Multi-Objective Optimization of Construction Worker Unsafe Behavior Inducement Prediction Model

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Abstract. The predictive model for the causative factors of unsafe behaviors among construction workers is optimized with a multi-objective approach, based on the analysis of 27 factors and the use of four machine learning algorithms (CART, RF, AdaBoost, and GBDT) and genetic algorithms. Through a three-dimensional analysis of importance, correlation strength, and influence, five factors, namely risk awareness, education and training, hidden danger investigation and control, supervision level, and planning and design level, were identified to have the most significant impact on unsafe behaviors. This study aims to support the high-quality development of modern construction industry by studying the causative factors of unsafe behaviors among construction workers.

Keywords: machine learning · unsafe behaviors among construction workers · multi-objective optimization model · modern construction industry · high-quality development

1 Introduction

Despite China's booming construction industry, the unsafe behavior of workers is a pressing issue that needs to be addressed. However, existing research lacks precision and comprehensive analysis, hindering effective interventions. Through extensive analysis, this study identified unsafe behaviors such as not wearing safety gear, irregular and illegal work practices, with root causes stemming from individuals, organizations, and the work environment Factors [1–12]. Using machine learning and genetic algorithms, we developed a multi-objective optimization model that accurately predicts the causes of unsafe behavior, providing valuable guidance for effective safety management.

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2 Overview of Theory and Methods

2.1 Theory of Cause of Accidents

Accident causation theory is a theory applied to the fields of engineering and risk management to identify and analyze the root causes of accidents. The basic premise of the theory is that accidents are not caused by a single cause, but by the interaction of multiple causes. Therefore, in order to prevent accidents, it is necessary to grasp these causes and take corresponding measures to control them.

2.2 Introduction to Research Methods

Machine learning is a type of artificial intelligence that automatically learns from data to make predictions or decisions using computer algorithms and mathematical models. It is used in tasks such as prediction, classification, and clustering, and is widely used in the security field. However, few studies have explored the triggers of unsafe behaviors. This study used four algorithms to establish a predictive model for unsafe behavior and selected the best route based on Fig. 1.

Genetic algorithm is an optimization algorithm that mimics natural selection and genetic processes to optimize individual fitness through continuous operations such as crossing, mutation, and selection. It is useful for solving complex optimization problems and is applied in machine learning, intelligent optimization, and engineering.

3 Identification of Indicators of Inducing Unsafe Behavior Among Construction Workers

This study analyzed data from 237 construction accidents sourced from various government websites and combined it with existing literature research. Using frequency statistics, the study identified 27 predisposing factors for unsafe behavior amongst construction workers after removing small, representative ones. The factors and their interpretations are presented in Table 1.

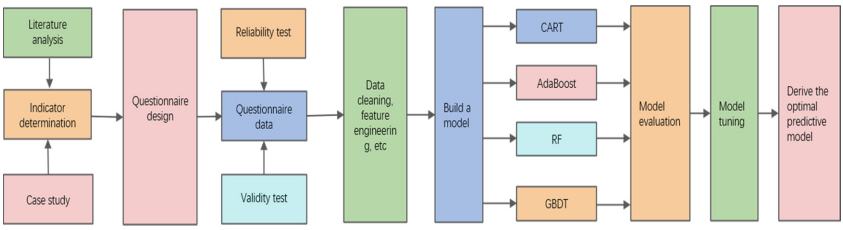

Fig. 1. Route map selected by the optimal predictive model

Table 1. List of predisposing factors and interpretations of unsafe behavior of construction workers

Level 1 indicators	Secondary indicators	Level 1 indicators	Secondary indicators
Personal factors	Risk awareness	Personal factors	Age factor
	Mental state		Personal qualities
	Education		Behavioral habits
	Work experience		Skill level
	Professional qualifications		Job attitude
Organizational factors	Education and training	Organizational factors	Safety management system
	Managers are derelict in their duties		Emergency response capability
	Level of supervision		Workload
	Hidden danger investigation and management		Supervision of relevant parties
	safety precautions		Planning and design level
	Leadership values		Subcontracting management
	Level of regulation		/
environmental factors	Engineering environment	environmental factors	Social norms
	corporate culture		Well equipped facilities

