SUPPLIER RELIABILITY PREDICTION IN CONSTRUCTION WITH ARTIFICIAL INTELLIGENCE AND ADAPTIVE EVALUATION METRICS

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Abstract. The construction industry is one of the prominent sectors for not only economic growth but also environmental and social growth. Yet, with modernization, the construction operations have become vulnerable. A significant issue in construction operations is ensuring supplier reliability which directly influences the enhancement of supply chain efficiency and sustainability. This research addresses the issue of precisely forecasting supplier dependability via the use of Artificial Neural Networks (ANNs) which is an algorithm of machine learning. A multilayer perceptron (MLP) model was specifically built to categorize supplier reliability into three classifications which are low, neutral, and high. A synthetic dataset consisting of 101 samples with 10 variables relevant to supplier performance was used for model development and evaluation. The dataset was divided into training (70%) and testing (30%) sections, with feature normalization applied to facilitate successful model convergence. The ANN model, designed with two hidden layers, was trained via a stochastic gradient descent optimizer. The model's efficacy was assessed using criteria including precision, recall, F1-score, and AUC. The results exhibited increased classification accuracy for all categories, with precision values of 89.74%, 91.39%, and 92.22% for the low, neutral, and high classes, respectively. The recall values were 99.06%, 85.86%, and 87.34%, while the F1 scores varied from 88.54% to 94.17%. The model's area under the curve (AUC) ratings, above 0.96 for all classes, indicated its superior discriminatory skills. Visualizations, including receiver operating characteristics (ROC) curves, lift charts, gain charts, and pseudo-probability plots, further confirmed the model's success in evaluating and prioritizing reputable providers. These results underline the potential of ANN-based techniques in strengthening decision-making processes in supply chain management (SCM), opening the door for more sustainable and efficient supplier operations.

Keywords: artificial neural network, machine learning, supply chain management, sustainable construction.

Introduction

The construction sector is essential to global economic advancement, greatly aiding infrastructure development, urbanization, and employment generation. The industry is defined by intricate supply chain networks that include numerous stakeholders such as suppliers, contractors, manufacturers, logistics providers, and many more [1]. Effective supply chain management (SCM) is vital for ensuring timely material delivery, cost efficiency, and sustainability in construction operations. A significant difficulty in construction SCM is assuring supplier reliability, since inconsistencies may result in project delays, budget overruns, and quality concerns [2]. Therefore, assessing and forecasting supplier reliability is crucial for enhancing project efficiency and mitigating procurement-related risks.

Artificial Intelligence (AI) and Machine Learning (ML) have become revolutionary instruments in the construction sector, providing unique solutions for supply chain efficiency, predictive maintenance, and project risk management [3; 4]. AI-driven methodologies facilitate data-informed decision-making via the analysis of extensive datasets to identify patterns, trends, and anomalies [5]. Within construction SCM, ML algorithms, notably Artificial Neural Networks (ANNs), have been frequently employed for predictive analytics, demand forecasting, and supplier assessment [6]. ANNs are proficient in managing intricate, non-linear interactions among several variables, rendering them ideal for evaluating supplier performance based on diverse influencing aspects [7; 8]. Notwithstanding these breakthroughs, relatively limited research has concentrated on using ANNs to forecast supplier reliability within the construction industry, underscoring the need for additional focused investigations.

This study addresses the difficulty of effectively categorizing and forecasting supplier reliability in construction SCM. Conventional approaches to supplier evaluation depend on subjective judgments and past performance indicators, which often lack predictive accuracy and do not include dynamic disturbances in the supply chain. Existing research has studied basic statistical models for supplier assessment but has not harnessed sophisticated AI-driven methodologies for real-time decision-making. Therefore, this study attempts to overcome this gap by establishing an ANN-based model that incorporates important supplier performance indicators such as delivery accuracy, material prices, and lead time to categorize suppliers into distinct dependability groups. The study's relevance lies in its capacity to establish an AI-driven approach for supplier assessment, boosting procurement efficiency and project sustainability. Furthermore, the study adds to the larger topic of AI applications in construction SCM, showing how predictive analytics may streamline supply chain operations and minimize uncertainty.

