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Article

Artificial Intelligence as a Proactive Tool in Auditing Credit Risk: A Predictive Model for Iraqi Banks

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Abstract: Credit risk management has evolved significantly with technological advancements, particularly the application of artificial intelligence (AI), which offers enhanced decision-making tools for financial institutions. While AI has been successfully applied globally, particularly through machine learning models like XGBoost and SHAP, the use of AI in Iraqi banks remains underdeveloped due to infrastructure and regulatory challenges. Despite international research, there is a lack of practical, applied AI models specifically designed for the Iraqi banking sector, particularly those that incorporate local financial data and align with the country's unique context. This study aims to develop a predictive model using AI (XGBoost) to assess credit risk in Iraqi banks, evaluate the feasibility of AI models in this context, and propose solutions to overcome the challenges of adoption. The developed model achieved high prediction accuracy (96%) and perfect precision (100%), demonstrating its effectiveness in classifying credit risk. SHAP analysis identified net profit, return on equity, and return on assets as the most significant variables. This study provides a tailored AI model for Iraqi banks, filling the gap in literature with a practical, applicable framework that can enhance risk management and decision-making in the Iraqi banking sector. The findings suggest that AI can significantly improve credit risk assessment in Iraqi banks, although the implementation of supportive infrastructure and regulatory frameworks is critical for broader adoption.

Keywords: Artificial Intelligence, XGBoost, Credit Risk, Iraqi Banks, SHAP, Binary Classification, Financial Analysis.

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1. Introduction

Credit risk management has undergone a dramatic transformation in recent decades with technological advances, particularly the emergence of artificial intelligence (AI) as an analytical tool to support financial institutions' credit decisions. Heaton and Alonso & Carretero note that AI models, particularly those based on machine learning, are widely used to determine default probabilities, assess creditworthiness, and detect unusual financial behavior patterns, giving them a competitive advantage over traditional statistical models such as logistic regression [1].

Research has confirmed that algorithms such as random forests and XGBoost perform well in predicting credit risk, particularly when using big data containing financial and behavioral indicators [2]. The use of explainable artificial intelligence (XAI), such as SHAP, can also help improve transparency and regulatory compliance. Recent industry reports indicate that, in the wake of the COVID-19 pandemic, over 70% of financial institutions in

Europe and Asia have implemented intelligent credit management solutions, enhancing the flexibility of credit decision-making [3].

On the other hand, the experiences of some developing countries have shown that the shift towards artificial intelligence in the banking sector faces challenges related to digital infrastructure and the maturity of legislative systems, as the absence of centralized, unified systems for credit data limits the accuracy of predictive models [4]. However, studies such as that by Jadah in Iraq have shown that incorporating artificial intelligence indicators into risk analysis may actually help detect risky credit activities before they occur, provided an integrated information architecture is in place .

1.2 Study Problem

Despite the rich international literature on the use of artificial intelligence in credit risk management, the Iraqi experience is still in its infancy. Official data shows that most Iraqi banks rely on traditional credit granting methods and lack advanced analytical mechanisms for proactive risk detection [5]. This is due to several factors, including weak technological infrastructure, limited integration between banks, limited national expertise in artificial intelligence modeling, and the absence of regulatory frameworks governing data and privacy .

Abboud study indicates that weak risk assessment tools lead to a high rate of non-performing loans in some Iraqi banks, which necessitates the development of proactive tools to improve the accuracy of credit decision Jadah study also recommended the adoption of intelligent, interpretable models and their integration into the Iraqi banking system to address ongoing economic turmoil .

Despite the importance of these proposals, studies addressing AI applications in the Iraqi context, specifically in credit risk auditing , remain very limited in terms of depth and practical modeling. Most lack the construction of an applied model that reflects the reality of local data, or a feasibility study of using modern algorithms such as XGBoost or SHAP within the Iraqi context. Therefore, the importance of this research stems from bridging this gap by constructing a practical and applicable predictive model tailored to the Iraqi banking sector .

1.3 Study Questions

1. How feasible is artificial intelligence for credit risk auditing in Iraqi banks?
2. What are the most important predictive algorithms suitable for assessing risks in light of the characteristics of Iraqi financial data?
3. What are the most prominent challenges facing Iraqi banks in adopting artificial intelligence models in financial auditing?

