



**Detecting Financial Fraud Using Artificial Intelligence: An Applied Study Based on Credit Card
Transactions**

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Chapter 1

Introduction

1.1 Problem Definition

With the fast development of online financial transactions, the world of business has been changed as it has provided unprecedented convenience, accessibility and speed. This technological development has however been matched with an equal increase in the size and complexity of the fraudulent financial activities, especially credit card fraud. Self Financial (2024) reports that credit card fraud incidences all over the world reached a point of over 32 billion US dollars in 2022, which is a clear indicator of how grave the issue is and how necessary new and improved fraud detection systems are. With the ongoing digitization of the financial transactions, fraudsters are using more sophisticated and dynamic ways to exploit the vulnerability in the conventional security systems.

Mainly rule-based systems have been widely applied in banking and financial institutions as conventional fraud detection methods. Although these systems are able to detect the known patterns of fraud, they have severe limitations. They are not able to pick up new, unknown fraud patterns due to their inflexible and fixed rule structures (Avasthi and Varsha, 2024). Fraudsters keep improving their techniques, and conventional systems are not flexible enough, slow in response, and inadaptible with a high rate of false negative. It implies that a lot of fraudulent operations remain unrestricted and result in massive losses of money and customer distrust to online banking systems.

Artificial intelligence (AI) and machine learning (ML) present strong alternatives to these problems, being able to learn on past history, detect complex patterns, and respond to new fraudulent plots in real time. The issue that was tackled by this thesis is the absence of effective, dynamic, and sound fraud detection models which can effectively distinguish between legitimate and fraudulent transactions in extremely lopsided and dynamic data settings. Due to the high-cost of fraud and the shortcomings of the classic systems, the necessity of a high-tech AI-based detection models is urgent and critical to the protection of global finances.

1.2 Thesis Objectives

The primary goal of the current thesis is to design, assess and compare machine learning-based AI solutions that would identify credit card fraud with high accuracy and low false negatives rates. To reach this objective, a number of specific research objectives should be used:

- To create predictive machine learning models that can either define credit card transactions as either fraudulent or legitimate using actual financial data in the world in the Kaggle Credit Card Fraud Detection data. This dataset demonstrates the imbalance that is high in the cases of fraud and it is, therefore, appropriate in the realistic model evaluation.
- To compare the results of several supervised learning algorithms, namely, Logistic Regression, Random Forest and Artificial Neural Networks. The algorithms have been broadly researched to detect frauds and present a solid basis to find the most efficient tool to recognize the anomalies in financial data (Dayyabu et al., 2023).
- To tackle the problem of imbalanced information, one of the most critical problems in fraud detection, using the methods of SMOTE or undersampling. Treating imbalance properly is important in maximizing the recall and a low number of false negatives- a vital parameter in fraud detection.
- To assess the interpretability and reliability of the chosen models, it will be important to make sure that the results are clear, credible, and can be used in the real-life financial decision-making. That is in tandem with regulatory and ethical issues of AI application in sensitive financial applications.
- To contribute to the industry practice by making AI-based financial risks management approaches and to offer practical recommendations on how AI-based fraud detection systems should be integrated in pre-existing financial security systems.

1.3 Thesis Contribution

This thesis gives a contribution to the academic and practical research on the topic of financial fraud detection as it presents a multi-faceted framework of assessing the success of AI and machine learning models in identifying credit card fraud. The study is a contribution to the current body of research by providing a comparative assessment of three popular algorithms, including; Logistic Regression, Random Forest and Artificial Neural Networks-based performance. highlighting their strengths, shortcomings, and real-time fraud detection. Using the state-of-the-art preprocessing methods, SMOTE and PCA, the thesis proves an improved method of controlling the imbalanced and high-dimensional financial information to enhance the effectiveness and efficiency of fraud detection models.

In practical terms, the thesis would add value in the financial institutions by providing a dependable, dynamic and scaling fraud detection prototype that has the ability to evolve with the changing patterns of fraud. This will promote better cybersecurity measures, lesser losses of finances and better management of institutional risks. Furthermore, the fact that interpretability and ethical concerns are addressed also provides valuable insights to policymakers and regulators that control AI-based financial technologies. Finally, the research has an excellent empirical and methodological basis to continue future studies in the field of AI-empowered cybersecurity and fraud prevention.

