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An Artificial Neural Network Approach for Construction Project Risk Management

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ABSTRACT

Effectively managing strategic risks within the realm of Internal Security of Establishments (ISE) is crucial for safeguarding data and preserving a company's information assets. The construction industry is notably one of the riskiest sectors, susceptible to diverse risks that can adversely impact the three crucial aspects of projects: time, cost, and quality. In the context of construction projects, inherent risks and the susceptibility to data loss are intricately linked, primarily stemming from the prevalent utilization of computerized project management systems. Throughout the project lifecycle, tasks are significantly reliant on sophisticated software tools and integrated packages. The increasing reliance on technology renders projects vulnerable to information security threats, including cyberattacks, human errors, technical failures, or natural disasters, thereby disrupting managerial processes and resulting in substantial data losses. Consequently, risk management has emerged as a pivotal area of study, demanding increased attention and focus from professionals within the construction industry. This study aims to delve into how different stakeholders perceive various types of risks, including risk information specific to construction projects. An artificial neural network (ANN) was employed to predict risk. The study identified four categories of responsibility: shared responsibility, contractor responsibility, client responsibility, and data loss responsibility. The ANN topology was optimized based on changes in mean square errors (MSE) and correlation coefficients (R^2). The numerical results demonstrated the model's strong performance, with a low MSE of 0.0029 and a high R^2 value of 0.9666, indicating its reliability and effectiveness in risk prediction. The findings indicated that the model suggested could serve as a viable approach to the most efficient methods of preventative risk management. By using an ANN model, the study offered a novel approach to risk management in construction projects and ISE, suggesting avenues for further research and application in similar contexts.

1. INTRODUCTION

Owing to its intrinsic complexity, the construction industry confronts a multitude of risks capable of significantly influencing the outcomes of its projects. Throughout each phase, spanning from initial development to final delivery, a construction project remains susceptible to unpredictable factors, including adverse weather conditions, fluctuations in costs, schedule delays, and other variables that can potentially affect the aspects of quality and safety. Consequently, the adoption of proactive risk management becomes imperative to guarantee the seamless advancement of construction projects [1].

In order to mitigate these risks, professionals in project construction industry employ various risk management methods. Factors that need to be considered include risk identification, risk analysis, the current state of risk management systems within organizations, and obstacles to effective risk management from the viewpoint of key stakeholders. Financial and economic factors are deemed to be the most crucial risks, followed by quality, and the industry typically endeavours to either avoid or transfer these risks [2].

The challenges within the construction industry are numerous and diverse, posing potential threats to the success of projects. These challenges include the increasing number of stakeholders involved, the complexity of resource coordination, and the continuous advancements in technology which elevate the importance of risk information, as projects inevitably rely on software and/or tools for risk management.

It is crucial to adopt a proactive approach to risk management, addressing financial, material, and human aspects, as well as safeguarding project data. Our approach aims to offer a comprehensive and practical perspective for anticipating risks in the context of construction projects. In risk management, having a clear perception of potential risks is crucial for effective decision-making and proactive measures.

Perception, understood, interpreted, or sensed by an individual's mind, particularly through the use of the senses, involves the awareness and recognition of information received through sight, sound, touch, taste, or smell. It also refers to the way individuals evaluate and interpret the risks surrounding them. Influenced by cognitive, emotional, cultural, and social factors, perception plays a crucial role in decision-making, adaptive behaviors, and attitudes towards risk [3].

Researchers in social sciences and psychology have identified several cognitive biases that can influence risk perception, such as the availability heuristic (evaluating the likelihood of an event based on how easily we can recall similar examples), the representativeness heuristic (making judgments based on superficial similarities), and vulnirability (underestimating risks for oneself compared to others) [4].

Risk perception has implications in various domains, such as public health, environment, finance, and security. Understanding how individuals perceive and evaluate risks can help develop effective communication strategies, design risk management policies, and promote informed decision-making for responsible risk behaviors. The analysis of hazard perception indicates that different cognitive processes are involved, among them vulnerability, which refers to the extent to which an asset (a person or property) is likely to experience negative consequences due to its situation, intrinsic characteristics, or location. Risk perception and vulnerability are closely related concepts when it comes to understanding how individuals perceive and react to potential risks [5]. These vulnerable assets, such as project stockholders, may be more sensitive to risks and less capable of protecting themselves due to their specific circumstances [6].

