

Effectiveness of Using Artificial Neural Networks in Mitigating Audit
Risks: Case Study of Setif Cement Company

Asma Djarmouni ^{1*}

¹ University setif 1 (Algeria), asma.djarmouni@univ-setif.dz

Received: D/M/YAccepted: D/M/YPublished: 01/12/2026

.....

Abstract:

Study investigates effectiveness of applying artificial neural networks in reducing audit risks at Setif Cement Company, exploring how Artificial intelligence techniques can revolutionize audit practices by transforming traditional manual processes into technology-enhanced digital audits. A neural network model was developed and tested using SPSS v26 to classify audit risks across three levels (low, medium, high) within various operational domains including financial, commercial, production, maintenance, and purchasing activities.

Study reached a set of results, most important of which are: artificial neural network achieved perfect classification accuracy (0.0% error) across the three risk categories, demonstrating superior performance with lift values of 5.0-10.0 compared to traditional methods while effectively managing complex relationships between audit risk variables, as it enhanced risk management culture by providing advanced analytical tools.

Keywords: artificial neural networks, audit risk, risk assessment, artificial intelligence.

Jel Classification Codes: XN1, XN2.

* Corresponding author

I. Introduction

The detection and prevention of audit risks are crucial for maintaining the integrity and reliability of financial statements, as undetected fraudulent activities can severely impact organizational financial health and erode stakeholder trust (Al-Hayik & Abu-Naser, 2023, p. 43) . The rapid evolution of Artificial Intelligence (AI) has significantly influenced various sectors, with the accounting industry experiencing profound changes in its auditing practices. Traditional audit methodologies, relying heavily on manual reviews, periodic testing, and sample-based assessments, often fall short of quickly identifying emerging risks in today's complex financial systems that generate massive data volumes (Du, 2024, p. 83). Since audit risk assessment relies heavily on auditor subjective opinion, building an automated risk assessment system based on objective criteria could enable faster and more accurate risk evaluation.

Artificial intelligence represents a disruptive technology in accounting, capable of increasing process efficiency and improving information usage quality, with expectations to replace up to 96% of human workers in the coming years (Lecci & Hanne, 2025, p. 2). Over the past two decades, audit analytics has evolved from basic data sampling to incorporate advanced analytical techniques revealing insights within extensive datasets, with Artificial Neural Networks (ANNs) emerging as powerful computational tools for organizing and correlating information (AlZwainy & al, 2024, p. 57) . While AI exceeds human capabilities in examining large databases, effective implementation requires qualified employees who understand how to manage AI capabilities, as the combination of AI with human resources enables systematic error tracking and fraud detection through auditor evaluation.

1.1Research Problem Statement :

Current audit practices in cement companies rely heavily on conventional methods that may not adequately capture the multifaceted operational risks including production inefficiencies, commercial market volatilities,

industrial equipment failures, financial cash flow challenges, and procurement supply chain disruptions . Therefore, this study seeks to investigate: **To what extent can Artificial Neural Networks effectively reduce operational audit risks in cement manufacturing companies Setif compared to traditional audit risk assessment approaches?**

1.2.Study Importance

This study addresses a critical gap in audit practices by developing specialized Artificial Neural Network models for cement manufacturing companies Setif, where traditional audit methods prove inadequate for managing complex operational risks encompassing production, commercial, industrial, financial, and procurement challenges. The research contributes to enhanced audit accuracy and objectivity by providing interpretable AI-driven risk assessment tools that can identify key operational factors influencing audit risks in cement industry environments.

1.3. Research Methodology

This study relied on the descriptive analytical methodology in order to highlight the study variables of audit risks and artificial neural networks. In the applied aspect, a program Spss V26 was used to analyze the network and its effectiveness in reducing audit risks.

