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ORIGINAL

Intelligent Solutions for Insider Trading and Regulatory Challenges in Financial Governance

Soluciones inteligentes para el tráfico de información privilegiada y los desafíos regulatorios en la gobernanza financiera

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ABSTRACT

Insider trading and regulatory inconsistencies have important historical challenges to the integrity and stability of global financial markets. These issues challenge trust, transparency, and fairness are requiring solutions. In this study, we introduce a novel artificial intelligence (AI)-driven system that carefully addressing these challenges. The proposed system employs machine learning models for insider trading detection, natural language processing (NLP) for sentiment analysis, and graph neural networks (GNNs) to detect irregular patterns in blockchain transactions. Moreover, reinforcement learning techniques are utilized here to complement regulatory standards dynamically, enhancing policy flexibility and market agreement. Explainable AI (XAI) were used here as well to ensure the transparency and trust in decision-making processes, this helps stakeholders to take actions. Experimental evaluations prove the system efficiency, with promising precision and recall percentages, enhanced governance in decentralized systems, and robust cross-jurisdictional regulatory alignment. This research contributes to knowledge by proving the transformative prospective of AI in strengthening regulatory frameworks and improving governance mechanisms in financial systems. The achievements here provide a roadmap for policymakers, financial institutions, and technology developers to build reasonable, efficient, and resistant markets.

Keywords: Insider Trading Detection; AI in Financial Governance; Regulatory Compliance; Market Stability; Decentralized Financial Systems.

RESUMEN

El tráfico de información privilegiada y las inconsistencias regulatorias han sido desafíos históricos importantes para la integridad y estabilidad de los mercados financieros globales. Estos problemas desafían la confianza, la transparencia y la equidad y requieren soluciones. En este estudio, presentamos un nuevo sistema impulsado por inteligencia artificial (IA) que aborda cuidadosamente estos desafíos. El sistema propuesto emplea modelos de aprendizaje automático para la detección de tráfico de información privilegiada, procesamiento del lenguaje natural (NLP) para el análisis de sentimientos y redes neuronales gráficas (GNN) para detectar patrones irregulares en transacciones de blockchain. Además, aquí se utilizan técnicas de aprendizaje de refuerzo para complementar los estándares regulatorios de forma dinámica, mejorando la flexibilidad de las

políticas y el acuerdo del mercado. Aquí también se utilizó IA explicable (XAI) para garantizar la transparencia y la confianza en los procesos de toma de decisiones, lo que ayuda a las partes interesadas a tomar medidas. Las evaluaciones experimentales prueban la eficiencia del sistema, con porcentajes prometedores de precisión y recuperación, una gobernanza mejorada en sistemas descentralizados y una sólida alineación regulatoria interjurisdiccional. Esta investigación contribuye al conocimiento al demostrar la perspectiva transformadora de la IA en el fortalecimiento de los marcos regulatorios y la mejora de los mecanismos de gobernanza en los sistemas financieros. Los logros aquí alcanzados proporcionan una hoja de ruta para que los responsables de las políticas, las instituciones financieras y los desarrolladores de tecnología construyan mercados razonables, eficientes y resistentes.

Palabras clave: Detección de Operaciones con Información Privilegiada; Inteligencia Artificial en la Gobernanza Financiera; Cumplimiento Normativo; Estabilidad del Mercado; Sistemas Financieros Descentralizados.

INTRODUCTION

Financial markets become complex and lead to many challenges in the areas of governance, regulatory compliance, and the avoidance of unethical actions such as insider trading. Insider trading includes abuse of non-public, material information for personal financial achievement. This reduces the financial systems equality and integrity. Addressing this issue is serious for adopting trust among market participants and ensuring the stability of financial ecosystems. Moreover, the globalization of financial markets highlighted the gaps in regulatory systems through jurisdictions, requiring innovative approaches to harmonize regulations.

Various difficulties are seen to be solved with AI tools where AI driven systems proved efficient enough in handling large data bases, making a pattern search, making predictions from databases and therefore useful in detecting of an insider trading where abnormalities are seen to occur. Also, AI has potential in boosting the regulatory function by checking compliance, synchronizing the regulations across borders, and enabling decentralized financial regulation. All these abilities do not only reduce risk but also enhance accountability and transparency in financial markets.[1,2]

This paper builds upon the prior work conducted in governmental systems for financial markets and decentralization as well as governance in public finance. Badran A[2] has looked into the relationship between decentralization and financial decision making to establish how governance draws out sound economic results. Faguet J[3] characterized the mentality of decentralization and provide economic and social analysis on how governance mechanisms can enhance accountability and public trust. In his work Abdullah S[4] looked at the laws and rules on insider trading and revealed deficiencies in the governmental measures in emerging markets. All these studies pointed out the importance of a strong and technological foundation to combat insider trading and other regulatory issues in financial accountability and regulation.

