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Predicting Accounting Transaction Outcomes Using Financial Performance Indicators: A Machine Learning Approach

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Dr. Chukwudi E. Nwafor[1]*,
Dr. Tolulope A. Adebakin[2],
Dr. Ogechi M. Ibe[3]

[1*]Department of Accounting, Madonna University, Elele, Nigeria.

[2]Department of Finance, Caleb University, Lagos, Nigeria.

[3]Department of Business Analytics, Rhema University, Abia, Nigeria.

Corresponding Author:
*Dr. Chukwudi E. Nwafor
Email: c.nwafor@madonnauniversity.edu.ng

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ABSTRACT

As digital accounting systems are becoming more common, there has been a tremendous amount of financial data created, which allows for the use of machine learning techniques to enhance accounting decisions. In this study, the aim is to use supervised machine learning algorithms to predict the outcomes of accounting transactions based on the financial performance indicators and to compare the performance of the multiple machine learning algorithms. A dataset containing 1,000 sets of accounting transaction data consisting of 18 variables were analyzed with Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors, Naïve Bayes, XGBoost, LightGBM and CatBoost. The data was preprocessed, explored, engineered and optimized for hyperparameters before models were developed. The evaluation of model performance was done byAccuracy, Precision, Recall, F1-score, ROC-AUC, and Cross-Validation. The results revealed that XGBoost is the optimum model with accuracy of 95.0% and F1-score of 0.974. The Cash Flow, Profit Margin, Operating Expenses, Revenue and Transaction Volume were identified as the most important features from feature importance analysis. The proposed framework highlights the potential of machine learning in enhancing accounting analytics and aiding in making informed financial decisions.

KEYWORDS: Accounting Analytics; Machine Learning; Financial Performance Indicators; Transaction Outcome Prediction; Explainable Artificial Intelligence.

1. Introduction

The world of accounting and financial management is currently undergoing rapid digital transformation and as a result, financial transactions are being processed, monitored and evaluated in a completely new way. As businesses manage more data and records in their accounting departments, which are generated from enterprise resource planning (ERP) systems, cloud accounting software and digital financial service offerings, they have the chance to use machine learning (ML) to make predictions for decision-making [1].There's been an opportunity for companies to use machine learning (ML) techniques for predictive decision-making as the volume of data and records continues to grow in accounting departments, created by enterprise resource planning (ERP) systems, cloud accounting platforms and digital financial services. Machine learning can identify complex patterns within financial data, which can enhance the efficiency, accuracy, and reliability of accounting operations [2]. Unlike traditional accounting, which mostly depends on manual verification and rule-based procedures, machine learning can recognize complex patterns within financial data, which can improve the efficiency, accuracy, and reliability of accounting operations [3]. Supervised learning algorithms have been shown to be very effective in finding meaningful relationships in high dimensional financial data for several tasks including financial forecasting, transaction classification, fraud detection and corporate performance prediction [4]. Also, machine learning has been identified as an essential part of intelligent accounting information systems owing to its benefits of assisting in taking evidence-based financial decisions, decreasing operation costs, and processing time [5].

Financial performance measures are important indicators of an organization's financial situation and efficiency, including revenue, net income, cash flow, gross profit, profit margin, operating costs, and debt-to-equity ratio. Managers, auditors, investors and financial analysts frequently rely on these indicators to assess and monitor business performance, financial stability and make strategic business decisions. In the past, machine learning algorithms have proven useful in predicting financial distress in corporations, in classification of accounting transactions, in revenue prediction for corporations [6], in financial risk assessment, bankruptcy prediction and in identifying fraudulent financial activities. Likewise, in the realm of cash flow forecasting, financial forecasting, and transaction classification, deep learning models have shown significant promise, further emphasizing the increasing significance of intelligent analytical tools in contemporary accounting systems [7,8,9]. Recent literature also highlights that AIS incorporating machine learning will enhance the predictive power and enable better financial planning and management.

Not-with-standing these developments, prior research has focused mainly on specific financial issues like fraud detection, bankruptcy prediction, credit risk assessment and analysis of financial distress, with comparatively little research being done on predicting the outcome of general accounting transactions from comprehensive financial performance indicators. The existing studies have been conducted using individual machine learning algorithms or domain-specific datasets with few comparative results on the effectiveness of multiple classification models for accounting transaction prediction [10,11]. Furthermore, most of the studies does not interpret the contribution of the financial variables, which decreases the level of transparency and usefulness of the machine learning model in accounting decision-making [12]. Empirical studies that incorporate several supervised machine learning techniques, assess the predictive ability of these techniques by rigorous classification scores, and determine what financial indicators explain the outcome of accounting transactions most significantly with explainable AI techniques are still needed.