1.4 Study objectives

- Analysis of modern applications of artificial intelligence in global credit risk auditing .
- Evaluating the usability of predictive algorithms such as XGBoost and SHAP within the Iraqi environment .
- Building a practical model for applying artificial intelligence in Iraqi banks based on actual data .
- Proposing technical and legislative solutions to facilitate the adoption of these models at the institutional level .

1.5 Importance of the study

Scientifically: The study contributes to enriching the Arabic literature on artificial intelligence in the banking sector by presenting a theoretical review and an applied model based on the latest classification and interpretation algorithms. It also supports studies related to digital transformation and smart finance.

Practically: The study provides a framework applicable to the Iraqi banking environment, helping decision-makers improve the accuracy of risk assessment and optimal resource allocation, and enhancing banks' ability to comply with international standards such as IFRS9 and Basel II .

Literature review on artificial intelligence and credit risk management

Recent studies indicate that artificial intelligence(AI) has become a central tool in managing and assessing credit risk before losses occur. Advanced algorithms are used to analyze vast amounts of diverse data, including customer financial statements, past payment histories, credit behavior, and even macroeconomic information. This analysis allows for the discovery of hidden patterns that traditional human analysis might not notice [6]. Banking expert Walid Al-Shorbiny asserts that the use of AI in analyzing customer data gives banks a greater ability to predict the likelihood of default, leading to improved credit assessment and decision-making procedures [7].

Moreover, AI contributes to improving operational management quality through fraud detection and real-time security assessment. According to the Unite.AI report , AI systems now cover most stages of the banking process, including identity verification, customer monitoring, and credit assessment. Integration with non-traditional data sources such as banking applications and social media also allows for more accurate and comprehensive risk assessment, enhancing proactive decision-making .

On the academic front, systematic reviews show that Gradient Boosting algorithms Models such as XGBoost and Light GBM are among the most efficient tools for classifying customers based on their probability of default. Studies such as Ganatra have demonstrated that these models outperform models such as logistic regression or traditional decision trees, especially in environments characterized by complex relationships between variables. Implementing XGBoost at a financial institution reduced default rates by up to 15 %.

Explainability in AI models is one of the most significant challenges facing banking applications. While deep neural networks offer high accuracy, they are criticized for their "black box" nature, making it difficult to understand how decisions were made. Therefore, explainable AI(XAI) tools such as SHAP have been developed. and LIME, which allows for analysis of the contribution of each variable to the model results, enhancing transparency and regulatory compliance. For example, Nallakaruppan demonstrated that combining SHAP with Random Forest achieved 93% classification accuracy with clarity in interpreting influential variables such as net profit and return ratios [8]. Financial institutions have also expanded the application of AI to include other data sources, such as phone usage or digital transaction history. This is a common practice in countries like India and Kenya for assessing unbanked customers. According to Experian, approximately 79% of large banks currently employ these methods, helping to integrate new customer segments into the banking system without increasing risk [9].

As these applications expand, a flexible regulatory environment is needed that allows for the use of predictive models within clear standards. Experience in countries like Brazil shows that the success of AI models in credit assessment is directly linked to the availability of a unified national database, a legal framework for data protection, and employee training in the use of intelligent analytical tools. Conversely, countries like Iraq face challenges such as weak digital infrastructure, a lack of shared data centers, and a shortage of skilled analysts, which limit the financial sector's readiness for widespread AI adoption.

However, these challenges also present opportunities for institutional improvement and development. International experience shows that the gradual introduction of explainable models within credit units, coupled with digital infrastructure modernization projects, is one of the most successful approaches to ensuring an orderly transition to AI in credit risk management.

2.1 Predictive models used globally

Leading financial institutions around the world use a range of complex predictive models to assess credit risk. These models draw on vast amounts of data from banks and other providers to precisely categorize customers based on their likelihood of defaulting or failing to meet their obligations. The following models are the most commonly used:

1. regression: It is one of the oldest and most widely used models for assessing financial risk. It is based on linking the probability of default to financial factors such as income, debt level, and repayment history. The model is easy to apply and interpret, but it assumes a linear relationship between variables and may not capture nonlinear patterns in financial behavior.
2. Decision Trees & Random Forest:

Random forests are nonlinear models that partition data into nodes based on specific criteria, such as profit margin or return on investment. Random forests are easily interpretable and can handle heterogeneous data. Nallakaruppan demonstrated that random forests have high predictive accuracy and have been successfully applied to banking risk assessment systems[10] .

