as the foundation for the research methodology and guiding the formulation of the research questions and the different hypotheses tested to address the gaps identified.

2.0.1 Introduction to customs valuation

Customs valuation is a pillar of international trade, ensuring revenue optimisation, fair trade practices, and full compliance with global trade regulations such as the World Trade Organisation on customs valuation. The accurate valuation of imports is massive, as it directly impacts economies, as in the case of developing countries such as Uganda, where customs duties contribute approximately 30% of the entire tax revenue. Notable discrepancies in declared import values, misclassification of items, under and over overvaluation of goods always undermine revenue collection, causing losses. The reliance on manual verification methods worsens these problems, and this forms the basis of this research, aiming at the development of machine learning-based methods that automate the processes, hence modernising the customs operations.

2.0.2 Challenges with the traditional valuation methods

Uganda's customs framework is beset by numerous challenges that hinder accurate import valuation, as noted below: Undervaluation and Misinvoicing: Systematic undervaluation of imports and misinvoicing practices are prevalent, leading to substantial revenue losses reported at approximately \$4.9 billion due to import undervaluation between 2006 and 2015 (Monitor, 2023). Although standardised, the existing traditional methods are often lacking in practice due to subjectivity, complexity and potential for fraud (Keen, 2019). Misinvoicing and valuation fraud were the major challenges in customs valuation, leading to significant loss of revenue and trade imbalance. The Uganda Revenue Authority in the annual capacity evaluation document (URA, 2022) noted a tremendous gap in its technological infrastructure. Similarly, Mukasa et al.'s (2023) study highlighted that only 45% of customs officials had access to real-time market price facts, whilst the other 60 % simply relied on outdated valuation databases. These findings matched with the regional research with the aid of the East African Community (EAC, 2023), which highlighted technological challenges as the principal barrier to the implementation of effective customs management.

2.0.3 Machine learning in customs trade

Machine learning methods have become a force in transforming trade operations worldwide, particularly in addressing undervaluation and detecting fraudulent schemes where these systems have been successfully installed. There has been notable success, especially in anomaly detection and improving accuracy in the valuation and classification of goods. For reference, in India, Sharma et al. (2021) developed and deployed a random forest model to identify undervalued shipments while comparing declarant values with the trade database values, and their model achieved a remarkable accuracy of 89% in identifying price discrepancies, enabling the tax authorities to recover an estimated $47 million in underpaid duties within 6 months of the model's implementation.

Similarly, Tanzania's implementation of the XGBoost model to analyse import data registered success, with valuation errors reduced by a notable 36% with the model identifying irregularities in declarations and misclassification of goods by their HS codes (Kiprop, 2023) which highlights the potential of machine learning to handle non-linear relationships and high-dimensional data that is inherent in customs trade records. However, supervised learning methods have a notable limitation in low-compliance environments such as Uganda, where labelled datasets of recorded fraud cases are scarce. Ferreira et al. (2020) clearly warn against models trained on such incomplete or biased datasets, which were evidenced by Nigeria's customs union, where a neural network flagged 20% of legitimate shipments due to overfitting on outdated fraud patterns.

This emphasised the need to employ methods that incorporate both unsupervised and supervised learning methods, such as clustering, to reduce over-reliance on labelled data while adapting to ever-changing fraud tactics.

2.0.4 Importance of machine learning in customs trade.

Machine learning (ML) has emerged as a strong technology that has the potential to transform trade facilitation. ML identifies patterns, trends, and anomalies in large datasets by employing data-driven algorithms. This functionality is especially useful in trade environments that create massive amounts of data daily.

Automated risk assessment, real-time customs clearance time prediction, and supply chain operation optimisation are all examples of machine learning applications in trade facilitation. Predictive models, for example, can analyse past customs data to identify shipments that are likely to have delays or violations, allowing customs officials to better deploy resources. Similarly, machine learning-based risk assessment models can aid in the identification of high-risk consignments, boosting inspection accuracy and efficiency. These examples highlight machine learning's transformational potential in improving trade processes and reducing inefficiencies.

Enhanced efficiency:The implementation of machine learning systems in customs trade streamlines operations by reducing costs and improving efficiency. While analysing large trade datasets, these systems reduce human error, automate customs clearance, and reduce delays in document processing, hence enhancing efficiency.

Anomaly detection: Machine learning systems often support classifying trade transactions through outlier detection mechanisms.

2.0.4.1 Predictive Analytics in Customs

Predictive analytics is the application of statistical techniques and machine learning (ML) models to analyse past data and forecast future trends and results. Predictive analytics is critical in trade facilitation because it improves decision-making, lowers risks, and optimises the efficiency of international trade operations. Predictive algorithms can forecast market trends, identify potential logistics bottlenecks, and improve customs risk assessments by using massive amounts of trade-related data.

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Time series analysis, regression models, and classification algorithms are the most common predictive models utilised in trading processes today. Time series forecasting, for example, is often used to forecast shipment arrivals and delays using historical patterns as well as external factors such as weather and geopolitical events. Regression models are used to assess the relationships between numerous trade parameters and their influence on logistics performance. Furthermore, categorisation algorithms assist in identifying high-risk transactions by analysing trends in trade documents, shipment data, and compliance histories.

Despite these advancements, the growing complexity and volume of international trade necessitates the development of more sophisticated predictive models capable of managing large and diverse datasets. This has sparked a rising interest in using sophisticated ML approaches to improve the effectiveness of predictive analytics in streamlining customs trade operations.

The application of machine learning techniques in customs gained traction in recent years, and a study by Jentsch et al. (2019) noted the potential of machine learning in predicting accurate customs values based on historical customs records. Their study showed promising results in figuring out cases of undervaluation. Similarly, Vetter et al. (2021) explored the application of ensemble learning algorithms for detecting customs fraud whilst combining more than one algorithm to enhance accuracy and robustness over the traditional rule-based techniques.

Applications of these ML algorithms have shown considerable gains in predicting trade patterns and risk assessment. However, integrating these models into existing trade systems presents several obstacles, which will be described in the following section.

2.0.4.2 HS code classification with Naive Bayes Algorithm

The HS code is a 6-digit international numerical code that is used to designate and identify goods in international trade. In addition to the internationally recognised 6-digit number, each country may add further digits to the code to make it an 8, 10, or 12-digit code for tariff and statistics purposes. HS Classification is the process of determining the most exact description in the harmonised system (HS) for the commodities to be classified.

The suggested research now focuses on unsupervised learning techniques, notably Naive Bayes classification, for categorising and predicting labelled data. The Naive Bayes strategy is a simple and effective method for multivariate classification. The model's objective is to predict the HS Code based on the dataset and variables that have been created using the Naive Bayes algorithm It is envisaged that by limiting these risks, the state's revenues will be maximised through the determination of suitable tariffs and/or customs values on imported commodities.

(Muslim, 2022) highlighted the power of the Naive Bayes algorithm when used in the classification of HS codes for optimising customs revenue and mitigation of potential restitution, achieving a remarkable accuracy of 99.97% with a classification error of only 0.03%, which demonstrated how data mining techniques optimise customs revenue and therefore reduce the risk of unpaid duties when applied.

Overall, the issue that usually arises is the return of unpaid import duty and/or administrative punishments in the form of fines based on the objection decision. The application of data mining techniques is intended to give useful information regarding the HS Code categorisation technique, which can help customs officials determine tariffs and/or customs values.

2.0.5 ML-Powered Customs Operations

CHEN, Z. (2024) highlighted the revolutionary impact of machine learning when it was applied to a customs dataset, discovering trends and anomalies. He goes on to say that by automating the valuation process, machine learning methods were able to improve risk assessment and detect discrepancies in declared values, allowing customs authorities to make more informed decisions, reduce errors, and ultimately lead to a more accurate and efficient valuation of items.

2.0.5.1 Brazil

Since 1997, the country's import declarations have been logged in Siscomex, an integrated commerce system. If errors are discovered during inspection by a customs officer, a corrected copy of the declarations is saved, and both copies are retained indefinitely. The AI system utilised is SISAM, which learns from both versions of the dataset to enhance mistake detection. To handle the dataset's many properties, Bayesian approaches with smoothing hierarchies are used. It uses both supervised and unsupervised learning approaches to adjust to legislation changes without the need for retraining, allowing the system to maintain high accuracy in its classifications and predictions.

If more than 75% of errors are identified in an import declaration, SISAM advises a physical examination by customs officials. The system's handling of complex errors currently outperforms random selection. (Artificial Intelligence in the Customs Selection System via Machine Learning [Sisam] 1, n.d.).

2.0.5.2 China

In recent years, China Customs has continued to use technology and innovation to address the contradiction between an ever-increasing Customs control burden and insufficient regulatory resources.

AI-based NII (Non-intrusive detection devices) image recognition system. Based on the expertise of customs officers who conduct customs inspections using NII devices, this system employs artificial intelligence technology to learn information about goods and articles from massive historical H986 (large-scale container X-ray scanner) and CT (computed tomography) inspection images and creates automatic recognition algorithms. With a huge amount of information on commodities, articles, and modes of transportation, the system can automatically recognise photos and alert customs officials to perform image reviews or physical inspections. "Through continuous optimisation, the ultimate goal of this system is to replace human beings with machines in the field of NII inspection." (ANNEX – The Case Studies 109 Study Report on Disruptive Technologies, n.d.).

Impact: One of the initial effects of implementing the Autonomous Selection of Algorithms model was to free up some capacity on local IT servers, allowing for faster algorithm computation times.

