A Machine Learning Approach for Accurate Valuation of Imports in Uganda

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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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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

This chapter introduces research on the application of machine learning methods to enhance import items valuation accuracy within the Uganda's customs framework. It serves as the foundation for the research providing context, stating the problem, the research objectives and the questions that guide the research, and justification for the study.

1.1 BACKGROUND TO THE STUDY

"Customs duties are a backbone of Uganda's economy with a contribution to tax revenue estimated at 30% " (URA, 2023). However, the customs framework faces significant and persistent challenges such as under-declaration of goods, misclassification of goods based on their Harmonized system codes (HS codes), and inaccurate and inconsistent application of transaction value methods of valuation. These challenges have greatly impacted the country's revenue where an estimated $ 200 million in revenue is lost annually (World Bank, 2022).

The traditional import valuation methods such as rule-based checks and manual audits are often too slow, subjective, labor intensive and prone to human error and manipulation. With the digital era, comes the machine learning technologies that offer the transformative capacity to automate tasks and enhance accuracy in the customs valuation process, streamlining customs operations as demonstrated in countries that have adopted these technologies such as India, China and Kenya (UNCTAD, 2021)

The increasing volume of transactions and the complexity of the matter of international trade further exacerbate the problem calling for the adoption of automated valuation methods.

The statistics in Table 1.1 highlight the need for improvement in valuation. The volumes of imports have been on the rise year on year.

1.1.0.1 Contextual Background

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

Year	TIV (M Tons)	TIV (USD B)	Top Imports	GDP (%)
2020	8.5	7.3	Machinery, Petroleum, Vehicles	18.2
2021	9.1	8.1	Petroleum, Electronics, Pharma	19.5
2022	9.8	9.0	Machinery, Petroleum, Food	21.0
2023	10.2	9.8	Vehicles, Chemicals, Consumer Gds	22.5

TABLE 1.1 Statistics on Import Volumes and Values in Uganda

Key: TIV = Total Import Volume, TIV (USD B) = Total Import Value in Billion USD, GDP (%) = Percentage of GDP, Pharma = Pharmaceuticals, Consumer Gds = Consumer Goods.

Valuation, n.d.), replaced the GATT Valuation Code during the Uruguay Round discussions that founded the WTO in 1994. This Agreement establishes a Customs valuation system based principally on the transaction value of imported goods (the price paid or due when sold for export), subject to certain adjustments. When estimating Customs value based on transaction value is not feasible, alternative approaches must be used in the following hierarchical order:

- The transaction value of identical goods
- The transaction value of similar goods
- The deductive value method
- The computed value method
- The fallback method

These methods seek to establish a fair, standard system for valuing imported commodities that is consistent with market reality while banning arbitrary or fraudulent Customs values.

1.1.1 Theoretical background

The theoretical foundation of this research is anchored in artificial intelligence (AI), particularly its subset known as machine learning (ML). By adopting machine learning techniques, this study illustrates how AI can enhance accuracy and efficiency within customs processes while contributing valuable insights into its application across various sectors of public administration and policy formulation.

1.2 PROBLEM STATEMENT

Uganda relies heavily on customs revenue which accounts for an estimated one-third of the national tax base. This funds key public service projects and infrastructures. However, the Uganda Revenue Authority continues to face significant and persistent problems arising out of failure to appropriately address inconsistent and inaccurate valuation of imported goods resulting in an estimated $200 million in lost revenue annually. The key identified causes of this include misclassification of goods, under declaration of goods by the importers yet is aided by the subjective valuation

methods, poor audit mechanisms and fragmented data systems. The current valuation methods in Uganda, also often referred to as the traditional valuation methods in this study mainly rely on the declarant disclosed transaction values as guided by the World Trade Organization (WTO's) transaction value means. The approach is meant to provide simplicity, but it lacks a standard mechanism to verify the declared values against the global actual benchmarks, resulting in vulnerabilities that are exploited by fraudulent schemes such as the manipulation of invoices and the misclassification of HS codes. The operational inefficiencies worsen the situation where manual system audits are reported to only cover 5% of the imports due to resource constraints. (Okello, 2022) and since Uganda's Customs databases are often isolated from external price references such as the UNcomtrade, it restricts the ability to identify price irregularities on time.

The neighbouring countries have already shown the transformative power of machine learning methods in their customs, whereas Kenya and Tanzania have recorded success in reducing discrepancies (Kiprop, 2023).

