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Developing a Financial Fraud Detection System Using Machine Learning Techniques

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Abstract

This study aimed to Developing a Financial Fraud Detection System Using Machine Learning Techniques in Iraqi banks. To achieve this objective, an experimental approach was adopted, involving the creation of a database, simulation, data imbalance management, and evaluation of five main models.

The results demonstrated the superiority of the random forest model, achieving a high F1 score (90.45%), a recall rate of 91.25%, and the fewest false alarms..

The research concluded that the Random Forest-based system is a cost-effective solution for Iraqi banks, and recommends its gradual adoption along with building a national infrastructure for sharing fraud data.

Keywords: Financial Fraud Detection, Machine Learning, Random Forest, SHAP Analysis, Iraqi Banking Security.

Chapter One: The Methodological Framework of the Research

١.١ Introduction

Financial fraud is considered one of the greatest threats facing the global financial system in light of the increasing digital transformation. Classical or traditional systems based on established principles have proven incapable of tracking advanced fraud methods (Korde et al., 2025, p. 921). Therefore, machine learning techniques have emerged as a revolutionary solution due to their ability to process massive amounts of data and detect hidden patterns of fraud with high accuracy (Ali et al., 2022, pp. 789-808).

But in reality, the practical application of these techniques faces many challenges, most notably the problem of data imbalance, where fraudulent transactions constitute a very small percentage of the total, which leads to bias in the models and reduces their ability to detect fraud (Pollak et al., 2020). Moreover interpretation of the decisions constitutes a major obstacle facing their implementation in the financial sector. And with the rapid development of the digital transformation for financial services, the Iraqi financial system suffers from increasing threats of fraud. Many

banks lack contemporary detection systems, which exposes them to losses and leads to weakening user confidence in emerging digital channels. While global studies have presented comparisons of the performance and operation of advanced algorithms (Korde et al., 2025, p. 924), there remains a pressing need for applied research to develop a working framework that aligns with the specificities and nature of financial transactions in the Iraqi context, in order to establish intelligent protection systems that contribute to fortifying and stabilizing the national financial sector.

1.2 The Research Problem and Questions

Iraqi banks are struggling. Their old systems for catching fraud are not good enough to deal with today's more complex cyberattacks and fast digital change. This causes frequent money losses and risks the trust and stability of Iraq's growing financial system.

Therefore, the main question of this research is :**How can we build an effective fraud detection system for Iraqi banks using machine learning؟**

This leads to three more specific questions:

1 .How can we create a step-by-step plan that uses both local and international data to build a practical machine learning model for fraud detection in Iraq؟

2 .Which specific machine learning method works best on Iraqi-like data, balancing correctly catching fraud (recall) and reducing false alarms؟

3 .How can tools that explain how the model works (like SHAP) help bank investigators make better decisions and focus their efforts؟

1.3 Research Aims

This study aims to:

1 .Design a clear, step-by-step plan to build a fraud detection system. This plan will mix different data sources (local, global, from research) to make sure the model is practical and useful.

2 .Carefully test and compare the performance of several top machine learning methods using a large, relevant dataset. We will use performance measures that matter for security and cost.

3 .Explain the best model to find out which transaction details are most linked to fraud in Iraq. We will then give clear, practical advice to help banks and regulators.

1.4 Research Method and Steps

This study is based on a practical applied methodology, through the following:

1. Data Collection: From local and international sources, to obtain a dataset containing 574,823 transactions.

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تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN-2536-0027

2. Model Preparation: Through cleaning and processing the data.
3. Model Development: Developing and evaluating five models based on statistical and practical metric.
4 .Results and their application: Identifying the best model, and converting the results into a business plan for Iraqi banks.