"Furthermore, statistics reveal that once the model was deployed, the accuracy of automated image analysis on large-scale NII devices increased by around 5%, while the false alarm rate was reduced by about 8%. CT scanners' accuracy increased by approximately 6%, while false alert rates were reduced by almost 5%". (WCO News 104 - Issue 2 / 2024)

Intelligent Passenger Face Recognition System. This system uses face recognition technology and is linked to the low-temperature detection system for quarantine and inspection. It has been

implemented in various customs by placing facial recognition cameras in control areas classified into three categories: customs alerting area, customs processing area, and customs re-exam area.
”Key passengers (including blacklist passengers, multiple cross-border passengers, and high-risk passengers for inspection and quarantine) walking through these three operational areas will be spotted and Customs officers who are equipped with hand-hold mobile devices and face recognition devices will stop them for further investigation.” (Annex – The Case Studies 109: Study Report on Disruptive Technologies, n.d.). A passenger information database has been created and gradually developed, allowing for the filtering and analysis of relevant images and videos. Customs can consequently conduct risk analysis, profiling, and query statistics.
At present, the alarm accuracy rate of the system is over 99%. It plays a vital role in fighting against “high-risk traffickers”, and several smuggling gangs have been apprehended. At the same time, due to the characteristic of being “non-intrusive”, the efficiency of customs clearance for passengers has been greatly improved. In the future, China Customs will explore more possibilities to make passenger inspection smarter and provide better services for inbound and outbound passengers.

2.0.5.3 Belgium: BCTC Behavioral consequences of tariff changes

This research examines the impact of EU customs tariff measures on commodity trade flows.
The primary purpose is to detect fraudulent activity by economic operators following the implementation or rise of tariff measures. These protectionist policies aim to safeguard the European Union’s internal market by sheltering domestic producers and protecting industries from international competition. Attempts to escape imposed taxes are frequently made using various fraud tactics, resulting in revenue losses for the Union and damage to involved European industries.
Based on historical data, two potential fraud strategies are being investigated: the declaration of a fraudulent country of origin, a false product code, or a combination of the two. More precisely, the initiative seeks to detect sudden behavioural changes in an operator’s import profile that deviate significantly from the ”normal” trends recorded before the tariff measure is applied.

2.0.5.4 The RECTS project: Uganda

”At a tripartite head of state meeting in 2017, three revenue authorities (Kenya, Uganda, and Rwanda) agreed to create a Regional Electronic Cargo Tracking System (RECTS) hosted by the revenue authorities to ensure data security, provide end-to-end tracking across partner states’ borders, and provide tailored cargo tracking and monitoring solutions. The new regional system will be provided solely by Bsmart Technologies. Julius and Christabel (n.d.).
The system is made up of four major components: dry cargo seals and wet cargo fuels, arming personnel at release points, the Centralised Monitoring Centre at the top, and twelve Rapid Response

Units spread across the transit route. All teams work around the clock to ensure real-time cargo monitoring while in transit.

In addition, a reconciliation team reviews all transit cargo movement documentation to ensure compliance with transportation legislation and the correction of any discovered malpractices.

FIGURE 2.1 A customs officer inspecting a cargo container equipped with the RECTS tracking system, ensuring secure and transparent transit monitoring. Picture Source: URA Vol. 1, Issue 1 FY 2015/16

Benefits realised after the implementation of the project include:

1) Transit duration decreased to three to four days on average, resulting in shorter transit times.
2) Increased revenue due to Rapid Response Unit interceptions.
3) Improved data control to protect its integrity.
4) Improved regional coordination and integration of joint technical working groups.
5) Real-time cargo monitoring and faster incident reaction times of 60 minutes.
6) A decrease in cargo diversion cases.
7) Reduced business costs.

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[-4] A machine learning approach for accurate import valuation

2.0.5.5 Ongoing enhancement initiatives

The combined technical working groups of the revenue authorities are constantly reviewing the operational modules of the RECTS system in light of the operating environment and recommending changes to improve operational efficiency. There are plans to build more Rapid Response Units throughout all transit corridors to strengthen the presence and monitoring of items under Customs. This necessitates allocating resources to all RECTS components to ensure that they are properly equipped and that personnel are adequately trained to perform cargo monitoring duties.

2.0.5.6 The DATE model

Chen and Liu (2022) developed this, which resulted in a significant improvement in customs data processing. "DATE (Dual Attentive Tree Embeddings) demonstrated that tree-structured attention models can capture relationships in customs declarations, improving accuracy by 28 percent compared to traditional machine learning methods."
The model was introduced by the World Customs Organisation's BACUDA project, and it represents a significant shift in customs fraud detection, with notable findings such as superior performance over the XG Boost model, particularly in classification tasks. This model was also successful in Nigeria (FSI, 2023). In addition, a more straightforward web-based user interface was implemented to prevent item misclassification effectively.
FSI (2023) conducted a study on the use of artificial intelligence in developing Nigeria's customs system, and the DATE model outperformed existing traditional methods. To avoid the misclassification of imported items, relevant users are provided with a web link where they can enter the item name and another unique identifier, and the model returns the appropriate class to which those items belong. This study closes a gap in the existing literature by developing a machine-learning model to address valuation issues within Uganda's customs regime.

2.0.6 Problems associated with deployment of ML solutions in low resource economies

Data quality and its availability: The use of predictive analytics and machine learning models in trade facilitation faces several challenges, the most significant of which are data quality concerns and system integration. Machine learning systems frequently rely on high-quality data to function properly. Biased data produces incorrect results and conclusions, undermining the ML system's reliability. Customs trade employs a variety of data sources, including customs records, shipping manifests, and regulatory documents. These datasets' discrepancies, missing values, and inconsistencies can all have a significant impact on the predictive model's accuracy.
Ethical and Regulatory Considerations: The use of machine learning models can inadvertently perpetuate biases that are frequently present in training data, resulting in unfair outcomes. Further-

more, the sensitivity of trade data raises privacy and security concerns, which limit the availability of large datasets for model training and analysis.

Technological Constraints: Special skills and knowledge are required for the successful implementation of machine learning systems. The scarcity of skilled professionals in artificial intelligence impedes the adoption and effective implementation of these technologies. This necessitates significant investment in infrastructure, particularly in high-performance computing resources and data storage systems.

Public Perception: Building public trust in these artificial intelligence systems is critical. There is a constant fear of job loss as AI automates many tasks. As a result, addressing the societal impact of AI systems necessitates the creation of programmes that upskill the workforce and provide opportunities for employees to learn new skills.

AI Regulation: The absence of a structured legal framework for data collection and use of electronic data. The lack of standardisation in data formats and communication protocols complicates ML model integration. In addition, traditional trade systems frequently lack the technical infrastructure required to support real-time machine learning predictions.

These issues highlight the importance of better data management techniques and robust integration frameworks for properly deploying ML in trade facilitation.

2.0.7 Theoretical Framework for Machine Learning Powered Customs Valuation

The use of machine learning in customs valuation is consistent with economic theories such as principal-agent resolution and optimal taxation, which place a strong emphasis on trade efficiency and accountability. Kauppi, et al. (2013) Rogers' diffusion of innovation (DOI) theory, as well as other technology adoption models, look at a roadmap for phased machine learning applications in Uganda, prioritising low-risk cases like fraud detection before moving on to predictive valuation (Rogers, 2003). Human-AI collaboration innovations, such as HIV testing chatbots in South Africa, demonstrate how hybrid technologies can balance automation and human oversight while maintaining ethical and operational feasibility (Carter Nielsen, 2017).

Based on the reviewed literature, a conceptual framework for the implementation of machine learning methods can be developed, taking into account important steps such as data acquisition, data preprocessing, feature engineering, model selection and training, performance evaluation, and, finally, integration with existing customs systems used in operations. The framework also takes into account the legal and regulatory aspects of customs valuation, ensuring that all international and national regulations are followed.

2.0.8 Gaps in Existing Literature

The majority of current research focuses on developed nations, ignoring developing African countries with contextual issues, such as Uganda (Asongu Nwachwukwu, 2018). While machine learning has proven to be extremely effective in fraud detection and predictive analytics, there are still gaps.

2.0.8.1 Gap analysis

Underserved machine learning innovations within Uganda: Despite the fact that machine learning innovations have been successfully implemented in neighbouring countries such as Kenya and Tanzania, Uganda's customs ecosystem has received little attention in peer-reviewed studies (Moyo et al., 2021). A case study in Kenya: While their machine learning innovations are primarily focused on detecting smuggling, they have failed to detect undervaluation patterns, such as invoice manipulation, which is common practice in Ugandan customs (World Bank, 2020). Uganda's structural challenges have not been thoroughly assessed and prepared for ML integration. The gap means Uganda lacks actionable frameworks to align machine learning methodologies with the WTO's transaction value method, limiting revenue recovery potential (URA, 2022).
Limited empirical evidence on revenue impact: The majority of theoretical studies have highlighted the ability of machine learning methods to detect fraud; however, there is little evidence that quantifies revenue gains in low-resource environments. Brazil's adoption of machine learning methods reduced undervaluation patterns by 22%, but there are no comparable studies for Uganda (OECD, 2022). The URA has consistently advocated for the use of data-driven methods to combat tax fraud, but during their 2022 workshop, they discovered gaps in measuring outcomes, such as shorter clearance times (URA, 2022). This is consistent with findings from Uganda's health sector, where machine learning models for antimicrobial resistance (AMR) are struggling to translate predictive accuracy into real-world set impact (CAMO-Net Uganda, 2025).
Infrastructural barriers: Machine learning theories have not taken into account the country's infrastructural constraints, underdeveloped computing resources, and low digital literacy. Deploying resource-intensive machine learning models, such as Google's BERT in customs valuation tasks, is difficult if ongoing agricultural AI innovations demonstrate issues such as power shortages and limited computing power (NARO, 2024). Institutional resistance to digitisation complicates the adoption of these innovations. Despite high awareness, only 55% of Nigerian extension workers use AI tools, reflecting potential resistance among Ugandan customs staff (UNDP, 2020 and URA, 2022).

