

ARTIFICIAL NEURAL NETWORK BASED PREDICTION OF CONSTRUCTION WORKERS ACCIDENT RISK FOR PROACTIVE SAFETY MANAGEMENT

Dhamotharan Valaguru¹, Arumugaprabu Veerasimman^{1*} and Ajith Subbiah^{2*}

¹Department of Mechanical Engineering, Kalasalingam Academy of Research and Education, Krishnankoil-626126, India

²Department of Fire Prevention & Protection Engineering, College of Engineering and Information Technology, Buraydah Private Colleges, Buraydah, 51418, Kingdom of Saudi Arabia

*Corresponding Author Email id: v.arumugaprabu@klu.ac.in and ajithadhavan@gmail.com

Abstract

Although machine learning techniques have been widely applied in construction safety, only a few studies have focused on predicting the accident risk level of individual workers before an accident occurs. This study develops a three-layer backpropagation Artificial Neural Network (ANN) model to predict the accident risk level of construction workers using eight parameters. Data were collected through a questionnaire survey conducted among 450 construction workers. The actual accident risk level was determined independently by three experienced safety officers using the majority voting method. The proposed ANN model was evaluated under four experimental conditions. Among the four conditions, Condition 4 achieved the best performance, with prediction accuracies of 93%, 91% and 89% for the training, testing and validation datasets. The corresponding classification errors were 7.0%, 8.9% and 11.1%. The results show that the proposed ANN model can accurately predict the accident risk level of construction workers. The developed model can also support proactive safety management by identifying high-risk workers and implement suitable preventive measures before accidents occur.

Keywords: ANN, Safety Management, Risk and Construction workers

1. INTRODUCTION

The construction industry is known to be one of the hazardous industries in India because of its dynamic work environment and parallel high-risk activities. Construction workers are regularly exposed to hazards such as working at heights, operating heavy equipment, electrical work, material handling and confined spaces [1]. There is a fact that every construction industry should follow the guidelines established by the central and state government. Even though

accidents continue to cause injuries, fatalities, property damage, project delays and financial losses. Several studies have reported that human error and behaviour based safety are the key factors for a large proportion of these accidents. Therefore, improving worker safety requires a proactive approach which can identify accident risks before an incident occurs rather than relying only on accident investigations after the event [2].

It is an acceptable fact that construction site accidents are also due to many worker-related factors such as safety training, toolbox talks, safety supervision, worker competency, work experience and working hours [3]. Each of these factors contributes to a worker's ability to identify the hazards, follow safe work practices and respond to unsafe conditions. Since these factors interact with one another, the relationship between the workers and accident risk is high [4]. As a result, conventional statistical methods may not be sufficient to determine their combined effect accurately.

Artificial Intelligence (AI) is an important tool for improving construction safety management in today's scenario. Among the different AI techniques, Artificial Neural Networks (ANN) are widely used because they can learn complex nonlinear relationships directly from the data sets. Unlike conventional mathematical models, ANN does not require predefined equations and can identify hidden patterns from historical data [5]. This makes ANN highly suitable for construction safety applications, where worker behaviour and site conditions change continuously.

Several researchers have successfully applied ANN in construction safety. ANN model is used to assess construction safety performance using safety-related indicators. ANN is used to predict construction site incidents based on task characteristics, workplace conditions and human factors. ANN is used to predict worker performance and support worker-task allocation for improving site safety. These studies clearly demonstrate that ANN is an effective tool for analyzing construction safety data and supporting safety-related decisions [6, 7].

More recent studies have also reported the successful use of ANN and other machine learning techniques for predicting accident occurrence, injury severity, unsafe behaviour and overall safety performance [8-10]. Their ability to analyze large datasets and identify hidden relationships has made them valuable in construction safety management related decisions. However, most of these studies focus on site-level safety performance, accident occurrence or worker performance [11, 12]. Only a limited number of studies have attempted to predict the

accident risk level of individual workers before an accident occurs. In addition, many existing models mainly depend on historical accident records or project-level safety indicators, while worker-specific safety factors have received comparatively less attention.

Another limitation in the existing literature is the way the target output is determined. Most previous studies use accident records or predefined safety indices as the model output [13, 14]. In practice, experienced safety officers assess workers every day based on their competency, safety compliance, work experience and performance at the site [15]. Their professional judgement provides valuable information for identifying workers who are more likely to be involved in accidents. Incorporating this expert knowledge into ANN model development can improve the practical usefulness of the prediction model and make it more suitable for real construction projects.

