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AN ARTIFICIAL NEURAL NETWORK-BASED MODEL FOR MATERIAL DEFECTS CLASSIFICATION IN OIL AND GAS PROJECTS IN SAUDI ARABIA

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Abstract. Maintaining the quality of materials supplied in construction projects is challenging, prompting government and businesses to dedicate substantial efforts and resources to ensure the highest quality standards. Any material defects can be a substantial threat to a project's safety, schedule, cost, or scope. In addition, the literature review reveals a significant gap in the integration of data-driven models, such as Artificial Neural Networks (ANN), with construction material control processes. Furthermore, there is a lack of studies implementing these models specifically in the context of Saudi Arabia, which is currently experiencing an increase in construction projects. Consequently, this paper proposes a data-driven model based on a Feedforward Neural Network (FNN) to classify and predict construction material defects. The proposed model is designed to classify the material defects and propose a robust model that helps the stakeholders to avoid and minimize material defects in construction projects. The proposed model utilizes fully connected architecture with multiple hidden layers to learn complex relationships between input features that influence the quality of the supplied construction material. In addition, the proposed model is compared with support vector machine (SVM) model. These factors are identified based on previous studies and experts. Moreover, the relationship between the input factors and between the input and output is investigated. The proposed model is developed and trained using 494 real-world data points from Saudi construction projects based on sixteen input variables. The model classifies material defects, with 66.19% identified as minor and 33.81% as major, supporting quality control through data-driven insights. Furthermore, the proposed model is evaluated using 10-fold cross-validation. To the best of our knowledge, this is the first application of an ANN model specifically developed to classify construction material defects into major and minor categories using real-world industrial data. This also investigates the relative importance of each input factor in the classification process. The findings indicate that the proposed model achieves up to 90% F-score in classifying the case defects and outperforms the SVM. The developed model is extremely useful to decision-makers in predicting and classifying material defects in construction.

Keywords: construction projects, Artificial Neural Networks, material defects, classification.

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1. Introduction

As markets become increasingly global, there is a critical need to overcome supply chain management challenges (Thomas & Griffin, 1996). Quality management has a substantial impact on the performance of the supply chain of construction, which ultimately affects the strategic goals and competitive capabilities (Soares et al., 2017). The quality of the material being delivered plays a major role in the satisfaction of the end customer and can drive the project toward success (Wong, 2000). The global market has evolved over time with dynamic changes, which in turn result in an incredibly challenging environment. Companies nowadays deviate from integrating the quality management system with the supply chain and focus on economic factors, i.e., cost (Zu & Kaynak, 2012). This is a traditional view in which market competitiveness is built based on cost value without considering other crucial factors, such as quality. Organizations that follow this traditional view have a high probability of being eventually taken out of the market competition. Thus, every construction organization is required to enhance its supply chain process with a special focus on quality to leverage its competitive edge. Additionally, it has been demonstrated by some organizations that have worked to overcome market threats by challenging the traditional supply chain process and placing a high emphasis on the quality of supplied material in order to avoid leaving the market due to the highly competitive environment (Soares et al., 2017).

Moreover, the quality of the materials supplied for construction projects is the main concern for governments and businesses all over the world (Love & Li, 2000). The importance of supplied material quality to a construction project can be found during the material receiving stage at the project site, commissioning stage, start-up stage, or during operation (Bezelga & Brandon, 2006). Material defects, being major or minor in nature, are identified as a discrepancy in the design, material, or fabrication work that can cause damage to the human being or the assets. Any failure, regardless of its size, would have substantial consequences on the project safety or the project management triple constraints, which include the schedule, cost, and scope baselines. Thus, if material defects are not controlled in a systematic manner, they can pose a risk to construction projects, leading to customer dissatisfaction.

The Saudi construction industry is rapidly expanding. It is the largest construction market in the Middle East. Currently, Saudi Arabia is preparing for massive change with an accelerated rate of transformation (Vision 2030). An astonishing volume and variety of construction projects varying in their size from small to mega and giga projects have been rolled out. According to industry sources (Boustani, 2021), there are currently more than 5200 active construction projects with a total value of $ 819 billion which represents around 35% of all current construction projects in the Gulf Cooperation Council (GCC). Therefore, it is pertinent to study issues in defective materials delivery in construction in the context of the Saudi construction industry.

Despite growing interest in quality management and defect detection across various engineering domains, there remains a significant lack of data-driven approaches tailored specifically to the classification of material defects in construction projects. Most existing studies either focus on image-based or sensor-driven detection methods or apply general classification models without addressing the unique constraints of construction supply chains. Moreover, very few studies incorporate real-world datasets from active construction environments, especially within the context of the Middle East and large-scale infrastructure projects. This gap is particularly evident in the underutilization of artificial neural networks (ANNs) for material defect classification, and the absence of explainable AI techniques that support model transparency and user trust. Consequently, this paper proposes a data-driven model to classify the defects of materials supplied to construction projects in oil and gas sector using an Artificial Neural Network (ANN). Based on the literature and expert interviews, the factors influencing the quality of supplied materials are identified. The proposed model is built, evaluated, and verified with actual data to assure its accuracy and effectiveness. Also, the proposed model is compared with support vector machine (SVM) model. Furthermore, the relationship between the input variables is explored. The proposed model is characterized by its carefully identified input features, which were derived from an extensive literature review and empirically validated for their effectiveness in defect prediction. Additionally, the model employs a custom-optimized deep feedforward neural network with multiple hidden layers, ensuring a highly reliable defect classification system with minimal manual intervention. The focus on the oil and gas construction sector is due to its strategic importance to the national economy as well as its distinct operational characteristics, which include complex supply chains, strict legal standards, and high safety and quality expectations. These conditions make material quality control especially important, developing a desirable context for defect prediction and classification. Furthermore, this sector accounts for a significant portion of Saudi Arabia's construction activity and is known for enforcing strict quality management standards. The proposed model will assist current and future project stakeholders in taking the necessary actions to avoid and minimize material defects in construction projects. In addition, the developed model can be utilized to classify and predict the defects of materials in other fields.

The paper is organized into several traditional sections. Section 2 introduces literature review. It is followed by Section 3, which introduces research materials and methods. Section 4 discusses the results of the study, Finally, Section 5 concludes the main findings of this research.

2. Literature review

Quality is a critical factor in construction supply chain management, influencing competitive capabilities. Various studies highlight the role of quality management across various industry sectors, employing diverse methodologies such as case studies and expert perspectives. The primary challenge in quality assurance is defect detection, which impacts inspection costs, efficiency, and material procurement. Emerging technologies have been explored for defect detection across industries like steel (Pernkopf, 2004) and textiles (Zhang et al., 2018). However, traditional inspection methods are costly and time-consuming, leading researchers to develop cost-effective alternatives (Trétout et al., 1995; Benitez et al., 2007, 2009; Maldague et al., 1998; Oukhellou et al., 2010; Dudzik, 2013, 2015; Tang et al., 2016). Few studies have used data-driven models to predict defects in several fields. Jamadar and Vakharia (2016) used artificial neural networks for bearing defect evaluation. Choi et al. (2019) integrated deep learning with image processing for detecting material failure in turbine tubes. Other researchers leveraged convolutional neural networks (CNNs) for defect detection in rotating machinery (Janssens et al., 2016), bearing fault diagnosis

(Guo et al., 2016), motor fault detection (Weimer et al., 2016), and structural damage detection (Abdeljaber et al., 2017). In ceramic manufacturing, Bhuvaneswari and Sabarathinam (2013) validated an artificial neural network-based flaw detection method. Other studies have expanded data-driven defect classification. Chakraborty et al. (2022) classified fabric printing defects using industrial images, while Garillos-Manliguez and Chiang (2021) combined visible-light and hyperspectral imaging for fruit maturity classification. Wu et al. (2022) explored machine learning models for predicting hazardous waste material composition.