The same innovations have registered success elsewhere in developed economies such as Brazil with SISAM and Nigeria with the DATE model where the valuation of items is automated valuation giving a success rate (of 75% error reduction in Brazil) and 28% fraud detection improvement in Nigeria.

On the other hand, Uganda has been stuck on traditional rule-based valuation methods that lack adaptability to ever-changing fraud schemes. This not only causes a loss in revenue but also hinders fair trade practices. In this context, the study aims to answer a very critical question: How can machine learning models be effectively applied to improve the accuracy of the valuation of imported items in Uganda's customs framework?

The study aims to provide the URA with a scalable system to minimize revenue losses and improve compliance with trade regulations by bridging technological adoption and context-specific policy implementation.

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 questions as follows:

- **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 the introduction of 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 organized as follows:

Chapter 2 of this thesis provides a comprehensive literature review, especially on machine learning applications in customs, and international trade with a focus on valuation and pricing.

Chapter 3 of the thesis details the methodology used to complete the study. It explains the data collection, preprocessing and statistical techniques used in the process.

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.

Overall, the section serves as the foundation for our research methodology and guides the formulation of the research questions, and the different hypotheses tested to address the gaps identified.

2.1 Customs valuation: Concepts

Customs valuation refers to the process of determining and assigning a monetary value of imported items to assess duties and taxes. This is crucial for revenue collection and trade facilitation. The practice of valuation dates to the 1947 General Agreement on Tariffs and Trade (GATT), which established the first globally accepted principles of customs valuation (Wulf & Sokol, 2019).

The World Trade Organization's Agreement on Customs Valuation and Actual Cash Value (ACV) later standardized these practices by providing six traditional methods for determining the customs value in a hierarchical order (WTO, 2020). These include: The transaction value method, The transaction value of identical goods, The transaction value of similar goods, The deductive method, The computed method, and the Fall-back method. The Uganda Revenue Authority (URA) as the regulator, notes that the primary method of determining the customs value of imported goods is the transaction value method as per Article 1 of the agreement on customs valuation (GATT, 1994).

The World Trade Organization (WTO) further clarified that the basic principle is the transaction value, whereby the agreement stipulated that customs valuation shall, except in specified circumstances, be based on the actual price of the goods to be valued, which is generally shown on the invoice. This price, plus adjustments for certain elements listed in Article 8, equals the transaction value, which constitutes the first and most important method of valuation referred to in the Agreement.

The methods highlighted above are often referred to as the traditional valuation methods throughout this thesis. These have been inconsistent, leading to disputes and revenue losses.

Imports valuation processes in Uganda are slow and cumbersome primarily due to the reliance on these traditional valuation methods. In contrast, adopting machine learning has revolutionized these processes by automating tasks such as document classification and risk assessment while significantly reducing processing times in countries where machine learning methods have been implemented.

Amid evolving trade policies, machine learning's capacity for data analysis allows it to predict potential disruptions, ensuring compliance with regulations while facilitating efficient trade practices.