Therefore, risk perception must be studied in a more appropriate context; specifically, a recurrent context such as state construction projects, considering both measurable and repetitive aspects of risk, the objective involvement of stakeholders, in addition to a consistent and recognizable aspect: costs and timelines. Moreover, risk management in the construction industry remains a major challenge for practitioners, and many studies have been conducted to find effective solutions. Among innovative approaches, the use of artificial neural networks (ANN) is increasingly considered a promising solution for risk management in the construction industry [7]. Indeed, artificial neural networks (ANN) are mathematical structures and their software- or hardware-based models that compute or process signals. The network's structure and mode of operation are based on the brain and learning phenomenon, although neural networks are a highly simplified model. The theory of neural networks is extensively discussed in literature. The primary applications of artificial neural networks include: prediction, approximation, control, association, classification and pattern recognition, data association, data analysis, signal filtering, and optimization. The employment of artificial neural networks in construction project management began in the early 1990s.

Since then, numerous attempts have been made to leverage artificial neural networks in engineering construction processes, addressing issues such as implementation time analysis, efficiency and productivity in construction projects, predicting maintenance costs of construction equipment, forecasting the potential adoption or acceptability of new construction technologies, construction company management, and facilitating decision-making processes in construction projects [8].

ANN is capable of modeling risks more accurately than traditional methods, considering numerous variables and learning from historical data [9, 10]. It can be employed to predict risks in construction projects, assisting industry professionals in making more informed decisions and minimizing risks. This study will explore the integration of artificial neural networks (ANN) in risk management within construction industry, including ISE risks, and evaluate the benefits of their use [11].

2. LITERATURE REVIEW

Machine learning, a subset of artificial intelligence, has emerged as a powerful method for extracting insights from extensive datasets and constructing predictive models [12]. Within this domain, the application of artificial neural network (ANN), particularly Multilayer Perceptrons (MLP), has shown significant promise in construction risk modelling**.** These models are capable of performing tasks such as classification and regression, which are essential for predicting complex risk scenarios in construction projects [13]. This technology empowers the exploration of vast datasets, revealing diverse patterns [14] that encompass association, classification, prediction, clustering, estimation, and sequence-related structures. Specifically, the utilization of a Multilayer Perceptron (MLP) can facilitate tasks of classification and prediction. In the context of classification, an MLP employs inductive training datasets to discern the underlying relationship between a "target" and a "label".

The utilization of MLP in construction risk analysis is particularly relevant due to its ability to handle non-linear relationships and adapt to diverse data patterns. This is crucial in the construction industry, where risks are multifaceted and influenced by a range of unpredictable factors [14]. However, while the literature acknowledges the potential of ANN in general machine learning applications, its specific application in construction risk management, especially in integration with information security (ISE) risks, remains underexplored. These training datasets comprise well-established target-label pairs, enabling the MLP to initially grasp the connections between targets and labels. Subsequently, these learned relationships are extended to predict labels for previously unlabeled targets [15]. Essentially, machine learning lies in acquiring rules from instances, exemplified by examples within a training dataset. These acquired rules can then be harnessed to construct a classifier, capable of categorizing novel instances [16]. Machine learning methodologies are divided into two main categories: supervised learning and unsupervised learning. Supervised learning involves the utilization of a labeled training dataset to construct models for classification or regression, enabling the prediction of unknown labels. This process entails inputting distinct features of a sample into the model, which subsequently produces the corresponding label for that specific sample. On the contrary, unsupervised learning operates without the necessity of labeled samples. Instead, the learning algorithm generates predictions based on the features it has extracted from the input samples.

Additionally, the training process for unsupervised learning doesn't require labeled training data, allowing the developed algorithm to autonomously cluster the input data. Due to the absence of a need for labeled training data, this approach is particularly suitable for identifying optimal eigenvectors used in data classification [17]. Nonetheless, it is important to note that machine learning as a whole demands a substantial volume of labeled data to perform effectively [12].

The primary objective of supervised learning is to construct a model or function that can accurately anticipate uncertain outcomes for upcoming instances [14]. Supervised learning models are categorized into two main types: classification models and regression models. Classification models are utilized when the outputs are discrete, while regression models are used for predicting continuous outputs. Both types of models serve the purposes of prediction, classification, and the identification of unknown data patterns.

A variety of algorithms are employed in classification tasks, such as decision trees, Naïve Bayes classifiers, Bayesian networks, and logistic regression. For regression tasks, algorithms like linear regression, K-nearest neighbors, and AdaBoost are commonly utilized. Depending on the nature of the desired output data, sophisticated techniques like Multilayer Perceptron (MLP), Support Vector Machines (SVM), Random Forests, and Classification and Regression Trees (CART) can be applied to execute either classification or regression models.

