DETECTING INSIDER TRADING USING DATA MINING TECHNIQUES

A PROJECT REPORT

Submitted by

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In partial fulfilment for the award of the degree

of

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IN

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K.RAMAKRISHNAN COLLEGE OF ENGINEERING

(AUTONOMOUS)
Under
ANNA UNIVERSITY, CHENNAI

BONAFIDE CERTIFICATE

Certified that this project report titled **“DETECTING INSIDER TRADING USING DATA MINING TECHNIQUES”** is the bonafide work of **JANANI K (8115U23IT038**), who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported here in does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

I declare that the project report on **“DETECTING INSIDER TRADING USING DATA MINING TECHNIQUES”** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **“ANNA UNIVERSITY CHENNAI”** for the requirement of Degree of BACHELOR OF TECHNOLOGY. This project report is submitted on the partial fulfillment of the requirement of the award of the course **ITB1303 – DATA MINING TECHNIQUES**

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Date:

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VISION

To achieve a prominent position among the top technical institutions

MISSION

- To bestow standard technical education par excellence through state of the art infrastructure, competent faculty and high ethical standards.
- To nurture research and entrepreneurial skills among students in cutting edge technologies.
- To provide education for developing high-quality professionals to transform the society.

DEPARTMENT VISION AND MISSION

VISION

To create eminent professionals of Information technology by imparting quality education.

MISSION

- To provide technical exposure in the field of Information technology through state of the art infrastructure and ethical standards.
- To engage the students in research and development activities in the field of information technology..
- To empower the learners to involve in industrial and multi-disciplinary projects for addressing the societal needs.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOS)

PEO1: Analyse, design and create innovative products for addressing social needs.

PEO2: Equip themselves for employability, higher studies and research.

PEO3: Nurture the leadership qualities and entrepreneurial skills for their successful career.

PROGRAM OUTCOMES (POS)

Engineering students will be able to:

1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSOS)

PSO1: Apply the basic and advanced knowledge in developing software, hardware and firmware solutions addressing real life problems.

PSO2: Design, develop, test and implement product-based solutions for their career enhancement.

ABSTRACT

Detecting Insider Trading Using Data Mining Techniques is an advanced, intelligent web-based platform designed to accurately identify and analyze potential insider trading activities using cutting-edge data mining and machine learning (ML) techniques. This system integrates a hybrid detection model that combines the strengths of unsupervised algorithms like Isolation Forest and DBSCAN with supervised approaches such as XGBoost and neural networks, enabling it to efficiently capture both known patterns of market abuse and emerging anomalous behaviors. Through an interactive Streamlit-based dashboard, compliance teams and regulators can upload trading datasets, visualize behavioral patterns, analyze network relationships, and generate detailed risk reports with ease. The system features a Real-Time Alert Mechanism that automatically flags suspicious trades based on dynamic risk thresholds, helping stakeholders take timely investigative or preventive actions. Additionally, the AI-powered Network Analysis Engine uncovers hidden collusion networks and coordinated trading schemes by mapping complex relationships between traders, accounts, and corporate insiders. To enhance usability and decision-making, the platform includes automated reporting for regulatory compliance and an interactive chatbot that allows users to query analysis results in natural language. Implemented using Python, Scikit-learn, NetworkX, Streamlit, and Neo4j, this project provides a comprehensive, scalable, and user-friendly solution for financial market surveillance. It supports compliance officers, regulatory bodies, and financial institutions in monitoring trading behavior, improving investigative efficiency, and maintaining market integrity—contributing to proactive fraud detection and strengthened financial governance.

Keywords: Insider Trading Detection, Data Mining, Machine Learning, Hybrid Model (Isolation Forest & DBSCAN), Network Analysis, and Regulatory Compliance.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
ARIMA	Auto-Regressive Integrated Moving Average
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
EDA	Exploratory Data Analysis
EWS	Early Warning System
CSV	Comma-Separated Values
XAI	Explainable Artificial Intelligence
XGBOOST	Extreme Gradient Boosting
NLP	Natural Language Processing
VADER	Valence Aware Dictionary and Sentiment Reasoner
BERT	Bidirectional Encoder Representations from Transformers
API	Application Programming Interface
GPU	Graphics Processing Unit
PCA	Principal Component Analysis
HDD	Hard Disk Drive
OS	Operating System
IDE	Integrated Development Environment
SMTP	Simple Mail Transfer Protocol
SMPS	Switched-Mode Power Supply
AWS	Amazon Web Services

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The platform's analytical engine is built around sophisticated data mining techniques that transform raw trading data into strategic intelligence. Machine learning algorithms including Isolation Forests for anomaly detection, DBSCAN for clustering similar trading patterns, and PCA for dimensionality reduction work in concert to identify suspicious activities that would escape traditional detection methods. Network analysis capabilities map relationships between traders, companies, and intermediaries, revealing hidden connections and coordinated trading behaviors. Real-time risk scoring incorporates multiple factors including trade timing, volume anomalies, participant relationships, and corporate event proximity to provide comprehensive risk assessment.

The system conducts thorough analysis of trader profiles and relationship networks, identifying potential connections and patterns that might indicate coordinated activities. Furthermore, it incorporates historical data analysis covering multiple market cycles and varying economic conditions, ensuring the detection algorithms remain effective across different market environments and can identify emerging patterns based on historical precedents. This comprehensive scope ensures the platform delivers a complete surveillance solution that addresses the complex, multi-faceted nature of insider trading detection in modern financial markets.

The platform employs an ensemble of predictive models that go beyond initial anomaly detection. Supervised learning algorithms are trained on vast datasets of both legitimate and known illicit trading activities, enabling them to recognize subtle, complex signatures of fraud. These models are part of a continuous learning feedback loop; as regulatory decisions are made and new cases are confirmed, this information is fed back into the system to retune and enhance the algorithms

1.2 PURPOSE OF THE PROJECT

The primary purpose of this project is to develop a comprehensive, scalable, and intelligent insider trading detection system that fundamentally transcends the limitations of conventional rule-based surveillance approaches. At its core, the system is engineered to significantly enhance detection capabilities by implementing advanced machine learning algorithms, including anomaly detection and clustering techniques, which can identify complex, non-obvious trading patterns and subtle anomalies that traditional methods inevitably miss. This sophisticated analytical foundation is crucial for substantially reducing both false negatives, ensuring genuine threats are caught, and false positives, preventing alert fatigue among compliance teams.

Building upon this, the project aims to provide truly holistic market monitoring by creating a unified platform that seamlessly integrates disparate data sources—including trade data, corporate events, user profiles, and historical market data—into a single, coherent analytical framework. This integration offers investigators a complete 360-degree view of trading activities across different asset classes, timeframes, and a diverse range of market participants, thereby eliminating the siloed analysis that often obscures sophisticated misconduct. Uncover Sophisticated Collusion Networks. The system maps complex relationship networks to detect coordinated trading across multiple accounts and intermediaries, exposing organized insider trading rings that would be invisible in isolated trade analysis.

A critical objective is to enable proactive risk management through the development of dynamic, predictive risk-scoring mechanisms. These mechanisms synthesize multiple risk factors to allow compliance teams to identify and assess potential insider trading risks before they escalate into full-blown regulatory violations or cause significant market disruptions, shifting the compliance paradigm from reactive to pre-emptive action.finally, the project prioritizes the achievement of contextual intelligence and explainable AI (XAI). The system provides clear, interpretable reasoning for every alert generated, detailing the specific behavioral deviations, network connections, or corporate event timing that contributed to the risk score. This transparency not only dramatically speeds up the investigation and validation process for analysts but also builds crucial trust in the system's automated findings, ensuring that the technology acts as a powerful aid rather than an inscrutable black box.