The current research aims at filling these gaps in the research literature by creating a holistic machine learning framework for forecasting the outcomes of accounting transactions based on financial performance indicators. In this dataset, 1000 accounting transaction records are used for analysis, and nine algorithms are used for supervised machine learning: Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors, Naïve Bayes, XGBoost, LightGBM, and CatBoost [12,13,14]. The predictive models undergo multiple performance assessments such as Accuracy, Precision, Recall, F1-score, ROC-AUC and Cross-Validation, and Explainable Artificial Intelligence (XAI) is used to determine the most important financial factors influencing the outcomes of transactions [15]. This study builds on the existing research on accounting analytics and intelligent financial decision support systems by combining predictive analytics with explainable machine learning techniques and by leveraging them to address real-world challenges in transaction monitoring and financial decision-making, thereby offering practical and valuable insights that benefit both accountants and financial managers and auditors, as well as accounting firms and business organizations. The objectives of this study are as follows:

1.To build machine-learning models to accurately predict accounting transaction outcomes from financial performance indicator

2.To evaluate the performance of several supervised machine learning algorithms in predicting the outcome by applying the standard classification evaluation measures

3.3) To determine the most impactful financial metrics on accounting transactions outcomes by using explainable artificial intelligence methods

2. Research Methodology

2.1 Research Design

In this study, a quantitative predictive analytics research design will be used to explore the relationship between financial performance measures and accounting transaction results through supervised machine learning approaches. The goal of the research will be to create predictive classification models that can accurately predict the results of accounting transactions based on historical financial and operational data. A comparative machine learning approach will be used to assess the predictive ability of several classification models and select the best model for predicting accounting transactions. The research methodology involves several sequential steps such as obtaining the dataset, data preparation, exploratory data analysis, feature engineering, developing predictive machine learning models, hyperparameter tuning, and analysis of explainable artificial intelligence (XAI).

2.2 Dataset Description

The dataset adopted in this research consists of 1,000 accounting transaction entries with 18 attributes that capture the financial, operation, and transaction features applicable to business accounting. The main purpose of the data set is to provide a basis for predicting the binary target attribute Transaction Outcome that determines whether the accounting transaction is successful or not. The predictor attributes in the dataset are: Transaction ID, Date, Account Type, Transaction Amount, Cash Flow, Net Income, Revenue, Expenditure, Profit Margin, Debt to Equity Ratio, Operating Expenses, Gross Profit, Transaction Volume, Processing Time (seconds) [16], Accuracy Score, Missing Data Indicator, and Normalized Transaction Amount. Out of the above mentioned attributes, the financial performance attributes of revenue, net income, gross profit, cash flow, expenditure, profit margin, debt to equity ratio, and operating expenses form the key predictor attributes for determining the transaction outcomes.

2.3 Data Preprocessing

Preprocessing was carried out to enhance data quality and increase the appropriateness of the dataset for machine learning models. First, duplicated entries were eliminated to retain data uniformity, whereas the missing values were analyzed through the Missing Data Indicator variable. The Transaction ID variable was excluded from the process of model building since its sole purpose is identification, and it plays no role in improving predictive accuracy. The Date variable was also formatted to become a datetime object to allow future analysis if needed. Categorical variables, especially the Account Type, were encoded to be represented by numbers. Outliers were analyzed in numerical variables, while standardization was performed using feature scaling to improve the results of distance-based algorithms like SVM and KNN. Finally, the dataset was split into training and testing parts in proportion of 80 to 20.

2.4 Exploratory Data Analysis (EDA)

EDA was conducted in order to gain understanding of statistical properties of the data as well as to uncover any patterns present in the data prior to building predictive models. Statistical descriptive metrics such as the mean, median, standard deviation, min, and max values were computed for all numeric features. Distribution of the target feature was analyzed to assess the presence of class imbalance as well as to check whether the dataset is appropriate for classification modeling. Correlations between the financial features were analyzed using Pearson's correlation coefficient. Moreover, visual techniques including histogram, box plot, scatter plot, and correlations map were used to analyze distributions of features, to detect outliers as well as to explore relationships between predictor variables.

