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Enhancing Land Valuation Using Artificial Intelligence, A Case Study of Mutundwe Hill, Kampala District

BY

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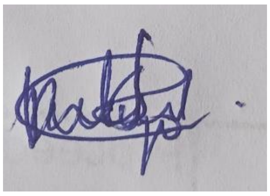
Declaration

I **LUKWAGO RICHARD,** hereby declare the work presented in this report is out of my own effort and has never been submitted to any other institution of higher learning for the award of a Master's degree in Land Management or its equivalent.



Date: 5^{th} /06/2025

APPROVAL

I Dr. Lilian Oryema do certify that this piece of work has been under my close supervision

DR. LILIAN ORYEMA

Supervisor

Dedication

This proposal report is dedicated to the Almighty God who has provided me with wisdom, knowledge and understanding and finances throughout this journey.

Acknowledgment

I am grateful to the Almighty God who has continuously provided financially and guided me throughout this research.

I am thankful to you Dr. Lilian Mono and Dr. Brian Makabayi for your close supervision which has led to the success of this proposal. May God bless you abundantly!

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Lastly, my appreciation goes to my fellow MSc. Land Management Class that has always encouraged me to keep pushing on. Without your advice and academic guidance, I would not have made it this far. Am forever grateful. May the Almighty GOD bless you.

Table of contents

Table of Figures

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
RF	Random Forest
ISU	Institution of Surveyors of Uganda
SRB	Surveyor’s Registration Board
NDP4	National Physical Development Plan 4

ABSTRACT

Uganda has undertaken a step into the new National Physical Development Plan 4 which requires a lot of infrastructural development. As part of the agenda, a lot of transactions on land are being carried out which includes compensation of PAPs for different projects. Thus, Property valuation is a critical concept for a variety of applications in the real estate market such as transactions, taxes, investments, and mortgages. It entails a lengthy process of planning, data collection, analysis and estimation of the land prices. The traditional methods of valuation that include replacement cost, discounted cash flow, hedonic, comparative method and income capitalization are lengthy, costly and subject to the valuer's level of bias. A new method that is fast, accurate, handles a lot of data and is less costly known as Artificial Intelligence was looked at in this study. Thus, this paper aims at seeing how land valuation can be enhanced using Artificial Intelligence. Among the various AI valuation methods, Random Forest (RF) as the machine learning algorithm was applied in this study in a case study of Mutundwe Hill, Kampala District, Uganda. The data consisted of 50 plots assumed to be of the same size but with varying distance to the nearest water source, electricity pole, location and nearest primary school forming different datasets each were used in the study. Valuation data was obtained from KCCA and it was split into training and testing data. These datasets will be used to train and test all the models. The performance evaluation and measurement of each model will base on four performance indicators: R-squared, MSE, RMSE, and MAPE. The results from both data splitting circumstances have shown that the accuracy of random forest is the highest among the regression models. The discussions point out the causes of the models' performance changes once applied on different datasets obtained from different data splitting techniques. Limitations are also pointed out at the end of the study for future improvements.

CHAPTER ONE

INTRODUCTION

1.1 Background

Property valuation is the estimation of the properties´ market value which is significantly important in decision-making in real estate investment, transaction, development, taxation, and credit loan. Considering these applications, the quality, and accuracy of appraisal are critically important. In the traditional type of property valuation, appraisers are responsible for the estimation of the value based on their opinion and judgment (Abidoye et al., 2019). To ensure quality, appraisers are required to follow the professional, technical and performance standards that are regulated by the government and global professional bodies such as the Institute of Surveyors of Uganda (ISU), Surveyor's Registration Board (SRB) and Royal Institution of Chartered Surveyors (RICS). However, several studies have discussed and proved that appraisers have caused biases including anchoring the value to the recent transaction price by paying less attention to the current market conditions (Diaz III & Wolverton, 1998), making judgments on the property value based on their opinions (Gallimore, 1996) and clients' influences on valuer judgment (Diaz & Hansz, 1997). In turn, it increases the inaccuracy of the valuation. The advanced valuation method involves multi-regression methods and big data such as the hedonic pricing model and artificial intelligence has been claimed as new methods to improve the value accuracy (Diaz & Hansz, 1997; Yacim & Boshoff, 2014; Yilmazer & Kocaman, 2020).

The rise of AI has become deeply embedded in land management, fostering advanced systems that empower humans to achieve remarkable progress at an unparalleled pace. In particular, AI has enhanced the sophistication of land management models by leveraging large datasets and algorithms to support decision-making (Garijo, Khider, Osorio, & Shu, 2021). It is evident that land management is undergoing a transformative shift driven by technological advancements, especially through artificial intelligence (AI) (Wu & Silva, 2019). The integration of satellite imagery has further enabled real-time soil monitoring through AI tools, revolutionizing the way land terrains are analyzed and understood.

Artificial Intelligence (AI) is revolutionizing various industries worldwide, including real estate and land valuation (Alsahan, & Alzaidan, 2024). Traditionally, land valuation in Uganda has relied on manual assessments, expert opinions, and comparative market analysis, which can be time-consuming, subjective, and prone to human errors (Mirembe, 2022). AI-powered pricing models, which leverage big data, machine learning, and predictive analytics, are transforming this process by providing more accurate, data-driven, and efficient property valuations (Topraklı, 2024). AI pricing integrates real-time market data, land characteristics, and economic trends to generate objective valuation estimates, reducing inconsistencies and improving decision-making in Uganda's real estate sector.

The application of AI in land valuation is particularly relevant in Uganda, where rapid urbanization and fluctuating land prices present challenges for property owners, investors, and policymakers (Bruin, 2023). AI-based pricing systems analyze historical transaction data, geographical information, and socio-economic factors to predict future land values with greater precision. This is crucial in addressing the inefficiencies of traditional valuation methods, which often result in price distortions, under- or overvaluation, and disputes. Studies have shown that AI models can enhance valuation accuracy by up to 25% compared to conventional methods, leading to fairer pricing structures and improved market transparency.

Despite the potential benefits, the integration of AI pricing in Uganda's land valuation sector faces several challenges, including limited access to reliable data, regulatory concerns, and the need for skilled AI professionals (Turyasingura, Ayiga, 2024). Additionally, questions remain regarding the ethical implications of AI-driven pricing, particularly in ensuring fairness and preventing market manipulation. This study seeks to explore the impact of AI pricing on land valuation in Uganda, examining its effectiveness, challenges, and potential implications for the real estate industry.

1.2 Problem statement

Land valuation in Uganda, particularly in rapidly urbanizing areas such as Mutundwe Hill in Kampala District, is predominantly a human-driven process, often marred by inconsistencies, subjective biases, and a lack of standardization (Muchimba, E., 2024). The reliance on manual valuation methods where human assessors determine land prices based on personal expertise, market conditions, and limited datasets has led to significant variations in property values for similar parcels of land. These discrepancies have created opportunities for manipulation, favoritism, and inaccuracies, which has ultimately result in disputes among buyers, sellers, investors, and government agencies. The challenge is further compounded by the absence of a transparent, data-driven approach that ensures fairness and precision in land valuation. This bias has raised critical concerns about the reliability and credibility of land valuation in high-value urban locations, necessitating a more robust and objective alternative.

Artificial Intelligence (AI) presents a transformative solution to the problem of valuation bias by leveraging big data, machine learning algorithms, and geospatial analysis to generate more precise, consistent, and transparent land valuations (Topraklı, 2024). However, despite AI's potential, its application in Uganda's land valuation sector remains limited, partly due to legal uncertainties and the entrenched reliance on traditional valuation methods. The legal framework governing property valuation has yet to comprehensively integrate AI-driven models, raising questions about the acceptability and enforceability of AI-generated valuations in official land transactions (Abdul-Al, 2024). Skepticism remains among policymakers, valuation professionals, and stakeholders, as concerns persist regarding the adaptability of AI to local valuation norms, data privacy, and the ethical implications of automation in decision-making.