II. Literature Review :

1. Conseptual framework :

1.1. Artificial Neural Networks

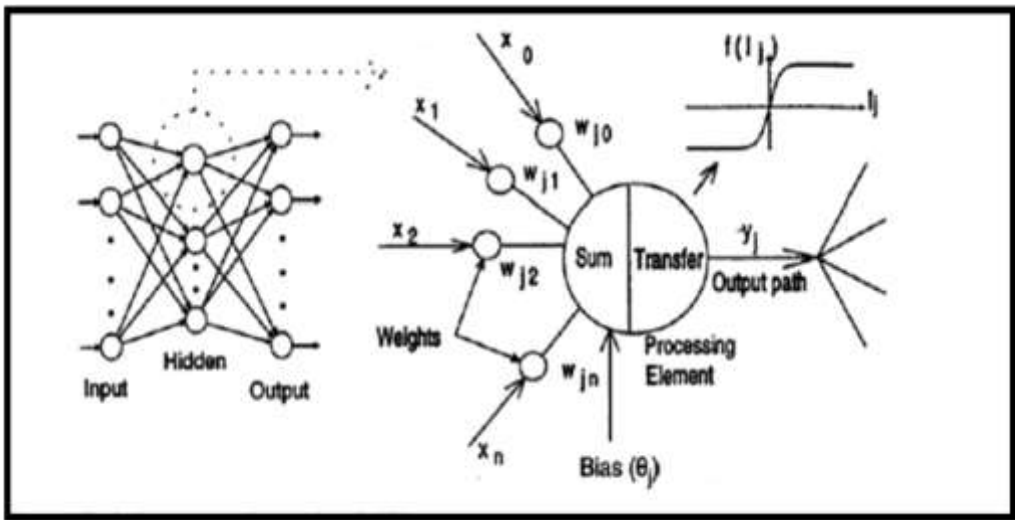
The development of artificial neural networks traces back to 1943 when scientists McCulloch and Pitts constructed the first artificial neuron model using threshold logic to exhibit all-or-none behavior and represent logical functions (Fan & al, 2025, p. 1). This foundation was strengthened in 1949 when Hebb introduced the Hebbian Learning Rule, establishing that neurons firing together should be wired together, which became fundamental for developing learning algorithms (HACHI & LEBBAZ , p. 909). These early developments have evolved into the current third wave of artificial intelligence revolution, where deep learning through deep artificial neural networks dominates numerous research fields (Fan & al, 2025, p. 1).

Artificial neural networks represent mathematical models designed to replicate the composition, capabilities, and operating principles of biological neural systems, particularly the mammalian cerebral cortex (BENTAYEB & al, 2024, p. 39). They function as multivariate nonlinear nonparametric models capable of capturing effects from multiple variables simultaneously, enabling them to identify complex data relationships that traditional non-linear models cannot detect (MOKRANI & CHERABI, 2018, pp. 281-282). These networks serve as thinking models inspired by the human brain's structure, which contains approximately 10 billion neurons and 60 trillion synaptic connections, allowing simultaneous processing that surpasses current computer speeds (Saleh & salman, 2022, p. 187). The artificial neural network structures were developed from biological nervous system models, where computational components called artificial neurons represent simplified versions of biological neurons that generate and propagate electrical impulses (BENLARIA & BOUBEKEUR, 2021, p. 808).

The architectural design varies according to neuron organization, with processing elements distributed across layers including input, hidden, and output layers, where the number of layers and elements in each defines the network architecture (Monteiro & al, 2023, p. 3). Each architectural level includes nodes serving as nerve binding points between network levels, layers as sets of nodes receiving inputs and producing outputs, and weights indicating neural correlation strength between levels, with each node having weights connecting it to previous and subsequent levels (HACHI & LEBBAZ, p. 910). The input layer receives external data ranging from images and text to numerical values, initiating the network workflow. Hidden layers process data through mathematical operations and transformations, with deep networks containing multiple hidden layers justifying the "deep" terminology. The output layer generates final computational results, with neuron quantities depending on specific task requirements and functioning as the network's final performer nodes. (Singh & al, 2025, p. 129)

The artificial neuron operates through a mathematical paradigm encompassing multiplication, addition, and activation processes, functioning as the essential network building block (BENTAYEB & al, 2024, p. 39)The mathematical operation follows specific equations where input from each processing element (x_i) multiplies by adjustable connection weight (w_{ij}), weighted signals are summed, and threshold value (θ_j) may be added, with the combined input (I_j) passing through a transfer function ($f(\cdot)$) to produce output (y_j), (AlZwainy & al, 2024, pp. 57-58)This is illustrated by the following figure.

Figure(1) : Artificial neural network elements



Source : (AlZwainy & al, 2024, p. 58)

Learning algorithms divide into supervised and unsupervised approaches, where supervised learning generates results through dataset labels indicating correct answers and requires comprehensive damage scenario data for detection applications, while unsupervised learning operates without preestablished labels and needs only normal system condition data (Monteiro & al, 2023, p. 3). The system functions through highly interconnected processing elements working collaboratively to solve problems and transmit information via synapses, with data flowing layer by layer from input to output while maintaining unpredictable exact flow patterns (Dastres & Soori, 2021, pp. 18-19).