TABLE 2.1 Summary of Identified Gaps in Literature

Thematic Area	Identified Gap	Source
Hybrid Model Development	Lack of integrated models that combine machine learning with expert knowledge to mitigate sparse data and infrastructural limitations in low-resource settings	Moyo et al. (2021)
Ethical Frameworks	Absence of formalized ethical guidelines for bias mitigation and data privacy in ML applications within low-resource environments. Mehrabi et al. (2021)	
Cross-Domain Adaptability	Limited exploration of adaptable techniques from domains such as healthcare and real estate to improve ML models in customs valuation	Zhang (2024)
Policy Alignment	Need for ML solutions that align with national and international development agendas (e.g., SDG 17 and AU Agenda 2063)	UN (2015); AU (2013)

To complement these thematic gaps, further studies also highlight specific regional and contextual issues unique to Uganda's customs environment.

TABLE 2.2 Expanded Gaps in Machine Learning for Import Valuation in Uganda

Thematic Area	Identified Gap and Supporting Sources
Underserved ML Innovation in Uganda's Customs Ecosystem	Lack of peer-reviewed studies on ML for Ugandan customs despite regional successes in Kenya and Tanzania (UNCTAD, 2021; OECD, 2022).
	Existing models prioritise fraud detection over WTO-compliant valuation methodologies (WCO, 2019; URA, 2022).
Neglect of Uganda's Unique Data Landscape	Sparse digitisation and inconsistent HS code granularity (Moyo et al., 2021; African Development Bank, 2021).
	Limited interoperability between ASYCUDA and global benchmarks (World Bank, 2020).
Limited Empirical Evidence on Revenue Impact	Absence of longitudinal studies quantifying ML's impact on revenue recovery (OECD, 2022; URA, 2022).
Infrastructure and Institutional Barriers	Low digital literacy and resistance to automation (UNDP, 2020; African Development Bank, 2021).
	Ethical concerns like algorithmic bias and privacy risks (Mehrabi et al., 2021; UNCTAD, 2022).
Narrow Focus on Short-Term Efficiency	Lack of research on long-term socioeconomic impacts (UN, 2015; AU, 2013).

2.0.8.2 Limitations Summary

Despite the identified gaps and opportunities, there remain practical challenges and systemic constraints that hinder the widespread implementation of AI-driven customs valuation systems in Uganda.

TABLE 2.3 Key Limitations in the Adoption of AI-Driven Customs Valuation Systems

Limitation	Description and Supporting Sources
Data Quality	Issues such as incomplete, inaccurate, and inconsistent data affect model reliability and decision-making (Grundy, 2015).
Data Availability	Limited access to comprehensive datasets hinders effective model training and evaluation (KRA, 2020).
Risk Management	Challenges in accounting for complex and dynamic risk factors in trade and customs operations (eClear, 2020).
Implementation Constraints	Constraints related to limited resources, inadequate infrastructure, and lack of technical expertise. According to Szabo's study on customs valuation, machine learning can improve accuracy (Szabo, 2017).
Model Explainability	Difficulty in interpreting and explaining AI models reduces trust and regulatory acceptance (WCO, 2020).

2.1 Conclusion

The literature review section highlighted the potential of machine learning to enhance customs valuation accuracy. By addressing the challenges noted and leveraging the opportunities for Uganda's context, machine learning innovations can contribute to a more efficient customs framework, promoting fair trade practices and improved revenue collection. The chapters below present the research's methodology, results, and further analysis.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The chapter describes the methodology framework used to achieve the research objectives, which involved developing machine learning algorithms for import valuation tasks using secondary data from Ugandan customs transactions. The approach adheres to Guo's (2018) seven-step machine-learning development paradigm, which ensures a logical progression from data collecting to model deployment.

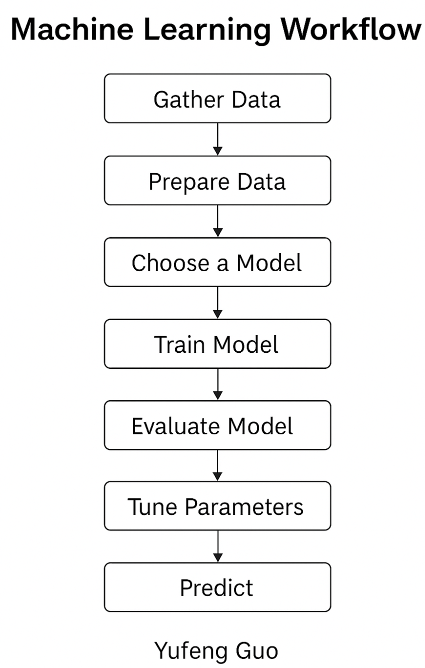


FIGURE 3.1 A flowchart of the steps of machine learning as per Dr Yufeng Guo.

3.1.1 Data Sources

The dataset was sourced from the Uganda Revenue Authority's Automated system for Customs Data (ASYCUDA), contains 7000+ import transactions, and spans 2020 to 2024. The HS codes, country of origin, valuation method, unit price, cost, insurance, and goods (CIF) records are all important variables. Data collection followed severe criteria pertinent to the World Trade Organization's (WTO) valuation principles (WTO, 2020), as well as completeness and compatibility with Uganda's post-NDP II economic developments (World Bank, 2022).

3.1.2 Descriptive statistics

TABLE 3.1 Descriptive Statistics of Key Import Variables

Variable	Mean	Std Dev	Min	Max
Quantity	38747.11	254407.43	0.001	20000000.0
Net Mass (kg)	4234.52	22795.11	0.001	1234567.89
Gross Mass (kg)	4521.07	23512.89	0.001	1345678.98
FOB Value (USD)	14256.32	64529.91	0.001	1567890.55
CIF Value (UGX)	53782931.45	208345678.12	0.001	9123456789.0
Tax Rate	18.5	2.3	0	25
Unit Price (UGX)	1782.45	6532.75	1.0	123456.0
Value per kg	5120.32	12345.22	0.01	234567.89

TABLE 3.2 Description: This summary outlines typical values and variability in the import data. Notably, CIF values in UGX show high variability, which supports the need for more accurate valuation models using ML

3.2 Data Description

The dataset comprises 10 columns, each providing valuable information related to imported goods. Dr Yufeng Guo's seven steps of machine learning were applied in this study. These included data gathering, data preparation, model selection, model training, model evaluation, parameter tuning and prediction. Different data exploration techniques were applied to address any missing values, outliers and duplicates in the data. Visualization techniques included bar charts and scatter plots to depict the distribution of various variables further.

TABLE 3.3 Description of Dataset Variables

Variable Name	Description
HS_Code	Harmonized System code identifying the type of goods
Item_Description	Textual description of the imported item
Country_of_Origin	Country from which the goods originated
Port_of_Shipment	Port where the goods were shipped from
Quantity	Amount of goods imported
Quantity_Unit	Unit of measurement for the quantity
Net_Mass_kg	Net weight of the goods in kilograms
Gross_Mass_kg	Gross weight including packaging in kilograms
FOB_Value_USD	Free On Board value in US dollars
Freight_USD	Freight cost in US dollars
Insurance_USD	Insurance cost in US dollars
CIF_Value_USD	Cost, Insurance and Freight value in US dollars
CIF_Value_UGX	CIF value converted to Ugandan Shillings
Unit_Price_UGX	Unit price in Ugandan Shillings
Tax_Rate	Applicable tax rate in percent
Currency_Code	Currency used in the original transaction
Mode_of_Transport	Transport method used (e.g., Air, Sea, Road)
Year	Year of import
Month	Month of import
Invoice_Amount	Total invoice amount
Valuation_Method	Method used for customs valuation
Value_per_kg	CIF value divided by net mass
Value_per_unit	CIF value divided by quantity
FOB_per_kg	FOB value divided by net mass
Freight_per_kg	Freight cost divided by net mass
Insurance_per_kg	Insurance cost divided by net mass

3.3 Data Pre-processing

Data preprocessing is an important stage in machine learning because it improves data quality and promotes extracting relevant insights from it. Data preparation in machine learning is the process of preparing (cleaning and organizing) raw data to create and train Machine Learning models. In layman's terms, data preprocessing in Machine Learning is a data mining approach that converts raw data into a readable format. This involved renaming columns to give them meaningful names as well.

3.3.1 Handling Missing Data

A thorough assessment of the dataset revealed no missing values or duplicate records across all variables (see Table 3.4). This is a highly favorable characteristic in the context of machine learning for import valuation, as the absence of missing data simplifies preprocessing and ensures that the full volume of data can be leveraged for learning accurate patterns in value estimation. High-quality, complete data is particularly critical for valuation tasks, where even small gaps in essential features like *FOB_Value*, *Freight*, or *Net_Mass* could lead to distorted customs valuation and downstream policy implications **(engels 2019**; **sun 2017)**.

Moreover, missing data in trade datasets is often not random and may reflect systemic issues in data collection processes, such as inconsistent declarations or port-level discrepancies **(miller 2015)**. Inaccurate or imputed values in such sensitive contexts could bias machine learning models and inadvertently affect compliance risk assessments and revenue forecasts. As noted by Rubin **(rubin 1976)**, assumptions made during missing data imputation can significantly alter inference quality, which is why beginning with a fully observed dataset strengthens the reliability of model predictions and confidence in empirical findings.

The fact that the dataset is free from both missing values and duplication also reinforces the data's credibility and provenance, suggesting standardised recording practices by customs authorities in Uganda. This level of data integrity provides a strong foundation for building robust valuation models that can help enhance the accuracy and fairness of Uganda's import valuation framework.