Furthermore, several studies have been conducted to evaluate the performance of suppliers using data-driven models. Sueyoshi (1999) and Boudaghi and Saen (2015) predicted group membership of suppliers in the supply chain without addressing the nature of suppliers' inputs and outputs. The limitation of the study conducted by Sueyoshi (1999) is ignoring the characteristics of inputs and outputs. In addition, a data-driven system to assess supplier access in the automotive industry is addressed by Simchi-Levi et al. (2015). The developed system estimated supplier risk exposure, assessed risk reduction steps taken prior to disruption, and determined the best post-disruption contingency deployment. The system combines databases, a quantitative risk-exposure model, and a tool for visualizing output performance. The purchasing database, the material requirements planning system, and information about sales volume planning based on the supply chain mapping methodology are the data sources (Gusikhin & Klampfl, 2012). Ivanov and Dolgui (2018) demonstrated the applicability of using data analytics to classify supplier risk exposure during the design phase and to support monitoring and identifying disruptions during the reactive stage. Their findings are consistent with those of the study conducted by Choi (2018) which offered a practical viewpoint on the application of big data-related technologies for international supply chains with a system of systems mindset. Alsugair et al. (2023) designed an ANN model to predict final construction contract duration at early project stages using input variables including contract cost, planned duration, and sector (e.g., public, private). The dataset consisted of 135 Saudi projects, and the model was trained using standardized and augmented data to compensate for the limited sample size. The ANN model achieved a mean absolute percentage error of 12.22%, outperforming three regression models. The approach offers a practical tool for stakeholders to estimate realistic project durations during pre-tender phases. Hamdi et al. (2018) also identified four supplier selection decision-making methodologies using artificial intelligence, simulation tools, qualitative, and quantitative. The variables or criteria being examined are evaluated and numerically measured in quantitative techniques, such as delivery reliability (Wetzstein et al., 2016). Furthermore, Shavaki and Ghahnavieh (2023) reviewed the previous studies related to the applications of data-driven models in supply chain management. The study findings indicated that there is still a gap in using such models in the supply chain management field.

On the other hand, several studies used ANN in the construction industry. Maya et al. (2023) developed an ANN model to predict construction project performance in Syria. The identified 34 influencing factors and refined to six key variables through expert surveys and structured interviews. These included coordination among stakeholders, scheduling accuracy, and team experience. The ANN model demonstrated strong predictive capabilities, achieving 96.1% accuracy, and showcased the potential of ANN for forecasting project outcomes in data-constrained environments. Lin et al. (2022) introduced a hybrid model that integrated the Analytic Hierarchy Process (AHP) with ANN to assess risks affecting construction quality in Taiwan. Utilizing 948 inspection reports from the national construction database, the study identified 19 critical risk factors categorized into five dimensions. AHP was used to prioritize the risks, which were then input into an ANN that achieved an 85% accuracy rate in predicting quality outcomes. The model effectively demonstrated the benefits of combining expert judgment with data-driven techniques. Nabawy and Mohamed (2024) developed an infrastructure neural risk model to assess cost-related risks in Egyptian infrastructure projects. The authors identified 157 risk factors from the literature to 10 key risks using a structured evaluation process. The trained ANN model yielded R^2 values of 0.872 and 0.777 for training and testing datasets, respectively, offering a reliable tool for cost impact forecasting and proactive risk prioritization. Dong and Qiu (2024) applied a BP neural network enhanced with dropout regularization to forecast resource conflict risks in scientific research project management. The model used six dimensions of risk, including time, materials, and finance and achieved 97.21% accuracy in predicting time-related risks. The study provides a valuable decision-support tool for optimizing resource allocation in research-intensive environments.

While artificial neural networks (ANNs) have been widely recognized for their predictive capabilities in construction and supply chain contexts, several alternative data-driven models, such as decision trees, support vector machines (SVMs), and ensemble methods like random forests and gradient boosting, have also been explored in the literature. For instance, Guo et al. (2009) utilized decision trees and SVM for multi-class supplier selection problems, benefiting from their simplicity and interpretability. Egwim et al. (2021) demonstrated that ensemble models combining decision trees and naïve Bayes classifiers improved the prediction of construction delays through enhanced robustness and generalization. Despite these merits, ANNs exhibit distinct advantages in handling large-scale, high-dimensional data with complex and nonlinear relationships, which are commonly found in construction quality assessments. Unlike decision trees and SVMs, ANNs are highly adaptable to noisy and incomplete datasets and excel in identifying intricate patterns that may not be captured by rule-based or linear models. Similarly, Mir et al. (2021) adopted an ANN-based interval forecasting method for material price prediction, but also benchmarked it against regression techniques, highlighting the superiority of neural networks under high uncertainty conditions. Moreover, recent studies such as those by Maya et al. (2023) and Lin et al. (2022) have shown that ANNs outperform traditional models in terms of accuracy and generalization in construction-related predictions.

The aforementioned literature indicated the effectiveness of artificial neural networks for defect prediction in several fields. In addition, the literature revealed that there is a lack of development of a data-driven model for predicting and classifying material defects supplied to construction projects. Therefore, this paper proposes a data-driven model based on an artificial neural network (ANN) for material defects classification in construction projects. ANN is selected in this paper due to its strong ability to model complex, nonlinear relationships commonly found in construction and project management data. Its key strengths include high predictive accuracy, flexibility in handling incomplete or noisy datasets, and the capacity to learn from historical patterns (Maya et al., 2023; Lin et al., 2022; Nabawy & Mohamed, 2024). In addition, the factors influencing the material defects are also identified based on two main sources: literature review and experts' reviews. Moreover, the correlation between the factors influencing material quality is investigated. The parameters of the developed neural network are tuned well to obtain robust results. Actual data for some of Saudi Arabia's oil and gas field construction projects are used to develop and validate the proposed model.

3. Materials and methods

In this paper, data-driven models based on ANN and SVM are developed for predicting and classifying material defects using actual project-based data. This work will help supply chain and logistics companies, as well as material procurement companies, to predict and identify defect types in material procurement. As a result, the model will significantly reduce inspection, administrative, and operational costs. Furthermore, it saves time and material return costs in the case of major defects. The methodology used to achieve the aims of this study consists of six main steps, as shown in Figure 1. The first stage is to collect the dataset required to train and validate the data-driven model. The dataset contains several factors with corresponding outputs as either minor or major defects. The factors are identified based on two main sources: literature review and expert judgment. Then, the dataset is converted into numerical data to be processed by the classifier and represented using one-hot encoding. One-hot encoding utilizes a nominal scale of measurement where no ordinal relationship exists in the dataset. The third stage of the methodology is to analyze and filter the data with the aim of cleaning, extracting relevant information, and investigating the correlation among input factors and between inputs and output. The next step is building a deep learning classifier based on an artificial neural network. The collected dataset has been split for training and testing purposes. Cross-validation is one of the common techniques used in machine learning models to compare and select a model for a predictive modeling problem. It is mainly applied to estimate the performance of the machine learning model in predicting future data. Some of the advantages of this technique are easy to understand and implement and its results generally have lower bias compared to other techniques. The procedure of this technique is as follows:

- Starts first by randomly shuffling the dataset;
- Splitting the data set into K equal-size subsets;
- For each individual subset:
  1. Consider the subset as a test data set;
  2. Consider the rest of the subsets to be the training set;
  3. Run the model on the training dataset;

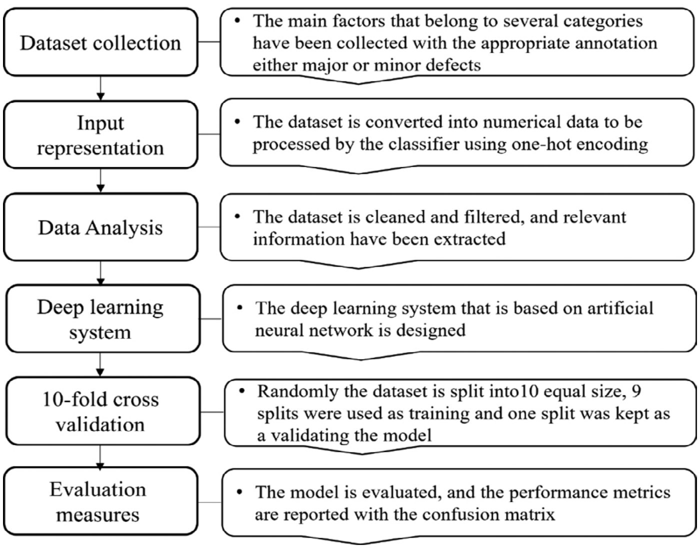

Figure 1. Research methodology

4. Assess the test data set;
5. Maintain the output;
6. Discard the model;
- Finally, the results of the K iterations can be averaged or combined to produce a single estimated value.

