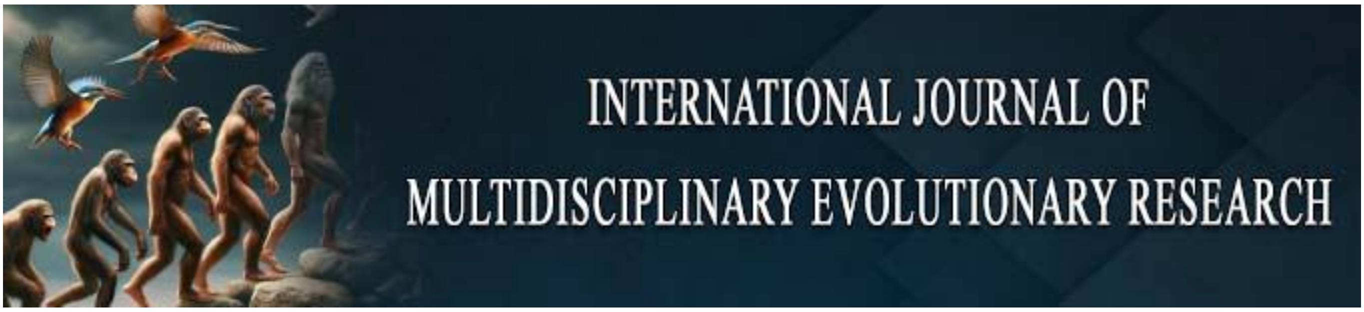

Machine Learning-Powered Systems for Fraud Prevention and Compliance Forecasting in Investment Advisory Services

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Abstract
Investment advisory services are increasingly exposed to sophisticated fraud schemes and dynamic regulatory environments, necessitating advanced technological solutions for risk mitigation and compliance assurance. Machine learning (ML), with its capacity for real-time pattern recognition, anomaly detection, and predictive analytics, has emerged as a transformative tool in this sector. This review explores the landscape of ML-powered systems specifically designed for fraud prevention and compliance forecasting in investment advisory domains. It examines supervised and unsupervised learning approaches for detecting fraudulent activities, evaluates regulatory compliance models driven by natural language processing (NLP), and highlights the integration of real-time risk engines. Furthermore, the paper assesses challenges such as data privacy, model interpretability, regulatory alignment, and the implications of algorithmic bias. By synthesizing recent advancements and practical applications, this review underscores the role of ML in enhancing financial integrity, regulatory readiness, and operational resilience across advisory practices. The study concludes with strategic recommendations for future research and deployment within a governance-driven AI framework.

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1. Introduction
1.1 Background and Relevance of ML in Investment Advisory
Investment advisory services operate in a complex, high-stakes environment that demands precision, transparency, and trust. Traditionally, fraud detection and compliance monitoring relied on rule-based systems and manual audits, which often failed to adapt to evolving risks and regulatory expectations. The rise of machine learning (ML) presents a transformative opportunity to augment these processes by enabling dynamic analysis of large and diverse datasets, real-time risk identification, and predictive forecasting. ML algorithms, especially supervised and unsupervised models, can identify subtle patterns, behavioral anomalies, and regulatory breaches far more efficiently than conventional systems. In the context of advisory services, these capabilities are critical for enhancing fiduciary duty, safeguarding client assets, and upholding compliance with evolving financial regulations. The relevance of ML continues to grow as advisory firms face increasingly sophisticated fraud threats and must navigate multi-jurisdictional compliance landscapes. Moreover, the integration of ML with RegTech tools fosters scalable, automated solutions that reduce costs while maintaining governance integrity. This backdrop underlines the strategic importance of ML not just as a technological upgrade, but as a fundamental pillar of sustainable, risk-resilient advisory operations.

1.2 Evolution of Fraud in Financial Services
Fraud in financial services has evolved from simple transactional manipulation to complex, multi-vector schemes that exploit system vulnerabilities, behavioral inconsistencies, and regulatory loopholes. In the investment advisory space, threats have expanded beyond identity theft and phishing to include front-running, insider trading, social engineering, and algorithmic manipulation. With the digitization of financial services, cyber-enabled fraud has surged, often evading legacy detection systems. Adversaries now leverage advanced tools such as deepfakes, synthetic identities, and spoofed trading behavior, making fraud detection increasingly challenging. These developments underscore the limitations of static, rules-based monitoring systems that lack adaptability and contextual learning. In response, financial institutions are turning to machine learning technologies that can dynamically adapt to evolving threats. ML models can ingest vast volumes of historical and real-time data, continuously learning and updating risk profiles to detect novel fraud patterns. This adaptive intelligence is critical in reducing false positives, enhancing threat detection, and enabling faster incident response. As financial fraud grows more elusive and sophisticated, ML-powered defenses are becoming indispensable in protecting investor assets and institutional reputations.