To overcome these limitations, the present study develops a three-layer backpropagation Artificial Neural Network to predict the accident risk level of individual construction workers. The proposed ANN model classifies each worker into one of three accident risk categories such as low, moderate and high. The main contribution of this study is the development of a practical ANN-based decision-support model for predicting the accident risk level of individual construction workers. Unlike previous studies that mainly assess construction site safety performance or worker performance, the proposed model focuses directly on worker-level accident risk prediction using worker-specific safety indicators and expert judgement. The developed model can help safety officers identify high-risk workers at an early stage and implement suitable preventive measures, such as additional training, closer supervision or task reassignment, before accidents occur. This proactive approach can support better safety management and contribute to reducing construction site accidents.

2. CASE STUDY

The proposed study was conducted at a large building construction site with approximately 450 workers involved in different construction activities. A structured questionnaire survey was used to collect the required data for the selected input variables. The workers provided information related to their work experience, participation in toolbox talks, daily working hours and the level of safety supervision at the site. Information on safety training was verified from the site records wherever available. To improve the accuracy and reliability of the data, the site safety officers were

also consulted. They were asked to assess the worker competency, PPE compliance and the hazard level of the assigned tasks. The collected data were checked for completeness and consistency before being used to develop the proposed ANN model.

3. MODEL DEVELOPMENT

The proposed ANN model was developed using a standard three-layer backpropagation neural network, as shown in Figure 1. The network consists of an input layer, a hidden layer and an output layer. The input layer receives the eight safety-related parameters collected from the construction site namely safety training (I_1), toolbox talks (I_2), safety supervision (I_3), PPE compliance (I_4), worker competency (I_5), work experience (I_6), working hours (I_7) and task hazard level (I_8). These inputs are processed in the hidden layer to learn the relationship between the safety factors and the accident risk level. Based on this learning, the output layer classifies the accident risk as Low, Moderate or High.

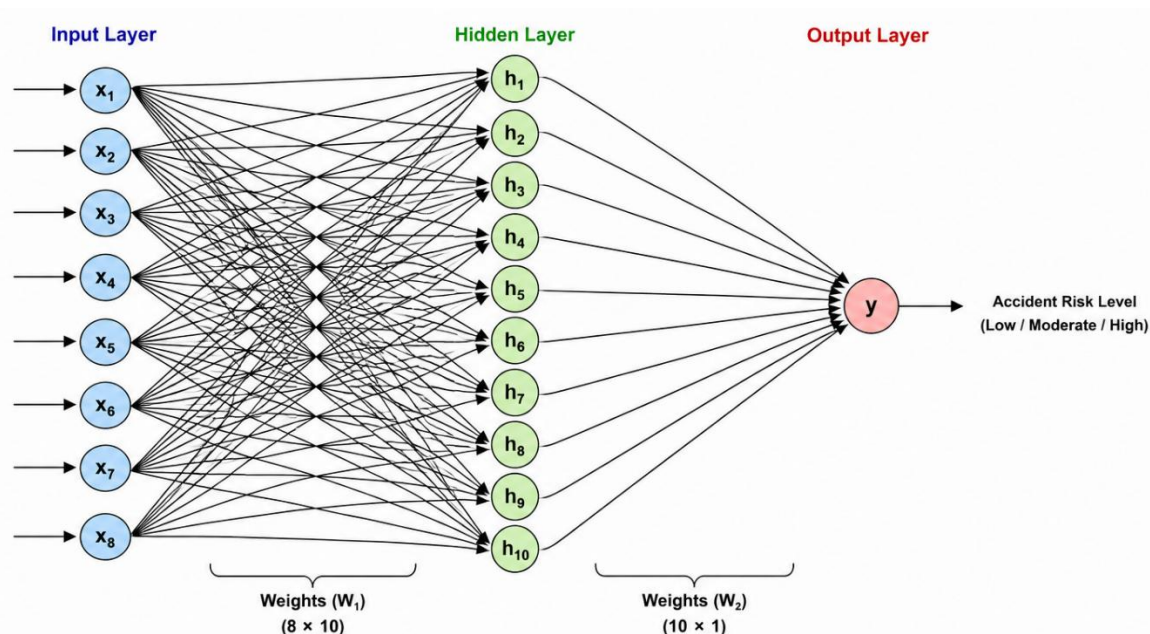


Figure 1 Three layer backpropagation ANN architecture

During the initial stage, different activation functions such as linear, hyperbolic tangent (tanh) and logistics were tested. Among these, the logistic activation function provided better prediction accuracy. The model was trained using the backpropagation algorithm, which updated the connection weights continuously to reduce the prediction error. The learning rate and

momentum were both set to 0.1, while the initial connection weight was fixed at 0.3. These values were finalized after several trial runs to obtain stable learning and consistent performance. For each experimental condition, the dataset was divided into 60% for training, 30% for testing and 10% for validation. The number of hidden neurons was also determined using a trial-and-error approach and 10 hidden neurons produced the best results for all four conditions. Then the predicted accident risk level was compared with the expert assigned risk level and the model performance was assessed using prediction accuracy and classification error.