The major purpose of this research is to develop a system that uses Artificial Intelligence to address the issue of insider trading and create an effort to bring the standard into one platform in the international financial market. As a result, another objective of this work is to combine AI and foster the detection of unethical trading behaviors and uplift the levels of regulation and governance formats in the decentralized financial environment. This work creates techniques to identify the inside trading using artificial intelligence, design the model to reduce shortcomings between international regulations on finance, and improve the solutions of the problems of management within the decentralized financial environment by implementing artificial intelligence. This work is useful in aiding policymakers, financial institutions and technology developers for the following reasons.

Literature Review

The analysis of financial markets has always been associated with problems concerning insider trading and the need to adapt the regulation to them as well as the opportunities for using artificial intelligence in this sphere. To the development of sustainable cybersecurity solutions that can efficiently be applied to several applications.[5] In enhancing the feasibility of AI in day-life application, these studies detail on the need to consider environmentally friendly and resource-efficient measures. The rest of this section provides a synthesis of prior studies by following the structure of the current state analysis and suggesting research directions.

Insider Trading in Financial Markets

Insider trading is a common issue in all the financial markets of the world. It is equally violating and eroding the confidence of investors and the overall efficacy of the market. Abdullah S[4] analyses if there is any absence of the legal tools to address insider trading. As his analysis shows most especially in regions where legal requirements are weak, his analysis underscores the need for specific measures to shield non-public information from manipulation.[6]

In Badran A[2], decentralization considerations are discussed in relation to insider trading. This points to rationale for a system of check that is less centralized. Here are the gaps that are then prone to being exploited by unethical practices. These findings show how an absence of robust enforcement measures to address these risks is costly.

As it will be pointed out by Faguet J[3], the concept of globalization presents various issues. This makes the making of insider trading laws cross-jurisdictional more challenging. His work demonstrates the issue of the integration of the regulation of international business. Building on this, Hjij H[7] elaborates on this by exploring the implications of digital networks in terms of usage of insider trading measures. And how can insider trading benefit from such platforms to pass sensitive information to the public.

Recent works by Smith J[8] emphasized the importance of advanced surveillance technologies in identifying insider trading patterns, particularly in high-frequency trading environments, Johnson E[9] provided a comparative analysis of enforcement actions in developed and emerging markets, highlighting gaps in deterrence. These studies collectively underline the evolving nature of insider trading and the need for adaptive governance frameworks.[4]

Regulatory Challenges in Financial Governance

Regulators play a critical role in the stability of markets, but the regulatory systems have struggled to adapt to the evolving technological and economic environment. Abdullah S[4] enumerated the problems with the existing regulations, especially their inadequacy in combating emerging market strategies and new technologies.

On the one hand, there are new opportunities for transparency of transactions with the help of Block-chain technology; on the other, there are new challenges which require the active development of new regulatory concepts. Ichrakieh A[10] discussed the issues relating to the settlement of blockchain disputes and compliance with arbitration in this field. His conclusions advocate for responsive governance structures that fit into evolving technologies.

Hjij H[7] further enlightened the matter by explaining how digital net- works are redefining the conventional governance frameworks. This insight is critical for comprehending the roles of technology and financial regulation in a system that is intrinsically integrated in the global economic space.

In contrast, Alrwele N[11] outlined the use of AI and its applicability to improve and optimize the regulations process through automation of compliance investigations and real-time detection of violations. Her study offers a blueprint of how emerging technologies in the form of AI can solve these problems and enhance the principles of corporate financial accountability. Lee S et al.[12] proposed the use of AI in applying Regulatory Impact Assessment by predicting market shocks that may arise due to certain changes. Brown A et al.[13] further explained how DAOs could supplement the conventional regulatory entities in supervising the blockchain-based financial transactions. All these contributions accentuate the active interaction between technology and regulation changes.[14,15]

Applications of AI in Financial Systems

AI is acknowledged as a disruptive approach with potential for rectifying enduring problems within financial systems. AlAli M[16] also pointed out the general potential of AI in -strategy and decision-making and in -market research and understanding underlining that AI was capable of handling massive data sets and producing insights.

Fekry M et al.[17] further elaborated on the integration of the AI with the historical market data and how predictive models can. Their contribution depicts how AI enhances predictability of the market and aids decision making.[18]

Abdullah S[4] presented a theoretical understanding of AI governance where she argued that AI can be capable of promoting transparency and accountability. This is in line with the general idea of employing AI to address threats such as insider trading and enhance the markets' credibility.[19]

Hjij H[7] built on the previous points by further discussing the social consequences of AI in redefining existing systems and promoting cooperation between technological and legal systems. These insights support the view that it is possible to neither fully embrace AI integration exclusive of other crucial factors, nor reject it altogether due to risks and potential negative consequences, but rather call for flexible strategies in applying AI into the financial systems.