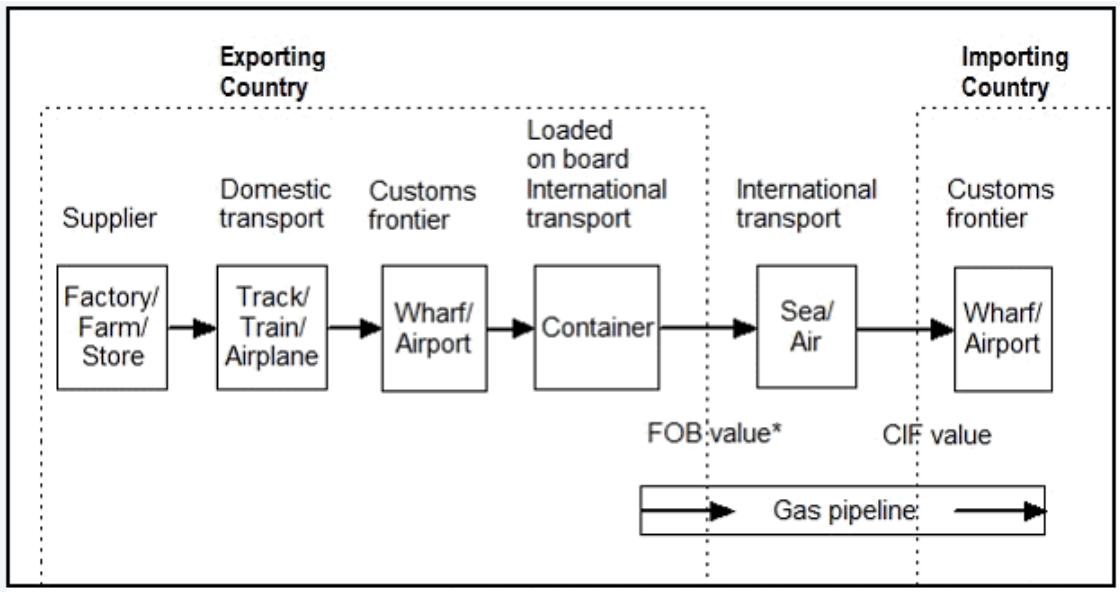

FIGURE 2.1 A flowchart illustrating the physical movement of goods in international trade. Goods start from a supplier in the exporting country (Factory/Farm/Store) and move through domestic transport (Truck/Train/Airplane) to the customs frontier (Wharf/Airport). They are then loaded onto international transport (Container) and shipped via sea or air. Upon arrival in the importing country, they pass through the customs frontier before reaching their final destination. Additionally, goods transported via gas pipelines are valued at the point of entry into the pipeline (FOB) in the exporting country and upon arrival in the importing country (CIF).

2.1.1 Machine learning in 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 analyze import data registered success where valuation errors were 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 the Nigeria's customs union where a Neural Network flagged 20% of legitimate shipments due to over-fitting on outdated fraud patterns.

This emphasized 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.

2.1.1.1 Predictive Analytics in Customs

Predictive analytics is the application of statistical techniques and machine learning (ML) models to analyze past data and forecast future trends and results. Predictive analytics is critical in trade facilitation because it improves decision-making, lowers risks, and optimizes 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 utilized 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, categorization algorithms assist in identifying high-risk transactions by analyzing 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.

2.1.1.2 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 recognized 6-digit number, each country may add further digits to the code to make it 8, 10, or 12-digit for tariff and statistics purposes. HS Classification is the process of determining the most exact description in the harmonized system (HS) for the commodities to be classified.

The suggested research now focuses on unsupervised learning techniques, notably Naive Bayes classification, for categorizing 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 maximized 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 optimizing customs revenue and mitigation of potential restitution achieved a remarkable accuracy of 99.97% with a classification error of only 0.03% which demonstrated how data mining techniques optimize customs revenue and therefore reducing 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 categorization technique, which can help Customs officials determine tariffs and/or customs values.

2.1.2 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.

2.1.2.1 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 utilized 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% 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.).

2.1.2.2 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 number of information on commodities, articles, and modes of transportation, the system can automatically recognize photos and alert Customs officials to perform image reviews or physical inspections. "Through continuous optimization, 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.

2.1.2.3 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.

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2.1.2.4 The RECTS project: Uganda

”Three revenue authorities (Kenya, Uganda, and Rwanda) agreed in 2017 at a tripartite head of state meeting to establish 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. Bsmart Technologies was contracted as the sole provider of the new regional system. Julius and Christabel (n.d.).

The system consists of four major components: dry cargo seals and wet cargo fuels, arming personnel at the release locations, the Centralized Monitoring Center at the head, and twelve Rapid Response Units throughout the transit route. All teams operate around the clock to ensure real-time cargo monitoring while in transit.

In addition, a reconciliation team checks all transit cargo movement documentation to guarantee compliance with legislation governing their transportation and that any malpractices discovered are corrected.

FIGURE 2.2 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 realized 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.

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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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2.1.2.5 Ongoing enhancement initiatives

The combined technical working groups of the revenue authorities are constantly examining the operational modules of the RECTS system in light of the operating environment and suggesting changes aimed at improving 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 control. This requires allocating resources to all RECTS components to ensure that they are well-equipped and that personnel are sufficiently trained to perform cargo monitoring duties.

2.1.2.6 The DATE model

Chen and Liu (2022) developed this, which showed 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% compared to traditional machine learning methods.”

The World Customs Organization’s BACUDA project introduced the model, which represents a significant shift in customs fraud detection with notable findings including superior performance as compared to the XG Boost model, especially in classification tasks. This model was also successfully used in Nigeria (FSI, 2023). Additionally, a simpler web-based user interface was used to effectively prevent item misclassification.

FSI (2023) conducted a study on the use of artificial intelligence in developing Nigeria’s customs system, and the DATE model demonstrated superior performance to existing traditional methods. To avoid misclassification of imported items, relevant users are given a web link where they can enter the item name and another unique identifier, and the model returns the correct class to which those items belong. This study fills gaps in the existing literature by creating a machine-learning model to address valuation issues inside Uganda’s customs regime.