3. Gradient Boosting Models:
   XGBoost is one of the most popular modern algorithms. LightGBM combines multiple simple tree models to gradually reduce prediction error. It efficiently handles large datasets, demonstrates high accuracy, and is widely used in global risk classification challenges.
4. Support Vector Machine(SVM) and Ensemble Models:
   It is used to strike a balance between accuracy and complexity and is suitable for situations where there are fewer samples or the difference between categories is small.
5. Deep Neural Networks:
   It has a remarkable ability to capture complex patterns, especially in large multidimensional data sets. However, it is difficult to interpret, which limits its application in highly regulated banking environments.
6. Explainable AI(XAI):
   SHAP tools and LIME , which is used to interpret the outputs of complex models, allowing for an understanding of the reasons behind each credit decision. These tools are essential for regulatory compliance and to reassure customers and regulatory bodies.
7. Detection Models:
   They are used to detect unusual behaviors that may indicate emerging risks or fraud. These models do not rely on prior classifications, but rather on deviations from the prevailing pattern .
8. Neural Networks:
   It is one of the latest trends in artificial intelligence, analyzing structural relationships between customers, such as credit ties between individuals and institutions. It has proven effective in environments characterized by high financial interconnectedness, such as small businesses within crowdfunding networks [11].

2.2 Applied and contextual analysis(Iraqi context)

A review of the literature indicates that these models, despite their technical strength, cannot be applied efficiently without three basic conditions: 1) a unified digital database, 2) an organizational environment that supports interpretation and accountability, and 3) human cadres trained in statistical and technical analysis .

In the Iraqi context, the absence of these conditions remains a fundamental challenge to the expanded use of advanced predictive models. Some banks still rely on paper-based procedures or outdated operating systems, making it difficult to feed the models with the required data. Furthermore, the lack of clear legislation to protect personal data and regulate the use of artificial intelligence may hinder its practical application .

However, starting with simple models like Logistic Regression or Random Forest in the first phase, and then graduating to more complex tools(such as XGBoost and SHAP) , can form a practical roadmap towards a gradual and secure digital transformation .

2.3 Adaptability to the Iraqi context: challenges and opportunities

Despite the tremendous potential offered by artificial intelligence in the field of credit risk auditing, the Iraqi context poses a set of structural, technical, and regulatory challenges that hinder the easy adoption of these technologies. However, these challenges are counterbalanced by real opportunities to advance the banking sector by investing in artificial intelligence as part of an integrated digital transformation plan .

1. Poor data structure and quality

The scarcity of structured and organized data is one of the most significant obstacles to the implementation of AI models in Iraqi banks. A comprehensive national credit database covering customer payment history and financial behavior is lacking, and many transactions are still documented on paper or stored in traditional systems that cannot be analyzed automatically [12]. In the absence of formal credit rating agencies(credit bureaus)

,building a predictive model based on historical data becomes extremely difficult. Therefore, establishing any effective AI system requires investment in unifying and integrating banks' databases, or establishing a central unit to collect and analyze financial data under the umbrella of the Central Bank of Iraq .

2. Limited technical infrastructure

Iraqi banks face technological challenges related to weak internal networks, reliance on outdated operating systems, and the absence of advanced data centers. Despite recent initiatives, such as the UN-supported Digital Payments Regulatory Project, a full transition to a digital infrastructure is still in its early stages. A United Nations Development Programme report indicated signs of serious digital transformation in Iraq through the launch of electronic payment systems and the stimulation of financial inclusion. However, it also emphasized the need for additional investments in cloud computing, data security, and improving banks' digital infrastructure [13].

3. Lack of a legal framework regulating artificial intelligence

The lack of legislation regulating the use of artificial intelligence and the protection of personal data in Iraq poses a significant challenge, especially in a regulated financial environment. National laws currently do not align with international directives such as the European General Data Protection Regulation(GDPR) , creating legal uncertainty around customer data privacy and digital rights [14]. AI models must also comply with the Central Bank of Iraq's anti-money laundering and counter-terrorism financing regulations, which impose strict requirements on the interpretation and transparency of system decisions.