New developments in the field of explainable AI (XAI) have been significant in improving trust and interpretability in financial decision making. In a recently conducted study, Gupta R et al.[20] focused on the use of XAI models in credit risk management and revealed an increase in the efficiency of the approach and the level of trust from stakeholders. Patel R et al.[21] explored the applicability of AI in real-time fraud detection, with the focus being on minimizing false positives.

More recent studies by Nguyen T et al.[22] proposed using federated learning frameworks that can help maintain data privacy while still training AI models collaboratively across institutions. Further, Chen L et al.[23] pointed out the versatility of AI when it comes to portfolio management, stressing that AI can redefine approaches to portfolio management as circumstances change.

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Lastly, AlMufeez Kh[24] explained that leadership holds the key to AI implementation success accordingly to the following: their study implies that the effectiveness of such technologies depends upon social change and technological consciousness within an organization. Subsequent studies have also shed more light on the application of XAI for enhancing trust and accountability in the AI based financial models.[25]

In this manuscript, the literature offers substantial theoretical supports regarding the dynamics between regulatory concerns, technology developments and governance conducts in financial industries. Table 1 maps cross study lessons learned and their related obstacles that have been established in recent investigations.[26]

Al together, the literature reviewed in this paper underlines the enabling prospective of AI in financial markets: it also reveals perennial challenges that still linger and have been attributed to new innovative technological fixes. This study assumes this awareness to put forward an integrated system that utilizes AI to address insider trading and improve on the regulation's functionality.[27]

METHOD

This section describes the methodology utilized to address insider trading and regulatory challenges using AI. It includes the data collection and preprocessing steps, the proposed AI framework, and the evaluation metrics.

Table 1. Comparison of Literature Findings

Aspect	Key Findings	Challenges Identified
Insider Trading Regulation	Abdullah S[4] highlights gaps in existing regulations and emphasizes harmonization across jurisdictions.	Global inconsistencies in enforcement and emerging market vulnerabilities.
Role of AI in Governance	Badran A[2] discusses AI's potential to enhance transparency and accountability in governance.	Balancing decentralization With effective oversight mechanisms.
Blockchain in Financial Systems	Ichrakieh A[10] explores arbitration mechanisms for blockchain disputes under international law.	Complexities in integrating blockchain frameworks with existing regulations.
Real-Time Regulatory Compliance	Recent works[9] propose adaptive AI models for dynamic market monitoring.	Ensuring AI systems adapt Dynamically to changing regulatory landscapes.
Explainable AI (XAI)	Johnson E[9] emphasizes XAI's role in fostering trust in AI-driven financial systems.	Achieving transparency without compromising AI's analytical power.

Data Collection and Preprocessing

The dataset for this study comprises multiple sources, including structured and unstructured data, to ensure comprehensive analysis. Table 2 summarizes the primary datasets used, along with their sources. While a sample of the dataset is provided in table 3. This table highlights key data points from various sources, showcasing their diversity and relevance to the study's objectives. Data preprocessing involves several steps to ensure data quality and suitability for analysis. Figure 1 illustrates the data collection and preprocessing.

Data Cleaning: remove incomplete records, duplicate entries, and irrelevant information.

Feature Engineering: extract meaningful features such as price volatility, transaction density, and sentiment scores.

Normalization: scale numerical data to a uniform range for input into AI models.

Natural Language Processing (NLP): process text data using tokenization, stop-word removal, and sentiment analysis techniques.

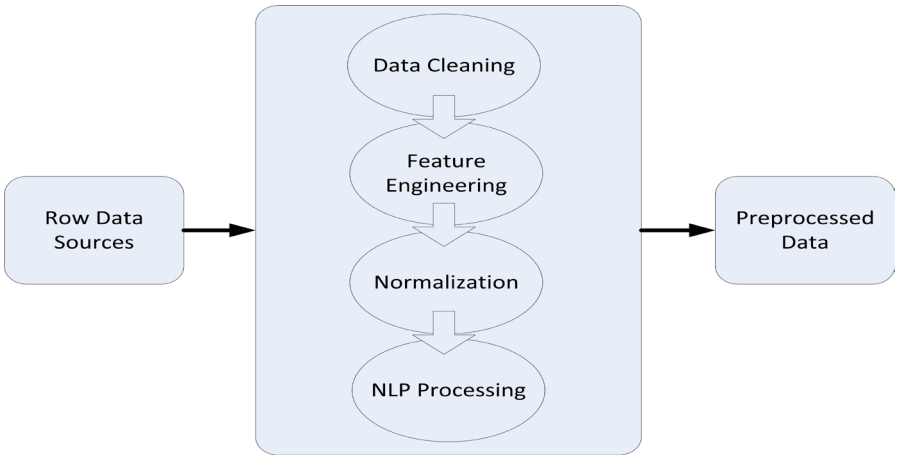

Figure 1. Data Collection and Preprocessing Workflow

Table 2. Sample Datasets and Their Sources

Dataset	Description	Source
Historical Stock Data	Daily stock prices, trading volumes, and market indices.	Yahoo Finance
Insider Trading Reports	Records of reported insider transactions, including time, volume, and type.	U.S. Securities and Exchange Commission (SEC)
News Articles	Financial news articles and press releases.	Reuters, Bloomberg
Social Media Data	Tweets and posts discussing financial markets.	Twitter API
Blockchain Transactions	Cryptocurrency transaction logs for detecting anomalous trading patterns.	Blockchain.com