On the other hand, unsupervised learning involves tasks like clustering and association rule mining. Notable unsupervised learning algorithms in these areas include K-means clustering and the Priory algorithm for mining association rules.

Numerous studies have utilized machine learning algorithms within construction projects. For example, Gondia et al. [18] and Farag et al. [19] demonstrated the application of decision trees, Naïve Bayes classifiers, and genetic algorithm-based clustering in identifying and analyzing construction risks. However, these studies primarily focused on conventional risk factors, such as delays and cost overruns, rather than the comprehensive risk landscape that includes ISE risks.

Our research aims to fill this gap by specifically focusing on the application of ANN, particularly MLP, in modelling the broader spectrum of risks in construction projects, including ISE risks. This approach is expected to provide a more holistic understanding and management of risks, transcending the limitations of traditional methods [20, 21].

De Klerk et al. [22] turned to random forests to forecast risks linked to contractual changes within early-stage architectural improvement projects. In a different endeavor, Kifokeris and Xenidis [17] employed Support Vector Machines (SVM) to effectively pinpoint and evaluate potential risk sources within projects. This endeavor resulted in a classification model capable of accurately predicting a project's constructability type. Moreover, the integration of ANN models into existing risk management frameworks in construction has not been adequately addressed in existing literature. Our study intends to contribute to this area by exploring how ANN can be integrated with traditional risk management practices to enhance decision-making and risk mitigation strategies [22, 23].

In conclusion, while machine learning, and specifically ANN, has been recognized for its potential in various domains, its application in construction risk management, particularly in relation to ISE risks, represents a novel and necessary advancement. This research builds upon existing studies by extending the application of ANN to a wider range of risk factors and by integrating these models into conventional risk management frameworks, thereby filling a crucial gap in the field.

It is important to recognize that traditional machine learning techniques might encounter challenges when attempting to provide precise predictions for data characterized by high levels of volatility and uncertainty [12]. Utilizing a Multilayer Perceptron (MLP) model can be a valuable approach for creating models that capture the complexities of nonlinear variables, effectively addressing challenges related to random variables and forecasting intricate, highly nonlinear functions. MLPs are particularly well-suited to handling incomplete or noisy data and tackling intricate, uncertain problems by incorporating human intuition into the decision-making process [24].

In the past, practical applications of machine learning heavily relied on descriptive data or features engineered by experts. The quality of these features played a critical role in determining the generalization performance of a machine learning model. However, MLPs, leveraging the power of neural network technology, have the capacity to learn specific features autonomously, enabling them to proficiently handle complex learning tasks.

Initially, Multilayer Perceptrons (MLPs) were primarily used in the domain of pattern recognition [25]. Their robust learning capabilities and ability to capture nonlinear relationships have led to their application across various fields, serving as robust tools for solving numerical simulation problems [26]. Ashtari et al. [21] conducted pioneering research on neural network applications in civil and structural engineering. This marked the beginning of widespread adoption of neural networks in the civil engineering sector. They have been effectively employed to address concerns related to construction safety [27], predict construction project costs [28, 29], and forecast the strength of concrete materials [30, 31]. Thanks to their potent nonlinear fitting ability, MLPs can accurately represent intricate relationships.

Scholars have successfully harnessed MLPs to predict risks in construction projects. For example, Debalina Banerjee Chattapadhyay et al. [32] utilized an MLP model to forecast the severity of project risks. Shi and O'Brien [33] employed an MLP to assess potential risks in the vicinity of underground box structures. Liang et al. [34] conducted sample-based learning and prediction using a Back propagation Neural Network (BPNN) model to establish risk scores for construction projects. In the present study, our focus is on exploring the integration of artificial neural networks (ANN) in risk management within the construction industry, specifically addressing ISE (Information Security and Environment) risks. We aim to evaluate the benefits that their implementation can bring to the field.

3. RESEARCH METHODOLOGY

The importance of identifying and managing risks in the construction industry, as well as the various models of risk assessment used in construction projects, are discussed in the studies of Jordan and Mitchell [12], and Singh et al. [13]. The aim of this study is to examine the primary risks faced by construction projects and the strategies implemented to minimize them, with a particular emphasis on the use of artificial neural networks (ANN) for risk prediction. The reasons of choosing (ANN) are multiple; first, its ability to learn from new data makes it a valuable tool for ongoing risk management. As new information becomes available during a project, ANN can adapt its predictions and recommendations, contributing to a more dynamic and responsive risk management approach. Also utilizing ANN in risk management allows for more accurate risk assessments and predictions. It can process and analyze vast amounts of data, including historical project performance, external factors, and stakeholder perceptions, to predict potential risks and their impacts.