1.3 Increasing Regulatory Complexity and Compliance Demands
The global investment advisory industry is subject to a rapidly expanding regulatory landscape shaped by jurisdictional diversity, data protection mandates, and evolving investor protection rules. Compliance requirements from authorities such as the SEC, FINRA, GDPR, and MiFID II impose stringent obligations on data handling, reporting, disclosure, and operational transparency. The growing emphasis on Environmental, Social, and Governance (ESG) criteria and anti-money laundering (AML) protocols further complicates compliance management. Traditional compliance systems, reliant on periodic audits and siloed reporting tools, often struggle to keep pace with these demands. Machine learning offers a paradigm shift by enabling predictive compliance—proactively identifying regulatory risks before they materialize. NLP techniques can extract actionable insights from complex legal texts, while classification algorithms can forecast potential violations based on historical patterns. These technologies allow advisory firms to transition from reactive compliance to continuous monitoring and forecasting, thereby reducing regulatory penalties and enhancing operational agility. As global oversight becomes more complex and enforcement more aggressive, ML-driven compliance systems offer a scalable, intelligent solution to meet regulatory expectations.

1.4 Objectives and Scope of the Review
This review aims to critically evaluate the application of machine learning technologies in fraud prevention and compliance forecasting within the investment advisory domain. It focuses on assessing the effectiveness, adaptability, and limitations of various ML models in addressing fraud threats and navigating regulatory complexities. By analyzing recent advances in supervised learning, unsupervised clustering, natural language processing, and real-time anomaly detection, the review outlines how these tools support predictive governance and operational integrity. The scope includes both academic research and industry use cases, highlighting the convergence of ML and RegTech in advisory services.

1.5 Structure of the Paper
The paper is structured into five main sections. Section 1 introduces the topic, offering background, problem context, and research objectives. Section 2 explores the application of ML in fraud detection, including model types and real-world use cases. Section 3 focuses on ML-based compliance forecasting tools and their alignment with global regulatory standards. Section 4 discusses implementation challenges, ethical considerations, and risk factors associated with ML adoption. Finally, Section 5 presents strategic recommendations and outlines future research directions for enhancing fraud resilience and regulatory compliance through machine learning.

2. Machine Learning in Fraud Prevention
2.1 Supervised Learning Models for Transaction Monitoring
Supervised learning models play a pivotal role in transaction monitoring by utilizing labeled datasets to distinguish between legitimate and fraudulent financial activities. These models, including decision trees, support vector machines (SVM), logistic regression, and random forests, are trained on historical transaction data tagged as either compliant or anomalous. By learning from these patterns, the system can predict the probability of fraud in new, incoming transactions in near real time. In the investment advisory context, such models enhance surveillance over portfolio activities, wire transfers, asset reallocations, and client behavior (Mgbeadichie, 2021). Additionally, the inclusion of temporal features, such as transaction frequency or unusual timing, improves prediction accuracy. These models can be continuously retrained with feedback loops to accommodate evolving fraud tactics. However, overfitting, label noise, and imbalanced datasets remain critical challenges, especially in environments where fraudulent activity represents a small proportion of transactions. Techniques such as SMOTE (Synthetic Minority Over-sampling Technique) and cost-sensitive learning are employed to improve model robustness. When integrated into compliance workflows, supervised learning enhances early fraud detection, reduces false positives, and improves regulatory audit readiness, thereby empowering advisory firms to meet fiduciary responsibilities more effectively. (Daraojimba, A. (2021).

2.2 Unsupervised Learning for Anomaly and Behavioral Analysis
Unsupervised learning techniques are essential in identifying anomalies and behavioral shifts in financial transactions without requiring labeled datasets. These models—such as k-means clustering, principal component analysis (PCA), isolation forests, and autoencoders—detect deviations from established norms by grouping similar transaction patterns and flagging outliers (Mgbeadichie, 2021). In the context of investment advisory services, unsupervised learning is particularly valuable for detecting previously unknown fraud types or emerging suspicious behaviors that do not match historical profiles. For example, a sudden spike in high-risk investment allocations or repetitive micro-transactions could indicate insider manipulation or unauthorized access. Unsupervised models excel in dynamic, high-volume

environments where rule-based systems fall short. By continuously profiling clients' historical behavior, these models enable real-time alerts for deviations, facilitating proactive risk assessment. However, they are susceptible to false positives and require post-processing validation to interpret flagged anomalies meaningfully. Visualization tools and hybrid approaches—combining unsupervised outputs with supervised confirmation—are increasingly adopted to enhance decision-making. Overall, unsupervised learning serves as a critical early-warning system in fraud prevention frameworks, improving detection of atypical behaviors while minimizing reliance on pre-defined fraud patterns. (Oyeniyi, L. (2021)).