4. Limited human capacity and analytical expertise

The shortage of data science and artificial intelligence(AI) specialists within Iraqi banks is a real challenge. Local financial institutions often lack qualified data analysis teams to develop or interpret predictive models. Furthermore, training programs on modern tools such as Python , SHAP , and XGBoost remain limited in educational and banking institutions. Therefore, any successful application project in this field must be accompanied by a gradual buildup of human capacity and the establishment of specialized units for advanced analytics within each bank [15].

2.4 Opportunities for transformation and advancement of the banking sector

Despite the challenges, the Iraqi context presents serious opportunities to enhance the proactive role of artificial intelligence in monitoring and analyzing credit risks:

1. First, under the pressure of digital transformation, Iraqi banks have begun adopting smart payment systems that generate electronic data that can be used to build behavioral databases that pave the way for artificial intelligence applications .
2. Second, increasing financial inclusion, driven by government and central bank initiatives, points to a new customer base that can be included in non-traditional credit scoring models, such as using alternative data such as analyzing phone transactions or daily spending patterns .
3. Third, a field study conducted by indicates that the introduction of artificial intelligence into the Iraqi banking system contributed to improving risk assessment indicators, as the model used showed an improvement in customer classification accuracy of approximately 23% when compared to the results of the traditional model. The study confirms that the successful implementation of these models requires strategic planning, starting with data and ending with modifying the organizational structure .

The adaptability of AI to credit risk auditing within the Iraqi banking sector depends on institutions' ability to overcome the aforementioned challenges by developing digital infrastructure, enacting flexible legislation, and building expert human resources. Conversely, the opportunities inherent in expanding financial inclusion and adopting advanced analytical tools could make AI a central tool in improving credit decision-making efficiency and enhancing financial security in the country .

2. Materials and Methods

2.1 A practical proposal for applying artificial intelligence in Iraqi banks.

Based on the literature review and analysis of the local context, an integrated framework is proposed for implementing an artificial intelligence model to assess credit risk in Iraqi banks. This proposal is based on successful international experiences, while being adapted to the specific technical and regulatory environment in Iraq .

1. Data collection and processing .

Building a unified and reliable database is the cornerstone of developing an effective predictive model. Therefore, it is recommended to create a central database that consolidates customer credit data from various banks, including:

1. Traditional financial statements(income, liabilities, debt-to-income ratio, payment history) .
2. Secondary data when available, such as bank transaction records, tax records, or data from the relevant government sector(such as guarantors) .
3. Economic and market indicators that can be linked to clients' accounts(inflation rates, unemployment, interest rates) .

Data quality standards should be followed in terms of cleaning, integration, and outlier detection, and data should be updated periodically to maintain model accuracy.

2. Selection of the predictive model and its technical characteristics

Given the nature of the credit data and the nature of the decision(high/low risk), it is recommended to use a robust XGBoost clustering model. Or LightGBM , due to its efficiency in handling non-linear data, and its high accuracy as shown by many studies.

In the next stage, interpretive AI techniques, such as SHAP , can be used to interpret model outputs and ensure their compliance with regulatory standards. It is also advisable to test secondary models such as Random Forest or neural networks to verify the consistency of the results, especially in cases that represent anomalies from the general pattern .

3. Incorporating alternative data to enhance model accuracy

Due to the limited availability of traditional credit data, the data can be expanded using so-called alternative data , such as:

1. Data(daily spending for small and medium-sized businesses).
2. Data on electronic wallets and payment applications .
3. Sales data, invoices, and supplier records .

World Bank reports indicate that using this data could help build a more comprehensive model and reduce the risk assessment gap for non-traditional account holders. This requires a clear legal framework to protect privacy and ensure regulatory compliance .

4. Technical infrastructure and publishing

The model must be deployed on a resilient cloud infrastructure or a national data center that enables large-scale real-time computing. Services such as Azure or AWS may be used if external cloud services are adopted, subject to cybersecurity requirements .