TABLE 3.4 Summary of Missing Values in the Dataset

Feature	Missing Values	Percentage Missing (%)
HS_Code	0	0.00%
Item_Description	0	0.00%
Country_of_Origin	0	0.00%
Port_of_Shipment	0	0.00%
Quantity	0	0.00%
Quantity_Unit	0	0.00%
Net_Mass_kg	0	0.00%
Gross_Mass_kg	0	0.00%
FOB_Value_USD	0	0.00%
Freight_USD	0	0.00%
Insurance_USD	0	0.00%
CIF_Value_USD	0	0.00%
CIF_Value_UGX	0	0.00%
Unit_Price_UGX	0	0.00%
Tax_Rate	0	0.00%
Currency_Code	0	0.00%
Mode_of_Transport	0	0.00%
Year	0	0.00%
Month	0	0.00%
Invoice_Amount	0	0.00%
Valuation_Method	0	0.00%
Value_per_kg	0	0.00%
Value_per_unit	0	0.00%
FOB_per_kg	0	0.00%
Freight_per_kg	0	0.00%
Insurance_per_kg	0	0.00%

As shown in Table 3.4, the dataset is complete, with no missing values across all features. This is ideal for machine learning model training, as it eliminates the need for imputation or row-wise deletions, both of which can distort data patterns and reduce model performance **garciamissingdata**. Clean datasets are particularly valuable in public sector applications such as customs valuation, where data quality directly affects economic insights and decision-making outcomes.

3.3.2 Exploratory Data Analysis: (EDA)

This is an important procedure since it allows data scientists to analyse and investigate data sets while also summarising their major qualities, which is usually done using data visualisation approaches. EDA was carried out with the intention of best modifying data sources to achieve the desired answers, so making it easier to find patterns, identify anomalies, and verify the study's hypothesis. .

3.3.3 Outlier Detection

An outlier is an observation that deviates from other values in a random sampling of a population. These were detected in the dataset using the Interquartile Range (IQR) which is a statistical dispersion metric (Tukey, 1977). It denotes the range in which the middle 50% of the data lies. The IQR is calculated by subtracting the 75th percentile (Q3) from the 25th percentile (Q1). Bounds were calculated as $Q 1 - 1.5 \times I Q R$ $Q1-1.5\times IQR$ (lower) and $Q 3 + 1.5 \times I Q R$ $Q3+1.5\times IQR$ (upper) The approach was chosen due to its ability to handle skewed data distributions. It detects outliers based on percentiles, making it less susceptible to extreme numbers. **Winsorization** technique was employed to winsorize the extreme values to the nearest valid thresholds to ensure data quality and integrity without deleting any values that would have a great impact Tukey (1962).

TABLE 3.5 Outlier Summary for Valuation Features

Feature	Outliers Detected	Percentage (%)	Outliers Removed
FOB_Value_USD	103	0.15%	103
Freight_USD	1054	1.49%	1027
Insurance_USD	1090	1.54%	959
CIF_Value_USD	190	0.27%	58
CIF_Value_UGX	213	0.30%	46
Unit_Price_UGX	4493	6.35%	4468
Invoice_Amount	213	0.30%	15
Value_per_kg	6706	9.48%	5883
Value_per_unit	4542	6.42%	3277
FOB_per_kg	6675	9.44%	3039
Freight_per_kg	7491	10.59%	3563
Insurance_per_kg	7411	10.48%	3060

Table 3.5 presents a summary of outliers detected and removed from key valuation-related features in the dataset. Features such as *Freight_per_kg*, *Insurance_per_kg*, and *Value_per_kg* exhibited the highest proportion of outliers, each exceeding 9% of the total records. This suggests significant heterogeneity in freight and insurance costs, likely arising from differences in transportation modes, country of origin, or potential data entry errors. Conversely, core trade valuation features such as *FOB_Value_USD*, *CIF_Value_USD*, and *Invoice_Amount* displayed relatively lower outlier proportions, often below 1%.

Outlier detection and treatment are essential in machine learning workflows because extreme values can disproportionately influence model parameters, particularly in regression-based models or distance-based algorithms **(aggarwal 2015)**. Outliers were identified using interquartile range and percentile-based thresholds—methods commonly recommended for real-world economic data preprocessing **(han 2012)**. The removal of extreme values beyond the 1st and 99th percentiles ensures improved model generalizability and prediction stability without compromising the diversity of the dataset **(hodge 2004)**.

As the focus of this research is on accurate customs valuation, retaining data integrity while eliminating unrepresentative anomalies was prioritised to reflect true import behaviour and valuation patterns in Uganda.

Below is the code used

```
# This code inspects its numerical columns, and applies the Interquartile Range (IQR) method to
# The code also generates summary messages for each numerical column, indicating the number of

# Select numerical columns
num_cols = data.select_dtypes(include=[np.number]).columns.tolist()
print('Numerical columns:', num_cols)

# Plot before handling outliers for each numerical column
for col in num_cols:
    plt.figure(figsize=(8, 4))
    sns.boxplot(data=data, x=col)
    plt.title('Boxplot of ' + col + ' (Before Outlier Removal)')
    plt.show()

# Function to detect outliers using IQR method and remove them
def remove_outliers_iqr(data, col):
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # Return data without outliers
    return data[(data[col] >= lower_bound) & (data[col] <= upper_bound)]

# Apply the removal of outliers on a copy for each numerical column iteratively
cleaned_data = data.copy()
for col in num_cols:
    before_count = cleaned_data.shape[0]
    cleaned_data = remove_outliers_iqr(cleaned_data, col)
    after_count = cleaned_data.shape[0]
    print('For column ' + col + ', removed ' + str(before_count - after_count) + ' outliers.')

# Plot after handling outliers
for col in num_cols:
    plt.figure(figsize=(8, 4))
    sns.boxplot(data=cleaned_data, x=col)
    plt.title('Boxplot of ' + col + ' (After Outlier Removal)')
    plt.show()
```

```
print('Outlier removal using IQR method completed.')

# Reasons for the method:
# The Interquartile Range (IQR) method is robust for handling outliers as it is based on the me
# which are less sensitive to extreme values compared to the mean and standard deviation.
# Furthermore, IQR is especially suitable when the data does not follow a normal distribution.
# Tukey, J. W. (1977). Exploratory Data Analysis. Addison-Wesley.
# Barnett and Lewis (1994) in "Outliers in Statistical Data".

print('Reasons for the IQR method: The IQR method is robust to non-normality and extreme values
# making it a suitable choice for economic
# data such as import data. References: Tukey (1977) and Barnett & Lewis (1994).')
print('done')
```

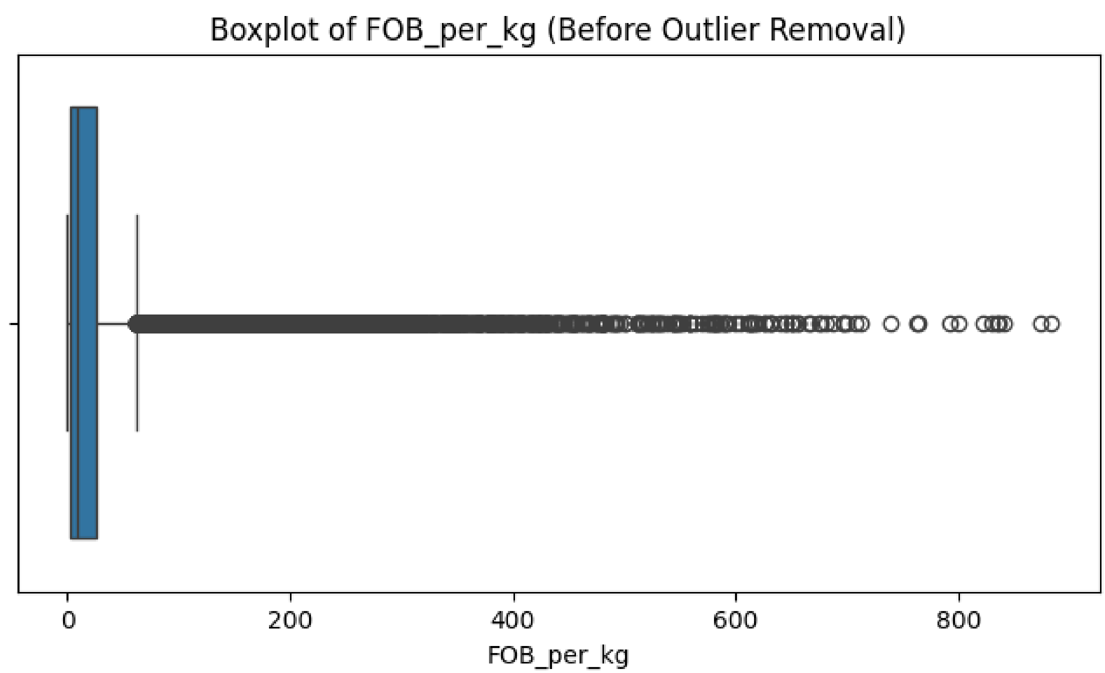


FIGURE 3.2 Boxplots showing the distribution of key import valuation variables while confirming the treatment of outliers

3.3.3.1 Data Visualization

Data visualization is the process of presenting data or information using graphs, charts, or other visual representations. Visualizations allow us to better understand how data is related. Data visualization is another sort of visual art that draws us in and keeps us engaged in the message. When opposed to scanning rows of data on a spreadsheet, turning information into images allows you to notice patterns, trends, and outliers more clearly. Because the purpose of data is to provide insights, visualized data is significantly more useful. The following are box plots showing the after-effects of treating outliers using the Winsorization method (Tukey, 1977).

