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Using Artificial Neural Networks in Improving the Efficiency of External Auditors in Detecting Financial Fraud

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Abstract:

With the growing sophistication of financial fraud and the limitations of traditional audit methods, there is an urgent need to adopt artificial intelligence to enhance external auditors' efficiency in detecting fraud, especially in light of the scarcity of applied evidence on this impact in the Egyptian context. The study aimed to evaluate the impact of using artificial neural networks on improving the efficiency of external auditors in detecting financial fraud, through examining the impact of adopting artificial neural networks on external auditing and the impact of artificial neural networks on the efficiency of external auditors in detecting financial statement fraud.

The study relies on a sample of non-financial companies listed on the Egyptian Stock Exchange, which number 126 companies in different sectors. This study depends on 1000 firm-year observations from the Egyptian environment through the period 2012 to 2022.

The researchers found that artificial neural networks adoption has a significant impact on the external auditing by the auditor's opinion, and adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit fees and audit report lag in detecting financial fraud.

Keywords: Artificial neural networks, Deep neural network, Efficiency of External Auditors, Auditors' opinion, Detecting Financial Fraud

المستخلص:

يهدف البحث إلى اختبار أثر استخدام الشبكات العصبية الاصطناعية في تحسين كفاءة مراقبي الحسابات في كشف الاحتيال المالي، وذلك من خلال اختبار أثر تطبيق الشبكات العصبية على المراجعة الخارجية، وأثر تطبيق الشبكات العصبية على كفاءة مراقبي الحسابات في اكتشاف الاحتيال المالي.

اعتمدت عينة البحث على ١٢٦ شركة غير مالية مدرجة في البورصة المصرية بواقع (١٠٠٠) مشاهدة خلال الفترة من ٢٠١٢ إلى ٢٠٢٢.

وتوصلت الدراسة إلى وجود أثر ذو دلالة إحصائية لتطبيق الشبكات العصبية على المراجعة الخارجية من خلال رأي مراقب الحسابات، ووجود أثر ذو دلالة إحصائية لتطبيق الشبكات العصبية على كفاءة المراجع من خلال اتعاب المراجعة وطول مدة التقرير في اكتشاف الاحتيال المالي.

الكلمات المفتاحية:

الشبكات العصبية الاصطناعية، الشبكات العصبية العميقة، كفاءة مراقب الحسابات، رأي مراقب الحسابات، اكتشاف الاحتيال المالي.

1. General Framework of study:

1.1 Introduction:

Fraud in the accounting world is a significant issue that impacts businesses, governments, and individuals alike. The implications of accounting fraud are profound, extending beyond financial loss to include damaged reputations, legal consequences, and diminished stakeholder trust. High-profile company scandals, such as those involving WorldCom, Enron, and more recently, Wirecard, highlight the severe repercussions of fraudulent activities and underscore the critical need for effective fraud detection mechanisms (Mutschmann et al., 2021, p. 7).

Accounting fraud typically involves the intentional manipulation of financial statements or the misuse of assets. These actions are designed to deceive stakeholders, including investors, creditors, and regulatory bodies, regarding the financial health and performance of an organization. Accounting fraud commonly involves fraudulent financial reporting, asset misuse, and corruption. Given the complexity and sophistication of modern financial systems, detecting fraud has become increasingly challenging (Hilal *et al*., 2022, p. 6). Effective fraud detection is critical for many reasons. Firstly, it helps to maintain the integrity of financial reporting, which is essential for informed decision-making by creditors, investors, and other stakeholders. Secondly, it protects the organization's assets and reduces financial losses. Thirdly, robust fraud detection mechanisms enhance the credibility and reputation of an organization, fostering trust among stakeholders. Lastly, it ensures compliance with regulatory requirements, thereby avoiding legal penalties and sanctions.

Traditional approaches to detecting fraud in accounting primarily depend on three methods: manual reviews, periodic audits, and rule-based automated systems. Although these methods form the basis of fraud detection, they have significant weaknesses that reduce their effectiveness in today's complex financial environment and advanced fraudulent tactics. The audit process, a cornerstone of traditional methods, requires accountants to manually inspect financial documents to verify their correctness and adherence to accounting principles (Shahana et al., 2023). While audits play a vital role in identifying unusual or improper transactions, they have two major drawbacks. First, since audits are typically conducted only once a year or every three months, fraudulent activities may continue unnoticed for months. Second, being manual processes, audits are not only slow but also prone to mistakes. Rule-based detection systems operate by applying predefined criteria to identify potentially fraudulent transactions (Gianini et al., 2020, p. 556). While effective for simple fraud cases, they struggle with modern, sophisticated schemes, where fraudsters can easily adapt to bypass static rules, reducing their effectiveness over time. Hence, the growing volume and complexity of financial data, the speed at which transactions occur, and the sophistication of fraud techniques necessitate more advanced, adaptive, and proactive fraud detection solutions (Shoetan *et al*., 2024, p. 385).

Artificial Intelligence (AI) is a transformative technology with the potential to revolutionize fraud detection in accounting. AI comprises a variety of technologies, among them Artificial Neural Networks (ANN), which allow systems to learn from data, determine patterns, and make decisions with minimal assistance from humans.

Neural networks can autonomously learn complicated patterns and relationships within large datasets, enhancing the detection of subtle anomalies indicative of fraudulent behavior. Integrating ANN into fraud detection provides various transformational benefits. ANN algorithms can process and analyze huge amounts of data more accurately and efficiently than auditors. Traditional methods may miss subtle patterns and correlations that ANN algorithms can identify. ANN can monitor transactions in real time, enabling the immediate identification and investigation of suspicious activities (Shabbir *et al*., 2022, p. 2). This proactive approach helps to prevent fraud before significant losses occur. Unlike rule-based systems, ANNs can adapt to evolving fraud techniques. They continuously learn from new data and improve their detection capabilities. ANN's ability to analyze data holistically minimizes the occurrence of false positives (legal transactions tagged as fraudulent) and false negatives (fraudulent transactions that go undetected) (Reddy *et al*., 2024).

Thus, ANN has the potential to enhance the efficacy of fraud detection efforts significantly. As technology advances, its incorporation into auditing methods will become critical for protecting the integrity of financial systems and sustaining stakeholder trust.

1.2 Study Problem:

As financial fraud grows increasingly sophisticated, it presents major challenges for businesses and auditors alike, underscoring the urgent need for stronger fraud detection methods to protect financial integrity and maintain public trust. While traditional auditing techniques remain useful, they may not always uncover highly complex and evolving fraud schemes hidden in financial records. This escalating risk demands the adoption of innovative solutions, such as artificial intelligence (AI), to modernize and strengthen fraud detection in audits. Financial fraud—defined as the intentional manipulation or misrepresentation of financial data for personal or organizational gain—harms stakeholders through various schemes, including embezzlement, falsified reports, insider trading, and Ponzi schemes. With the growing complexity of financial transactions and advancements in technology, fraudsters are constantly refining their methods to exploit weaknesses. This evolution calls for more advanced detection strategies to effectively combat these threats (Hilal et al., 2022, p. 6).

Concurrently, financial audits are vital in preserving financial information integrity and ensuring transparency in business operations by systematically examining financial records, transactions, and internal controls to ensure the accuracy and reliability of financial statements. Independent auditors play a critical role in evaluating the fairness of financial reporting practices and detecting instances of fraud or financial irregularities, contributing to the maintenance of trust and accountability in the business world, given the significant impact of financial fraud on investor confidence and market stability (Grissa and Abaoub, 2024, p. 2).

The evolution of fraud detection has always been a race against increasingly sophisticated criminals. As fraudsters continuously adapt their methods to exploit weaknesses in financial systems, auditors and regulators must constantly upgrade their defenses. Early fraud detection relied heavily on manual reviews and rule-based systems, which, while somewhat effective, struggled to keep pace with complex and evolving fraud schemes. This ongoing battle mirrors a cat-and-mouse game—fraudsters find new loopholes, while defenders develop innovative tools to detect and prevent emerging threats (Pinzón *et al.*, 2023, p. 2).

The motivation for using artificial intelligence (AI) in fraud prevention arises from the necessity for enhanced, adaptable, and real-time detection capabilities (Javaid *et al.*, 2022, p. 84). AI's machine learning algorithms and data processing capabilities add a transformational dimension to fraud prevention. AI systems' ability to analyze huge datasets, identify intricate patterns, and adapt to evolving fraud strategies makes them an effective ally in the fight against financial crime. The integration of AI is motivated not only by the necessity to improve fraud detection efficiency and effectiveness but also by a desire to stay ahead of increasingly complex fraudulent activities that traditional methods struggle to solve (Vyas, 2023, p. 59).

Many studies have provided qualitative evidence for the impact of artificial neural networks on external auditing, but these studies mainly focus on a systematic literature review and have not provided applied evidence. Also, there is a scarcity of previous studies that addressed the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud, especially in Egypt. Thus, the problem of the study is summarized in the following main question:

What is the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud?

This study attempted to answer this main question by answering the following sub-study questions:

1. What is the impact of adopting artificial neural networks on external auditing?
2. What is the impact of artificial neural networks on the efficiency of external auditors in detecting financial statement fraud?

1.3 Study Objectives:

The main objective of this study is to investigate the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud.

It can be achieved through studying the following sub-objectives:

1. The impact of adopting artificial neural networks on external auditing.
2. The impact of artificial neural networks on the efficiency of external auditors in detecting financial statement fraud.

1.4 Study Significance:

The study derives its importance from the fact that it addresses an important and recent issue in the field of financial fraud detection using artificial neural networks and its impact on the efficiency of external auditors in detecting financial fraud, which has a positive impact on the capital market, its operating companies, and the entire national economy. The study’s importance can be classified into scientific and practical importance as follows:

1.4.1 The Scientific Significance of the Study:

This study holds particular importance as it addresses a contemporary and critical issue that has recently gained considerable attention in academic circles: the application of artificial intelligence (AI) technologies, with special focus on neural networks. The integration of these advanced technologies has become a global and local imperative, being increasingly adopted across corporate operations in various sectors, as well as in the field of external auditing.

The study will contribute significantly to the expanding body of knowledge about how artificial intelligence will affect the auditing profession. The study will focus on the impact of ANN on the necessary skills and competencies for auditors, how ANN will impact audit efficiency, and audit quality in an AI audit environment.

1.4.2 The Practical Significance of the Study:

The practical significance of the study lies in the use of artificial intelligence techniques, especially deep neural networks, to enhance the efficiency of external auditors in detecting financial fraud, where fraud negatively impacts investors, reduces the efficiency of financial markets, and limits the role of these markets.

The study will have practical importance for audit professionals, audit firms' management, and academic institutions. Auditor professionals will understand the employment opportunities available in the audit sector, the skills and competencies needed to seize these opportunities, as well as how they may continue adding value to their work. Audit firms' management becomes more aware of industry trends, the type of training programs that must be arranged for their staff, and how to better strategize to acquire relevant technology that will add value to their services and allow them to detect fraud. Educational and academic institutions will learn the skills needed for today's auditors to be more efficient in detecting fraud.

1.5 Study Hypotheses:

Based on the study problem and objectives, the main hypothesis can be stated in a null form to be tested as follows:

There is no significant impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud.

The main hypothesis can also be divided into two sub-hypotheses:

1. Adopting artificial neural networks has no significant impact on the External auditing.
2. Artificial neural networks have no significant impact on the efficiency of external auditors in detecting financial fraud.

1.6 Contents of the study:

The researchers address the remaining part of the study in the following points: literature review, theoretical framework of the study, the empirical study, and conclusions, recommendations, and suggestions for future studies.