Recent applications demonstrate increasing utilization in brain data analysis and modeling, providing substantial evidence for neuroscience research value (Dehgan & al, 2025, p. 1). Networks exhibit superior learning abilities for complex tasks including handwriting recognition and function as nonlinear data display devices demonstrating data source relationships ((Qamar & Zardari, 2023, p. 130). Modern implementation spans business environments including production, sales, marketing, human resources, accounting, and distribution, where AI tool integration proves essential for progress and automation (Sakhno & al, 2024, p. 359).

From the above, we can conclude that Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks in the human brain. They consist of interconnected nodes (neurons) organized in layers that process information through weighted connections. Each neuron receives inputs, applies an activation function, and produces an output that serves as input to other neurons.

1.2. Artificial Neural Networks for Reducing Audit Risks

Audit risk assessment is a vital auditing process that involves thoroughly analyzing an organization's financial statements and internal controls to identify the nature, scope, and extent of audit risks. It ensures the authenticity, legality, and completeness of financial records while evaluating the effectiveness of internal controls, significantly impacting audit quality and efficiency. By pinpointing risks, auditors can focus their efforts, develop targeted strategies, and reduce audit risks (Yang, 2025, p. 4). Audit risks arise when auditors fail to detect significant errors, potentially issuing misleading reports (FEKIR & al, 2024, pp. 383-384) . These risks include challenges in evidence collection and the economic consequences of audit outcomes. Auditors mitigate risks by designing procedures to detect errors, fraud, and irregularities, prioritizing high-risk areas for effective planning (Nikolovski & al, 2016, p. 23).

Audit risk assessment is a cornerstone of the auditing process, involving a detailed evaluation of financial statements and internal controls to identify the nature, scope, and extent of potential risks. This process ensures the

authenticity, legality, and completeness of financial records while assessing the effectiveness of internal controls. By pinpointing high-risk areas, auditors can develop targeted strategies, enhancing audit quality and efficiency while minimizing the likelihood of undetected errors that could mislead stakeholders (Yang, 2025, p. 4). The risk arises when auditors fail to detect significant misstatements, potentially issuing misleading reports, and includes both evidence collection challenges and the economic consequences of audit outcomes (Nikolovski & al, 2016, p. 23).

Traditional auditing methods struggle to address the increasing complexity of financial data in the digital era, contributing to persistent audit quality issues. High-profile corporate scandals, such as Enron and WorldCom, and the 2007/2008 financial crisis exposed the limitations of conventional approaches and raised concerns about auditor integrity, despite regulatory frameworks like IFRS (Oluwasegun & al, 2023, p. 756). Audit quality hinges on an auditor's ability to detect and report material misstatements, reflecting both competence and independence, yet research on long-term auditor behavior and comprehensive quality frameworks remains limited (Namazi & al, 2025, pp. 72-73).

Artificial Neural Networks (ANNs) offer a powerful solution for audit risk assessment by modeling complex, non-linear relationships in financial data. Unlike traditional statistical methods, ANNs excel at processing large datasets, detecting anomalies, and predicting risks, making them well-suited for identifying fraud and assessing internal controls (Al-Hayik & Abu-Naser, 2023, p. 44) .They automate repetitive tasks, enhance decision-making through real-time insights, and improve audit efficiency by prioritizing high-risk areas (Ghafar & al, 2024, pp. 70-71).

The adoption of ANNs and broader AI technologies marks a shift toward proactive auditing, driven by the need to manage vast amounts of digital data. Major audit firms are investing heavily in AI, with initiatives like PwC's \$12 billion plan by 2026, to enhance accuracy and fraud detection (Karmańska, 2022, p. 88). However, challenges such as data privacy, integration complexities, and the need for auditors to develop AI expertise

must be addressed to ensure ethical and reliable outcomes (Leocádio & al, 2024, p. 2) .

From the above, we can conclude that Artificial Neural Networks offer superior audit risk assessment capabilities compared to traditional methods, but their implementation requires addressing technical and expertise challenges.

III.CASE STUDY :

3.1. Introduction to the Cement Company

The cement industry is considered a strategic sector due to its direct connection to construction, urban development, and infrastructure. The Umm al-Kabir Cement Company (SCAEK) is a leading institution in this field, distinguished by its expertise and proficiency in the industry. It is one of the twelve branches of the Algerian Cement Industrial and Commercial Group (GICA - Group Industriel des Ciments d'Algérie). SCAEK is a joint-stock company focused on the production and marketing of cement, located in the municipality of Ouled Adouane, Umm al-Kabir District, Setif Province, covering an area of 60 hectares. Its social capital amounts to 2,200,000,000.00 DZD, with a production capacity of 3 million tons through two production lines.