4. RESULTS AND DISCUSSION

4.1 Data Pre-processing

To predict the accident risk level eight input variables were selected which is related to worker, management and task. Safety training, toolbox talks and safety supervision represent the safety practices followed by the organisation. Regular training, frequent toolbox talks and effective supervision improve workers' awareness of hazards and encourage safe work practices. PPE compliance and worker competency represent the worker's ability to work safely. Workers who consistently use the required PPE and possess the necessary skills are less likely to be involved in accidents. Work experience and working hours were also considered, as they influence both performance and safety. Experienced workers can generally identify the hazards, whereas longer working hours may lead to fatigue and reduced concentration. Task hazard level represents the level of risk associated with the assigned construction activity. High-risk tasks, such as working at heights or electrical work, naturally have a greater chance of accidents. The input data were pre-processed and converted into three levels as 1 – low to 3 – high as shown in Table 1.

Table 1 Data Pre-processing

Input	Measurement Method
Safety training	1 - No training (0 –2 hours) 2 - Basic training (3 – 8 hours) 3 - Comprehensive training (>8 hours)
Toolbox talks	1 - Once or less per week 2 – 2 – 3 times per week 3 - Daily or before every major task
Safety supervision	1 - Poor supervision 2 - Moderate supervision

	3 - Regular and effective supervision
PPE compliance	1 - PPE used in less than 50% of observations 2 - PPE used in 50–80% of observations 3 - PPE used in more than 80% of observations
Worker competency	1 - Unskilled 2 - Semi-skilled 3 - Skilled
Work experience	1 - Less than 2 years 2 - 2–5 years 3 - More than 5 years
Working hours	1 - More than 10 hours/day 2 – 8 –10 hours/day 3 - Less than 8 hours/day
Task hazard level	1 - High-risk task 2 - Medium-risk task 3 - Low-risk task

A three-level scale (low, medium, high) was adopted because it is simple and practical for use at construction sites. It allows site engineers and safety officers to assess workers quickly and consistently without complex calculations. The clear categories also help reduce subjectivity during data collection.

4.2 Conditions for the Models

The model was evaluated under four different conditions to assess its prediction performance. The model was evaluated under four different conditions to assess its prediction performance. In Condition 1 (C_1), the model performance was assessed using workers categorised to the low accident risk category. Condition 2 (C_2) evaluated the prediction performance for workers in the moderate accident risk category, while Condition 3 (C_3) evaluated on workers classified under the high accident risk category. Condition 4 (C_4) included workers from all three accident risk categories, representing the actual construction site environment.

4.3 Determination of Actual Accident Risk Level

Since the accident risk level cannot be measured directly, it was determined using expert judgement. Three experienced safety officers, each with more than five years of experience in construction safety management, were selected as the expert panel. Before the assessment, the experts were briefed on the objectives of the study and the evaluation criteria to ensure a common

understanding of the process. Each expert independently reviewed the input data of every worker. The assessments were carried out independently without any discussion among the experts to avoid bias. After the evaluation, the three ratings were compared and the majority voting method was used to determine the final accident risk level as shown in Table 2. For example, if two experts assigned moderate risk and one expert assigned High risk, the final classification was moderate. The final accident risk level was considered as the experimental value and was used as the target output for training and testing the proposed ANN model.

Table 2 Actual Accident Risk Level

S. No	Expert 1	Expert 2	Expert 3	Accident Risk Level
1.	Low	Low	Moderate	Low
2.	Moderate	Moderate	High	Moderate
3.	High	High	High	High
4.	Low	Moderate	Low	Low
5.	Moderate	High	Moderate	Moderate
6.	High	Moderate	High	High
7.	Low	Low	Low	Low
8.	Moderate	High	High	High
9.	Low	Moderate	Moderate	Moderate
10.	High	Low	High	High

4.4 Determination of Predicted Accident Risk Level

The model parameter such as learning rate, activation function, initial weight, momentum and neurons are chosen randomly and refined on trial and error basis. The prediction accuracy of the proposed ANN model under the four experimental conditions (C1–C4) is presented in Figure 2. The training dataset achieved the highest accuracy in all the conditions. The accuracy then decreased slightly for the testing and validation datasets, showing that the model performed well even on unseen data. Among the four conditions, C₄ (Mixed Risk) gave the best results, with prediction accuracies of 93%, 91%, and 89% for the training, testing, and validation datasets, respectively. This was closely followed by C₃ (High Risk), which achieved 92%, 90% and 87%.