1. Literature Review:

This section introduces and analyzes relevant studies on the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud. Previous studies can be classified into two groups. The first group is previous studies about the impact of adopting artificial neural networks on external auditing. The second group is previous studies about the impact of artificial neural networks on the efficiency of external auditors in detecting financial statement fraud, as follows:

2.1 Studies about the impact of adopting artificial neural networks on external auditing:

A study by Ting (2019) titled *"Applying Deep Learning to Audit Procedures: An Illustrative Framework"* addressed the impact of adopting artificial intelligence techniques on external auditors. By analyzing a systematic literature review, Ting discussed how deep learning in text understanding, speech recognition, and visual recognition, as well as structured data analysis, can be fitted into the audit environment. The study concluded that deep learning holds significant potential to enhance various audit procedures, especially in areas such as text understanding and visual recognition, which streamline the auditing process. Additionally, it was also found that the adoption of deep learning could lead to increased audit efficiency by automating routine tasks, focusing on complex analytical work, boosting data analysis, enhancing accuracy in anomaly identification, and enhancing decision-making abilities in audit practices.

Nawaiseh's (2021) study titled *"Audit Opinion Decision using Artificial Intelligence Techniques: Empirical Study of UK and Ireland"* evaluated the performance of nine classifiers—support vector machines, the decision trees, naïve Bayes network, logistic regression, artificial neural networks, K-nearest neighbor, linear discriminant analysis, the boosting ensemble, and also a novel DL model—as classification tools for an accurate audit opinion. By analyzing datasets collected from firms in Ireland and the UK through the Financial Analysis Made Easy Database (FAME). The study found that the deep learning algorithm exhibited superior capability in classifying the opinions of auditors accurately, outperforming all other classification models. Afterward, statistical tests confirmed that the deep learning algorithm offered the best accuracy in audit opinion classification.

Ganapathy's, (2023) study titled “AI in Auditing: A Comprehensive Review of Applications, Benefits and Challenges” provided an overview of AI techniques in auditing and highlighted the advantages of integrating AI in the audit process, its challenges, and suggested future research, through analyzing the literature review and analyzing current trends. The results revealed that auditing has been revolutionized by artificial intelligence technologies, which are machine learning, deep learning, natural language processing, and data analysis, as these technologies provide high-level data analysis and enhance pattern recognition, anomaly detection, and risk assessment, as well as these technologies enable auditors to concentrate their efforts on high-risk issues and conduct in-depth analyses, then boost audit effectiveness and efficiency. Further, many tools of AI in auditing have been provided by the study, which are automated data analysis, predictive analytics, fraud detection, NLP, and continuous monitoring. Additionally, the challenges for AI in the audit process, which include data quality, interpretability, ethical considerations, and regulatory compliance, are presented by the study. Finally, the study recommended that challenges related to data quality, transparency, ethics, skills, and regulations must be handled to successfully integrate AI into auditing. Auditors and stakeholders must cooperate while maintaining the integrity and credibility of the audit process as AI technologies continue to evolve.

Mitan, (2024) study titled “Enhancing Audit Quality through Artificial Intelligence: An External Auditing Perspective” investigated the transformative impact of AI on external auditing, with a focus on audit quality improvements. Through a comprehensive literature review, industry insights, and professional publications, the study found that AI can simplify labor-intensive audit tasks, enhance data analytics capabilities, and support accurate risk assessment and fraud detection. Additionally, AI-driven tools such as ML, DL, as well as NLP can expedite the audit process and shift the auditor’s role concerning analytical and decision-making functions. These tools improve evidentiary reasonable assurance of audits, enhance stakeholder trust in audited financial statements, and support higher-quality audits. However, the study highlights limitations in AI implementation regarding data privacy and transparency, which generated uncertainty about the implementation of AI. Based on these results, the study recommended that auditors embrace AI through training programs and set clear AI regulations to ensure ethical and reliable auditing outcomes.

By inductively analyzing previous studies, the researcher can evaluate them based on fundamental elements as follows:

Several prior studies have collectively emphasized the growing importance of artificial intelligence, particularly deep learning and artificial neural networks, in enhancing audit procedures.

1. For instance, Ting (2019) and Ganapathy (2023) highlighted the potential of deep learning (DL) to automate and streamline audit procedures, improve anomaly detection, and enhance decision-making. These studies confirmed that DL can significantly contribute to audit efficiency by handling unstructured data, such as text and images, and by supporting accurate analysis of financial anomalies. This aligns with the current study’s aim of using ANNs to improve auditor performance, particularly in detecting fraud through complex financial patterns.
2. Nawaiseh (2021) offered strong empirical support for deep learning’s superiority over other classifiers in predicting audit opinions, reinforcing the current study’s hypothesis that ANNs can enhance audit accuracy and judgment when applied to fraud detection.
3. Furthermore, Mitan (2024) provided field-based evidence showing that AI techniques—especially neural networks and NLP—improve audit quality, reliability, and timeliness. These findings are particularly relevant to this study, which measures auditor efficiency through audit fees and report issuance lag, offering a direct point of comparison.
4. Despite these alignments, a key difference is that most of the aforementioned studies focused on broad audit efficiency or AI feasibility in general, without specifically integrating AI tools within a fraud theory framework like the Diamond Fraud Theory—which is central to the current study. Moreover, none of the reviewed studies examined the Egyptian audit environment (emerging market contexts with distinct regulatory and technological infrastructures) specifically,

making the current study unique in its focus on applying ANN models to detect fraud based on pressure, opportunity, rationalization, and capability factors, while also considering audit efficiency metrics. Third, while Ganapathy (2023) comprehensively reviewed AI applications, neither provided empirical measurement of neural networks' efficiency in fraud detection. Though Mitan (2024) highlighted AI's transformative potential for audit quality, the study remained theoretical without testing specific ANN architectures.

In conclusion, previous studies support the use of deep neural network to enhance audit practices. The current study agrees with these findings regarding the potential of ANN to improve audit performance but differs by grounding the analysis in an applied fraud framework (Diamond Fraud Theory) and applying the model within the specific context of Egypt, using measurable indicators of auditor efficiency such as audit fees and reporting delays. *Thus, the researcher can formulate the first null sub-hypothesis as follows:*

$H_{0.1}$: Adopting artificial neural networks has no significant impact on the External auditing.

2.2 Studies About the Impact of Artificial Neural Networks on the Efficiency of External Auditors in Detecting Financial Statement Fraud:

One study addressing the artificial neural networks' impact on external auditors' efficiency in detecting financial statement fraud was Riany et al. (2021), titled *"Detecting Fraudulent Financial Reporting Using Artificial Neural Network"*. This study tested if the Artificial Neural Network (ANN) method could effectively detect fraudulent financial reporting at firms. Data from 506 companies listed on the Indonesia Stock Exchange in 2019 have been analyzed by the study, including companies confirmed to have engaged in fraudulent activities. The ANN method has been utilized for data analysis, and ten variables as fraud risk indicators have been used by the authors. The study showed that the ANN model successfully detected instances of fraudulent financial reporting in the financial statements.

the study of Xiuguo and Shengyong, (2022) titled *"An analysis on financial statement fraud detection for Chinese listed companies using deep learning"* aimed to establish an enhanced system that detects financial fraud using cutting-edge DL models based on a mix of numerical features generated from financial statements and textual data from managerial comments of 5130 Chinese listed firms' annual reports. The study revealed a great performance enhancement of the proposed DL algorithms against traditional machine learning algorithms on detection of financial fraud, and LSTM and GRU methods work with samples tested in correct classification rates of 94.98% and 94.62% respectively, showing that the extracted textual features of the Management's Discussion and Analysis (MD&A) section show promising classification findings and significantly improve financial fraud detection.

The study by Pramudito et al., (2024) titled *"Deep Learning for Real-time Fraud Detection in Financial Transactions"* used a qualitative research approach and collected the views of financial analysts, industry experts, and data scientists through personal interviews and focus groups to test how the deep learning techniques are detecting fraudulent activities in financial transactions in real-time effectively. The study also addressed the main opportunities and constraints these algorithms face in detecting fraud through thematic analysis. The study results indicated that deep learning algorithms, especially RNN and CNN, excelled traditional methods in significantly detecting fraudulent patterns. Despite the effectiveness of deep learning in detecting fraudulent patterns, challenges remain, including data privacy concerns, computational costs, and the need for large-scale labeled datasets. Therefore, the study called for further research as well as development to address these challenges and improve the scalability of these algorithms in practical financial environments.

Grissa and Abaoub (2024) study titled "Enhancing Fraud Detection in Financial Statements with Deep Learning: An Audit Perspective," analyzed a large sample of 100 companies in the European Union, Latin America, and Asia from 2010 to 2023 to explore the use of DL techniques within fraud detection in financial audits, highlighting the essential role that audits play in maintaining trust and also transparency in business practices. The study revealed that using deep learning techniques can significantly enhance financial statement fraud detection, as well as DL techniques can provide auditors with advanced tools to detect anomalies and irregularities accurately and efficiently. Further, the study argued that integration of DL not only strengthens the detection of fraudulent activities but also equips auditors to respond to the evolving challenges of financial crime. Finally, the authors recommended auditors collaborate with data scientists to foster a partnership that enhances the integrity and reliability of financial reporting. The necessity of embracing innovation and leveraging deep learning capabilities so that auditors can better protect the interests of stakeholders and uphold the trust and credibility of financial markets.

By inductively analyzing previous studies, the researcher can evaluate them based on fundamental elements as follows:

1. Several of the reviewed studies (such as Riany et al., 2021; Xiuguo & Shengyong, 2022; and Grissa & Abaoub, 2024) affirm that artificial neural networks (ANN) and deep learning (DL) models are highly effective in detecting fraudulent financial reporting. These findings align closely with my study's focus on leveraging ANN as a tool to enhance the external auditor's ability to detect fraud.
2. Pramudito et al. (2024) emphasized that deep learning models like RNN and CNN outperform traditional approaches in real-time fraud detection, supporting my argument that ANN can enhance fraud detection efficiency and timeliness.

Therefore, the application of artificial intelligence in auditing has significantly transformed audit objectives and methodologies, where historically, auditing concentrated on ensuring compliance with generally accepted accounting principles (GAAP) via traditional inspection methods. With the emergence of AI technologies, the emphasis has transformed to ensuring the reliability of accounting information rather than adhering to reporting standards. The artificial neural network models demonstrate accuracy in classifying audit opinions, outperforming other models. ANNs have shown great potential in fraud detection due to their capacity to analyze unstructured data. Therefore, this study will focus on integrating artificial neural networks in auditing to enhance audit efficiency in detecting financial statement fraud. *Thus, the researcher can formulate the second null sub-hypothesis as follows:*

$H_{0.2}$: Artificial neural networks have no significant impact on the efficiency of external auditors in detecting financial fraud.

2.3 Study Gap:

In light of the objectives and the findings of previous studies in the available literature, the researchers can identify the study gap in the following points:

1. Most previous studies applied ANN or DL from either a data science, financial technology, or algorithmic performance perspective, focusing primarily on classification accuracy or model development. My study is audit-focused and applies ANN

within the practical auditing environment, specifically evaluating its impact on the external auditor's efficiency in the Egyptian audit context, which is underrepresented in the existing literature.

2. Prior studies did not examine how ANN affects measurable audit efficiency indicators, such as audit fees and audit report lag.
3. None of the previous studies explicitly relied on a fraud detection theory, while my study integrates the Diamond Fraud Theory (covering pressure, opportunity, rationalization, and capability) to guide ANN-based fraud prediction.
4. While most studies analyzed data from Indonesia, China, Europe, or global markets, my study focuses on Egypt, a developing economy with a distinct regulatory and auditing environment, offering a novel contribution to region-specific audit literature.

2. Theoretical framework of the study:

We are in the era of 4.0, driven by AI and automation, where smart technologies like IoT, cloud computing, and cyber-physical systems transform industries. Unlike the internet-driven 3rd revolution, Industry 4.0 focuses on data-powered intelligence, reshaping how machines and humans interact.