3.1. Dataset collection

The first step in developing a data-driven model based on a neural network for defects classification in construction projects is data collection. The dataset is collected from Saudi Arabia's oil and gas field construction projects that contain material defects data for three consecutive years (2020, 2021, and 2022). A number of parameters influencing material defects were included in the data collection and used as input data for the ANN model. The output of the ANN model included the parameter of material defects. The dataset was subsequently filtered by removing unusual parameters. The collected dataset includes 494 observations. We extracted one output variable and sixteen input variables. The collected data was structured in Microsoft Excel worksheets for ease of use. The data was then screened for outliers, which may influence a model's ability to predict. Table 1 summarizes the frequency of material defect classification. 66.19% of defects are classified as minor defects, whereas 33.81% are classified as major defects. The defects are classified by the end-user at the time of creating the material deficiency report. The classification of material defects into "major" and "minor" categories was carried out by experienced end users during the creation of material deficiency reports. These classifications were not arbitrary but followed a defined set of practical criteria grounded in industry practices and project-specific quality control procedures. In the context of the oil and gas construction projects from which the dataset was derived, these criteria were based on risk severity, functional impact, and compliance with standards. A defect was classified as major if it satisfied any of the following conditions: it posed a danger to people or assets, it violated regulatory codes or technical specifications, or it represented a repeated occurrence of a previously reported minor defect from the same supplier. The presence of a safety hazard or a breach of standard conformance automatically triggered a major classification due to the potential for serious project delays, failures, or liability. Additionally, repeated minor defects were treated as indicative of systemic quality issues and were escalated accordingly.

On the other hand, a defect was categorized as minor if it did not compromise safety, functionality, or regulatory compliance. Examples include cosmetic flaws, missing markings, or non-critical documentation issues that could be corrected without affecting installation, operations, or compliance. These minor defects typically required simple rework or administrative correction and did not pose a risk to project performance. By adhering to these criteria, end users ensured a consistent and risk-informed approach to defect classification. This process reflects real-world decision-making in industrial construction projects and strengthens the practical relevance of the data used to train and validate the proposed ANN model.

Table 1. Frequency of material defects classification

Classification	Frequency	Percent frequency
Minor	327	66.19%
Major	167	33.81%
Total	494	100%

3.2. Factors identification

In this study, the factors influencing material defects are determined through interviews with experts and the literature. First, the previous studies have been reviewed to collect the factors impacting material defects (Nwachukwu & Emoh, 2010; Kazaz et al., 2008; Osmani et al., 2006, 2008; Ekanayake & Ofori, 2004; Manavazhi & Adhikari, 2002; Zakeri et al., 1996; Toor & Ogunlana, 2008; Navon & Berkovich, 2006). Then these factors are validated by acquiring experts' inputs to obtain the factors that are utilized in practice. The identified factors are categorized into the following categories based on their thematic similarities:

- Factors related to materials specifications nonconformance (standard violation, performance, function, appearance, removable mark, traceability, and missing part);
- Type of material;
- Discipline (instrumentation, mechanical, electrical, coating, and structure);
- Geographical location (Europe, Middle East, North America, and Asia);
- Inclement weather conditions.

Then, a panel of experts with extensive experience in quality control, material inspection, and construction defect analysis was consulted to refine and validate the factors. The expert panel consisted of professionals from various disciplines, including mechanical, electrical, instrumentation, coating, and structural engineering. Two phases are used in the validation process. First, structured interviews and surveys were conducted to collect expert opinions on the applicability and significance of each factor. Experts were also encouraged to propose additional factors that may have been ignored in the literature. This phase helped assess the real-world relevance of the identified factors and filter out those considered less impactful. Based on expert input and statistical analysis, the final list of factors was refined to include conformance with specifications (standard violation, performance, function, appearance, removable mark, traceability, and missing part), discipline or material type (instrumentation, mechanical, electrical, coating, and structure), and geographical location (Europe, Middle East, North America, and Asia). The factor related to inclement weather conditions was excluded due to its strong correlation with geographical location, as confirmed by expert judgment. Also, the type of material is removed due to its strong correlation with discipline. Table 2 presents the frequency distribution of these factors. Given the evident imbalance in factor distribution, both accuracy and F1-score were used to evaluate the model's performance.

3.3. Representation of the data set

Data representation is a crucial step for model development. In this study, all data of input factors and the output are qualitative data, which is represented as a label or name values, rather than numeric values, to identify specific attributes of an element. One of the encountered constraints in the analysis of qualitative data is the complexity of building the model. Thus, it is necessary to convert all input and output data to numerical values using either integer encoding or one-hot encoding. Ordinal scales of measurement are used in integer encoding when the order or rank of the data is meaningful. One-hot encoding, on the other hand, uses a nominal scale of measurement when there is no ordinal relationship in the dataset. In such cases, dummy variables must be assigned to each categorical value. In this study, the inputs and outputs are represented by 0–1 numbers. A value of 1 indicates that the factor appears in the data set, while a value of 0 indicates that the factor does not appear. In the output representation, 1 denotes a major defect, and 0 denotes a minor defect.

Table 2. Frequency of all input factors

Category	Factor	Frequency	Percent Frequency
Conforming with specification	Removable mark	41	8.30
	Standard violation	111	22.47
	Function	101	20.45
	Missing part	14	2.83
	Performance	109	22.06
	Traceability	34	6.88
	Appearance	84	17.00
Discipline	Instrumentation	32	6.48
	Mechanical	244	49.39
	Electrical	87	17.61
	Coating	77	15.59
	Structure	54	10.93
Geographical location	Europe	167	33.81
	Middle East	203	41.09
	North America	39	7.89
	Asia	85	17.21

3.4. Data analysis

Correlations between the input and output variables are performed in order to analyze the data quality and produce meaningful results. First, the correlations between the factors within different categories are investigated. A fully positive correlation is given a value of +1, a fully negative correlation is given a value of –1, and no relationship is allocated a value of zero. The weaker the relationship, the closer the value is to zero. Tables 3a and 3b show that the correlations between the factors are not significant in the most of factors. The highest correlation is between appearance and coating and between appearance and structure. However, this correlation is still insignificant. In addition, Figure 2 shows the correlation between input factors and output. It is clear that Europe, Asia, coating,

Table 3. Correlations analysis: a – Part 1; b – Part 2

a)

	Removable mark	Standard violation	Function	Missing part	Performance	Appearance	Traceability
Instrumentation	–0.020	0.134	–0.093	0.054	0.038	–0.053	–0.072
Mechanical	–0.062	0.196	0.232	–0.144	0.080	–0.339	–0.157
Electrical	–0.024	–0.122	0.095	0.081	0.036	–0.054	0.042
Structure	0.102	–0.192	–0.293	0.063	–0.143	0.461	0.181
Coating	0.102	–0.192	–0.293	0.063	–0.143	0.461	0.181
Europe	–0.153	0.241	0.338	–0.045	–0.205	–0.175	–0.144
Middle East	0.077	–0.144	–0.230	0.031	0.091	0.159	0.114
Asia	0.116	–0.091	–0.111	–0.046	0.081	0.036	0.046
North America	–0.034	–0.032	–0.018	0.086	0.080	–0.033	–0.020

b)

	Europe	Middle East	Asia	North America
Instrumentation	–0.049	–0.003	–0.033	0.136
Mechanical	0.347	–0.373	0.097	–0.064
Electrical	–0.106	0.154	–0.126	0.081
Structure	–0.274	0.291	0.018	–0.074
Coating	–0.274	0.291	0.018	–0.074

structure, and mechanical factors have the highest correlation coefficients with the output. This result is also supported by constructing scatter plots to demonstrate the relationship between the input factors and the output as shown in Figure 3. From Figure 3, it is obvious that the location, Europe, and structure have a significant relationship with the material defect.