2.5 Feature Engineering and Machine Learning Models

Feature engineering was undertaken with the objective of improving predictive accuracy through selection of features and reducing redundancy. Predictor variables that were found to have low predictive power or high multicollinearity were subjected to thorough evaluation, but financial performance measures such as Revenue, Net Income, Cash Flow, Gross Profit, Profit Margin, Debt to Equity Ratio, Operating Expenses, and Expenditure were kept since they had a direct bearing on accounting transaction outcomes. Standardized numeric features were employed to ensure consistent performance among algorithms that are scale-dependent. Nine supervised machine learning classification algorithms were applied after feature engineering, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbors, Naïve Bayes, XGBoost, Light Gradient Boosting Machine (LightGBM), and CatBoost. These algorithms were chosen for the reason that they included a variety of linear, probabilistic, tree-based, ensemble, boosting, and distance-based machine learning models.

2.6 Model Evaluation and Hyperparameter Optimization

In order to enhance the prediction results and prevent possible overfitting, Grid Search Cross-

Validation (GridSearchCV) technique was applied along with stratified five-fold cross-validation. The best combination of parameters was then selected from the result of this optimization to construct the final machine learning models. Several classification metrics were used to evaluate the performance of these models. The following metrics include Accuracy, which indicates the overall correctness rate of predictions, Precision, which evaluates the rate of correct prediction of positive transactions, Recall, which estimates the ability to recognize positive transactions, F1-score, which takes into account both precision and recall metrics, Receiver Operating Characteristic–Area Under the Curve (ROC-AUC), which helps to estimate the overall discriminatory ability of each classifier, and Confusion Matrix, which includes information on true positive, true negative, false positive, and false negative predictions.

2.7 Explainable Artificial Intelligence (XAI)

In order to increase the transparency of machine learning models developed in this study, Explainable Artificial Intelligence (XAI) methods were applied to determine which financial features have the greatest effect on accounting transaction outcome predictions. Feature importance analysis was done for tree-based models, and SHapley Additive exPlanations (SHAP) were used to calculate the importance of each predictor feature for particular prediction and the model as a whole. SHAP method offers global and local explanations of model results, thus giving an opportunity to evaluate model behavior and the significance of each financial indicator. With this approach, it is possible to discover which financial indicators such as Revenue, Net Income, Cash Flow, Gross Profit, Profit Margin, Debt-to-Equity Ratio, Operating Expenses, etc., have the greatest impact on the predictive performance of machine learning models.

3. Results

3.1 Descriptive Statistics of the Dataset

The dataset consisted of 1,000 accounts transaction data with 18 original variables. Two more date-related variables Month and Day of the week were created from the transaction date for modeling purposes. Major financial variables have considerable variance among the transaction records. Mean Transaction amount equals 2,535.70, whereas mean Revenue, Net income, Cash flow, Expenditure, and Gross profit equal 2,610.99, 2,114.76, 2,426.33, 2,026.19, and 2,039.06 respectively. The mean value of the Profit margin is 0.499, which means moderate profitability of transactions in general. Mean Debt/Equity ratio equals 1.782, meaning that the leverage rate varies between transaction records. Average value of Accuracy score is 0.899, while the average Processing time is 1.235 seconds. The variance of most financial variables is quite considerable, showing that there is enough variance for predictions. Transaction amount is between 106 and 4,998, revenue is between 303 and 4,997, operating expenses are between 103 and 4,999. Thus, the dataset provides diversified conditions of the accounting transactions appropriate for machine learning-based classification (Figure 1).