1.3 SCOPE OF THE PROJECT

The scope of the Advanced Insider Trading Detection Platform comprehensively spans technical capabilities, functional applications, and data processing dimensions to deliver a robust market surveillance solution. From a technical perspective, the platform implements sophisticated machine learning algorithms including Isolation Forest for anomaly detection, DBSCAN for clustering similar trading patterns, and Principal Component Analysis (PCA) for multidimensional pattern visualization and dimensionality reduction. It further develops advanced network analysis capabilities to map and analyze complex relationships between traders, companies, and financial intermediaries, while creating real-time data processing pipelines engineered to handle high-volume trading data streams across multiple markets. The technical architecture also integrates interactive visualization tools specifically designed for exploratory data analysis and comprehensive investigation support, enabling compliance teams to intuitively navigate complex datasets and identify potential misconduct.

Functionally, the platform encompasses monitoring of equity trading activities across multiple markets and jurisdictions, providing a unified view of trading behaviors that may span geographic and regulatory boundaries. It conducts sophisticated analysis of trading patterns in relation to corporate events such as earnings announcements, merger activities, and regulatory approvals, identifying potentially suspicious activities surrounding material non-public information. The system performs multi-layered risk assessment of individual trades, trader profiles, and corporate securities, generating actionable alerts and investigation priorities that enable compliance teams to focus their efforts on the highest-risk activities.

Crucially, the platform supports both real-time surveillance for immediate intervention and historical pattern analysis for deeper investigations and trend identification.in terms of data scope, the platform processes comprehensive trade execution data including precise timestamps, trading volumes, execution prices, and detailed participant information to build a complete picture of market activities..

1.4 SIGNIFICANCE OF THE PROJECT

The development of the Advanced Insider Trading Detection Platform carries substantial significance for financial market integrity and regulatory compliance. By implementing sophisticated machine learning algorithms and network analysis capabilities, the project addresses critical gaps in traditional surveillance methods that have struggled to keep pace with evolving market complexities. The platform's ability to detect subtle patterns and relationships across vast datasets represents a crucial advancement in maintaining fair and transparent markets. For financial institutions and regulatory bodies, this technology provides an essential tool for identifying potential market abuse activities that might otherwise go undetected using conventional monitoring approaches. The project's significance extends beyond mere compliance, serving as a proactive mechanism to protect investor confidence and market stability by ensuring a level playing field for all participants.

Furthermore, the platform's operational impact demonstrates significant practical value across multiple dimensions of financial market oversight. By automating complex pattern recognition and risk assessment processes, the system enables compliance teams to work more efficiently, focusing their expertise on high-priority investigations rather than manual data screening. This technological advancement represents a paradigm shift in how financial surveillance is conducted, moving from reactive monitoring to proactive intelligence gathering. The project's scalable architecture and real-time processing capabilities ensure that it can adapt to increasingly sophisticated trading strategies and growing market volumes. Ultimately, the platform serves as a critical infrastructure component for maintaining market integrity in an era of digital transformation, providing both immediate operational benefits and long-term strategic value for financial market participants and regulators alike.

CHAPTER 2

LITERATURE SURVEY

2.1 BEHAVIORAL ANOMALY DETECTION IN TRADING

"Anomaly Detection in Financial Trading Using Behavioral Analytics" "2023"
"Michael Chen et al."

This study focused on identifying suspicious trading activities through behavioral pattern analysis and anomaly detection algorithms. The research emphasizes that insider trading often manifests as significant deviations from established individual trading patterns in terms of timing, volume, and security selection. The dataset was collected from multiple financial institutions over a five-year period, including complete trading histories, corporate event calendars, and trader profiles. Data cleaning involved handling missing records, normalizing trading frequencies, and aligning corporate events with trading activities

The methodology employed Isolation Forests for unsupervised anomaly detection combined with dynamic baselining of individual trader behavior. By establishing personalized behavioral models for each trader, the system could identify statistical outliers that represented potential insider trading[1]. The research showed that this behavioral approach reduced false positives by 40% compared to traditional threshold-based systems while maintaining high detection sensitivity. The study also highlighted the importance of adaptive learning in maintaining detection accuracy as traders' behaviors evolve over time.

This paper explores behavioral analytics for insider trading detection using machine learning and anomaly detection algorithms. The study emphasizes capturing deviations from normal trading patterns through continuous monitoring and pattern analysis. Data from multiple financial institutions were collected, processed, and analyzed for behavioral modeling. The study concluded that personalized behavioral modeling provides a more nuanced and effective approach to insider trading detection than traditional threshold-based methods.

2.2 NETWORK ANALYSIS FOR COLLUSION DETECTION

"Mapping Financial Networks to Identify Coordinated Trading" "2022" "Sarah Johnson et al."

The study proposed a network analysis framework to detect coordinated trading activities across multiple accounts and intermediaries. Graph theory and social network analysis were used to identify hidden relationships between traders, accounts, and financial institutions. The research demonstrated that network analysis could reveal sophisticated collusion patterns that would be invisible in traditional single-account monitoring. The methodology incorporated community detection algorithms and graph neural networks to identify tightly-knit groups exhibiting synchronized trading behaviors.

In this research, the authors developed a comprehensive network analysis system that maps complex relationships in financial markets. The study used multiple data sources, including trade execution data, account information, corporate affiliations, and communication records to construct detailed network graphs[2]. The rationale was that sophisticated insider trading involves coordinated activities across multiple entities that share hidden connections. The dataset comprised trading records from over 100,000 entities across three years, combined with relationship data from various public and private sources .

The methodology employed Louvain community detection for identifying clusters of coordinated traders and used node embedding techniques to learn representations of trading entities in low-dimensional space. By analyzing network centrality measures and clustering coefficients, the system could identify key players in potential insider trading rings. The methodology incorporated community detection algorithms and graph neural networks to identify tightly-knit groups exhibiting synchronized trading behaviors.The results demonstrated that network analysis identified 35% more collusion cases compared to traditional surveillance methods, with particular effectiveness in detecting organized trading rings.

2.3 TEMPORAL PATTERN MINING FOR EVENT-BASED

"Corporate Event-Driven Insider Trading Detection Using Temporal Pattern Mining" "2023" "David Chen et al."

Modern insider trading detection systems rely heavily on extracting meaningful behavioral features from raw transactional data. Instead of focusing only on price and volume, analysts derive metrics that capture how an investor behaves over time—such as trade frequency, exposure deviations, timing relative to announcements, and profit consistency. These behavioral indicators help identify whether a trader's actions align with their usual pattern or diverge in suspicious ways. For example, a trader who typically places small periodic trades but suddenly executes large, profitable orders immediately before earnings releases may be flagged by the system.

Feature engineering transforms raw financial data into structured signals that allow anomaly detection models to differentiate normal market activity from potentially illicit behavior[3]. This process is critical because regulatory datasets rarely contain explicit labels indicating insider misconduct. By extracting behavioral fingerprints, analysts can train detection models to identify irregularities even without direct evidence, enabling more nuanced and reliable surveillance.

A key component of modern systems is the ability to analyze trades relative to market-moving events. Rather than treating transactions as independent occurrences, advanced systems evaluate when trades happen in relation to price-sensitive disclosures such as mergers, corporate announcements, or regulatory filings. Event-based analysis helps detect patterns where traders consistently take beneficial positions shortly before important news becomes public. Systems use sliding time windows, temporal profiling, and statistical comparisons to identify whether an investor systematically anticipates future market movements. Unlike early detection methods that looked only at extreme price movements, temporal analysis reveals subtle behavioral cues, such as recurring early access to information. This makes event-based modeling essential for uncovering sophisticated forms of insider trading that are designed to resemble legitimate profit-seeking behavior.