Although C₁ (Low Risk) and C₂ (Moderate Risk) showed slightly lower accuracies, both maintained more than 82% prediction accuracy across all datasets. The small reduction in accuracy from training to validation indicates that the proposed ANN model has good generalization capability. The results confirm that the proposed ANN model can accurately predict the accident risk level of construction workers under different conditions.

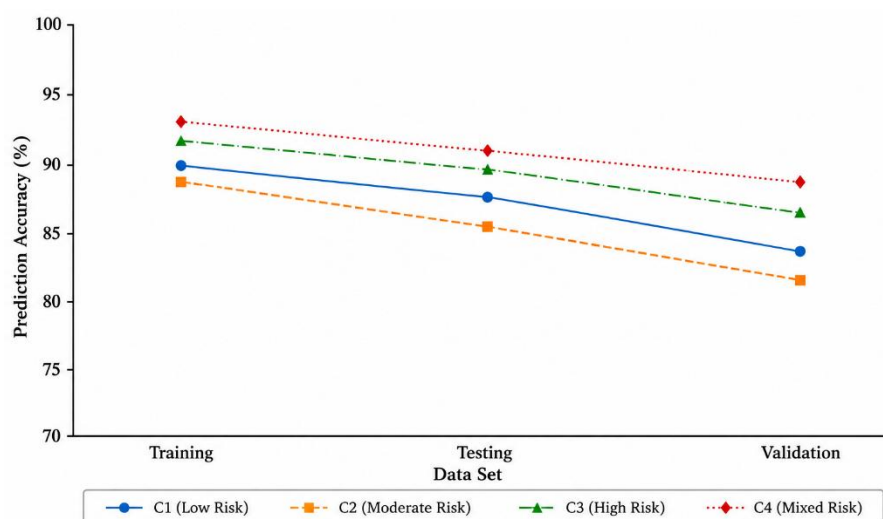


Figure 2 Prediction Accuracy

4.5 Classification Error of the Proposed ANN

The classification error of the proposed ANN model under the four experimental conditions is presented in Table 3. In all the conditions, the training dataset recorded the lowest error, followed by the testing and validation datasets. This shows that the model learned the training data well and maintained good prediction performance for unseen data. Among the four conditions, C₄ (Mixed Risk) achieved the lowest classification error, with 7.0%, 8.9%, and 11.1% for the training, testing, and validation datasets, respectively. This was closely followed by C₃ (High Risk), which recorded error values of 8.1%, 9.6%, and 13.3%. On the other hand, C₁ (Low Risk) and C₂ (Moderate Risk) showed slightly higher error values, with C₂ recording the highest validation error of 17.8%. However, the error remained below 18% in all the experimental conditions. This indicates that the proposed ANN model can classify the accident risk level of construction workers with good accuracy and consistent performance.

Table 3 Classification Error

Condition	Data Set	No. of Data	Correct Predictions	Incorrect Predictions	Error (%)
C1	Training	270	243	27	10.0
	Testing	135	119	16	11.9
	Validation	45	38	7	15.6
C2	Training	270	240	30	11.1
	Testing	135	116	19	14.1
	Validation	45	37	8	17.8
C3	Training	270	248	22	8.1
	Testing	135	122	13	9.6
	Validation	45	39	6	13.3
C4	Training	270	251	19	7.0
	Testing	135	123	12	8.9
	Validation	45	40	5	11.1

5. CONCLUSION

This study developed a three layer backpropagation ANN model to predict the accident risk level of construction workers using eight safety-related input parameters. The actual accident risk level was determined through expert judgement by experienced safety officers and used as the target output for training and evaluating the ANN model. The model was then tested under four experimental conditions to assess its prediction performance.

The results showed that the proposed ANN model performed well under all four conditions. Among them, Condition 4 achieved the highest prediction accuracy with 93%, 91% and 89% for the training, testing and validation datasets. The classification error remained below 18% in all the conditions. This indicates that the model has good prediction capability.

The developed model can serve as a practical decision-support tool for construction safety officers. It helps identify workers with higher accident risk at an early stage, allowing suitable preventive measures such as additional safety training, closer supervision, improved PPE

compliance. This proactive approach can support better safety management and help reduce accidents at construction sites.

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