AI is revolutionizing all sectors, including auditing—a process that verifies financial data accuracy, tests transactions, and ensures compliance. Auditors assess financial statements for errors or fraud, issuing reports on their reliability. AI can enhance audit efficiency, reduce costs, and improve accuracy, making it a game-changer for the profession (Kokina and Davenport 2017).

3.1 External Audit Efficiency Concepts:

The efficiency of the audit process is an effective factor for companies seeking high-quality audit services. Efficiency is seen primarily as the extent to which the project's objectives are achieved across all areas. In the context of the audit, audit efficiency is seen as the optimal use of resources available by the auditor to achieve audit objectives. The researcher can address the concepts and the determinants of external audit as follows:

Audit efficiency is classified into four competencies that form the basis for an efficient audit process. These competencies emphasize the importance of resource management, alignment of objectives, and systematic performance of audit functions to achieve effective and reliable results. Audit efficiency is structured around four core competencies, as follows (Mezioud and Tani, 2021, p. 1115):

1. **Professionalism:** In accordance with generally accepted auditing standards (GAAS), it is required by auditors to hold the professional training and competence necessary to carry out the audit process.
2. **Technical competence:** This refers to the accurate knowledge of the auditor of the applicable professional standards and rules, laws, and regulations, and also a technical understanding of the client's industry and business sector. It also includes an understanding of corporate governance, the financial reporting process, and basic internal control for effective audit.
3. **Practical efficiency:** This means the auditor's ability to select appropriate audit procedures to collect sufficient and reliable evidence at different stages of the audit process implementation.
4. **Reporting efficiency:** This relates to the auditor's capability and commitment to detecting and reporting material deviations, ensuring transparency and accuracy in financial reporting.

These competencies collectively enhance the auditor's ability to achieve efficiency by optimizing resource utilization and ensuring the reliability of the audit outcomes.

AI further enhances audit efficiency by automating data analysis, speeding up processes, and improving error/fraud detection beyond human capabilities. It assists auditors in preparation, evaluation, and reporting, making audits faster, more accurate, and more reliable.

3.2 Role of External Auditors in Detecting Financial Fraud:

Detecting fraud in financial services has always been a continuous challenge. The dangers of financial fraud are not limited to the significant risks threatening consumers but extend to include threats to the integrity and stability of the entire financial system. Fraud detection provides for the process of identifying and preventing deceptive actions aimed at manipulating financial transactions for illegal benefits. In the complex world of finance, where substantial amounts of money are traded daily, distinguishing between legitimate and fraudulent transactions is critical (Wali et al., 2023, p. 4). The importance of fraud detection is demonstrated by its role in protecting financial stability for companies and ensuring the overall safety of the financial sector as a whole.

3.2.1 Nature of Fraud and Fraud Detection:

Fraud arises when an individual wrongfully attains something, typically for financial gain. It is broadly characterized as a term that encompasses various deceptive methods used by individuals to gain an advantage over others through false representations. There is no fixed definition of fraud, as it can involve surprise, trickery, cunning, as well as unfair practices that lead to deceit (Whiting et al., 2012). According to ISA, fraud is an intentional act committed by individuals within management or governance that involves deception to gain an unjust or illegal advantage (ISA 240) (IAASB, 2009). The Corporate Finance Institute (CFI) further describes fraud as the act of deception using illegal practices to obtain benefits or value.

SAS No. 99 specifies that fraudulent financial reporting occurs when there are intentional inaccuracies or omissions of monetary values and disclosures in financial statements, aimed at misleading external users and neglecting essential financial information, thus violating generally accepted accounting principles (GAAP). The AICPA characterizes financial statement fraud in SAS No. 99 as a purposeful act or omission that leads to significant material misstatements in financial statements, which are the subject of the audit (Nakashima, 2017, p. 9). This type of fraud typically involves management intentionally deceiving stakeholders to achieve illicit gains. Furthermore, Meiryani (2020, p. 693) suggests that the risk of fraud increases in the absence of effective prevention and detection techniques.

Additionally, fraud has been described by the Association of Certified Fraud Examiners (ACFE) as illegal actions conducted with the intent to mislead others, such as submitting false reports. These fraudulent activities can be committed by individuals within the organization or by external parties, often for personal or collective advantage, causing harm to others either directly or indirectly (ACFE, 2021). Also, the Financial Supervisory Agency defines fraud as a deliberate, unlawful act aimed at acquiring something through deceit (Iskandar et al., 2022, p. 181).

Thus, in summary, the researchers can define fraud as "the exploitation of one’s position for personal gain by intentionally misusing or misapplying the resources or assets of the employing organization." Additionally, it may involve unintentional actions by individuals within an organization's management, staff, or third parties, leading to the presentation of inaccurate financial reports.

The fraud detection process means designing a series of activities aimed at preventing the unauthorized acquisition of money or assets by fraudsters. This process also helps in avoiding fake users, individuals with duplicate accounts, prospective customers with problems, or transactions recorded at unusually high values. The approach used to detect fraud always varies from one organization to another based on organization-specific requirements. To enhance the auditor's role in preventing and identifying fraud, the various types of fraud that happen in the organization must be understood by auditors. Generally, fraud includes three phases, which are the action itself, the concealment of that action, and the conversion of the illegal gains (Indarto et al., 2023, p. 21).

3.2.2 Financial Statement Fraud:

Financial statement fraud refers to the deliberate manipulation of financial reports through omissions or misstatements, resulting in a misleading representation of a company's financial condition due to material misstatements. This type of fraud can also include actual transactions that have an indirect impact on the financial statements (Pavone, 2018, p. 39). The primary objective of such fraudulent activities is to mislead users by either presenting inflated superior performance to entice investors or by concealing performance data to reduce tax obligations.

Following International Standards on Auditing (ISA) 240, it is important to differentiate between an error and a misstatement when evaluating the potential for fraud in financial statements. Financial statement fraud takes place when individuals manipulate the financial reports by exaggerating revenues or downplaying liabilities and expenses (Deterrence and detection of financial fraud - EY). While this type of fraud may not be the most frequently encountered form of occupational fraud, it is recognized as the most costly (Report to the Nations on Occupational Fraud and Abuse). Statement on Auditing Standards (SAS) 99 notes that fraudulent financial reporting does not necessarily require a significant scheme or conspiracy. Instead, management may justify a material misstatement as an aggressive yet indefensible explanation of intricate accounting standards or as a temporary error in the financial statements, including interim reports, which are anticipated to be corrected once operational performance improves.

Financial statement fraud happens when companies intentionally mislead users of their published financial reports, including investors and creditors, by producing and disseminating materially inaccurate statements. This type of fraud involves both intent and deception by knowledgeable perpetrators, such as senior executives, who employ well-conceived strategies and demonstrate significant competitiveness (Pavone, 2018, p. 39). Below are some examples of these schemes:

1. Falsifying, altering, or manipulating material financial documents, supporting records, or business transactions.
2. Intentional misstatements, omissions, or misrepresentations of critical events, transactions, accounts, or other vital information used to prepare financial statements.
3. Deliberate misapplication, intentional misinterpretation, and improper implementation of accounting standards, principles, policies, and methods for measuring, recognizing, and reporting economic events and business transactions.
4. Purposeful omissions and inadequate disclosures concerning accounting standards, principles, practices, and relevant financial information.
5. Utilization of aggressive accounting practices through illegal earnings management.

Following the Center for Audit Quality (CAQ), management is responsible for overseeing the financial statement process within an organization and plays a key role in detecting and preventing financial statement fraud, however, this can lead to conflicts when the individuals responsible for committing the fraud are also those tasked with auditing the financial statements.

3.2.3 Fraud Theories:

Initially, the actions of individuals engaged in fraud were explained by the Fraud Triangle theory, which includes three elements: pressure, rationalization, and opportunity (Machado and Gartner, 2017). Over time, this theory evolved into the Fraud Diamond by incorporating an additional factor known as capability (Wolfe and Hermanson, 2004). Moreover, Marks (2012) expanded on the Fraud Triangle by introducing the Pentagon Fraud model, which adds two more components: competence and arrogance. The latest evolution of fraud theory is the Fraud Hexagon, proposed by Vousinas (2019), which includes a collusion factor. The key theories are summarized as follows:

3.2.3.1 Fraud Triangle Theory:

The fraud triangle is a key component of fraudulent activity prevention and detection. It was introduced by Cressey (1953). It identifies three critical factors contributing to the prominence of fraudulent financial statements, as noted by Arens et al. (2023), which are pressure, opportunity, and rationalization.

Following SAS No. 99, three conditions typically occur with instances of fraud: Firstly, management may face pressures or incentives to engage in fraudulent behavior. Secondly, the lack of effective internal controls or the ability of managers to bypass existing controls leads to creating an environment conducive to fraud. Finally, management involved in the fraud often possesses a mindset that allows them to justify their fraudulent activities. These three factors, as defined in SAS No. 99, manifest in fraudulent behaviors as follows:

Pressure: Among the risk factors in the fraud triangle, pressure is recognized as the most significant motivator. This pressure arises when management or employees feel an incentive to engage in fraudulent activities. Such pressures can lead individuals to consider illegal actions, like misappropriating firm assets or intentionally misstating financial statements. For instance, managers might manipulate earnings to create a more favorable financial picture than what truly exists. ISA 240 highlights that the stress element within the fraud triangle can be exemplified by the risk of bankruptcy. According to Omar et al. (2017, p. 373), bankruptcy is a situation that arises when a company faces solvency issues, often leading to fraudulent financial reporting.

Opportunities: Opportunities arise from specific conditions that provide the opportunity to perpetrate financial fraud (Lou and Wang, 2011, p. 65). Such circumstances may include weak or nonexistent internal controls or instances where management can override these controls, providing a chance for fraudulent activities. ISA 240 describes the opportunity element by focusing on accounts that are challenging to monitor and cases of insufficient oversight by management.

Rationalization: Rationalization is the hardest element of the fraud triangle to measure. Rationalization involves the mindset or behaviors that allow individuals to justify fraudulent actions. It often appears in situations where stress or other pressures lead individuals to view fraud as a justified or acceptable act. In cases of financial statement fraud, perpetrators may convince themselves that their actions align with personal or corporate ethics (Manurung and Hadian, 2013, p. 6).

The fraud triangle has been widely used to explain the causes of fraud, but it faces certain criticisms. One limitation of the model is that it primarily addresses individual fraud committed by a single offender. Sadaf et al. (2018) argue that the fraud triangle's theoretical basis is overly focused on one-dimensional psychology, overlooking collaborative or contextual factors. Maulidi and Ansell (2021) also contend that more complex elements beyond Cressey's model (Cressey, 1953) are relevant. They highlight that the surrounding environment significantly impacts individual factors, suggesting a need to consider intrinsic factors that may trigger fraudulent intentions.

3.2.3.2 Fraud Diamond Theory:

The literature evolving to critique earlier fraud models has introduced updated frameworks, such as the fraud diamond model. Wolfe and Hermanson (2004) expanded on Cressey's (1953) original three conditions by including capability as a fourth factor influencing a person's likelihood of committing fraud. They suggest that fraud requires individuals with the skills and traits necessary to execute complex schemes, bypass organizational controls, and manipulate social dynamics to gain compliance from others (Vousinas, 2019, p. 373).

Free (2015) describes **capability** as a combination of factors like positional authority, intellectual capacity, confidence, resilience to stress and also guilt, and the ability to influence others. The significance of capability in driving fraud is highlighted by the ACFE, which reports that those in senior management roles tend to engage in fraud more frequently than those in mid-level management (ACFE, 2021). Therefore, higher management roles are often associated with greater capability. Given that individual characteristics are highly influenced by environmental factors, it's essential to focus on intrinsic traits that may predispose someone to fraud.