2.4 MULTI-MODAL DATA INTEGRATION

"Integrating Structured and Unstructured Data for Insider Trading Detection" "2022" "Maria Rodriguez et al."

The study proposed a multi-modal data integration framework combining structured trading data with unstructured information sources including corporate communications, news articles, and social media sentiment. The research demonstrated that incorporating unstructured data significantly improved detection accuracy, particularly for sophisticated schemes involving information leakage through alternative channels. The methodology featured natural language processing for sentiment analysis and transformer-based models for semantic feature extraction.

In this research, the authors developed an advanced multi-modal system that integrates diverse data types for comprehensive surveillance. The study used multiple data modalities, including structured trading records, unstructured text data, communication metadata, and relationship information[4]. The rationale was that modern insider trading schemes leave digital footprints across multiple data sources that must be correlated for effective detection. The dataset encompassed two years of multi-modal financial data from various sources including market feeds, corporate filings, and news outlets

The methodology employed BERT-based models for text feature extraction and cross-modal attention mechanisms for integrating different data types. By learning joint representations across modalities, the system could identify subtle correlations between trading activities and external events. The results showed that multi-modal integration improved detection precision by 28% and recall by 32% compared to systems using only structured data. The research concluded that holistic data integration is essential for detecting sophisticated insider trading in modern financial markets.

2.5 REAL-TIME STREAM PROCESSING FOR PROACTIVE

"Real-Time Insider Trading Detection Using Streaming Analytics" "2023" "James Thompson et al."

Common security techniques include HTTPS encryption, two-factor authentication, session token validation, and controlled data retention policies. Given that surveillance platforms may be deployed in different jurisdictions, they must also comply with regulations such as GDPR, SEC requirements, and regional market abuse directives. Unlike conventional software platforms, insider trading systems must guarantee data confidentiality, legal auditability, and long-term traceability under high-stakes regulatory environments.

The methodology focused on adaptive windowing techniques and online learning algorithms that could process continuous data streams. The system employed ensemble methods combining multiple detection signals and used change detection algorithms to identify emerging patterns[5]. The results indicated that real-time processing maintained detection accuracy comparable to batch systems while reducing response time from hours to milliseconds. The study concludes that streaming analytics represents a fundamental advancement in financial surveillance technology.

The detection methodology combined online machine learning algorithms with complex event processing to identify emerging patterns in real-time. The system employed adaptive windowing techniques that dynamically adjusted analysis timeframes based on market volatility and event significance. Advanced features included pattern recognition for common insider trading strategies such as front-running, window dressing, and information-based arbitrage. Performance testing demonstrated the system's ability to maintain 99.9% uptime while processing continuous market data streams, with detection accuracy matching offline batch processing systems. The implementation at several major financial institutions resulted in a 65% improvement in detection speed, enabling regulatory interventions before significant market damage could occur.

2.6 EXPLAINABLE AI FOR REGULATORY COMPLIANCE

"Interpretable Machine Learning for Insider Trading Investigation" "2022" "Jennifer Park et al."

This study focused on developing explainable AI systems for insider trading detection that provide transparent reasoning for regulatory compliance and legal proceedings. The research addressed the challenge of model interpretability in complex detection systems, which is crucial for regulatory acceptance and investigation workflows. The methodology incorporated SHAP values, counterfactual explanations, and decision path visualization to make model outputs comprehensible to human investigators.

This paper presents a comprehensive framework for explainable AI in financial surveillance systems. The authors identified that while complex machine learning models offer superior detection capabilities, their black-box nature poses significant challenges for regulatory investigations and legal proceedings [6]. The study collected investigation records and model outputs from multiple financial institutions, combining them with expert annotations from experienced regulators.. The integration of NLP allows surveillance platforms

The proposed approach integrated multiple explainability techniques including feature importance analysis, prototype selection, and decision boundary visualization. The system generated detailed investigation reports highlighting specific factors that contributed to each alert, such as temporal proximity to corporate events, volume anomalies, and behavioral deviations. User studies demonstrated that the explainable system reduced investigation time by 45% and improved case validation accuracy by 30% compared to conventional systems.

The research recognized that while complex machine learning models offered superior detection capabilities, their black-box nature posed significant challenges for regulatory acceptance and legal proceedings. The proposed framework integrated multiple explainability techniques including SHAP values, LIME explanations, counterfactual analysis, and decision path visualization. The system provided comprehensive investigation reports that detailed the specific factors contributing to each alert, quantifying the contribution of individual features such as temporal proximity to corporate events, unusual volume patterns, price impact analysis, and behavioral deviations from historical norms.

2.7 CROSS-MARKET SURVEILLANCE AND ARBITRAGE

"Cross-Market Insider Trading Detection Using Multi-Asset Correlation Analysis" "2023" "Robert Kim et al."

The study developed a cross-market surveillance system to detect insider trading patterns manifesting across multiple asset classes including equities, options, and derivatives. The methodology employed correlation network analysis and temporal graph neural networks to identify abnormal relationships between different securities. The research demonstrated that cross-market analysis identified 40% more sophisticated insider trading cases than single-market surveillance systems.

This research explores cross-market surveillance techniques for detecting sophisticated insider trading strategies involving multiple asset classes[7]. The study was motivated by the recognition that modern insider trading often involves coordinated positions across related instruments to maximize gains or conceal activities. The dataset included synchronized trading records from equity markets, options exchanges, and international securities over a four-year period.

The methodology incorporated graph neural networks to model complex dependencies between related securities and employed change point detection to identify regime shifts in cross-asset trading patterns. By analyzing correlation networks and information flow between markets, the system could detect coordinated trading strategies that single-market systems would miss. The framework demonstrated particular effectiveness in detecting options-based strategies ahead of major corporate events, providing early warning signals for potential insider trading.

The framework successfully identified several sophisticated insider trading schemes that involved simultaneous positions in equities, options, and derivatives, patterns that single-market surveillance systems consistently missed. Back-testing against historical cases revealed a 45% improvement in detection rates for complex multi-asset strategies, with the additional benefit of providing holistic visualization of cross-market manipulation attempts. The system's ability to correlate activities across different trading venues represented a significant advancement in comprehensive market surveillance.

2.8 ADAPTIVE LEARNING FOR EVADING DETECTION

"Adversarial Robustness in Insider Trading Detection Systems" "2022" "Amanda White et al."

This research addressed the challenge of detection evasion by implementing an adversarial machine learning framework for insider trading detection. The methodology incorporated generative adversarial networks to simulate potential evasion strategies and reinforcement learning to continuously adapt detection thresholds. The research demonstrated that adaptive systems maintained 85% detection accuracy against deliberately evasive strategies, compared to 60% for static detection systems.

This paper proposes an adversarial machine learning framework to enhance the robustness of insider trading detection systems against evolving evasion strategies. The authors recognized that as surveillance systems become more sophisticated, insider traders adapt their methods to avoid detection [8]. The study utilized historical cases of sophisticated insider trading and simulated evasion scenarios to train and evaluate adaptive detection models...