This approach involves identifying, analyzing, evaluating (weighing), and mitigating two major risks families of that we have respectively labelled as physical risks (such as theft, sabotage, etc.) and information-related risks (encompassing both the information itself and its support within the project). These types of risks, often underestimated by project risk management professionals involving various stakeholders, significantly impact measurable project parameters, such as costs (and associated resources) and timelines. Consequently, they directly influence the success or failure of any project.

The data for this study were collected through a three-part survey administered to prominent industries in Algeria, such as SONATRACH, GICA, and COCIDER CONSTRUC–TION, encompassing over 135 projects. The survey focused on the significance of risks, the responsibility of various stakeholders (vulnerability), and the effectiveness of risk management techniques [14-27]. These survey data form the foundation for the development of the ANN model. The ANN model was designed to assess various parameters of construction projects, including the significance of risks, assigned responsibilities (asset vulnerability), and risk management methods, with the aim of effectively predicting construction project risks.

The initial step in this process involves identifying risks, which includes creating a list of the two risk categories submitted to various stakeholders for each of the 135 projects. Risks are assessed and rated intrinsically to establish the initial value for each risk based on multiple rating criteria, such as severity and probability of occurrence. The assessment is represented by the formula:

$$R=(P\times G) / R$$

where, R is the risk, P is the probability, and G is the severity. Because the values of probabilities vary significantly within the same analysis, so the logarithmic approach is necessary.

$$P= 1 / 105\text{-}NP;\ NP = 5 - \log(1/P)$$
$$NP=5: P=100\%;\ NP=4: P=10\%;\ NP=3: P=1\% \ldots$$

The levels are associated with a "common" estimation of probabilities. Refer to Table 1.

Table 1. Levels of probabilities

Level	Description	Probability
5	Systematic	100%
4	Very frequent	10%
3	Frequent	1%
2	Infrequent	1/1’000
1	Rare	0.1/1’000

Severity characterizes the significance of damages induced by the risk, and the levels are used to estimate severities, with the values employed for calculations.

NG=5: Total project failure,

NG=4: Significant additional budget,

NG=3: Significant project delay,

NG=2: Project delay,

NG=1: Optimized project.

Estimating a single risk: $R=P\times G=P\times 10^{NG}$,

$NR=\log(R)$.

This evaluation treats the risk as a raw or unmitigated risk, meaning a risk without any form of protection or prevention. In reality, each risk has preventive and protective measures. To calculate these measures, we refer to the risk weighting.

The weighting of the Initial or Raw Risk is determined based on existing preventive measures, yielding a value for Residual or Net Risk [35]. Several factors are considered to ensure the highest level of relevance: the number of existing preventive measures, the number of preventive measures to be implemented, the typology and nature of these measures (refer to Table 2).

Table 2. Risk weighting

Means of Protection and Prevention	Risk Weighting
Prevision of additional budget	0.5
Extended deadline	0.2
Cyber security protection	0.7
Transportation insurance contract	0.5
Legal protection (contracts and transactions)	0.9
Equipment protection	0.5
Project information protection	0.5

The assessment of the weighted risk involves evaluating the risk by taking into account the factual adherence to all available prevention and protection measures. These weightings have been assigned to each of the two risk categories, and the result of this multiplication is referred to as the Risk Prediction, as depicted in Tables 3 and 4.

The second step in this approach involves developing the neural network model. The input data for the model comprises the two risk categories (physical risks and informational risks). The learning process for the different layers is structured as follows: measurable project parameters (resources and timelines), the evaluation of the net project risks, and their criteria. Additionally, it includes measures of protection and prevention, detailing their nature and type. The risk weighting and the parameters for weighting, stakeholder categories, and their roles in the projects are also part of the learning process. Moreover, the vulnerability of projects in terms of stakeholder feedback and experience is considered in the model and the output is risk prediction.

The two risk families are assessed in this study through the same questionnaire related to Internal Security of Establishment (ISE) risks, commonly referred to as malicious risks. To precisely delineate Internal Security of Establishment (ISE) risks in construction projects, we have identified a list of two risk families by collecting answers to this question: 'Which types of malicious acts are most likely to have a significant impact on the project?' The first stage of the work revealed that, alongside the specific risks associated with construction projects, there are other risks that have a significant impact on these projects. These are Internal Security of Establishment (ISE) risks (see Figure 1), particularly risks of malicious activities that target project information, such as cyber espionage, hacking, and information theft. These risks can lead to irreversible damages on these projects.