Beyond legal considerations, AI could serve as an essential tool for cross-verifying human-driven valuations, minimizing variations, and ensuring greater fairness in property transactions (Balammagary, 2024). Through the analysis of vast datasets including historical land prices, infrastructure developments, and economic trends AI can provide independent valuation benchmarks that help reduce the influence of human error and bias. The lack of a structured framework to incorporate AI as a complementary or alternative valuation method means that many land transactions continue to suffer from inefficiencies and disputes.

Therefore, there is an urgent need to explore the integration of AI into Mutundwe land valuation system, addressing both legal barriers and practical implementation challenges to create a more reliable and equitable valuation process.

1.3 Objectives

1.3.1 General objective

To enhance land valuation using artificial intelligence in Mutundwe Hill, Kampala District.

1.3.2 Specific Objectives of the study

i. To assess the application of AI driven Valuation Model in improving land valuation accuracy, transparency and efficiency using Artificial neural network modelling in Mutundwe Hill, Kampala District.

ii. To investigate the ethical considerations, challenges and regulatory implications of using ai valuation in Mutundwe Hill, Kampala District.

1.4 Research Questions

i. How can the application of AI driven Valuation Model be used in improving land valuation accuracy, transparency and efficiency using Artificial neural network modelling in Mutundwe Hill, Kampala District?

ii. What are the ethical considerations, challenges and regulatory implications of using ai valuation in Mutundwe Hill, Kampala District?

1.5 Study Area

Figure 1: Map of Kampala

Mutundwe Hill is a prominent and rapidly developing area located in Kampala District, Uganda. It is situated southwest of Kampala's central business district, bordering key suburbs such as Lubaga, Ndeeba, and Nateete. The area has gained significance due to its strategic location, offering a blend of residential, commercial, and industrial developments. Mutundwe

Hill is known for its mixed land use, with high-end residential properties, rental apartments, small-scale businesses, and infrastructural developments, making it an ideal case study for analyzing land valuation dynamics.

1.6 Significance of the study

This study will hold significant importance for as follows;

Enhancing valuation accuracy and efficiency. Traditional land valuation methods in Uganda often rely on manual assessments, which can be time-consuming and prone to human error. Implementing AI can process vast datasets rapidly, leading to more precise and efficient valuations. This technological advancement can streamline the valuation process, reducing delays and improving overall accuracy.

Reducing disputes and improving transparency. Inconsistent land valuations have historically led to disputes among stakeholders in Uganda. AI-driven valuation models offer standardized approaches, minimizing subjectivity and enhancing transparency. This standardization can foster trust among landowners, investors, and government agencies, potentially reducing conflicts related to land valuation.

Informing policy and regulatory frameworks. As AI technology becomes more integrated into land valuation practices, understanding its impact is crucial for developing appropriate policies and regulations. Insights from this study can guide policymakers in crafting frameworks that ensure ethical AI use, protect stakeholder interests, and promote sustainable development in Uganda's real estate sector.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section reviews the literature on enhancing land valuation using artificial intelligence in Mutundwe Hill, Kampala District. The section further discusses the main variables of the study, and empirical review according to the objectives of the study.

2.2 Land Valuation

According to the International Valuation Standards Council (IVSC, 2021), land valuation is defined as the process of estimating the monetary worth of land based on its characteristics, market conditions, and potential use, considering economic, legal, and environmental factors. American Society of Appraisers (ASA, 2019) defined land valuation as the process of determining the value of land through systematic analysis of its location, market trends, highest and best use, and comparable sales data.

Land valuation is the assessment of the economic worth of a parcel of land, considering factors such as its geographical location, accessibility, zoning regulations, and market demand (Bello & Akinjare, 2019). Land valuation is the professional estimation of the price at which a land parcel would transact under fair market conditions, based on factors like land use, development potential, and prevailing economic circumstances. It involves systematic process of determining land value for taxation, investment, and development purposes, incorporating legal, physical, and economic considerations to ensure fairness and accuracy in property assessments (Almy, 2018).

Land valuation is a fundamental process in real estate and property management that determines the monetary worth of land based on various economic, social, and environmental factors (Oladokun, 2023). It plays a crucial role in transactions, taxation, compensation, and investment decisions, making accurate valuation essential for fairness, economic development, and regulatory compliance. The concept of land valuation is rooted in economic theories like Ricardian Rent Theory, which links land value to location and productivity, and the Highest and Best Use (HBU) principle, which focuses on the most profitable use of land. Traditional methods of land valuation include the Comparative Market Approach, Cost Approach, and

Income Capitalization Approach, each of which has its strengths and limitations. The Comparative Market Approach relies on the sale of similar properties but can be limited by data availability, while the Cost Approach estimates value based on development costs, and the Income Capitalization Approach uses potential income to determine value. Despite their long-standing use, these methods often face challenges, such as subjectivity, human bias, data limitations, and external economic factors that lead to inconsistent valuations.

The integration of Artificial Intelligence (AI) into land valuation is transforming the process by using data-driven models, machine learning, and Geographic Information Systems (GIS) (Droj, Kwartnik-Pruc, & Droj, 2024). AI enhances the accuracy of land valuations by analysing large datasets, historical transaction data, and spatial information, which can be continuously updated as new data becomes available (Rotich, 2024). Machine learning models, for instance, learn from data to predict land values with precision, while satellite imagery and GIS tools enable real-time monitoring of land features, improving understanding of terrains. Automated Valuation Models (AVMs) have emerged as a significant AI application, allowing for quicker, more accurate assessments without manual inspections. These AI-powered tools reduce human bias and are increasingly used by financial institutions and government agencies for property assessments, particularly in urban areas where market conditions can shift rapidly. However, while AI offers many benefits, its integration into land valuation must be supported by appropriate legal and regulatory frameworks. In Uganda, for example, existing laws like the Land Act (1998) and valuation standards may need to be adapted to accommodate AI-driven models. Globally, countries such as the United States and the United Kingdom have developed guidelines to incorporate AI into land valuation practices, emphasizing the need for ethical, transparent, and legally compliant systems.

The future of land valuation is increasingly linked to AI's potential to improve accuracy, efficiency, and fairness. However, challenges such as algorithmic biases, legal acceptance, and ethical concerns remain. As AI continues to evolve, there is a need for further research into how these technologies can be integrated with traditional valuation methods and how they can be applied within the context of Uganda's rapidly urbanizing areas, such as Mutundwe Hill. AI has the capacity to provide more reliable, transparent, and objective land valuations, reducing discrepancies and fostering better decision-making for investors, property owners, and policymakers. However, more research is needed to understand how AI can be harmonized with existing legal frameworks, ensuring that its implementation is both effective and ethically sound.

2.3 Artificial Intelligence

Artificial Intelligence (AI) has emerged as a transformative force across various industries, reshaping traditional processes and improving efficiency, accuracy, and decision-making. AI encompasses machine learning, neural networks, natural language processing (NLP), computer vision, and robotics, among other technologies, to simulate human intelligence in problem-solving and automation. (McCarthy et al., 1956) first introduced the concept of AI, envisioning machines that could perform tasks requiring human-like reasoning. Since then, AI has rapidly evolved, with applications spanning healthcare, finance, transportation, agriculture, and real estate. AI models are now capable of predictive analytics, pattern recognition, and autonomous decision-making, reducing human intervention and minimizing errors. The integration of AI in big data analytics has further propelled its adoption, allowing businesses and governments to derive meaningful insights from vast datasets.