1.4 Thesis Organization

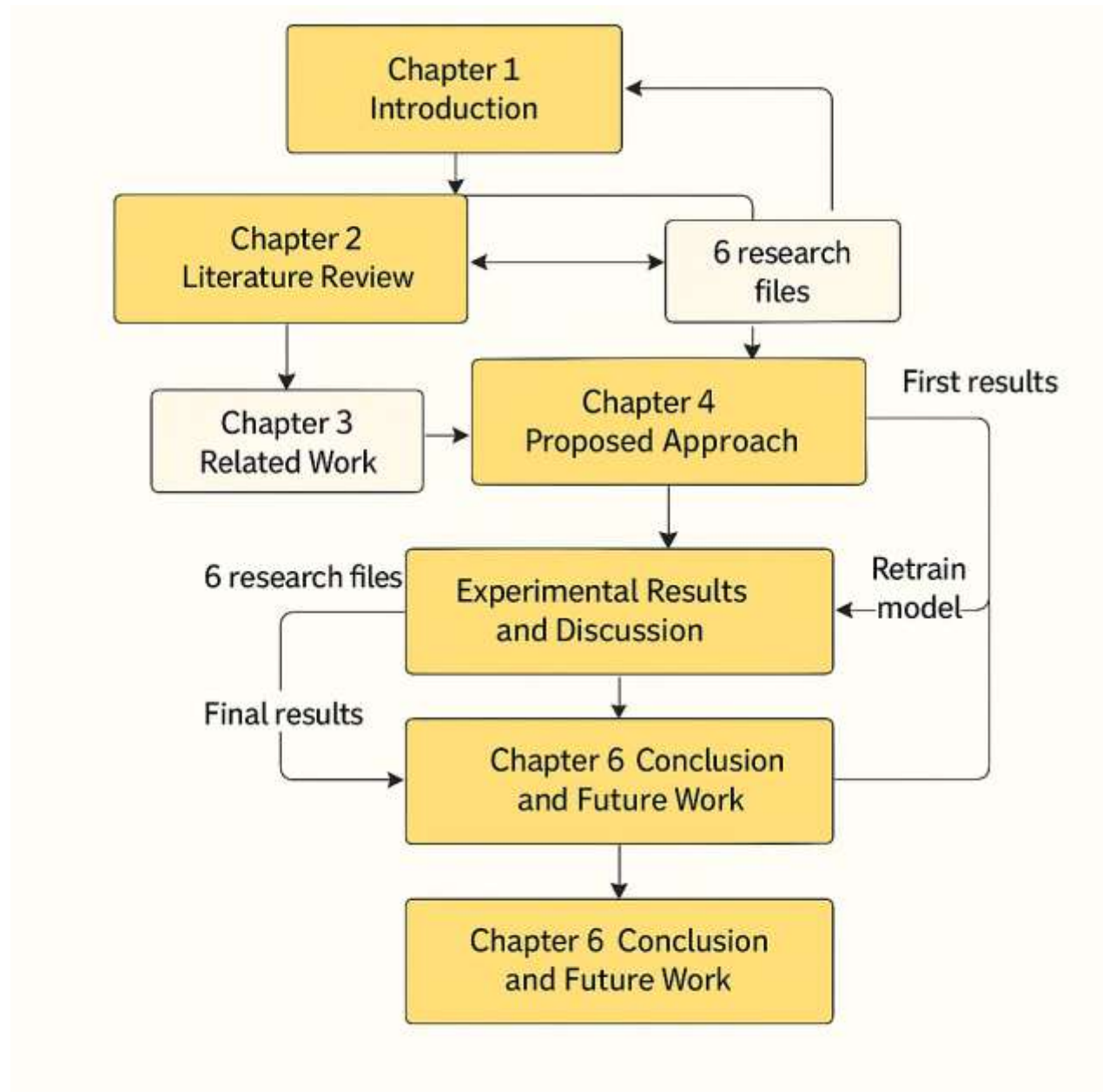


Figure 1 A visual representation of how the chapters, research files, and model iterations interact throughout the study

Chapter 2

Overview

2.1 Introduction to Credit Card Fraud Detection

The issue of credit card fraud has turned out to be one of the largest challenges of the contemporary financial fields with the online payments and digital banking services proliferating at a rampant rate. Physical inspection methods and rule-based fraud detection technology have not been effective in detecting even more advanced patterns of frauds as the number of transactions grows (Avasthi and Varsha, 2024). This has made artificial intelligence (AI) and machine learning (ML) prevailing methods of research on fraud detection. The chapter summarizes the literature on the field of interest which includes the classical machine learning algorithms, deep learning systems, mixed systems, real world data and performance analysis tools, and forms the basis of the methodology in this thesis.