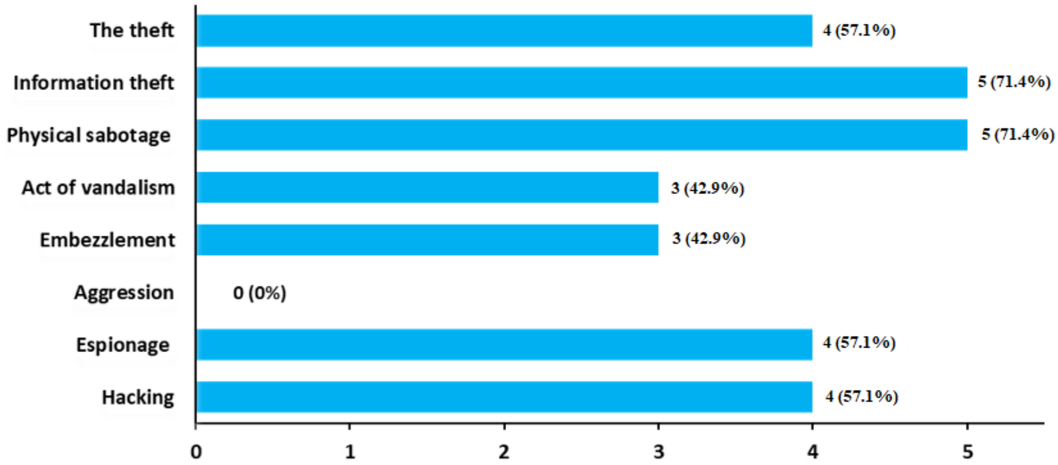

Figure 1. Internal Security Establishment (ISE) risks related to project information in construction projects

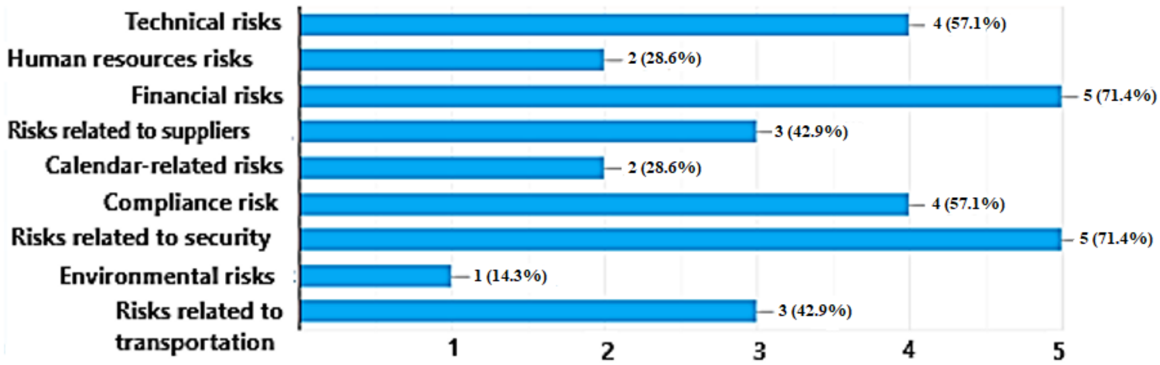

Figure 2. Perception of specific risks related to construction projects by different stakeholders

Table 3. Percentage of obtained score for physical threat

	Type of Physical Threat	RP	Impact on Project Cost	Impact on Project Schedules	Risk Prediction
1	On-site material theft	RP1	2%	1.3%	14.63%
2	Sabotage	RP2	1%	8%	10.12%
3	Piracy on the high seas	RP3	45%	62%	0.1%
4	Hold-up	RP4	4%	2.4%	2.5%
5	Misappropriation of funds	RP5	7%	5.5%	31.25
6	Attack	RP6	1.6%	0.5%	79%
7	Abduction	RP7	0.1%	0.6%	82.5%
8	Assault	RP8	0.4%	0.2%	80%
9	Armed attack on site	RP9	0.5%	0.8%	89%
10	Intrusion	RP10	20%	1%	64%
11	Vandalism/ destruction	RP11	13%	16%	44%
12	Unknown shrinkage	RP12	0%	0%	91%
13	Intentional fire	RP13	6%	1.7%	63%