3.2.3.3 Fraud Pentagon Theory:

The evolution of fraud theories continued with Crowe's enhancement of Cressey's original model. Crowe identified an additional element—arrogance (or ego)—as a factor that can contribute to fraudulent actions. Crowe's work combined the original fraud triangle with the capability factor introduced by Wolfe and Hermanson, resulting in what is now known as the fraud pentagon, which includes five factors: pressure, opportunity, rationalization, capability, and arrogance. Presented in 2011, Crowe's model was developed to address the modern fraud landscape, where perpetrators often have greater access to information and assets than in Cressey's time. Arrogance (ego) refers to a sense of superiority where an individual believes they are exempt from company policies and controls (Iskandar et al., 2022, p. 181). However, Sari et al. (2020) suggest that ego may not fully capture the concept of arrogance among managers, indicating a need for further model refinement. Building on this, Vousinas (2019) introduced the fraud hexagon theory, incorporating an additional element for a more comprehensive fraud detection model.

3.2.3.4 Fraud Hexagon Theory:

The Fraud Hexagon, introduced by Vousinas in 2019, includes collusion as an additional factor that can drive fraudulent behavior. This factor involves a secret agreement between two or more individuals, allowing one party to take actions that ultimately serve a dishonest purpose, often depriving a third party of their rightful claims or information.

The researchers deduced that the Fraud Hexagon theory advances our understanding of fraud drivers, evolving from Cressey's (1953) original Fraud Triangle. This foundational model attributed fraud to three core conditions: pressure, opportunity, and rationalization. Wolfe and Hermanson's (2004) Fraud Diamond later expanded this by introducing capability as an essential factor. With arrogance as an additional element, the model evolved into the Fraud Pentagon, indicating persistent drivers of fraud. Collectively, these frameworks—the Fraud Triangle, Diamond, and Pentagon—led to the Fraud Hexagon, which deepens and broadens the conceptual model of fraud motivation.

3.2.4 External Auditors' Responsibility for Fraud Detection:

The primary fraud prevention and detection responsibility lies on the organization's senior management and governing bodies. Therefore, promoting a culture of integrity, identifying the appropriate ethical tone, and upholding high moral standards by management, along with those overseeing the financial reporting process (such as the board of directors, audit committee, and board of trustees), is essential to detect and prevent fraud, as are strict controls by them to help prevent and detect fraud. In addition, external auditors also share responsibility in such areas, as detailed in the International Auditing Standard (ISA) 240: Auditor's Responsibilities Related to Fraud in Auditing Financial Statements (IAASB, 2009) and the United States equivalent, Auditing Standards Data (SAS) 99: Considering Fraud in

Auditing Financial Statements (ASB, 2002). ISA 240 and SAS 99 establish similar obligations concerning external auditors' roles in fraud detection; however, ISAs are internationally recognized, while SASs are specific to the U.S. (Kassem, 2023, p. 5).

ISA 240 and SAS 99 standards require external auditors to assess and address the risk of fraudulent financial reporting by analyzing these frauds through the fraud triangle model, which classifies the risks as: pressure or motive to commit fraud, opportunity to commit fraud, and rationalization of fraud. When planning an audit, auditors must evaluate the potential for fraud and error that yield material misstatements in the financial statements. So, based on this assessment, auditors must design effective procedures to identify any misstatements caused by fraud or error. In addition, external auditors need to take into account management's integrity, apply professional skepticism, and account for the risk of management overriding controls. Auditors are also expected to hold discussions among engagement team members, including the business partner, to identify areas where the client's financial statements may be subject to material misstatements because of fraud. Where suspected fraud is identified, any concerns to senior management and governing bodies must be reported immediately by the external auditors. If fraud involving senior management or governing bodies is suspected, auditors must inform a party outside the organization and recommend that the entity seek legal advice. Consequently, there is a significant impact of external auditors' efficiency on the detection of financial fraud.

3.3 Impact of Artificial Neural Networks in Enhancing Audit Efficiency and Timeliness:

ANNs represent one of the rapidly advancing techniques in AI. These networks function as computational algorithms designed to model data, taking inspiration from the biological nervous system, which is reflected in their name (Jafarian et al., 2013). An ANN comprises a network of interconnected processing units known as neurons. These neuronal structures collaborate harmoniously to address specific complex issues, particularly in fault detection systems. ANNs are particularly beneficial in situations where detecting trends or patterns is difficult. Despite being around for nearly 50 years, ANNs have recently surged in popularity. Although the fundamental principles behind ANNs have long existed, their resurgence has been greatly aided by the widespread adoption of powerful computational tools in modern society, benefiting experts, engineers, and consumers alike (Abdolrasol et al., 2021, p. 2). Generally, ANNs can be characterized by their connection structure between the neurons (referred to as their topology), the method for determining the strength or weights of these connections (known as their training and learning algorithm), and also their activation function.

3.3.1 Definition of Artificial Neural Networks:

The ANN is a computational and mathematical model inspired by the structure and functions of biological neural systems. This technology is widely accepted as an alternative approach to solving complex problems (Bouselham et al., 2017, p. 924). Additionally, ANNs are recognized as modern systems and computational techniques for machine learning and knowledge representation, as well as the practical application of the acquired knowledge to optimize the output of complex systems (Chen et al., 2019). An artificial neuron is a core information-processing unit essential for neural network operations (Al-Haija and Jebril, 2020). As noted by Neofytou et al. (2020), neural networks enable computer systems and programs to acquire learning capabilities systematically.

An artificial neural network (ANN) is a highly parallel, distributed processor composed of simple processing units with an inherent ability to store experiential knowledge for later use (Sharkawy, 2020, p. 8). According to García-Nicolás et al. (2021), NNs simulate human brain functions through structural simulations enabled by the neural network framework. Dastres and Soori (2021, p. 13) also define ANNs as data processing models inspired by how biological nervous systems, including the brain, handle information, focusing on mimicking the neuronal structures of the mammalian cerebral cortex, albeit on a much smaller scale. Additionally, Rosid (2022) describes ANNs as a widely used technique for predictive data mining due to their accuracy, flexibility, and ease of use, particularly in complex scenarios.

ANNs mimic the human brain by using multiple perceptrons, or "neurons," that process and convey information, with their function depending on the network's weights. The term "network" in neural networks refers to the interconnected structure of neurons across different layers within the system. These weights define the connections among neurons, influencing how one neuron affects another. The foundation of ANNs lies in the concept that relationships between independent and also dependent variables can be estimated using nonlinear mathematical functions (Aryadoust and Baghaei, 2016).

Neurons in the input layer receive data and pass it to the neurons in the first hidden layer via weighted connections. The data is mathematically processed, and the resulting output is then passed to the neurons in the subsequent layer. The final output of the network comes from the neurons in the last layer. In each hidden layer, the $j-^{th}$ neuron processes incoming data (xi) by: (i) calculating the weighted sum and adding a "bias" term (θ_j) as follows:

$$net_j = \sum_{i=1}^{m} x_i * w_{ij} + \theta_j; where\ j = (1,2,3,n).$$

In such networks, if a cell is damaged, other cells can compensate for its absence and support its regeneration. These networks possess the capability to learn, which is a key feature of any intelligent system. A system that can learn is inherently more adaptable and simpler to program, enabling it to respond more effectively to new challenges and equations. Similar to human learning, artificial neural networks acquire knowledge through diverse examples and are designed to perform specific tasks, such as pattern recognition and information categorization, during the learning phase.

ANNs are increasingly utilized to control or model systems with unknown or highly complex internal structures. Learning in these systems is adaptive, meaning that, through parables, the weights of synapses adjust so the system can produce accurate responses when new inputs are provided (Wu and Feng, 2018). Furthermore, during training, a neural network is supplied with a set of inputs and their respective outputs, which are used in one of the available training methods.

Based on the above, ANNs can be defined as nonlinear statistical modeling tools used to represent complex relations between inputs and outputs or to identify underlying patterns. An ANN functions as an information-processing system, sharing certain characteristics with biological neural networks. The primary advantage of ANNs lies in their ability to recognize and classify patterns because of their non-linear, adaptive learning capabilities that are not constrained by specific parameters.

3.3.2 The Artificial Neural Network Architecture:

The standard model of the ANN consists of three interconnected layers and an activation function, as described below:

3.3.2.1 The Input Layer:

The input layer of the neural network consists of a group of artificial input neurons that transmit information from the initial neuron layers to the system for processing. This layer serves as the starting point for the workflow of the neural network.

3.3.2.2 Hidden Layer:

The hidden layer of the ANN is composed of the input and the output layers, where the inputs and outputs of the artificial neurons are influenced by the weights assigned to each input.

3.3.2.3 The Output Layer:

The final layer in an ANN is the output layer, which delivers specific outputs to the programmer. As the last set of "performer" nodes in the network, the neurons within the output layer can be designed and managed differently (Batina et al., 2019, p. 131).

3.3.2.4 Activation Functions of ANN:

The activation function represented by $\varphi(s)$ determines the output of the neuron based on the induced local field s.

3.3.3 Learning Techniques of Neural Networks:

There are three main learning paradigms in ANNs. Each paradigm can be applied to various neural network architectures, and each encompasses multiple training algorithms.

1. **Supervised Learning of Neural Networks:**

Supervised learning is a ML technique where an ANN adjusts its parameters based on training data. The learning ANN's task is to set the correct parameter values for any valid input after seeing the corresponding output value. Supervised learning involves providing the neural network with specific output values in response to input sample data during training. In supervised learning, the match is made between the input data provided to the NN and the output values derived from these inputs, allowing the network to learn the relationships between them (Dike et al., 2018, p. 323).

The researchers argued that supervised learning involves the presence of a "teacher" who provides the expected outputs during the learning process. Each input pattern is used for training the network, with the learning process relying on comparing the network's computed output to the correct expected output. This comparison generates an "error," which is then used to adjust the network's parameters, leading to improved performance.

2. Unsupervised Learning of Neural Networks:

In unsupervised learning, the neural network is provided with only input examples, and it must independently learn the patterns within the data. The network processes the input data and generates output values on its own. As a result, this learning method enables classification based on specific characteristics using unstructured data (Sah, 2020, p. 2).

The researchers argued that in unsupervised learning, there is no teacher involved. The neural network does not receive any expected or desired outputs. Instead, the system independently learns by identifying and adjusting to the underlying structural characteristics within the input patterns.

3. Reinforcement Learning of Neural Networks:

Reinforcement learning utilizes a different framework compared to supervised and unsupervised learning. In this type of learning, the network does not receive output values directly related to the input values provided. Instead, the learning occurs after these outputs are assessed against specific criteria. This approach employs a learning structure known as an agent. In reinforcement learning, knowledge is acquired through trial and error, relying on feedback derived from the agent's experiences and actions. Figure (4.6) illustrates the structure of reinforcement learning (Mohammed et al., 2016).

The researchers argued that in reinforcement learning, while a teacher is involved, they do not provide the expected or desired outputs. Instead, the teacher indicates whether the computed output is correct or incorrect. This feedback aids the network in its learning processes. A reward is granted for the correct computation, whereas a penalty is imposed for an incorrect response.

3.3.4 Classification of Artificial Neural Networks:

ANNs are composed of interconnected neurons and are categorized based on the structure of their network connections. These networks can be organized in three main forms: feedforward, feedback, and Deep Learning, as follows (Dike et al., 2018, Pp. 323- 325; Sah, 2020, Pp. 2-3):

3.3.4.1 Multilayer Feedforward Neural Network (MLFFNN):

The feedforward neural network is the most basic type of ANN commonly used for standard classification and recognition tasks. This network does not contain any cycles; instead, data flows unidirectionally through each layer. Perceptrons can be either single-layer or multi-layer networks. They function as linear (binary) classifiers and are employed in supervised learning.