2.3 Deep Learning and Pattern Recognition in Insider Threats

Deep learning models, particularly those based on artificial neural networks (ANN), convolutional neural networks (CNN), and recurrent neural networks (RNN), are revolutionizing the detection of insider threats in investment advisory services. These systems can process large-scale, unstructured, and sequential data such as user activity logs, email communications, and transaction timelines to identify subtle and complex behavioral patterns indicative of insider fraud (Isibor *et al*, 2021). For instance, recurrent models like LSTM (Long Short-Term Memory) networks are effective in modeling sequential dependencies—enabling the detection of behavioral drifts over time, such as repeated access to sensitive portfolios outside work hours or gradual changes in communication tone before illicit actions. Deep learning's ability to extract features automatically from raw data eliminates manual feature engineering, reducing human bias and enhancing adaptability to emerging threat vectors. Despite their strength in representation learning, deep models face limitations in explainability and computational intensity. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) are increasingly used to improve transparency in financial compliance as seen in Table 1. Deep learning's integration into insider threat management provides a scalable, proactive defense mechanism for advisory firms, especially in hybrid work environments where digital surveillance is paramount. (Fredson, G. (2021)).

Table 1: Deep Learning and Pattern Recognition in Insider Threats

Deep Learning Technique	Application in Insider Threat Detection	Advantages	Limitations
Artificial Neural Networks (ANN)	Used for general pattern recognition across multiple user activities, including financial access and anomalies.	Adaptive to nonlinear relationships; reduces manual rule creation.	Requires large training datasets and high computation.
Convolutional Neural Networks (CNN)	Excels in analyzing structured digital communication like emails or logs with spatial patterns.	Effective feature extraction from complex datasets.	May be data-hungry and less effective on sparse logs.
Recurrent Neural Networks (RNN) - LSTM	Captures sequential behaviors such as time-based anomalies and gradual user behavior drift.	Temporal learning for detecting delayed or evolving fraud patterns.	Computationally expensive and sensitive to input noise.
Explainability Tools (SHAP, LIME)	Enhances model interpretability, helping analysts understand model decisions in compliance contexts.	Improves trust and auditability of deep learning decisions.	Adds complexity and may not fully resolve black-box issues.

2.4 Case Studies of ML-Based Fraud Detection in Advisory Firms

Several investment advisory firms have successfully adopted machine learning (ML) systems to strengthen their fraud detection capabilities. A notable example is Charles Schwab's deployment of supervised learning algorithms to monitor abnormal fund transfers and detect suspicious account takeovers. Their models incorporate behavioral analytics, device fingerprinting, and transaction velocity metrics to trigger real-time alerts (Sharma, 2021). Similarly, Morgan Stanley implemented unsupervised clustering techniques to identify anomalous investment patterns among client advisors—revealing internal misconduct that traditional compliance tools had missed. In another case, Fidelity Investments integrated deep learning with NLP to analyze email communications for potential regulatory breaches and insider trading indicators. These implementations not only improved fraud detection rates but also reduced operational overhead and investigation timelines. Additionally, third-party platforms such as Darktrace and ThetaRay have been adopted by mid-sized advisory firms to provide AI-driven anomaly detection-as-a-service. These platforms use hybrid approaches combining unsupervised learning and reinforcement learning to adapt to unique business contexts. Despite their success, challenges remain around false positives, model drift, and regulatory validation. These case studies underscore the transformative impact of ML on compliance infrastructure and highlight the importance of context-aware model deployment in investment advisory environments. (Ogunsola, K. (2021)).