Table 4. Percentage of obtained score for cyber threat

	Type of Cyber Threat	RI	Impact on Project Cost	Impact on Project Schedules	Risk Prediction
1	Theft of computer equipment	RI1	7%	25%	16%
2	Project data violation	RI2	45%	79%	5%
3	Data destruction	RI3	12%	91%	0.01%
4	Data dissemination	RI4	0.2%	5%	23%
5	Compromise	RI5	0%	0%	47%
6	Intrusion	RI6	13%	26.5%	14%
7	Infiltration	RI7	1%	4%	68%
8	Phishing	RI8	0%	0%	73%%
9	Online account hacking	RI9	0.1%	0.3%	38%
10	Denial of service attack	RI10	0%	0%	63%
11	False payment instructions	RI11	0%	0%	47%
12	Fake tech support scam	RI12	0%	0%	85.26%
13	Virus	RI13	0.2%	0.6%	53%
14	Identity theft	RI14	0%	0.4%	65%

Figure 1 clearly illustrates that Internal Security of establishment risks (ISE) risks related to project information in construction projects are substantially more prevalent than other risks. Information theft constitutes 71.4%, while espionage and computer hacking stand at 57.1% each. Thus, the cumulative total of these rates exceeds 84%. The second step of this work involved assigning weights to all the risks inherent in the construction project. The weighted risk is estimated according to this definition: The residual risk is calculated by considering the actual effectiveness of all current prevention and protection measures.

The risks were categorized into physical threats (as shown in Table 3) and cyber threats (as detailed in Table 4), with their impacts on project cost, schedules, and Risk Predictions quantified. This categorization and quantification of risks serve as inputs for the ANN model, and its output is risk prediction.

This table categorizes various types of physical threats RP (R - risk, P - Physical) encountered in construction projects and assesses their impact in terms of three key parameters: project cost, project schedules, and Risk Prediction or risk weighting. Each threat type, such as on-site material theft, sabotage, and piracy, is assigned a risk percentage value. These values reflect the perceived impact of each threat on the project's cost, schedule, and the margin of safety. For instance, 'Piracy on the high seas' might have a higher percentage impact on project schedules compared to 'On-site material theft', indicates its greater potential to disrupt timelines.

In this table, the focus shifts to cyber threats. Similar to Table 3, it evaluates the impact of various types of cyber threats, such as theft of computer equipment, project data violation, and data destruction, on the same three parameters: project cost, project schedules, and Risk Prediction. Each cyber threat is assigned a risk index (RI: R - risk, I - Information) value. These values provide insights into how each cyber threat could potentially affect the project's cost and timeline, as well as the Risk Prediction (risk weighting). For example, 'Data destruction' might have a significant percentage impact on project schedules, highlighting its criticality in terms of project timeline disruption.

These data consist of estimations presented as percentages. The risks most perceived by the different stakeholders are financial cost risks, which account for 71.4% of the responses. The second most perceived risks are those related to security risks, including malicious activities, also at a rate of 71.4% Figure 2.

4. ANN MODELING AND EVALUATION

The artificial neural network (ANN) model for risk analysis in construction projects involves a structured and precise approach. A database was established from the collection of data from 135 projects, organized around two main variables: 'Type of physical threat' and 'Type of cyber threat.' To ensure a balanced and representative distribution, this database was divided into segments for training, validation, and testing. Specifically, 70% of the projects (i.e., 95 projects) were allocated for the training phase, while the remaining 15% (i.e., 20 projects for each category) were reserved for the testing and validation phases. The analysis of this data (refer to Tables 3 and 4) informed the ANN model regarding the frequency and severity of different risk types.

The training phase of the model is a key process, requiring precise determination of the network architecture to match the specific dual inputs of the project. This phase includes several important steps: Dividing the data, selecting the network architecture and training parameters, and repetitive evaluations with the validation and testing sets to refine the model [24]. The model's performance is measured through the test base, and our proposed approach to identifying the optimal parameters can be found in Figure 3.