Several studies have examined the effectiveness of AI in different domains. Brynjolfsson and (McAfee, 2017) explored AI's impact on the global economy, highlighting how automation and intelligent systems are enhancing productivity while simultaneously posing challenges such as job displacement. In healthcare, (Rajpurkar et al., 2017) demonstrated that AI-driven diagnostic models could outperform human radiologists in detecting pneumonia from chest X-rays, showcasing AI's potential in medical imaging. Similarly, in financial markets, (Bertsimas et al., 2020) found that AI-driven algorithms significantly improved stock market predictions and risk management strategies. AI has also revolutionized natural language processing, with OpenAI's GPT models proving capable of generating human-like text, thereby transforming content creation, customer service, and legal document processing. These studies indicate that AI is not only streamlining traditional workflows but also introducing innovative solutions that challenge conventional methodologies.

Despite its numerous advantages, AI faces several challenges, including ethical concerns, data privacy issues, and algorithmic biases. Researchers such as (O'Neil, 2016) argue that biased training data can lead to unfair AI decisions, particularly in hiring, lending, and law enforcement. Additionally, concerns over AI-driven job displacement have prompted discussions on regulatory frameworks and reskilling programs to mitigate economic disruption. The European Union's General Data Protection Regulation (GDPR) and similar policies worldwide have introduced stringent rules on AI's use of personal data to ensure transparency and accountability. Future research is focusing on explainable AI (XAI), aiming to make AI models more interpretable and trustworthy. As AI continues to evolve, it is expected to play a critical role in shaping industries and societies, necessitating further studies to balance technological advancement with ethical considerations.

2.3.1 Land Valuation and Artificial intelligence

Land valuation is a crucial process in real estate, urban planning, taxation, and investment decision-making. Traditionally, land valuation has relied on human-driven methods, including the market comparison approach, the cost approach, and the income capitalization approach. While these methods have been widely used, they often suffer from subjectivity, inefficiencies, and inconsistencies due to human bias and market fluctuations. The emergence of Artificial Intelligence (AI) in land valuation is transforming the field by leveraging machine learning algorithms, big data analytics, and automated valuation models (AVMs) to enhance accuracy and objectivity in property appraisal. AI-driven valuation methods help eliminate discrepancies in pricing, streamline processes, and ensure data-driven decision-making, making them increasingly essential in the modern real estate industry.

Artificial Intelligence is applied in land valuation through various technologies, including machine learning algorithms, artificial neural networks (ANNs), geospatial analysis, and Automated Valuation Models (AVMs). Machine learning models analyse large datasets comprising property characteristics, historical transactions, and socioeconomic factors to refine valuation estimates. Neural networks, in particular, can identify complex patterns in property pricing, allowing for more precise and reliable valuations. Geospatial technologies, such as Geographic Information Systems (GIS) and satellite imaging, provide real-time data on land use, environmental conditions, and urban development, further improving valuation accuracy. Additionally, Natural Language Processing (NLP) techniques are used to extract relevant information from legal documents, land records, and market reports, enhancing the comprehensiveness of valuation assessments.

The adoption of AI in land valuation presents numerous benefits, including increased accuracy, efficiency, scalability, cost reduction, and standardization. AI models can process vast amounts of data in real-time, reducing the time required for property assessments and minimizing human error. Automated valuation methods are particularly useful for large-scale land valuation by government agencies, banks, and real estate firms. Despite these advantages, AI-driven valuation systems face challenges such as data availability, regulatory barriers, ethical concerns, and cybersecurity risks. Issues related to algorithmic transparency, compliance with property laws, and biases in training data must be addressed to ensure responsible AI implementation. Future advancements in AI-powered land valuation will likely include explainable AI models, blockchain integration for secure land records, real-time market analysis, and AI-driven smart city initiatives. As technology continues to evolve, AI will play an increasingly critical role in shaping the future of land valuation, providing more reliable and equitable property assessments.

2.3.2 Hedonic Price Model

Market Price = f (tangible & building characteristics, other influencing factors)

The hedonic pricing model is the conventional regression model developed by Lancaster in (Wing & Chin, 2003). The theory bases on consumer demand which means the characteristics of the goods are the main drivers of consumptions (Ceh et al., 2018).

Regression analysis could be in the form of simple regression or multiple regression. In the case of simple regression, the analysis is geared toward evaluating the relationship between one independent variable and a dependent variable. Whereas, when the relationship under consideration is between a dependent variable and more than one independent variable, then it is referred to as Multiple Regression Analysis (MRA**).** MRA is largely employed for the analysis of real estate property price because the value of a real estate property is dependent on more than one attribute (Selim, 2008). In this case, structural, locational, and environmental attributes are the characteristic of property that drive consumer demands. So, it is broadly applicable regarding predicting housing prices (Choi & Kim, 2020).

Advantages of Hedonic Price Modelling

- The method's main strength is that it can be used to estimate values based on actual choices.
- Property markets are relatively efficient in responding to information, so they can be good indications of value.
- Property records are typically very reliable.

- Data on property sales and characteristics are readily available through many sources and can be related to other secondary data sources to obtain descriptive variables for the analysis.
- The method is versatile, and can be adapted to consider several possible interactions between market goods and transportation benefits.

Limitations of Hedonic Price Modelling

- The scope of benefits that can be measured is limited to things that are related to housing prices.
- The method will only capture people's willingness to pay for perceived differences in attributes.
- The method assumes that people have the opportunity to select the combination of features they prefer, given their income. However, the housing market may be distorted by outside influences, like taxes or interest rates.
- The method is relatively complex to implement and interpret, requiring a high degree of statistical expertise.
- The results depend heavily on model specification.
- Large amounts of data must be gathered and manipulated.

The model is directly built on the preferences of households and strict housing assumptions, which create requirements for perfect competition and market equilibrium (Hong, Choi & Kim, 2020). The same conclusion was drawn by (Fan et al., 2006), where they stated the relating criticisms of the hedonic regression approach about its model assumptions and prediction requirements. Thus, considering the problems that might be associated with the hedonic model, the complexity of implementation in practice might be somehow simplified. There would be a need to look for some other models that might be harder to implement however can better explain the complicated relationships in reality.

2.3.3 Fuzzy Logic System

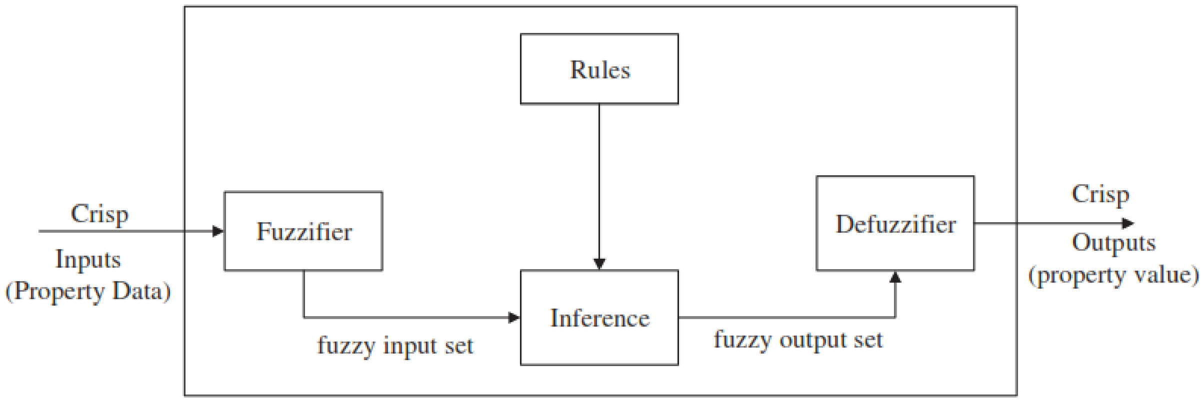


Figure 2: Fuzzy Logic System (Mendel, 1995)

The vagueness and ambiguity associated with property price analysis may render property price modelling estimates unreliable (González & Formoso, 2006). The FLS technique is an advanced valuation approach that has been designed to handle this vagueness – ambiguous, inaccurate market data in property price modelling. (Zadeh, 1965) introduced FLS technique and argued that the fuzzy set of an element in a group is characterized by a membership function, the value of this membership function ranges between 0 and 1. The principle of FLS is based on the translation of vague property information into meaningful numeric value, by following some defined set rules in the analysis. These rules are expressed as "if", "or", and "then" to produce the output.