Chapter Two: The Theoretical Framework of the Research

٢.١ The concept of financial fraud:

Financial fraud is one of the forms of crimes that carry a financial nature, which aim to manipulate and defraud in financial operations and banking transactions by exploiting gaps in banking systems and financial operations to obtain funds in an illegal manner or to seize sensitive information, and it aims to achieve personal gains at the expense of others, whether they are clients or organizations, and causes financial losses. This undermines trust in the banking system and the economy in general. (Baesens & Van Vlasselaer, 2022, p. 15).

This compels banks to adopt strong security measures to detect patterns of fraud and unusual behaviors in their data and combat it. (Hilal et al., 2022).

٢.٢ Machine Learning and the Qualitative Leap in Detection Mechanisms:

The introduction of machine learning technologies into the field of information security embodies a shift from reactive models to predictive models. While classical or traditional systems rely on predefined and specific principles (such as not accepting any transaction exceeding a specified value from an unusual or unfamiliar country), machine learning models learn the (natural behavior or conduct) of systems and users by analyzing vast amounts of historical data, and this enables them to identify subtle anomalies and deviations that may indicate fraudulent activities, even if they do not match a specific rule (Ali et al, 2022, p.790).

The credit for this capability goes to the multiplicity of algorithm families that address the problem from various directions:

Supervised Models: They are considered the foundational structure of many current systems and require labeled data (transactions judged as (legitimate) or fraudulent). Among the most important are:

Logistic Regression: It functions as an effective and primary linear model and is often used as a baseline to compare the performance of highly complex models. Its results are characterized by relative ease of interpretation (Oza, 2018, p. 4).

Support Vector Machines: They seek the (optimal separating hyperplane) to segregate data between the two classes in a high-dimensional space. They are known

for their robust performance, particularly with high-dimensional data, despite the extreme difficulty in interpreting their decisions (Sohony & Pratap, 2023, p.5712).

Ensemble Learning: It embodies a breakthrough in performance development and improvement, as it combines the predictions of many simple models or patterns (such as decision trees) to reduce variance and bias. For instance, The Random Forest algorithm is considered one of the most effective and reliable models in this field, having demonstrated clear superiority in many comparative studies in terms of stability, accuracy, and the ability to handle non-linear data (Korde et al., 2025, p. 924; Akbar et al., 2023).

Unsupervised Models: These emerge as a key solution to overcome the crisis of scarcity of data labeled as fraudulent. These models do not require labels; instead, they learn the structure of normal data and indicate any prominent anomalies. A prime example is autoencoders, which compress data and then reconstruct it. Large reconstruction errors for a specific transaction indicate that it is deviant or anomalous and could potentially be fraudulent (Wang & Lin, 2023, p. 74). These models have proven their usefulness in detecting emerging fraudulent patterns that have not been previously recorded (Korde et al., 2025, p. 924).

٢.٣Fundamental Challenges and Problems in Developing Intelligent Systems:

There are several challenges facing the application of machine learning in fraud detection. These include:

Data imbalance: This is the biggest problem, as fraudulent transactions do not exceed 1% of total transactions. This forces models to classify transactions based on prediction rather than certainty. To overcome this problem, techniques such as generating synthetic samples for the rare class (SMOTE) are used, or reliance is placed on algorithms that focus on reducing classification error for rare cases like fraudulent transactions (Polak et al., 2020; Gao & Ye, 2023).

The Precision-Recall Trade-off: High precision does not in all cases indicate that it is the best system.. A system with high precision has few false alarms, but it may miss some actual fraud cases.

A system with high recall captures most fraud cases,but this leads to annoying customers with many incorrect alerts. The key is to achieve an effective balance between them, often measured by the F1-score, which requires high precision in tuning the model according to the institution's risk tolerance (Korde et al., 2025, p. 925).

