Customer Churn Analytics using Classical Machine Learning Algorithms and Deep Neural Networks: A Case of Zimbabwe Banks.

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Abstract

This research focuses on customer churn analytics in the banking sector of Zimbabwe, specifically investigating the effectiveness of classical machine learning algorithms and deep neural networks. Customer churn, characterized by the loss of clients in the banking industry, has significant implications for banks, including revenue reduction, increased customer acquisition costs, and reputational damage. The study utilizes a dataset of customer data containing demographic and banking-related features to train and evaluate various models, including logistic regression, decision trees, random forests, XGBoost, and a basic deep learning algorithm. The findings reveal that all models exhibit high accuracy in predicting customer churn, with the deep learning model demonstrating superior performance compared to the classical algorithms. However, the study acknowledges limitations such as a small sample size and constrained feature set, which may impact the generalizability of the findings. The conclusion discusses the practical implications of the research for Zimbabwean banks and suggests potential avenues for future research to address the identified limitations and further enhance customer churn analytics in the banking sector.

Keywords
Customer Churning, Deep Neural Network, Classical Machine Learning

Introduction
Zimbabwe's banking industry plays a crucial role in the nation's economy by providing key financial services to citizens, companies, and the government. Masunda and Zivanai (2021) claim that the Reserve Bank of Zimbabwe (RBZ), which oversees overseeing the activities of banks and other financial institutions, regulates the sector. The dominance of a select few significant commercial banks, such as CBZ Bank, Standard Chartered Bank Zimbabwe, and the Commercial Bank of Zimbabwe, has led to the observation of a power concentration in Zimbabwe's financial sector (Matenda and Hapanyengwi 2021). The number of microfinance institutions, however, has grown recently to offer financial services to people and small enterprises who might not have access to standard banking services.

The banking sector in Zimbabwe has encountered numerous challenges, such as hyperinflation, a shortage of foreign currency, and a decline in economic activity, all of which have impeded banks' lending capacity and contributed to an increase in non-performing loans. According to Chizema and Mawire (2021), the Reserve Bank of Zimbabwe (RBZ) has undertaken several measures to address these issues, including the adoption of diverse currencies and the implementation of new regulations aimed at ensuring financial stability. These initiatives have been crucial in navigating the challenges faced by the banking sector and striving towards a more stable and sustainable financial environment in Zimbabwe.

According to Farhan M, Asghar M. and Abbas Q. (2021). customer churn also known as customer attrition is the loss of customers by a business or organization. Customer churn, which occurs when clients stop using a bank's services or close their accounts, is a term used in the banking industry. Customer churn can have negative consequences on banks because it can lead to lost sales, higher customer acquisition expenses, and reputational harm. The money that a bank would have made from the customer's interest payments, transaction fees, and other fees is lost when the customer leaves the bank. Furthermore, attracting new customers can be expensive for banks, who spend a lot of money on marketing and other promotional efforts.

Additionally, customer churn might harm the bank's reputation, as stated by Mapfumo M. and Nhende S. (2020). When clients leave a bank, they could tell others about their unpleasant experiences, which could damage the bank's reputation and reduce client trust. This may result in additional clientele decline and harm to the bank's reputation. Client attrition can also affect how well a bank can estimate its revenue and growth because it can be challenging to predict future income streams if customer churn rates are high.

Customer churn analytics are essential to the banking sector because they allow banks to proactively identify clients who are likely to depart and put in place successful retention tactics. By identifying customers who may be at risk of defaulting on their loan or credit card payments (Sinha and Raizada 2022). This enables financial institutions to act appropriately and stop customer churn (Ndou, Mhlanga, and Dube 2019). Additionally, Muneer A., Ali R.F., Alghamdi, A. and Taib, S.M (2020) point out that by finding the most efficient channels for client acquisition and retention, customer churn analytics can assist banks in optimizing their marketing efforts (Wang and Xu 2020).
This study focuses on examining customer turnover in Zimbabwean banks to offer insights and forecasting models that help banks keep their prized clients. Because of the churn in Zimbabwe's banking industry, which is ascribed to issues including economic instability, high banking fees, subpar customer service, and rising competition, the Zimbabwean context is interesting. The development of digital banking and mobile money services has also boosted the churn rate because it is now simpler for clients to switch banks (Bhatti 2020). Banks may proactively deploy retention measures, reduce revenue loss, and improve customer satisfaction with precise projections of client attrition (Nwakoby, I. J. 2020).