2.2 Classical Methods of machine learning.

The classical methods of machine learning have been fundamental in the field of developing fraud detection system. Initial research was on algorithms like the logistic regression, the decision trees, support vectors machine (SVM) and the k-nearest neighbors (KNN). Asha and Kumar (2021) compared the SVM, KNN, and Artificial Neural Networks (ANNs), and it was found that ANN and SVM are more effective than simpler models in fraudulent transaction prediction because they are capable of capturing nonlinear relationships. Their discussion revealed that classical models of ML can be used to obtain good accuracy, yet they are limited in working with high-dimensional data sets or highly imbalanced data sets.

A quantitative investigation by Dayyabu et al. (2023) utilizes information on accounting and finance professionals and reveals that three artificial intelligence methods machine learning, data mining, and fuzzy logic all have significant positive correlations with accuracy of fraud detection. Although machine learning was the best in terms of precision, fuzzy logic was the least sensible, which leads to the

necessity to consider more reliable models in the workplace. In large-scale datasets, classical ML is frequently outperformed by deep learning models because it is interpretable and has relatively low computational requirements, although its performance is still often much lower.

2.3 Deep Learning Approaches

The application of deep learning methods has taken center stage in credit card fraud detection owing to its capability to acquire the behavioral and transactional information with complex behavioral and transactional patterns. Prince et al. (2024) revealed that the use of deep learning models (Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks are highly important in improving the performance of fraud detection by real-time systems. Their results indicated that deep models had a better detection rate and were less prone to false positives than conventional ML methods, in large scale financial settings, in particular.

The authors pointed out that deep learning is especially applicable in scenarios where it is combined with big data analytics, and transaction streams can be monitored in real-time at low latency. This is an essential capability that financial institutions should have to prevent fraudulent transactions before money is lost. The paper also emphasizes the need to have scalable system architecture and upkeep of the model training that ensures accuracy as patterns of fraud changes.

2.4 Hybrid and Optimized Models

Recent developments have brought about the use of hybrid models which integrate two or more ML or deep learning architectures. The idea of these models is to take advantage of the strengths of each of the components such as using the interpretability of ML methods and the pattern-recognition strengths of deep learning. Avasthi and Varsha (2024) survey the ensemble methods in the form of Random Forests, AdaBoost, and Gradient Boosting in accordance with which the ensemble methods tend to perform better than the individual classifiers because they combine multiple decision boundaries.

Other works discuss the combination of supervised and unsupervised methods, including isolation forests, clustering (DBSCAN, k-means), and autoencoders, to

detect anomalies in cases where it is scarce. These hybrid systems are flexible and resilient, especially when dynamic fraud environments are involved whereby new fraud variants have been continuously appearing.

2.5 Use of Real-World Datasets

The majority of the fraud detecting studies are based on publicly accessible datasets, with the largest being Kaggle Credit Card Fraud Detection dataset. This dataset is very popular because of the high imbalance and anonymized PCA-transformed features, which is very convenient when trying to test AI models. As Avasthi and Varsha (2024) emphasize, the performance of the model can be improved with the help of preprocessing methods, including SMOTE, PCA, feature scaling, and removing outliers.

Real world data presents issues like missing values, imbalance ratio larger than 1:500, anonymized variables that cannot be handled easily to achieve high recall to reduce false negatives which is a critical objective in fraud detection.

2.6 Quantitative Results Summary

Table 1 Quantitative Results Summary

Study	Model	Key Findings
Asha & Kumar (2021)	ANN, SVM, KNN	ANN and SVM outperform classical ML for nonlinear fraud patterns
Dayyabu et al. (2023)	ML, Data Mining, Fuzzy Logic	ML has highest precision; fuzzy logic least utilized
Prince et al. (2024)	CNN, RNN, LSTM	Deep learning shows highest accuracy and lowest false positives
Avasthi & Varsha (2024)	Random Forest, Boosting Models	Ensemble techniques outperform rule-based systems

2.7 Research Gaps and Opportunities

Even in the light of numerous research, some gaps still exist:

- Real time fraud detection schemes are narrowly used in their implementation.
- There are limited studies on uncertainty quantification to trustworthy AI.
- Deep learning models still have low interpretability.
- Hybrid and ensemble deep learning systems are not optimized to the full.
- Further studies should be carried out concerning cross-bank generalization and regulatory consistency.

