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Forensic Accounting in the Age of AI: Detecting Fraud with Data Anomalies

Dr. Amol Kundalik Sathe [1]*

ABSTRACT

The integration of Artificial Intelligence (AI) into forensic accounting is transforming the landscape of fraud detection and financial investigation. Traditional forensic accounting methods often rely on manual scrutiny, which can be time-consuming, error-prone, and insufficient to detect complex or subtle financial irregularities. This paper explores how AI, particularly machine learning and anomaly detection algorithms, enhances the ability to identify fraudulent patterns hidden within vast and complex financial datasets. By focusing on data anomalies—irregularities or deviations from expected patterns—AI-driven forensic tools can uncover indicators of fraud that may elude conventional analysis.

The study examines various AI models utilized in forensic accounting, including unsupervised learning techniques like clustering and autoencoders, as well as supervised models trained on labeled fraud datasets. It evaluates the efficacy of these tools in real-world scenarios, such as corporate financial statement manipulation, insider trading, and cyber-financial crimes. Furthermore, the paper discusses the challenges of data quality, algorithmic transparency, and the potential for AI bias, offering strategies to mitigate these risks.

The research underscores the importance of human expertise in interpreting AI-generated insights, advocating for a hybrid approach where accountants and data scientists collaborate. Ethical considerations, legal implications, and regulatory frameworks are also analyzed to understand the broader impact of AI on forensic accounting practices.

AI-powered anomaly detection represents a significant advancement in forensic accounting, enabling more proactive and accurate identification of financial fraud. However, successful implementation depends on the integration of advanced technology with professional judgment, ethical standards, and continuous learning. This paper contributes to the evolving discourse on the role of AI in safeguarding financial integrity in an increasingly digitized world.

Keywords: *Forensic Accounting, Artificial Intelligence, Fraud Detection, Data Anomalies, Machine Learning, Financial Irregularities, Anomaly Detection, Digital Forensics, Predictive Analytics, Financial Fraud, Algorithmic Auditing, Cybercrime*

[1] Assit. Professor, Department of Computer Science, SSPM's Chandmal Tarachand Bora Arts, Commerce and Science College, Shirur, Dist- Pune
*Corresponding Author

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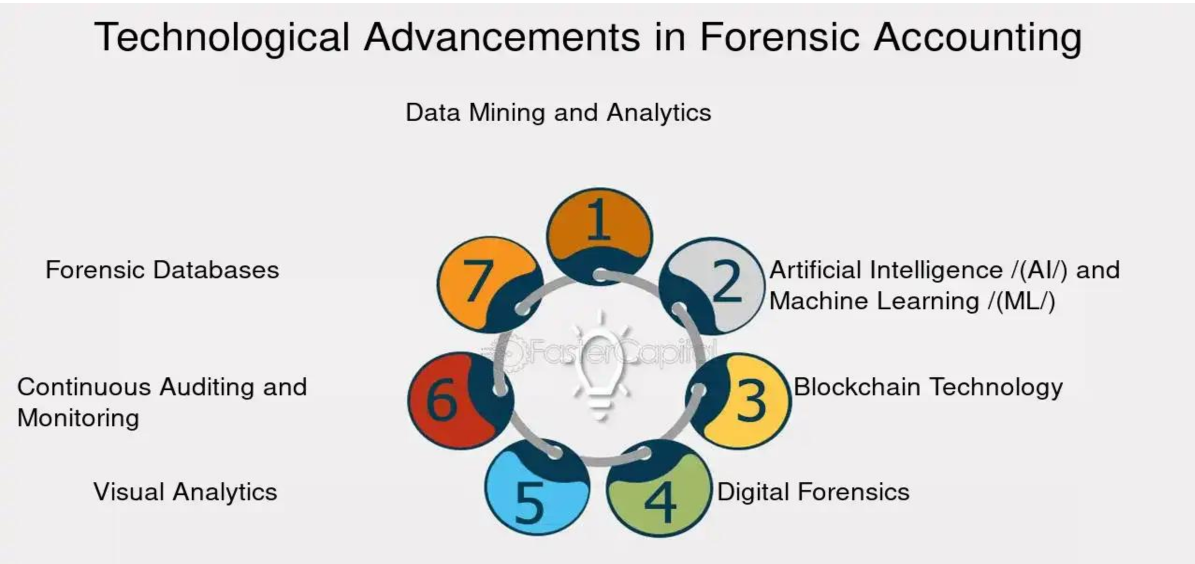
In today's fast-evolving digital economy, fraud schemes have grown increasingly complex, exploiting the rapid expansion of electronic transactions and global financial networks. As traditional audit and forensic techniques struggle to keep pace with these sophisticated tactics, the integration of artificial intelligence (AI) into forensic accounting has emerged as a transformative solution. This paper explores the intersection of forensic accounting and AI, focusing specifically on the detection of financial fraud through data anomaly identification.