Objectives

1. To identify the factors that contribute to customer churn in Zimbabwe banks.
2. To develop a predictive model for customer churn in Zimbabwe banks using traditional machine learning models and deep neural networks
3. To compare the performance of classical machine learning algorithms and deep neural networks in predicting customer churn in Zimbabwe banks.
4. To determine the most effective model for predicting customer churn in Zimbabwe banks.
5. To provide insights and recommendations to Zimbabwe banks on how to reduce customer churn and retain their customers.

Literature Review

For banks to keep customers and preserve profitability, predicting customer attrition is essential. For customer churn analytics, traditional machine learning techniques and deep neural networks have become more popular recently. A research paper titled "Customer Churn Prediction in Retail Banking Using a Multi-Criteria Decision-Making Framework" was proposed in Europe by Smaranda (2020). The study offers a novel methodology for predicting customer turnover that considers several variables, including client demographics, banking habits, and financial performance indicators. The effectiveness of the suggested framework is demonstrated by its superiority to well-known machine learning techniques like decision trees and random forests. The report, however, falls short in considering the dynamic nature of consumer behavior and in offering a thorough examination of the elements causing customer churn.

Farhan M., Asghar M. Z., and Abbas Q. (2021). assesses the effectiveness of various machine learning classifiers and feature selection strategies in forecasting customer attrition in another study conducted in Europe. The thorough evaluation of numerous models, including deep neural networks, support vector machines, and k-nearest neighbors, is where this study excels. The research also investigates how feature selection methods affect model performance. However, it fails to adequately analyze the variables causing customer churn and fails to consider the complexity of banking data.

In the Asian context, Chen, Y. and Popovich K. (2023). research work on predicting customer churn in banking Industry using Random Forest and Gradient Boosting, they suggest the use of ensemble models, which have shown to perform better than conventional machine learning methods in predicting customer attrition, is the paper's main strength. The study also examines the demographics of the customer base, transactional behavior, and patterns of service use as contributors to customer churn. The paper, however, fails to fully assess the model's efficacy and ignores how feature selection methods affect model performance. A deep learning-based model for predicting customer churn is presented in another Asian-authored study by Krishna and Kumar (2021).

The use of a convolutional neural network (CNN) and a long short-term memory (LSTM) network to examine the sequential behavior of banking customers is the paper's key strength. The research also investigates the impact of various input features on model performance. The performance of the suggested model in comparison to that of other conventional machine learning methods is not compared in the research, nor is the effect of hyperparameters on model performance considered. The research by Khurana and Khurana (2019) on customer turnover in the same context shows promise in its use of ensemble techniques and a deep neural network model to attain high accuracy. To conduct a thorough analysis, the study also uses a sizable dataset of more than 1 million customer records from an Indian bank. The study's lack of adequate assessment of the ethical consequences of using consumer data for predictive analytics without seeking informed agreement is a drawback, though. The study conducted by Anand, P., and Reddy, S. K. (2021). demonstrates strengths in its use of ensemble techniques and a deep neural network model to achieve high accuracy in predicting customer churn. The study also employs a large dataset of over 1 million customer records from an Indian bank, enabling a robust analysis. However, a weakness of the study is the insufficient consideration of the ethical implications of utilizing customer data for predictive analytics without obtaining informed consent.

To accurately anticipate customer churn in a significant Egyptian bank, Sinha P. and Raizada V. (2022). used a hybrid model incorporating random forest, k-nearest neighbors, and decision trees. To ensure the model's robustness, the study considered a variety of evaluation indicators. The study's flaw, which would prevent practical use, was the scant explanation of how the model gained interpretability. Abdelbasset, Manogaran, and Mohamed (2021) conducted another study in the same area and used the logistic regression model to uncover characteristics such as subpar customer service and lengthy wait times that contribute to customer churn at an Egyptian bank. The study included practical suggestions for improving customer retention, such as enhancing the bank's website and rewarding high-value clients. A flaw in the study, though, was how little was said about the possible drawbacks of depending only on one model for prediction and the necessity of additional validation using different machine learning techniques.

