Journal of Accounting Advances, (2025) 17(1): 79-114
Doi: 10.22099/jaa.2025.52908.2495

Journal of Accounting Advances (JAA)
Journal homepage: www.jaa.shirazu.ac.ir/?lang=en

Shiraz University

1. Introduction

The primary purpose of this research is to address the critical challenge of detecting anomalies and fraudulent activities in accounting records through advanced machine learning techniques. Financial reporting and auditing environments are increasingly characterized by high data volumes, complexity, and the necessity for timely detection of irregularities. Traditional audit methods—primarily based on sampling and red-flag indicators—are limited in scope and often incapable of identifying rare, sophisticated, or concealed fraudulent activities. These limitations create substantial audit risks, reduce the reliability of financial reporting, and undermine stakeholder confidence.

From a theoretical perspective, the study seeks to fill a gap in the accounting and auditing literature by applying the application of deep learning methods, specifically autoencoder neural networks, to journal-level transaction data. While anomaly detection has been widely studied in fields such as cybersecurity and network intrusion detection, its application in accounting information systems remains underexplored. This research responds to this gap by adapting deep learning methodologies to the unique characteristics of financial transactions, where anomalies may not be obvious single-point outliers but instead subtle deviations in complex attribute relationships.

From a practical perspective, the study aims to contribute to the advancement of auditing practice by offering auditors, regulators, and organizations a robust AI-driven tool for full-population testing. Unlike sample-based approaches, the proposed model enables continuous monitoring and detection of anomalies across all journal entries, thereby enhancing the timeliness and effectiveness of fraud detection and internal control systems. Moreover, the integration of anomaly detection into accounting information systems can support proactive risk management, reduce the likelihood of undetected fraudulent activity, and ultimately strengthen investor confidence and corporate governance.

Accordingly, the overarching purpose of this research is twofold: (i) to extend the academic understanding of anomaly detection in the accounting domain by applying deep autoencoder neural networks at the transaction level, and (ii) to provide actionable insights and technological solutions that can transform audit methodologies in line with the data-intensive demands of modern financial systems.

2. Methodology

This applied and quantitative study was conducted using two real datasets extracted from widely implemented Iranian accounting systems: (1) Rahkaran containing 36,538 journal entries, and (2) Sepidar containing 30,000 journal entries. Controlled artificial anomalies were injected into both datasets to systematically test the performance of the proposed model. A deep autoencoder network was designed and trained using PyTorch. The model minimized reconstruction error between input and output vectors, with anomalies identified when reconstruction errors exceeded a statistically determined threshold. The performance of the model was benchmarked against alternative approaches, including statistical outlier detection and clustering-based techniques, to ensure result robustness.

3. Results

The study yielded several significant findings:

The autoencoder demonstrated superior detection performance, outperforming traditional methods in detecting rare and complex patterns.

Increasing network depth enhanced detection capabilities, highlighting the need to model nonlinear relationships in accounting data.

Reconstruction error distributions varied across subsystems, emphasizing context-sensitive detection (e.g., sales, inventory, payroll).

Key features included subsidiary account, general ledger code, cost center, and last modification date.

4. Conclusion

This study provides theoretical and practical contributions to the accounting and auditing literature. Theoretically, it extends anomaly detection research by applying deep autoencoder networks directly to journal entries, rather than to aggregated financial statements. Practically, it offers auditors and regulators a data-driven, AI-enabled tool for moving from traditional sample-based procedures toward full-population testing. By integrating such models into audit workflows, stakeholders can significantly reduce the risk of undetected fraud, strengthen internal control systems, and enhance investor confidence in financial reporting. The findings confirm the potential of deep learning approaches to transform the auditing profession in an era of increasingly complex and data-intensive financial systems.

Keywords: Anomaly detection, accounting information systems, autoencoder neural networks, deep learning, fraud detection.