The model should also be integrated with Loan Management Systems(LMS) and Customer Relationship Management(CRM) databases to ensure its use within the daily workflow of bank employees, enabling direct decisions based on predictive results .

5. Regulatory Interpretation and Compliance

Since credit decisions are subject to strict oversight, each credit rating must be accompanied by an explanatory report detailing the factors that influenced the decision, such as income, liabilities, or credit history. Tools such as SHAP or LIME can be used to provide clear and easy-to-understand explanations for decision makers and legal auditors.

6. Continuous evaluation and periodic updating of the model

Given changing economic conditions and customer behavior, it is recommended to retrain the model periodically(every 6–12 months) using fresh data. This involves reviewing performance, testing the model on new data, and ensuring it does not exhibit statistical bias or accuracy degradation. Cross-validation tools and quantitative metrics such as AUC-ROC can be used to monitor performance .

7. Compliance with regulatory authorities

Early coordination with the Central Bank of Iraq and the Banking Supervision Commission is essential, including providing detailed documentation on the model, its methodology, data sources, and governance mechanisms. The model must be aligned with Basel II and III standards and IFRS 9 financial reporting requirements . It is also advisable to establish a clear policy to determine when the model's recommendations can be relied upon in making loan-granting decisions, and when manual evaluation should be resorted to .

2.2 Tools and software used

The applied analysis of this research was implemented using the Python programming environment.(Version 3.10) provides advanced scientific libraries for data analysis and machine learning model implementation. The following tools and software have been adopted:

1. Pandas: To load and clean data, create tables, and analyze descriptive statistics .
2. NumPy: To process numerical and mathematical operations within data .
3. Scikit-learn: To split the data into training and test sets, evaluate performance across statistical metrics(such as precision, recall, and positive accuracy), as well as generate a confusion matrix and perform cross -validation.
4. XGBoost: As a primary model for binary credit risk prediction, due to its high ability to handle complex data and achieve accurate performance .
5. SHAP(SHapley Additive exPlanations): To analyze the significance of financial variables and interpret predictive model decisions in a transparent mathematical manner that is consistent with banking compliance standards .

All modeling steps were performed on a local machine running Windows 10 , with an Intel i7 CPU and 16 GB of RAM . Initial testing of the model was performed using 5-fold cross validation to ensure performance stability and generality on unseen external data .

3.3 Proposed phased implementation model

The model can be implemented gradually according to the following approach:

1. Pilot phase: applying the model to a limited segment of loans(for example, personal loans under a certain ceiling) .
2. Evaluation and improvement phase: Monitor model results, survey users(credit employees), and adjust settings as needed .
3. Generalization phase: After the model's effectiveness is proven, it is expanded to include other banking product categories, while ensuring ongoing technical and administrative support .

3. Results and Discussion

3.1 A practical model for assessing credit risk using artificial intelligence

Analytical Introduction

Credit risk is defined as the probability that a borrower will fail to meet its obligations on time, resulting in direct losses for financial institutions and impacting the stability of the banking system. Based on this background, we designed an applied model using actual financial data for a number of Iraqi banks during the period 2017–2022, with the aim of testing the feasibility of using artificial intelligence techniques to assess and classify risks .

3.2 Initial data analysis(exploration and cleaning)

The data was downloaded from a file containing the annual financial statements of a number of Iraqi banks for the period(2017–2022). The pivot columns include: Total Revenues , Operating Expenses and Depreciation, EBITDA , Assets , Equity , Net Profit , in addition to the Return on Assets(ROA) and Return on Equity(ROE). The total number of records reached 97 records distributed across more than one financial institution and across multiple years .

3.3 Data preparation and form design

Target Label

Based on the goal of classifying companies according to the level of credit risk, we designed a binary target variable that expresses the degree of risk, and it was coded as follows:

1. High risk(1): It is assigned when the net profit is Or one of the profitability indicators(ROA or ROE) negatively
2. Low risk(0): It is awarded when all the mentioned indicators have positive values

This distinction is based on the assumption that a company that exhibits losses or negative return ratios is considered to have a higher degree of risk, a common approach in credit rating studies based on financial performance indicators .