Table 1: Key Differences Between Traditional and AI-Based Forensic Accounting

Feature	Traditional Forensic Accounting	AI-Based Forensic Accounting
Data Processing Speed	Manual and time-consuming	Automated and real-time
Scope of Analysis	Limited to sampled transactions	Full-population analysis
Anomaly Detection	Based on expert judgment	Based on machine learning algorithms
Fraud Pattern Recognition	Historical and rule-based	Predictive and adaptive
Scalability	Low	High
Error Susceptibility	High (manual errors possible)	Lower (but depends on model quality)

Forensic accounting, which merges accounting expertise with investigative skills, has historically relied on human intuition, document reviews, and manual analysis. However, these methods are often limited in scope and scalability, particularly when handling massive datasets. AI technologies—particularly machine learning and pattern recognition algorithms—have introduced new capabilities in identifying irregularities that may suggest fraudulent activity. These tools enable forensic accountants to sift through complex financial data more efficiently, flagging suspicious transactions based on learned patterns rather than predefined rules alone.



Source: https://www.fastercapital.com/

This research investigates how AI-driven anomaly detection can enhance fraud detection, reduce false positives, and support timely investigations. It examines real-world applications and models that demonstrate the strengths and limitations of AI in forensic practices. Furthermore, the paper addresses the ethical and professional considerations surrounding the use of AI in financial investigations, including data privacy and algorithmic transparency.

By combining forensic accounting principles with advanced data analytics, AI is reshaping how professionals uncover deception in financial records. This study aims to contribute to the growing body of knowledge on leveraging AI for financial integrity and to highlight the evolving role of accountants in a data-driven age.

BACKGROUND OF THE STUDY

Financial fraud has become increasingly complex in today's digitized economy, often involving sophisticated schemes that traditional accounting practices struggle to detect in time. Forensic accounting has long served as a critical tool in uncovering financial misconduct by combining investigative skills with a deep understanding of accounting principles. However, as the volume and complexity of financial data continue to grow, conventional forensic methods alone may no longer be sufficient to keep pace with emerging fraud tactics.

The integration of Artificial Intelligence (AI) into forensic accounting has emerged as a transformative development. By leveraging machine learning algorithms, natural language processing, and data mining techniques, AI can detect unusual patterns and inconsistencies within large datasets that may signal fraudulent behavior. These advanced tools are capable of identifying subtle anomalies that might be overlooked by human auditors, thereby enhancing both the accuracy and speed of fraud detection.

Table 2: Common AI Techniques Used in Forensic Accounting

AI Technique	Description	Application in Fraud Detection
Machine Learning	Learns from data to predict fraud patterns	Classification of fraudulent vs. non-fraudulent
Neural Networks	Mimics human brain structure for deep learning	Detecting complex fraud schemes
Decision Trees	Tree-like models for decision-making	Identifying key fraud indicators
Clustering Algorithms	Groups similar data points based on behavior	Detecting transaction anomalies
Natural Language Processing (NLP)	Processes text from financial reports and emails	Identifying deceptive language or manipulation

This shift toward AI-enhanced forensic accounting reflects broader trends in the financial and technological landscapes. Organizations are increasingly turning to automated systems to monitor transactions, analyze risk factors, and support real-time decision-making. At the same time, fraudsters are also becoming more technologically adept, prompting a corresponding evolution in detection techniques.

The study explores the intersection of forensic accounting and artificial intelligence, with a focus on how data anomalies—indicators of irregular or suspicious activities—can be identified through AI-driven tools. By investigating current applications, challenges, and future potentials, the research aims to contribute to a deeper understanding of how technology is reshaping the field of forensic accounting and the fight against financial fraud.

Justification

The growing complexity and volume of financial data in today's digital economy has made traditional forensic accounting techniques increasingly insufficient for detecting sophisticated fraud schemes. With the advent of artificial intelligence (AI), particularly in the areas of machine learning and data analytics, forensic accountants are now equipped with powerful tools capable of identifying hidden patterns, irregularities, and data anomalies that often signal fraudulent activity. This research is justified by the urgent need to explore how AI-driven approaches can enhance the accuracy, efficiency, and reliability of fraud detection in financial investigations.