3. Compliance Forecasting Using ML

3.1 Natural Language Processing for Regulatory Text Mining

Natural Language Processing (NLP) enables investment advisory firms to systematically interpret and extract actionable insights from complex and evolving regulatory documents. Regulations issued by bodies such as the U.S. Securities and Exchange Commission (SEC), Financial Industry Regulatory Authority (FINRA), and the European Union's GDPR are often lengthy and written in legal jargon, posing challenges for timely compliance. NLP-based systems can automate the parsing of these texts, identifying obligations, compliance clauses, and enforcement triggers (Mgbeadichie, 2021). Named Entity Recognition (NER), part-of-speech tagging, and dependency parsing allow firms to classify critical entities like risk thresholds, transaction categories, and reporting deadlines. Topic modeling algorithms such as Latent Dirichl*et al*location (LDA) help cluster related provisions and detect thematic changes over time, aiding compliance officers in regulatory change management (Isibor *et al*, 2021). Moreover, semantic similarity techniques using transformer models like BERT can align regulatory text with internal policies, flagging misalignments. This level of intelligent automation enhances the speed, accuracy, and consistency of compliance interpretations while reducing reliance on manual legal reviews. As regulators increase transparency and enforcement rigor, NLP offers a scalable, real-time method to operationalize compliance language and monitor updates efficiently across jurisdictions. (Adesemoye, O. (2021)).

3.2 Predictive Models or Compliance Risk Scoring

Predictive analytics in compliance risk scoring leverages historical data to anticipate areas where an investment advisory firm might breach regulatory norms or attract scrutiny. These models use supervised machine learning algorithms—such as logistic regression, decision trees, and ensemble methods like XGBoost—to assign risk scores to specific transactions, accounts, or business units. Inputs to these models typically include transactional behaviors, client profiles, KYC documentation, prior audit outcomes, and regulatory history. The goal is to quantify the probability of non-compliance or regulatory infractions, enabling firms to implement preemptive controls (Isibor *et al*, 2021). For example, deviations in trading patterns or rapid changes in client investment profiles can trigger alerts based on learned risk signatures. Advanced models may also incorporate sentiment analysis from client communications or advisor notes to capture hidden compliance risks. Over time, these models improve their accuracy through continuous retraining on updated datasets, enabling dynamic risk profiling (Sharma, 2021). By prioritizing high-risk entities, these systems help compliance teams allocate resources more effectively. Moreover, compliance risk scores are often integrated into broader Governance, Risk, and Compliance (GRC) systems, offering real-time dashboards and executive insights that support proactive decision-making in regulatory strategy and internal auditing (ADEWOYIN, M. (2021)).

3.3 Automation of Audit Trails and Reporting

Machine learning and robotic process automation (RPA) play a crucial role in automating audit trails and regulatory reporting within investment advisory services. Traditionally, audit trails—comprising transaction logs, advisory recommendations, and client communications—are maintained manually, which increases the risk of errors, omissions, and non-compliance. By integrating ML with RPA, firms can automate the continuous recording, timestamping, and categorization of all compliance-relevant events. These systems ensure traceability and immutability, crucial for satisfying the audit requirements of SEC and FINRA. For example, NLP algorithms can extract and flag advisory language in client emails or meeting transcripts that may require disclosure or additional documentation. Automated reporting systems, on the other hand, compile structured data into regulator-specific formats and submit them within required timelines, often triggered by event-based conditions. These systems also adapt dynamically to new reporting requirements by updating templates using learned regulatory schemas. Moreover, the integration of anomaly detection models helps identify inconsistencies or gaps in the audit log, prompting corrective actions before formal reviews. This automation not only reduces compliance overhead but also improves transparency and regulatory confidence through consistent, verifiable reporting practices (Afolabi, S. (2021)).

3.4 Integration with Regulatory Frameworks (e.g., SEC, FINRA, GDPR)

Seamless integration with global regulatory frameworks is essential for machine learning systems deployed in investment advisory compliance. Each jurisdiction imposes distinct requirements—such as transaction monitoring by the SEC, conduct and suitability standards by FINRA, or data protection obligations under GDPR (Isibor *et al*, 2021). ML systems must be designed to interpret and align with these standards at both policy and implementation levels. For instance, rule-based engines embedded in advisory platforms can be calibrated to detect violations of SEC's Regulation Best Interest (Reg BI), ensuring that recommendations are in line with fiduciary duties. Similarly, GDPR mandates data minimization and subject access rights, necessitating ML architectures that incorporate explainability and data traceability features. Compliance-aware data pipelines are critical to ensuring auditability, anonymization, and retention in line with legal expectations (Sharma, 2021). Cross-regulatory alignment is increasingly enabled through RegTech platforms that integrate APIs and ontology-based knowledge graphs, allowing ML systems to adapt to changes across multiple jurisdictions. This ensures that firms remain compliant as laws evolve, reducing the risk of fines and reputational damage. Ultimately, the integration of ML with regulatory frameworks enables a proactive, automated, and globally consistent approach to compliance in advisory services (Ike, C. (2021)).