Moreover, Figure 4 presents the relative importance of various factors in influencing the target outcome as determined through a feature importance analysis. The analysis reveals that geographical origin technical characteristics and compliance-related variables are the most significant contributors within the predictive model. The feature labeled as Europe demonstrates the highest relative importance with a normalized value of 100%. This indicates that products or components originating from Europe exert a dominant influence on the outcome, potentially due to differences in manufacturing standards, supplier quality or regulatory frameworks. Technical attributes such as Mechanical and Function follow with relative

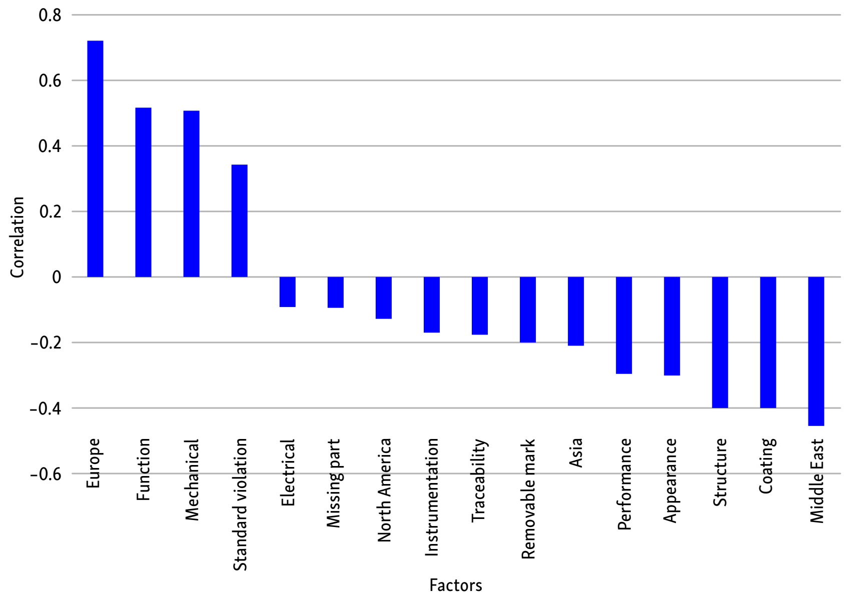

Figure 2. Correlations between input factors and output

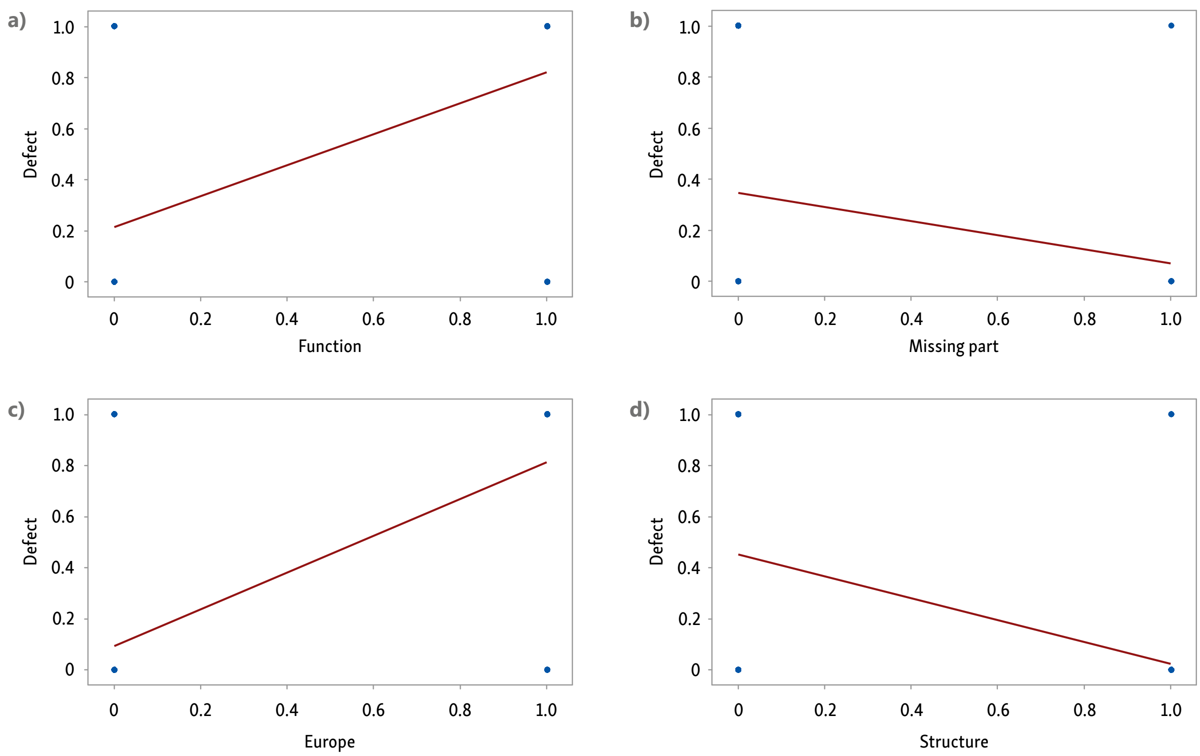

Figure 3. Scatter plots of input factors versus output: a – location versus defect; b – missing part versus defects; c – Europe versus defect; d – structure versus defect

importance values of 76.2% and 67.6%, respectively. These findings emphasize the critical role of mechanical integrity and functional performance in determining product conformity or defect risk. In industrial applications, these aspects are often considered essential due to their impact on reliability and safety. Other factors with notable influence include Coating at 53.6%, Middle East at 49.6% and Standard Violation at 38.6%. These variables indicate that surface treatment, regional sourcing and adherence to standards play substantial roles in determining quality outcomes. Each of these factors may reflect regional manufacturing conditions, supplier practices or levels of compliance. Moderately important features include Performance at 23.3%, Asia at 13% and Appearance at 12.6%. These variables contribute meaningfully, though less decisively. For example, performance may capture degradation over time, appearance may relate to customer perception and regional influence from Asia may vary depending on supplier and process conditions. At the lower end of the scale, Instrumentation, Electrical Removable mark, Missing part and Traceability show limited relative importance, ranging from 9.1% to 0.8%. These variables likely represent infrequent or narrowly scoped issues that do not significantly influence the overall prediction. The lowest-ranked feature is North America with a relative importance of only 0.3%, indicating minimal influence on the modeled outcome.

The distribution of relative importance values demonstrates that technical and regional factors are the primary drivers in the model. This insight is valuable for guiding quality assurance and supplier evaluation practices by identifying where the greatest risks and variations may lie. Low-impact factors may still be relevant in specific contexts but they generally exert a limited effect on the broader assessment.

3.5. The proposed model development

In this study, a deep learning artificial neural network is proposed to classify the defects in construction projects. The proposed model is compared with the support vector machine algorithm. This section discusses the proposed model's structure and the hyperparameter tuning process.