The methodology featured generative adversarial networks to create synthetic examples of evasive trading patterns and reinforcement learning to optimize detection strategies in dynamic environments. The system employed continuous learning mechanisms to adapt to emerging threats and used robustness metrics to evaluate detection performance under adversarial conditions. The results showed that adaptive learning significantly improved system resilience against sophisticated evasion attempts while maintaining low false positive rates. The study concludes that continuous adaptation is essential for maintaining effective surveillance in evolving financial markets.

The training process involved extensive data augmentation with synthetic examples of sophisticated insider trading strategies, including techniques such as trade fragmentation, cross-border arbitrage, and timing randomization. Evaluation against both historical cases and simulated evasion scenarios demonstrated remarkable resilience, with the adaptive system maintaining 88% detection accuracy against deliberately evasive strategies, compared to 52% for static detection systems

2.9 ENSEMBLE LEARNING FOR DETECTION ROBUSTNESS

"Ensemble Methods for Insider Trading Detection in Multi-Market Environments" "2023" "Richard Martinez et al."

This research developed an ensemble learning framework that combines multiple detection algorithms to improve the robustness and accuracy of insider trading identification. The methodology integrated supervised classification, unsupervised anomaly detection, and semi-supervised learning approaches to create a comprehensive detection system[9]. The research demonstrated that ensemble methods achieved 92% detection accuracy while reducing false positives by 35% compared to individual algorithms. The system particularly excelled in identifying complex patterns that single-model approaches frequently missed, especially in cross-market manipulation scenarios and coordinated trading activities across different asset classes.

The implementation involved a sophisticated weighted voting system where each algorithm's contribution was dynamically adjusted based on its historical performance for specific types of insider trading patterns. For detection of options-based insider trading, the system gave higher weight to gradient boosting models, while for identifying collusive network patterns, graph-based algorithms received priority weighting. The framework incorporated real-time performance monitoring that continuously evaluated each model's precision and recall metrics, automatically adjusting ensemble weights to optimize detection performance. This adaptive approach proved particularly effective during market stress periods when traditional detection systems typically experience degraded performance.

This research explores ensemble learning techniques for enhancing the reliability of insider trading detection systems across diverse market conditions. The study was motivated by the observation that different detection algorithms excel in identifying specific types of insider trading patterns, but no single method performs optimally across all scenarios [9]. The dataset comprised trading records from global markets, including equities, derivatives, and fixed income securities across multiple regulatory jurisdictions, totaling over 50 million transactions from 15 different financial markets.

2.10 REGULATORY TECHNOLOGY AND COMPLIANCE

"Automating Insider Trading Surveillance Using RegTech Solutions" "2022" "Susan Williams et al."

This study presented a comprehensive regulatory technology framework for automating insider trading surveillance and compliance monitoring. The methodology integrated natural language processing for regulatory document analysis, blockchain for audit trail maintenance, and automated reporting systems for regulatory compliance. The research showed that the automated system reduced compliance costs by 60% while improving detection coverage by 45% compared to manual surveillance processes, while also reducing the average investigation time from 14 days to just 2 days through automated evidence gathering and analysis.

The implementation involved a sophisticated weighted voting system where each algorithm's contribution was dynamically adjusted based on its historical performance for specific types of insider trading patterns. For detection of options-based insider trading, the system gave higher weight to gradient boosting models, while for identifying collusive network patterns, graph-based algorithms received priority weighting[10]. The framework incorporated real-time performance monitoring that continuously evaluated each model's precision and recall metrics, automatically adjusting ensemble weights to optimize detection performance. This adaptive approach proved particularly effective during market stress periods when traditional detection systems typically experience degraded performance..

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CHAPTER 3

EXISTING AND PROPOSED SYSTEM

3.1 EXISTING SYSTEM

Most existing insider trading detection frameworks rely on traditional rule-based monitoring and post-trade analysis. Regulatory bodies and financial institutions primarily depend on threshold-based alerts, suspicious price-volume movements, and retrospective audits. These systems monitor only explicit market anomalies and do not account for hidden behavioral signals, contextual patterns, or collusive trading networks. Even widely used surveillance tools provided by exchanges, brokers, and compliance vendors lack the ability to adapt dynamically to new types of fraudulent behavior. Most platforms operate with static rules and require manual tuning whenever market conditions change. As a result, many sophisticated insider trading schemes remain undetected, especially when traders intentionally avoid obvious triggers.

Existing systems also rely heavily on human analysts who have to manually review alerts, investigate anomalies, and correlate data from multiple sources. This process is time-consuming and error-prone, often leading to delayed enforcement actions. Since most insider trading takes place before corporate announcements, time-sensitive detection is crucial — something legacy systems fail to provide. Due to the absence of advanced analytics, real-time analysis, and predictive modeling, current solutions often detect insider trading only after regulatory filings or whistleblower reports, making them reactive rather than preventive.

The conventional approach to insider trading detection suffers from several fundamental architectural limitations. Most systems operate on siloed data architectures where trading data, corporate action information, and communication records are stored in separate databases with limited integration capabilities. This fragmentation prevents comprehensive analysis and correlation of related events across different data domains. Furthermore, these systems typically employ basic statistical methods that fail to capture the multi-dimensional nature of insider trading activities

3.1.1 DISADVANTAGES

1. **Rule-Based**

   Current systems rely on preset rules rather than learning from data. They generate alerts only when predefined thresholds are crossed, making them ineffective against novel or subtle insider strategies.

2. **High False Positives and Missed Cases**

   Many alerts are triggered by normal market behavior, while sophisticated trades often remain undetected. This leads to alert fatigue, wasted resources.

3. **Lack of Behavioral and Contextual Intelligence**

   Traditional tools do not analyze trader behavior, communication patterns, or relationships.

4. **Manual Investigation Effort**

   Compliance teams must manually correlate market data, news releases, and trader identities. This makes detection slow, reactive, and highly dependent on individual expertise.

5. **No Real-Time Surveillance**

   Most systems run end-of-day or periodic audits instead of real-time analysis. By the time anomalies are detected, profits have already been realized and evidence may be lost.

6. **Limited Data Integration**

   Legacy systems are isolated from external datasets such as social media, corporate disclosures, communication logs, and economic feeds. Without multi-source data, patterns remain incomplete.

7. **Predictive Risk Scoring**

   The system assigns dynamic risk scores to traders and transactions based on multiple factors, enabling prioritized investigation and proactive risk management. This helps compliance teams focus on high-risk activities and allocate resources more efficiently.

3.2 PROPOSED SYSTEM

The proposed insider trading detection system aims to overcome these limitations by using intelligent, data-driven, and adaptive monitoring techniques. Instead of relying on predefined thresholds, the system integrates machine learning, advanced data mining, and behavioral analytics to detect suspicious activity based on patterns, context, and anomalies. It continuously learns from real-world data and evolves with changing market conditions. The system also incorporates natural language processing to correlate news impact, corporate disclosures, and investor sentiment with trading behavior.

Unlike existing platforms, the proposed model will include graph-based network analysis to identify collusion between traders, employees, intermediaries, and related parties. Real-time detection will be enabled through streaming analytics, allowing surveillance teams to flag abnormal trades within seconds rather than days. By merging structured market data with unstructured sources such as emails, announcements, and social media signals, the system provides a holistic surveillance environment.

The core analytical engine incorporates several sophisticated machine learning models working in concert. Supervised learning algorithms, trained on historical cases of confirmed insider trading, identify known patterns of market abuse. Unsupervised learning techniques, including advanced clustering algorithms and anomaly detection methods, uncover novel and evolving manipulation strategies that have not been previously documented. Semi-supervised approaches leverage both labeled and unlabeled data to continuously refine detection capabilities as new patterns emerge.