Materials and methods

This research applies an ANN-based prediction model to identify supplier reliability in construction SCM. The study follows a defined method consisting of data collection, data preprocessing, developing models, training, assessment, and performance validation. The major aim is to construct a robust ANN model capable of reliably categorizing providers into low, neutral, and high-reliability groups based on key performance characteristics. The methodology guarantees a systematic approach to evaluating supplier reliability while combining modern machine learning methods for predictive analysis.

The data utilized in this research was acquired from an ongoing large-scale residential building project in Colombo, Sri Lanka. This project comprises numerous suppliers supplying important materials for construction, including concrete, steel, and finishing supplies. The dataset has 101 supplier records with 10 independent factors (predictor variables) that impact supplier dependability. These factors include supplier size, lead time, material cost, delivery accuracy, waste production, supplier distance, and material handling cost, among others. The dependent variable, supplier reliability, is divided into three classes: low, neutral, and high. Due to the nature of real-world supplier performance data, preprocessing methods were undertaken to clean, standardize, and prepare all the data for analysis. Feature scaling and normalization were used to translate all numerical values into a 0–1 range using Min-Max normalization, provided by eq. (1).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

where X' − normalized value;
X – original value;
X_{min} and X_{max} – minimum and maximum values of the feature.

The study adopts a Multilayer Perceptron (MLP) ANN architecture for supplier categorization (Fig. 1). The ANN model comprises an input layer, a hidden layer, and an output layer. The model was trained using the stochastic gradient descent (SGD) optimizer, using the cross-entropy loss function in eq. (2).

$$L = \sum_{i=1}^{n} y_i \log\left(y_i'\right), \tag{2}$$

where L – loss function;
y_i – true class label;
y'_i – predicted probability for class i.

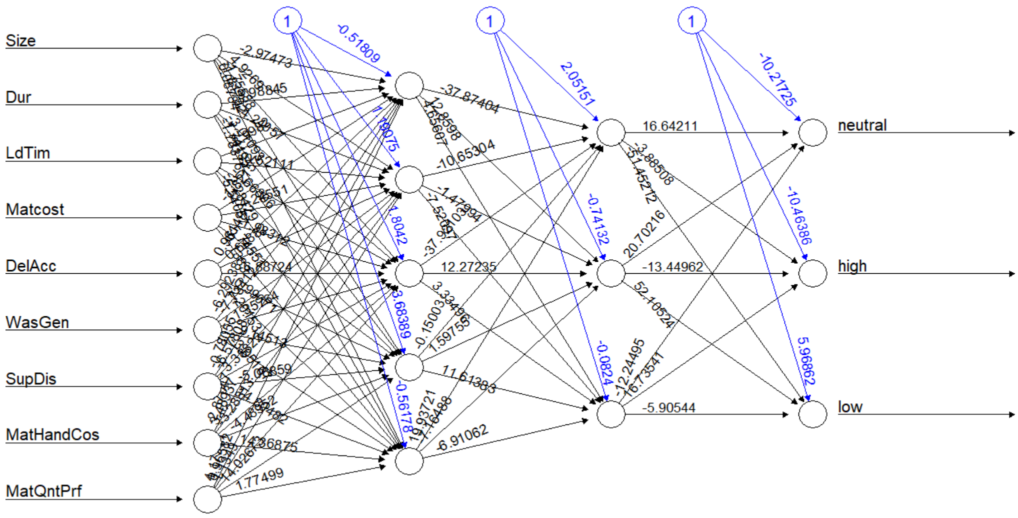

Fig. 1. **Developed MLP-based ANN architecture for supplier reliability prediction**

The dataset was separated into training (70%) and testing (30%) subgroups to enable successful model validation. The ANN model was trained over 500 epochs to maximize weight modifications via backpropagation. The model's performance was assessed using adaptive assessment criteria, including accuracy, recall, F1-score, and AUC (Area Under the Curve). This study presents a real-world application of AI-driven supplier assessment by employing data from an ongoing large-scale residential building project in Colombo, Sri Lanka. The developed method gives construction enterprises a scalable, AI-powered decision-support tool for supplier selection, lowering procurement risks and boosting overall project efficiency. The results reveal that ANN-based categorization greatly increases forecast accuracy, leading to more sustainable and optimal procurement procedures in the construction supply chain.