2.1.3 Importance of Machine Learning in Trade Facilitation.

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

[-6] A machine learning approach for accurate import valuation

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 optimization are all examples of machine learning applications in trade facilitation. Predictive models, for example, can analyze 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 analyzing 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.

2.1.4 Barriers to successful implementation of Machine learning in Customs Trade Practices

Data quality and its availability: The use of predictive analytics and machine learning models in trade facilitation confronts several challenges, the most significant of which are data quality issues and system integration. Machine learning systems often rely on high-quality data to operate smoothly. Biased data leads to incorrect results and conclusions which undermines the reliability of the results of the ML systems.

Customs trade uses a variety of data sources, such as customs records, shipping manifests, and regulatory documents. These datasets' discrepancies, missing values, and inconsistencies can have a major impact on predictive model accuracy.

Ethical and Regulatory Considerations: The adoption of machine learning models sometimes inadvertently perpetuates biases that are often present in the training data which leads to unfair results. Furthermore, the sensitivity of trade data poses privacy and security concerns, restricting the availability of large datasets for model training and analysis.

Technological Constraints: Successful implementation of machine learning systems requires special skills and knowledge. The lack of enough skilled professionals in Artificial Intelligence hinders the adoption and effective adoption of these technologies. This calls for substantial investment in infrastructure especially investing in high-performance computing resources and data storage mechanisms.

Public Perception: Building public trust in these AI systems is critical. There is a constant

fear of loss of jobs due to many tasks being automated by AI. Therefore addressing the societal impact of AI systems requires the development of programs to up-skill the workforce and to provide opportunities for employees to acquire new skills.

AI Regulation: The lack of an organized legal framework for data collection and use of electronic data. The absence of standardization in data formats and communication protocols makes ML model integration problematic. In addition, traditional trade systems frequently lack the technical infrastructure needed to support real-time ML predictions.

These problems underscore the importance of improved data management techniques and strong integration frameworks to properly employ ML in trade facilitation.

2.1.5 Gaps in Existing Literature

Despite the demonstrated success of machine learning in neighbouring economies, Uganda's customs ecosystem has been noticeably under served by such innovations. Even though Uganda shares structural challenges such as porous borders, informal trade networks, and limited audit capacity with Kenya and Tanzania, where ML adoption has yielded measurable gains, no peer-reviewed studies or policy frameworks have explored the application of ML to Ugandan import valuation. Existing research in the region is primarily concerned with fraud detection as a standalone goal, frequently ignoring integration with the WTO's transaction value methodology or Uganda's legal valuation frameworks. Models developed in Kenya, for example, prioritize identifying outright smuggling while failing to address more nuanced forms of undervaluation, such as manipulating invoices for high-risk goods such as used vehicles and textiles (Nattuthurai, 2021). This creates a critical gap: while anomaly detection models can identify suspicious shipments, they lack the methodological accuracy to establish contextually accurate values that are consistent with global price benchmarks or Uganda's tariff laws. Furthermore, Uganda's unique data landscape, which includes sparse digitization of paper-based declarations, and inconsistent HS code granularity, has received little attention in the ML literature.

Bridging this gap necessitates not only adapting proven algorithms to Uganda's infrastructural realities, but also reviewing model design to align with the URA's operational priorities, such as minimizing clearance times while increasing revenue recovery. By addressing these issues, this research seeks to advance a comprehensive ML framework that goes beyond fraud detection to provide actionable, policy-compliant valuation findings

Despite the rising volume of research on predictive analytics and machine learning applications in trade, there are still several gaps in the present literature. One notable gap is the limited investigation into the applicability of machine learning to the context of developing economies that face challenges with data integrity and transparency.

While some studies have looked at individual ML algorithms, there has been little research into merging these approaches with decentralized data storage options to increase forecast accuracy and

trust.

Another undiscovered field is the use of reinforcement learning in complex trading scenarios with several stakeholders and dynamic conditions. While preliminary findings are promising, additional research is needed to construct scalable reinforcement learning models capable of optimizing whole trade networks in real time.

The scope of the research noted insufficient study of data approaches, especially for Uganda's context. While some countries have successfully implemented data-driven approaches, Uganda's special trade patterns, border practices and existing technological infrastructure presented distinct challenges that are yet to be addressed adequately in the current research. For instance, the integration of data from the Automated System for Customs Data (ASYCUDA) world system and extraction of regional trade database data requires special approaches that consider local data quality and accessibility constraints.