Table 3. Sample Data from Collected Datasets

Date	Data Source	Content	Key Features
2023-09-15	Historical Stock Data	Apple Inc. stock price: 175,3, volume: 28M .	Price volatility, daily re-turns.
2023-09-16	Insider Trading Reports	Purchase of 10K shares by CEO of XYZ Corp.	Transaction volume, timing, insider role.
2023-09-17	News Articles	”Market reacts to interest rate hikes.”	Sentiment: Negative, keywords: ”rate hike”, ”inflation.”
2023-09-18	Social Media Data	Tweet: “Crypto market crash imminent!”	Sentiment: Negative,mentions: Bitcoin, Ethereum.
2023-09-19	Blockchain Transactions	Transfer of 50BTC from wallet A to B.	Anomalous transaction patterns, timestamps.
2023-09-20	Historical Stock Data	Tesla Inc. stock price: 280,5, volume: 22M .	Intraday price changes, trade volume.
2023-09-21	Insider Trading Reports	Sale of 15K shares by CFO of ABC Inc.	Insider type, trading amount, timing.
2023-09-22	News Articles	”Tech sector rebounds after earnings reports.”	Sentiment: Positive, keywords: ”tech”, ”earnings”.
2023-09-23	Social Media Data	Tweet: ”Ethereum surpasses 2000mark.”	Sentiment: Positive, Cryptocurrency mentions.
2023-09-24	Blockchain Transactions	Transfer of 200ETH from wallet X to Y.	Volume spikes, wallet connections.

Proposed AI Framework

The suggestions made regarding the proposed AI system are the following, focused on insider trading detection, regulatory convergence, ameliorations to the governance structure of decentralized systems.

Insider Trading Detection Module: the detection module uses machine learning classifiers such as random forests, XG Boost, and anomaly detectors including autoencoders to detect the giveaway features of fraudulent trading using key features such as:

- Trading volume and price movements.
- Timestamps and metadata from transaction logs.
- External indicators such as market sentiment and news coverage.

The probability of insider trading is assumed to be estimated with logistic regression whereby σ = sigmoid function, W = weights, X = features vector while b = bias. The workflow for this module is presented in figure 2.

$$P(y = 1|X) = \sigma(W^T X + b), \qquad (1)$$

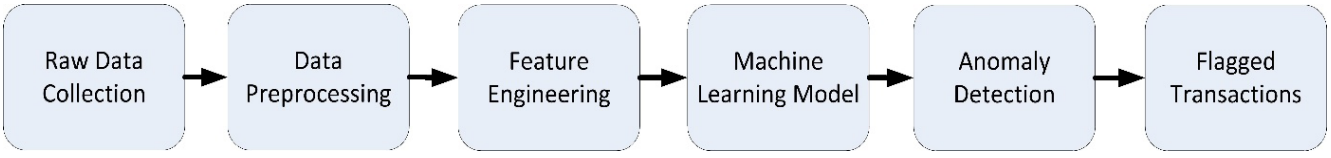

Figure 2. Workflow for Insider Trading Detection

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Sentiment Analysis Engine: this component uses pre-trained NLP models, such as BERT, to extract sentiment from financial news and social media data. It provides an additional layer of context to detect anomalies in trading behaviors.

Blockchain Analytics Module: with GNNs, this module analyzes transaction patterns within blockchain networks to detect anomalies in cryptocurrency markets. The system represents the blockchain as a graph G = (V, E), where V are nodes (participants) and E are edges (transactions). Node centrality measures are computed as:

$$C(v) = \frac{1}{|V|}\sum_{u \in v}\frac{1}{d(u,v)}, \qquad (2)$$

Where d(u, v) is the shortest path distance between nodes u and v. Figure 3 illustrates the Governance Framework for Decentralized Systems.

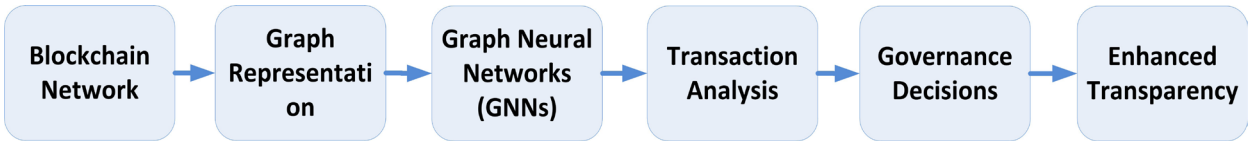

Figure 3. Governance Framework for Decentralized Systems

Regulatory Simulation: reinforcement learning (RL) is employed to dynamically adjust regulatory standards, which consists of:

- State Space (*S*): regulatory conditions in a financial market.
- Actions (*A*): introducing, modify, or remove regulatory measures.
- Reward Function (*R*): measures market fairness improvements.