Advantages of Fuzzy Logic

- Handles Uncertainty and Ambiguity: Fuzzy logic excels at dealing with imprecise or incomplete information, making it suitable for real-world scenarios where data is often vague.
- Mimics Human Reasoning: It emulates human decision-making by considering various possibilities and degrees of truth, leading to more intuitive and robust systems.
- Flexibility and Adaptability: Fuzzy logic systems can be easily adapted to changing conditions and can handle a wide range of inputs.
- Ease of Implementation: Fuzzy logic algorithms are often easier to code than traditional logical programming due to their similarity to natural language.

- Reduced Storage Requirements: Fuzzy logic algorithms can require fewer instructions and memory storage compared to traditional methods.
- Cost-Effectiveness: Fuzzy logic systems can be implemented using inexpensive sensors and components, reducing overall system cost.

Disadvantages

- Dependence on Human Expertise: Developing and tuning fuzzy logic systems requires expertise in defining fuzzy rules and membership functions.
- Difficulty in Tuning: Optimizing fuzzy logic systems can be challenging, as it involves finding the right combination of fuzzy rules and parameters.
- Limited Accuracy: The imprecise nature of fuzzy logic can lead to less precise results compared to traditional logic systems.
- Computational Complexity: Fuzzy logic systems can be computationally intensive, especially for complex problems.
- Lack of Standardized Methods: There is no universally accepted methodology for designing and implementing fuzzy logic systems, which can lead to inconsistencies.
- Potential for Inaccurate Results: Fuzzy logic systems, designed to handle imprecise data, must be tested and validated to prevent inaccurate results.

2.3.4 Artificial Neural Network (ANN)

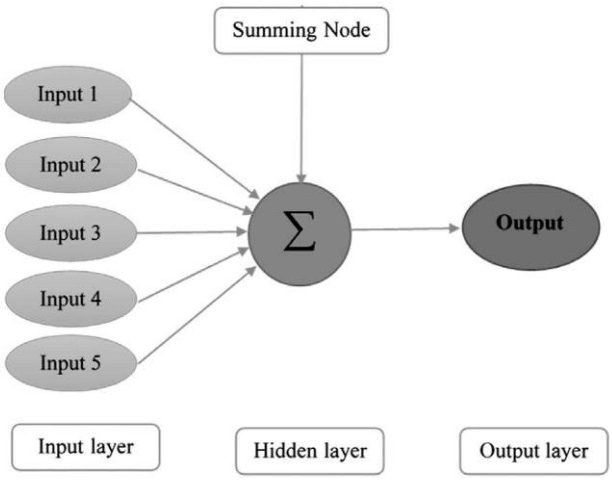


Figure 3: structure of Random forest architecture. source: adopted from (McGreal et al, 1998, p. 59).

ANN as a "computer system whose micro-processors, rather than laid out in series as in traditional computers, are connected in parallel, forming layers and making multiple connections, imitating the way the neuronal network is organized in the brain" (Mora, 2004).

(Tay, 1992) recognised the nature of property appraisal as a problem of "pattern recognition" and notes that ANN would be able to learn from historical sales and apply the sale prices to the respective 'pattern' identified. (Borst, 1995) suggests that ANN is the next logic step in the chain of tools used for mass appraisal to build upon the two most common used tools, Multiple Regression Analysis and the Feedback Method. The ANN model is suitable for property price prediction because the model mimics humans and hence, the output produced by it could be close to the estimation of a real estate valuer (Borst, 1991). Its ability to Capture the non-linear relationship between property attributes and property values (Ge, 2004) makes it more suitable for property valuation than other appraisal techniques (Cechin et al, 2000). Artificial Neural Networks are based upon the structure of the brain. Based upon neurons, the smallest unit in the brain. ANN forms layers of interconnected neurones. The ANN model is made up of three layers, namely input, hidden and output layers. Property attributes are fed from the input layer into the network, the mathematical processing takes place in the hidden layer(s) and the result of the transformation is produced at the output layer, which is where the predicted property value is obtained.

The above figure shows an example of an ANN architecture with five inputs, one hidden neuron and one output neuron.

(Borst, 1991), explains that "there is an input layer, a hidden layer, and an output layer. In mass appraisal, the input neurones represent the input data in much the same fashion as the X, (independent variables) in the linear model. The output layer represents the output sought by the model of the process of interest. In mass appraisal, one output neuron would be used to represent estimated selling price. The hidden layer allows for the combination of input data in a near infinite number of ways."

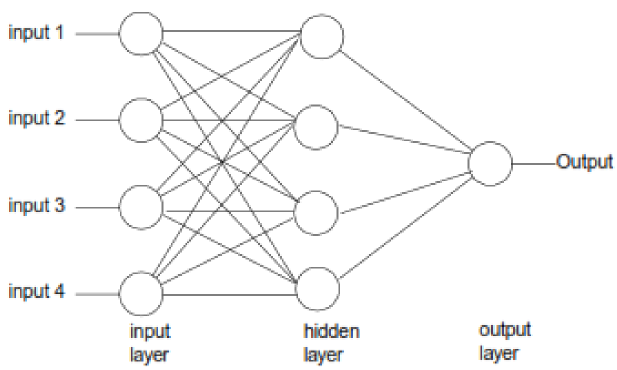


Figure 4: Structure of the ANN components

Weights (analogous to regression coefficients) are used with the input data to try to model the output layer. The process of training the network involves the establishment of weights such that the average square error over the training set is minimized. Indeed feedforward /back-propagation network models are the most common form of ANN models used for land valuation. ANN algorithms typically begin with randomly determined or equal default weights for each of the nodes in each of the hidden layer(s). In each model-training, each attribute is entered into the model, the network sums and transforms the values of the input variables into the predicted output value(s). The model then compares the ANN's estimated price to the actual price. If a discrepancy exists, then the software works backwards to adjust the hidden layer weights to minimize the prediction error. While training, ANN models repeat these steps as the data for each new land values are added, always adjusting the hidden layer weights to minimize the total prediction error. In supervised training, we present a pattern to the neural network, it makes a prediction, and we compare the predicted output to the desired output.

2.3.5 Random Forest Model (RFM)

Random Forest (RF) is a popular machine learning technique in the field of data mining (Rushall et al, 2013). It operates under the supervision of a group and has received significant recognition. Data mining can be categorized into two primary types: descriptive and predictive. Descriptive data mining is primarily concerned with providing detailed descriptions and summaries of data. On the other hand, predictive data mining involves studying historical data to identify patterns and trends that can be used to make predictions about the future. Metadata Mining is the process of de-scribing and summarizing data, uncovering patterns and relationships within the data, and using historical data to make predictions about future trends. Predictive models are constructed by analyzing the features of predictive factors to provide hypotheses that assist in making future decisions. Predictive models are constructed by analyzing the characteristics of variables used for forecasting, and the results are hypotheses that can be empirically examined. The precision of such models relies on error estimating techniques. Metadata mining often employs unsupervised machine learning methods, whereas predictive data mining use supervised machine learning methods. Random forests are created by generating several decision trees. This is done by gathering random samples of data using Bootstrap samples and randomly selecting input features. Each decision tree is considered a simple decision tree (Leo, 2001). One advantage of random forests is their high accuracy compared to other approaches like as bagging and boosting. They also function effectively on huge databases and can accommodate many variables, allowing us to analyze thousands of input variables without the need to delete any of them. In order to balance the category error in unbalanced data sets and assess the importance of variables, an unbiased estimation of the configuration error is necessary.