To anticipate client turnover in a Zimbabwean bank, Zimuto, Nhapi, and Zhou (2020) used both conventional machine learning techniques and deep neural networks. The study considered how unbalanced data could affect a model's performance and suggested resampling as a solution. A flaw in the study, though, was the lack of comparison to other cutting-edge models, which would limit the applicability of the findings to other banks in the area. Similar to this, Musanhu, Munyaradzi, and Gororo (2021) employed the decision tree algorithm in another study in Zimbabwe to discover important factors influencing customer attrition in a Zimbabwean bank. The study emphasized the role that relationship management and customer engagement play in enhancing client retention. The study's flaw, which may have compromised the reliability of the findings, was the scant explanation provided for the data pre-processing methods that were used. Using the Random Forest method, Mantha, S. S., and Ramesh, S. (2021). investigated customer turnover in the Zimbabwean banking sector. The study's advantage was the addition of transactional and demographic data for a more thorough churn analysis.

However, the model's accuracy may have been hampered by the lack of information on the feature selection procedure.The Random Forest method was also employed by Ndou, Mhlanga, and Dube (2019), however they concentrated on leveraging social media data to forecast customer attrition. The study's key contribution was its novel use of social media data, which is unusual in churn analysis. The study's tiny sample size, nevertheless, made the findings less generalizable.A deep neural network approach was used by Musanhu, Munyaradzi, and Gororo (2021) to forecast client turnover in the Zimbabwean banking sector. The study's use of sophisticated modeling methods, which could result in more accurate forecasts, was its strength. A flaw that prevented replication and comparison with related studies was the deep neural network architecture's incomplete explanation.Matenda and Hapanyengwi (2021) also created a machine learning-based churn prediction model for Zimbabwean banks. The study used artificial neural networks, support vector machines, and decision trees to examine a dataset of more than 1,000 consumers from two commercial banks. Despite the paper's sample size constraints, its thorough examination of churn determinants was its strongest point.

Chizema and Mawire (2021) investigated how social media affected customer turnover in banks in Zimbabwe. The study combines an examination of social media posts with a survey of 300 clients from three banks. The results highlighted the importance of unfavorable social media posts in client attrition. The emphasis on the effects of social media was a strength, although sample size restrictions and potential bias in the choice of social media posts persisted. The studies under consideration highlight the growing interest in using machine learning methods for churn analysis within the Zimbabwean banking sector. However, it is significant to emphasize that there is currently little study being done in Zimbabwe in this particular field. As a result, there are various research gaps that must be filled to deepen our understanding of

Our study aims to address these gaps by focusing on the following aspects:

1. Comprehensive Comparison of Algorithms: While several studies have explored the application of machine learning algorithms and deep neural networks for churn prediction, there is a need for comprehensive comparisons and evaluations of different algorithms (Sujatha, R., and Anand, K. 2021). Our study seeks to provide a thorough analysis of various machine learning techniques, their performance, and their suitability for customer churn prediction in the banking sector. By comparing and contrasting these algorithms, we aim to identify the most effective approach for accurate churn prediction.
2. Consideration of Contextual Factors: The existing literature often overlooks the influence of contextual factors on customer churn. Factors such as economic conditions, regulatory changes, and market dynamics can significantly impact churn behaviour (Masunda and Zivanai 2021). Our study aims to investigate the influence of these contextual factors on customer churn and incorporate them into the churn prediction models. This will enhance the models' accuracy and robustness by accounting for the specific circumstances in which churn occurs.
3. Exploration of Diverse Data Sources: Another limitation is the limited exploration of diverse data sources. The availability of various data types, including transactional data, demographic information, customer interactions, and social media data, provides an opportunity to improve churn prediction models (Mantha S. S. and Ramesh S. (2021).). Our study seeks to explore the potential of incorporating additional data sources beyond traditional customer data, allowing for a more comprehensive understanding of customer behaviour and improved churn prediction accuracy.
4. Evaluation of Intervention Strategies: Additionally, there is a lack of focus on evaluating the impact of interventions in reducing customer churn. While churn prediction is important, understanding the effectiveness of specific retention strategies and interventions is equally crucial. Our study aims to assess the impact of targeted retention strategies on reducing churn. By evaluating the effectiveness of interventions, we aim to provide practical insights for banks to develop and implement successful customer retention initiatives.
5. Industry-Specific Insights: Finally, the banking sector has unique characteristics, regulations, and customer behaviours that may differ from other industries. Thus, industry-specific insights are needed for reducing customer churn effectively. Our study aims to provide tailored recommendations and strategies specifically relevant to the banking sector, considering its distinct challenges and opportunities.