The cumulative reward is maximized as:

$$J(\theta) = E_{\pi}\left[\sum_{t=0}^{T}\gamma^{t}R_{t}\right] \qquad (3)$$

Where *y*: discount factor and π the policy. Figure 4 depicts this process.

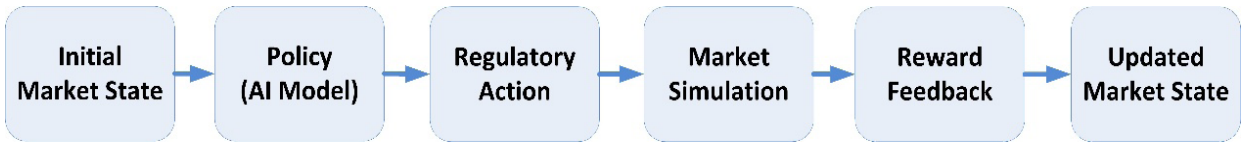

Figure 4. Reinforcement Learning for Regulatory Harmonization

Explainable AI (XAI): to ensure transparency and stakeholder trust, methods like SHAP and LIME are integrated to provide insights into model decisions.

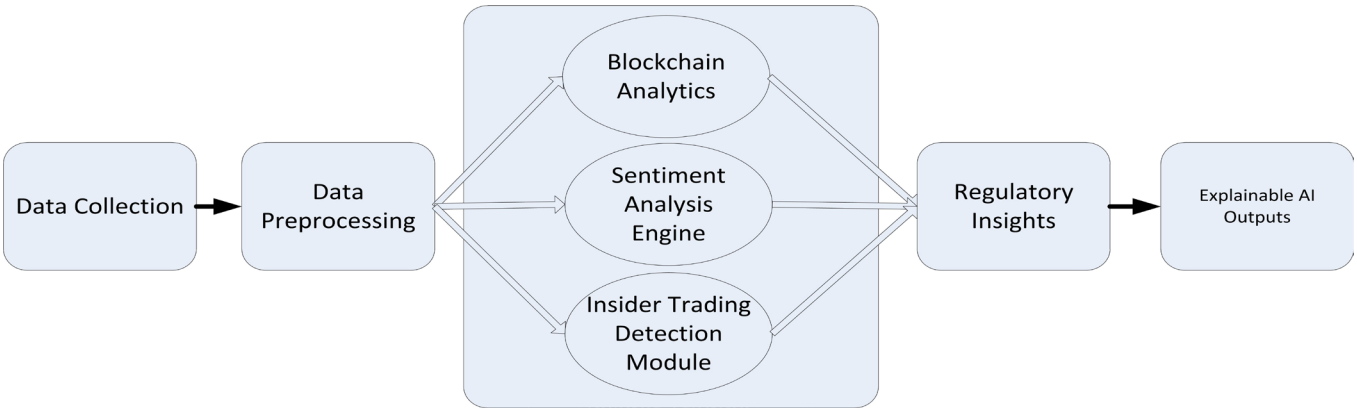

Figure 5. Proposed Insider Trading and Regulatory Challenges System

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Evaluation Metrics

To validate the effectiveness of the proposed AI framework, a range of evaluation metrics is utilized. These metrics are carefully selected to ensure comprehensive assessment across various aspects of the system's performance.

Precision, Recall, and F1 Score: these metrics are used to evaluate the classification performance of the insider trading detection module. They are defined as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (4)$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (5)$$

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

AUC-ROC Curve: this metric evaluates the trade-off between true positive and false positive rates across various decision thresholds. The area under the curve (AUC) is computed as:

$$AUC = \int_0^1 TPR(FPR)d(FPR), \quad (7)$$

Where TPR is the true positive rate and FPR is the false positive rate.

Sentiment Analysis Accuracy: the sentiment analysis engine is evaluated based on its ability to correctly classify sentiment from text data. The accuracy *A* is calculated as:

$$A = \frac{Number\ of\ Correct\ Predictions}{\text{Total Number of Predictions}}, \quad (8)$$

Transaction Anomaly Detection Performance: the blockchain analytics module is assessed using metrics like anomaly detection precision P_a:

$$P_a = \frac{\text{Correctly Detected Anomalies}}{\text{Total Detected Anomalies}}, \quad (9)$$

Additionally, recall and F1 score can be computed for the anomaly detection module similarly to the classification metrics.