3.5.1. Artificial Neural Network model development

The proposed model is based on a deep learning artificial neural network which uses dense layers or fully connected layers in its implementation. The proposed model is built using sequential dense layers that are stacked to build, which is known as a multilayer perceptron. The first layer receives input from 16 input neurons represented by an input layer, and 12 output neurons are activated using one of the prevalent activation functions called Rectified Linear Unit (ReLU). Similarly, the second layer uses ReLU to activate and contains 8 output neurons. The selection of two hidden layers with 12 and 8 neurons was the result of iterative experimentation aimed at optimizing model performance while avoiding overfitting. Various configurations were tested, and this structure demonstrated the best validation metrics during tenfold cross-validation. The architecture allows the model to gradually compress the input data and extract essential features, enhancing its generalization capability. Moreover, the use of ReLU activation in both layers supports effective learning of nonlinear relationships within the input features. The information is condensed into a pretty small space to allow the model to pick up on the most crucial patterns, facilitating the generalization to new data. Since the problem is of type binary classification, the last layer uses sigmoid activation function with only one neuron to classify the in-

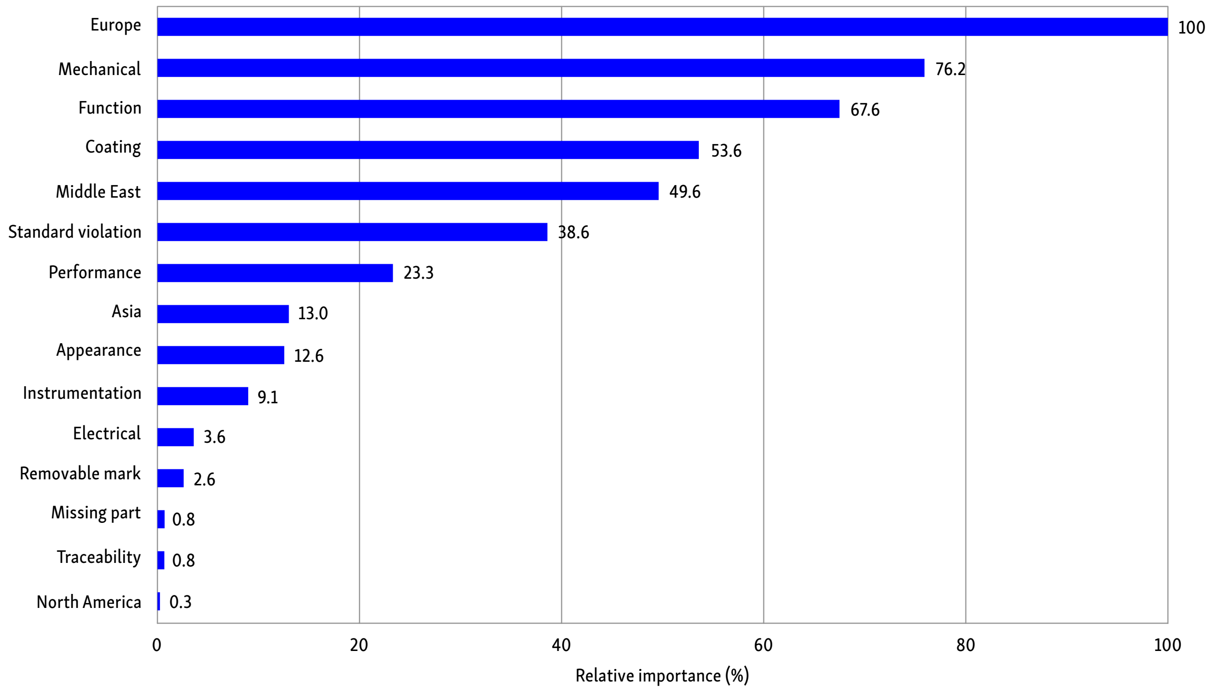

Figure 4. Relative importance of the features

put into two classes, either minor or major by representing the probability of the class. Using a threshold of 0.5, the value is converted to class 0 if the value is below the threshold. Otherwise, the value is converted to class 1. Figure 5 shows the developed neural network used to predict and classify material defects in construction projects. Figure 6 represents the difference between the two activation functions that have been used.

Moreover, the hyperparameters are set individually in the trials to achieve higher validation data scores through an iterative procedure. The neural network has been designed and tested iteratively to reach the optimal number of layers and neurons by monitoring the validation metrics. In addition, the simplicity of the model is required to alleviate overfitting in the proposed models to the trained samples. Different parameters are tuned, such as the loss function, which is considered as one of the most important parameters in the machine learning model. It is intended to calculate the error between the predicted value and the actual output value. So, the loss function helps the neural network process to minimize the error and achieve the expected output value as much as possible.

Binary cross-entropy loss; a special case of the cross-entropy function has been selected to find out the loss or error between the actual value and the predicted value for a binary classification model. The model has been improved using the Adam optimizer which is the most often utilized optimizer nowadays. It adds a number of enhancements to the conventional stochastic gradient descent method. Another important hyperparameter is the epoch which is defined as one full cycle of processing the entire data set through the neural network. Gradually, the model has been trained using different numbers of epochs to get better evaluation measures. We intentionally select small values to be tested to prevent overfitting and to mitigate the consequences of a limited number of samples in the dataset.

In this study, different values have been examined to distribute the samples in different batches with the aim to find the optimal batch size before any updates to the model. Then, these values are compared to the actual or expected values to calculate the error. After that, the model uses the updated algorithm to improve the model in the direction of minimizing the error (gradient descent). Moreover, the model checkpoint tool is used to save the processed data and operations, and prevent the model from losing whatever has been processed. The function of a checkpoint can be used to allow the user to use a pre-

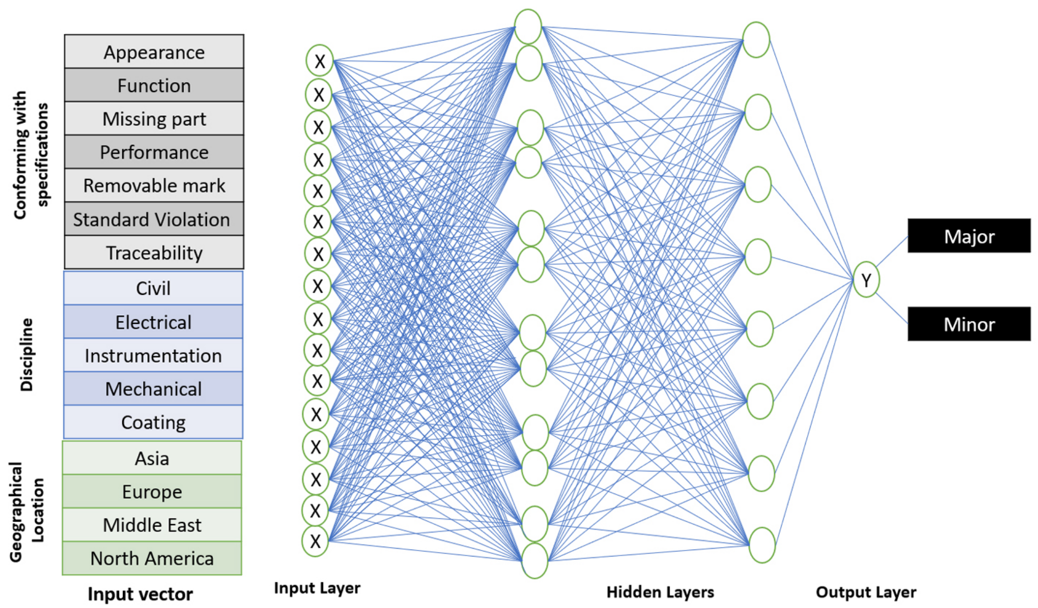

Figure 5. Structure of the developed neural network

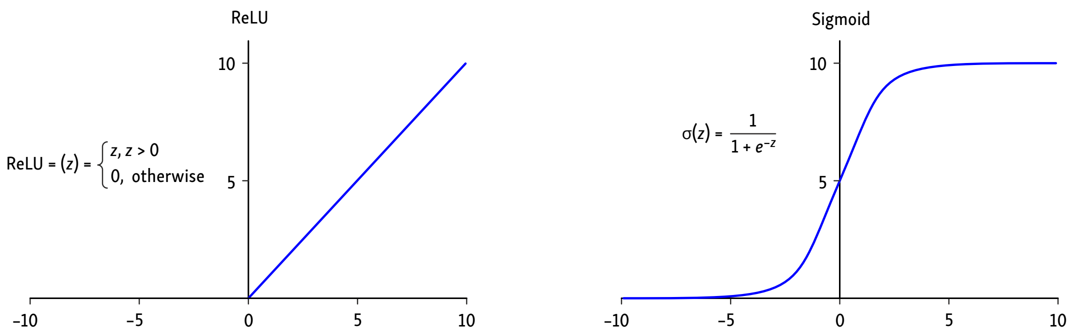

Figure 6. Activation functions

trained model for any purpose without the need to retrain the model from scratch. The model that has achieved the best performance needs to be saved or at the end of each epoch, regardless of the model's performance. In addition, defining the best performance is essential utilizing this tool which includes defining the monitored quantity and whether it should be maximized or minimized, and the accuracy of the validation part have been used in the monitoring. Then, the frequency of saving the model is at the end of each epoch. Finally, the checkpoint is used to save the weights of the model which are used to predict the output values.