.32. Risks encountered by Setif Cement Company :

The most important risks facing cement companies, particularly the internal ones, fall under financial risks, production risks, maintenance risks, commercial risks, financial risks, and purchasing risks The following will list the most significant of these risks through interviews with company officials, The following table shows the risk level adopted by the Company.

Table(1) : Degree of risk

Degree of risk	
Negligible risk	2<R<8
Acceptable risk	9<R<15
Moderate risk	16<R<53
Management risk	54<R<127
Unacceptable risk	128<R<250

Source : By author basing on Setif Cement Company reports

When the risk score ranges between 2 and 8, the risk is negligible to the organization and no consideration is given. If it ranges between 9 and 15, the risk is acceptable. When it ranges between 16 and 53, it is moderate for the company, requiring no specific actions in this case. When the score ranges between 128 and 250, the risk level becomes unacceptable. In these latter two cases, immediate intervention is mandatory with implementation of necessary corrective measures to reduce this type of risk through risk re-analysis to prevent its propagation and impact.

The risk degree or RPN (Risk Priority Number) is calculated according to the following relationship : (Aditya & al, 2025, p. 32)

$$\text{RPN} = \text{Severity} \times \text{Occurrence} \times \text{Detection}$$

The table below demonstrates the calculation for RPN factors: severity, occurrence, and detection.

Table(2) : Scale for RPN factors: severity, occurrence, and detection

RPN factors	Range	Description
Severity Scale	3-1	Minimal consequences with trivial disruption
	6-4	Manageable effects with controllable outcomes
	9-7	Substantial effects with notable implications
	10	Extreme consequences involving serious safety risks
Occurrence scale	3-1	Infrequent events
	6-4	Sporadic incidents
	9-7	Regular occurrences
	10	Near-certain probability
Detection Scale	3-1	High probability of identification
	6-4	Reasonable chance of detection
	9-7	Low detection likelihood
	10	Extremely difficult to identify

Source : (Ding Hock & al, 2024, p. 183)

The adoption of risk classification into financial, production, industrial, commercial, and purchasing risks, along with the use of the RPN (Risk Priority Number) equation in this study, is based on fundamental practical and methodological considerations. From a practical standpoint, Setif Cement Company actually relies on this functional risk classification and the risk matrix model with the equation RPN in its internal risk management system.

3.2.1 Production risks:

Below are the key risks that Setif Cement Company may encounter concerning production:

Table (3) : RPN Of Production

The Risk	S	O	D	RPN	Risk category
Explosive procurement issues halt raw material extraction operations.	10	5	2	100	Management risk
Machinery failures and shortages interrupt production processes.	8	7	2	112	Management risk
Environmental emissions create dust, gas, and contamination risks.	3	3	5	45	Moderate risk
Equipment accidents cause worker injuries and material damages.	10	1	1	10	Acceptable risk
Weather conditions disrupt production and endanger worker safety.	6	5	3	90	Management risk
Raw material shortages of clay, limestone, and gypsum stop production.	2	3	2	12	Acceptable risk
Environmental violations result in fines and operational shutdowns.	3	1	1	3	Negligible risk
Unqualified workers reduce efficiency and compromise product quality.	8	6	5	240	Unacceptable risk

Source : By author basing on Setif Cement Company reports.

From the table above, risk levels at Setif Cement Company range from acceptable to management risk, with lack of qualified workers being the highest risk due to its comprehensive impact on operations and lengthy resolution time.

3.2.2 Maintenance risks:

Below are the key risks that Setif Cement Company may encounter concerning Maintenance:

Table (4) : RPN Of Maintenance

The Risk	S	O	D	RPN	Risk category
Maintenance part shortages cause equipment downtime and production delays.	7	3	5	105	Management risk
Low-quality spare parts increase equipment failure frequency.	6	2	7	84	Management risk
Equipment breakdowns disrupt production and raise operating costs.	8	3	6	144	Unacceptable risk
Instrument reading errors affect process control and product quality.	8	2	2	32	Moderate risk
System breakdowns eliminate maintenance tracking and planning capabilities.	4	3	3	36	Moderate risk
Unqualified workers cause maintenance errors on advanced equipment.	3	2	4	24	Moderate risk
External service delays prolong equipment downtime periods.	4	3	8	96	Management risk

Source: By author basing on Setif Cement Company reports.