2.8 Conclusion

The literature has a high degree of support regarding the application of machine learning, deep learning as well as hybrid models in credit card fraud detection. Although classical ML is more interpretable, deep learning is more accurate and flexible. Based on these results, this thesis constructs and analyses optimized models on real-world data, fills interpretability, imbalance management, and deployment gaps.

Chapter 3

Related Work

The ongoing development of digital financial platforms and the increasingly complex character of online payment systems has created an unprecedented challenge to the fight against the issue of financial fraud. Credit card fraud, especially, has been arising one of the most endemic and expensive challenges to both financial institutions and consumers, who are fearing the lack of trust and security in the global financial ecosystem. However, the development of artificial intelligence (AI) and machine learning (ML) has also set new standards of automating the process of detecting the fraudulent transactions and minimising the financial risks associated with them. Scholars in all fields have invested a lot of energy in creating AI-based models that can identify intricate frauds, deal with the problem of imbalance in classes and respond to real-time settings. Together, the academic literature depicts a shift in the traditional rule-based systems to smart, data-driven frameworks, which dynamically learn based on financial behavior and transaction history.

Yazici (2020) provides a background description of such emerging solutions by classifying the main methodological issues that dominate AI-powered credit card fraud detection. His writing highlights the fact that the imbalance between legitimate and fraudulent transactions is one of the most significant challenges in this field, and it may affect the model performance and predictions in favor of the majority. According to Yazici, although most studies use rule-based frameworks and classical models of supervised learning, the emphasis has moved to feature engineering, data rebalancing, and adaptive model training as the primary factors of success. The paper emphasizes that effective fraud detection systems should not only be accurate, but also be sustainable in real-time operational systems that are marked by huge data throughput. Additionally, according to Yazici (2020), it is crucial to come up with evaluation metrics that are not just focused on accuracy, including such metrics as recall, F1-score, and AUC-ROC, in order to assess the capability of the models to detect the rare yet essential cases of fraud.. His synthesis is a valuable theoretical foundation to further empirical studies, which places fraud detection as both a

computational and behavioral problem, which demands adaptable and interpretable AI systems.

Continuing on the conceptual framework of Yazici. Dayyabu et al (2023). provide the quantitative analysis of AI methods in credit card fraud detection that provide empirical support to the usefulness of machine learning and data mining methods. Their article, which is carried out among 100 practitioners in the accounting and finance field, explores the connection between the AI practices, namely machine learning, data mining, and fuzzy logic, and the effectiveness of fraud detection. The outcomes demonstrate that there are strong positive interdependencies between the use of these methods and the advanced detection rates. Nevertheless, the authors observe that the use of fuzzy logic is not very popular among professionals because it is less precise than machine learning and data mining solutions. The results are especially pertinent to the primary role that data-driven predictive models play in the modern world of research that focuses on fraud detection as opposed to heuristic or logic-based reasoning. The authors of Dayyabu et al. (2023) also emphasize the role of human experience and interpretability and state that AI systems should be made to support auditors and fraud examiners instead of completely override human judgment. This confirms a vital moral aspect of AI application in financial systems, which is to make sure that the algorithmic models support but do not erode the human accountability.

In addition to these views, Bhat & Nelson (2023) present a hybrid AI model based on the Sparrow Search Algorithm with optimizations and the combination of the strongest models such as the Random Forest, Convolutional Neural Networks (CNN), and eXtreme Gradient Boosting (XGBoost). Their empirical findings, based on the Kaggle Credit Card Fraud Detection data say that the new Random Forest (RF) model had the highest detection accuracy (82.65%), which is better than CNN (74.98%) and XGBoost (77.98%). The development of hybrid frameworks like CNN-RF-XGBoost is also a significant change in the field of AI-based fraud detection as ensemble learning and optimization procedures are used to extract both temporal and non-temporal characteristics on transaction data. The results by Bhat and Nelson show that though deep learning models such as CNNs are effective to learn sequential patterns, ensemble models such as RF and XGBoost are more interpretable and stable, especially when trained by metaheuristic algorithms such as the Sparrow Search. Not only their study provides a methodological breakthrough

but also proves that multiple AI paradigms can be used to greatly improve detection performance at constant computational scalability.