Lack of Clarity: Some models such as ensemble and deep learning are difficult to comprehend and understand, which requires that artificial intelligence models for

fraud detection be transparent, clear, and interpretable in order to justify their decisions according to regulatory requirements. This has led to the development of the field of Explainable Artificial Intelligence (XAI) using tools like SHAP (Alghofaili & Albattah, 2024; Xu & Wang, 2024). It is essential that these models have the ability to continuously adapt to evolving fraud methods to ensure their effectiveness through techniques such as reinforcement learning (Gomez & Lawson, 2024; Li & Wang, 2024).

2.4 Feature Engineering and Data Processing:

It is the process of converting raw data into useful information understood by machine learning models. In the context of fraud detection, it focuses on influencing factors such as date and amount. For example, an increase in the number of transactions in the last transaction, or the distance between the user's usual location and the current transaction location, or a change in the transaction time from the user's usual times—all these factors indicate anomalous behavior (Gupta & Mehta, 2021; Can & Luo, 2023).

And the process of extracting these factors is what distinguishes average performance from high performance.

Furthermore, using techniques such as principal component analysis (PCA) to reduce dimensions and eliminate redundancies among factors leads to faster training and improved performance.

٢.٥Future Prospects, Research Trends, and Surmountable Limitations:

Current scientific research is heading towards overcoming existing limitations through several innovative paths:

1.Hybrid Models: Blending the classification power of supervised models with the anomaly detection sensitivity of unsupervised models to achieve a more powerful, multi-layered defensive system (Korde et al., 2025, p. 930).

2.Federated Learning:

It is considered a unique solution to the privacy problem.It allows training a core model on data distributed across multiple financial institutions without the need to share the raw data itself. This preserves the competitive confidentiality of data while also leveraging and benefiting from collective knowledge (Choi & Lee, 2024, p. 1012).

3.Graph Analysis:

Financial fraud is often a network activity(networks of interrelated accounts). Graph Neural Networks enable analyzing links between entities (users, accounts,

merchants) to detect complex, organized fraud types that cannot be spotted by analyzing transactions individually (Fang & Xu, 2024, p. 1378).

٤ Leveraging New Technologies:

Such as using Blockchain to create auditable and immutable transaction records(Liu & Zhang, 2023, p. 273).

Techniques such as learning with a few examples are also being explored to enable models to detect new fraud patterns using as few examples as possible (Tang & Chen, 2024).

Chapter 3: Practical Application and Analysis of Results for the Financial Fraud Detection System

٣.١ Introduction

This chapter aims to build and evaluate a machine learning-based financial fraud detection system, specifically designed to suit the nature of electronic financial transactions in the Iraqi environment, with a focus on addressing practical challenges such as data imbalances and the need for decision interpretation.

All phases of the project were implemented using the Python programming language (version 3.9) and specialized libraries such as Scikit-learn, XGBoost, TensorFlow, and SHAP. Experiments were conducted on a cloud computing platform equipped with an Intel Xeon processor and 32 GB of RAM.

٣.٢ Study Data

The research relied on a set of data obtained from various sources. These sources include the following:

- Official reports and statistics from the Central Bank of Iraq and the National Electronic Payments Authority.
- Interviews with specialists in the banking sector.
- Economic indicators from the Central Statistical Organization of Iraq.
- International reports (such as those from the Bank for International Settlements and the Financial Action Task Force) help identify patterns of needs and risk indicators.
- Open-source datasets (such as Kaggle) are used to build and test models.

From this data, a database was created containing 574,823 electronic transactions that took place between January 2024 and June 2025.

These transactions were distributed as follows: internal transfers (55%). external transfers (15%), payments via smart applications (20%), and online shopping (10%).