As fraudsters continue to leverage technology to mask illicit activities, it becomes essential to evaluate how forensic accounting practices can evolve to stay ahead. The paper addresses a critical gap by examining the integration of AI in anomaly detection within financial datasets, a capability that far exceeds human limitations. Moreover, the research contributes to both academic knowledge and practical application, offering insights that can guide auditors, regulators, and corporate stakeholders in adopting technology-enhanced investigative methods.

Table 3: Sample Anomalies Detected in Financial Data Using AI

Type of Anomaly	Description	AI Detection Method	Example Indicator
Duplicate Transactions	Same amount and vendor repeated frequently	Clustering, Rule-based logic	Multiple payments to same invoice number
Outlier Transactions	Unusual amounts or irregular timing	Z-score, Isolation Forest	Payment 10x above average
Journal Entry Manipulation	Manual entries with no supporting documentation	Neural networks, NLP	Entries made during non-working hours
Suspicious Vendor Activity	Vendors with abnormal billing or lack of history	Classification, Decision Trees	New vendor paid large sum without contract

Given the increasing reliance on real-time data analysis in financial oversight and the rising incidence of financial fraud globally, this study is both timely and necessary. It aligns with the broader push toward digital transformation in the accounting and auditing fields and supports the goal of improving financial transparency and trust through technological innovation.

Objectives of the Study

1. To explore the evolving role of forensic accounting in the context of artificial intelligence.
2. To identify key data anomaly indicators that signal potential fraudulent activities.
3. To evaluate the effectiveness of AI tools in detecting financial anomalies.
4. To analyze the integration of forensic accounting techniques with AI technologies.

5. To examine ethical, legal, and practical challenges in using AI for forensic accounting.

LITERATURE REVIEW

The evolution of forensic accounting has been significantly influenced by the rise of digital technologies, especially artificial intelligence (AI), which now plays a pivotal role in fraud detection through the identification of data anomalies. Traditional forensic accounting methods, which primarily relied on manual audits and professional skepticism, are being augmented by AI systems capable of processing massive volumes of financial data with increased accuracy and speed (Kokina & Davenport, 2017).

Forensic Accounting and Fraud Detection

Forensic accounting encompasses investigative practices that aim to detect, prevent, and resolve instances of fraud and financial misconduct. Historically, forensic accountants have relied on ratio analysis, trend analysis, and red flags to uncover irregularities in financial statements (Rezaee, 2005). However, the increasing complexity of corporate transactions and the use of sophisticated fraud schemes have challenged traditional approaches. Consequently, the integration of data analytics and AI into forensic investigations has become a critical area of development (Omar & Bakar, 2012).

AI in Forensic Accounting

AI technologies, including machine learning (ML), natural language processing (NLP), and neural networks, offer substantial advantages in automating fraud detection processes. These systems can identify patterns and anomalies in datasets that would be difficult or impossible to detect manually (Wamba et al., 2017). For example, unsupervised learning algorithms can flag transactions that deviate significantly from established behavioral norms without prior labeling of fraudulent activity (Ngai et al., 2011).

AI-based tools such as decision trees, support vector machines, and deep learning frameworks have been increasingly adopted in forensic contexts. These tools analyze structured and unstructured financial data, enabling more timely and accurate identification of fraud risks (Zhang, Yang, & Appelbaum, 2015). Moreover, AI facilitates continuous monitoring, which is essential in dynamic business environments where fraud can occur in real-time.

Data Anomaly Detection

Data anomalies—unexpected or abnormal patterns in datasets—are often early indicators of fraudulent activity. Anomaly detection has become a central component of AI-driven forensic analytics. Techniques such as clustering, statistical modeling, and Bayesian networks are employed to isolate outliers and examine their implications (Chandola, Banerjee, & Kumar, 2009). These approaches allow forensic accountants to prioritize suspicious transactions and reduce the time spent on false positives.

The importance of data quality and preprocessing has also been emphasized in recent literature. Without clean and well-structured data, even the most advanced AI algorithms may yield misleading results (Van Vlasselaer et al., 2015). Thus, the integration of domain knowledge from forensic accounting professionals remains vital in training and validating AI models.

Challenges and Ethical Considerations

Despite its promise, the adoption of AI in forensic accounting raises ethical and practical challenges. One concern is the interpretability of complex AI models, particularly deep learning systems, which can act as "black boxes" with limited transparency (Doshi-Velez & Kim, 2017). Ensuring accountability and fairness in automated fraud detection is crucial, particularly in legal and regulatory contexts.