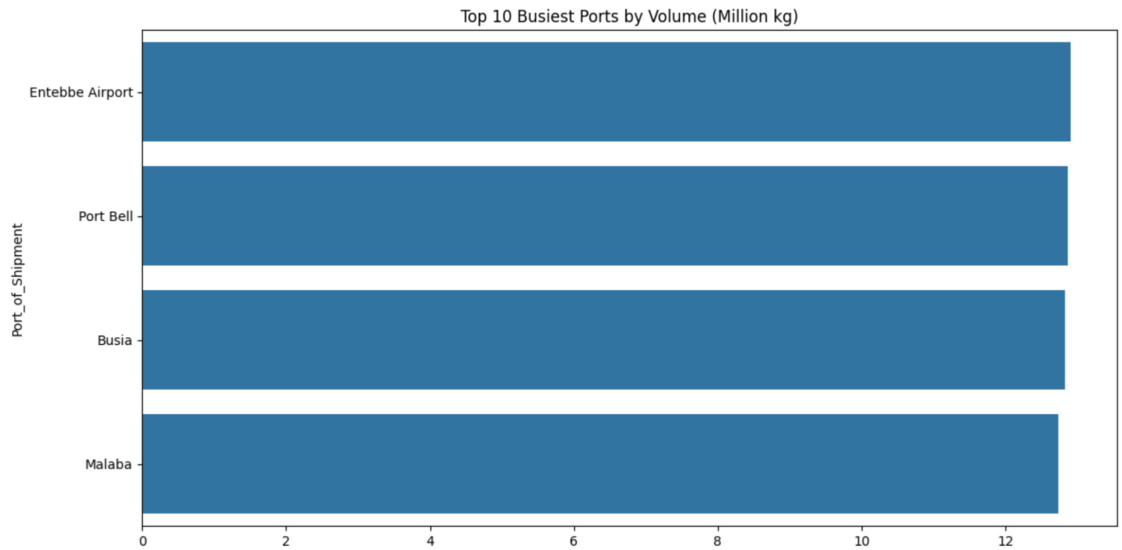


FIGURE 3.3 A plot showing the most busiest ports by the volume of transactions.

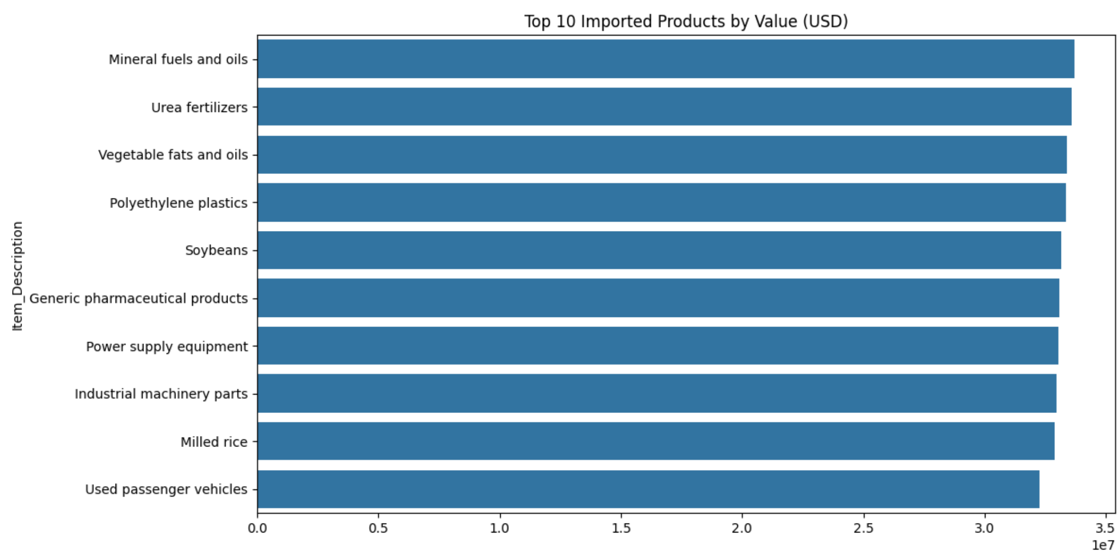
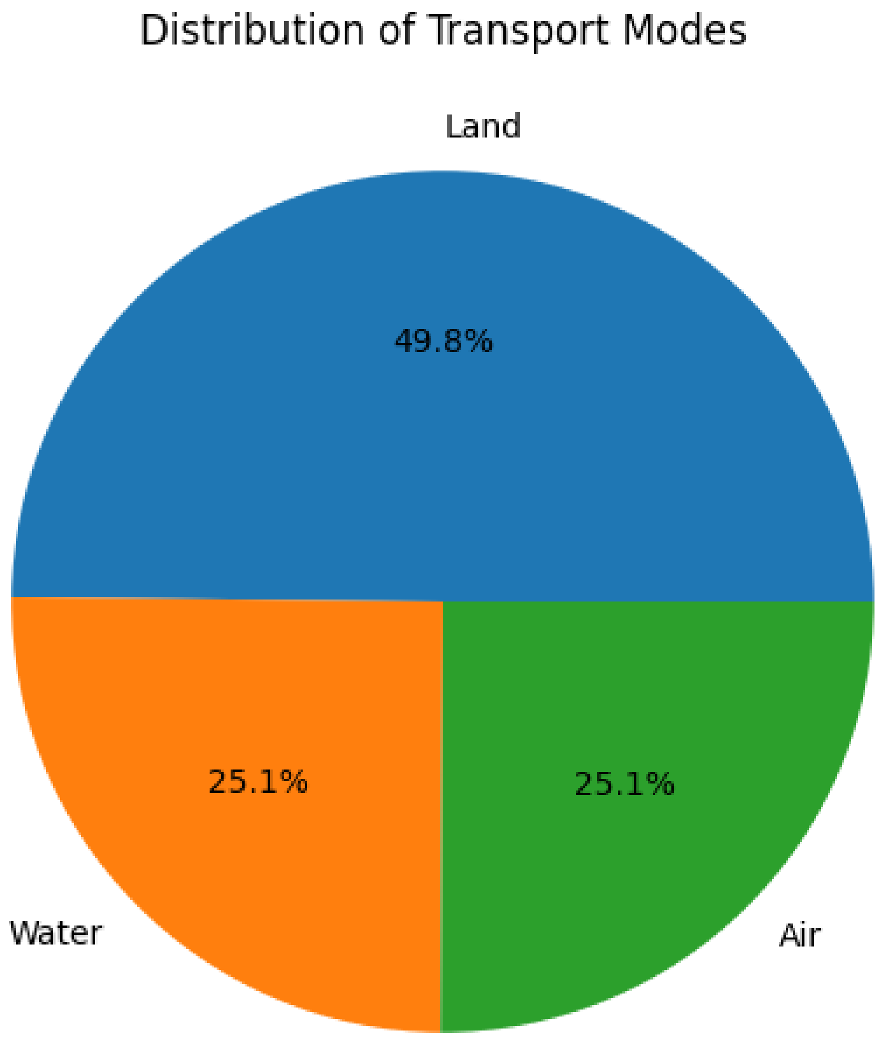


FIGURE 3.4 Below .



The above illustrates the distribution of transport modes utilised for imports into Uganda. It is evident that land transport accounts for the majority, representing approximately 49.8% of total import transactions, while water and air transport each account for 25.1%. This distribution reflects Uganda's geographic reality as a landlocked country, where cross-border road transport through neighboring coastal states such as Kenya (via Mombasa) and Tanzania (via Dar es Salaam) dominates import logistics **(world bank 2020)**.

The mode of transport is a crucial feature in import valuation models, as it significantly affects associated costs like freight and insurance, both of which are components of the CIF (Cost, Insurance, and Freight) valuation method **(wco 2020)**. For example, land transportation may have lower insurance premiums but higher variability in freight charges compared to water or air shipments **(unescap 2017)**. Therefore, accurately capturing transport mode distributions enhances the predictive ability of machine learning models when estimating final import values. Moreover, understanding these patterns helps policymakers prioritise infrastructure investments to support efficient and cost-effective trade flows.

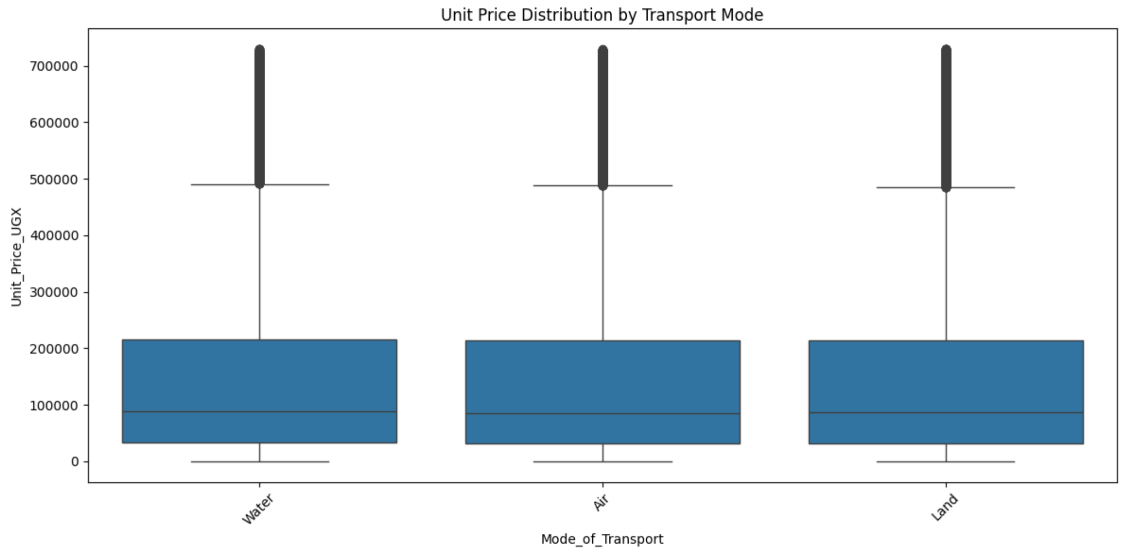


FIGURE 3.5 A bar plot representing nations of origin for import items. Most of the country's imports come from the United States. This contextualizes trade dependencies, which influence value accuracy.