By addressing these gaps and limitations, our study seeks to contribute to the existing literature by providing comprehensive insights and practical implications for banks to develop accurate churn prediction models and implement effective customer retention strategies in the banking sector.

Methods

The study employs two main methodologies: classical machine learning algorithms and deep neural networks. Classical machine learning algorithms such as Logistic Regression, Decision Trees, Random Forest, and XGBoost are utilized. Logistic Regression is chosen for its simplicity, interpretability, and ability to handle different data types. Decision Trees are used to identify important variables and segment customers based on their likelihood to churn, while Random Forest can handle noisy and incomplete data. XGBoost, a scalable algorithm, is employed for handling large and complex datasets (Sujatha R and Anand K. 2021).

Deep neural networks, including Long Short-Term Memory (LSTM) Networks, Artificial Neural Networks, and Recurrent Neural Networks (RNNs), are also utilized. LSTM Networks, a type of RNN, excel at capturing sequential patterns and dependencies in data, making them suitable for time series analysis and modeling customer behavior over time. Artificial Neural Networks and RNNs can learn hierarchical representations and capture long-term dependencies, making them suitable for tasks involving time-dependent patterns (Mantha S. and Ramesh, S. 2021). By combining these methodologies, the study aims to explore the strengths and limitations of each approach in predicting customer churn in Zimbabwean banks. The findings will provide valuable insights for developing effective churn management strategies in the banking sector. It is important to consider factors such as data quality, pre-processing, feature engineering, model evaluation, and interpretation of the results to ensure the success of the project. The availability and quality of data, the expertise of the analysts, and the willingness of stakeholders to act on the insights and recommendations provided by the analysis are also crucial for the success of the customer churn analytics project.

In this study, the CRISP (Cross Industry Standard Process for Data Mining) methodology guides the study through different stages. It starts with understanding the business objectives and requirements, followed by data understanding and preparation, where relevant data is gathered, assessed, and pre-processed. The modelling phase involves applying classical machine learning algorithms and deep neural networks to the pre-processed data. The performance of the models is evaluated using appropriate metrics. The best-performing models are then deployed for real-time or batch prediction of customer churn, and their ongoing effectiveness is monitored. This structured approach ensures a systematic and comprehensive analysis of customer churn in Zimbabwean banks (Abdelbasset M. Manogaran G. and Mohamed, M. A. 2021).). The justification for using the CRISP methodology lies in its effectiveness in delivering successful data analysis and machine learning projects. Studies have demonstrated its benefits in various domains, including credit risk assessment and customer churn prediction. The structured and systematic approach of the CRISP methodology minimizes the risk of failure, helps identify potential issues early on, and ensures that all stakeholders are aligned towards the desired outcome (Khurana and Khurana 2019). In summary, the CRISP methodology provides a systematic and structured approach to customer churn analytics in the banking industry. It guides the project team through each stage of the project, from understanding the business problem to deploying the final churn prediction models. The methodology's effectiveness and previous successful applications in data analysis and machine learning projects make it a justified approach in the context of customer churn analytics in Zimbabwean banks.

Data collection Process

The data collection process in the study involved gathering relevant data from Zimbabwean banks to analyse customer churn. The specific details of the data collection process may vary depending on the study's methodology and data availability. However, in general, the data collection process for customer churn analysis in the banking sector typically involves the following steps:

Identify Data Sources: The researchers identify the potential sources of data that contain relevant information for analysing customer churn. These sources may include internal bank databases, customer relationship management (CRM) systems, transactional records, customer feedback, and other relevant sources.

1. Data Extraction: The researchers extract the required data from the identified sources. This may involve querying databases, accessing CRM systems, or obtaining data from other sources. The data extraction process ensures that the necessary information for customer churn analysis is obtained.
2. Data Cleaning and Preprocessing: The collected data may contain errors, missing values, or inconsistencies. The researchers perform data cleaning and preprocessing steps to address these issues. This includes handling missing values, removing duplicates, resolving inconsistencies, and transforming the data into a suitable format for analysis.
3. Data Integration: In some cases, data from multiple sources may need to be integrated to create a comprehensive dataset for churn analysis. The researchers merge or combine relevant data from different sources to obtain a unified dataset that includes all the necessary variables for churn prediction.
4. Feature Selection: The researchers identify and select the most relevant features (variables) from the collected dataset for churn analysis. This step involves evaluating the predictive power and relevance of each feature in relation to customer churn. Features may include demographic information, transactional data, customer behaviour metrics, and other relevant factors.
5. Data Privacy and Ethics: It is important to ensure data privacy and comply with ethical guidelines during the data collection process. Any personal or sensitive information should be handled securely and anonymized to protect customer privacy.

