AI in Finance: A Comparative Investigation of Machine Learning and Deep Learning Techniques for Financial Applications

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Abstract. The financial industry faces challenges like market volatility, large data volumes, and complex fraud, where traditional models like Autoregressive Integrated Moving Average (ARIMA) and logistic regression fall short. This paper reviews Artificial Intelligence (AI) applications in finance to overcome these limitations. It explores three domains: stock price forecasting, credit scoring, and fraud detection, employing AI techniques such as machine learning, deep learning, and hybrid models. These methods are compared with traditional approaches using recent studies, integrating sentiment analysis (e.g., FinBERT) and explainability tools e.g., SHapley Additive exPlanations (SHAP). Results show AI outperforms traditional methods, with up to 57% accuracy in stock prediction, 0.92 Area Under Curve (AUC) in credit risk, and 10% F1-score improvement in fraud detection. Challenges include interpretability, generalizability, privacy, and regulation. Future directions involve explainable AI, transfer learning, federated learning, and the EU AI Act. This review offers a comprehensive overview, guiding researchers and practitioners in AI-driven finance.

Keywords: Artificial intelligence, finance, machine learning, deep learning.

1. Introduction

Finance plays a central role in modern economies. It enables capital allocation, risk management, and financial stability across sectors such as banking, insurance, securities, and asset management. As a critical infrastructure for national and global economic development, the financial industry affects a wide range of stakeholders, including individual consumers and institutional investors. However, this industry faces growing challenges, including heightened market volatility, exponential data generation, systemic risk, and complex fraudulent behavior. Traditional analytical and econometric models, while foundational, often lack the capacity to process high-frequency and high-dimensional data or to adapt to rapidly changing market conditions. These limitations have motivated the integration of advanced computational techniques to enhance decision-making accuracy and improve risk management.

In recent years, AI has demonstrated remarkable advances across multiple fields, such as healthcare, logistics, and chemical engineering [1-3], where it has been used for diagnostic support, supply chain optimization, and materials discovery. The financial sector has similarly benefited from the adoption of AI technologies. A wide range of methods, including machine learning algorithms, deep neural networks, and hybrid models, have been employed to address complex financial problems. Bibliometric data shows that the number of published studies related to AI in finance has increased substantially since 2018. Applications include credit risk evaluation, fraud detection, asset price forecasting, and portfolio optimization. According to a recent review [4], stock market forecasting and volatility prediction are the most studied tasks, comprising over one-third of all reviewed papers. For example, Saberironaghi et al. review various AI techniques used in market forecasting and highlight that deep learning models like Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) consistently outperform traditional statistical approaches. In the domain of credit risk [5], Shi et al. demonstrate the superiority of ensemble models such as Random Forest and XGBoost over conventional classifiers like logistic regression and Support Vector Machine (SVM) [6]. In sentiment analysis applications, Jiang and Zeng demonstrate that integrating FinBERT-based sentiment features with LSTM networks yields superior performance compared to both standalone transformer and traditional statistical models. These examples illustrate the growing maturity and diversity of AI applications in the financial domain [7].

In response to these developments, this paper aims to provide a comprehensive overview of artificial intelligence in finance. Section 2 provides an integrated overview of both the key application areas and the corresponding AI methodologies within the financial industry. The discussion is structured around three major domains: stock price forecasting, credit scoring, and fraud detection. For each domain, the paper examines representative artificial intelligence techniques, such as machine learning algorithms, deep learning models, and hybrid approaches. These methods are analyzed in terms of their specific use cases and documented performance in recent empirical studies. Section 3 discusses the challenges faced by researchers and practitioners, such as data availability, model interpretability, and regulatory constraints. Finally, Section 4 outlines future research directions and concludes the paper. This review seeks to consolidate recent findings, highlight current limitations, and offer practical insights for future innovations in AI-driven finance.