4. Challenges and Ethical Considerations

4.1 Data Quality, Privacy, and Access Limitations

The success of machine learning (ML) systems in fraud prevention and compliance forecasting relies heavily on the quality, completeness, and granularity of financial datasets. However, investment advisory firms often encounter fragmented, unstructured, or siloed data, limiting the efficacy of training robust and generalizable models (Sharma, 2021). Missing values, labeling errors, and outdated client profiles can skew fraud detection algorithms, resulting in false positives or negatives. Furthermore, stringent data privacy regulations such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) restrict the extent to which personal financial data can be shared, thereby affecting data availability for model training and validation. The challenge is further compounded by legal uncertainties surrounding cross-border data transfers and proprietary data ownership. Privacy-preserving techniques, including federated learning and differential privacy, offer promising solutions, allowing firms to develop predictive models while maintaining data confidentiality. However, these approaches also present trade-offs in terms of model accuracy and computational efficiency. To address access limitations, firms must invest in secure data governance frameworks, consent-driven data sharing agreements, and real-time data integration pipelines. Ensuring data integrity and ethical access is foundational to trustworthy AI deployment in advisory services. (Ogbuefi, E. (2021)).

4.2 Explainability and Interpretability in Financial AI Systems

The use of black-box models in financial decision-making, especially for fraud detection and compliance assessment, has raised significant concerns regarding transparency and accountability. Regulatory agencies such as the U.S. Securities and Exchange Commission (SEC) and the Financial Industry Regulatory Authority (FINRA) demand clear documentation of how decisions—particularly those affecting clients' investments or risk profiles—are made. Traditional machine learning models, including support vector machines and deep neural networks, often lack the interpretability necessary to satisfy these regulatory demands (Mgbeadichie, 2021). This opaqueness hinders the adoption of AI systems in high-stakes environments where human advisors must trust and validate algorithmic outputs. Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention-based models offer interpretable insights by identifying key features that influence model predictions. These tools not only increase user trust but also support compliance audits and reduce legal exposure. However, a trade-off often exists between explainability and predictive accuracy, necessitating a balanced approach in model selection. Embedding interpretability into AI systems from design through deployment ensures that financial institutions can both leverage cutting-edge analytics and meet ethical and regulatory obligations. (Ezeife, E. (2021)).

4.3 Algorithmic Bias and Fairness in Decision Making

Algorithmic bias in machine learning systems poses a significant risk to fairness and equality in investment advisory services. Bias can emerge from imbalanced training data, systemic socioeconomic disparities, or historical decision patterns embedded in financial datasets. When left unaddressed, such biases may result in discriminatory outcomes—for example, misclassifying minority clients as high-risk or denying them access to tailored investment opportunities. This undermines not only client trust but also regulatory compliance, as fairness mandates are increasingly embedded in laws such as the Equal Credit Opportunity Act (ECOA) and guidelines from the Consumer Financial Protection Bureau (CFPB). Financial ML systems must incorporate fairness-aware learning frameworks, including re-sampling techniques, adversarial debiasing, and fairness constraints during model optimization. Additionally, firms should implement continuous fairness audits and performance benchmarking across demographic groups. Fairness metrics such as equal opportunity difference, disparate impact ratio, and demographic parity are essential tools for evaluating and mitigating bias. However, ensuring fairness often involves complex trade-offs between accuracy, efficiency, and equity. Investment firms must embrace responsible AI governance to balance these priorities, protect vulnerable groups, and ensure ethical and lawful decision-making in advisory practices. (Kisina, D. (2021)).

4.4 Governance, Accountability, and Model Validation Standards

Robust governance and accountability frameworks are critical to the ethical deployment of ML systems in financial advisory services. Given the opaque nature of many ML algorithms, it is imperative to establish clear guidelines that define who is responsible for algorithmic decisions and how models should be validated over time. Regulatory bodies like the Basel Committee and the Office of the Comptroller of the Currency (OCC) require rigorous model risk management (MRM), including independent validation, performance monitoring, and stress testing of predictive systems. Governance structures should include cross-functional committees with expertise in data science, legal compliance, risk management, and audit (Sharma, 2021). These bodies should oversee model lifecycle processes from development to decommissioning, ensuring transparency in data sources, feature selection, and parameter tuning. Accountability also involves traceability—maintaining logs of model predictions, training versions, and rationale for changes to algorithmic parameters. Documentation and reproducibility are central to defending AI decisions in case of disputes or regulatory scrutiny. As model complexity increases, standardized validation protocols, such as the use of challenger models and backtesting, become necessary. Embedding governance and validation standards into ML workflows strengthens institutional resilience and ensures alignment with both fiduciary duties and evolving regulatory expectations. (Hassan, Y. (2021)).