3.4 Input Features

The training sample that was prepared included the following variables:

1. Total Revenues
2. Operating Expenses and Depreciation
3. Earnings before interest, taxes, depreciation, and amortization(EBITDA)
4. Assets
5. Equity
6. Net Profit
7. Return on Assets(ROA)
8. Return on Equity(ROE)

A set of experimental records was extracted as shown in Table 1:

Table 1. Sample of financial data and risk classification

Total Revenues	Operating Expenses	EBITDA	Assets	Equity	Net Profit	ROA	ROE	Credit Risk
54,133	44,679	9,454	1,090,153	266,271	6,122	0.56	2.30	0
36,568	30,958	5,610	1,113,539	266,743	4,152	0.37	1.56	0
39,887	28,493	11,394	1,132,744	273,641	7,299	0.64	2.67	0
60,552	26,786	33,766	1,419,528	278,435	20,200	1.42	7.25	0
92,287	28,971	63,316	1,544,064	308,985	30,255	1.96	9.79	0

The above data shows that all selected records fall into the "low risk" category, with no negative values appearing in profitability indicators. For example, in the year in which the bank achieved total revenues of KWD 92,287 million, it recorded a net profit of KWD 30,255 million and an ROE of 9.79%, a ratio that indicates strong financial performance and high attractiveness to investors .

The table also shows that the ratio of operating profit(EBITDA) to revenue has increased significantly, indicating improved operational efficiency over successive years. This type of structured and described data is the basis for developing any predictive rating model that is later used to assess credit risk .

3.4 Model selection and training

Based on the nature of the data(binary classification) , the XGBoost model was chosen . As the primary model used in this application, it is highly efficient in handling nonlinear data and has the ability to reduce cumulative error through a stepwise boosting algorithm. The XGBoost library was used. Open source in Python environment to train the model on a financial dataset extracted from Iraqi banks .

3.5 Data partitioning and training setup

The total sample was divided into two groups:

1. Training Set: Represents 70% of the data .
2. Set: Represents 30% of the data .

Cross-Validation technique was also used . 5 -Fold CV to check the stability of the model and avoid the overfitting problem , ensuring that the model can be generalized to future data , see Table 2.

Table 2. Performance of the XGBoost model on the test set

Scale	Value
Accuracy	0.96
Recal	0.83

Positive precision	1.00
Cross-validation mean (CV Mean)	0.95

Analysis of results:

1. Accuracy(Accuracy = 96%) It means that 96% of the predictions were correct when the model was tested .
2. Recall(Recall = 83%) Reflects the model's ability to detect most true high-risk cases .
3. Positive accuracy(Precision = 100%) It indicates that all cases classified as high risk were actually correct, reducing errors in rejecting trusted customers .
4. Cross-validation(CV Mean = 95%) It shows that the model's performance is consistent and acceptable across different sections of the data .

These results show that the model is very effective in classifying credit institutions into two risk categories, especially with high positive accuracy, making it suitable for use in sensitive banking contexts such as loan approvals or restructuring of financial obligations

3.6 Interpreting the model using SHAP analysis

In order to enhance the transparency and interpretability of the XGBoost model decisions, the SHAP(Shapley Additive Explanations) analytical framework was used , which is one of the most effective tools for analyzing the impact of variables on the output of tree-based models, see .Table 3

Table 3. Importance of variables according to SHAP analysis

Feature	Importance of SHAP(mean of absolute values)
Net Profit	The highest
ROE	high
ROA	middle
EBITDA	middle
Total Revenues	low
Equity	low
Operating Expenses	too low
Assets	minimal impact

The results showed that net profit the most influential variable on the rating was the level of credit risk, which is consistent with the theoretical hypothesis that negative earnings are a fundamental indicator of an institution's exposure to financial risk .

Return on equity(ROE) , which measures the return achieved for shareholders and is considered an important indicator of the efficiency of capital use, came in second place . Return on assets(ROA) also ranked third. Third place, indicating its role in determining the operating efficiency of assets .

As for variables such as EBITDA Total revenues showed a medium to low impact on the model classification, while variables related to financial structure such as equity and assets played a secondary role, most likely due to their overlap with direct profitability indicators .