2. AI Methods and Their Applications in Finance

2.1. Algorithmic Trading

Stock price forecasting and algorithmic trading have long been central topics in financial research. Accurate price prediction enables investors and financial institutions to optimize portfolio allocation, manage risk exposure, and exploit short-term market opportunities. However, financial markets are highly volatile and influenced by complex, nonlinear factors such as macroeconomic indicators, market sentiment, and unexpected events. Traditional econometric models, including Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and vector autoregressions, often fail to capture these nonlinear dependencies and adapt to rapidly changing market conditions.

AI techniques address these challenges by leveraging data-driven learning to detect intricate temporal and cross-sectional patterns in financial data. In algorithmic trading, AI models can generate trading signals or optimize order execution, while in stock price prediction, they enhance both point forecasts and directional accuracy. Among these methods, deep learning models such as LSTM networks and CNN have demonstrated strong predictive capabilities. For instance, Fischer and Krauss trained an LSTM model using S&P 500 daily returns from 1992 to 2015 with an 80/20 train-test split. The model achieved 57% directional accuracy, roughly 10% higher than logistic regression and random forest baselines, highlighting LSTM's ability to capture sequential dependencies under volatile market conditions [8]. Building on this foundation et al. reviewed and benchmarked multiple AI models for international equity markets, including CNN-LSTM hybrids and attention-based mechanisms. Their study reported that hybrid deep learning models consistently outperformed ARIMA and support vector regression, particularly during periods of high market turbulence [5].

Furthermore, Jiang and Zeng combined FinBERT-based sentiment analysis with an LSTM model to predict daily stock movements on a U.S. market news dataset. Integrating textual sentiment features improved directional prediction accuracy by 5.3%, demonstrating the value of fusing financial text data with time-series models [7]. These studies illustrate that AI techniques, especially deep learning and Natural Language Processing (NLP) -based sentiment models, significantly enhance the accuracy and robustness of stock price prediction and algorithmic trading strategies compared to conventional statistical approaches.

2.2. Credit Scoring

Credit scoring is a critical component of modern financial systems because it directly affects loan approvals, interest rate determination, and overall portfolio risk management. Accurate assessment of a borrower's creditworthiness allows financial institutions to reduce default risk and improve lending efficiency. Traditional models, such as logistic regression and linear discriminant analysis, assume linear relationships and rely on limited feature sets, which constrains their ability to capture complex patterns and interactions in borrower data, especially under class imbalance conditions.

AI methods overcome these limitations by automatically identifying nonlinear feature interactions in high-dimensional datasets. Ensemble learning algorithms, such as random forests and gradient boosting machines (e.g., XGBoost), and deep neural networks have demonstrated strong predictive power in default classification tasks.

Shi et al. conducted a systematic review of machine learning applications in credit risk assessment and reported that ensemble models consistently outperformed classical logistic regression, with Area Under the Curve (AUC) values reaching approximately 0.92 compared to 0.85 for traditional methods [6]. More recently, Liang et al. introduced the DeRisk deep learning framework, which was evaluated on multiple real-world credit datasets characterized by imbalanced default distributions. Their model achieved notable improvements in predictive accuracy and AUC over random forest and XGBoost baselines, demonstrating superior robustness and generalization [9]. Another study by Paz et al. combined machine learning models with metaheuristic feature selection algorithms, such as particle swarm optimization and genetic algorithms. This approach improved F1-score and recall by around 10% on consumer credit datasets compared to standard modeling pipelines [10].

These examples illustrate that AI-driven credit scoring methods, particularly ensemble and hybrid deep learning approaches, significantly enhance the accuracy, robustness, and adaptability of risk evaluation compared to traditional statistical models. Their adoption enables financial institutions to better identify high-risk borrowers, minimize losses from defaults, and improve overall portfolio quality.

2.3. Fraud Detection

Fraud detection is a vital task in financial risk management because fraudulent activities such as credit card fraud, identity theft, and money laundering cause significant financial losses and undermine consumer trust. Traditional rule-based and statistical models, although interpretable, are often inadequate in the face of highly imbalanced datasets and adaptive fraud behaviors. These models rely on fixed thresholds or linear assumptions, making them less effective when fraudsters change their strategies or when data volumes grow rapidly.