From the table above, risk levels at Setif Cement Company range from acceptable to management risk, with sudden or planned equipment breakdowns identified as the highest risk due to immediate production disruptions, revenue losses, and cascading effects including safety hazards and long-term reliability issues that exceed preventive maintenance costs

3.2.3 Commercial risks:

Below are the key risks that Setif Cement Company may encounter concerning Commercial:

Table (5) : RPN Of Commercial

The Risk	S	O	D	RPN	Risk category
Customer loss reduces revenues and market share due to poor quality.	8	3	3	72	Management risk
New competitors threaten market position through improved products and pricing.	7	6	5	210	Unacceptable risk
Market saturation limits growth and intensifies customer competition.	4	5	5	100	Management risk

Delivery delays damage customer satisfaction and reputation.	2	1	1	2	Negligible risk
Non-compliant products result in rejections and compensation claims.	1	1	1	1	Negligible risk
Rising material costs pressure margins and competitiveness.	6	6	6	216	Unacceptable risk
New regulations affect demand and increase operational costs.	5	6	6	180	Unacceptable risk
Lost contracts and tenders significantly impact company revenues.	5	3	6	90	Management risk

Source: By author basing on Setif Cement Company reports.

From the table above, risk levels at Setif Cement Company range from acceptable to management risk, with rising costs of basic materials being the highest risk due to its direct impact on profit margins and competitive positioning in the market.

3.2.4 Financial risks:

Below are the key risks that Setif Cement Company may encounter concerning Financial:

Table (6) : RPN Of Financial

The Risk	S	O	D	RPN	Risk category
Invoice delays hinder accounting and reconciliation processes.	4	2	3	24	Moderate risk
System breakdowns disrupt operations and cause data loss.	8	3	6	144	Unacceptable risk
Duplicate recordings create financial data errors.	4	4	2	32	Moderate risk
Unapplied penalties cause losses and weaken negotiating power.	3	2	2	12	Acceptable risk
Payment delays damage supplier relationships and supply chains.	4	6	5	120	Management risk
Duplicate payments result in direct financial losses.	5	3	3	45	Moderate risk
Exchange rate changes impact import/export costs.	3	1	2	6	Negligible risk
Cash shortages prevent meeting short-term obligations.	3	2	2	12	Acceptable risk

Effectiveness of Using Artificial Neural in Mitigating Audit Risks: A Case of the Setif Cement Company

Planning errors lead to poor resource allocation.	5	2	4	40	Moderate risk
---	---	---	---	----	---------------

Source: By author basing on Setif Cement Company reports.

From the table above, risk levels at Setif Cement Company range from acceptable to management risk, with computerized accounting system breakdown being the highest risk due to its severe impact on purchasing operations and critical data loss.

3.2.5 Purchasing risks:

Below are the key risks that Setif Cement Company may encounter concerning Purchasing:

Table (7) : RPN Of Purchasing

The Risk	S	O	D	RPN	Risk category
Non-compliant materials affect production and product quality.	2	3	2	12	Acceptable risk
Poor storage causes material spoilage and financial losses.	4	3	2	24	Moderate risk
Delivery delays disrupt production schedules and commitments.	3	2	3	18	Moderate risk
Supplier dependence weakens negotiating power and raises costs.	6	4	7	168	Unacceptable risk
Payment disputes harm cash flow and financial stability.	4	2	3	24	Moderate risk
Poor communication creates misunderstandings and supply delays.	3	4	5	60	Management risk

Source: By author basing on Setif Cement Company reports.

From the table above, risk levels at Setif Cement Company range from acceptable to management risk, with dependence on few suppliers identified as the highest risk due to weakened negotiating power and supply chain vulnerability that can halt operations entirely.

III. Artificial Neural Network Analysis Phase

In this phase, SPSS v 26 software will be used, which enables us to access the network through Analyze, then Neural Networks, then Multilayer Perceptron. All available information about production, financial, maintenance, commercial, and purchasing risks that were previously calculated will be entered as inputs to the network, while the RPN variable will be entered as outputs. The numbers (0) acceptable, (1) Moderate, and (2) Unacceptable have been assigned to variables to indicate whether the risk is acceptable, moderate, or Unacceptable. The network will separate the samples into training and testing sets as shown in the following figure.

Table(8) : Data Processing Summary

		N	Percentage
Sample	Training	30	78,9%
	Test	8	21,1%
Valid		35	38
Excluded		3	0
Total		38	38

Source: Processed Data on SPSS V 26

From the above table, we observe that the network divided the study sample consisting of 38 units into two parts: one related to training, which identified 30 units representing 78,9%, and the other for testing, estimated at 8 units representing 21,1%. Additionally, 3 factors were excluded from the network.