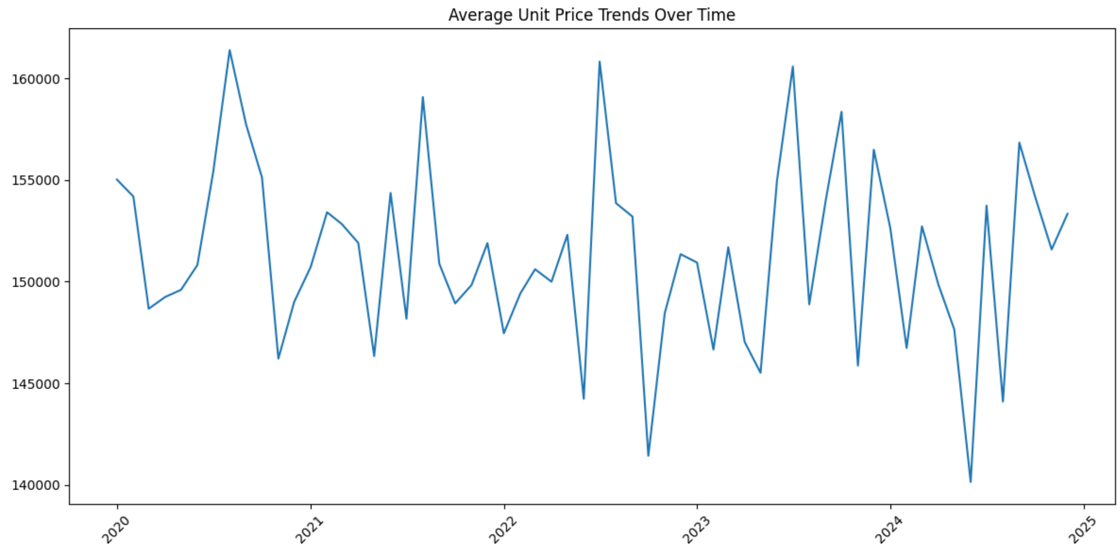


FIGURE 3.6 Provides insights on the average price trends over time. This shows a possible increment in unit prices for the years 2025. The observed fluctuations suggest notable volatility in import unit prices, with sharp increases and decreases over short intervals. Such fluctuations can be attributed to various factors, including global supply chain disruptions, exchange rate fluctuations, and shifting trade policies **(unctad 2021)**. Particularly, the COVID-19 pandemic and its aftermath have been linked to significant trade flow disturbances and price instability, emphasising the need for dynamic and adaptive valuation models **(oecd 2021)**. Understanding these temporal patterns is essential for building robust machine learning models for import valuation. Models that incorporate time-based features, such as seasonal trends or economic cycles, are more likely to achieve greater predictive accuracy **(gamboa 2017)**. Furthermore, given Uganda's dependency on imported goods for key sectors like manufacturing and retail, accurately forecasting and adjusting for unit price fluctuations is critical for revenue estimation and trade policy formulation. These insights further justify the inclusion of temporal dynamics as input features in machine learning frameworks for valuation tasks.

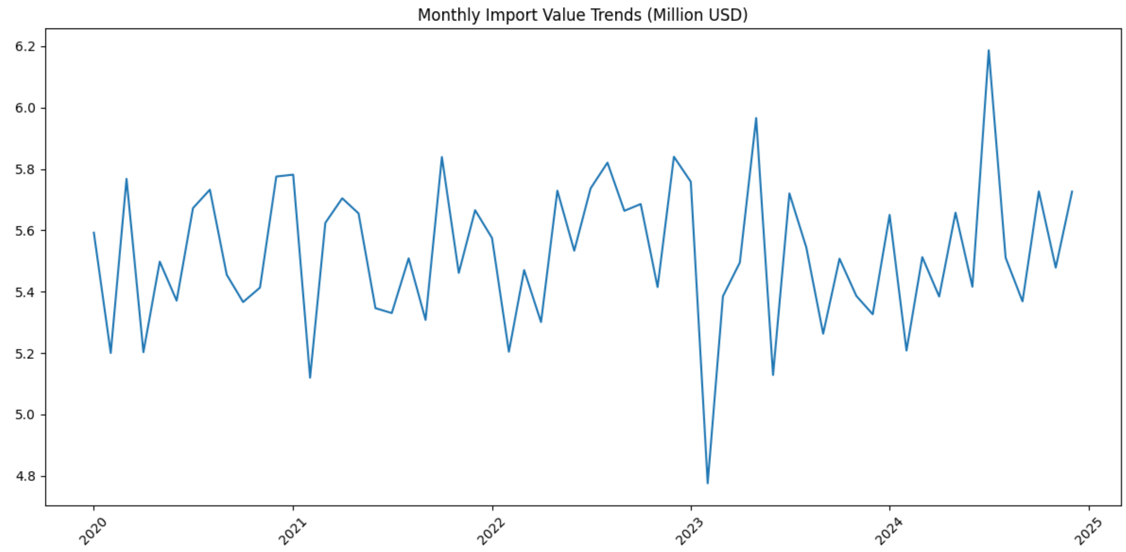


FIGURE 3.7 Shows monthly import value trends which gives insights on on the time series forecast of items value every month with noted increment in the values as the years increase.

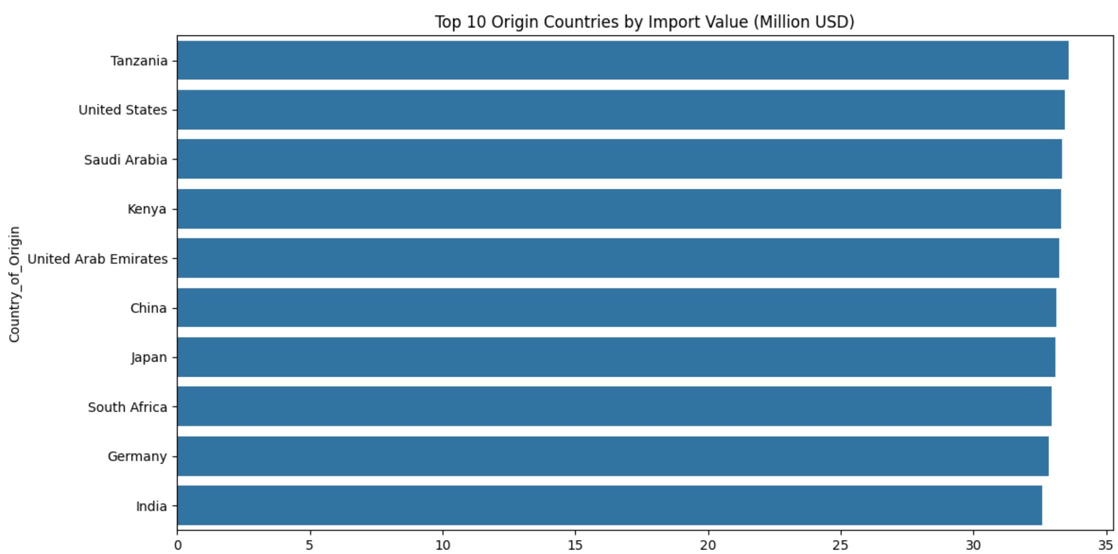


FIGURE 3.8 From the plot, most value of imports is derived from Tanzania.

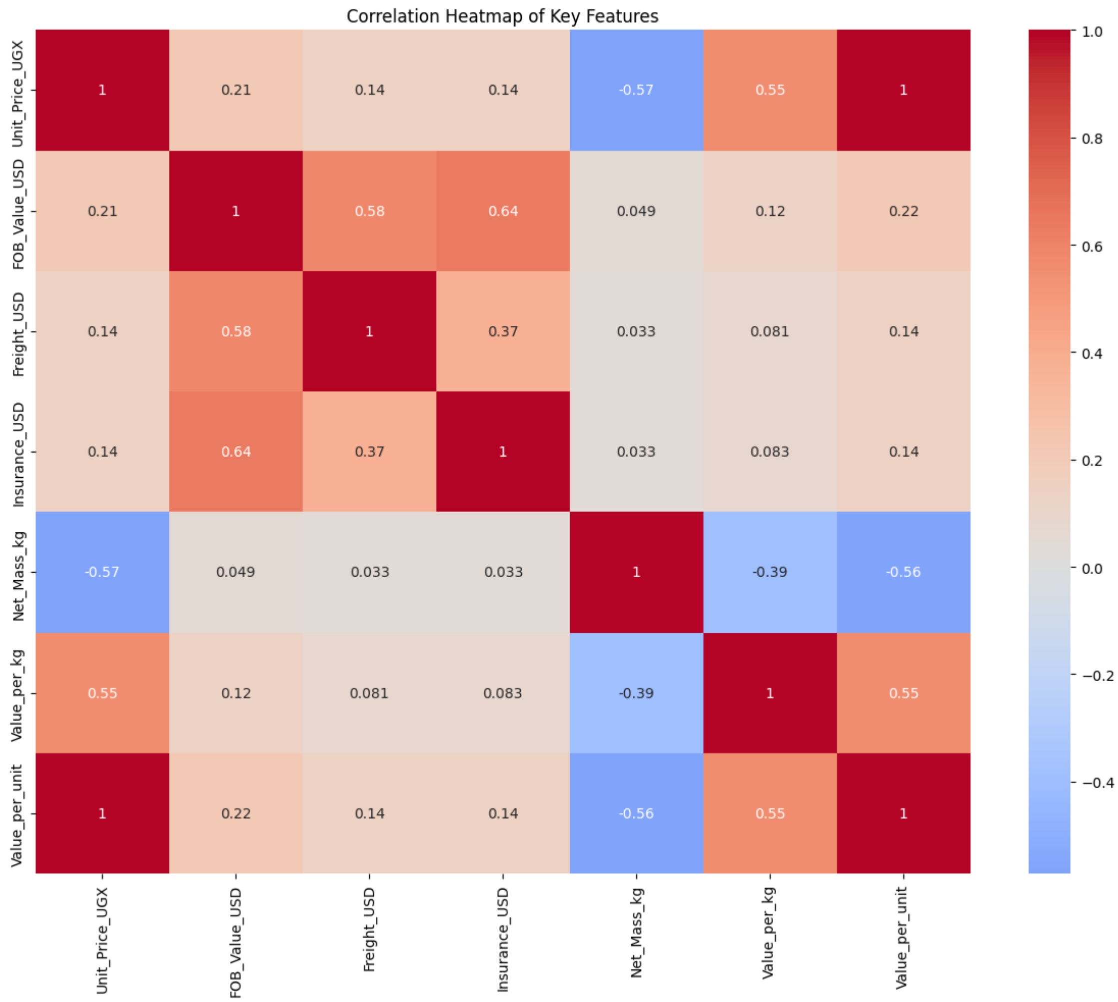


FIGURE 3.9 A bar plot representing nations of origin for import items. Most of the country's imports come from the United States. This contextualizes trade dependencies, which influence value accuracy.