AI methods, particularly machine learning and graph neural networks, have substantially enhanced the accuracy and robustness of fraud detection by identifying complex, nonlinear patterns in both transactional and relational data. Several representative studies illustrate these advancements.

Hernandez Aros et al. conducted a comprehensive literature review of machine learning applications in financial fraud detection, analyzing over 100 studies from 2012 to 2023. Their review highlights that support vector machines, random forests, and neural networks remain the most frequently applied methods, and that deep learning and hybrid models achieve superior results on precision, recall, and AUC compared with traditional rule-based approaches [11].

Tian et al. proposed the Adaptive Sampling and Aggregation Graph Neural Network (ASA-GNN) for transaction fraud detection. The model leverages neighbor diversity and weighted aggregation to enhance the representation of transactional networks. Evaluated on three real-world financial datasets, ASA-GNN achieved the best overall performance, with F1-score improvements of up to 10% and ROC-AUC gains of around 7% over baseline GNN and classical machine learning methods [12].

Sha et al. introduced a heterogeneous graph neural network with graph attention for credit card fraud detection. The model was tested on the IEEE-CIS Fraud Detection dataset, achieving an accuracy of 94.7% and an AUC of 0.921, outperforming GCN, GAT, and GraphSAGE baselines. The incorporation of temporal decay and attention mechanisms allowed the model to capture dynamic and relational fraud patterns more effectively than traditional techniques [13].

These studies collectively demonstrate that AI-based fraud detection approaches, especially those incorporating graph neural networks and deep learning, provide substantial improvements in detection accuracy and adaptability. By capturing temporal and relational features, modern models can better address imbalanced data and evolving fraudulent behaviors, reducing losses and strengthening the security of digital financial services.

3. Discussion

3.1. Challenges and Limitations

Although significant progress has been achieved, several enduring challenges hinder robust deployment and broader adoption of artificial intelligence in finance. Four principal limitations are highlighted in the research:

3.1.1. Model Interpretability and Transparency

Many high-performance models in finance operate as opaque systems, limiting their interpretability for both regulators and financial institutions. This lack of clarity impedes trust and threatens responsible adoption. For instance, research on large language models reveals that mechanistic interpretability—understanding internal activations and circuits—is critical for ensuring compliance and accountability in financial settings [14]. Recent systematic reviews of explainable AI in financial services highlight the absence of standardized evaluation protocols for interpretability, particularly regarding post-hoc explanation fidelity and stability across market conditions. Such gaps hinder consistent benchmarking and make it difficult for regulators to compare model transparency across institutions [15, 16].

3.1.2. Generalizability Across Institutions and Markets

AI models trained within one institution or market often fail to generalize effectively when deployed in different environments. In credit risk applications, behavioral-based models that perform well on one dataset often degrade when applied to different institutional data due to variations in borrower demographics, lending norms, and data collection methods. Evidence from a transferability study shows that models trained on bureau credit data lose predictive power when tested on bank-level behavioral datasets, revealing a vulnerability in model robustness across domains [17]. Additionally, in volatile market conditions afflicting emerging economies, machine learning models built with non-traditional data outperform conventional statistical models during stress periods, suggesting that instability and context shifts severely impair model reliability [18]. These observations indicate that poor generalizability threatens both model validity and financial stability when AI is scaled across diverse contexts.

3.1.3. Data Privacy and Security Risks

The sensitive nature of financial data poses significant risks, particularly when centralized storage and unregulated data pooling create vulnerabilities to data leakage and governance breaches. A recent review emphasises that financial institutions remain highly exposed to privacy violations due to weak enforcement of data minimisation and insufficient governance mechanisms, which amplify the likelihood of misuse of customer information [19]. Empirical evidence further shows that financial datasets are attractive targets for cyberattacks, with ransomware and model inversion attacks being increasingly deployed against banks and FinTech providers, exposing structural weaknesses in current protective measures [20]. Additionally, a comprehensive systematic review identifies data privacy and security challenges in digital finance, including third-party vulnerabilities, regulatory non-compliance, and evolving cyber threats, while highlighting that technical and compliance gaps remain unaddressed in many institutions [21]. These risks underscore that without robust safeguards, reliance on AI systems in finance may amplify existing vulnerabilities rather than mitigate them.