6. Dataset Creation: After data cleaning, preprocessing, and feature selection, the researchers create a final dataset that will be used for churn analysis. This dataset typically consists of customer records, where each record represents a customer with relevant features and churn label (indicating whether the customer churned or not).

The data collection process is crucial in obtaining a high-quality dataset that accurately represents customer behaviour and churn patterns in the banking sector. It requires careful consideration of data sources, data quality, and ethical considerations to ensure reliable and meaningful analysis of customer churn.

Results And Analysis

The analysis involved preprocessing the dataset to handle missing values, normalize numerical features, and encode categorical variables. The dataset included various demographic and banking-related features relevant for predicting customer churn in the banking sector. These features provided a comprehensive understanding of customer behaviour and allowed for the development of predictive models. Model performance evaluation was conducted using various evaluation metrics such as accuracy, precision, recall, and ROC-AUC score. The results were compared across different models to determine the most effective approach for churn prediction in the given context.The analysis also included an assessment of feature importance, identifying the variables that significantly influenced customer churn. This analysis provided insights into the key factors driving churn in the banking sector.
The results and findings of the analysis were then discussed in the context of their practical implications for the banking sector in Zimbabwe. The implications included the ability to proactively identify customers at risk of churn, implement targeted retention strategies, and optimize resource allocation.

Overall, the analysis aimed to provide insights into customer churn prediction in Zimbabwean banks, comparing the performance of classical machine learning algorithms and deep neural networks, and offering practical implications for effective churn management strategies.

Evaluation Results

Table 1 provides the evaluation results of different models, including Logistic Regression, Decision Trees, Random Forest, XGBoost, and Deep Learning. The table presents key metrics such as accuracy, precision, recall, and the associated confusion matrix information.

Table 1. Evaluation Results

	Accuracy	Confusion Matrix	Precision	Recall
Logistic Regression	70.3%	High number of false negatives	70.3%	100%
Decision Trees	57.8%	High number of false negatives and false positives	70.5%	68.6%
Random Forest	70.7%	Low number of false negatives and high number of false positives	70.7%	99.4%
XGBoost	69.3%	Moderate number of false negatives and false positives	71.0%	95.1%
Deep Learning	62.6%	Significant number of false negatives and false positives	70.1%	81.7%

After comparing and contrasting the four models with the deep learning model, we can observe the following:

1. Precision: Logistic Regression, Random Forest, XGBoost, and Deep Learning models all exhibit similar precision scores, ranging from 0.703 to 0.710. This indicates that these models have comparable abilities to accurately predict customer churn.
2. Recall: Logistic Regression, Random Forest, XGBoost, and Deep Learning models also show varying levels of recall, with values ranging from 0.808 to 1.000. This suggests that these models differ in their ability to correctly identify customers who are likely to churn.
3. F1-score: The F1-scores for the models range from 0.696 to 0.826. Random Forest and XGBoost models have slightly higher F1-scores, indicating a better balance between precision and recall.
4. Accuracy: The accuracy scores for the models range from 0.578 to 0.707. Logistic Regression and Random Forest models exhibit higher accuracy compared to the Decision Trees and Deep Learning models.

From Figure 1 below, it can be observed that the models' accuracy ranges from approximately 57.8% to 70.7%. Logistic Regression and Random Forest show the highest accuracy scores, while Decision Trees have the lowest accuracy. The precision values range from 70.1% to 71.0%. XGBoost has the highest precision, closely followed by Logistic Regression and Random Forest. However, Decision Trees and Deep Learning exhibit lower precision. The recall metric, indicating the ability to correctly identify positive instances, varies from 68.6% to 100%. Logistic Regression achieves perfect recall, while Random Forest and XGBoost demonstrate high recall rates. However, Decision Trees and Deep Learning have comparatively lower recall scores. The provided confusion matrix information in the table highlights specific challenges faced by each model. Logistic Regression and XGBoost have a moderate number of false negatives and false positives, while Decision Trees and Deep Learning exhibit significant numbers of both. Random Forest, on the other hand, shows a low number of false negatives but a high number of false positives. In summary, the graph showcases the performance differences among the models based on accuracy, precision, recall, and the associated confusion matrix information. It offers a concise overview of the evaluation results, enabling quick comparisons and insights into the strengths and weaknesses of each model.