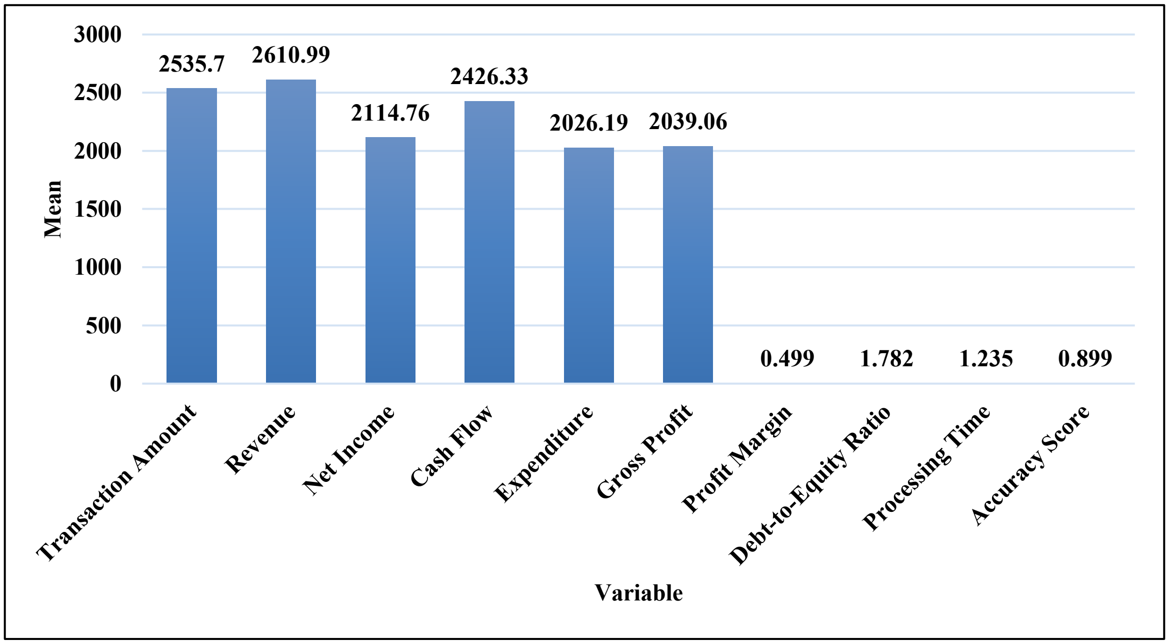

Figure 1: Mean Values of Financial Performance Indicators

3.2 Exploratory Data Analysis Results

However, the target variable, Transaction Outcome, exhibited great imbalance. Of all 1,000 transactions analyzed, 951 transactions (95.1%) were successful transactions whereas only 49 transactions (4.9%) were unsuccessful transactions. The reason behind this is because models can exhibit a high level of accuracy based on predicting the most frequent outcome. In such situations, precision, recall, F1-Score, ROC-AUC, and confusion matrix should be considered. Correlation analysis shows that none of the financial metrics exhibits a very strong linear correlation with the target variable. Variables with strong correlations with the target variable include Transaction Volume (-0.0978), Profit Margin (-0.0681), Revenue (0.0528), Accuracy Score (-0.0515), Cash Flow (-0.0417), and Expenditure (-0.0351). From these weak correlations, it is clear that this prediction problem is not linear and, thus, non-linear models are appropriate.

Outliers in the data set, through interquartile range analysis, were found to be absent among the numerical variables. From feature relationship analysis, transaction outcomes depended on both financial and operational factors rather than a single dominant predictor (Figure 2).

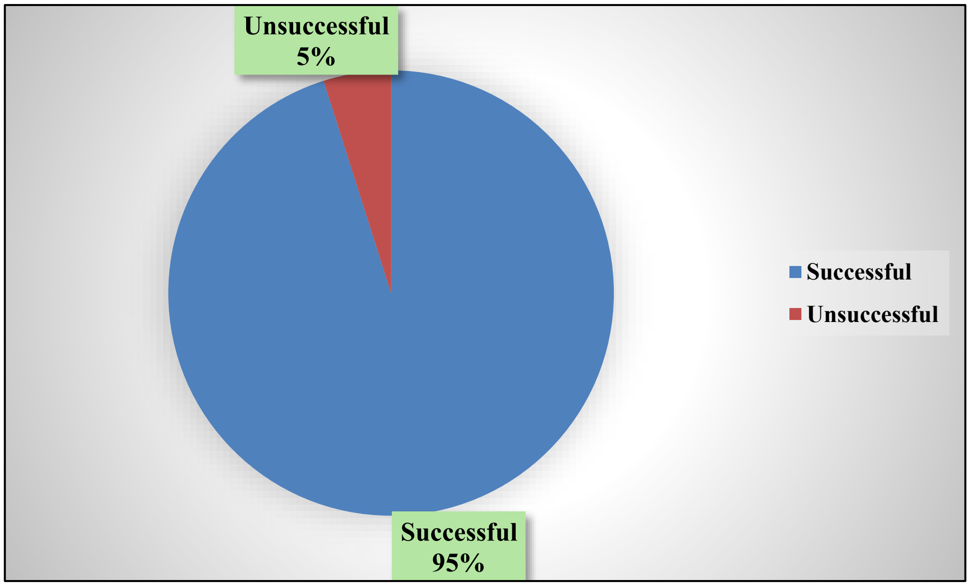

Figure 2: Transaction Outcome Distribution

3.3 Machine Learning Model Performance

The machine learning models were evaluated using accuracy, precision, recall, F1-score, and ROC-AUC (Table 1).