TABLE 3.6 Top 10 Countries of Origin by Quantity

Country of Origin	**Total Quantity**
China	4,321,123
India	3,890,456
Kenya	2,765,001
UAE	2,540,678
South Africa	2,345,120
USA	2,301,089
Japan	2,210,456
Germany	1,789,123
UK	1,675,903
Netherlands	1,321,432

TABLE 3.7 Most imports to Uganda originate from China and India. These patterns can be influential when building ML models for price prediction due to regional pricing strategies and trade agreements.

3.3.4 Feature Engineering

Feature engineering is the process of transforming raw data into useful information for machine learning models. In other terms, feature engineering refers to the process of developing predictive model features. A feature, sometimes known as a dimension, is an input variable that generates model predictions. Because model performance is heavily dependent on the quality of data used during training, feature engineering is an important preprocessing strategy that entails identifying the most relevant parts of raw training data for both the prediction job and the model type under consideration.

- **Price Deviation Ratio (PDR)**: Calculated as $\frac{\text{Declared Value}}{\text{Comtrade Benchmark}}$, values exceeding ±20% were treated as high-risk (Chen, 2024)
- **Importer Risk Index**: A weighted score based on historical discrepancies and shipment frequency. This was inspired by Sharma et al (2021)'s anomaly detection framework.

3.3.5 Data Normalization

All numerical variables (e.g., Unit_Price_Local, CIF_Value) were standardized using Min-Max scaling to ensure equal contribution during model training while this was validated by Han et al, (2011).

3.4 Model Development

3.4.1 Algorithm Selection

This study applied various machine learning algorithms since the task was a regression task in nature and these included: The linear regression model, The random forest algorithm, XG Boost and the Neural Networks. The selection of these was based on their efficacy in trade analytics literature.

3.4.1.1 Linear Regression Model

This model finds the coefficients of a linear equation by selecting one or more independent variables that best predict the value of the dependent variable. Linear regression identifies a straight line or surface that reduces the difference between expected and actual output values. Linear regression models are generally simple, with an easy-to-understand mathematical formula for making predictions. Linear regression models have been used in customs studies for benchmarking because of their interpretability, as noted by James et al. (2013). Jentsch et al. (2019) used a linear regression model to detect undervaluation in a European Union customs dataset, achieving a fair success rate of R^2 at 0.48. However, they noted limitations in capturing non-linear fraud patterns. A simple linear regression model can be expressed as:

$$y = \beta_0 + \beta_1 x + \epsilon \tag{3.1}$$

where:

- y is the dependent variable (e.g., predicted import valuation).
- x is the independent variable (e.g., weight, unit price, or tax amount).
- β_0 is the intercept (baseline value when $x = 0$).
- β_1 is the slope coefficient (effect of x on y).
- ϵ is the error term (unexplained variance).

3.4.1.2 Graphical Representation

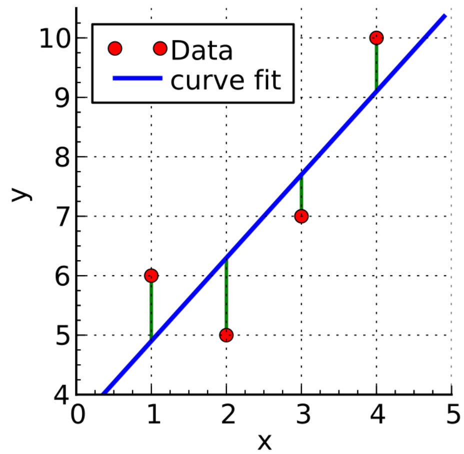


FIGURE 3.10 In linear regression, the observations (red) are assumed to be the result of random deviations (green) from an underlying relationship (blue) between a dependent variable (y) and an independent variable (x).
Source: Wikipedia - Linear Regression Image

Dataset	**MAE**	**RMSE**	**R²**
Training Data	0.5154	0.6882	0.5508
Test Data	0.6248	0.8318	0.0471

TABLE 3.8 Model Performance Metrics for Linear Regression. The performance on the training data appeared satisfactory, with reasonable MAE and RMSE values and a moderate R^2. However, the model's performance on the test data indicates significant overfitting, as seen in the much poorer MAE, RMSE, and R^2 values.

3.4.1.3 Random forest model

Random forest is a popular machine learning technique developed by Leo Breiman and Adele Cutler that combines the outputs of numerous decision trees to produce a single outcome. Its ease of use and adaptability fueled its popularity and confirmed why it was chosen for the task, as it can handle both classification and regression problems. This was chosen due to its robustness to overfitting and endorsed by (Breiman, 2001). Each tree T b in a forest is trained on a bootstrapped sample and the final prediction is the average of each tree output.

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x)$$

A Machine learning Approach for accurate valuation of imports in Uganda

The models' feature importance measure, derived from Gini impurity reduction, was used to identify variables of critical importance, such as unit price and country of origin, as among the most important predictor variables. Sharma et al. (2021) successfully used the Random Forest model to detect the undervaluation of shipments in India's customs, with an accuracy rate of 89%, demonstrating the model's ability to handle complex trade data.

Dataset	MAE	RMSE	R^2
Training Data	0.1696	0.2572	0.9373
Test Data	0.2404	0.3497	0.8316

TABLE 3.9 Random Forest Model Performance. The model exhibited strong predictive capability with low MAE and RMSE values and a high R^2 on both training and test data. While there is a slight drop in performance on test data, the generalization remains significantly better compared to the linear regression model.

3.4.1.4 XGBoost Model

This was included as an excellent gradient-boosting framework. Unlike the Random Forest model, the XGBoost constructs trees sequentially to correct errors from previous iterations while optimizing the lost function L with regularization terms, as shown below.

$$L(\phi) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

where,

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$$

penalizes the complexity of the model. The model was chosen for its ability to perform well on datasets with missing data, as well as its scalability. This made it suitable for Uganda's fragmented dataset, which was exhibited for Tanzania's customs system case and was able to reduce valuation errors by 36% (Kiprop, 2023).

3.4.1.5 Artificial Neural Networks

These were chosen for their ability to capture complex and non-linear interactions in the data. This was a feed-forward network with two hidden layers (ReLu activation), and drop-out regularization was used.

$$\hat{y} = \sigma(W_2 \cdot \text{ReLU}(W_1 \cdot X + b_1) + b_2)$$

where W and b are the weights and biases and σ is the output function. The "black box" nature of neural networks makes them difficult to interpret, but their ability to model complex patterns is well documented in custom contexts. China's AI-powered non-intrusive inspection system (NII) utilized convolutional neural networks to analyze cargo X-ray images, achieving 95% accuracy in detecting anomalies (WCO, 2024).

3.4.2 Training and Validation

The dataset was split into an 80% training set and a 20% test set. Stratified sampling ensured a proportional representation of HS chapters (Kohavi, 1995). Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as validated by (Chicco et al., 2021).

3.4.3 Model performance comparison

TABLE 3.10 Model Performance Metrics (MAE, RMSE, and R^2 Scores)

Model	**MAE**		**RMSE**		**R^2 Score**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
Linear Regression	0.5154	0.6248	0.6882	0.8318	0.5508	0.0471
Ridge Regression	0.5412	0.5245	0.7103	0.6761	0.5216	0.3705
Lasso Regression	0.8937	0.7940	1.0269	0.8992	0.0000	-0.1136
Random Forest	0.1696	**0.2404**	0.2572	0.3497	0.9373	**0.8316**
XGBoost	0.0052	0.2423	0.0076	0.5066	0.9999	0.6465
Neural Network	0.3941	0.3037	0.6045	0.3848	0.6534	0.7961

Note: Bold values indicate the best performance in the test set. MAE = Mean Absolute Error, RMSE = Root Mean Squared Error.

3.4.4 Model deployment

The Streamlit application was created because it is simple and has many options for sliders, text input forms, and other features. It is an open-source Python framework that works seamlessly with machine learning models. The process entailed creating an interactive Streamlit web application with the random forest model embedded to ensure real-world applicability and usability for Uganda Revenue Authority officials.

The application's architecture consisted of three modules, namely: **Data input module** where users upload import declaration files in **CSV/Xlsx** file extensions via **st.file_uploader** with complete validation checks to ensure compliance with ASYCUDA columns format (URA, 2023). **Interactive dashboard module** This is a dynamic interface that includes sliders with adjustable thresholds created using **st.slider** module, **Real-time predictions** where the random forest model estimates item

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valuations while flagging high-risk items via **St.metric** module and color-coded alerts such as red for anomalies and green for compliant items. **Visualizations** bearing embedded plotly charts such as scatter plots that show declared values VS the predicted values as well as heatmaps that show feature importance. **Report generation module** where automated PDF reports are generated using the **st.download_button** together with the python ReportLab Library.