Decision Tree

Decision Trees are a technique utilized in the fields of Statistics, data mining, and machine learning. It falls within the category of supervised machine learning. Data analysis technology categorizes data into different entities that are potentially associated with a specific procedure. There are two categories of such entities: contract and paper. The supervised learning approach employs the decision tree as a prediction model to examine the observations of an item in the branches and deduce the target value of the item in the leaves. The decision nodes symbolize the segmentation of data, while the sheets symbolize the outcomes. A decision tree typically embodies cognitive processes resembling human thinking in order to facilitate informed decision making. Therefore, Decision trees are highly comprehensible. Furthermore, there Exists a hierarchical structure known as a decision tree, which greatly facilitates the comprehension of the underlying reasoning. For clarity, the following is the operational process of the terminal for your attention.

The root node: the starting point of the decision tree. The root node symbolizes the complete dataset, which is partitioned into two or more groups that can be compared.

Leaf node: The leaf nodes correspond to the ultimate result. The algorithm is unable to further divide the tree once it reaches the leaf node. Splitting refers to the process of separating the root node or decision node into distinct sub-nodes based on specific parameters. Pruning is the act of removing superfluous branches from a tree. By eliminating irrelevant branches, one can reach a conclusion much more quickly. The parent node is the root node of the tree, while the other nodes are its children. A subtree is created when the primary tree is divided, resulting in new subtrees and branches. Machine learning encompasses two primary categories of decision trees, which are distinguished by the goal variable.

Thus, random forest model was used to see the feasibility of AI in land Valuation in Mutundwe Hill, Kampala District, Uganda.

Benefits and Challenges of Random Forest

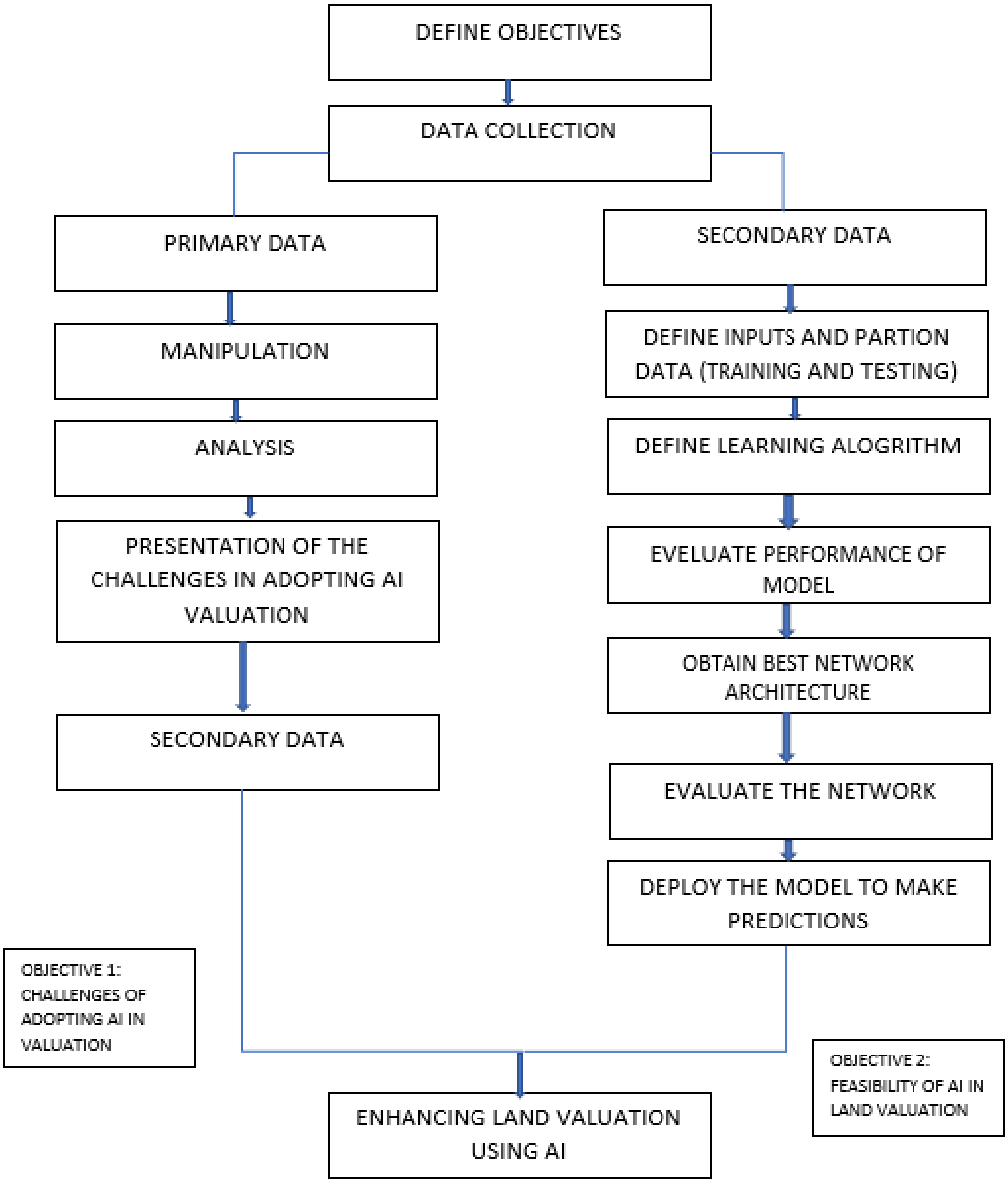
One advantage of the random forest algorithm is its versatility. This approach is applicable to both regression and classification issues. The alga rhythm might be deemed advantageous as it yields superior outcomes even in the absence of hyperparameter adjustment. Furthermore, they possess a high level of clarity, making them easily comprehensible. Additionally, their number is quite limited.

Overfitting is a significant issue in machine learning. We must develop a universal model capable of achieving satisfactory outcomes on the test data. The random forest overcomes this dilemma by aggregating multiple decision trees, resulting in reduced bias and volatility.

The primary constraint of random forests is the extensive number of trees, resulting in a prolonged training time that renders it sluggish and inefficient for real-time predictions. Typically, these algorithms exhibit rapid training speed but significantly slower prediction speed after training. While the random forest algorithm is often efficient in real-world applications, there may be situations where runtime performance is crucial and alternative approaches may be more desirable.

CHAPTER THREE

3.0 RESEARCH METHODOLOGY



3.1 OBJECTIVE 1- CHALLENGES OF ADOPTING AND USING AI LAND VALUATION

This section provided methods and procedures that helped the researcher in collection of data, cleaning, analysis, presentation and interpretation that helped to achieve the first objective. In this section, with respect to the first objective, the research methodology was presented in the following order: research design, target population, sampling method, sample size, source of data, data collection method, data collection tools, quality control techniques, measurement of the study variables, challenges faced in adopting AI Valuation.

3.1.1 Research Design

The study adopted case study and descriptive research designs. The case study research was utilized because it enhanced the investigation of the relationship between the study variables and with flexibility towards gathering data using different methods (Schoch, 2020). The case study design was used because it enhanced the collection of data at a single point in time while the descriptive research design was used because it determined the characteristics of a given population and also allowed utilization of a variety of research methods to examine variables. In addition, the case study design was used because the study involved an in-depth analysis of information from Mutundwe Hill.

3.1.2 Research Approaches

In this study, a mixed-methods approach was employed to collect data, integrating both quantitative and qualitative techniques to provide a comprehensive understanding of the topic. Quantitative research approach which allowed coverage of a wider spectrum of respondents being studied (Dix & Anderson, 2000) was adopted in this study. A questionnaire survey is a form of quantitative research approach that adopted to measure the perception of respondents in respect of the subject matter under study. Online questionnaire approach was adopted in the study to capture the opinion of real estate valuers on the research topic under investigation. As opined by (Gillham, 2000) and (Mooya, 2015), the survey instrument was validated by a group of real estate experts that have good knowledge of the Ugandan Real Estate Market before the administration of questionnaire to the respondents.