Table(9) : Network Information

Input Layer	Covariates	1	Severity
		2	Occurence
		3	Detection
	Number of units ^a		3
	Rescaling method for covariates		Standardized
Hidden Layer(s)	Number of hidden layers		1
	Number of units in hidden layer 1 ^a		2
	Activation function		Tangent Hyperbolic
Output Layer	Dependent variables	1	RPN

Effectiveness of Using Artificial Neural in Mitigating in Mitigating Audit Risks: A Case of the Setif Cement Company

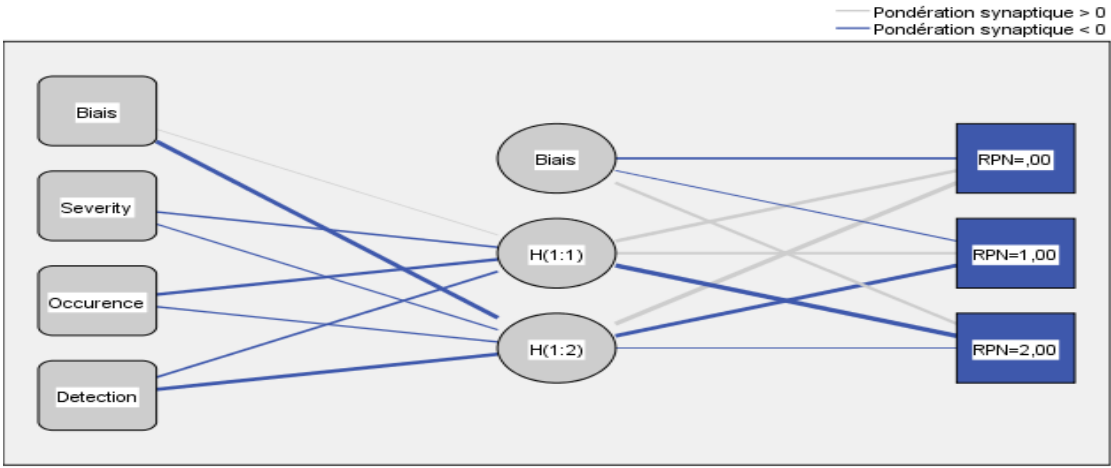
Number of units	3
Activation function	Softmax
Error function	Cross-entropy

Source: Processed Data on SPSS V 26

Based on the table shown in your image, here's a rewritten explanation that aligns with the actual network configuration:

- **Input Layer Configuration:** Contains 3 standardized covariates (Severity, Occurrence, Detection) with rescaling normalization for optimal performance.
- **Hidden Layer Architecture:** Single hidden layer with 2 units using tangent hyperbolic activation functions selected through automated process.
- **Output Layer Structure:** Configured with 3 units using softmax activation and cross-entropy error function for multi-class classification.
- **Network Parameters:** Uses RPN architecture with all remaining parameters following standard default settings.

Figure(2) : Neural Network Architecture



Couche masquée pour la fonction d'activation : Tangente hyperbolique

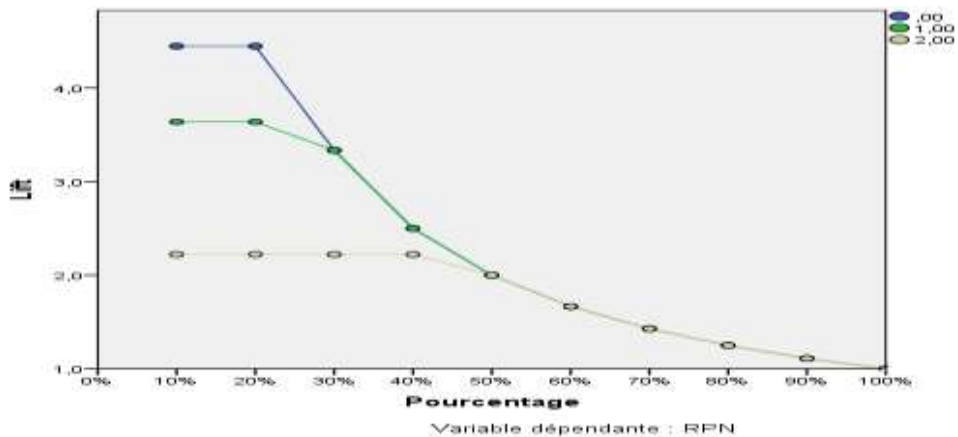
Couche de sortie pour la fonction d'activation : Softmax

Source: Processed Data on SPSS V 26

The multilayer perceptron neural network architecture shown in Figure 2 demonstrates a streamlined structure for RPN classification, consisting of

an input layer with four nodes (bias plus Severity, Occurrence, and Detection), a hidden layer containing two processing units (H(1,1) and H(1,2)) with hyperbolic tangent activation functions, and an output layer with three nodes representing discrete RPN categories using softmax activation. This compact yet effective architecture enables the network to learn complex non-linear relationships between FMEA variables while maintaining computational efficiency, with all remaining network parameters following standard default settings to ensure reliable risk priority level classification in industrial applications.