4 Model Establishment and Analysis Based on Machine Learning

4.1 Data Preprocessing and Feature Engineering

Data preprocessing and feature engineering are crucial steps in machine learning to make raw data more suitable for training and prediction of machine learning algorithms. Data preprocessing includes data cleaning, data integration, data transformation and data normalization; Feature engineering includes feature extraction, feature selection, feature transformation, and feature construction. In this study, the raw data has been preprocessed and feature engineered to ensure data quality and extract effective features.

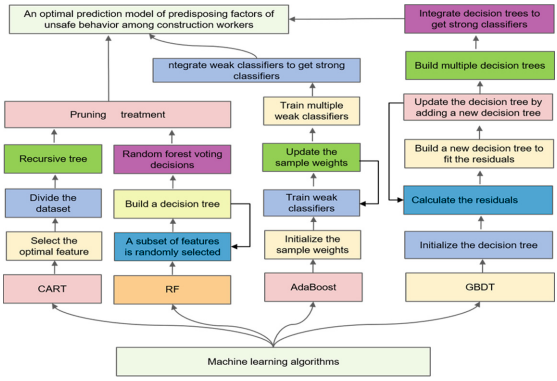

Fig. 2. Algorithm flowchart

4.2 Algorithm Selection

Building predictive models for the causes of unsafe behavior in construction workers is complex, requiring consideration of multiple factors. Since the problem involves classification and regression, several machine learning algorithms are used. CART identifies important factors, RF improves accuracy and stability, AdaBoost enhances accuracy in imbalanced or noisy data, and GBDT improves accuracy with nonlinear relationships or interaction effects. The use of these four algorithms comprehensively considers multiple factors and improves the model's accuracy and stability.

4.3 Algorithm Modeling Process

The machine learning modeling process involves data collection & preprocessing, feature engineering, model selection/training/evaluation/tuning, deployment, and monitoring. This study simplified the first three stages and selected four algorithms (CART, RF, AdaBoost, GBDT) to predict unsafe behavior in construction workers. Figure 2 shows the algorithm flow.

4.4 Model Evaluation

The model's optimal parameters are obtained through iteration and adjustment on the training set, while the accuracy, precision, and recall on the test set are used to evaluate the model's performance. The final parameters and evaluation accuracy are essential indicators to assess the model's quality and select the appropriate one. This study utilizes four machine learning algorithms (CART, RF, AdaBoost, and GBDT) to build a more accurate and reliable model. The iterative training process involves cross-validation to assess model performance. The evaluation results are presented in Figs. 3–5 for comparative analysis.

This study assessed four classification algorithms (CART, RF, AdaBoost, GBDT) using 3-10x cross-validation. The results showed that AdaBoost and GBDT had high accuracy and recall rates, while RF had the highest accuracy and F1 metrics. However,