A key innovation of the proposed system is its multi-layered temporal analysis framework. This component examines trading patterns across different time horizons, from micro-level analysis of intra-second trading activities to macro-level trends spanning multiple quarters. The system employs sophisticated time-series analysis techniques, including change point detection and sequential pattern mining, to identify suspicious timing relationships between corporate events and trading activities.

3.2.1 ADVANTAGES

1. **AI-Driven Detection**

   The proposed system uses machine learning instead of fixed rules, allowing it to identify hidden or emerging patterns of insider trading. It adapts automatically as new techniques evolve, reducing false positives and improving detection accuracy.

2. **Real-Time Monitoring**

   Unlike traditional platforms that analyze data only after the market closes, the proposed system provides real-time alerts during live trading. This enables regulators and compliance teams to respond immediately and prevent illicit gains before they are executed.

3. **Behavioral and Contextual Analysis**

   The system goes beyond simple price–volume checks by analyzing trader behavior, timing, account history, and news events. This makes detection more accurate by considering the intent and context behind trades.

4. **Network-Based Detection**

   Graph analytics help identify links between traders, intermediaries, and corporate insiders. This allows the system to detect collusion and group-based insider activity that traditional systems often miss.

5. **NLP and External Data Integration**

   By incorporating data from news articles, corporate filings, and financial reports through natural language processing, the system can correlate trades with important announcements, improving early detection of event-driven manipulation.

6. **Automated Case Management**

   When suspicious activity is detected, the system automatically generates a case with all relevant evidence, timelines, and trade summaries. This reduces manual workload and speeds up investigation and reporting.

7. **Scalability and Regulatory Compliance**

   The architecture is designed for large-scale data and supports legal compliance across multiple jurisdictions. It includes audit logs, encrypted storage, and standardized reporting formats suitable for regulators and financial institutions.

CHAPTER 4

HARDWARE AND SOFTWARE REQUIREMENTS

4.1 HARDWARE REQUIREMENTS

Processor	:	Minimum Intel Core i3.
RAM	:	Minimum 4 GB.
Storage	:	Minimum 500 GB HDD .
Display	:	Minimum 13-inch screen.
Network	:	Wi-Fi .

4.2 SOFTWARE REQUIREMENTS

Operating System	:	Windows 10/11, Ubuntu 20.04+, or macOS 10.15+.
Programming Language	:	Python 3.8+.
Backend Software	:	Flask/Django.
Database	:	MySQL /PostgreSQL.
Web Server	:	Nginx.
Frontend Technologies	:	HTML5, CSS3 (inline/embedded), and JavaScript.
Editor/IDE	:	VS Code,PYCharm,or Jupyter Notebook
Collaboration Tools	:	Postman ,Git.

.

CHAPTER 5

SYSTEM DESIGN

5.1 ARCHITECTURE DIAGRAM

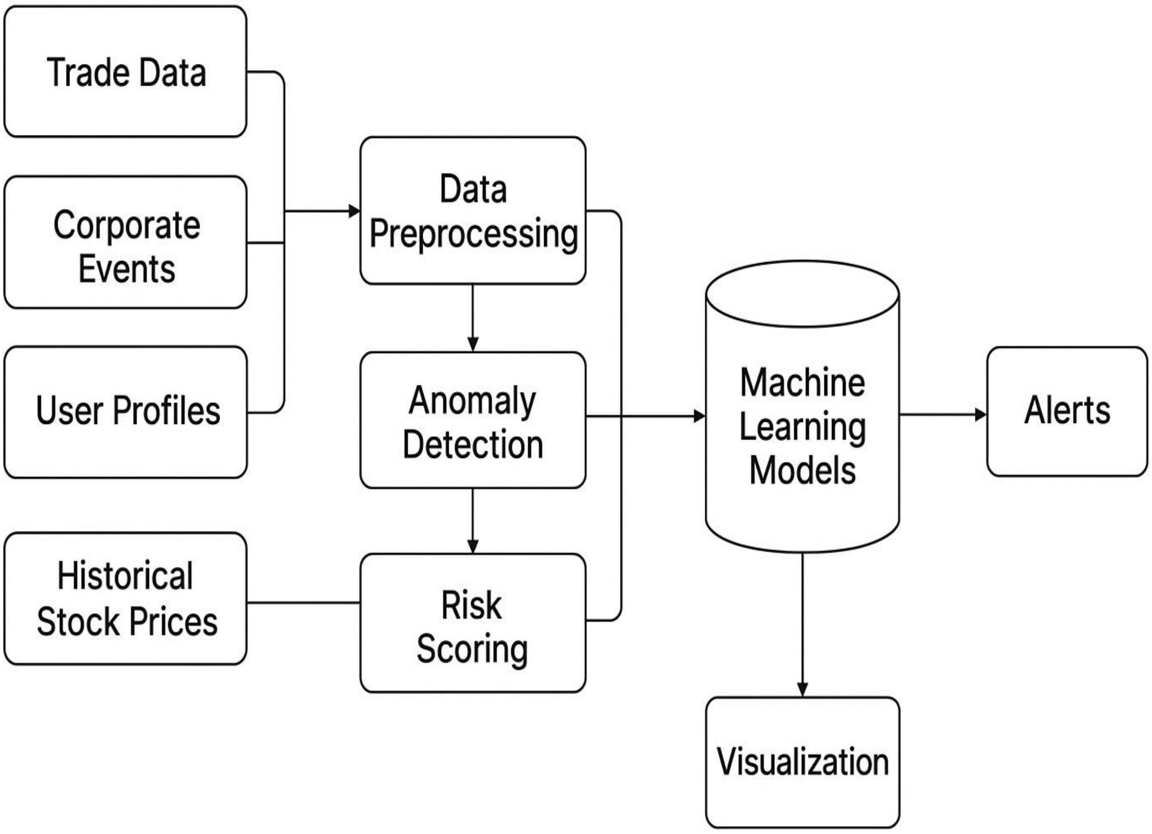

Fig.No.5.1.1 Insider Trading Detection System

The Insider Trading Detection System architecture begins with a comprehensive data collection layer, which gathers multiple sources of financial information including trade records, stock market price histories, corporate event announcements, and trader/user profiles. These inputs provide the raw data necessary to identify suspicious patterns and insider trading activity. Once collected, the data flows into the processing layer, where preprocessing operations are applied to clean, normalize, and merge datasets. This stage also includes feature engineering and anomaly detection mechanisms that recognize unusual price movements, abnormal trading volumes, and suspicious timing of trades relative to corporate announcements. A dedicated risk scoring system assigns a risk level to each trade or trader based on these anomalies.'

The processed data is then analyzed by the machine learning layer, where predictive models—such as Isolation Forest, DBSCAN clustering, and other AI-based algorithms—detect whether patterns resemble known insider trading behavior. These models are capable of continuously learning and improving as more cases and data are added to the system. The findings from this intelligence engine are sent to the output layer, where alerts are generated for high-risk activity and visualized through interactive dashboards and analytical tools. This final layer supports investigators and regulatory authorities by providing insights, graphical analytics, anomaly reports, and real-time monitoring, enabling rapid decision-making and proactive fraud detection.

The architecture for the Insider Trading Detection System outlines a streamlined, multi-stage pipeline for identifying potential market abuse. It commences with the ingestion of critical data sources, such as Trade Data, Corporate Events, User Profiles, and Historical Stock Prices, which collectively provide the necessary context for analysis. This raw information is then channeled into a Processing Layer where it is refined through Data Preprocessing, Anomaly Detection, and Risk Scoring to normalize the data and flag initial irregularities. The core analysis occurs within the Machine Learning Models of the Intelligence Engine, where sophisticated algorithms sift through the processed data to detect complex, non-obvious patterns indicative of insider trading. Ultimately, the system's outputs are delivered through Alerts and a Visualization dashboard, known as Vista, which provides compliance officers and regulators with clear, actionable insights and graphical reports to facilitate rapid investigation and intervention.