Figure(4) : The lift neural network



Source: Processed Data on SPSS V 26

The lift chart demonstrates exceptional model performance with the highest-performing curve achieving a lift of 10.0 at the 10% percentile, indicating ten times better performance than random selection. The curves show strong discrimination across different RPN categories (ranging from 1.00 to 2.00) with lift values between 5.0-10.0 for top predictions, declining to 2.0-3.0 at higher percentiles while consistently remaining above baseline. This confirms the neural network's significant operational value for risk management, particularly when targeting the highest-risk cases identified by the model.

IV.Conclusion :

The application of artificial neural networks in audit risk assessment has shown significant potential for enhancing decision-making capabilities and improving the accuracy of risk detection compared to traditional methods.

This study applied these networks to the cement institution in Sétif, demonstrating their practical effectiveness in real organizational settings. While some studies indicate mixed results regarding AI's impact on internal audit quality, with effectiveness depending on auditor independence and internal control system quality, research demonstrates that neural networks can successfully classify audit risks with high accuracy levels. The study results revealed that artificial neural networks, despite their advanced technical capabilities, cannot operate independently to achieve optimal results in audit risk assessment. The human element remains the primary actor in the process, as the effectiveness of these technologies depends on auditors' expertise and their ability to interpret results and guide the network toward correct analysis. Neural networks function as sophisticated supporting tools that enhance human auditor capabilities rather than replace them, confirming the necessity of integrating technology with human expertise to ensure audit quality and reliability. The following are the findings reached.

Result :

The artificial neural network achieved perfect classification accuracy (0.0% error) across 3 RPN categories, demonstrating superior performance with lift values of 5.0-10.0 compared to traditional methods while effectively managing complex relationships between FMEA variables.

- The system significantly enhanced decision-making processes through accurate risk predictions, enabling efficient resource allocation and reducing analysis time
- Implementation resulted in substantial cost reductions through accurate failure prediction and optimized resource allocation,
- The neural network approach enhanced risk management culture by providing advanced analytical tools, improving understanding of complex risk relationships, and supporting data-driven decision making while ensuring better compliance with international quality standards.
- The study demonstrated that artificial neural networks cannot operate independently but serve as sophisticated support tools, with the human

element remaining the primary actor in interpreting results and ensuring audit process effectiveness.

Recommendations :

- Invest in developing artificial neural network systems and training audit teams in artificial intelligence techniques to ensure maximum benefit from these advanced technologies.
- Organizational Integration: Develop clear policies for integrating neural networks into audit processes while adopting a comprehensive approach that combines human expertise with artificial intelligence capabilities to enhance a data-driven decision-making culture.
- Future Research and Development: Conduct extensive applied research across different sectors to determine the relationship between artificial intelligence tools and audit quality while developing sophisticated predictive models.

Bibliographie

Aditya, A., & al. (2025). Enhancing Reliability and Maintenance Efficiency of Screw Press Machines in Palm Fruitlet Processing Mills: A Failure Mode and Effect Analysis (FEMA) Approach. *Abbiyu Bima Aditya*, 04(02).

Al-Hayik, S.-D., & Abu-Naser, S. (2023). Neural Network-Based Audit Risk Prediction: A Comprehensive Study. *International Journal of Academic Engineering Research (IJAER)*, 7(10).

Ding Hock , H., & al. (2024). Synergizing FMEA and PDCA for superior risk management and process improvement in the semiconductor industry: a case study. *International Journal of Production Management and Engineering*, 12(2).

BENLARIA, A., & BOUBEKEUR , L. (2021). Forecasting Exchange Rates Using Artificial Neural Networks. *Al Bashaer Economic Journal*, VII(2).

Fan, F.-L., & al. (2025). Towards NeuroAI: introducing neuronal diversity into artificial neural networks. *Med-X*, 3(2).