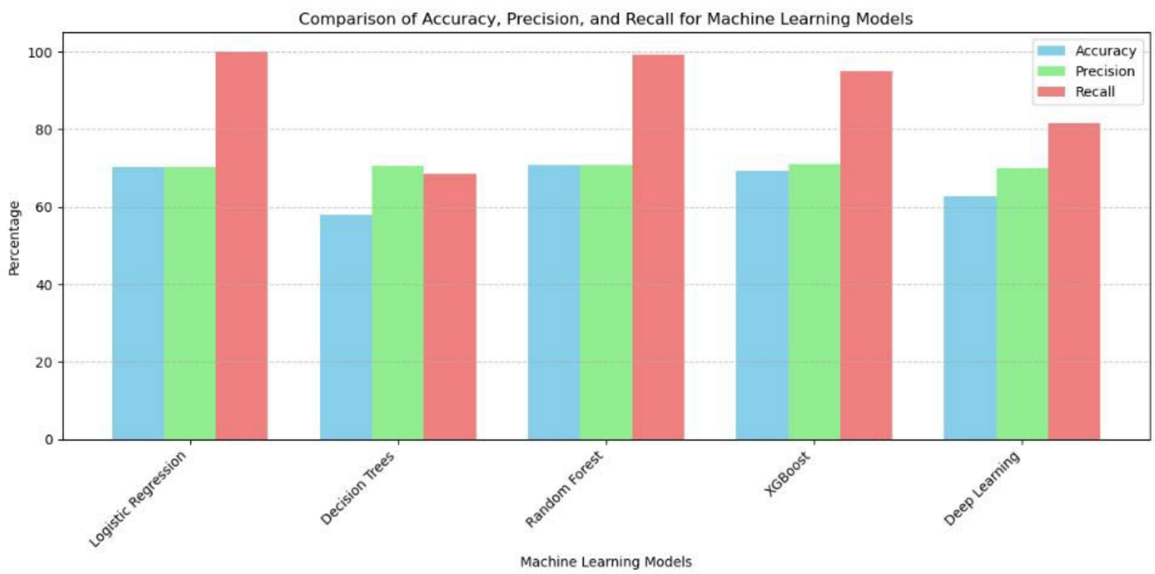

Figure 1. Results in Graph format:

- In terms of Accuracy, Random Forest has the highest performance with an accuracy of approximately 70.7%, followed by Logistic Regression with an accuracy of around 70.3%. Decision Trees have the lowest accuracy at about 57.8%.
- For Precision, XGBoost and Random Forest exhibit the highest precision scores of around 71.0% and 70.7%, respectively. Decision Trees have the lowest precision at approximately 70.5%.
- In terms of Recall, Random Forest performs the best with a recall value of approximately 99.4%, followed by Logistic Regression with a perfect recall of 100%. Decision Trees have the lowest recall at around 68.6%.