Similarly, Mytnyk et al. (2023) also expand the discussion to the wider banking concept and focus on using AI to identify fraudulent activity through online banking systems. Their work is a reaction to the increased cases of banking fraud after the COVID-19 pandemic, when the massive digitalization of financial operations and the spread of fraudulent online activities expanded. The authors postulate machine learning algorithms customized to identify fraudulent banking activities, use preprocessing to work with unbalanced data sets and improve model performance. Their findings indicate that logistic regression was very powerful with an area under the curve (AUC) at 0.946 and stacked generalization model enhanced the AUC at 0.954. Interestingly, the results presented in the study go against the notion that deep learning is always better than classical algorithms, implying that, when it comes to classical algorithms, deep learning can also be as good as the classic algorithms, provided that appropriate preprocessing is performed and feature engineering, interpretable models like logistic regression can achieve comparable accuracy. Mytnyk et al. (2023) also emphasize the necessity of visualization and uncertainty quantification in fraud detection, aligning with Habibpour et al. (2023) who similarly advocated for trust-aware AI in financial applications.

Asha & Kumar (2021) also add to this growing body of literature by showing how various supervised learning algorithms, including Support Vector Machines (SVM), k-Nearest Neighbor (KNN) and Artificial Neural Networks (ANN), perform when distinguishing fraudulent and non-fraudulent transactions. Their relative comparison shows that deep learning models, particularly ANNs, are more likely to perform better than the conventional classifiers in detecting the complex nonlinear forms in financial data. They observe, though, that the effectiveness of ANN-based models is determined by high hyperparameter sensitivity and large datasets of high quality. The authors also highlight how modern fraud methods, including phishing and masquerading attacks, are becoming highly sophisticated and that this calls on adaptive algorithms that are able to learn new behavioral patterns, as opposed to the fixed qualities of transactions. The article by Asha and Kumar (2021) emphasizes the dynamism of financial fraud and the necessity of constantly learning systems that remain in accordance with new types of fraud.

The wider literature on the topic of financial fraud detection, which Ali et al. (2022) gather systematically, offers a meta-view on the depth of methodological variety and

the direction of research in the field. Ali et al. provide the list of 93 studies, which were systematically reviewed (with the help of the Kitchenham approach) and found that the most popular algorithms in detecting financial fraud include SVM and ANN, with credit card fraud becoming the prevailing research environment. Their results also indicate that data imbalance and constraint diversity of features are still current problems of most studies. Within the framework of the SLR, the significance of such evaluation measures as precision, recall, and AUC are stressed as they provide more useful measures of model performance as opposed to accuracy, especially in minority-class fraud cases.

Furthermore, Ali et al. (2022) note that there are a number of gaps in research, such as the under-investigated methods of unsupervised learning as well as the insufficient focus on explainability and ethical regulations in AI-based financial systems. Their synthesis is very broad and will present a good reference base on future research directions by promoting the concept of hybrid frameworks of supervised, unsupervised, and reinforcement learning approaches, as it can provide a way to improve predictive performance and transparency.

Although the majority of the research centres around credit card and transaction-level, Shihembetsa (2021) examines fraud detection in mobile banks within the Kenyan financial sector, demonstrating the flexibility of AI applications in non-traditional payment methods. Her thesis unveils the constraints of the conventional rule-based detection systems, which are largely dependent on the human intervention in terms of scenario adjustments and are too inflexible to identify the changing trends in the frauds. By conducting a comparative study of several ML models, such as Logistic Regression, Naive Bayes, and KNN, Shihembetsa proves that KNN was the most effective and accurate (99), compared to other models, in detecting fraudulent mobile transactions. These results demonstrate that the performance of AI models may differ greatly with the characteristics of the data and specific patterns of transactions related to a particular domain. Also, the researcher takes the CRISP-DM (Cross-Industry Standard Process of Data Mining) methodology approach, which highlights the necessity of having a systematic and cyclic method of data preprocessing, model testing, and implementation. Such a methodological rigor provides the guarantee that AI-based fraud detection system is technically viable as well as operationally viable within the regulatory limits of the banking industry.