There exists a gap in understanding the real impact of AI-based valuation systems on revenue collection. While the theoretical analysis suggests potential improvement, there has been limited empirical evidence that quantifies the real-world impact of such systems on customs revenue especially in developing countries. Research needs to not only focus on the revenue impact but also on other effects such as reduced clearing times, decrease in valuation disputes and cases and improved compliance of traders.

There also exists challenges in implementing the technology advancements as highlighted in this research. The current literature predominantly focuses on the implementation of these innovations in well-developed economies, but a gap remains regarding the adoption of these innovations for developing economies like Uganda that are associated with challenges like intermittent internet connectivity and specialized manpower. For instance, the implementation of some algorithms like BERT models in environments with inadequate computing resources needs further exploration.

There is a crucial need for research on the institutional resistance to change regarding customs modernization, staff adaptation and organizational change at large needs to be studied more.

Finally, there is a need for comprehensive research into the long-term influence of predictive analytics on customs trade practices. The existing literature focuses mostly on short-term improvements in efficiency and risk management, leaving the broader economic, social, and regulatory ramifications unexplored.

These gaps point to potential future study topics, emphasizing the necessity of multidisciplinary techniques that combine machine learning, blockchain, and trade research to progress the subject of customs trade and valuation efficiency.

2.1.6 Conceptual Framework for Machine Learning Powered Customs Valuation

Based on the literature reviewed, the conceptual framework for the installation of machine learning methods can be developed while considering 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 considers legal and regulatory aspects of customs valuation, ensuring full compliance with both the international and national set regulations.

2.1.7 Limitations of the study

Although the purpose of the study was to provide comprehensive solutions for import assessment, several obstacles must be acknowledged. While the study aimed to develop models suitable for all import categories, the unique characteristics of certain goods required further adaptation and refinement of the models.

External factors such as changes in international trade policies, economic fluctuations and global supply chain disruptions can affect the effectiveness of proposed solutions, requiring constant monitoring and adaptation to meet these dynamic conditions. Recognizing these limitations, research can strategically address potential challenges and provide robust, adaptive solutions to improve the value of Uganda's imports.

The accuracy and efficiency of machine learning methods are extraordinarily dependent on the volume and completeness of available information. Incomplete or incorrect information may also influence the reliability of the results. Deploying these models requires tremendous technical infrastructure and expertise, and URA's resource constraints can present situations in deploying and maintaining those systems.

Institutional resistance to exchange and the need for considerable education of customs officials can prevent the adoption of new innovative methods, which require careful planning and stakeholder engagement.

2.1.7.1 Limitations summary

Limitation	Description	Reference(s)
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 related to limited resources, inadequate infrastructure, and lack of technical expertise.	Szabo (2017). According to Szabo's study on customs valuation (**szabo2017**), machine learning can improve accuracy.
Explainability	Difficulty in interpreting and explaining AI models reduces trust and regulatory acceptance.	WCO (2020)

TABLE 2.1 Key limitations in the adoption of AI-driven customs valuation systems

2.2 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 and Scope

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.

3.1.1 Data Sources and Selection Criteria

The dataset was sourced from the Uganda Revenue Authority's Automated system for customs data (ASYCUDA), contains 111,000+ import transactions, and spans 2013 to 2023.

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). Columns with missing values exceeding 60%, such as the Valuation_Method, were eliminated to limit bias following Grundy et al. (2015), whereas partial missing values in columns less than 10% were addressed via median imputation to preserve data distribution integrity (Allison, 2001)

Feature	Record 1	Record 2	Record 3	Record 4	Record 5
HS Code	91338102.5	91338102.5	85181000.0	91338102.5	85163100.0
Country of Origin	CN	CN	CN	CN	CN
Gross Mass	194.54	194.54	77.82	972.72	155.64
Net Mass	150.0	150.0	50.0	900.0	124.0
Item Price	1285.39	1344.86	102.91	1543.66	164.66
CIF Value (Local)	1285.39	1344.86	102.91	1543.66	164.66
Duties	447.56	468.26	35.81	537.49	92.55
Unit Price (Local)	257.08	268.97	51.46	61.75	41.17
Invoice Amount (Local)	1285.39	1344.86	102.91	1543.66	164.66
Currency	USD	USD	USD	USD	USD
Added Costs	0.0	0.0	0.0	0.0	0.0
Internal Freight	0.0	0.0	0.0	0.0	0.0