3.1.3 Target Population

The primary target population of the study was registered valuers in Uganda. This target selection ensured that we get the right feedback from the actual professionals to investigate the challenges and regulatory implications of using AI valuation. According to the 2021 membership directory of the Surveyor's Registration Board (SRB), there are 104 registered valuers in the country.

3.1.4 Sample Determination

The sample size was determined using Yamane's (1967) formula for finite populations, given by:

$$n = \frac{N}{1 + Ne^2}$$

Where:

- *n* is the desired sample size.
- *N* is the size of the target population.
- *e* is the desired level of precision.

This formula ensured a scientifically calculated sample size that balanced the need for representation with practical considerations. Yamane's formula was chosen for its suitability in determining sample sizes for finite populations (Sarmah & Hazarika, 2012).

3.1.5 Data Source

Multiple data sources were employed to gather comprehensive insights into the enhancement of AI in land price valuation in Mutundwe Hill, Kampala District. Both primary data and secondary data will be collected in order to address all the objectives.

Primary Data

Questionnaire Administration

The Google forms platform was utilized to design the online questionnaire. The questionnaire was segmented into five parts. The first section centred on the characteristics of the respondents. Sections 2–5 contained questions on; knowledge of the AI valuation techniques, measures that will enhance the adoption of the AI valuation techniques and benefits of adopting the AI valuation techniques, respectively. Responses were ranked on a five-point Likert scale (where 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree). This scale is common and appropriate for the study of this nature (Allen & Seaman, 2007; Dawes, 2008).

Key Informant Interviews

Key informant interviews targeting individuals with specific expertise and administrative roles relevant to land valuation profession was carried out to ensure insights from key stakeholders

(Elmendorf & Luloff, 2006; Kumar, 1989). This method, according to (Eppich et al., 2020) allowed for a more qualitative exploration of their opinion basing on the experiences, challenges faced, and successes achieved as well as recommendations on how AI should be adopted in land valuation. Open-ended questions were employed, enabling participants to share detailed narratives and providing a deeper understanding.

3.1.6 Data Analysis

The collected data was analyzed using the Statistical Package for the Social Sciences (SPSS) 20.0 software. This tool was used to conduct descriptive analyses in terms of percentile distribution and mean score (MS). Also, the Chi-square (χ) test was done to examine the statistical relationship (if any) that exists between the valuers' profile and the factors that affect the issues under investigation. The MS was adopted in ranking the factors included in the survey instrument. This approach has been adopted in previous built environment studies, see, for instance, (Frank et al, 2007) among others.

$$\mathrm{MS} = \frac{5n_5+4n_4+3n_3+2n_2+1n_1}{N}$$

The estimation of the MS was performed by adopting the expression above, as adopted in (Ameyaw and Chan, 2015). where n is the score given by valuers based on a five-point scale of 1–5 and N is the number of valuers that rated a variable.

3.1 OBJECTIVE 2 – FEASIBILITY OF APPLICATION OF AI RANDOM FOREST MODEL LAND VALUATION

This section of the methodology looked at achieving the second objective which was looking at the feasibility of AI in land Valuation in Uganda. It looked at the steps of seeing the practicability of AI in Valuation in Kampala.

3.2.1 Data Collection and preparation

The data collected was basically secondary data from different sources. Mutundwe hill is within Kampala district and data about land prices of 50 parcels was got from KCCA Valuation Department. Other datasets like distance from the nearest primary school, water source, electricity pole and location were obtained from Open Strip Map (OSM).

The collected data was cleaned and standardized for easy input into the model. This involved converting all distance to meters and land prices to Uganda shillings. A residential price index of 5.6% which is available from the Uganda National Bureau of Statistics (UBOS, 2024) was used to deflate the current land prices to the constant prices. The purpose of this was to reduce the variations due to inflationary tendencies in the economy.

$$\text{Current property price} = \text{Base year price} \times \frac{\text{Current CPI}}{\text{Base year CPI}}$$

The data was arranged in and excel sheet and later imported into the model as a drive was used as a database.

```
#This uses the same mechansims.
%matplotlib inline
```

```
import pandas as pd
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
valuationdata=pd.read_csv('/content/drive/My Drive/VALUATIONDATA_lukwago.csv')
```

3.2.2 Data Partition

This data was verified, standardized and partitioned. This involved splitting the data into training, testing and validation data. The data consisted of 50 parcels, 80% was used for training, 10% was used for testing and the remaining 10% was used for validation in a feed forward manner. Weights and biases were randomly initialized.

3.2.3 Model Parameters

Four independent variables were identified in the model explicitly stated in the model. These included distance from the nearest primary school, water source, electricity pole and location.

3.2.4 Model Execution

The training data was subjected to the model and trained. The results of training were analyzed, it was tested using the root mean square, and r squared values. It was then deployed to predict other land prices of the parcels that are not within the training dataset.

CHAPTER FOUR: RESULTS

4.1 RESULTS FROM THE FIRST OBJECTIVE

CHALLENGES ASSOCIATED WITH THE USE OF AI

4.1.1 Reliability test

The reliability of the data collected was evaluated in order to ascertain the suitability of the data for this research. The Cronbach's alpha test was carried out in order to confirm the extent of the internal consistency among all the respondents of the survey (Tavakol & Dennick, 2011). The Cronbach alpha's score ranges between 0 and 1, and a value close to 1 depicts a high reliability and internal consistency. Hair, Black, Babin, Anderson, and Tatham (2010) claimed that a Cronbach alpha value that is above .70 is satisfactory. Coincidentally, a Cronbach's alpha value of .7 was recorded in this study which signifies a satisfactory reliability and internal consistency.

4.1.2 Discussion of Results from Objective 1

Valuers' profile

The characteristics of valuers in terms of the employment (private of government), professional experience on AI Valuation, satisfaction of the AI results, legal backup on AI among other factors, had an influence on the subject under consideration.

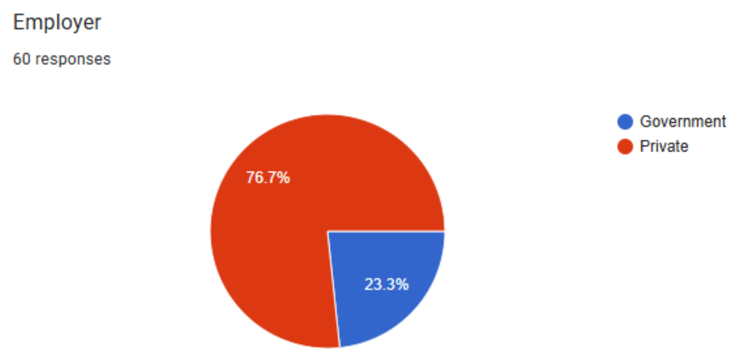


Figure 5: Nature of employment of Valuers

From the above figure, it was noted that majority of the respondents about 76.7% were privately employed Valuers and 23.3% were government employed. It implied that the private sector took the lion share in employing the valuers in the country's economy.

Knowledge of the AI valuation techniques

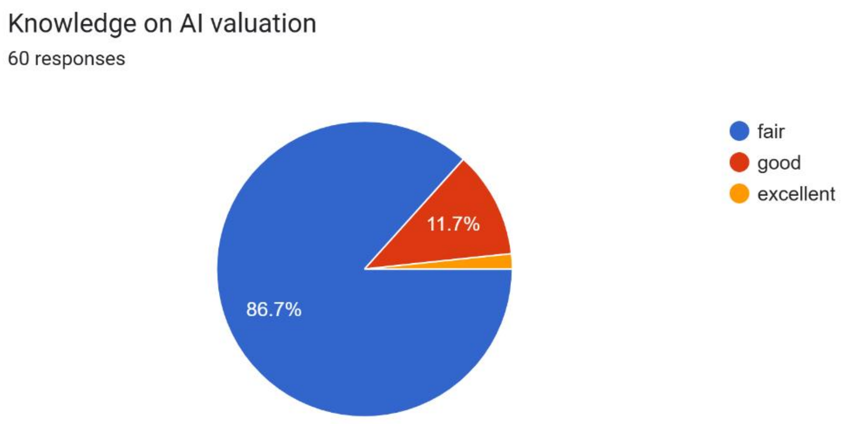


Figure 6: Knowledge on AI valuation

The questions contained in the above table was posed to the valuers in order to ascertain their level of awareness of the AI techniques and some other issues relating to the knowledge of AI techniques. Almost 86.7% of the valuers either fairly disagreed to be aware of these techniques, while the 11.7% consented to having good knowledge and the rest 1.6% strongly agreed to having excellent knowledge about the approach. On the use of AI techniques in practice, only 13% of the valuers adopt the approaches in practice. The low knowledge would be attributed to teaching of rudimentary valuation methods in schools and also in practice in Uganda.