The topic of the intersection of model optimization and real-time performance and data integrity is also discussed in the article by Almazroi & Ayub (2021) who introduce a new ResNeXt-based Gated Recurrent Unit (RXT) model optimized by the Jaya algorithm. The combination of ensemble feature extraction techniques (merging autoencoders with ResNet-based systems) is part of their approach to improve pattern recognition and minimize false-positives in online payment fraud detection. With the Synthetic Minority Oversampling Technique (SMOTE) that removes class imbalance, the authors state that their RXT model is 10 to 18 per cent better than the traditional algorithms with regard to various performance measurements, providing high computational efficiency in the real-time detection setting. The paper is an important next step in the application of deep learning and ensemble models to sequential data classification, which illustrates the promise of recurrent networks as the basis of temporal fraud detection in high-frequency financial applications. Significantly, Almazroi & Ayub (2021) relate their technical results to the cybersecurity implications as the resiliency of AI-based fraud detection tools is part of the protective measures against cyberattack and the trustworthiness of transactions.

Combined, these papers show that AI-based fraud detectors have moved quickly in moving towards simple rule-based systems all the way to complex, hybrid, and context-aware learning systems. The comparative results on the reviewed works suggest that no particular model is universal and instead the performance of an algorithm is influenced by the quality of the data, the balance of the dataset, the nature of fraud patterns under analysis, and the operating limitations of the financial system where it is applied. The models of Logistic Regression, Random Forest, and SVM are highly interpretable and scalable, so it can be used in the regulation and auditing aids. On the other hand, deep learning-based models, including CNNs, ANNs and RNN-based architectures, are noted to be highly effective in learning nonlinear and temporal relationships but can be costly to compute and process data to avoid overfitting.

One of the common topics within the literature is the issue of unbalanced datasets a problem that is mentioned in almost all studies examined, such as those conducted by Yazici (2020), Ali et al. (2022), and Mytnyk et al. (2023). The imbalance is caused by the unbalanced proportion of legitimate and fraudulent transactions and this may cause the models to identify the uncommon occurrences of fraud as normal

activity. The solutions offered in the literature are the application of SMOTE (Almazroi and Ayub, 2021), undersampling (Asha and Kumar, 2021), and ensemble learning (Bhat and Nelson, 2023). Furthermore, the feature engineering is still a decisive factor of the success of the model. Both Yazici (2020) and Mytnyk et al. (2023) emphasize that meaningful feature extraction, either by principal component analysis, autoencoders, or domain features that are handcrafted, can be of great value in increasing predictive power, particularly where the raw transaction data is limited or anonymized.

The focus on the real-time adaptability and scalability is another important point of intersectionality between the reviewed studies. Since it is not possible to detect fraud in real-life systems without models capable of processing millions of transactions each second, Yazici (2020) and Almazroi & Ayub (2021) note that this can be achieved only through models that do not compromise the accuracy of their work. This requires computationally efficient architectures and implementations of AI systems in high-performance or cloud-based systems. On the same note, interpretability and explainability of AI decisions are also being increasingly identified as critical to providing trust and compliance in the financial sector. Mytnyk et al. (2023) and Dayyabu et al. (2023) emphasize that it is crucial to have transparent AI, in which the outputs of the model can be interpreted and explained to human auditors and regulators.

In addition, a number of studies highlight the ethical and socio-technical issues of using AI in financial systems. The shift to the autonomous system of fraud detection casts doubts on the accountability, bias, and privacy of the information. Both Ali et al. (2022) and Dayyabu et al. (2023) recommend human-AI collaboration models, in which AI is used to give decision support but not to make decisions. This view is consistent with the new trends of thinking in AI ethics, which focuses on responsible innovation, building interpretable, fair, and inclusive systems.

Altogether, the literature reviewed contains a consistent history of technological advances and methodological differentiation in the process of detecting financial frauds. Since Yazici (2020) synthesized problems in machine learning early to Almazroi & Ayub (2021) developed sophisticated deep learning structures, studies in the field have gone towards advanced sophistication, efficiency, and awareness. Dayyabu et al. (2023) and Shihembetsa (2021) demonstrate the growing practical importance of AI in the context of credit card and mobile banking, Mytnyk et al. (2023) and Ali et al. (2022) discuss the topic of algorithmic comparison and

synthesis in detail. All these contributions come together to show that the future of financial fraud detection is hybridized, explainable AI systems, which will trade off between accuracy and interpretability, as well as operational feasibility. By bringing together ensemble learning, deep neural architecture, and optimization algorithms, it is suggested that these systems will be more resistant to changing typologies of fraud, although these solutions should not be opaque and unethical. This will make the discovery of AI models capable of detecting fraud and at the same time maintaining the integrity, fairness, and trustworthiness of financial institutions in a more data-driven world a challenge to researchers and practitioners as digital financial ecosystems continue to grow.