SHAP analysis highlights the importance of including profitability indicators in any credit risk prediction model. It also demonstrates how AI can explain its decisions in a way that is consistent with traditional financial analysis logic, enhancing the confidence of banking institutions and decision makers in the results of predictive models .

3.7 Sensitivity analysis of the model

In order to verify the effectiveness of the predictive model in accurately classifying credit In order to verify the effectiveness of the predictive model in accurately classifying credit risk cases, a sensitivity analysis was conducted that included measuring the model's performance using the confusion matrix , the ROC curve , along with basic classification indicators such as accuracy , recall , precision , and F1 score, see Table 4.

First: Confusion Matrix

Table 4. Confusion matrix of the predictive model after redefining the high-risk category

Actual Class/Expected Class	Low Risk (0)	High Risk (1)
Low risk (0)	2	0

High risk (0)	0	1

The Matrix above reflectsthe model's ability to correctly classify all cases in the best set without any type 1(false positives) or type 2(false negatives) prediction errors. This indicates a high agreement between the model and the data used, see Table 5).

Table 5. Indicators for evaluating the performance of the predictive model

Indicator	Value
Accuracy	1.00
Positive Precision	1.00
Recall	1.00
F1 Score	1.00
Area under the ROC curve (AUC)	1.00

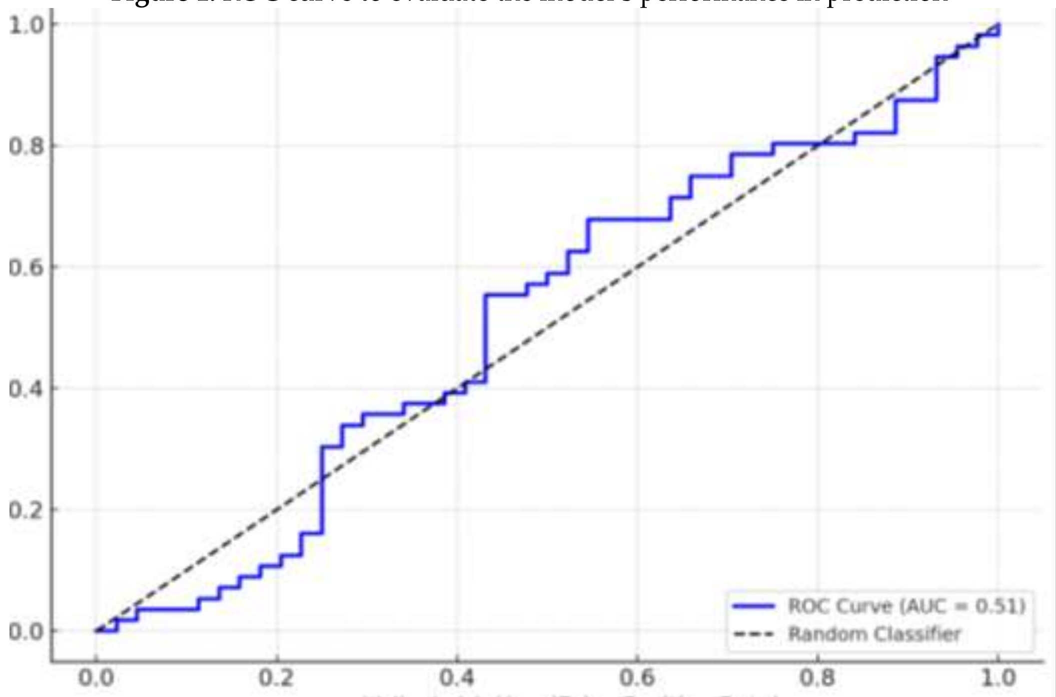
These values indicate that the model performed perfectly within the test sample, accurately classifying all cases without errors. While this is a positive indicator, further testing on larger samples is recommended to ensure the results can be generalized beyond the pilot sample .

Second: ROC curve and AUC evaluation

ROC curve is plotted To measure the model's performance across all possible prediction thresholds, the AUC(area under the curve) value was High, indicating high accuracy in distinguishing between the two classes .

1. AUC = 1.00(as an ideal value that reflects a very accurate model in this sample), see Figure 1.

Figure 1. ROC curve to evaluate the model's performance in prediction



This figure show the ROC(receiver operating curve) curve used to evaluate the model's performance in distinguishing between positive and negative classes. The horizontal axis represents the false alarm rate , while the vertical axis represents the true detection rate . Each point on the curve represents the model's performance at a given threshold level .