To divide the dataset equally among the ten folds, stratified tenfold cross-validation was utilized as a training and validation division technique. Nine groups were used as training data and one group was kept as validation data for testing the model. It is important to note that this technique gives a chance for each group to be a test data set and for sure to be a training data set. The number of epochs were 15 and each epoch was a full cycle of processing the entire data set forward and backward through the neural network to achieve the optimum results. Table 4 shows the model parameters. The model's batch size was 8 which was used for training the samples before any updates to the model. In this study, all experiments were carried out on Google Colab with the Keras library running on the TensorFlow system.

Table 5 shows the summary of the developed ANN model. The parameter number is the count of a trainable element in any specific layer. It is basically the weight that contributes to the model's predictive power. The change in the weight occurs during the backward propagation process.

3.5.2. Support vector machine

In this study, a support vector machine is developed to compare with the proposed ANN. The Support Vector Machine (SVM) is a well-established supervised learning algorithm widely used for binary classification tasks due to its strong theoretical foundation and effectiveness in high-dimensional spaces. SVMs work by identifying the optimal hyperplane that maximally separates the data points belonging to different classes. This characteristic makes SVM particularly well-suited for problems where the number of features is relatively large compared to the number of training instances, an aspect often encountered in quality assessment tasks involving diverse categorical and engineering-related variables. In this study, the SVM model was trained on the same preprocessed dataset used for the proposed artificial neural network (ANN) model. The radial basis function (RBF) kernel was selected for the SVM due to its ability to model non-linear relationships, which is essential given the complex and potentially non-linear nature of material defect patterns in construction data. To optimize the performance of the SVM classifier, a grid search was conducted over a range of hyperparameters using 10-fold stratified cross-validation. This process ensures that each fold preserves the proportion of major and minor defect classes. The best-performing configuration was found with C = 10, γ = 0.01, and kernel = 'rbf', which provided a strong balance between margin maximization and misclassification tolerance. The results of the SVM were then compared against the ANN to assess the relative effectiveness of both approaches in material defect classification.

Table 4. Model parameters

Parameter	Number
Fold	10
Epoch	15
Batch Size	8

Table 5. Model summary

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 12)	168
dense_1 (Dense)	(None, 8)	104
dense_2 (Dense)	(None, 1)	9

Total params: 281
Trainable params: 281
Non-trainable params: 0

3.6. Evaluation measures

Four metrics are selected from the literature to report the classifier's performance. A confusion matrix with two rows and two columns is utilized to assess the performance of a prediction model. The confusion matrix measures the model's two dimensions actual and predicted values as shown in Figure 7. The Figure reports the number of prediction model results such as true positive, true negative, false positive and false negative. Confusion Matrix stems its name from the fact that it can be visualized easily whether the model is confusing the two classes in a way that one class is being labeled as the other class. The table is extremely easy to understand and immensely helpful to visualize and interpret the model performance, but its relevant terminology is a little bit confusing. Because the dataset is imbalanced, using the accuracy is not enough to measure the proposed technique's performance. As a result, the F1-score is the harmonic average of precision and recall that was utilized for assessment. In general, four measures are utilized to present the results: recall, precision, accuracy, and F1-score.

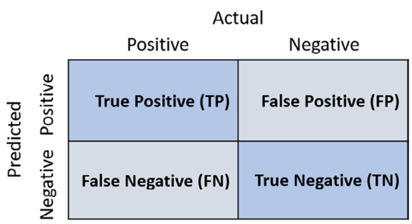

Figure 7. Confusion matrix

The definitions of accuracy, precision, recall, and F1-score using the confusion matrix are explained as follows:

- is obtained by dividing the total number of classifications by the number of correct classifications. It is defined as in Eqn (1):

$$Acc = \frac{(\text{true negatives} + \text{true positives})}{(\text{true positives} + \text{false positives} + \text{true negatives} + \text{false negatives})}; \quad (1)$$

- Precision: estimates the total number of correct classifications with respect to the number of classifications retrieved. It is defined as in Eqn (2):

$$\text{Precision} = \frac{(\text{true positives})}{(\text{true positives} + \text{false positives})}; \quad (2)$$

- Recall: estimates the percent of correct classifications. It is defined as in Eqn (3):

$$\text{Recall} = \frac{(\text{true positives})}{(\text{true positives} + \text{false negatives})}; \quad (3)$$

- F-Score is the harmonic average of precision and recall. It is defined as in Eqn (4):

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}. \quad (4)$$

4. Results and analysis

This section presents the outcomes of the proposed Artificial Neural Network (ANN) model developed to predict and classify material defects in construction projects. The model was trained and validated using a dataset comprising real-world observations from Saudi construction projects. In addition, the results obtained by the proposed model is compared with support vector machine algorithm.

4.1. Results and discussion

10-fold cross-validation has been used to randomly split the dataset into 10 equal-sized groups. The effectiveness of each fold is assessed using the F-score metric which is a performance metric that combines precision and recall metrics and offers a break-even point between them. The harmonic mean of recall and precision is used to calculate the F-score. Figure 8 depicts the evolution of F-score values with the number of folds, measuring the accuracy, precision, and recall. The figure highlights the variations of performance among the ten-fold experiments. Fold nine yields the best value of F-score. The model standard deviation of the accuracy metric is minimal which is ±2 while the precision and recall standard deviation are ±6 and ±5, respectively. The f-score standard deviation is ±3.5 which indicates the stability in the model performance in the reported ten different experiments.

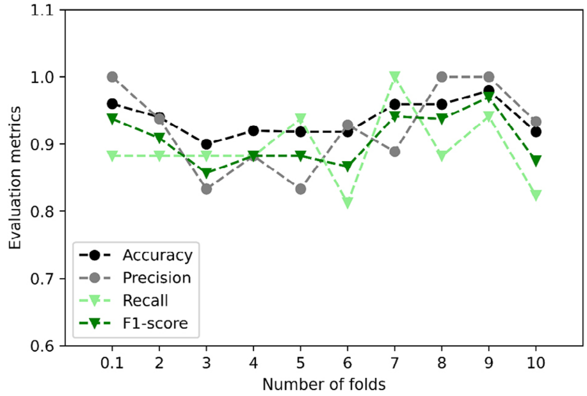

Figure 8. F-score per number of folds for the material defects predictive models

Different scenarios have been tested to select the best factor combination. For each scenario, to predict and classify the material defects, the performance measures are computed for the proposed neural network model. Table 6 shows all tested combinations. First, performance measures for each category influencing the material defects are computed. Then, the impact of the combination between the two categories is tested. From the table, it is clear that the performance measure of the proposed model has been improved in the case of combining each two categories. This indicated that all categories have an impact on material defects. In addition, it is obvious that the best F-score has been obtained in the case of combining all three categories' factors. This supports that all factors in the three main categories are essential to developing the model for predicting material defects in construction projects. As a result, the model accuracy is 93.73% which shows that the model predicted 463 samples correctly out of all samples. The model has 89.26% recall and 92.37% precision. The only difference between them is the basis where precision considers the model predictions as a baseline, unlike recall where it considers the fact as a baseline.

Table 6. The developed model's performance for different scenarios

Factors	Accuracy	precision	Recall	F-score
Conforming to specifications	85.64%	73.20%	92.24%	81.31%
Discipline	74.29%	85.07%	58.28%	68.98%
Geographic	87.44%	82.34%	81.47%	81.36%
Conforming with specifications + Discipline	91.32%	88.28%	85.59%	86.48%
Conforming with specifications + Geographic	90.47%	91.84%	79.67%	84.87%
Discipline + Geographic	91.29%	95.36%	78.46%	85.74%
Conforming with specifications + Discipline + Geographic	93.73	92.37	89.26	90.58%

The model has a 90.58% F-score which is a harmonic mean or the balance of precision and recall. It indicates the overall health or overall performance of the model.