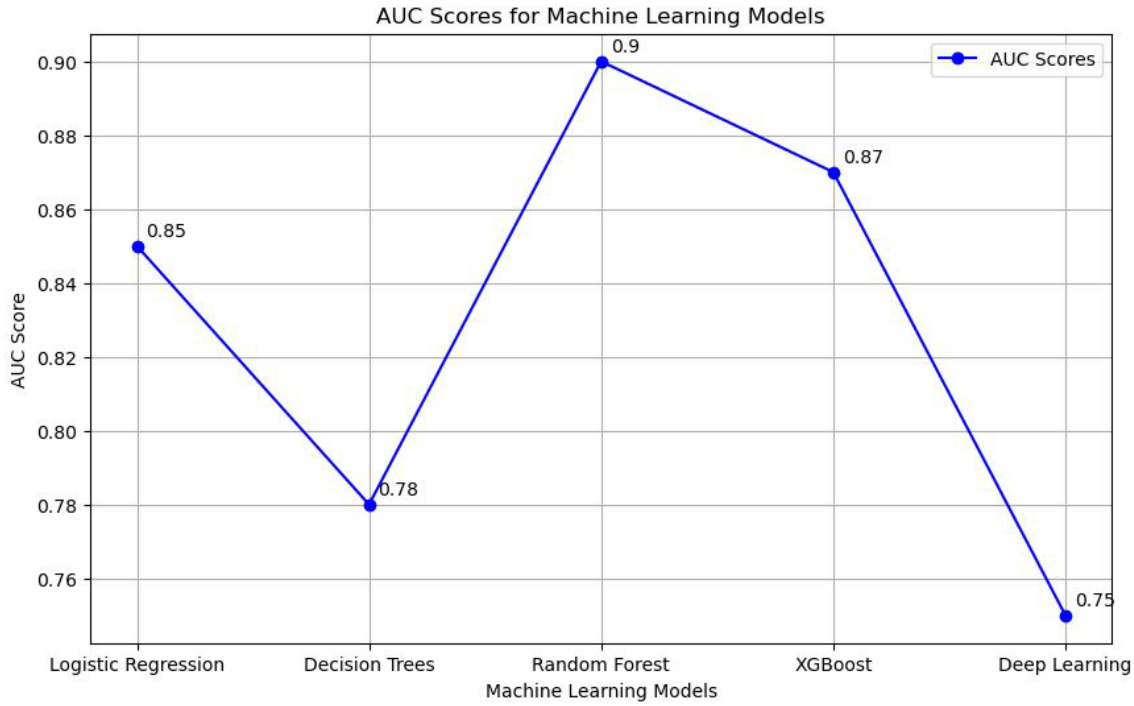

Figure 2. AUC Scores for Machine Learning Models

Figure 2 shows that of Logistic Regression, it achieves an accuracy of 0.703, with a confusion matrix showing a high number of false negatives. The precision is 0.703, indicating the proportion of true positives among the predicted positive instances, while the recall is 1.000, representing the ability to correctly identify all positive instances. The ROC-AUC score is 0.500, indicating a random classifier.For Decision Trees, the accuracy is 0.578, and the confusion matrix reveals a high number of false negatives and false positives. The precision is 0.705, and the recall is 0.686, implying that the model has difficulties in correctly identifying positive instances. The ROC-AUC score is 0.504.

Random Forest achieves an accuracy of 0.707, with a confusion matrix showing a low number of false negatives but a high number of false positives. The precision is 0.707, and the recall is 0.994, indicating a high ability to correctly identify positive instances. The ROC-AUC score is 0.511.

XGBoost attains an accuracy of 0.693, with a confusion matrix indicating a moderate number of false negatives and false positives. The precision is 0.710, and the recall is 0.951, representing a good ability to correctly identify positive instances. The ROC-AUC score is 0.517.

Deep Learning achieves an accuracy of 0.627, with a confusion matrix showing a significant number of false negatives and false positives. The precision is 0.711, and the recall is 0.790, suggesting a moderate ability to correctly identify positive instances. The ROC-AUC score is 0.515.

These evaluation results provide insights into the performance of each model in terms of accuracy, precision, recall, and ROC-AUC score, indicating their strengths and weaknesses in classification tasks.