3.3.4.2 Recurrent Neural Network or Feedback Neural Network:

The Feedback Neural Network (FBNN), known as a recurrent neural network (RNN) too, was initially introduced by Rumelhart in a 1986 Nature publication. It describes a new self-organizing learning process. RNN is a layered neural network where information flows from the input to the output, incorporating feedback loops that direct the output back to the input. Neurons within the same layer do not connect with each other, but are linked to all neurons in the preceding and subsequent layers (Sharkawy et al., 2018).

The researchers argued that, unlike a traditional backpropagation neural network, an RNN's hidden layer input includes not only the output from the upper layer but also output between nodes within the same hidden layer at the previous time. This structure allows RNNs to enhance predictive accuracy by utilizing historical photovoltaic power data. In theory, the length of the historical photovoltaic series used can be indefinite.

3.3.4.3 Deep Learning (DL):

DL refers to neural networks (NN) with numerous variables and layers, utilizing a fundamental architecture that includes unsupervised pre-trained networks, convolutional neural networks (CNNs), recursive neural networks, and recurrent neural networks (RNNs) (Abiodun et al., 2018, p. 9).

According to Dastres and Soori (2021, p. 18), DL is defined as neural networks that consist of more than three layers of neurons, including both the input and output layers. These layers' representations are learned through models called "neural networks", with each layer built upon the previous one, allowing for the learning of complex representations.

DNNs are a type of ML technique with multiple hidden layers. These networks handle the information flow from the input layer to the output layer by adjusting weights and utilizing backpropagation to reduce errors. While increasing the number of hidden layers can enhance the performance of DNNs, it also leads to greater demands on computational power and memory (Bajić et al., 2023, p. 2). Furthermore, DNNs tend to outperform artificial neural networks (ANNs) in predicting unknown data (Han et al., 2018, p. 337).

3.3.5 Using Artificial Neural Networks in Enhancing the Efficiency of External Auditors in Detecting Financial Fraud:

Financial fraud schemes are constantly evolving in complexity and sophistication as perpetrators use advanced technologies and regulatory gaps to obscure fraudulent activities and evade detection (Aslan et al., 2023, p. 1), thus presenting enormous challenges to detection and prevention efforts (Hilal et al., 2022, p. 6). Traditional audit methodologies may fail to keep pace with these rapidly developing schemes, as fraudsters use to perpetrate their crime tactics, which are cyber fraud, identity theft, and other intricate financial instruments. Therefore, auditors have an urgent need to adapt their approaches and tools to effectively detect and mitigate emerging risks. This also demands a proactive stance in audit planning and execution by integrating advanced analytical techniques and data-driven methodologies. As a result, auditors must enhance their understanding of new fraud typologies and adapt technological innovations like artificial intelligence to enhance detection capabilities (Aslan et al., 2023, p. 1).

3.3.5.1 The Reason of Using Artificial Neural Networks in Auditing:

Three urgent problems affect the performance quality in auditing, which leads to an increase in auditing costs at present. These problems are (Taha, 2012, Pp. 48-49):

1. **Complexity of Tasks:** The complexity of auditing tasks negatively affects the auditor's performance quality, and there is a need therefore to “decision assistant” and to change “training programs” to improve the auditor’s performance, judgment, and evaluation.
2. **Need for Expert:** There is a difference between expert auditor conduct and novice auditor conduct; if a less-skilled novice auditor is assigned a complex task, it is at risk and increases the negative impact of task complexity on performance quality,

consequently, the dire need for skills and experiences in implementing the auditing task.

3. **Scarce of Expertise:** The complex tasks of auditing negatively affect learning, i.e., improving judgment and evaluation performance over time and the need to "longer time" or "more practice" to learn and gain experience in taking complex tasks, as in most auditing tasks, which in turn affect "rarity" or "scarce" special expertise available to make auditing tasks in present time.

So, artificial neural networks can play a major role to help in overcoming these problems, consequently helping in achieving the two objectives that the companies and auditing offices seek, i.e., "cost reduction and increase of auditing quality".

3.5.5.2 The Necessity of ANN in Audit Decision-Making:

In a rapidly evolving world, there is a pressing need to embrace modern, data-driven technologies. Business applications, including ERP systems, cloud storage solutions, RFID readers, sensors, social media platforms, and remote communication tools, which are Skype and live streaming, have become integral to daily operations. These technologies significantly contribute to the generation and management of vast quantities of unstructured or semi-structured big data (National Research Council, 2013).

In addition to traditional structured financial data, unstructured data provides insights from a multitude of perspectives and sources, enabling businesses to assess the performance of their products, services, and operations more comprehensively. The abundance of big data enhances the reliability of evidence and reduces auditors' reliance on client-provided data (Yoon et al., 2015).

As a result, analyzing and extracting valuable patterns from big data can significantly inform audit decision-making (Sun and Vasarhelyi, 2018). However, leveraging big data analytics poses several challenges: (1) A significant portion of big data is semi-structured or unstructured, necessitating considerable effort from human experts for labeling and classification; (2) the sheer volume of data is often too extensive for manual processing; (3) big data is frequently generated in real-time, which demands quick responses; and (4) the complexity of big data arises from its diverse data types and origins. Consequently, understanding this data requires relevant knowledge and skills.

A survey conducted by the AICPA (2014) indicated that a quarter of 180 CPA participants view big data analysis as one of the foremost challenges for the future. To effectively utilize big data for audit decision-making, auditors—who often lack expertise in data mining and information systems—require an efficient and effective strategy to automate audit processes (Sun and Vasarhelyi, 2018). Implementing a deep neural network allows auditors to leverage a pre-trained deep neural network (DNN) tested by deep learning specialists, combined with their professional accounting judgment, to enhance their work. Many audit tasks can be both tedious and complex.

Automating these tasks is expected to greatly improve the effectiveness and efficiency of audit processes (Raphael, 2015). A deep neural network (DNN), trained on extensive samples that reflect how auditors make decisions in various scenarios (by providing different values of data attributes), can automate numerous structured or semi-structured tasks that have traditionally been performed manually, such as inventory checks, paperwork processing, contract reviews, and the drafting of audit reports. Even for risk assessment activities that necessitate professional judgment—often referred to as unstructured audit tasks—deep learning offers innovative support for audit decision-making. For example, financial statement items or other financial records can be automatically scanned and associated with relevant evidence, including inventory images obtained via webcams, shipping documents, sales invoices, bank confirmations, auditor working papers, and other supporting documentation that deep neural network systems have identified and classified. Additionally, these systems can provide a list of potentially risky items along with recommended responses.

3.5.5.3 Impact of Artificial Neural Network on Audit Procedures:

Audit procedures based on the application of artificial intelligence enable accurate and comprehensive audits. This way of conducting an audit can increase the efficiency of the audit (Hu et al., 2021). The form of conducting audit engagements is constantly transforming and evolving, using advanced software tools and application solutions. New technologies also introduce new ways of gathering audit evidence and performing audit procedures on it. Compared to traditional audit procedures, the application of artificial intelligence in auditing enables a more efficient and comprehensive implementation of the audit engagement. More efficient in terms of less time spent on the implementation of a specific audit engagement, and more comprehensive in terms of greater coverage of the population during sampling, with the possibility to include the entire population of the subject entity when drawing certain conclusions. Using artificial intelligence, a set of data can be skillfully analyzed in a way that increases overall performance (Frisk and Bannister, 2017). Hu et al., (2021, p. 460) identify five dimensions as a framework for the application of artificial intelligence technology in auditing, namely:

1. Gaining a preliminary understanding of the entity being audited during the acceptance or continuation of the audit engagement and preliminary planning.
2. Understanding of internal controls.
3. Control risk assessment.
4. Performing essential tests.
5. Compiling an audit report.

AI could impact different stages of auditing. **The phase**, which involves **gaining a preliminary understanding of the audited entity during the acceptance or continuation of the audit engagement and preliminary planning**, involves obtaining initial information about the audited entity in the event of a new client's acceptance or updating information gathered from previous engagements in the case of continued cooperation with an existing client. For the application of artificial intelligence to find its wider usefulness during this phase, it is necessary to enable the availability of relevant sources of potentially important information, primarily sources available on the Internet, such as newspaper articles, other relevant texts, ratings, and comments on social media and also publicly available databases and databases to which the audit firm is subscribed, and whose data may be useful for gaining a preliminary understanding of the entity being audited. A tool based on the application of artificial intelligence must be able to generate a clear and comprehensive report on the preliminary understanding of the audited entity after multiple analyses, which may include chapters such as a preliminary assessment of the entity's financial position in terms of relevant liquidity, solvency and profitability, entity status on social media and treatment in media circles.

The initial phase of audit planning is recognized as an iterative process and serves as a crucial step to ensure auditors concentrate on higher-risk areas. AI technologies, such as artificial neural networks (ANN) and advanced data analytics, play an essential role in the audit planning phase and in enhancing risk assessment processes. ANN is used to analyze large datasets and identify patterns, anomalies, and trends that may indicate potential risks (Odonkor et al., 2024, p. 174).

These algorithms can learn from historical data to make predictions and recommendations for risk mitigation. ANN enables advanced data analytics techniques to extract insights from unstructured data sources, such as emails, documents, and social media, that are traditionally challenging to analyze manually. ANN offers several advantages over traditional risk assessment methods, making it a valuable tool for auditors: ANN algorithms can continuously learn from new data, allowing them to adapt to changing risk environments and identify emerging risks in real-time (Mitan, 2024, Pp. 5-6).

This dynamic learning capability enhances the accuracy and effectiveness of risk assessment processes. ANN models can make more accurate predictions than static models used in traditional risk assessment methods. Through analyzing large datasets and identifying complex patterns, ANN can provide auditors with valuable insights into potential risks and their impact. Overall, the role of ANN in risk assessment is transformative. It enables auditors to improve the accuracy, efficiency, and effectiveness of risk assessment processes. By using ANN technologies, auditors can enhance their ability to identify and evaluate. They can also respond to risks by using ANN, ultimately improving audit quality and providing greater value to stakeholders. ANN enables real-time monitoring of risks through analyzing data streams and detecting anomalies or patterns that may indicate potential risks. This proactive approach enables auditors to respond to emerging risks rapidly and mitigate them before they escalate.

ANN automates repetitive and manual tasks involved in risk assessment, like data collection, entry, and analysis. This automation frees up auditors to focus on more strategic and value-added activities, enhancing overall audit efficiency (Landers and Behrend, 2023, p. 37). Therefore, ANN offers scalability and flexibility in risk assessment, allowing auditors to analyze large volumes of data quickly and efficiently. ANN algorithms can also be customized to meet specific audit requirements, ensuring that risk assessment processes are tailored to the unique needs of each audit engagement. ANN algorithms excel the manual methods in analyzing data with a level of accuracy and consistency. By reducing the risk of human error, ANN enhances the reliability of risk assessment outcomes and improves audit quality.

The second phase concerns understanding internal controls. Auditors are not required to give an opinion on internal controls unless specifically agreed. But during the audit engagement, they should gain an understanding of them to assess the reliability and relevance of the audit evidence gathered accurately, on which the audit opinion is based. Establishing appropriate internal control systems contributes to reducing business risks and increasing the value of the company (Cangemi and Taylor, 2018, p. 2). Audit analysis of internal controls usually involves reviewing large reports that can be considered unstructured data, and as such, is very suitable for the application of technology based on artificial intelligence, such as ANN, that can extract relevant data in a short time. In contrast to this approach with the use of artificial intelligence, the traditional approach involved a large time and cognitive burden for the person engaged in audit work to review reports related to internal controls and threatening documentation, which made his ability to draw relevant conclusions less than the application of artificial intelligence due to a large amount of time spent on gathering adequate information and evidence, which is a job that can be done very efficiently by a software tool that involves the use of neural networks.