Figure 7: Applying AI in your practice

The above table11 answered the application question of AI in Land Valuation and about 81.7% disagreed to applying it while 18.3% agreed to applying it. The low usage may be connected to the lack of introduction to these techniques during academic training at tertiary educational (universities and institutes).

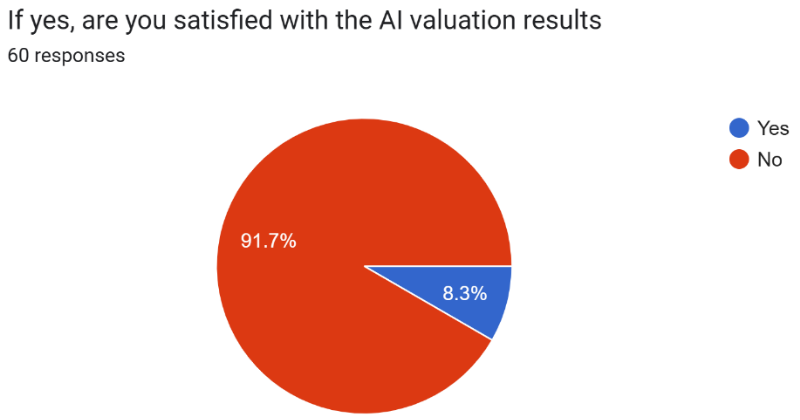


Figure 8: Satisfaction with AI results

Only about 8.3% agreed to be satisfied with the results of AI valuation while 91.7% disagreed with the satisfaction of the results. This could have been due to the above responses where majority of the respondents had little knowledge about valuation, low applicability and thus high level of unsatisfactory results.

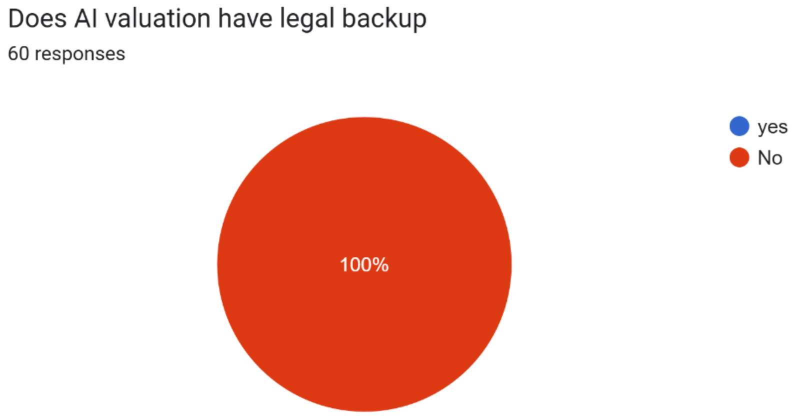


Figure 9: AI legal frame in Uganda

From the survey, it was observed from the respondents that AI Valuation in Uganda has no legal backing and that could be the reason as to why its not taught, has less applicability, and low levels of knowledge about.

Suggestions on Improving Ai Valuation in Uganda

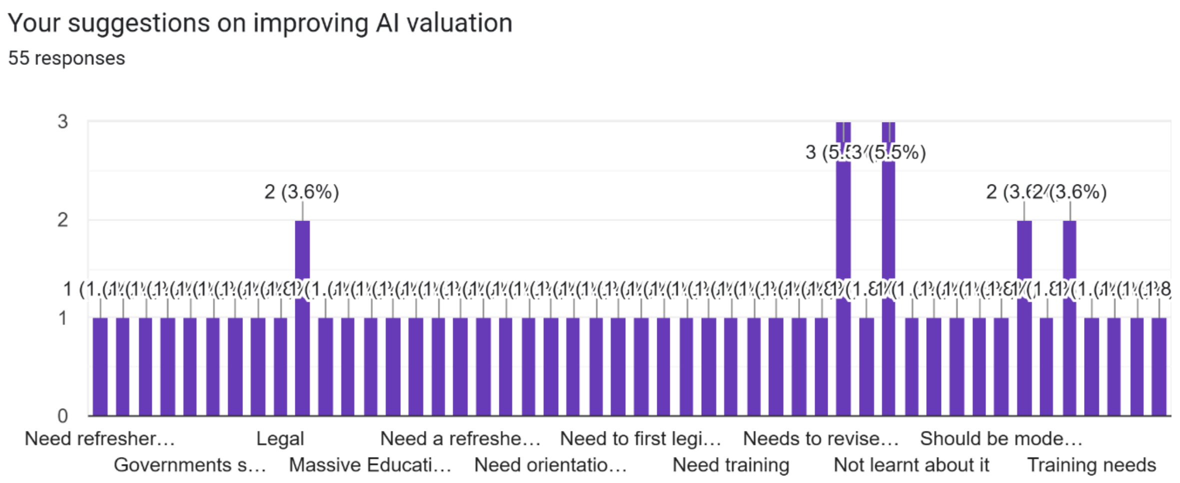


Figure 10: Suggestions on Improving AI valuation

4.1.3 Conclusion of the first objective

Different opinions from valuers were suggested in figure 14 for ways of improving AI valuation in Uganda. It was an open question but the highest number of valuers suggested that AI Valuation should have aa legal backup first in the laws of Uganda and acceptable in the valuation standards of Uganda. The second batch suggested training of Valuers about AI valuation through refresher courses, massive education, orientation and continuous professional development. Through this more knowledge would be spread, training programs started and thus Ugandan Valuers would appreciate AI valuation techniques.

4.2.1 RESULTS FROM THE SECOND OBJECTIVE

FEASIBILITY OF AI IN LAND VALUATION USING RANDOM FOREST MODEL

I took into account 5 parameters of which four were independent variables and one dependent variable for the study area. The independent variables included location of the plot, distance from nearest water source, distance from nearest electricity source, distance from nearest tarmacked road whereas the dependent variable included price of the land (assuming each plot is 11.5 decimals). 50 plots were inspected, verified and used as training data. A ration of 80:20 training and test data were used.

variable	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
		Dependent Variable		
Price (Uganda shillings)	138,000,000	154,676,000.6	120,000,000	600,000,000
		Independent		
Location	3	1.7	1	5
Distance to the nearest water source	0.9	0.14	0	1
Distance to the nearest electricity pole	0.9	0.14	0	1
Distance to nearest primary school	0.5	0.4	0	1

Figure 11: Descriptive statistics of variables

Figure 12: Formula for adjusting land prices

A three-layer model forward network was used where the hidden layer was used for handling complex real-life prediction. It was an iterative process so as to get the best fitting model for the data. An architecture of the model was developed; 4 input variables, 1 hidden layer with 4 neurons and 1 output layer (property price).