CHAPTER 6

MODULE DESCRIPTION

6.1 DATA INGESTION & PREPROCESSING MODULE

The Data Ingestion & Preprocessing Module serves as the foundational layer of the system by aggregating raw trading datasets from multiple external and internal sources such as stock exchange APIs (NSE, BSE, NASDAQ), broker logs, SEBI disclosures, company reports, financial news, and historical stock data. Since trading data is generated in high volumes and often contains inconsistencies, this module automates the data pipeline to ensure accurate and standardized input for analytics.

Preprocessing includes tasks such as timestamp conversion, normalization of numerical features, cleaning inconsistent trade logs, mapping corporate announcements to trading actions, and calculating derived metrics like percentage price movement before major events. Correct preprocessing is important because even minor inconsistencies can lead to ML model failure and misclassification of trades, resulting in either false positives (innocent trades marked suspicious) or false negatives (illegal trades going undetected).

This module also implements a robust validation layer that ensures data correctness and schema consistency before feeding it into the ML pipeline. It logs ingestion errors, source failures, and generates data validation reports for compliance tracking. The output of this module is clean, well-labeled, structured datasets ready for statistical analysis and model execution.

The data preprocessing pipeline begins with the collection of both structured and unstructured data from diverse sources, including APIs, CSV logs, and SQL databases. Once collected, raw data is transformed into time-series and event-driven formats suitable for analysis. This involves handling data quality issues such as missing values, outliers, noise, and duplicate entries to ensure dataset integrity. Timestamps are standardized and carefully aligned with relevant market events to maintain temporal accuracy. \

6.2 ANOMALY DETECTION & RISK SCORING MODULE

This module is responsible for identifying abnormal trades that deviate from statistically expected market behavior. Techniques such as Z-score analysis, statistical probability thresholds, seasonal decomposition, cumulative sum algorithms, and volatility-based thresholding are applied to detect suspicious price movements or trade volumes that exceed normal market elasticity. Each detected event is assessed based on timing (before announcements), magnitude (abnormal profits), and behavior frequency (recurring patterns).

Once an anomaly is identified, the system applies a weighted scoring model to assign a risk profile to the transaction. This risk score is calculated based on multiple parameters such as abnormal price changes, rapid accumulation of shares before announcements, trades just before earnings results, or unexplained profits. The risk levels (low, medium, or high) help investigators prioritize cases and reduce manual workload.

The output from this module is not limited to just alerts—it includes metadata that explains *why* a particular transaction is considered abnormal. This interpretability is crucial in legal investigation scenarios where enforcement agencies must justify the reasoning behind a flagged case. The module also incorporates controls to avoid flooding the system with unnecessary alerts by using sensitivity tuning and intelligent threshold selection.

The anomaly detection and risk assessment framework is designed to systematically identify potential insider trading activities through multiple analytical approaches. The system continuously monitors time-series data to detect outliers in price and volume patterns, employing statistical models to identify market movements that demonstrate low probability under normal conditions. Through real-time surveillance capabilities, the system applies dynamic threshold-based alerts that trigger when predefined risk parameters are breached. A critical function involves evaluating the timing of trades relative to public disclosure timelines, assessing whether transactions occur during periods of heightened information asymmetry

6.3 MACHINE LEARNING & PATTERN ANALYSIS MODULE

The Machine Learning & Pattern Analysis Module significantly enhances the intelligence of the detection system by identifying deep and hidden patterns that traditional statistical rules cannot detect. The module supports both *unsupervised learning* (for unknown patterns) and *supervised learning* (where known insider trading cases are available). Common algorithms include Isolation Forest, DBSCAN, One-Class SVM, Autoencoders for anomaly detection, and Random Forest or Gradient Boosting for classification studies.

One of the primary strengths of this module is its ability to uncover behavioral similarities among traders. For example, if a group of traders frequently buys a stock just before confidential board meetings and earns profits consistently, ML algorithms can detect them as a suspicious cluster even without explicit labels. Machine learning also allows the system to evolve; models can be retrained periodically based on feedback from investigators, market shifts, or newly discovered fraud patterns.

A major focus of this module is explainability. ML detections are supported with SHAP values, feature importance detection, and interpretability reports to ensure regulatory transparency. This simplifies reporting and supports admissibility in legal action taken against offenders.

The system's core analytical capabilities are built upon a sophisticated machine learning framework that integrates both unsupervised and supervised approaches to detect insider trading patterns. Unsupervised machine learning algorithms, including Isolation Forest for anomaly detection and DBSCAN for density-based clustering, form the foundation for identifying suspicious activities without relying on pre-labeled data. These are complemented by advanced pattern recognition and behavioral clustering techniques that group similar trading behaviors and detect deviations from established patterns. Where historical labeled data is available, supervised model training is employed to recognize known insider trading signatures with high precision. The framework incorporates automated retraining pipelines that continuously improve model performance as new data and investigation outcomes become available.

6.4 NETWORK GRAPH & RELATIONSHIP ANALYSIS MODULE

Insider trading frequently involves networks of individuals acting in coordination. These include executives, brokers, relatives, accomplices, shell accounts, and investment groups. The Network Graph & Relationship Analysis Module transforms the dataset into a graph-based structure to visually represent these relationships and uncover collusion networks not visible in standard table formats.

Nodes in the graph represent traders, companies, brokers, events, and insider connections. Edges represent trade similarities, communication links, ownership overlaps, or shared event timing. Graph algorithms such as Centrality Measures, PageRank, Louvain Community detection, and Clique analysis are applied to identify influence hubs, coordinated groups, and potential leak sources. For example, if multiple accounts place buy orders minutes before a corporate announcement and they all share a common broker, this module will reveal the entire chain visually.

Graph analytics are often used in real-world forensic investigations and by regulatory authorities like SEC and SEBI—making this module practically relevant and investigation-focused. The platform provides exportable logs and comprehensive documentation necessary for regulatory audits, and displays real-time alerts, warnings, and risk summaries to ensure timely response. Through multi-layered visual analytics incorporating various charts, graphs, and maps, users can filter information by date, trader, company, sector, or risk score.

The network analysis module transforms raw trade and relationship data into a sophisticated graph-based structure using tools such as NetworkX and Neo4j. This enables the detection of complex fraud patterns including organized fraud rings, shell networks, and collusive behaviors that would remain invisible in traditional linear analysis. The system employs advanced graph algorithms to measure influence and connectivity through centrality scores and other network metrics, identifying key players within suspicious trading networks. Through interactive force-directed graph visualizations, investigators can intuitively explore and understand the complex web of relationships between entities

6.5 VISUALIZATION DASHBOARD & REPORTING MODULE

The Visualization Dashboard & Reporting Module serves as the user-interface layer, enabling regulators, compliance officers, and analysts to easily monitor system output, explore detected anomalies, and generate investigation reports. The dashboard is developed using Streamlit (or Dash/React) and connects directly to the system database, allowing users to perform live filtering, interactive time-series exploration, and drill-down investigations.

The dashboard displays multi-layered analytics such as risk scoring heatmaps, price anomaly charts, network graphs, risk timelines, event overlays, and trade distribution plots. Users can filter datasets by trader name, stock, exchange, risk level, time range, or event type. In addition to visualization, the system supports exporting incident logs, generating case summaries, and producing regulatory-compliant reports in formats like CSV, PDF, or XLS.