The third phase refers to the performance of essential tests. Essential tests are used to examine and confirm account balances and represent a very important audit technique (Jakovljević, 2021, p. 279). ANN enables the person engaged in audit work during the performance of essential tests to achieve a clearer overview of data sources and a more reliable way of performing detailed tests and appropriate analytical procedures, which increases audit reliability.

3.5.5.4 Deep Neural Network (DNN) Techniques in Auditing to Detect Financial Statement Fraud:

Deep neural networks (DNNs) are employed to model and interpret complex data structures. Unlike traditional ML and ANN, DNN algorithms can autonomously learn hierarchical representations of data, facilitating the capture of intricate patterns and relationships within large datasets (Borhani and Wong, 2023, p. 6). DNN methodologies have gained significant popularity in various domains, including fraud detection, because of their ability to handle high-dimensional data and adapt to evolving fraud schemes. Neural networks perform simple computational tasks and transmit information to subsequent layers. Trained on labeled datasets, neural networks can classify and detect patterns indicative of fraudulent behavior.

CNNs and RNNs are commonly used architectures for fraud detection, leveraging their ability to extract spatial and temporal features from sequential and structured data. Anomaly detection, a crucial DNN application in fraud detection, aims to identify deviations from normal patterns or behaviors within financial transactions. DNN-based anomaly detection models learn the inherent characteristics of legitimate transactions and flag outliers exhibiting unusual or suspicious behavior (Borhani and Wong, 2023, Pp. 6-9).

Autoencoder architectures, which learn to reconstruct input data, are often employed for anomaly detection tasks. Anomalies typically cause reconstruction errors indicative of fraudulent activity. Predictive modeling uses Dl algorithms to estimate future events or behaviors based on past data and patterns. In fraud detection, predictive models can estimate potential fraudulent events. DNN techniques such as LSTM networks and GRUs outperform in sequential data analysis, making them suitable for predicting fraudulent activities detected over time. By incorporating predictive modeling in fraud detection approaches, auditors can identify and mitigate risks, thereby enhancing the efficiency and effectiveness of audit processes (Gu, 2022, p. 283-285).

The utilization of Dl techniques in enhancing fraud detection in financial statements presents a promising frontier for auditors (Lösse and Weißenberger, 2023). By the application of deep learning models, auditors can enhance traditional audit procedures (Craja et al., 2020), enabling them to identify anomalies and irregularities accurately and efficiently. The integration of deep neural networks into the audit process not only enhances the detection of fraudulent activities but also enables auditors to adapt to the evolving landscape of financial crime. By incorporating innovation and leveraging the capabilities of deep learning (Lösse and Weißenberger, 2023), auditors can fortify their ability to safeguard the interests of stakeholders and uphold the trust and credibility of the financial markets.

3. The Empirical Study:

3.1 Study Hypotheses:

Based on the study problem and objectives, the study hypothesis can be stated in a null form to be tested as follows:

$H_{0.1}$: Adopting artificial neural networks has no significant impact on the External auditing.

$H_{0.2}$: Artificial neural networks have no significant impact on the efficiency of external auditors in detecting financial fraud.

3.2 <u>Data Sampling:</u>

The study population consists of all companies listed on the Egyptian Stock Exchange, which number 236. In line with the study's aim to utilize content analysis methods for financial reports and board reports of companies listed on the Egyptian Stock Exchange, and given the study's relevance to measuring the impact of deep neural network on the efficiency of external auditing, the current study can rely on the most actively traded companies on the Egyptian Stock Exchange every year to achieve and monitor the relationship more realistically. Based on this, the researcher can rely on statistical sampling methods to select a deliberate control sample using the following conditions:

- This study depends on 1000 firm-year observations from the Egyptian environment through the period 2012 to 2022. The sample choice of this study depends on some criteria as follows:
  - All observations which are related to banks and all financial firms are excluded from the study sample.
  - Excluding all public business sector companies, due to their financial periods differing from the rest of the companies listed on the Egyptian Stock Exchange and affiliated with the private sector.

After deleting lost data, the number of companies that are characterized by continuity during the analysis period without delisting or recent listing is 126 companies. The researcher can show the distribution of these companies across the stock exchange sectors according to the auditor's opinion through the period through table (1) as follows:

The results included in table (1) ensure that the highest observations related to the unqualified audit opinions out of (763) reports by (76.3%) of the total sample, followed by observations of unqualified opinion with explanatory paragraphs by (87) reports and (8.7%), finally the qualified opinion by (150) reports and (15%).

Table (1): Distribution of observations by Industries & Audit Opinion

Sector	Total Sample	%	Unqualified	%	Unqualified with an explanatory paragraph	%	Qualified	%
Food, beverages, and tobacco	195	19.50	148	17.35	11	12.64	36	24.00
Communications, Media, and Technology	13	1.30	9	18.37	2	2.30	2	1.33
building materials	184	18.40	144	18.37	19	21.84	21	14.00
Basic Resources	71	7.10	61	20.41	5	5.75	5	3.33
Trade and Distributors	5	0.50	5	10.2	0	0.00	0	0.00
Transportation and shipping services	5	0.50	5		0	0.00	0	0.00
Industrial services and products, and cars	109	10.90	96	3.06	6	6.90	7	4.67
Health care and medicine	23	2.30	16		4	4.60	3	2.00
Tourism and entertainment	11	1.10	4		3	3.45	4	2.67
Chemicals	70	7.00	54	1.02	10	11.49	6	4.00
Engineering, contracting, and construction	242	24.20	176	1.02	18	20.69	48	32.00
Textiles and durable goods	72	7.20	45	10.2	9	10.34	18	12.00
Total	***1000***	***100***	***763***	***100***	***87***	***100***	***150***	***100***

3.3 <u>Prediction parameters definition:</u>

The most commonly used financial indicators in studies that have an impact on establishing an auditor's judgment of financial statements have been used to deal with the deep neural network technique. The following table summarizes these ratios based on the aforementioned investigations and the selection of 22 variables as prospective financial statement indicators:

Table (2): The most often utilized financial metrics that influence audit efficiency

Variables	Definition	Data Source			
		Financial Statements	**Audit Reports**	**Stock Market**	**General Assembly Meetings**
Y1	Dummies assigned the following codes to the auditor's report: 1 for unqualified, 2 for unqualified with rationale, and 3 for qualified opinions.		✓		
Y2	The natural logarithm of total fees paid to external auditors				✓
Y3	The natural logarithm of the number of days between the legal reporting deadline and the actual issuance date reflects the timeliness and audit completion			✓	
X1	Receivables/sales: calculated by a company’s receivables divided by its sales.	✓			
X2	Auditor’s size: dummy coded 1 for a Big 4 auditor, 0 otherwise.			✓	

Variables	Definition	Data Source: Financial Statements	Data Source: Audit Reports	Data Source: Stock Market	Data Source: General Assembly Meetings
X3	Market capitalization is computed as the number of outstanding shares multiplied by the end-of-year market price.			✓	
X4	Working capital equals current assets minus current liabilities.	✓			
X5	Company age is a proxy for a company's age based on the number of years it has been listed in the capital markets.			✓	
X6	EBIT margin is defined as a company's earnings before interest and taxes divided by its sales.	✓			
X7	Net income/net sales: computed by dividing a company's net income by its net sales for the fiscal period.	✓			
X8	Cash turnover is calculated by dividing a company's sales by its average cash over the period.	✓			
X9	Inventory turnover is calculated by dividing a company's sales by its average inventory for the period.	✓			
X10	Asset intensity is determined as total assets divided by total revenue.	✓			
X11	Total accruals are the gap between net income and operating cash flow.	✓			
X12	Debt ratio: a company's total debt divided by its assets.	✓			
X13	Financial leverage can be expressed as total liabilities divided by total assets.	✓			
X14	Loss is a dummy variable coded as 1 for loss-making enterprises and 0 otherwise.	✓			
X15	Return on total assets is computed as a company's net profit divided by its total assets.	✓			
X16	Return on shareholder equity is measured as a company's net income divided by its equity.	✓			
X17	Log of total assets (Size): natural logarithm of a company's total assets at the end of the fiscal year.	✓			
X18	Log of net sales: natural logarithm of a company's net sales during the fiscal year.	✓			
X19	Net income is a company's reported gain or loss for a certain fiscal period.	✓			
X20	Retained earnings/total assets: A company's retained earnings divided by total assets.	✓			
X21	The liquidity ratio (cash ratio) is derived by dividing a company's total	✓			

Variables	Definition	Data Source			
		Financial Statements	Audit Reports	Stock Market	General Assembly Meetings
	cash and cash equivalents by its current liabilities.				
X22	Quick ratio is derived by dividing a company's quick assets by its current liabilities.	✓			

3.4 Multistage deep neural network results:

A neural network (NN) is a network structure that consists of numerous connected units. It consists of three levels of units: input layers, hidden layers, and output layers (Figure 1). The neural network configuration is controlled by how the units are connected. A deep neural network (DNN) is one with at least two hidden layers. The feed-forward neural network is the most often used neural network model, and it is configured by connecting several units. According to Schreyer et al. (2022), the network propagation at each layer is achieved in the following ways.

Step 1: At each neuron, a weighted sum is calculated, which is the output value of each neuron in the next network layer multiplied by the weight of the link with that neuron.

Step 2: involves applying a transfer function (fs) to the weighted sum to calculate the neuron's output value.

Step 3: Express the output value (y) as a function of input values and network weights.

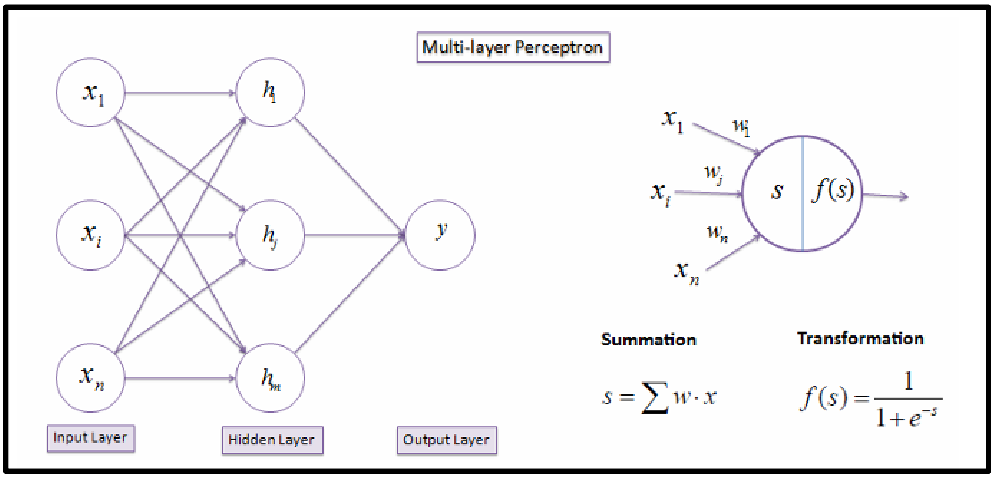

Figure (1). The architecture for a three-layer artificial neural network

Source: (Schreyer et al., 2022, p. 109)

This study employs holdout validation appropriate for Deep Neural Network (DNN) models in the creation of the prediction model utilizing Deep Neural Network (DNN) model methodologies. 80% of the data is used for modeling, whereas 60% (or 80% x 75%) is randomly selected as the training dataset to fit the model parameters during the learning phase. The training dataset is constantly refined to produce the best prediction model. To validate the state and convergence of the models during the modeling process, adjust hyperparameters, prevent overfitting, and decide when to stop training, 20% (=80% × 25%) of all the data is randomly chosen.