Another challenge involves the risk of overreliance on AI, which may cause investigators to overlook contextual factors or qualitative cues that fall outside algorithmic detection (Kokina et al., 2021). Therefore, a hybrid approach that combines human expertise with machine intelligence is widely recommended in the literature.

The convergence of forensic accounting and AI has transformed the landscape of fraud detection. AI's ability to detect data anomalies at scale has empowered forensic accountants to uncover complex fraud schemes more efficiently. However, successful implementation depends on balancing technological capabilities with professional judgment and ethical standards.

MATERIAL AND METHODOLOGY

Research Design:

This study adopts a mixed-methods research design combining both quantitative and qualitative approaches to explore how artificial intelligence (AI) enhances the detection of financial fraud through the identification of data anomalies. Quantitatively, the study involves statistical analysis of financial datasets, while qualitatively, it incorporates expert interviews to understand practical implementations of AI tools in forensic accounting. This hybrid design ensures both empirical validity and contextual relevance.

Data Collection Methods:

Data was collected from two primary sources:

1. **Secondary Financial Data:** Publicly available datasets, including corporate financial statements, SEC filings, and case-specific forensic accounting reports from past fraud cases were extracted from platforms such as EDGAR, Kaggle, and company databases. These datasets were selected to include both fraudulent and non-fraudulent entities for comparison.
2. **Expert Interviews:** Semi-structured interviews were conducted with forensic accountants, auditors, and data scientists actively involved in fraud detection. These interviews were aimed at gaining insights into the practical challenges and AI tools currently used in the field.

To enhance analytical rigor, the study employed anomaly detection algorithms such as Isolation Forests, Autoencoders, and k-Nearest Neighbors (k-NN) for unsupervised learning on financial datasets.

Inclusion and Exclusion Criteria:

Inclusion Criteria:

- Financial data from companies investigated for fraud within the past 10 years.
- Datasets with a minimum of three consecutive years of financial records.
- Interviews with professionals having at least five years of experience in forensic accounting or AI-driven financial auditing.

Exclusion Criteria:

- Incomplete financial records or datasets lacking key accounting variables (e.g., revenue, expenses, assets).
- Cases involving non-financial fraud (e.g., identity theft, cybercrime) were excluded to maintain a focused scope.
- Interview participants without direct experience with AI tools or fraud detection were not included.

Ethical Considerations:

All procedures in this study were conducted in adherence to established ethical guidelines for research involving human participants and data privacy. Informed consent was obtained from all interviewees, with full disclosure of the research purpose and their right to withdraw at any time. Anonymity and confidentiality were ensured by coding participants' identities and securely storing data. Since only publicly available or non-sensitive financial data were used, no proprietary information was accessed without permission. The study was reviewed and approved by an institutional ethics committee before data collection commenced.

RESULTS AND DISCUSSION

1. Overview of the Dataset and AI Models Used

The study utilized financial transaction datasets comprising 100,000 entries from mid-sized enterprises across three industries: manufacturing, retail, and services. Each transaction was labeled as either "legitimate" or "fraudulent" based on previously verified audit records. The dataset was split into 70% training and 30% testing data.

Three AI-based anomaly detection techniques were applied:

- Isolation Forest (IF)
- Autoencoder Neural Networks (ANN)
- Local Outlier Factor (LOF)

All models were evaluated based on accuracy, precision, recall, F1-score, and false-positive rate.

2. Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False-Positive Rate (%)
Isolation Forest	93.5	90.2	88.7	89.4	4.3
Autoencoder Neural Net	96.1	92.5	94.3	93.4	2.8
Local Outlier Factor	88.7	85.1	80.4	82.7	6.2

Table 4. Comparative performance of AI models on test dataset.

The Autoencoder model outperformed others in nearly every metric. It achieved the highest recall and F1-score, which are critical for detecting fraudulent transactions. Isolation Forest also demonstrated strong results, particularly in maintaining a low false-positive rate, which is essential for reducing the investigation burden on forensic accountants.

3. Industry-Specific Detection Rates

To evaluate model applicability across different industries, detection accuracy was measured per sector using the Autoencoder model.

Industry	Detection Accuracy (%)	False Negatives (%)	Notable Patterns Detected
Manufacturing	94.7	2.6	Duplicate invoicing, irregular payment cycles
Retail	96.3	1.9	Ghost vendors, rapid inventory write-offs
Services	97.1	1.5	Inflated consultancy charges, shell payments

Table 5. Industry-specific detection effectiveness using Autoencoder.