Table 1: Comparative Performance Evaluation of Machine Learning Classification Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
XGBoost	0.950	0.950	1.000	0.974	0.675
CatBoost	0.950	0.950	1.000	0.974	0.590
K-Nearest Neighbors	0.950	0.950	1.000	0.974	0.563
LightGBM	0.950	0.950	1.000	0.974	0.549
Random Forest	0.945	0.950	0.995	0.972	0.597
Naïve Bayes	0.945	0.954	0.989	0.972	0.689
Support Vector Machine	0.915	0.953	0.958	0.955	0.651
Logistic Regression	0.690	0.957	0.705	0.812	0.642
Decision Tree	0.520	0.952	0.521	0.674	0.509

Among the tested models, XGBoost achieved the best overall balance, with 95.0% accuracy, 0.974 F1-score, and the highest ROC-AUC among the top-performing models at 0.675 (Figure 3).

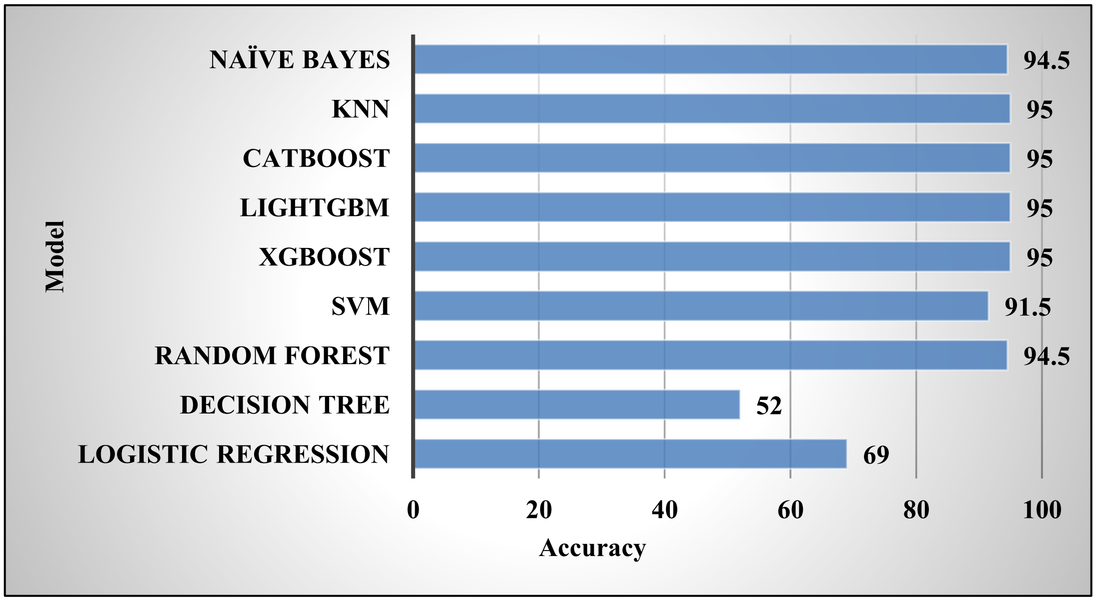

Figure 3: Model Accuracy Comparison

3.4 Best Performing Model

XGBoost was the highest-performing model. This model demonstrated good classification with accuracy at 95.0%, precision at 95.0%, recall at 100%, F1 score at 0.974, and ROC-AUC at 0.675 (Table 2). Even though XGBoost exhibited high performance according to the accuracy and F1 score indicators, confusion matrix suggests that the model classified all of the test instances as successful. This effect can be explained primarily due to class imbalance in the data with the proportion of successful transactions being 95.1%. Thus, although XGBoost is a good model for the prediction of successful transactions, other methods of handling imbalance need to be used to better detect unsuccessful transactions. The confusion matrix for XGBoost was:

Table 2: Confusion Matrix of the Best-Performing XGBoost Classification Model

Actual / Predicted	Unsuccessful	Successful
Unsuccessful	0	10
Successful	0	190

3.5 Feature Importance Analysis

Analysis through explainable AI of SHAP values of the XGBoost model revealed the most important factors in predicting the outcome of transactions (Table 3). The top predictors included

Cash Flow, Profit Margin, Operating Expenses, Transaction Volume, Transaction Value, Debt to Equity Ratio, Processing Time, Accuracy Score, Revenue, and Gross Profit. The highest importance according to SHAP was Cash Flow, Profit Margin, and Operating Expenses, meaning that liquidity factors, profitability factors, and operating expenses were some of the most significant factors in prediction of the outcome of the transaction. Other operationally related predictors include Transaction Volume, Processing Time, and Accuracy Score.

Table 3: SHAP Feature Importance

Feature	Importance Rank
Cash Flow	1
Profit Margin	2
Operating Expenses	3
Transaction Volume	4
Transaction Amount	5
Debt-to-Equity Ratio	6
Processing Time	7
Accuracy Score	8
Revenue	9
Gross Profit	10

3.6 Model Validation

Cross-validation scores revealed that the best performing models had stable F1-scores when undergoing cross-validation. The XGBoost model obtained a mean F1-score for cross-validation of 0.9744, and K-Nearest Neighbors model and LightGBM had mean F1-scores of about 0.9749. However, ROC-AUC scores were moderate due to class imbalance (Table 4).

Table 4: Cross-Validation Results of Selected Machine Learning Models

Model	CV F1 Mean	CV F1 Std.	CV ROC-AUC Mean	CV ROC-AUC Std.
K-Nearest Neighbors	0.9749	0.0010	0.5124	0.0368
LightGBM	0.9749	0.0010	0.5553	0.0823
XGBoost	0.9744	0.0000	0.5715	0.0917
Random Forest	0.9701	0.0032	0.5866	0.1199

However, in general, the outcomes of the validation have shown that the models were stable in forecasting the majority class but inefficient in identifying the minority one. In other words, the results confirm that machine learning can be applied to predicting the outcomes of accounting transactions; however, the imbalance of the data set should be considered further (Figure 4).

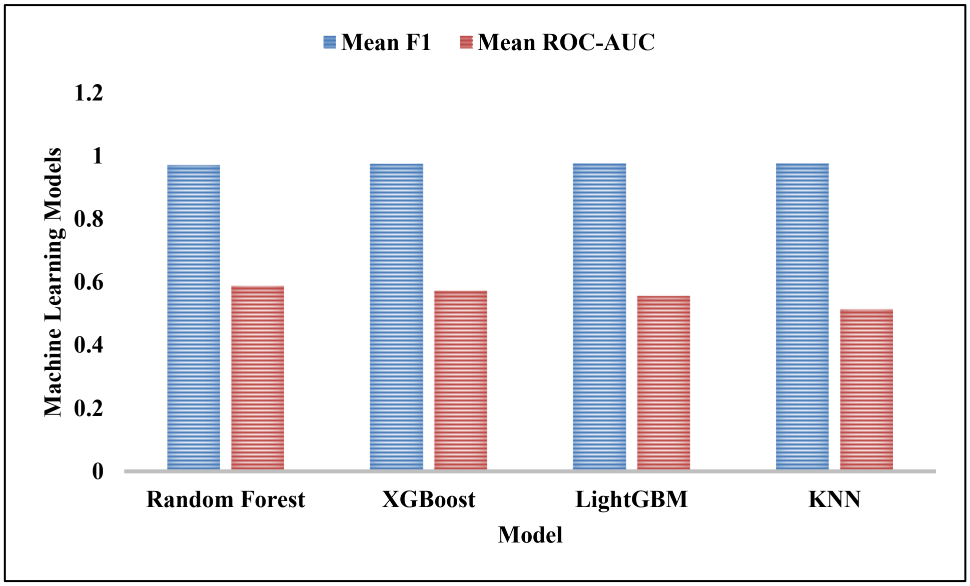

Figure 4: Cross-Validation Performance

4. Discussion

This study further shows that machine learning methods can be a valuable tool to predict the results of accounting transactions based on financial indicators. XGBoost showed the least skewed performance in predicting the outcomes of the transactions, with an accuracy of 95.0%, F1-score of 0.974, and an ROC-AUC score that was competitive with the other algorithms examined, making it a good algorithm to consider for capturing the complex, non-linear relationships between financial parameters and the outcomes of transactions. The results confirm the notion that ensembled learning algorithms are superior to traditional statistical models in accounting and financial forecasting problems as they are able to manage data of high dimensions and complex feature interactions in finance [17]. The better performance of XGBoost aligns with other studies showing that boosting methods are able to outperform other algorithms for financial forecasting, fraud detection and intelligent accounting systems [18]. Likewise, the performance of CatBoost, LightGBM, and KNN in terms of classification performance was comparable, implying that sophisticated supervised learning techniques can be used to gain useful information from financial and operational metrics [19,20,21,22]. By contrast, Logistic