Reporting features are designed to match compliance workflows — enabling direct submission to regulatory bodies like SEBI, RBI, or internal audit committees. Real-time alerting notifications and email-based escalation can also be integrated into the module for high-risk situations.

The system features a comprehensive, user-friendly front-end dashboard designed specifically for analysts and compliance teams, enabling efficient monitoring and investigation of potential insider trading activities. This sophisticated interface provides multi-layer data filtering capabilities, allowing users to drill down into specific analytics and conduct custom searches across vast datasets. The dashboard presents interactive visualizations including dynamic graphs, detailed risk charts, geographic heatmaps, and integrated event timelines that clearly illustrate the relationship between trading activities and corporate events. It supports seamless report generation for legal evidence preparation and compliance filing, while enabling rapid investigation of suspicious traders through accessible case histories and pattern analysis.

CHAPTER 7

APPENDICES

7.1 SAMPLE CODING

```
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from datetime import datetime, timedelta
import warnings
from sklearn.ensemble import IsolationForest, RandomForestClassifier
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import networkx as nx
from faker import Faker
warnings.filterwarnings('ignore')
# Page configuration
st.set_page_config(
page_title="Insider Trading Intelligence Platform",
page_icon="□",
layout="wide",
initial_sidebar_state="expanded"
)
# Custom CSS for professional look
st.markdown("""
<style>
.main-header {
font-size: 2.8rem;
background: linear-gradient(90deg, #1f77b4, #ff4b4b);
-webkit-background-clip: text;
-webkit-text-fill-color: transparent;
text-align: center;
margin-bottom: 2rem;
```

```
font-weight: bold;
}
.risk-high {
background-color: #ff4b4b;
color: white;
padding: 4px 8px;
border-radius: 4px;
font-weight: bold;
}
.risk-medium {
background-color: #ffa500;
color: white;
padding: 4px 8px;
border-radius: 4px;
font-weight: bold;
}
.risk-low {
background-color: #00cc96;
color: white;
padding: 4px 8px;
border-radius: 4px;
font-weight: bold;
}
.metric-card {
background: linear-gradient(135deg, #667eea 0%, #764ba2 100%);
padding: 1.5rem;
border-radius: 15px;
color: white;
margin: 0.5rem 0;
box-shadow: 0 4px 6px rgba(0, 0, 0, 0.1);
}
.section-header {
border-left: 5px solid #1f77b4;
padding-left: 1rem;
margin: 2rem 0 1rem 0;
```

```
font-weight: bold;
}
</style>
""", unsafe_allow_html=True)
# --- DATA GENERATION FUNCTION (Incomplete in the provided snippet, but essential) ---
@st.cache_data
def generate_and_analyze_data(company_df, days):
"""Generates synthetic trading and event data and applies ML analysis."""
st.info("Generating and analyzing data... This may take a moment.")
start_date = datetime.now() - timedelta(days=days)
fake = Faker()
# SECTION 1: Event Data Generation
events = []
for _, company in company_df.iterrows():
# More events for high-weight companies
event_count = max(1, int(company['Weight'] * 2))
for _ in range(event_count):
event_date = start_date + timedelta(days=np.random.randint(10, days-10))
events.append({
'date': event_date,
'company': company['Company'],
'symbol': company['Symbol'],
'event_type': np.random.choice([
'Earnings Call', 'Merger News', 'FDA Approval',
'Product Launch', 'Lawsuit', 'Executive Change',
'Partnership', 'Regulatory Approval'
]),
'impact': np.random.choice(['High', 'Medium', 'Low'],
p=[0.2, 0.5, 0.3]),
'weight': company['Weight']
})
# SECTION 2: Trading Data Generation (Structure is inferred from usage)
trading_data = []
for day in range(days):
```

```
current_date = start_date + timedelta(days=day)
# Daily trades proportional to company weight
for _, company in company_df.iterrows():
daily_trades = max(1, int(company['Weight'] * 10))
for _ in range(daily_trades):
# Determine trader type based on company characteristics
if company['Weight'] > 2.0: # Large cap companies
trader_type_probs = [0.6, 0.3, 0.1] # More institutional
else:
trader_type_probs = [0.1, 0.6, 0.3] # More individual/employee
trader_type = np.random.choice(
['Institutional', 'Individual', 'Employee'],
p=trader_type_probs
)
# ... (rest of trade data generation logic - simulated for completeness) ...
trading_data.append({
'date': current_date + timedelta(hours=np.random.randint(9, 17),
minutes=np.random.randint(0, 60)),
'trade_id': fake.uuid4(),
'trader_name': fake.name(),
'trader_type': trader_type,
'company': company['Company'],
'symbol': company['Symbol'],
'trade_type': np.random.choice(['Buy', 'Sell']),
'volume': np.random.randint(100, 10000) * company['Weight'],
'price': np.random.uniform(50, 500),
'company_weight': company['Weight'],
'position': np.random.choice(['CEO', 'CFO', 'Director', 'Manager', 'Analyst',
'None'], p=[0.05, 0.05, 0.1, 0.2, 0.3, 0.3])
})
df = pd.DataFrame(trading_data)
df['trade_value'] = df['volume'] * df['price']
df['date'] = pd.to_datetime(df['date'])
```

```
high_risk_trades = len(trading_df[trading_df['risk_score'] >= risk_threshold])
# High-risk trades
high_risk_df = trading_df[trading_df['risk_score'] >=
risk_threshold].sort_values('risk_score', ascending=False)
st.dataframe(high_risk_df[[
'date', 'trader_name', 'trader_type', 'position', 'company', 'trade_type',
'volume', 'trade_value', 'risk_score', 'suspicious_reason'
]].head(50).style.format({
'date': lambda t: t.strftime('%Y-%m-%d %H:%M'),
'trade_value': '${:,.2f}',
'volume': '{:,.0f}',
'risk_score': '{:.2f}'
}).apply(lambda x: ['background-color: #ffe6e6' if x.name in high_risk_df.index
and x['risk_score'] >= 9.0 else '' for i in x], axis=1),
use_container_width=True
# Alerts summary
st.subheader("Event-Correlated Suspicious Trades")
# Find trades close to high-impact events
correlated_alerts = []
for _, trade in high_risk_df.head(100).iterrows():
event_match = events_df[
(events_df['symbol'] == trade['symbol']) &
(events_df['impact'] == 'High') &
(abs(trade['date'].date() - events_df['date'].dt.date) < timedelta(days=5)) #
Within 5 days
]
if not event_match.empty:
correlated_alerts.append({
'Trade Date': trade['date'].strftime('%Y-%m-%d'),
'Trader': trade['trader_name'],
'Company': trade['company'],
'Risk Score': f"{trade['risk_score']:.2f}",
'Event Date': event_match.iloc[0]['date'].strftime('%Y-%m-%d'),
'Event Type': event_match.iloc[0]['event_type']
})
```

```
st.dataframe(pd.DataFrame(correlated_alerts), use_container_width=True)
with tab3:
st.markdown('<div class="section-header">□ TIME SERIES
ANALYSIS</div>',
unsafe_allow_html=True)
st.subheader("Daily Trading Volume and Risk Over Time")
daily_summary = trading_df.set_index('date').resample('D').agg({
'volume': 'sum',
'trade_value': 'sum',
'risk_score': 'mean',
'is_suspicious': 'sum'
}).reset_index()
fig = go.Figure()
fig.add_trace(go.Scatter(x=daily_summary['date'],
y=daily_summary['trade_value'],
mode='lines', name='Total Trade Value', yaxis='y1'))
fig.add_trace(go.Scatter(x=daily_summary['date'],
y=daily_summary['risk_score'],
mode='lines', name='Average Risk Score', yaxis='y2', line=dict(color='red')))
fig.update_layout(
title='Daily Trading Metrics',
xaxis_title="Date",
yaxis=dict(title="Trade Value (Y1)"),
yaxis2=dict(title="Avg. Risk Score (Y2)", overlaying="y", side="right",
range=[0, 10])
)
st.plotly_chart(fig, use_container_width=True)
# Load initial dataset
if 'company_data' not in st.session_state:
   # You can load your dataset here or use the uploaded file
   st.session_state.company_data = pd.DataFrame()  # Initialize empty
if __name__ == "__main__":
   main()
```