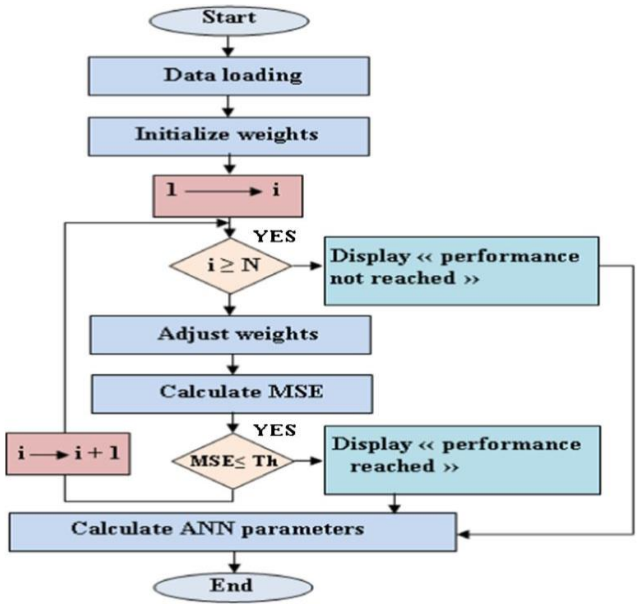

Figure 3. Training program flowchart

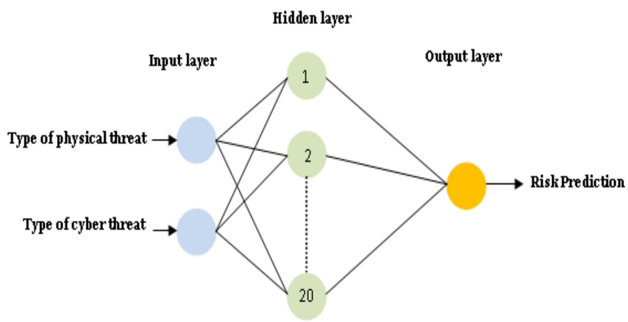

Figure 4. A typical layer neural network

After various experiments, an optimized ANN model was developed, using a multilayer perceptron (MLP) with a single hidden layer of 20 neurons (see Figure 4). The network was trained until the maximum epoch limit of 10,000 was reached, while utilizing a learning rate of 0.01 and a momentum constant of 0.9 [36]. To train the database, a BP (Back Propagation) neuronal network algorithm is utilized, which involves the training, test, and validation bases, as well as optimal architecture parameters like the number of layers and neurons and transfer function type [27].

Preliminary results using this data indicated that the ANN model could effectively categorize and predict the level of risk associated with various factors in construction projects. These initial findings demonstrate the feasibility of using ANN in this context and support further development and refinement of the model.

To assess the effectiveness of the artificial neural network that was developed, various metrics were employed. These included mean square errors (MSE), Correlation Coefficient

(R^2) and Mean Absolute Error (MAE), which are indicators of the average level of error in the model's predictions [28]. Meanwhile, R^2 is commonly utilized to assess the correlation between repeated outcomes [28].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{calc}^{i} - y_{exp}^{i}\right)^2 \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{calc}^{i} - y_{exp}^{i}\right)^2}{\sum_{i=1}^{n}\left(y_{calc}^{i} - \bar{y}\right)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_{exp}^{i}\right| \quad (3)$$

where:

x_i is the absolute differences between output values in Eqs. (1), (2) and (3),

x represents the mean,

n is the number of subjects,

y_{exp}^{i} are the observed values,

y_{calc}^{i} are the calculated [28].

5. RESULTS AND DISCUSSION

When constructing an artificial neural network (ANN) model, selecting the proper topology is of utmost importance. To determine the best topology for the model, the present investigation used MSE and R^2 values as criteria. A total of 20 neurons were organized in the ANN and scrutinized [22], with the outcomes of the assessment summarized in Table 5.

Table 5. The results of the artificial neural network model assessment

Number of the Neurons	MSE	R	MAE
01	0.0352	0.7729	0.1369
02	0.0317	0.7959	0.134
03	0.0249	0.8485	0.0089
04	0.0173	0.8949	0.0137
05	0.0159	0.9039	0.0098
06	0.0124	0.9258	0.0297
07	0.0108	0.9366	0.0116
08	0.0104	0.9383	0.0334
09	0.009	0.9466	0.0280
10	0.004	0.9505	0.0308
15	0.0035	0.9793	0.0076
20	0.0029	0.9832	0.0062

To enhance the performance of the neural network, the number of neurons in the hidden layer was adjusted to optimize R^2 values and minimize MSE values. The study found that the R^2 and MSE values varied independently of the number of neurons used, until 10 neurons were utilized. However, when 15 and 20 neurons were incorporated in the hidden layer, they yielded the same R^2 value of 0.966. The correlation coefficient, which gauges the degree of correlation between two variables that are measured continuously, is a useful tool for evaluating the strength of the relationship between the two variables [23]. To eliminate the possibility of random weight initialization by the software, each topology was replicated 10 times, and the mean MSE was calculated. The network's performance in terms of MSE and MAE was graphed against the number of nodes in the hidden layer, as depicted in Figures 5 and 6. It was observed that the network's error rate decreased and stabilized when the number of nodes in the hidden layer reached 10. Consequently, 10 neurons were utilized in the hidden layer for further development of the network.