3.1.4. Regulatory and Ethical Challenges

Financial AI systems operate in evolving regulatory environments that increasingly demand transparency, fairness, and auditability. A recent analysis of AI regulation in financial services notes persistent issues including algorithmic bias, fragmented compliance requirements across jurisdictions, and lack of clarity in liability frameworks [22]. A broader study by the IMF reviews regulatory efforts related to AI adoption and highlights market stability, data privacy, and ethics as ongoing concerns [23].

3.2. Challenges and Limitations

3.2.1. Enhancing Model Interpretability and Transparency

Addressing the interpretability gap in financial AI requires moving beyond post-hoc explanations toward inherently interpretable modelling frameworks. Recent developments demonstrate that integrating explainability tools such as Shapley values during model development can improve both transparency and predictive performance. For example, Babaei, Giudici, and Raffinetti developed an explainable credit risk assessment model that incorporates Shapley-based feature attribution to support decision-making in FinTech lending [24]. Similarly, Hjelkrem and Petter Eilif de Lange conducted a case study using open banking data to explain deep learning models for credit scoring with SHAP values, demonstrating that integrated interpretability techniques can enhance transparency without sacrificing predictive performance [25]. These approaches suggest that future systems will benefit from embedding interpretability in the modelling pipeline rather than relying solely on after-the-fact justifications.

3.2.2. Improving Generalizability Across Institutions and Markets

Enhancing the generalizability of AI models across different financial institutions and markets is essential for scalable deployment. Transfer learning and domain adaptation offer promising pathways to achieve this. Lanzetta provides a systematic review of transfer learning in financial prediction tasks, highlighting the value of pre-training on large cross-market datasets followed by targeted fine-tuning [26]. In the context of time-series data, Shi et al. survey deep unsupervised domain adaptation methods, identifying alignment techniques across input, feature, and output spaces that mitigate performance degradation due to distributional shifts [27]. Future research should prioritise standardized cross-domain evaluation protocols to ensure robust performance under diverse conditions.

3.2.3. Strengthening Data Privacy and Security

Safeguarding data privacy in financial AI applications will require integrating federated learning (FL) with advanced cryptographic methods. Kairouz et al. provide a comprehensive overview of FL, outlining key open challenges such as non-IID data, adversarial robustness, and communication efficiency [28]. Building on this foundation, Liu et al. review approaches that combine FL with multi-party computation to enhance privacy while preserving model utility, offering clear guidelines for deployment in regulated sectors [29]. Future implementations should aim to standardize privacy accounting methods and develop regulatory compliance toolkits tailored to the financial industry.

3.2.4. Advancing Regulatory Frameworks and Ethical AI in Finance

The sustainable adoption of AI in finance depends on harmonized regulatory standards and embedded ethical principles. The European Union's Artificial Intelligence Act introduces a risk-based classification system, mandatory technical documentation, and conformity assessments, which could serve as a blueprint for global financial AI governance [30]. Complementing this, Crisanto et al. from the Bank for International Settlements analyse recent supervisory developments, identifying gaps in model audit practices, third-party service oversight, and cross-border regulatory coordination [31]. These insights point towards a future in which regulatory frameworks evolve in parallel with technological advances, ensuring both innovation and systemic stability.

4. Conclusion

This paper provides a comprehensive review of artificial intelligence applications in finance, focusing on three core domains: algorithmic trading, credit scoring, and fraud detection. Across these scenarios, AI methods such as deep learning, ensemble models, and hybrid approaches have demonstrated clear advantages over traditional statistical techniques. The discussion identified four main challenges, namely model interpretability, generalizability, data privacy, and regulatory alignment, and outlined corresponding future prospects, including explainable AI integration, domain adaptation, privacy-preserving frameworks, and harmonised governance. By consolidating recent findings, this review offers a structured perspective on current limitations and emerging directions, aiming to guide researchers and practitioners toward responsible and effective AI adoption in the financial sector.

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