The obtained result is supported by the confusion matrix. Figure 9 shows the findings of the confusion matrix for a binary classifier resulting from two types of defects for each category. It is obvious that the best and most accurate model is developed using all combinations of categories. According to the confusion matrix, 314 out of 327 minor defects and 149 out of 167 major defects are correctly classified, as shown in Figure 9g. This indicates that the model can accurately classify material defects.

The performance of the developed model is also evaluated by performing receiver operating characteristic analysis by addressing true positive rate and false positive rate, as shown in Figure 10. The area under the receiver operating characteristic (ROC) curve is a popular metric for assessing the accuracy of ANNs in prediction and classification, with a ROC of 1 representing a perfect test. From the figure, the proposed model acquired an ROC of 0.92 and 0.97 for the training data set and validation, respectively. This indicates that the performance of the developed model is high, and it is capable of acquiring better classification results. This finding provides consistent and significant results that can be used in a material defects classification and prediction model.

Moreover, a comparative analysis was performed between the proposed ANN model and the optimized SVM classifier to assess their effectiveness in classifying material defects. The SVM model, configured with an RBF kernel using the optimal hyperparameters, was evaluated on the same dataset and under identical conditions as the ANN model. Figure 11 illustrates the confusion matrix for the SVM classifier, showing that the model correctly classified 307 out of 327 minor defects and 151 out of 167 major defects. This results in 20 false positives (minor predicted as major) and 16 false negatives (major predicted as minor), which are acceptable within the bounds of quality inspection scenarios.

Furthermore, Table 7 provides a comparative summary of the performance metrics for the proposed Artificial Neural Network (ANN) model and the optimized Sup-

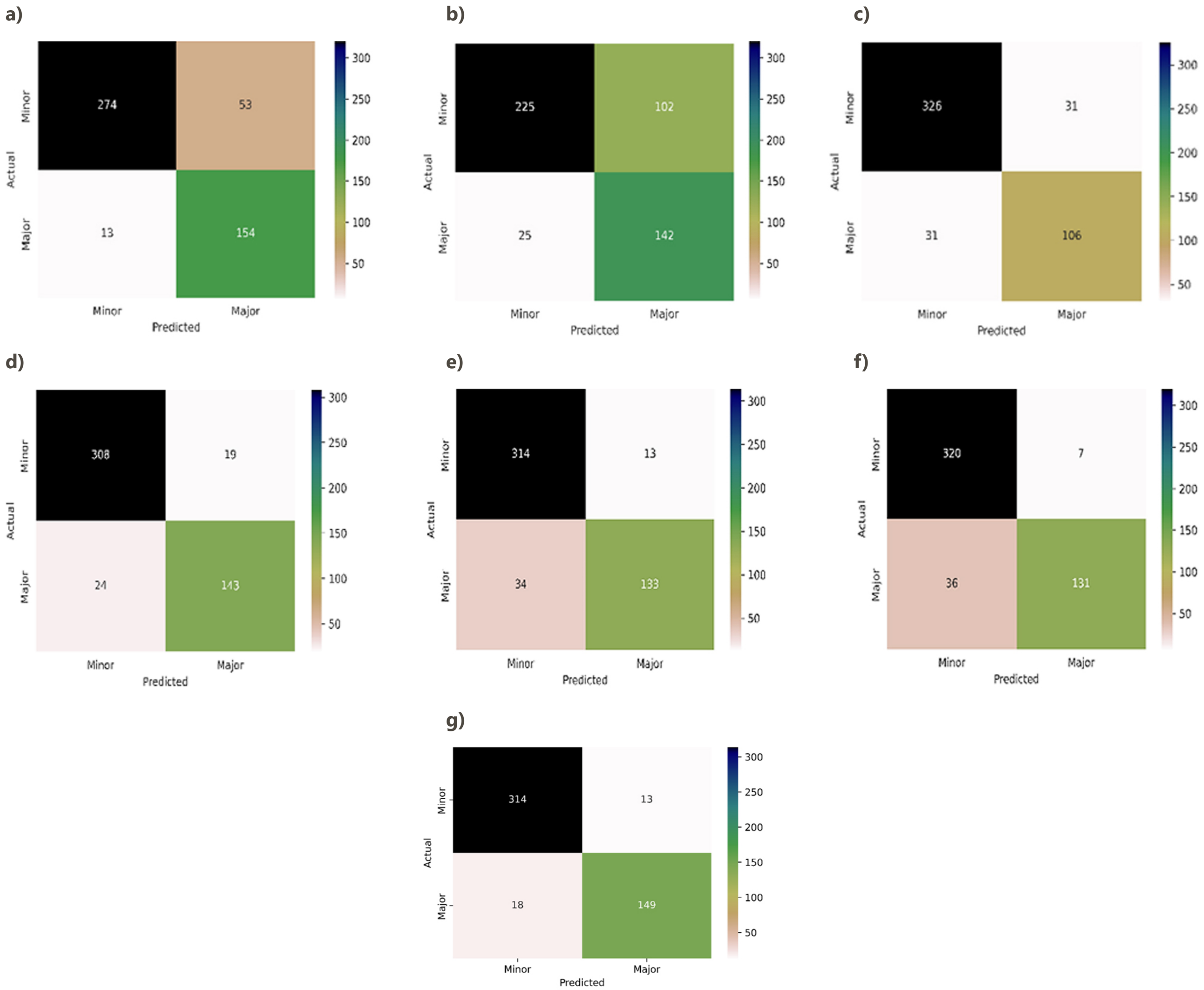

Figure 9. Confusion matrix: a – category 1; b – category 2; c – category 3; d – category 1 and 2; e – category 1 and 3; f – category 2 and 3; g – category 1, 2, and 3