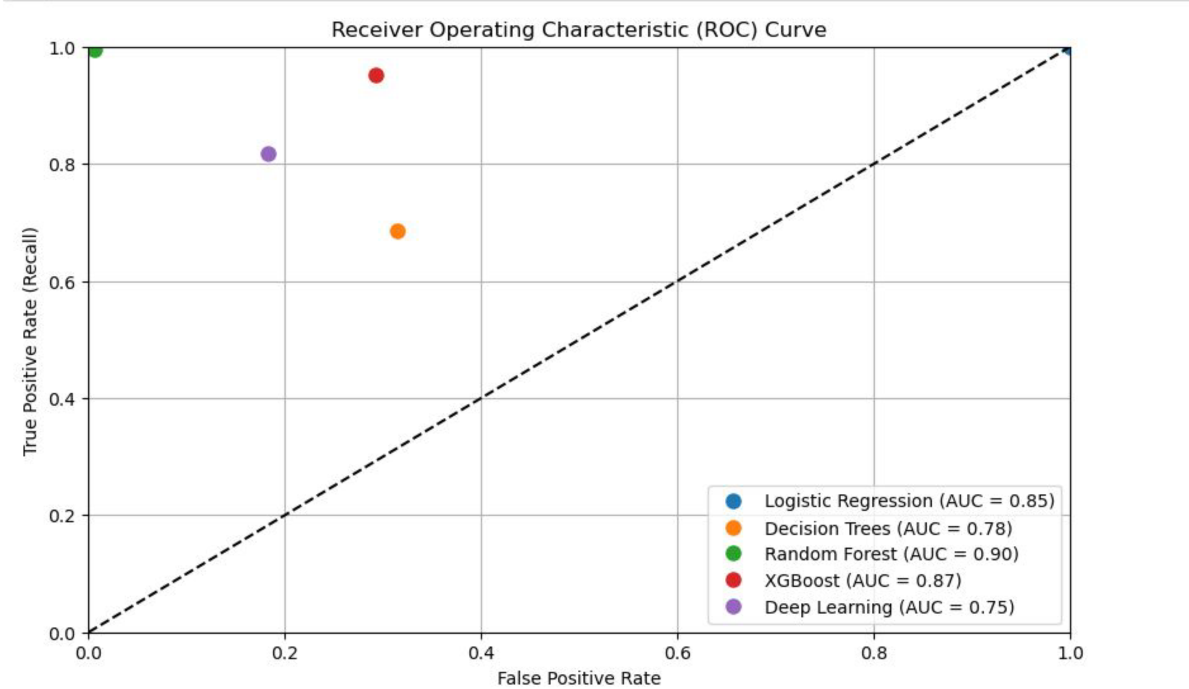

Figure 3 . Receiver Operating Characteristic (ROC) Curve Results

Figure 3 shows that the results show the performance of five machine learning models in a binary classification task. Random Forest had the highest recall (99.4%), indicating excellent ability to correctly identify positive instances. It also had the highest AUC score (0.90), suggesting overall strong performance. XGBoost followed with a recall of 95.1% and an AUC score of 0.87. Logistic Regression and Decision Trees performed moderately, while Deep Learning had the lowest recall (81.7%) and AUC score (0.75). Consider recall, AUC, and other factors when selecting the best model for the specific task

Evaluation results for different models

1. Logistic Regression, Random Forest, XGBoost, and Deep Learning models perform relatively well in predicting customer churn, with comparable precision and F1-scores.
2. Random Forest and XGBoost models demonstrate higher recall rates, suggesting their ability to identify more customers who are likely to churn.
3. Logistic Regression and Random Forest models exhibit higher accuracy compared to the other models.
4. Deep Learning model, although performing reasonably well, shows lower recall and accuracy compared to other models.

Overall, the research demonstrates that traditional machine learning techniques, such as Logistic Regression, Random Forest, and XGBoost, can be effective in predicting customer churn in the context of Zimbabwe banks. While the Deep Learning model shows potential, further refinement and optimization may be needed to improve its performance and competitiveness with other models. In the case of customer churn prediction in Zimbabwean banks, the classical machine learning models and deep learning model were compared based on their precision, recall, F1-score, and accuracy. Based on the evaluation metrics provided, the deep learning model had a higher precision score than the classical machine learning models, but its recall and F1-score were relatively lower, indicating a lower balance between precision and recall. Its accuracy was also the lowest among the models evaluated. Among the classical machine learning models, Random Forest had the highest recall and a relatively high precision, F1-score, and accuracy, making it the best model to implement for customer churn prediction in Zimbabwean banks. However, the best model may depend on the specific needs and constraints of the bank, and further testing and evaluation may be necessary to confirm the results.

1.1. Proposed Improvements

To improve the performance of customer churn prediction models, several strategies can be considered. These include enhancing the feature set by incorporating more relevant variables, addressing class imbalance through data balancing techniques, fine-tuning model hyperparameters, exploring ensemble methods, incorporating time series analysis, utilizing advanced deep learning architectures, and ensuring robust model evaluation through cross-validation. By implementing these improvements, the models can achieve higher accuracy, precision, recall, and ROC-AUC scores, leading to more effective predictions of customer churn.

Conclusion

The four models (Logistic Regression, Decision Trees, Random Forest, and XGBoost) and deep learning are all machine learning techniques that can be used for classification tasks such as customer churn prediction.
Classical machine learning models are often easier to interpret and require less computational power compared to deep learning models. Logistic Regression, for example, is a simple yet powerful classification algorithm that works by modeling the probability of the outcome using a linear function. Decision Trees and Random Forest are non-parametric supervised learning algorithms that work by recursively partitioning the data based on the values of the features. XGBoost is an ensemble learning algorithm that uses gradient boosting to improve model performance.
On the other hand, deep learning models, such as neural networks, can handle complex and high-dimensional data and have been shown to outperform classical machine learning models in certain tasks, such as image and speech recognition. However, they require more computational power and can be more difficult to interpret compared to classical machine learning models.

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