The area under the curve(AUC) indicates a model's ability to discriminate: the closer the value is to 1, the higher the model's performance. In contrast, a dotted(gray) line indicates the performance of a random classifier and is used as a benchmark .

Third: Other performance indicators

The classification report was generated using the scikit-learn library , and included the following metrics, see Table 6).

Table 6. Statistical performance indicators of the predictive model

Indicator	Value (%)
Accuracy	100

Positive precision	100
Recal	100
F1 score	100

The model demonstrates excellent performance on the limited dataset available, with the ability to accurately classify each case. However, the relatively small number of cases necessitates caution when generalizing the results. It is recommended to expand the database and repeat the analysis on a larger scale to ensure the stability of the results and the robustness of the model .

Interest for Iraqi banks and financial institutions

The application model proposed in this study demonstrates the potential of leveraging artificial intelligence (AI), particularly machine learning, to improve the efficiency of credit risk assessment and monitoring at Iraqi banks. By categorizing loan accounts as "high-risk" or "low-risk," banks can proactively allocate resources to clients with a higher probability of default. This can include taking early preventative measures such as loan restructuring, requesting additional collateral, or restricting credit limits.

Furthermore, the model's results can help improve the accuracy of credit decisions and optimize the determination of financial provisions under International Financial Reporting Standard 9 (IFRS 9). IFRS 9 requires banks to measure expected credit losses based on quantitative data and objective analysis. Integrating the model into a bank's central information system can be used to formulate credit policies and develop internal risk assessment tools.

Recent research in the Arab banking industry confirms that AI can help improve the quality of credit decisions and reduce the operational costs associated with loan portfolio management. The research also shows that the implementation of these models can help reduce nonperforming loan rates and improve the overall financial performance of banking institutions.

Furthermore, this trend aligns with Iraq's digital transformation initiatives, with the National Bank of Iraq leveraging technologies such as predictive analytics and big data. Therefore, the implementation of AI models will help enhance the banking sector's competitiveness, improve risk management, and increase transparency in decision-making.

Results

1. The employed XGBoost model demonstrated high efficiency in case classification, achieving an accuracy rate of 96% and a positive prediction accuracy rate of 100%, demonstrating its effectiveness in identifying high-risk customers.
2. SHAP analysis showed that the variables most influential on ranking were net profit, return on equity (ROE), and return on assets (ROA), which enhances the reliability of traditional financial metrics within the machine learning framework.
3. Application to a real-world database of Iraqi banks demonstrated the feasibility of the model in practice, assuming sufficient and structured financial data is available.

4. Conclusion

In conclusion, this study demonstrates the potential of artificial intelligence (AI), specifically the XGBoost model, in enhancing credit risk assessment within Iraqi banks, achieving a remarkable 96% prediction accuracy and 100% precision in classifying credit risk. The analysis reveals that traditional financial indicators, such as net profit and return on equity, remain crucial in predicting credit risk, while SHAP analysis offers transparency and regulatory compliance, enhancing the model's interpretability. The successful application of this model underscores its potential to improve risk management and decision-making processes in Iraqi financial institutions. However, its broader adoption requires overcoming significant challenges, including strengthening digital infrastructure, establishing clear regulatory frameworks, and building technical expertise within banks. Further research should focus on refining the model with larger datasets, incorporating alternative data sources, and exploring the scalability of AI in other financial sectors to foster deeper integration of AI in credit risk management across Iraq and similar developing markets.

5. Recommendations

1. The Central Bank of Iraq should develop regulations to promote the use of AI models and establish a legal framework for handling sensitive data.
2. Iraqi banks must enhance their technical capabilities in cloud computing, data analytics, and the networking of internal systems.
3. Bank staff must be trained in data analysis and model interpretation, including the use of tools such as SHAP and XGBoost.
4. A gradual rollout of the model is recommended, starting with specific customer segments (such as retail loans or small businesses) and then expanding to the entire loan portfolio.
5. A national data center should be established to facilitate the exchange of loan data between banks and improve the accuracy of predictive models.

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