The remaining data about 20% is utilized as a test dataset to assess the models' generalization abilities (prediction performance). This study employed a random sampling without replacement methodology. The study's performance measurements include accuracy, precision, sensitivity (recall), specificity, and the F1 score. The efficiency of the models is evaluated using the confusion matrix method.

In this regard, the researcher uses the modelling validation for the three dependent variables of this study, which are auditor opinion, audit fees, and audit report lag, as follows:

3.4.1 Deep Neural Network (DNN) model results for the audit fees:

To develop the best model, the key variables chosen to predict audit fees are used in the Deep Neural Network (DNN) model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the Deep Neural Network (DNN) model for the audit fees can be summarized in table (3).

According to the stated results on table (3), the training and validation datasets have accuracy rates of 93.01% and 91.10%, respectively, for the Overestimated fees; 93.48% and 89.30%, respectively, for the equally fees, finally 94.86% and 91.15%, respectively, for the underestimated fees.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for overestimated fees, equal fees, and underestimated fees are 0.54%, 1.90%, and 1.19%, respectively. Besides, Type II error rates for overestimated fees, equal fees, and underestimated fees are 6.53%, 4.05%, and 5.56%, respectively.

Table (3) shows the confusion matrix indicators for the Deep Neural Network (DNN) model: accuracy = 93.47%, 95.95%, and

94.44% for overestimated fees, equally fees and underestimated fees, respectively; precision = 86%, 87.97%, and 86.84%; sensitivity (recall) = 83.78%, 82.37%, and 82.35%; specificity = 96.64%, 97.21%, and 97.41%; and F1-score = 84.88%, 85.08%, and 84.54%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

Table (3): Deep Neural Network (DNN) model for the audit fees

Model		**Accuracy of the Deep Neural Network (DNN) model**					
Deep Neural Network	Dependent Variable	Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
Audit Fees (Y2)	Overestimated	93.01%	91.10%	90.81%	91.64%	0.54%	6.53%
	Equally	93.48%	89.30%	90.81%	91.20%	1.90%	4.05%
	Underestimated	94.86%	91.15%	91.01%	92.34%	1.19%	5.56%
	Confusion matrix indicators: Deep Neural Network (DNN)						
	Dependent Variable	Accuracy	Precision	Sensitivity (Recall)	Specificity	F1 Score	Training Time
Audit Fees (Y2)	Overestimated	93.47%	86.00%	83.78%	96.64%	84.88%	500 µs
	Equally	95.95%	87.97%	82.37%	97.21%	85.08%	500 µs
	Underestimated	94.44%	86.84%	82.35%	97.41%	84.54%	500 µs

	Type I Error	**Type II Error**
Overestimated Fees	Predicting the Error of overestimated fees when it may be equally or underestimated	Predicting the Error of an equal fee or underestimated when it may be overestimated
Equally Fees	Predicting the Error of an equal fee when it may be overestimated or underestimated	Predicting the Error of overestimated or underestimated fees when they may be equal fees
Underestimated Fees	Predicting the Error of an underestimated fee when it may be overestimated or an equally fee	Predicting the Error of overestimated fees, or equally, when it may be underestimated fees

Training (80%)-Testing (20%) split

3.4.2 Deep Neural Network (DNN) model results for the audit report lag:

To develop the best model, the key variables chosen to predict audit report lag are used in the Deep Neural Network (DNN) model and continuously trained until stable (150 epochs; training time: 500 microseconds). Consequently, the results of the Deep Neural Network (DNN) model for the audit report lag can be summarized in table (4).

According to the stated results on table (4), the training and validation datasets have accuracy rates of 94.87% and 87.93%, respectively for the Overestimated report time; 93.26% and 89.66%, respectively for the exact report time, finally 96.40% and 90.53%, respectively for the underestimated report time.

Furthermore, the accuracy rate of the model is tested using the test dataset, and the results show that the model is quite stable, with Type I error rates for overestimated report time, exact report time, and underestimated report time are 4.04%, 1.51%, and 2.82%, respectively. Besides, Type II error rates for overestimated report time, exact report time, and underestimated report time are 4.98%, 4.76%, and 5.84%, respectively.

Table (4) shows the confusion matrix indicators for the Deep Neural Network (DNN) model: accuracy = 95.02%, 95.24%, and 94.16% for overestimated report time, exact report time and underestimated report time, respectively; precision = 87.19%, 86.88%, and 86.59%; sensitivity (recall) = 84.33%, 83.24%, and 83.16%; specificity = 96.21%, 96.20%, and 96.04%; and F1-score = 85.74%, 85.02%, and 84.84%. These metrics are used in conjunction with accuracy to evaluate a model's performance. These numbers indicate that the model is doing well.

Table (4): Deep Neural Network (DNN) model for the audit report time

Model			**Accuracy of the Deep Neural Network (DNN) model**					
Deep Neural Network	Dependent Variable		Training Dataset	Validation Dataset	Test Dataset	Average	Type I Error	Type II Error
	Audit Report Lag (Y3)	Overestimated	94.87%	87.93%	93.12%	91.97%	4.04%	4.98%
		Exact	93.26%	89.66%	90.60%	91.17%	1.51%	4.76%
		Underestimated	96.40%	90.53%	93.11%	93.35%	2.82%	5.84%
	Confusion matrix indicators: Deep Neural Network (DNN)							
	Dependent Variable		Accuracy	Precision	Sensitivity (Recall)	Specificity	F1 Score	Training Time
	Audit Report Lag (Y3)	Overestimated	95.02%	87.19%	84.33%	96.21%	85.74%	500 µs
		Exact	95.24%	86.88%	83.24%	96.20%	85.02%	500 µs
		Underestimated	94.16%	86.59%	83.16%	96.04%	84.84%	500 µs
			Type I Error			**Type II Error**		
Overestimated report time			Predicting the Error of an overestimated report time when it may be exact or underestimated			Predicting the Error of an exact report time or underestimated when it may be overestimated		
Exact report time			Predicting the Error of an exact report time when it may be overestimated or underestimated			Predicting the Error of an overestimated or underestimated report time when it may be exact report time		
Underestimated report time			Predicting the Error of an underestimated report time when it may be overestimated or exact			Predicting the Error of an overestimated report time or the exact time when it may be an underestimated report time		
Training (80%)-Testing (20%) split								

3.4.3 Design hypotheses testing model:

This study aims to test the impact of adopting artificial neural networks on the external auditing by the auditor's opinion, testing the impact of adopting artificial neural networks on the external auditing efficiency by audit fees, and audit report lag. Consequently, the hypotheses testing models can be divided into two models as follows:

1. Regression specification for testing $H_{0.1}$ (the impact of deep neural network (DNN) on the external auditing by auditor opinion):

To investigate the impact of deep neural network (DNN) on the external auditing by auditor opinion, $H_{0.1}$ must be tested as follows:

μ Predicted auditor opinion ≠ μ Actual auditor opinion

$$AO = \beta0 + \beta1\ (DNN) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon \quad (1)$$

2. Regression specification for testing $H_{0.2}$ (the impact of deep neural network (DNN) on the efficiency of external auditors by audit fees and audit report lag in detecting financial fraud):

To investigate the impact of deep neural network (DNN) on the efficiency of external auditors by audit fees and audit report lag, $H_{0.2}$ must be tested as follows:

μ Predicted audit fees ≠ μ Actual audit fees

$$Ln\ AF = \beta0 + \beta1\ (DNN) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon \quad (2)$$

μ Predicted audit report lag ≠ μ Actual audit report lag

$$Ln\ ARL = \beta0 + \beta1\ (DNN) + \beta2\ (M.Cap) + \beta3\ (W.C\%) + \beta4\ (Cash\%) + \beta5\ (Loss) + \varepsilon \quad (3)$$

Where the researchers can define all the variables inserted in the regression models according to the following table (5):

Table (5): Variables Definition

Main Variable	Sub variable	Definition
Detection Fraud (DF)	Pressure (PR)	Solvency Ratio (SR): the debt-to-equity ratio; Liquidity (Liq): Current assets to current liabilities. Leverage Ratio (Lev): Total debt to total asset ratio. Sales Growth: (SG): change in sales- industry average change in sales. Assets Growth (AG): Percent change in assets for the two years before fraud. Cash Flow ratio (CF%): (operating income – cash flow from operations) / Total assets. Accounts receivable turnover (ART): Sales to accounts receivable.

Main Variable	Sub variable	Definition
		Capital turnover (CT): Sales to total assets. Inventory turnover (IT): Inventory to total sales. Return on Assets (ROA): Net income to total assets.
	Opportunity (OP)	Gross Profit Ratio (GP%): Gross profit to total assets; Firm Size (Size): logarithm of total assets. The board of directors' outside members (B.Ext): The percentage of board members who are outside members. Independence of board members (B.Ind): Non-executive directors to the total number of directors. Board size (B.Size): the total number of board members. CEO duality (Dual): Dummy variable with a value of 1 in case of duality and 0 otherwise. Audit committee size (AC.Size): The number of board members who are on the audit committee. Audit Committee independence members (AC Ind): The percentage of audit committee members who are independent of the company. Audit Committee Experience (AC. EXP): Dummy variable with the value of 1 if the audit committee includes at least one director who is (or has been) a CPA, investment banker, or venture capitalist, served as CFO or controller, or has held a senior management position (CEO, President, COO, VP, etc.) with financial responsibilities; and 0 otherwise. Managerial ownership (Man.Own): Percentage of ownership held by the board of directors; Institutional ownership (Ins.Own): Number of shares held by financial institutions to number of shares outstanding × 100
	Rationalization (RA)	Profitability ratio (PR): Net profit to sales. Auditor Change (AC): Dummy variable with a value of (1) in case of auditor change and (0) otherwise.

Main Variable	Sub variable	Definition
		BIG (4) index: Dummy variable with a value of (1) when a firm engaged with big 4 auditors and (0) otherwise. Auditor's opinion (AO): Dummy variable with a value of (1) in case of unqualified opinion and (0) otherwise. Total accruals to total assets (TACC): The change in current assets - the change in cash - changes in current liabilities + the change in short-term debt - depreciation and amortization expense - deferred tax on earnings + equity in earnings.
	Capability (Cap)	Dummy variable with a value of 1 if the CEO has a financial background and 0 if the CEO has no financial background.
Auditor opinion (AO)	Actual & Predicted	Gradual Scale, which takes (1) for the unqualified auditor opinion; (2) for the unqualified auditor opinion with the explanatory paragraph; (3) for the qualified opinion.
Audit Fees (Ln AF)	Actual & Predicted	Logarithm audit fees for the actual audit fees or the predicted audit fees from running the Deep Neural Network algorithms (DNN).
Audit Report Lag (Ln ARL)	Actual & Predicted	Logarithm audit report time for the actual audit report time or the predicted audit report time from running the Deep Neural Network algorithms (DNN).
Deep Neural Network (DNN)		Dummy variable which takes (1) for the predicted values of the dependent variables and (0) otherwise.
M. Cap		Market capitalization: calculated by the number of outstanding shares multiplied by the end-of-year market price.
W.C%		(Current Assets - Current Liabilities) / Total assets.
Cash%		Cash balances to total current assets.
Loss		Dummy variable which takes (1) in case of achieved loss and (0) otherwise.

By: The researcher

3.4.4 Hypotheses testing results:

In this part of my study the researchers seeks to test the impact of artificial neural networks on the external auditing by the auditor opinion in the first sub-hypothesis, finally predicting the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud by audit fees and audit report lag through the second sub-hypothesis as follow:

1. Firstly, testing $H_{0.1}$ (the impact of artificial neural networks on the External auditing by the auditor's opinion):

The first sub-hypothesis predicts the relationship between the artificial neural networks and the External auditing by the auditor's opinion, so the researchers can test the differences between the actual and predicted auditor opinion, then the model (1) can be run to test the first sub-hypothesis.