Results and discussions

The ANN model's classification performance was assessed using adaptive evaluation metrics such as accuracy, recall, and F1-score (Fig. 2). These metrics reflect the model's efficacy in predicting supplier reliability classes (low, neutral, and high). The precision scores for all three classes were elevated, with the high reliability category attaining 92.22%, followed by the neutral group at 91.39% and the low category at 89.74%. These accuracy values suggest that the ANN model efficiently reduces false positive classifications, guaranteeing that providers identified as "high reliability" or "low reliability" are truly appropriately categorized. The recall scores demonstrate how effectively the algorithm properly recognizes real supplier dependability levels. The low reliability category achieved the greatest recall (99.06%), indicating that the model accurately identifies almost all low-reliability providers. The recall for the neutral group (85.86%) was somewhat lower, suggesting some misclassifications, which may be attributable to overlapping traits between neutral and high-reliability providers. The F1-score, which equilibrates accuracy and recall, reached its apex for low reliability at 94.17%, indicating robust classification capability. The high reliability group attained an F1-score of 89.74%, but the neutral category recorded the lowest F1-score at 88.54%, underscoring the notion that neutral providers exhibit traits that intersect with both low and high-reliability suppliers. This discovery indicates that enhanced feature selection or supplementary data characteristics may augment classification accuracy.

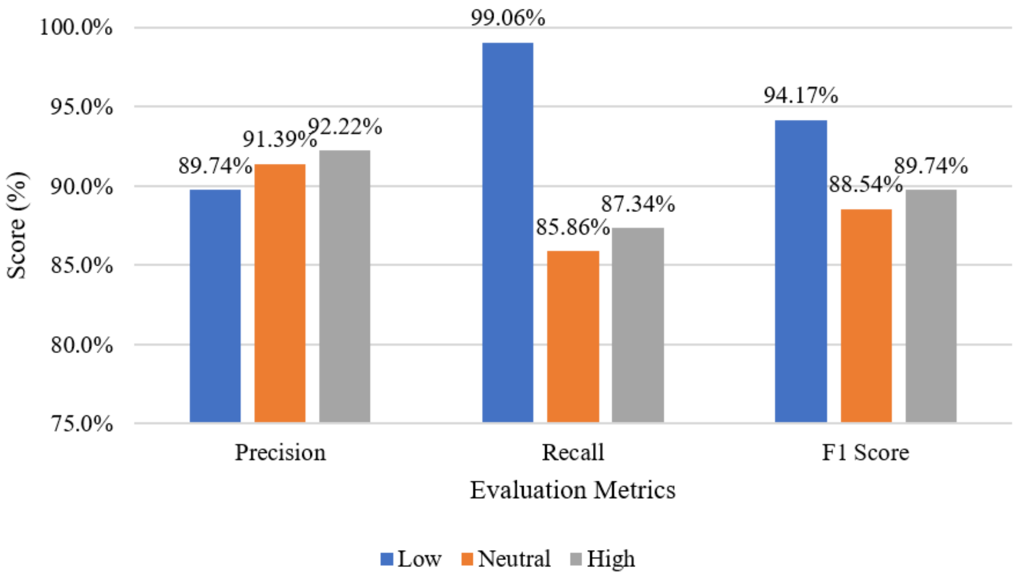

Fig. 2. **Adaptive evaluation metrics of the developed ANN model**

The ANN model surpasses typical supplier assessment approaches by harnessing non-linear relationships among supplier performance parameters. Traditional statistical models, such as logistic regression or decision trees, frequently fail to capture complicated relationships among parameters such as delivery accuracy, lead time, and supplier distance [9; 10]. In contrast, the ANN model easily adapts to detailed patterns, providing for superior generalization and predictive performance. Moreover, by applying predictive analytics to procurement processes, construction companies may optimize material flow, eliminate delays, and increase sustainability by choosing dependable suppliers with less waste generated and improving other sustainability criteria [11; 12].