HACHI , F., & LEBBAZ , E. (2024). Impact of the auditor's use of Artificial neural networks on the study of enterprise continuity- Case Study at Saidal Society 2017-2023 -. *Journal of Finance and Business Economics*, 9(2).

- Monteiro, D., & al. (2023). *Detection, Localization, and Quantification of Damage in Structures via Artificial Neural Networks*. Retrieved from Article ID 4829298. <https://doi.org/10.1155/2023/4829298>.
- Saleh, R., & salman, M. (2022). Comparison of some artificial neural networks for graduate students. *Periodicals of Engineering and Natural Sciences*, 10(3).
- Yang, R. (2025). Research on the Application of Artificial Intelligence in Audit Risk Assessment. *Financial Strategy and Management Reviews*, 1(1).
- AlZwainy, F., & al. (2024). Development Artificial Neural Network (ANN) computing model to analyses men's 100meter sprint performance trends. *Polish Journal of Physiotherapy*, 24(2).
- Artene , A., & Domil , A. (2025). Neural Networks in Accounting: Bridging Financial Forecasting and Decision Support Systems. *Electronics*, 14(399).
- BENTAYEB, A., & al. (2024). A QUALITATIVE STUDY ON THE APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN THE BANKING SECTOR. *21ST CENTURY MEDIA AND COMMUNICATIONS*, 8.
- Dastres, R., & Soori, M. (2021). Artificial Neural Network Systems. . *International Journal of Imaging*, 21(2).
- Dehgan, A., & al. (2025). Artificial neural networks for magnetoencephalography: a review of an emerging field. *Journal of Neural Engineering*, 22.
- Du, X. (2024). Impact of Artificial Intelligence on Auditing and the Future of Human Workforce Replacement. In *Proceedings of ICEMGD 2024 Workshop: Innovative Strategies in Macroeconomic Business Management*. DOI: 10.54254/2754-1169/115/20244BI0205.
- FEKIR, S., & al. (2024). The Relationship between Assessing Audit Risks and Revealing The Relationship Creative Accounting Methods in Accounting Estimates:The Perspective of Algerian External Auditors. *WSEAS TRANSACTIONS on BUSINESS and ECONOMICS*, 1.
- Ghafar, I., & al. (2024). The Role of Artificial Intelligence in Enhancing Global Internal Audit Efficiency: An Analysis. *Asian Journal of Logistics Management*, 3(2).
- GÖKOĞLAN, K., & al. (2025). Digital Transformation and Artificial IntelligenceAssisted Auditing: The Role of Technology in Internal Audit Processes in 2025. *Dynamics in Social Sciences and Humanities*, 6(1).

- Ilori, O. (2023). AI-DRIVEN AUDIT ANALYTICS: A CONCEPTUAL MODEL FOR REAL-TIME RISK DETECTION AND COMPLIANCE MONITORING. *Finance & Accounting Research Journal*, 05(12).
- Karmańska, A. (2022). ARTIFICIAL INTELLIGENCE IN AUDIT. *Research Papers of Wrocław University of Economics and Business*, 66(1).
- Lecci , M., & Hanne, T. (2025). Accounting Support Using Artificial Intelligence for Bank Statement Classification. *Computers*, 14(193).
- Leocádio, D., & al. (2024). Artificial Intelligence in Auditing: A Conceptual Framework for Auditing Practices. *Administrative Sciences*, 14(238).
- MOKRANI, A., & CHERABI , A. (2018). Artificial Neural Networks vs. ARIMA-GARCH in Stock Market Prediction: The Case of Tunisia and Morocco. *Journal of Economic Studies*, 5(2).
- Namazi , N., & al. (2025). Predicting the Relation Between Audit Quality and Share Return Using Artificial Neural Networks. *Journal of Hunan University*, 52(1).
- Nikolovski, P., & al. (2016). The Concept of Audit Risk. *International Journal of Sciences: Basic and Applied Research*, 27(1).
- Oluwasegun, I., & al. (2023). Artificial intelligence and audit quality: Implications for practicing. *Asian Economic and Financial Review*, 13(11).
- Qamar , R., & Zardari, B. (2023). Artificial Neural Networks: An Overview. *Mesopotamian journal of Computer Science*, 2023.
- Sakhno, L., & al. (2024). Exploring the Opportunities and Obstacles of Implementing Artificial Intelligence in Accounting and Auditing. *Journal of Information Systems Engineering and Management*, 10(2).
- Setif Cement Company documents. (2025).
- Singh, R., & al. (2025). Fingerprint Recognition Using Artificial Neural Networks. *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences*, 95.