TABLE 3.1 Top Records of the Dataset (Transposed)

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 3.2 Variables Description

Variable Name	Description
HS_Code	The Harmonized System code, a standardized classification of imported goods used globally.
Country_of_Origin	The country from which the goods originate, which may influence valuation due to trade agreements or tariffs.
Gross_Mass and Net_Mass	These variables provide insights into the weight of the imported goods, affecting transportation and duty costs.
Item_Price and CIF_Value	The declared price of items and their Cost, Insurance, and Freight (CIF) value, which represents the total landed cost.
Duties_Taxes	The taxes and duties levied on the imported goods based on their category and origin.
Unit_Price_Local	The price per unit of the goods in the local currency are crucial for understanding pricing variations.
Valuation_Method	The method used by customs officials to determine import values, though this field may have inconsistencies or missing values.
Invoice_Amount_NMU	The total invoice amount in the Non-Monetary Unit (NMU), which helps in determining valuation accuracy.
Invoice_Currency_Code	The currency used in invoicing, requiring conversion to a standardized currency for comparative analysis.
Additional Costs and Freight Charges	These include extra expenses such as handling fees, internal freight, and storage costs.

3.3 Data Pre-processing

Data preprocessing is an important stage in Machine Learning because it improves data quality and promotes the extraction of 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

The dataset went through a cleaning phase where missing data was detected in different columns and addressed by deleting columns with over 60% missing values apart from the Target variable (Unit price) using a method known as listwise deletion, validated by Graham (2009) for minimizing analytical distortion.

Median imputation was used to maintain the dataset's robustness in continuous columns such as the Unit_Price_Local, as recommended by Little and Rubin (2019).

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. **Descriptive statistics** were performed, revealing skewed distributions in key variables such as the target variable (Unit_Price_Local), which had a mean of Ugx 1,871.22 and a standard deviation of 6,908.06, indicating high volatility.

Statistic	Count	Mean	Std Dev	Min	25%	50%	75%
TAR_HSC_NB1	111	80,177,240	17,805,080	2,064,900	84,163,450	85,131,000	87,033,
VIT_WGT_GRS	111	9,737.87	20,139.52	1.00	200.00	6,352.00	15,664.
VIT_WGT_NET	111	5,638.93	7,616.08	1.00	200.00	920.00	6,804.0
TAR_PRI	111	3,361.90	8,487.76	6.81	140.17	471.88	1,800.2
VIT_CIF	111	3,387.01	8,490.17	6.81	140.17	471.88	1,800.2
TAX_AMT	111	784.88	2,300.13	1.45	38.83	136.13	413.30
UNIT_PRICE_LOCAL	111	1,871.22	6,908.06	0.02	5.00	33.85	264.23
VIT_INV_AMT_NMU	111	3,361.90	8,487.76	6.81	140.17	471.88	1,800.2
VIT_CST	111	25.12	264.63	0.00	0.00	0.00	0.00
VIT_IFR_AMT_NMU	111	25.12	264.63	0.00	0.00	0.00	0.00
VIT_OTC_AMT_NMU	111	0.00	0.00	0.00	0.00	0.00	0.00

TABLE 3.3 Descriptive Statistics of the Dataset (Transposed)

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 × I Q R Q1−1.5×IQR (lower) and Q 3 + 1.5 × I Q R Q3+1.5×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). This reduced skewness from 4.2 to 1.8.