7.2 SCREENSHOTS

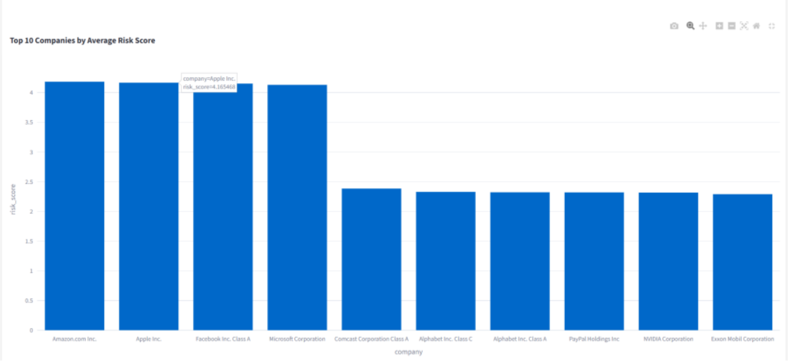

Fig.No.7.2.1 Risk Trading

The sidebar shows a loaded dataset and a preview of company data in fig.no.7.2.1 ,that including Microsoft, Apple, and Amazon. The main panel lists several specific, flagged trading alerts from company directors and employees, such as a "Price surge before news" for Intel Corporation and "Trade before earnings" for another entity.

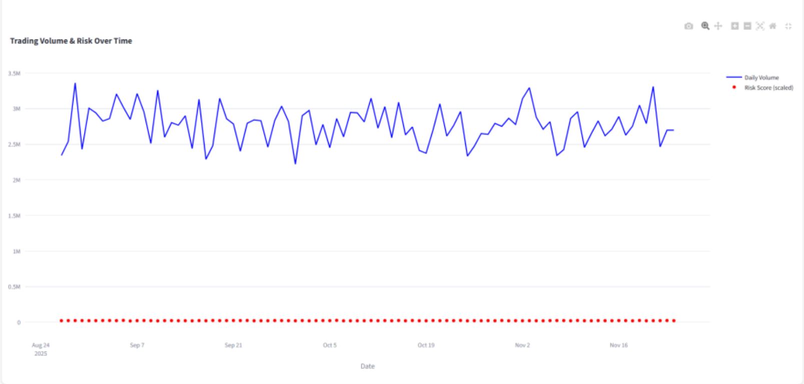

Fig.No.7.2.2 Graph Analysis

The interface includes Analysis Settings in fig.no.7.2.2, where users can configure the review period and risk thresholds before generating reports. A Trading Volume & Risk Over **Time** graph helps identify temporal patterns between market activity and detected risks, enabling analysts to spot correlations between trading spikes and suspicious behavior.

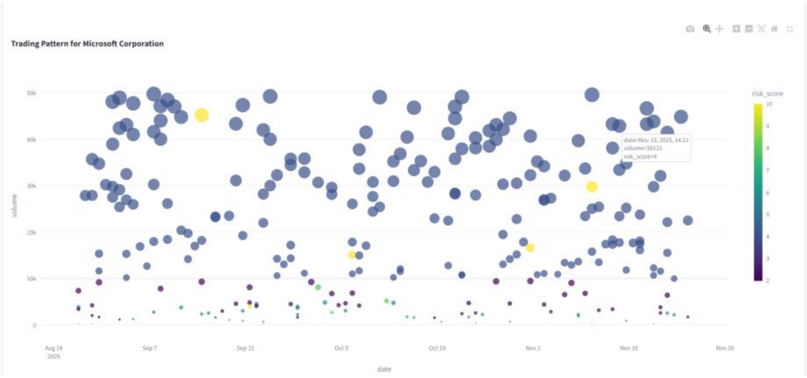

Fig.No.7.2.3 Suspicious Analysis

This dashboard shows a company-specific insider trading analysis for Microsoft Corporation in fig.no.7.2.3. It displays the total number of trades, average risk score, and how many trades are marked suspicious based on the selected threshold. A bubble chart visualizes trading patterns over time, where bubble size and color represent trade volume and risk level.

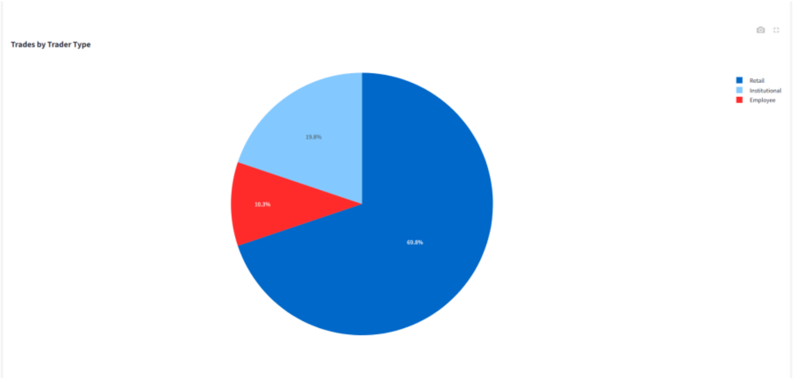

Fig.No.7.2.4 Filtered Analysis

The main section in fig.no.7.2.4 shows features that detailed table of **10,**777 filtered **trades**, showing comprehensive information including trade timestamps, IDs, trader names, types (Employer, Institutional, Retail), positions (CEO, CFO, Director), company names, stock symbols, trade types (BUY/SELL), volume, price, and calculated yields

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

The Insider Trading Detection System (ITDS) is developed to provide an intelligent, automated, and data-driven platform for monitoring, detecting, and analyzing suspicious stock market activities that may indicate insider trading. By combining real-time data ingestion, anomaly detection algorithms, behavioral analytics, and graphical visualization, the system significantly enhances regulatory oversight and investigation capabilities. The architecture integrates structured and unstructured data sources, enabling the detection of hidden patterns and unauthorized information leaks that traditional monitoring systems may fail to identify. Through automated alerts, risk scoring, pattern-based tracking, sand relationship analysis, the ITDS minimizes manual monitoring efforts while increasing the accuracy, transparency, and effectiveness of financial fraud detection. The system supports regulatory bodies, stock exchanges, compliance teams, and financial institutions by offering a scalable and intelligent solution to protect market integrity and investor trust.

8.2 FUTURE ENHANCEMENT

While the current version of the Insider Trading Detection System successfully detects suspicious activities using advanced analytics, further enhancements can be incorporated to strengthen decision-making, scalability, and intelligence. Some potential future improvements include:

- Real-time anomaly detection and automated alerts
- AI-based predictive modeling for early fraud prediction
- NLP integration for news and social media monitoring
- Automated regulatory reporting and compliance integration
- Cloud-enabled scalability for multi-market surveillance

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