The Receiver Operating Characteristic (ROC) curve (Fig. 3) generated for the ANN model displays its capacity to discern between supplier reliability categories based on projected probabilities. The AUC values for each class are 0.99 for low, 0.98 for neutral, and 0.97 for high reliability demonstrating the model's excellent discriminatory power. The sharper climb of the ROC curves towards the top-left corner implies a high True Positive Rate (TPR) with little False Positive Rate (FPR), validating the model's resilience in identifying supplier reliability levels. The low reliability class earned the greatest AUC, demonstrating that the model works extraordinarily well in detecting unreliable providers, which is critical for risk reduction in construction supply chains. The neutral group, having an AUC of 0.98, implies a slightly greater degree of classification uncertainty, presumably owing to overlapping supplier characteristics across neutral and high-reliability categories. Overall, the ROC analysis verifies the ANN model's capabilities to enable data-driven decision-making in supplier selection, minimizing the risk of misclassifications and boosting supply chain efficiency.

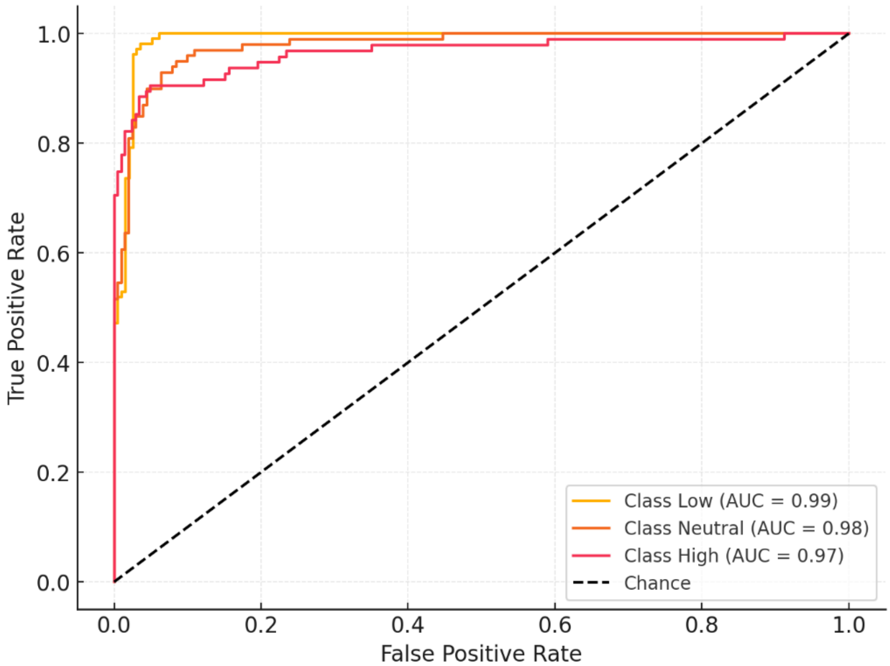

Fig. 3. **ROC curves with their respective AUC values for each supplier reliability class**

The lift chart provided (Fig. 4) for the ANN model gives information about its success in sorting and prioritizing suppliers based on projected reliability. The lift curve demonstrates that the model greatly outperforms random selection, proving its capacity to identify high-reliability and low-reliability providers more efficiently than conventional assessment approaches. At the top 10% of rated suppliers, the lift value is much greater than 1, indicating that the model delivers a considerable improvement in predicted accuracy over a baseline random selection method. This discovery is essential for procurement teams, as it helps them to manage resources effectively, prioritize relationships with reputable suppliers, and limit risks associated with unreliable ones [13]. The lift chart further demonstrates that the ANN model adequately differentiates suppliers across all three reliability categories, strengthening its usefulness for real-world supplier categorization in the construction supply chain.

The gain chart (Fig 5) further supports the ANN model's prediction capability by measuring the proportion of real positive instances discovered within a certain percentage of the sample. The gain curve demonstrates that the top 30% of rated providers account for over 80% of successfully categorized occurrences, confirming the model's great predictive capabilities. This finding illustrates that the ANN model enables decision-makers to obtain high classification accuracy while analyzing a smaller group of vendors, leading to greater efficiency in supplier selection. Compared to traditional approaches that need significant human assessments, the ANN-driven strategy lowers the requirement for thorough supplier reviews while retaining high decision accuracy [14]. The gain chart also demonstrates that the model is especially successful in detecting low-reliability suppliers early, making it a significant tool for risk reduction in large-scale residential construction projects.