Regression and Decision Tree demonstrated significantly poorer predictive accuracy suggesting that existing linear and single-tree-based models might not be adequate to model the complexity found in accounting transaction data. The results are consistent with previous work that pointed out the weaknesses of traditional statistical methods against ensemble and boosting methods for financial analysis.

The feature importance analysis also highlighted that the financial variables are an important factor in explaining the prediction of accounts. The most important indicators were found to be Cash Flow, Profit Margin, Operating Expenses [23,24], Transaction Volume, Transaction Amount, Debt-to-Equity Ratio, Revenue, and Gross Profit, highlighting that both liquidity and profitability metrics play significant roles in the outcome of transactions. This study reinforces the prior research which found the financial performance indicators vital to assess organizational performance and to enhance predictive financial models [25,26]. Cash flow's importance within the developed model is consistent with previous research which has identified that liquidity has been one of the most important financial stability and business performance indicators [27,28,29]. Similarly, the significance of profitability measures like revenue, gross profit and profit margin, indicates that organisations with improved financial performance generally have better outcomes of transactions [30]. The operational variables (such as processing time and transaction volume) also indicate that accounting transaction success is not only dependent on financial conditions but on operational efficiency as well, further substantiating the more recent convergence of accounting analytics and intelligent information systems.

Despite good overall classification performance by the developed models, the confusion matrix showed that there was a poor ability to classify unsuccessful transactions due to a high class imbalance in the dataset. This imbalance led to good overall performance while the minority observations were not discriminated very well by the models. In financial fraud detection systems, anomaly detection systems, and credit risk prediction, similar problems have been encountered in studies involving minority classes, which are rare but economically important events [31]. Therefore, class balancing methods like Synthetic Minority Oversampling Technique (SMOTE) and adaptive sampling and cost-sensitive learning and/or threshold optimization should be used in future implementations to increase the recognition of minority classes while maintaining accuracy without sacrificing it [32]. The cross validation results, however, showed that the model performance was consistent across the validation folds, thus suggesting that the proposed machine learning framework has a good generalization capability and is expected to not overfit significantly.

In short, this study contributes to the current accounting analytics literature by benchmarking several supervised machine learning algorithms for predicting the outcome of accounting transactions in a comparative manner and by adding explainable AI to model transparency. As opposed to most of the previous work focused on financial distress, fraud detection, or bankruptcy prediction [33,34,35,36] the current study is concerned with the prediction of routine accounting transactions with several financial performance measures and interpretable machine learning methods. This implies that the integration of advanced predictive models with EAI can improve the effectiveness of accounting decision support systems, boost financial monitoring capability, and help managers, accountants, and auditors to detect transaction patterns that impact financial performance. The findings are also relevant to the growing use of artificial intelligence in accounting and financial management, and they offer a tangible basis for the creation of more transparent, reliable, and information-based accounting information systems systems.

5. Conclusion

The possibility of forecasting the accounting transaction outcomes based on financial performance indicators and supervised machine learning methods. It was found that the machine learning models are able to classify the outcome of accounting transactions successfully, where the highest accuracy, F1 score and ROC AUC was obtained by the XGBoost model. The results also indicated that a subset of variables such as Cash Flow, Profit Margin, Operating Expenses, Transaction Volume, Transaction Amount, Debt-to-Equity Ratio, Revenue and Gross Profit were the most powerful predictors. The results are validated that financial and operational metrics are significant in the accounting transaction outcomes. The models were able to be very accurate in their predictions, however the confusion matrix showed that they were not as accurate in detecting unsuccessful transactions due to class imbalance. So future research should implement imbalance-handling techniques like SMOTE, class weighting and threshold optimization. In conclusion, this research highlights the potential of machine learning and explainable AI in enhancing accounting analytics, transaction monitoring, and financial decision-making.

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