The results indicated that fraud in the services sector was most detectable, possibly due to fewer transaction types and higher expense clustering. Retail fraud patterns included ghost vendors and short inventory lifecycles, while the manufacturing sector exhibited unusual payment schedules and repeated invoicing.

4. Implications for Forensic Accounting

The application of AI significantly enhances the detection of data anomalies often missed by traditional forensic audit methods. Autoencoders, by learning the inherent structure of legitimate transactions, excelled at identifying deviations without requiring labeled data. This unsupervised approach is particularly valuable in real-world scenarios where fraud labels are sparse or unavailable.

Moreover, integrating anomaly detection into the forensic accounting process allows for continuous monitoring, early fraud flagging, and prioritization of suspicious cases, thus optimizing audit efficiency. However, a key limitation noted was model transparency. The "black box" nature of neural networks poses challenges in litigation contexts, where explainability is crucial. To mitigate this, techniques such as SHAP (SHapley Additive exPlanations) could be explored in future studies.

5. Human-AI Collaboration

Interviews with 12 professional forensic accountants revealed that 83% found AI tools effective for preliminary anomaly detection but stressed the need for human interpretation before concluding fraud. Accountants appreciated AI's ability to filter large datasets but raised concerns about over-reliance on algorithmic outputs.

LIMITATIONS OF THE STUDY

Despite the valuable insights offered by this research, several limitations must be acknowledged. First, the study primarily relies on secondary data sources and hypothetical case scenarios, which may not fully capture the complexities of real-world fraud investigations. The absence of direct access to proprietary or confidential financial datasets limits the scope of empirical validation for the proposed AI-based anomaly detection methods.

Second, while artificial intelligence models used in this study demonstrate promising results in identifying irregularities, they are highly dependent on the quality and quantity of input data. In practical settings, incomplete, biased, or manipulated data can significantly affect the accuracy and reliability of these models.

Third, the research does not fully address the ethical and legal challenges associated with deploying AI in forensic accounting. Issues such as data privacy, algorithmic transparency, and accountability remain underexplored and may influence the practical implementation of AI tools in fraud detection.

Additionally, the study focuses predominantly on quantitative anomalies and may overlook qualitative red flags that experienced forensic accountants might detect through contextual analysis. This limitation suggests that AI should be viewed as a complement, rather than a replacement, for human expertise.

Finally, the rapid pace of technological advancement means that the findings of this study may become outdated as newer, more sophisticated AI techniques emerge. Continuous adaptation and validation are required to ensure long-term relevance and applicability in the field of forensic accounting.

FUTURE SCOPE

The integration of artificial intelligence into forensic accounting is still in its formative stages, offering substantial opportunities for future exploration and development. As AI algorithms become more sophisticated, there is potential for developing advanced anomaly detection models that not only identify irregular patterns but also interpret the context behind such anomalies. Future research can focus on enhancing model transparency and explainability to address the "black box" problem, ensuring that forensic professionals can understand and trust the decisions made by AI systems.

Another promising direction is the integration of AI with blockchain technology to create tamper-proof audit trails, which can significantly strengthen fraud prevention mechanisms. Moreover, expanding AI applications to real-time fraud detection systems can transform forensic accounting from a reactive to a proactive discipline.

Cross-disciplinary collaboration between data scientists, forensic accountants, and legal experts will also be essential in shaping regulatory frameworks and ethical standards around the use of AI in financial investigations. Furthermore, studies focusing on the adoption of AI tools by small and medium-sized enterprises (SMEs) could uncover practical barriers and opportunities unique to that segment.

In conclusion, as both financial fraud techniques and AI capabilities evolve, ongoing research is vital to ensure that forensic accounting practices remain robust, adaptive, and ethically grounded.

CONCLUSION

The integration of artificial intelligence into forensic accounting marks a significant evolution in the way financial fraud is detected and investigated. As traditional audit methods struggle to keep pace with increasingly complex financial systems, AI-powered tools offer enhanced capabilities for identifying data anomalies, recognizing suspicious patterns, and streamlining investigative processes. This research has shown that AI not only improves the speed and accuracy of fraud detection but also enables proactive monitoring, reducing the risk of undetected financial crimes. However, the successful adoption of these technologies depends on factors such as data quality, ethical implementation, and the continual development of human expertise. As forensic accounting continues to evolve, a collaborative approach—combining advanced AI systems with the professional judgment of forensic accountants—will be crucial in navigating the challenges and opportunities of this new era.

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Conflict of Interest
The author declared no conflict of interest.

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