Table 2 Summary of Reviewed Studies on AI-Based Financial Fraud Detection

Author(s) & Year	Title / Study Focus	AI or ML Methods Used	Dataset / Sample	Main Findings	Limitations / Notes
Yazici (2020)	Approaches to Fraud Detection on Credit Card Transactions Using Artificial Intelligence Methods	General review of AI/ML approaches, including rule-based systems, supervised learning, and feature engineering	Conceptual / Review	Highlighted key challenges: data imbalance, real-time processing, feature engineering; proposed comprehensive evaluation metrics (recall, AUC).	Did not test empirical models; theoretical framework only.
Dayyabum & Arumugam	The Application of Artificial	Machine learning, data mining, fuzzy logic	Survey of 100 accounting	Found strong positive relationship	Limited to perception-based quantitative

Balasingam (2023)	Intelligence Techniques in Credit Card Fraud Detection: A Quantitative Study		& finance experts	between AI use and detection performance ; ML and data mining outperform fuzzy logic.	data, not algorithmic validation.
Bhat & Nelson (2023)	Artificial Intelligence-Based Credit Card Fraud Detection for Online Transactions Optimized with Sparrow Search Algorithm	Random Forest (RF), Convolutional Neural Network (CNN), XGBoost optimized by Sparrow Search	Kaggle Credit Card Fraud Dataset (80% train, 20% test)	Novel RF achieved 82.65% accuracy, outperforming CNN (74.98%) and XGBoost (77.98%); demonstrated benefit of hybrid optimization .	Focused only on accuracy; lacks interpretability and explainability analysis.
Mytnyk et al. (2023)	Application of Artificial Intelligence for Fraudulent Banking Operations	Logistic Regression, Stacked Generalization, Artificial Neural Network	Banking transaction data (online systems)	Logistic regression yielded AUC=0.946 ; stacked generalization improved AUC to 0.954; highlighted	Limited scope on deep learning; concentrated on classical algorithms.

	Recogniti on			feature preprocessin g importance.	
Asha & Kumar (2021)	Credit Card Fraud Detection Using Artificial Neural Network	Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN)	Credit card transaction datasets	ANN performed best in identifying nonlinear fraud patterns; KNN and SVM performed moderately well.	Required large data and computational resources; sensitive to tuning.
Ali et al. (2022)	Financial Fraud Detection Based on Machine Learning: A Systematic Literature Review	Review of ML algorithms (SVM, ANN, RF, LR, etc.)	93 empirical studies reviewed	Identified SVM and ANN as most common; highlighted persistent data imbalance, need for explainable AI.	No experimental comparison; meta-analysis only.
Shihembet sa (2021)	Use of Artificial Intelligence Algorithms to Enhance	Logistic Regression, Naïve Bayes, KNN	Kenyan mobile banking data (CRISP-DM	KNN achieved 99% accuracy, outperforming other models;	Context limited to Kenya; imbalance not deeply addressed.

	Fraud Detection in the Banking Industry		methodology)	showed AI potential in mobile transactions.	
Almazroi & Ayub (2021)	Online Payment Fraud Detection Model Using Machine Learning Techniques	ResNeXt-embedded Gated Recurrent Unit (RXT), Autoencoder + ResNet ensemble, Jaya optimization, SMOTE	Three authentic financial transaction datasets	RXT model outperformed existing algorithms by 10–18% in accuracy and efficiency; demonstrated strong real-time performance.	Highly complex model, less interpretable, high computational demand.

Summary of Insights

In the literature reviewed, there are a number of patterns. To begin with, modern fraud detection studies are mostly based on machine learning and deep learning, the most effective performance of which is demonstrated by Random Forest, SVM, ANN, CNN, and ensemble models. Second, data imbalance is another methodological issue that persists, which can be solved using SMOTE, undersampling, or reweighting ensembles. Third, interpretability and real time scalability are now dimensions of critical evaluation since a financial institution needs models which are not only accurate but explainable. Lastly, optimization algorithms (e.g., Sparrow Search, Jaya) and hybrid architecture is an emerging trend in AI research in financial fraud detection and reflects a transition towards adaptive, self-learning, and responsible AI systems.

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