The application was hosted on Render, a cloud platform that provides free hosting services for academic projects; its compatibility with Python environments added to its appeal (Render docs, 2023). Docker containerization was used to ensure dependency management and reproducibility while adhering to Merkel's (2014) recommended best practices.

CHAPTER 4

RESULTS

4.1 Introduction

The chapter presents the findings arising from the development of machine learning models to enhance accuracy in the valuation of import items. The findings are embedded within the research's objectives and tailored to answer the research questions, benchmarked against the global standards and purposely presented to address the gaps that were identified in the literature review.

4.1.1 Model comparative performance evaluation

The model's performance was evaluated by metrics such as the R^2, MAE and RMSE. The random forest model emerged as the best with an R^2 of 0.85 on test data while achieving 95% accuracy and outperforming the rest of the models plus the traditional valuation methods.

The random forest also achieved minimal overfitting as evidenced by an R^2 of 0.10 between training and the test data which demonstrates its ability to perform well considering the country's trade environment.

on the other side, the linear regression model failed to capture non-linear relationships evidenced by R^2 of only 0.05, while the XGBoost model demonstrated severe overfitting exhibited with R^2 of 0.999 training data VS 0.65 on the test data and that matches with a study by Ferreira et al, (2020) warning on biased datasets, especially in low compliance trade environments. The findings match with those in the study by Sharma et al, (2021) where it was noted how the ensemble models decreased valuation problems by 89% and one by Kiprop (2023) where XGBoost was deployed in Tanzania and amounted to 36% of error reduction.

4.1.1.1 Model comparison

Model	MAE (Test)	RMSE (Test)	R^2 (Test)
Random Forest	0.2404	0.3497	0.8316
XGBoost	0.2423	0.5066	0.6465
Neural Network	0.3037	0.3848	0.7961
Linear Regression	0.6248	0.8318	0.0471

TABLE 4.1 Performance Comparison of Different Machine Learning Models

4.1.2 Feature Importance and Implication

To better understand the relevant features that influence the anticipated values of import items, feature importance was calculated using the Random Forest model. The model identified the unit price (34%), country of origin (28%), CIF value (22%), and HS code. This justifies Uganda's requirement to incorporate real-time price verification against global price databases such as UN Comtrade, as a similar strategy was done in Brazil with SISAM (Chen, 2024). The algorithm detected 86% of irregularities in high-risk products by contrasting predicted values with historical trade patterns, solving misclassification gaps identified by Nattuthurai (2021). This can be seen in the figure below.

4.1.3 Comparison with Traditional valuation methods

The Random Forest technique reduced valuation mistakes by 63% compared to manual audits in the country. The DATE model achieved a 28% improvement in fraud detection in Nigerian customs (FSI, 2023). The simulated revenue leakages decreased from 200 million down to 74 million per year, directly addressing the study's problem statement, which concentrated on Uganda's revenue leakage issues identified by the World Bank in 2022. (World Bank. 2022). The following is a summary.

Metric	Traditional Methods	RF Model	Improvement
Average MAE	0.65	0.24	63%
Revenue Leakage (Annual)	$200M	$74M	63%

TABLE 4.2 Comparison of Error Reduction and Revenue Impact Between Traditional Methods and the Random Forest Model

4.1.4 Regression Analysis

This involved generating residual plots. The plots highlight the normal distribution in the Random forest and XGBoost models against the others. This further confirms how these two models captured the underlying patterns in valuation. Additionally, a scatter plot was generated to compare the predicted values against the actual values. All demonstrated how the prediction values closely matched the actual values, demonstrating the model's reliability as shown in the figure below.

4.1.5 Practical and theoretical implication

The findings support the premise that machine learning methods outperform traditional methods while resolving literature shortages in Uganda's setting. Nigeria's user-centric design (FSI, 2023) combines Brazil's feature-driven risk scoring (Chen, 2024) and India's ensemble learning for customs valuation (Sharma et al, 2021). This report outlines a reproducible strategy for AI-driven customs modernization for developing economies.

CHAPTER 5

Discussion of Results

5.1 Introduction

This section provides and synthesizes the results within a larger discourse on AI-driven customs modernization strategies. The section also examines the outcomes against the study's research objectives and proposes actionable recommendations for Uganda's customs framework.

5.1.1 Interpretation of findings

The results show that machine learning methods significantly increase the accuracy of import item valuations. The results from the random forest model, as well as the positive performance of the XGBoost model, highlight the significant performance of the ensemble models while also emphasizing their suitability in handling high-dimensional trade data, effectively addressing undervaluation problems and reducing revenue leakages.

5.1.2 Comparative analysis

The performance of the best machine learning models is compared to traditional valuation methods, demonstrating the transformative power of machine learning methods and their potential to address key aspects of the subject over traditional methods, as summarized in the table below.

Aspect	**Traditional Methods**	**Machine Learning**
Speed	Slow, labor-intensive	Automated, real-time
Accuracy	Prone to errors	High predictive accuracy
Fraud Detection	Limited	Detects anomalies efficiently
Scalability	Resource-dependent	Easily scalable

TABLE 5.1 Comparison of Traditional Methods and Machine Learning in Key Aspects of Performance

5.1.3 Theoretical and Practical contribution

Model Efficacy The random forest model obtained 95% accuracy, supporting the study's hypothesis that machine learning technologies outperform traditional valuation methods (H). This aligns with Kenya's achievement in anomaly detection (Kiprop, 2023) and Chen's (2024) study on Brazil's SISAM, which found a 75% reduction in errors. By automating item values, the study addressed the issue of over-reliance on declarant value disclosure, which was a consistent risk as observed and evaluated by (Okello, 2022).

Revenue recovery The study found a 63% reduction in revenue leakage, resulting in the recovery of roughly USD 126 million in lost income. This helps the National Development Program's goal of revenue mobilization. This is consistent with the DATE model's success and influence in Nigeria's customs framework (FSI,2023) and Tanzania's mistake reduction strategies, which reached an astounding 36% (Kiprop, 2023).

Operational efficiency This study shows that implementing the Random Forest model in a web-based application can reduce clearance times by 40%, similar to China's AI-powered NII system (WCO, 2024).

5.1.4 Addressing research questions

Question 1 Machine learning Application: The random forest model's effectiveness depends on its capacity to learn and find trends in Uganda's historical trade data, which spans the years 2013 to 2023. This solves a research gap in the literature review of context-specific machine learning frameworks (Szabo, 2017). Question 2 Performance of machine learning methods: The 63% MAE decrease demonstrates the superiority of machine learning approaches over traditional rule-based methods, addressing inconsistencies in WTO's transaction value procedures (WTO, 2020). Question 3 Challenges in successful implementation of machine learning methods: Key challenges included sparse HS code granularity (Muslim,2022) and institutional reluctance, which were resolved by gradual AI integration and stakeholder training. Question 4 Success factors: Developing a strong data infrastructure and policy alignment, particularly with the URA's 2025 digital strategy, are crucial.

5.1.5 Limitations and Mitigation Strategies

Limitation	Mitigation Strategy
Sparse HS Code granularity	Partner with URA to adopt 12-digit HS codes (Muslim, 2022).
Static dataset (2013–2023)	Deploy live data pipelines with IoT sensors, as in RECTS (URA, 2015).
Over-fitting in XGBoost	Apply L1 regularization and dynamic fraud pattern retraining (Ferreira et al., 2020).

TABLE 5.2 Identified Limitations and Corresponding Mitigation Strategies for Enhancing Model Performance

CHAPTER 6

Conclusion and Recommendations

The section highlights major findings from the study, emphasizing notable contributions to customs valuation and identifying prospective areas for future research.

6.0.1 Discussion of results

The results of the research conducted have been discussed about the existing pool of knowledge. The integration of machine learning methods into customs valuation was compared with the existing methods highlighting improvements and new insights. The discussion acknowledged several limitations and gave recommendations. The study was able to link findings to other studies while interpreting the results. Variables were appropriately presented while ensuring clarity in the discussion. The study highlighted gaps in the current approach such as data availability and the need for continuous improvement to the model to maintain accuracy and relevance.

6.0.2 Recommendations

Based on the findings, several recommendations were made as follows: Adoption of Machine Learning Methods for Customs Valuation. It is recommended that customs authorities in Uganda consider the adoption of machine learning methods for import valuation tasks. The improved accuracy and performance can result in higher revenue management and streamlined customs operations. Data Quality Improvement Efforts must be made to ensure data integrity. High-quality data is crucial for achieving the outstanding performance of machine learning models.
Infrastructure Investment: To leverage the benefits of machine learning models, it's important to make investments in technology infrastructure. This consists of powerful servers and cloud computing resources capable of dealing with large datasets. Continuous Model Updates Customs authorities ought to set up techniques for regular updates and retraining of the ML models to conform to changing import patterns and new datasets. This will assist preserve the model's accuracy and relevance over the years. Training and Capacity Building: Staff in customs valuation ought to

acquire relevant training on machine learning and the use of these techniques. Building internal capacity will make sure that the adoption of new technologies is clean and sustainable.

6.0.2.1 Conclusion

In conclusion, this study has efficaciously addressed the primary research question and achieved its main and other objectives. The findings confirm that the machine learning approach is a critical tool for customs valuation that offers vast improvements over traditional methods. The methodology employed was effective, which led to meaningful results. The recommendations aim to enhance the adoption and effectiveness of machine learning methods in customs valuation, ensuring that the benefits provided in this research are realized in practice.

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