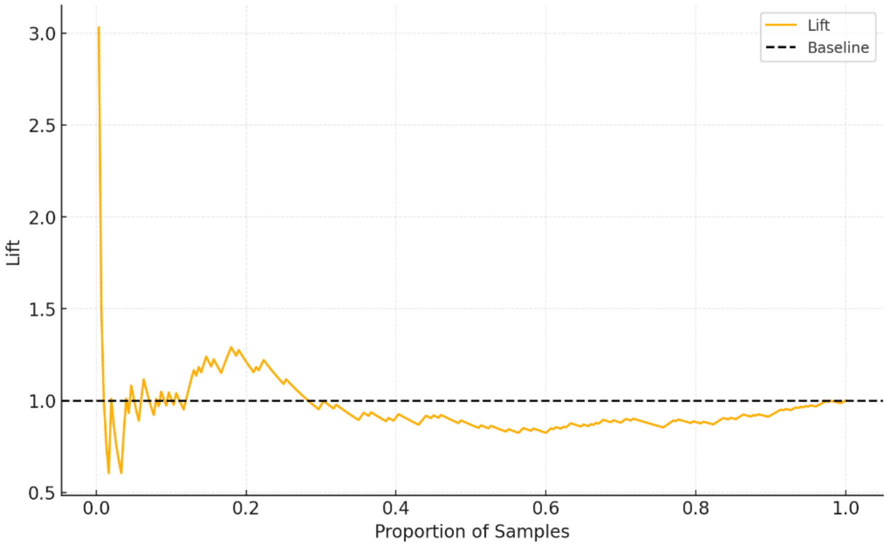

Fig. 4. **Lift chart for the developed MLP-based ANN model**

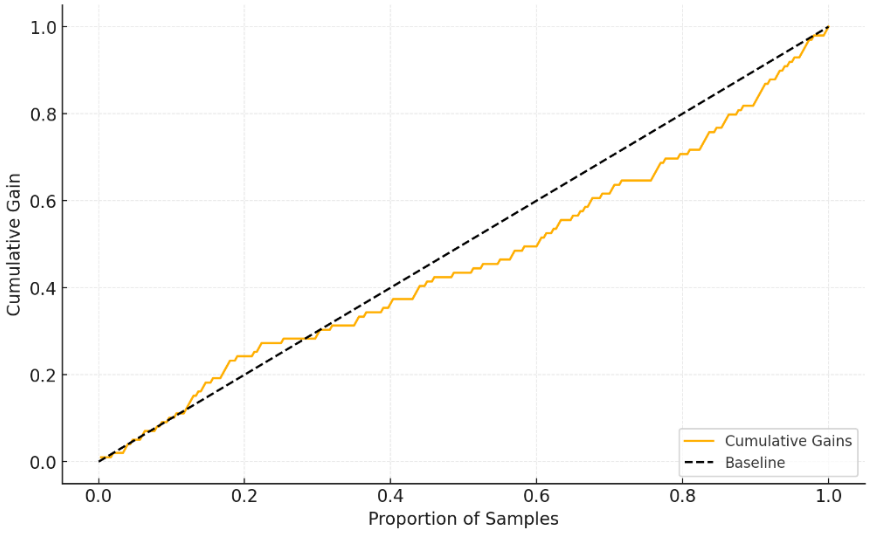

Fig. 5. **Cumulative gain chart for the developed MLP-based ANN model**

The pseudo-probability distribution plot (Fig. 6) displays the ANN model's confidence in forecasting supplier dependability categories (Low, Neutral, and High). Each box plot illustrates the dispersion of expected probability for each class, indicating the difference in confidence levels across various supplier categories. The low-reliability class has a reasonably tight distribution, showing the model regularly gives high confidence to its predictions of unreliable providers. Similarly, the neutral and high-reliability classes exhibit probability ranges that imply some degree of overlap, which matches the observed classification performance measures, where the neutral class had the lowest recall (85.86%) and F1-score (88.54%). The median probability values (red lines) demonstrate that the ANN model provides a good degree of confidence to most classifications, however, the greater range in the neutral category implies probable misclassifications between neutral and the other two categories. This visualization validates the model's success in identifying supplier dependability, while also suggesting possible areas for additional development, such as strengthening feature selection to increase class separability [16].