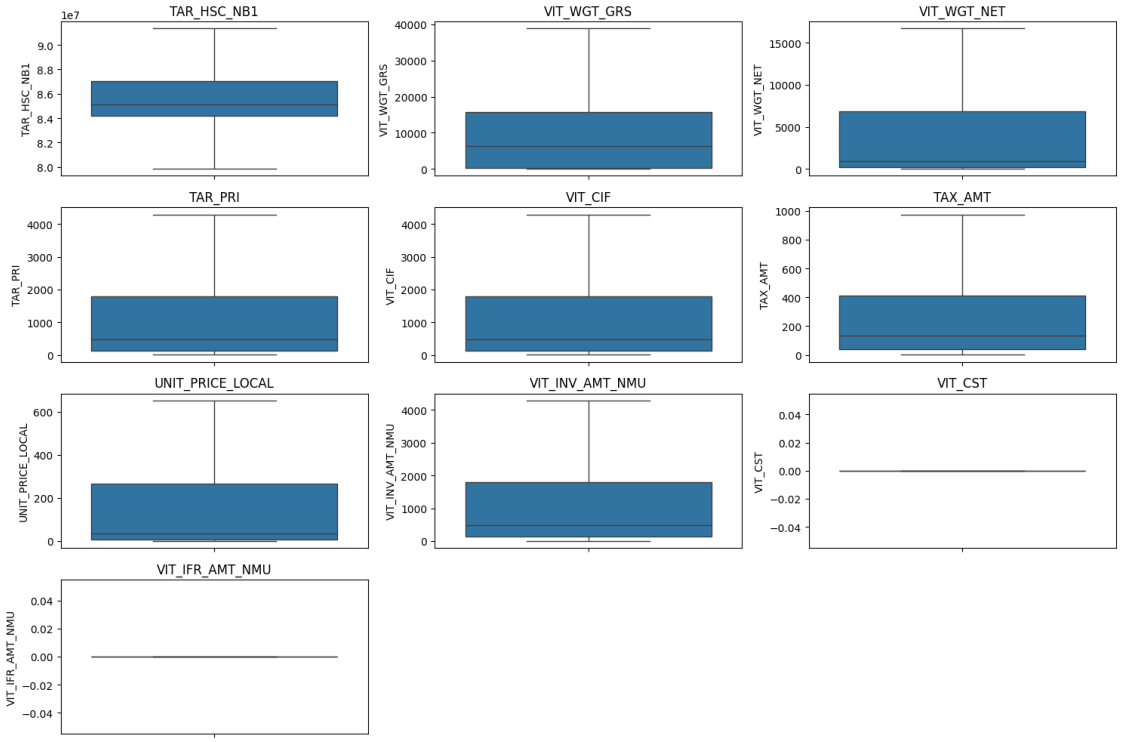

FIGURE 3.1 Boxplots showing the distribution of key import valuation variables while confirming the treatment of outliers

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)

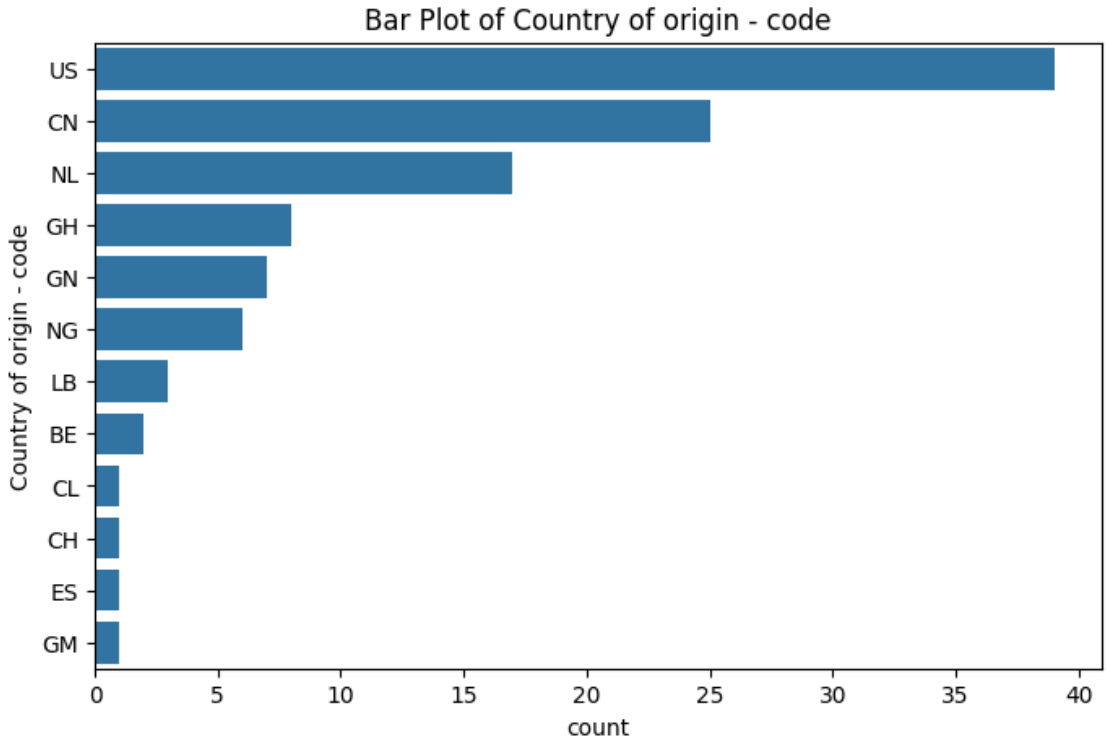

FIGURE 3.2 A bar plot representing nations of origin for import items. Most of the country's imports come from the United States. This contextualizes trade dependencies, which influence value accuracy.