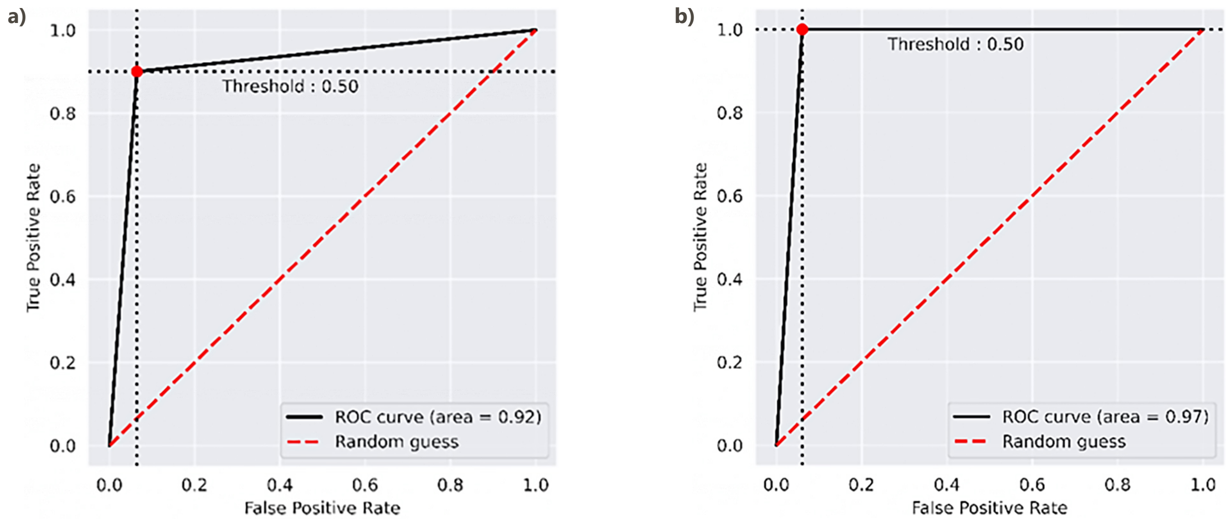

Figure 10. ROC curve analysis: a – training; b – validation

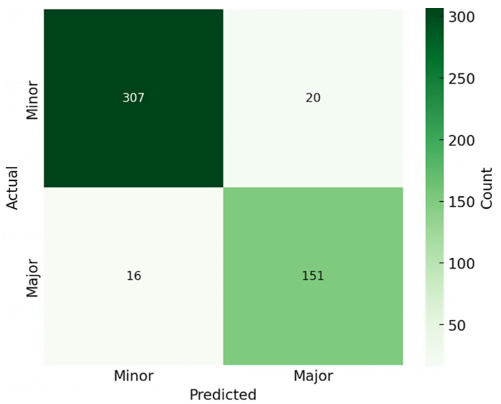

Figure 11. Confusion matrix obtained by the SVM

port Vector Machine (SVM) classifier. Overall, both models demonstrated strong predictive capabilities in classifying material defects into "major" and "minor" categories. However, the proposed ANN model consistently outperformed the SVM across three out of four key evaluation metrics. Specifically, the ANN achieved the highest accuracy of 94%, indicating its superior overall correctness in prediction. It also attained a precision of 92%, suggesting that its predictions of "major defects" were more reliable, with fewer false positives. While the SVM exhibited a slightly higher recall (91%) than the ANN (89%), indicating better sensitivity to actual major defect cases, this came at the expense of more false positives, as reflected in the lower precision. In terms of the F1-score, which balances precision and recall, the ANN achieved a higher value (0.91) compared to the SVM (0.89). This confirms the ANN's stronger overall performance in maintaining a balance between correctly identifying major defects and minimizing false alarms. These results suggest that while the SVM remains a competitive baseline, the ANN model offers better generalization and predictive power for this classification task, making it more suitable for deployment in quality assurance systems within construction projects.

Table 7. Comparative analysis

Model	Accuracy	Precision	Recall	F1-Score
The proposed ANN	0.94	0.92	0.89	0.91
SVM	0.92	0.89	0.91	0.89

4.2. Practical implications

The application of the proposed model for classifying material defects presents meaningful practical value for improving quality management practices in construction projects. In countries where construction activities are rapidly expanding and quality assurance is a national priority; the proposed model offers a systematic and data-driven method for identifying and predicting material defects. In addition, the model provides actionable insights that support early intervention and effective risk management. For project managers and engineers, this predictive capability enables more efficient allocation of inspection resources, timely identification of quality issues, and improved adherence to project schedules and budgets. Procurement teams can use the proposed model to assess the consistency and performance of material suppliers, thereby enhancing overall supply chain reliability and ensuring that materials meet the required standards before reaching the construction site. The model also helps in tracking recurring defect patterns, which can inform updates to procurement strategies, training programs, and supplier evaluation criteria. On a broader scale, government agencies and regulatory bodies can utilize such models to support quality compliance, improve transparency, and monitor industry-wide performance as part of digital transformation initiatives in the construction sector. The integration of the proposed model into quality control frameworks promotes continuous improvement, reduces the likelihood of costly rework, and contributes to the timely and safe delivery of high-quality construction projects.

Although the proposed ANN model was developed using data from oil and gas construction projects in Saudi Arabia, its architecture and methodology are not limited to this domain. The input features used in the model, such as conformity with material specifications, discipline, and geographical origin, are applicable across a wide range of construction contexts, including infrastructure, residential, and commercial projects. As such, the model can be retrained or fine-tuned using sector-specific datasets to suit different project types. Furthermore, the model's structure is highly scalable and capable of handling larger and more diverse datasets. The use of a feedforward neural network with multiple hidden layers allows it to capture complex, nonlinear relationships, making it adaptable to varied quality management practices and defect characteristics across sectors. With sufficient data and preprocessing, the model can be generalized to support predictive quality control in broader construction domains while maintaining its robustness and interpretability.

On the other hand, the application of the artificial neural network in safety-critical environments such as construction projects raises important considerations regarding liability, trust, and human oversight. AI-based decisions, particularly in areas affecting structural integrity and worker safety, must not operate in isolation. Instead, predictive outputs from the model should be used as a decision-support tool rather than a replacement for qualified human judgment. Liability concerns arise when automated systems make or influence decisions that lead to safety incidents or material failures. To mitigate this, organizations must clearly define responsibility boundaries and ensure that AI model outputs are always subject to human review, especially when high-risk components are involved. Building trust in AI systems is also essential for adoption; this can be supported by transparency measures such as model explainability, validation on diverse datasets, and continuous monitoring of model performance in real-world deployments. Furthermore, incorporating human oversight as a mandatory layer in the AI-assisted quality assurance process helps preserve accountability and allows field experts to interpret model predictions in light of contextual factors not captured by data. Future work may also explore the integration of AI systems into broader governance frameworks that emphasize auditability, safety certifications, and ethical standards in AI deployment within the construction industry.

4.3. Threats to validity

Although the proposed ANN model demonstrates strong performance and practical relevance in classifying material defects, certain limitations must be considered in interpreting and generalizing the findings. The model was developed using 494 labeled observations from oil and gas construction projects in Saudi Arabia. Although the input features, such as material specification conformity, discipline, and geographic origin, are broadly applicable across construction sectors, the dataset represents a single domain. As a result, the performance outcomes may not directly translate to other construction settings without retraining or fine-tuning the model with domain-specific data. To ensure the reliability of the results, stratified 10-fold cross-validation was employed, preserving class distribution in each fold and minimizing bias introduced by random sampling. This technique is widely recognized for its effectiveness in moderate-sized datasets and was selected to provide robust internal validation. Additionally, the model development process included a fixed random seed (42) for partitioning and hyperparameter tuning, and all modeling parameters were fully documented to support reproducibility.

Despite these measures, the relatively limited dataset may not capture the full diversity of defect scenarios, construction practices, or supplier variability encountered in other regions or project types. Differences in classification standards, data recording practices, or operational procedures across construction sectors could influence the model's external validity. These factors do not undermine the model's utility but highlight the need for cautious interpretation when applying it beyond the current study scope. Future research needs to focus on expanding the dataset to include a wider variety of project types (e.g., residential, infrastructure, and commercial) and regional contexts. Such an expansion would enable broader validation and adaptation of the model, thereby supporting the development of more generalized tools for predictive quality management in construction.

5. Conclusions

The quality of materials supplied to construction projects is one of the main concerns for which governments and businesses all over the world spend time and money to ensure the highest quality standards. This research proposed data-driven approaches based on ANN and SVM to predict and classify material defects in construction projects. The main aim is to classify material defects in construction projects and develop a robust model that can predict future material defects, allowing current and future project stakeholders to take the necessary actions to avoid or at least minimize material defects in building construction projects. Based on actual data, the neural network model was built and validated. A real-world data set from a large oil and gas sector organization was used to provide findings that can be used and replicated in practice. First, the main factors affecting the material defects in construction projects were identified based on the literature and reviewed by experts. Then, the best models were constructed and chosen among several developed models. The parameters of the proposed neural network model were set properly to achieve results with high performance. Moreover, the correlation between input factors and the output was investigated.

The results indicated that the proposed neural network model is capable and has high performance to classify and predict the material defects with an F-score of 90.50% and an accuracy of 93.74%. On the other hand, the findings revealed that the SVM achieves F-score with value of 89% and accuracy of 92%. The developed model is simple to use and will be extremely helpful to decision-makers in predicting and classifying defects in other fields. The effect of uncertainty in some parameters may be addressed in future research. In addition, other data-driven methods can be used to model such cases. As future work, developing hybrid models that combine ANNs with other machine learning techniques, such as decision trees and support vector machines, to enhance classification accuracy and robustness. Additionally, integrating the model into real-time IoT-enabled construction monitoring systems and deploying it on edge devices, such as smart cameras and mobile applications, can facilitate on-site defect detection with minimal latency. Future studies could also explore the application of the proposed model in other construction sectors, such as residential and commercial projects, to evaluate its generalizability across varying quality management practices and risk environments.

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Author's contributions

This work was equally contributed by all authors.

Conflict of interest

The authors reported no potential conflicts of interest.

Data availability statement

The data supporting the study's findings are available from the corresponding author upon reasonable request.

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