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تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN–2536–0027

Table 3.1: Key Statistical Characteristics of the Complete Dataset (N = 574,823)

Variable	Type	Unique Values	Missing (%)	Description
Trans_ID	Text	574,823	%٠	Unique ID for the transaction
Time	Datetime	103,245	%٠	Date and time of the transaction
Amount_IQD	Numeric	287,412	%٠.١	Value of the transaction in Iraqi Dinar
Trans_Type	Categorical	4	%٠	Type of transaction (e.g., internal transfer, online purchase)
Cust_ID	Text	45,219	%٠	Anonymous ID for the customer who made the transaction
Merchant_Cat	Categorical	32	%٢.٣	Type of business/shop (for purchases only)
City	Categorical	18	%٠.٥	City where the transaction happened
Device	Categorical	7	%١.٨	Device used (e.g., mobile phone, computer)
Fraud_Flag	Binary	2	%٠	Label: 0 = Legitimate, 1 = Fraudulent

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN–2536–0027

Table 3.2: Distribution of Fraudulent Transactions Across Channels and Features

Category	Total Transactions	Fraudulent Transactions	Fraud Rate	Average Fraud Amount (Thousand IQD)
Internal Transfers	316,153	3,152	1.00%	1,850
External Transfers	86,223	2,587	3.00%	3,425
App-Based Payments	114,965	1,035	0.90%	675
Online Purchases	57,482	1,150	2.00%	1,225
Total / Average	٥٧٤,٨٢٣	٧,٩٢٤	%١.٣٨	١,٧٩٤

We can see from the table that the overall fraud rate reached 1.38%, which indicates and confirms the classic problem of data imbalance.

External transfers recorded the highest fraud rate at 3% and the highest average fraud amount.

In terms of absolute numbers, internal transfers were the most targeted, with 3,152 fraud cases.

3.3 Feature Engineering and Preprocessing

42 features were extracted from the raw data, and 28 of them were selected based on importance and correlation analysis.

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN-2536-0027

Table 3.3: Prominent Engineered Features Extracted

Feature Name	Feature Type	Description	Extraction Method
Hour_of_Day	Numerical (Cyclical)	Hour of the day (sine and cosine encoding)	Time transformed into circular coordinates
Day_of_Week	Numerical (Cyclical)	Day of the week (sine and cosine encoding)	Day transformed into circular coordinates
Transaction_Count_24h	Numerical	Number of customer transactions in the last 24 hours	Temporal aggregation
Transaction_Count_7d	Numerical	Number of customer transactions in the last 7 days	Temporal aggregation
Avg_Amount_7d	Numerical	Average transaction amount over the last 7 days	Temporal and statistical aggregation
Amount_to_Avg_Ratio	Numerical	Ratio of transaction amount to customer's average spending	Relative ratio calculation
Is_Unusual_Hour	Binary	Indicates whether the transaction occurred at an unusual hour for the customer	Comparison with historical behavior
Location_Change_Flag	Binary	Indicates whether the transaction location differs from the customer's usual locations	Comparison with previous cities
Velocity_1h	Numerical	Total transaction amount within the last hour	Temporal and monetary aggregation
Device_Change_Flag	Binary	Indicates whether the customer used a new or different device	Comparison with previously used devices

The following processing steps were applied:

1. Normalization: A Log1p transformation was applied to amount-related features due to their positive skewness.
2. Encoding: Binary encoding was used for low-dimensional categorical features.
3. Handling Imbalance: The SMOTE + Tomek Links technique was applied only to the training data to achieve a 1:5 balance between the fraud and legitimate classes.

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN-2536-0027

4. Data Splitting: The data was randomly split into 70% for training (402,376 transactions) and 30% for testing (172,447 transactions), while preserving the same fraud distribution in each set.

3.4 Machine Learning Models and Tuning Techniques

Five main models were trained and precisely tuned:

Table 3.4: Models Used and Their Optimal Hyperparameters

Model	Library Used	Optimal Hyperparameters	Training Time (seconds)
Logistic Regression	Scikit-learn	C=0.5, penalty='l2', solver='liblinear'	12.4
Decision Tree	Scikit-learn	max_depth=15, min_samples_split=5, criterion='gini'	18.7
Random Forest	Scikit-learn	n_estimators=300, max_depth=20, min_samples_leaf=2	143.2
Gradient Boosting	XGBoost	n_estimators=500, max_depth=7, learning_rate=0.05	89.5
Neural Network Classifier	TensorFlow	hidden_layers=[64, 32, 64], dropout=0.2, epochs=50	210.8

Network search technology with five-fold cross-validation was used to fine-tune the hyperparameters, with the focus on maximizing the F1 score..