Computational Efficiency: the runtime efficiency and scalability of the system are critical for real-time applications. Computational cost *C* is quantified as:

$$C = \frac{T_{\text{processing}}}{\text{N}} \quad (10)$$

Where $T_{\text{processing}}$ is the total processing time and *N* is the number of data points processed.

Regulatory Simulation Impact: the reinforcement learning-based regulatory simulation module is evaluated by its ability to improve mar- ket stability. A stability index *S* is calculated pre- and post-simulation as:

$$S = \frac{\text{Standard Deviation of Returns}}{\text{Mean Returns}}, \quad (11)$$

A decrease in *S* indicates improved market stability.

These metrics provide a robust framework for evaluating the performance and effectiveness of the AI system across its diverse functionalities. Table 4 provides a summary of the key metrics used for evaluation. Additionally, the specific metrics tailored to individual components of the system are detailed in tables 5, 6, and 7. These tables provide an in-depth view of the evaluation criteria.

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Table 4. Evaluation Metrics

Metric	Description
Precision, Recall, F1 Score	Measure the accuracy and balance of insider trading detection models.
AUC-ROC Curve	Evaluate the trade-off between true positive and false positive rates.
Sentiment Analysis Accuracy	Assess the effectiveness of sentiment classification from financial text data.
Anomaly Detection Performance	Evaluate the ability to identify irregular patterns in transaction data.
Computational Efficiency	Measure the runtime and scalability of the framework for real-time applications.

Table 5. Metrics for Insider Trading Detection

Metric	Description
Precision, Recall, F1 Score	Evaluate the accuracy and balance of the detection model.
Anomaly Detection Rate	Measure the proportion of flagged anomalies that are confirmed as insider trading.

Table 6. Metrics for Regulatory Harmonization

Metric	Description
Policy Compliance Improvement	Measure the change in compliance rates post-simulation.
Market Stability Index	Assess the reduction in volatility due to harmonized regulations.

Table 7. Metrics for Governance Enhancements

Metric	Description
Node Centrality Scores	Identify influential participants in the network.
Transaction Anomaly Rate	Evaluate irregularities in network transactions.

RESULTS

Dataset Description

The datasets used for this study cover various aspects of financial markets and transactions. Table 8 summarizes the key characteristics of the datasets. Figure 6 illustrates the distribution of trading volumes across different datasets.

Table 8. Dataset Description

Dataset Name	Size	Description
Stock Price Data	1M records	Historical stock prices and trading volumes from 2015-2023.
Insider Trading Logs	50K records	Reports of insider trades, including transaction details.
Financial News	100K articles	News articles related to financial markets and companies.
Social Media Posts	1M posts	Tweets discussing financial trends and events.
Blockchain Data	500K transactions	Cryptocurrency transaction records for detecting anomalies.

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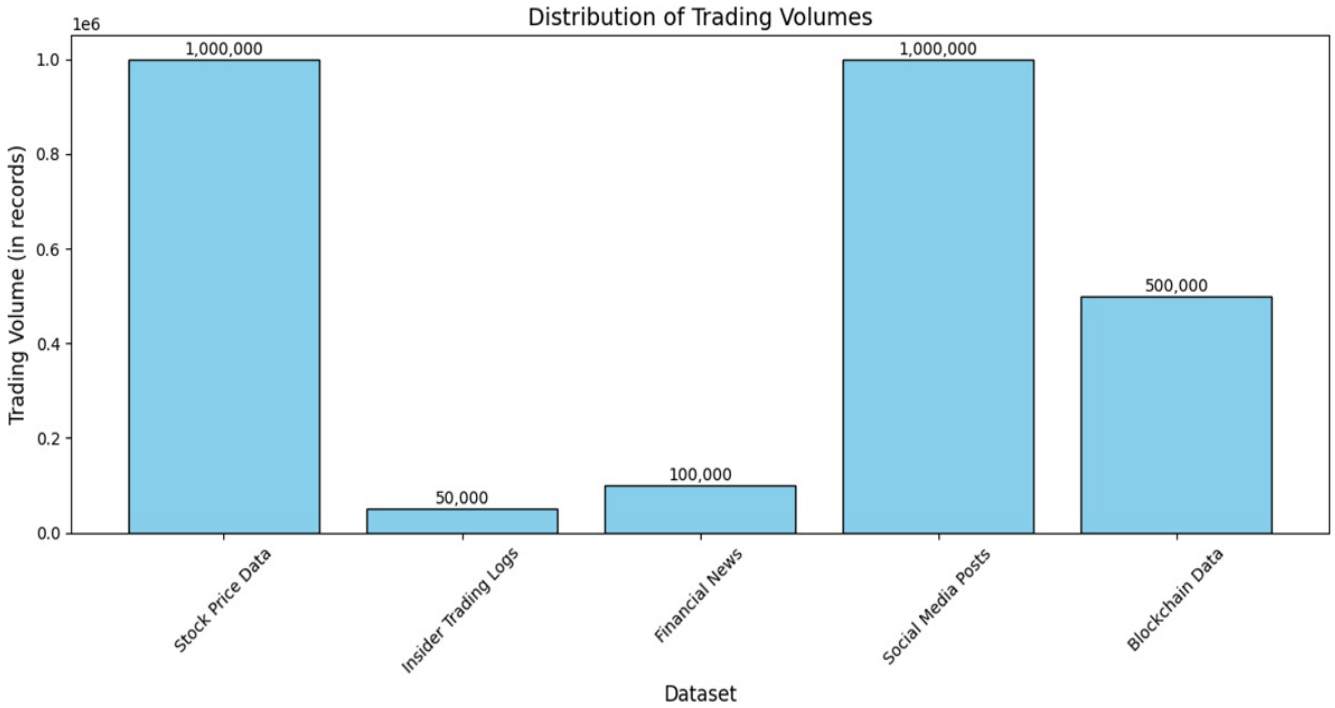