Scatter Plots revealed a correlation among Unit_Price_Local and CIF value, which exposed undervaluation cases in high-value items such as vehicles and heavy machinery

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

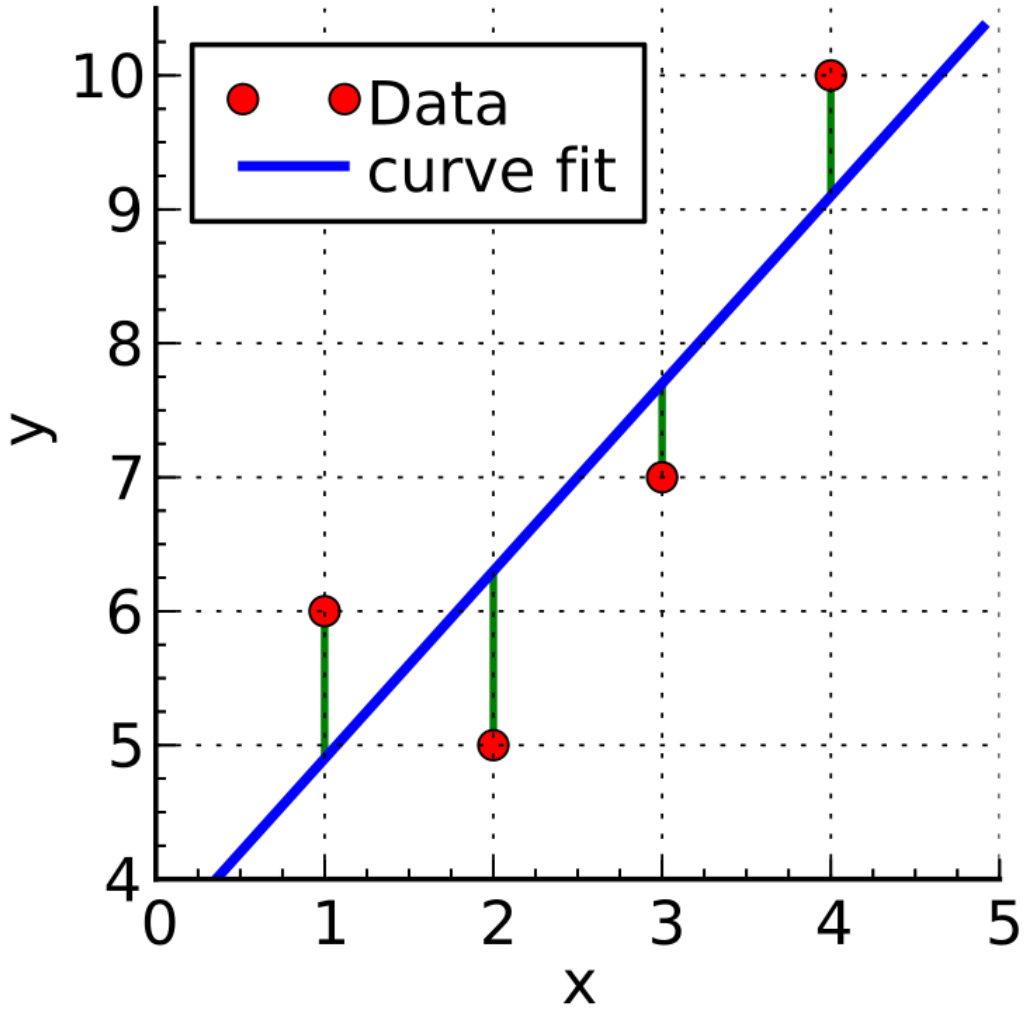

FIGURE 3.3 In linear regression, the observations (red) are assumed to be the result of random deviations (green) from an underlying relationship (blue) between a dependent variable (y) and an independent variable (x).

Source: Wikipedia - Linear Regression Image

Dataset	MAE	RMSE	R^2
Training Data	0.5154	0.6882	0.5508
Test Data	0.6248	0.8318	0.0471

TABLE 3.4 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.

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

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 3.5 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

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.

TABLE 3.6 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.

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 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.

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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.

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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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