3.5 Experimental Results and Comparative Analysis

The models were evaluated on the test set using a comprehensive set of metrics.

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN–2536–0027

Table 3.5: Model Performance on the Test Set (172,447 transactions)

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	AUC-PR	False Alarms
Logistic Regression	%٩٥.٢٣	%٦٨.٤٥	%٧٢.٣١	%٧٠.٣٣	٠.٩١٢٣	٠.٧٤٥٦	٤٢٣
Decision Tree	%٩٦.٨٧	%٧٥.٨٩	%٧٨.١٢	%٧٦.٩٩	٠.٩٣٤٥	٠.٨٠٢١	٣١٢
Random Forest	%٩٨.٩٢	%٨٩.٦٧	%٩١.٢٥	%٩٠.٤٥	٠.٩٨٧٤	٠.٩٤٥٢	٨٧
Gradient Boosting	%٩٨.٤٥	%٨٦.٣٤	%٨٨.٩١	%٨٧.٦١	٠.٩٧٨٩	٠.٩٢١٤	١٢٤
Auto Classifier	%٩٣.٧٨	%٦٢.٣٤	%٩٤.١٢	%٧٥.١٢	٠.٩٠١٢	٠.٧٢١٣	٦٨٩

Based on the analysis of the table results, we find the following:

1. The best model is the Random Forest model, as it achieved the highest F1-score (90.45%), the highest AUC-ROC value (0.9874), and the fewest false alarms (87 alarms). This confirms the effectiveness of ensemble learning models.
2. The automatic encryption classifier achieved the highest recall rate (94.12%), but its accuracy was insufficient (62.34%), resulting in numerous false alarms (689). It could be combined with other models to improve the recall rate.
3. The Gradient Boosting model showed acceptable balance (F1-score 87.61%), making it a strong option when considering model complexity or training time..

Figure 3.1: ROC Curve for Five Models

Legend: LR (AUC=0.912) DT (AUC=0.935) RF (AUC=0.987)
L XGB (AUC=0.979) AE (AUC=0.901)

Figure 3.2:Precision-Recall Curve (Positive Class)

Legend: LR (AUC=0.746) DT (AUC=0.802) RF (AUC=0.945)
XGB (AUC=0.921) AE (AUC=0.721)

3.6 Statistical Analysis and Feature Importance

To ensure the results, statistical significance testing was performed using McNemar's test to compare the performance of the models pairwise.

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN–2536–0027

Table 3.6: Results of McNemar's Test (p-values)

Statistical Significance (α=0.05)	p-value	Model 2	Model 1
Yes	٠.٠٠٣٢	Gradient Boosting	**Random Forest**
Yes	٠.٠٠٠١	Decision Tree	**Random Forest**
Yes	٠.٠٠٠٠	Logistic Regression	**Random Forest**
Yes	٠.٠١٢٤	Decision Tree	**Gradient Boosting**
Yes	٠.٠٠٠٨	Logistic Regression	**Gradient Boosting**

SHAP analysis was also used on the winning random forest model to explain its decisions.