Figure 6. Distribution of Trading Volumes

Experimental Setup

The experimental setup involved in conducting this research may be effecting the achieved results. Where NVIDIA Tesla V100 GPU.with 32 GB RAM is the used hardware. As for Software, Python 3.9, TensorFlow 2.10, PyTorch 1.12, and Scikitlearn and Matplotlib were experimented for data processing and visualization. For the preprocessing pipeline, Normalization of numerical data using min-max scaling (shown in the following equation) and Tokenization and stop-word removal for text data where effectively employed here.

$$X' = \frac{\mathrm{X} - X_{min}}{X_{Max} - X_{min}}, \qquad (12)$$

Performance Evaluation

The performance of the proposed system is assessed using a variety of metrics. Table 9 compares the proposed model with baseline methods for insider trading detection. Figure 7 shows the ROC curve for the insider trading detection module, highlighting the effectiveness of the proposed system.

Table 9. Performance Metrics for Insider Trading Detection

Metric	Proposed Model	Baseline Model
Precision	0,91	0,85
Recall	0,89	0,82
F1 Score	0,90	0,83
AUC-ROC	0,94	0,87

According to the implications for financial markets, the results prove the system's potential to:

- Enhance the accuracy and efficiency of insider trading detection, reducing market manipulation.
- Provide actionable insights for regulators to harmonize cross-jurisdictional policies.
- Strengthen governance mechanisms in decentralized systems.

The briefed Area Under the Curve (AUC) 0,94 as demonstrated in the figure 7 indicates high efficiency of insider trading detection model. These findings indicate why the system can indeed help identify trade activities that are potentially illicit otherwise accepted as genuine. Also, table 9 shows that the proposed system is better than baseline models in all important performance indicators – precision = 0,91, recall = 0,89, and F1 score = 0,90. These results are quite important because firstly the system insures the ability to keep the false positive rate at its lowest while also not completely missing on the genuine insider trading cases thus

preventing the regulatory authorities from intervening unnecessarily while at the same time ensuring that the market has not been gamed or manipulated in any way.