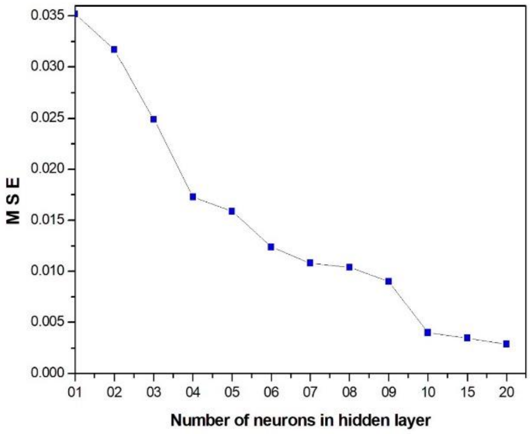

Figure 5. The network MSE vs the number of neurons in the hidden layer

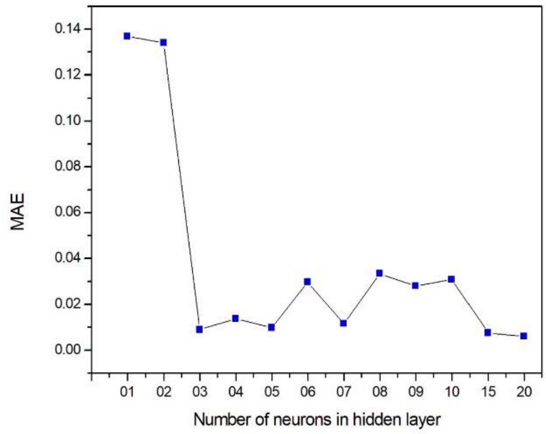

Figure 6. The network MAE vs the number of neurons in the hidden layer

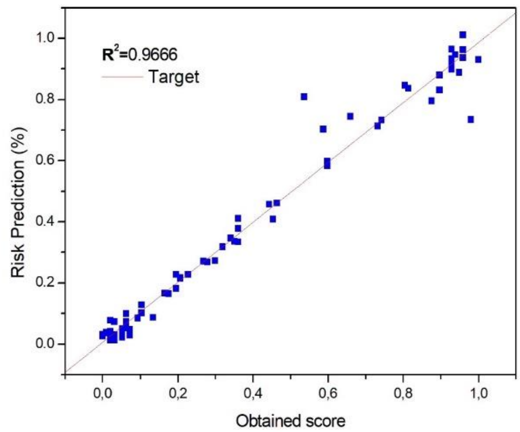

Figure 7. Predicted vs Obtained score plot obtained by developed ANN the optimum network with 1 hidden layer and 20 neurons per hidden layer was used

Using a network with 20 neurons in the hidden layer, the network was able to predict the Risk prediction, risk management, and obtained scores of various construction projects. After evaluating the performance of the developed ANN model, the values of MSE, R^2, MAE were found to be 0.0029, 0.966, and 0.0062, respectively. These performance metrics indicate that the developed ANN model was successful and met the performance criteria, showing a high degree of agreement between the predicted values and the observed data, as shown in Figure 7.

6. CONCLUSIONS

The construction industry is integral to economic growth, yet it is vulnerable to various risks that may hinder project success. Effective risk management is, therefore, essential in mitigating these risks to foster sustainable growth in the industry. This study has identified three primary categories of risk responsibility - client, contractor, and shared responsibility. Furthermore, it introduced an artificial neural network (ANN) model as a promising adjunct to traditional risk management methods in construction projects.

Utilizing the ANN model, the study demonstrated the potential for improved decision-making through more precise risk assessments and a reliable method for risk prediction and prevention. However, it is important to note that these findings, while encouraging, are based on a specific dataset and scenario, suggesting the feasibility of ANN models rather than providing conclusive evidence of their effectiveness across all construction projects.

The study's results should be considered as initial insights, highlighting the importance of effective risk management in construction and the potential contributions of ANN models to these practices. Stakeholders in the construction industry may find value in adopting ANN models as part of their risk management strategies. Yet, this should be approached as a complement to, rather than a replacement for, traditional techniques, considering the current study's limited scope. The integration of innovative methods like ANN models could bolster the success and growth of the construction industry, but further research is necessary to validate these findings more broadly and to explore the integration of these models into existing risk management frameworks.

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