5. Future Directions and Strategic Recommendations

5.1 Advancing Federated and Privacy-Preserving ML in Finance

Federated learning offers a decentralized approach to model training, enabling financial institutions to collaboratively detect fraud and assess compliance risks without sharing sensitive client data. This paradigm is especially valuable in investment advisory services, where regulatory constraints and client confidentiality hinder centralized data aggregation. By allowing institutions to train machine learning models locally and aggregate updates, federated learning preserves privacy while enhancing system-wide accuracy. Coupled with differential privacy and homomorphic encryption, these methods reduce the attack surface for data breaches and enable compliance with stringent data protection regulations such as GDPR and CCPA. However, challenges remain regarding model convergence, communication overhead, and adversarial attacks. Advancing federated learning in finance necessitates robust infrastructure, inter-institutional collaboration, and standardized protocols. As data security continues to be a priority, federated and privacy-preserving ML frameworks are poised to redefine risk analytics and regulatory adherence in a digitally connected financial ecosystem.

5.2 Cross-Border Regulatory Alignment through Reg Tech Innovations

The global nature of investment advisory services demands alignment with diverse and evolving regulatory landscapes across jurisdictions. RegTech (Regulatory Technology) innovations powered by machine learning can harmonize compliance operations through dynamic rule interpretation, regulatory change detection, and automated reporting. NLP-enabled tools can parse and analyze regulatory texts in real-time, allowing firms to adapt policies across the U.S. SEC, EU's MiFID II, and other frameworks without manual intervention. Cross-border data flows and jurisdictional inconsistencies, however, pose challenges in standardization and enforcement. Emerging AI-driven compliance engines can act as intermediaries, translating legal obligations into actionable compliance checklists while flagging potential conflicts across borders. Collaborative sandbox environments between regulators and firms can accelerate innovation and reduce implementation risks. Ultimately, ML-powered RegTech promotes not just operational efficiency but also transparency and accountability in global advisory networks, laying the groundwork for an interoperable regulatory compliance ecosystem.

5.3 Opportunities in Real-Time Compliance Monitoring Dashboards

Real-time compliance dashboards powered by machine learning enable investment advisory firms to monitor transactions, identify anomalies, and visualize compliance risks on a continuous basis. These systems consolidate structured and unstructured data from multiple sources—client portfolios, regulatory updates, internal audits—into dynamic visual interfaces that enhance decision-making and oversight. ML algorithms can flag suspicious activity or regulatory breaches as they occur, facilitating timely intervention and reducing reliance on retrospective audits. Integration with risk engines, sentiment analysis tools, and regulatory change feeds empowers compliance officers with actionable insights tailored to jurisdiction-specific rules. These dashboards also support transparency and traceability through audit logs and explainable AI components. Challenges include ensuring data consistency, model interpretability, and user interface scalability across organizational tiers. As financial institutions prioritize real-time governance, such dashboards represent a critical convergence of analytics, compliance, and user-centric design, offering a proactive defense against regulatory infractions and reputational damage.

5.4 Research Gaps and Next-Generation Advisory Architectures

Despite growing adoption of ML in fraud prevention and compliance, substantial research gaps remain in achieving scalable, explainable, and adaptive solutions tailored to investment advisory contexts. First, there is limited exploration of hybrid architectures that combine symbolic reasoning with machine learning for complex regulatory logic. Second, explainable AI (XAI) models tailored for non-technical compliance officers are underdeveloped, hindering trust and adoption. Additionally, most current systems lack real-time adaptability to legal updates or financial instrument innovations. Future advisory architectures must integrate spatio-temporal analytics, edge computing, and reinforcement learning to provide context-aware and self-optimizing capabilities. Blockchain-integrated audit trails and AI-driven policy simulation environments also represent promising avenues. Bridging these research gaps requires interdisciplinary collaboration across finance, law, and computer science. Establishing benchmarks, open datasets, and evaluation frameworks will accelerate innovation while ensuring regulatory trustworthiness and ethical deployment of ML-driven compliance and fraud prevention systems.

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