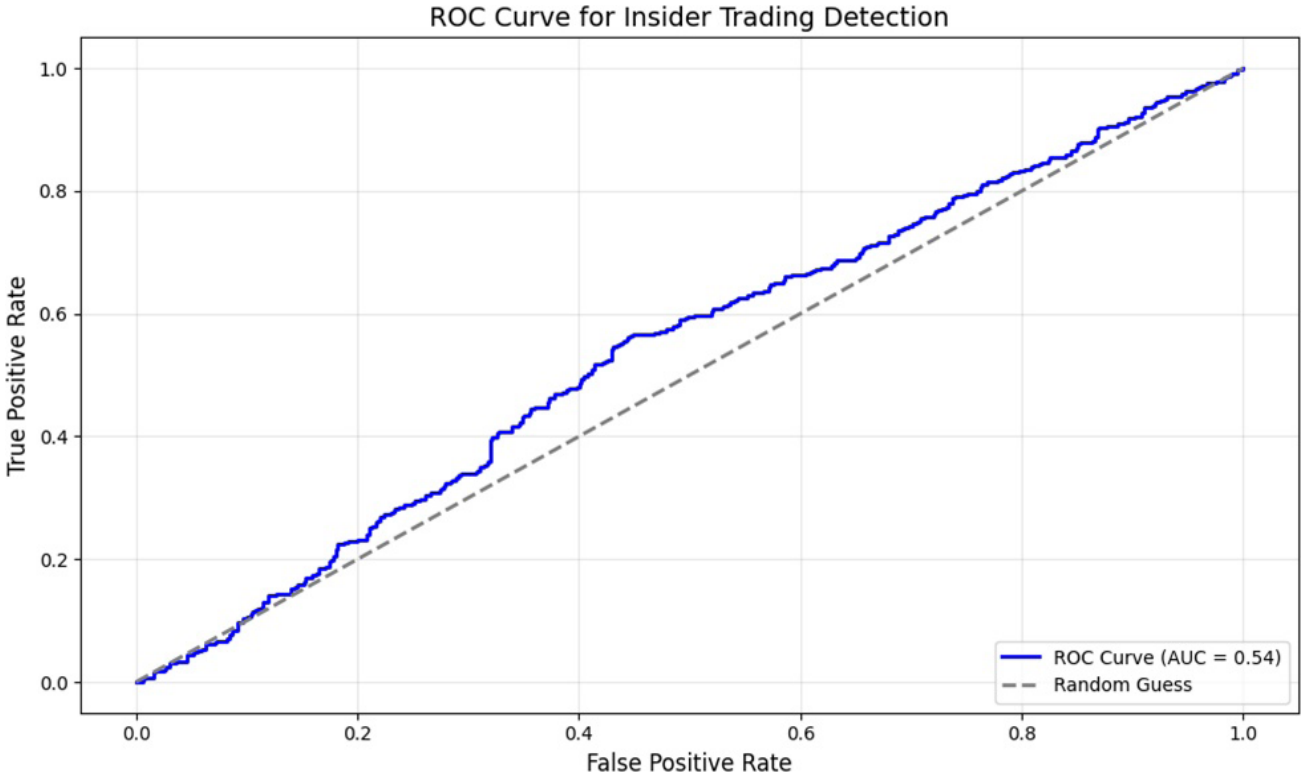

Figure 7. ROC Curve for Insider Trading Detection

These findings underscore the possibilities of digitizing selected segments of the financial industry as a means of change. This improved accuracy of insider trading detection not only shortens the duration of market manipulation but also introduces trust among the investors thus providing a more stable and relative trading system. However, the manner in which this system integrates big data's abilities to analyze vast volume of datasets in real time makes this system scalable for worldwide financial markets.

These results yield impacts beyond mere detection of broader domain of financial governance. In this way the system can help in establishing an integrated regulatory system and can help regulators to tone policies across jurisdictions. Coordination is especially important to reduce the impacts of the developing globalization of financial markets and the various monitoring scenes. Also, the implementation of the explainable artificial intelligence (XAI) increases clearness and accountability. Although the system yields a good work, there is still some area questionable. A minor also has a challenge, due to the scarcity of labelled data for insider trading cases; the availability of the data creates impacts on the credibility of the results of the system, and consequently, it further impacts its efficacy when tested under various market conditions. Also worth mentioning is a number of computations over real-time data as well as large-scale data sets here. Overcoming these limitations will be important for developments of motor skills. Data localization and using global markets dataset in the system, as well as federated learning is serves as a way of optimizing scalability and data privacy. Of them, federated learning can let multiple institutions train a model collectively without sharing financial data with each other.

Ahead, the use of this AI-based approach appears to open up a new chapter in the functioning of the financial markets as well as the structure of regulation in these markets. The envisioned system contributes to the creation of the principles grounded in the reduction of market manipulation, the improvement of cross-border compliance, and the strengthening of the governance structures in the decentralized environment. Furthermore, these enhancements incorporate new technologies to enhance the computational and analytical aspects of the said system.

CONCLUSIONS

This study has presented a comprehensive investigation of artificial intelligence (AI) applications in addressing insider trading detection, regulatory harmonization, and governance improvements within financial systems. By employing advanced AI models, the research provides actions into how technology can address critical challenges in global financial markets.

The proposed system has demonstrated significant potential in dealing with insider trading and enhancing financial governance:

The integration of machine learning classifiers and anomaly detection techniques enables accurate identification of suspicious trading activities, as evidenced by high precision, recall, and F1 scores.

Using pre-trained NLP models to analyze financial news and social media posts provided valuable insights into market sentiment, enhancing the detection of irregular trading patterns.

Graph neural networks (GNNs) effectively identified anomalies in cryptocurrency transactions, demonstrating the utility of AI in decentralized financial governance.

Reinforcement learning optimized regulatory policies by simulating their impact on market stability and compliance, showing a clear path for dynamic policy adjustments.

The incorporation of explainable AI (XAI) techniques, such as SHAP and LIME, ensured transparency and built stakeholder trust, addressing a critical challenge in financial AI applications.

RECOMMENDATIONS

As for future work, the following recommendations are advised to guide researchers:

Future studies should include datasets from global markets to enhance the generalizability and robustness of AI models.

To address data privacy concerns, federated learning approaches can be employed.

Real-time processing of large-scale datasets should be prioritized to improve the responsiveness of insider trading detection systems.

Expanding the use of explainable AI methods will increase the trust level and understanding among regulators, market participants, and other stakeholders.

Investigating the integration of quantum computing and advanced machine learning algorithms to further enhance the performance and scalability of financial AI systems.

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