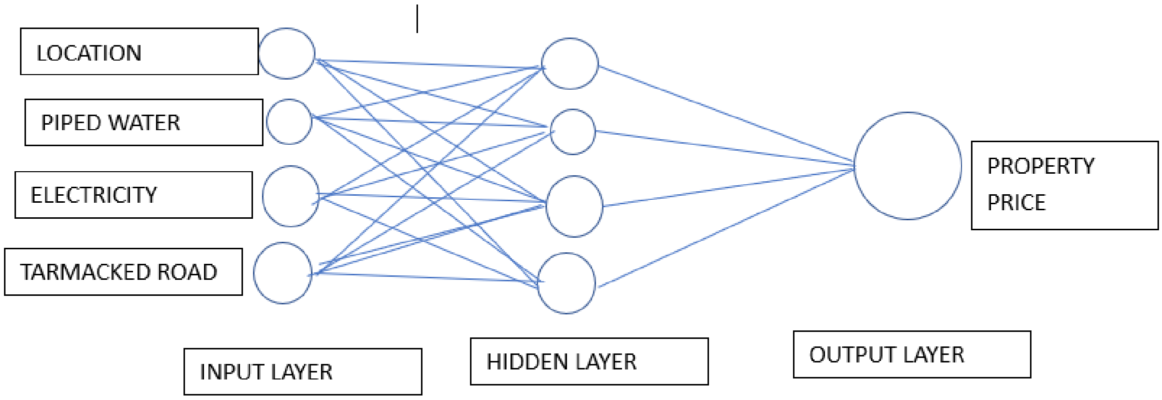


Figure 13: Shows the architecture of the model

4.2.2 DISCUSSION OF THE RESULTS

Estimation of error rate of the model

A 10-fold cross validation of error was used for the model. This included the root mean square error (RMSE), coefficient of determination (r^2), the mean absolute error (MAE) and mean absolute percentage error (MAPE). Below are the formulas I used to test the accuracy of the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{n}(P_i - \overline{P})^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}(P_i - \hat{P}_i)$$

$$MAPE = \frac{\sum_{i=1}^{n}\left(\frac{P_i - \hat{P}_i}{\hat{P}_i}\right)}{n} \times 100$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2}$$

Where n is the number of observations, P_i is the actual price of the property, and $\hat{P}_i$ is the predicted price property from the model.

Analysis of results

Figure 14: Graphical representation of predicted versus true land prices

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# Calculate predictions
prediction = model.predict(X_test)

# Calculate regression metrics
mae = mean_absolute_error(y_test, prediction)
mse = mean_squared_error(y_test, prediction)
rmse = np.sqrt(mse) # Calculate RMSE
r2 = r2_score(y_test, prediction)

print(f'Mean Absolute Error (MAE): {mae:.2f}')
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'Root Mean Squared Error (RMSE): {rmse:.2f}')
print(f'R-squared (R2): {r2:.2f}')
```

```
Mean Absolute Error (MAE): 170761225.60
Mean Squared Error (MSE): 40189040907975672.00
Root Mean Squared Error (RMSE): 200472045.20
R-squared (R2): -1.07
```

Figure 15: Summary of results from the Random Forest Model

After the validation of the model, the performance of the machine learning model was depicted by the following indicators; the r^2 value of the Random Forest model got was 1, the Mean Absolute Error (MAE) was recorded as 170,761,225.6 shillings, Mean Square Error (MSE) as 4,018,904,090,797,572, Root Mean Square as 200,472,045.2.

Interpreting the performance of the model

R-squared was calculated by comparing the amount of variation in the dependent variable that the model explains to the total amount of variation in the dependent variable. The r^2 value of the Random Forest Model got was 1 indicated a perfect fit; the model explains 100% of the variation in the dependent variable. It showed how well the data fitted the regression model (the goodness of fit).

These predicted estimates were compared with the expected values in order to establish the difference (if any) between the expected values and predicted values. The MAPE, MAE and RMSE figures recorded here suggests that the output of the Random Forest model is encouraging.

Plotting of the relationship between the expected property values and the ones predicted by the Random forest model was done as a scatter plot that depicted a good prediction.

The inconclusiveness of the findings could be attributed to the quality of the data sample used for these studies, as this may have an effect on the RF output (Lenk et al., 1997).

NB: The RF model should not be seen as a replacement for the valuer in a valuation but rather another valuation method exercise; it is a tool to achieving the end result.

4.2.3 Challenges faced

Inadequate data

For AI valuation to be successful, data is needed for the previous years and transactions which was not readily available and well documented. This gave a challenge in compiling, coding, analysis and merging of the data to validate the model.

Inconsistent data

Some data retrieved was in softcopy while the other was in hardcopy. This brought about time wastage in digitizing the hardcopy data and also standardizing it.

Hardship in acquiring software

MATLAB software is not opensource and the student version is limited to 1-month trial. This meant getting repeated licenses for the research period.

4.3 CONCLUSION

The analyses of the collected data revealed that majority of the valuers are unaware of the AI valuation techniques and thus do not adopt them in practice. This is largely due to the little or no continuous professional training and non-inclusion of the AI techniques in the Current curriculum of real Estate programs at universities and polytechnics. Valuers' length of professional Experience and the sector where they work was found to influence their willingness to adopt these AI techniques. Meaningful Collaboration and affiliation with international real estate professional bodies and the overhauling of the valuation curriculum at universities and polytechnics would aid the adoption of the techniques across the nation. This Would add value to the valuation practice, in terms of estimating and reporting reliable and accurate valuation estimates that would be a good representation of market value. The subjective interference of valuers in property valuation exercise can be reduced and then lessen the level of valuation inaccuracy prevalent in the property market to the lowest minimum. The earnest adoption of the AI techniques in practice may be triggered with research because research drives the sustainability of a profession.

The predictive ability of the model developed based on its satisfactory r^2, MAE and RMSE values, suggests that the Random forest appraisal technique can be both feasibly applied and produce satisfactory predictive accurate and reliable valuation estimates.
I suggest more research to be done in the future about Random forest and other models of AI valuation to compare results and customize it more for other areas.

RECOMMENDATION

I recommend decentralized databases for the Valuations in Uganda and standardization of valuation data connected to different servers so that it can easily be fed in to the AI model as well as traditional Valuation methods like hedonic.

I also recommend that AI be introduced in the valuation curriculum as an alternative method of valuation and also be included as a valuation method acceptable in the laws of Uganda.

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Questionnaire used

QUESTIONNAIRE FOR REGISTERED VALUERS IN UGANDA

I'm a graduate student undertaking a Master's Degree in Land Management and undertaking as research study on how to enhance Artificial Intelligence (AI) in Land Valuation in Uganda, a case study of Mutundwe Hill, Kampala District. The study will help to see how valuers can incorporate AI as another method of Land Valuation and also enable me to fulfill the requirements for the award of the Master of Science degree in Land Management from Makerere university. I pledge to conceal your identity and request you to provide answers which will answer my research questions.

(A) Background Information

1. Nature of employment
   - I. Government ☐
   - II. Private ☐

2. Age of Respondent
   - i. 20 - 29 ☐
   - ii. 30 - 39 ☐
   - iii. 40 - 49 ☐
   - iv. 50 - + ☐

3. Sex of respondent………………………………

4. Duration of Valuation practice ……………………………

5. Level of Education
   - i. No Education ☐
   - ii. Primary ☐
   - iii. Secondary ☐
   - iv. Tertiary ☐
   - v. University/Graduate ☐
   - vi. Post graduate ☐

(B) Knowledge about AI Valuation

1. What does AI mean to you?

   …………………………………………………………………………..

   …………………………………………………………………………..

2. Is AI important in land valuation?

   ………………………………………………………………………….

   ………………………………………………………………………….

3. Do you use AI in land price valuation?

   i. Yes ☐

   ii. No ☐

   iii. Not sure ☐

4. Are you satisfied with the results of AI in valuation?

   i. Yes ☐

   ii. No ☐

   iii. Not sure ☐

5. Is there a law governing the use of AI in land Valuation?

   ……………………………………………………………………………

   ……………………………………………………………………………

6. What are the suggestions for improving AI use in valuation in Uganda?

   ……………………………………………………………………………………………

   ……………………………………………………………………………