For the comparison between the actual and predicted auditor opinion by the deep neural network t-test can be used for the paired samples, and the results can be presented in the following table (6) as follows:

Table (6): Compared means between actual and predicted results of the auditor's opinion

	Variables	Mean	T	Sig. (2-tailed)
Pair (1)	Actual Audit opinion	1.325	3.877	0.000
	Predicted Audit opinion using DNN	1.055		

The results of comparing the means of the actual audit opinion and the predicted audit opinion using a deep neural network are presented in pair (1) in table (6). These results show that the actual audit opinion is biased toward the "qualified" or "unqualified with exp. language" opinion, suggesting that auditors may adopt a more conservative or risk-averse stance in issuing their reports. This conservatism could reflect auditors' sensitivity to litigation risk, regulatory scrutiny, or reputational concerns, especially when financial indicators raise red flags. On the other hand, the DNN model, which is trained purely on quantitative indicators and patterns, generates audit opinions based on objective input variables without the influence of human judgment, bias, or external pressure. Therefore, the lower average score in predicted opinions may reflect a more neutral or less conservative estimation. Thus, the difference is significant because of the high accuracy of deep neural network technology. As a result, the researcher concludes that actual audit opinions and deep neural network-predicted audit opinions (also known as biased actual audit opinions) differ significantly.

Moreover, the researcher ran the model (1) for the impact of deep neural network on the External auditing by the auditor's opinion, and the results can be presented in table (7) as follows:

Table (7): Regression model for the impact of deep neural network on the External auditing by the auditor's opinion

	Dependent Variable: Audit Opinion		
	Coef.	T	Sig.
Cons.	0.063	1.550	0.115
DNN	0.178	2.663	0.013
M.Cap	0.108	1.646	0.122
W.C%	0.277	2.442	0.026
Cash%	0.163	2.955	0.005
Loss	-0.260	-2.583	0.019
F-value		9.016	
VIF (MAX)		1.423	
R2		24.70%	

According to the results of table (5.14), it is obvious that the second model has a good significance in interpreting the changes in the dependent variables for the External auditing by the auditor's opinion, where (F = 9.016), respectively with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.423) which is less than 10, which means there is no multicollinearity.

Moreover, the Adjusted R Square equals 24.7%, which means that adopting artificial neural networks and the other control variables explain 24.7% of the change of the dependent variable for the external auditing by the auditor's opinion.

Adopting artificial neural networks has a significant impact on the external auditing by the auditor's opinion (where, $\beta = 0.178$; T-Stat. = 2.663 > 2; Sig. < 5%). Additionally, this means that increasing artificial neural networks adoption leads to an enhancement in the auditor's opinion. the researcher can attribute this result to the fact that greater reliance on deep neural network models enhances the quality of the auditor's opinion, where integrating DNNs into the audit process contributes to more precise, consistent, and possibly earlier detection of financial irregularities, which in turn influences the auditor's judgment and reporting, where auditors who incorporate DNN outputs into their assessments may be better equipped to identify risk factors or anomalies that traditional audit methods could overlook. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. This aligns with agency theory (Jensen & Meckling, 1976), which posits that information asymmetry exists between principals (investors) and agents (management). According to this theory, DNNs reduce this asymmetry by enhancing auditors' ability to detect hidden anomalies (e.g., earnings manipulation), thus strengthening monitoring mechanisms. **Therefore, the researcher *can argue that the adoption of artificial neural networks has a significant impact on the external auditing by the auditor's opinion.***

Based on the above results, the researcher can accept the first sub-hypothesis of this study in the alternative form as follows: $H_{0.1}$, *artificial neural networks adoption has a significant impact on the external auditing by the auditor's opinion.*

2. Secondly, testing $H_{0.2}$ (the impact of artificial neural networks on the efficiency of external auditors in detecting financial fraud):

The second hypothesis predicts the relationship between the artificial neural networks and the efficiency of external auditors by the audit fees and audit report lag in detecting financial fraud, so the researcher can test the differences between the actual and predicted audit fees and audit report lag, then the researcher runs the model (2) For testing the third hypothesis.

For the comparison between the actual and predicted audit fees and audit report lag by the deep neural network, a t-test can be used for the paired samples, and the results can be presented in the following table (8) as follows:

Table (8): Compared means between actual and predicted results of audit fees and audit report lag

	Variables	Mean	T	Sig. (2-tailed)
Pair (2)	Actual Audit Fees	4.521	4.530	0.000
	Predicted Audit Fees using DNN	3.236		
Pair (3)	Actual Audit Report Lag	51.321	5.818	0.000
	Predicted Audit Report Lag using DNN	44.126		

The results of comparing the means of the actual audit fees and the predicted audit fees using a deep neural network are presented in pair (2) in table (8). These results show that the actual audit fees are biased toward the "overestimated" or "underestimated" fees, where the difference is significant, because of the high accuracy of deep neural network technology. The existence of significant differences between the actual audit fees and report lag predicted by deep neural networks (DNN) suggests that the efficiency of external auditors may be influenced by management or the organizational environment, which could restrict their role in detecting financial fraud. Accordingly, enhancing the efficiency of external auditors—as proposed by DNNs—may contribute to increasing the likelihood of detecting fraud in financial statements through an objective and unbiased assessment of accounting and auditing performance indicators. As a result, ***the researcher concludes that actual audit fees and deep neural network-predicted audit fees (also known as biased actual audit fees) differ significantly***.

Moreover, the model (2) can be run for the impact of deep neural networks on the efficiency of external auditors by the audit fees and audit report lag, and the results can be presented in table (9).

According to the results of table (9), the third model has a good significance in interpreting the changes in the dependent variables for the efficiency of external auditors by the audit fees and audit report lag, where (F = 13.711 & 12.054) respectively, with P-Value < 0.05. Furthermore, the maximum value of VIF for all variables is equal (1.138) which is less than 10, which means there is no multicollinearity.

Table (9): Regression model for the impact of deep neural network on the efficiency of external auditors by the audit fees and audit report lag in detecting financial fraud

	Dependent Variable: Audit Fees			Dependent Variable: Audit Report Lag		
	Coef.	T	Sig.	Coef.	T	Sig.
Cons.	0.102	1.284	0.109	0.069	1.187	0.112
DNN	0.158	3.011	0.000	0.245	2.456	0.015
M.Cap	0.238	2.336	0.025	0.279	2.198	0.036
W.C%	0.089	1.069	0.089	0.107	1.098	0.094
Cash%	0.097	1.100	0.088	0.107	1.236	0.093
Loss	0.296	2.610	0.019	0.310	2.818	0.010
F-value	13.711			12.054		
VIF (MAX)	1.138					
R2	24.50%			34.80%		

Moreover, the Adjusted R Square equals 24.5% & 34.8% respectively, which means that adopting artificial neural networks and the other control variables explain 24.5% & 34.8% of the change of the dependent variable for the efficiency of external auditors by the audit fees and audit report lag, respectively.

From Panel (A) results, it is obvious that adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit fees (where, β = 0.158; T-Stat. = 3.011 > 2; Sig. < 5%). Additionally, this means that increasing artificial neural networks adoption leads to an increase in the efficiency of external auditors by the audit fees. Therefore, *the researcher can argue that adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit fees.*

In another vein, panel (B) results indicate that adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit report lag (where, β = 0.245; T-Stat. = 2.456 > 2; Sig. < 5%). Additionally, this means that increasing artificial neural networks adoption leads to an increase in the efficiency of external auditors by the audit report lag. **Therefore, *the researcher can argue that adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit report lag.***

Based on the above results, the researcher concludes that adopting deep neural networks (DNN) positively influences the efficiency of external auditors, as reflected in audit fees and audit report lag, potentially through automated data analysis, pattern recognition, and risk assessment capabilities that enable auditors to identify critical issues more rapidly. Enhanced auditor efficiency—driven by DNNs—improves the ability to detect fraud indicators through more precise and comprehensive data analysis while also reducing professional bias. Therefore, leveraging DNNs can enhance audit efficiency and increase the likelihood of detecting financial statement fraud. Thus, the researcher can accept the second sub-hypothesis of this study in the alternative form as follows: H_{02}, **adopting *artificial neural networks has a significant impact on the efficiency of external auditors by the audit fees and audit report lag in detecting financial fraud.***

4. Conclusions, recommendations, and suggestions for future studies:

4.1 Conclusions:

The researchers conclude that:

1. Adopting artificial neural networks has a significant impact on external auditing, where integrating DNNs into the audit process contributes to more precise, consistent, and possibly earlier detection of financial irregularities, which in turn influences the auditor's judgment and reporting, where auditors who incorporate DNN outputs into their assessments may be better equipped to identify risk factors or anomalies that traditional audit methods could overlook. The increase in audit opinion value (which may relate to more explanatory or qualified opinions) reflects this enhancement in detection and professional skepticism. This aligns with agency theory (Jensen & Meckling, 1976), which posits that information asymmetry exists between principals (investors) and agents (management), information asymmetry theory (Thammatucharee, 2021), and Continuous Auditing Theory. According to these theories, DNNs reduce this asymmetry by enhancing auditors' ability to detect hidden anomalies in real-time (e.g., earnings manipulation), thus strengthening monitoring mechanisms.
2. Adopting artificial neural networks has a significant impact on the efficiency of external auditors by the audit fees and audit report lag in detecting financial fraud, potentially through automated data analysis, pattern recognition, and risk assessment capabilities that enable auditors to identify critical issues more rapidly. Enhanced auditor efficiency—driven by DNNs—improves the ability to detect fraud indicators through more precise and comprehensive data analysis while also reducing professional bias. Therefore, leveraging DNNs can enhance audit efficiency

and increase the likelihood of detecting financial statement fraud. This aligns with agency theory (Jensen & Meckling, 1976) and information asymmetry theory (Thammatucharee, 2021), and the theory of inspired confidence (Elewa and El-Haddad, 2019).

4.2 Recommendations:

In light of the study's findings, the following recommendations can be proposed:

1. Professional standard-setters, particularly the Central Auditing Organization, should revise the accounting and auditing profession's ethical guidelines to incorporate stronger fraud prevention mechanisms and enhance the detectability of fraudulent activities.
2. Regulatory bodies, including the Financial Regulatory Authority, the Egyptian Exchange, the Egyptian Society of Accountants and Auditors, and the Egyptian Accounting Association, must emphasize to corporate boards the critical need to implement robust anti-fraud measures and controls.
3. Audit firms should adopt a phased strategy to integrate AI technologies, particularly deep neural networks, into their core processes, particularly since the findings demonstrated the accuracy and effectiveness of artificial neural network algorithms in predicting audit opinion, audit fees, report lag, and fraud detection. This requires financial investments in technological infrastructure along with comprehensive staff training programs. Large firms should establish dedicated digital transformation units to oversee this technological integration while ensuring compatibility with existing audit methodologies.
4. Auditors need to develop specialized training programs to enhance staff competency in working with AI outputs while maintaining professional skepticism.
5. Future studies should focus on expanding the application of AI models to detect specific types of financial fraud across different industries. Scholars need to conduct comparative studies evaluating the effectiveness of various AI algorithms in identifying complex fraud schemes. Additional investigation is required to examine the cultural and organizational factors that influence AI implementation success in auditing.

5.3 Suggestions for Future studies:

Based on the current study's findings, the researcher identifies several potential areas for future studies, most notably:

1. Evaluate the effectiveness of various AI tools—such as Decision Trees, Random Forest, Support Vector Machine, and Deep Neural Networks—in detecting specific types of financial fraud.
2. Explore the integration of AI outputs with auditors' professional judgment and its impact on audit quality
3. Investigate how AI affects auditor independence and the credibility of audit reports.
4. Studying the role of AI in auditing sustainability reports (ESG) and detecting greenwashing.

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