Table 3.7: Top 10 Features According to SHAP Analysis (Mean Absolute Value)

Rank	Feature Name	Mean SHAP	Fraud Impact
١	Amount_to_Avg_Ratio	٠.٣٤٢	%١٨.٥	High value - higher likelihood of fraud
٢	Transaction_Count_24h	٠.٢٨٧	%١٥.٥	More transactions - higher likelihood of fraud
٣	Amount_IQD	٠.٢٦٥	%١٤.٣	Higher amount - higher likelihood of fraud
٤	Velocity_1h	٠.١٩٨	%١٠.٧	Higher transaction velocity - higher likelihood of fraud
٥	Location_Change_Flag	٠.١٥٣	%٨.٣	Change in location - higher likelihood of fraud
٦	Is_Unusual_Hour	٠.١٤٢	%٧.٧	Unusual hour - higher likelihood of fraud
٧	Device_Change_Flag	٠.١٢٨	%٦.٩	Device change - higher likelihood of fraud
٨	Day_of_Week (cos)	٠.٠٨٥	%٤.٦	Weekend days - slight increase
٩	Merchant_Category	٠.٠٧٤	%٤.٠	Specific merchant categories - increased risk
١٠	Hour_of_Day (sin)	٠.٠٦٢	%٣.٤	Night hours - slight increase

مجلة كامبريدج للبحوث العلمية: مجلة علمية محكمة
تصدر عن مركز كامبريدج للبحوث والمؤتمرات–العدد الثالث والخمسون – آذار ٢٠٢٦– رمضان ١٤٤٧
ISSN–2536–0027

Figure 3.3: Feature Importance Plot Using SHAP

3.7 Cost-Benefit Analysis of the Proposed System

A cost-benefit analysis was conducted based on the best-performing model (random forest) to assess the economic viability of the system.

Table 3.8: Estimated Annual Cost-Benefit Analysis (in Iraqi Dinar)

Item	Estimate	Calculation	Result
Total Annual Fraud Loss	12.5 billion IQD	Based on 6 months data × 2	25.0 billion IQD
Detectable Fraud	91.25%	25.0 billion × 0.9125	22.81 billion IQD
Operational Cost	System including cloud, maintenance, staff	Annual comprehensive estimate	1.2 billion IQD
Human Review Cost	87 false alerts/day × 5 min × cost per min	87 × 5 × 250 IQD × 365	39.7 million IQD
Financial Value of Prevention	Fraud detected × recovery rate (60%)	22.81 billion × 0.60	13.69 billion IQD
Non-Financial Value	Customer trust, reputation, regulatory compliance	Relative estimate	3.0 billion IQD
Net Annual Benefit	Total Value - Total Costs	(13.69 + 3.0) - (1.2 + 0.0397)	15.45 billion IQD
ROI	Net Benefit ÷ Costs	15.45 ÷ 1.2397	1246%

3.8 Discussion

1.Interpreting the Clear Superiority of Random Forest:

A. Their ability to handle large and complex data.
B. They prevent overfitting.
C. Identifying the most important variables.
D. Performing well with imbalanced data.

2- The High Recall of the Auto-Encoder Classifier:

Regarding Autoencoders, it is possible to work on a system consisting of three layers, as follows:

A. Relying on random forests to analyze the majority of transactions.
B. Relying on automated encoding / Autoencoders to detect new fraud patterns.
C. Relying on human review for high-risk cases..

3- The Practical Implication of the Most Important Features:

A. When a transaction amount is significantly higher than the customer's average spending.
B. When repetitive operations occur, such as conducting multiple transactions within 24 hours.
C. A sudden change in the location or device usually used by the customer.

Conclusions and Recommendations

1. Conclusions

1. The successful implementation of the (Random Forest) model with excellent results (F1: 90.45%, Recall: 91.25%).
2. The use of SMOTE for addressing data imbalance was crucial for detecting rare fraudulent transactions.
3. The most important indicators of fraud can be summarized in three signs: a sudden increase in amount, transaction repetition, and a change in location or device.
4. The system is economically viable (ROI: 1246% and an annual net profit of 15.45 billion dinars).

2. **Recommendations**

1. For implementation in banks: Begin the pilot on high-risk channels and train specialized teams.
2. For legislators: Establish a national database for fraud data to set unified standards.
3. For Researchers: To explore new and hybrid systems such as reinforcement learning and federated learning.

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