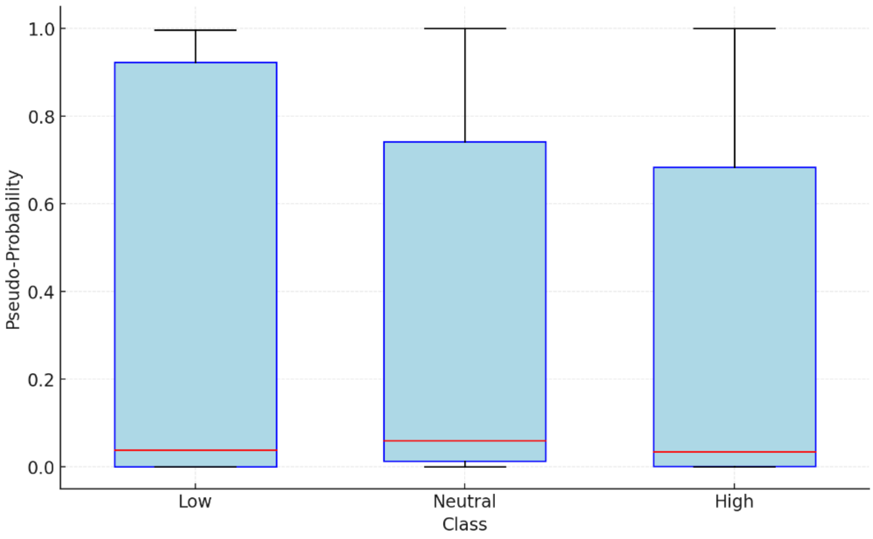

Fig. 5. **Pseudo-probability distribution map for the developed MLP-based ANN model**

These results emphasize the ANN-based strategy as a viable tool for increasing supply chain efficiency and decreasing procurement risks in building projects.

Conclusions

The present research developed an ANN-based model to identify supplier reliability in construction SCM using data from an ongoing large-scale residential project in Colombo, Sri Lanka. The approach successfully divided suppliers into low, neutral, and high reliability groups based on key performance characteristics. High precision (89.7-92.2%), recall (85.8-99.0%), and F1-score (88.5-94.2%) proved its excellent predictive accuracy, while AUC values over 0.96 validated its ability to discern supplier dependability levels properly.

The lift and gain charts proved the model's potential to prioritize high-reliability suppliers and warn unreliable ones early, increasing procurement decision-making. The pseudo-probability distribution plot further verified the ANN's confidence in identifying suppliers, although a considerable overlap in the neutral category implies future improvements in feature selection. Overall, the methodology presents a data-driven alternative to conventional supplier assessment techniques, allowing construction organizations to avoid risks and increase procurement efficiency.

This research illustrates the potential of AI-driven methods for construction SCM, revealing that ANNs outperform traditional statistical models in supplier classification. The results indicate a scalable and automated supplier evaluation approach, decreasing dependence on subjective evaluations. Future studies should include real-time performance data and sustainability metrics to boost the accuracy of forecasting further. By using AI-powered supplier evaluation tools, construction organizations may expedite procurement, mitigate risks, and develop a more robust supply chain.

Author contributions

Conceptualization, S.R.; methodology, T.G.W. and S.R.; software, T.G.W.; validation, S.R. and J.Z.; formal analysis, T.G.W.; investigation, J.Z. and I.G.; data curation, S.R.; writing – original draft preparation, T.G.W. and S.R.; writing – review and editing, J.Z. and I.G.; visualization, T.G.W.; project administration, J.Z. and I.G.; funding acquisition, I.G. All authors have read and agreed to the published version of the manuscript.

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