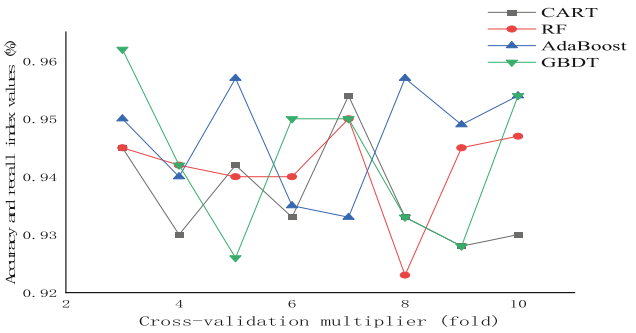

Fig. 3. Accuracy and recall index values

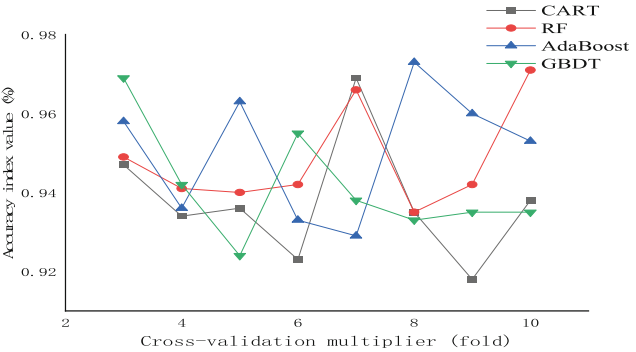

Fig. 4. Accuracy index value

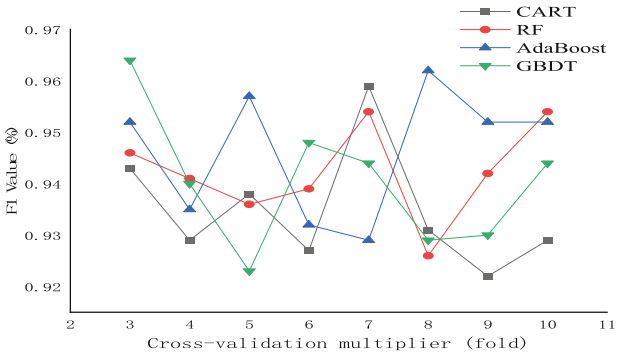

Fig. 5. F1 Value indicator value

since training and test sets differ for each cross-validation, averaging performance may mask differences. Therefore, separate accuracy and F1 values were calculated, and aggregated values were used as evaluation indicators. The AdaBoost algorithm was found to have the best performance in predicting unsafe behavior.

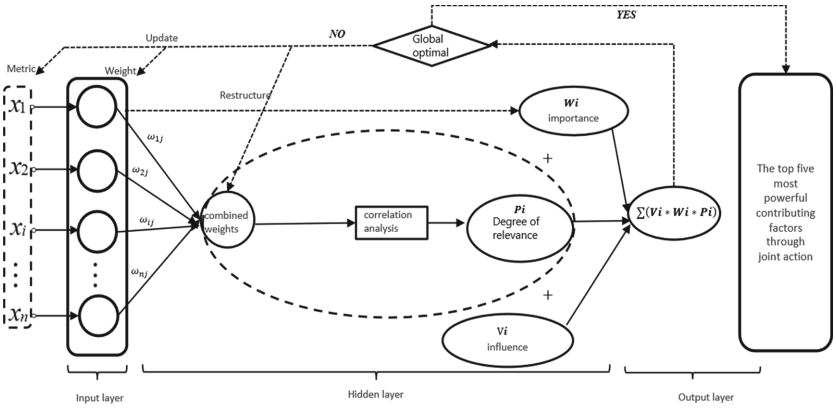

Fig. 6. Technology roadmap for the combination analysis of predisposing factors of unsafe behavior among construction workers

5 Analysis of the Combination of Factors that Predispose to Unsafe Behavior of Construction Workers

In this study, the number and frequency of triggers of 237 related accident cases were statistically analyzed, and it was found that the trigger frequency points of 3–7 accidents were more concentrated. On this basis, five indicators are selected for linkage and combination to better reflect the comprehensive risk degree of accidents. In this study, the inducing factors of unsafe behavior of construction workers were analyzed from three dimensions: influence, correlation degree and importance. The technical route of the combination analysis of the inducing factors of unsafe behavior of construction workers in this study is shown in Fig. 6.

5.1 Analysis of Results

Matlab was used to create a multi-objective optimization model in this study, with a population of 40, maximum 100 iterations, crossover probability of 0.8, and mutation probability of 0.1. Results showed that five factors - risk awareness, education and training, hidden danger investigation and governance, supervision level, and planning and design level - had the greatest impact on the unsafe behavior of construction workers.

6 Conclusion and Outlook

This study identified 27 triggers of unsafe behavior in construction workers and developed a machine learning model to predict unsafe behavior. The multi-objective optimization model ranked risk awareness, education and training, hidden danger investigation and management, supervision level, and planning and design level as the most significant factors. Future research can explore additional factors and use advanced techniques to optimize safety management for construction workers, providing a safer work environment.

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