Development of an Artificial Intelligence-Based Predictive Risk Assessment Framework for Industrial Construction Safety Using Near-Miss and Incident Data

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Abstract

Industrial construction projects involve numerous hazards associated with lifting operations, working at height, electrical installations, confined spaces, and heavy equipment. Conventional safety management often depends on inspections and retrospective accident analysis, limiting the use of historical safety information for proactive risk prediction. This paper proposes an artificial intelligence (AI)-based predictive risk assessment framework integrating near-miss reports, incident records, safety observations, and project characteristics to estimate future safety incident likelihood. The framework incorporates data preprocessing, feature engineering, machine learning, natural language processing, probabilistic risk estimation, and explainable AI. Logistic regression, random forest, and gradient-boosting algorithms are proposed for comparative evaluation. Performance will be assessed using precision, recall, F1-score, area under the receiver operating characteristic curve, precision-recall area under the curve, and probability calibration. The proposed framework aims to identify recurring hazards, prioritise high-risk activities, and support preventive safety interventions. Empirical validation using real industrial construction data is required before implementation.

Keywords: Artificial intelligence, industrial construction, predictive risk assessment, near-miss reporting, machine learning, incident prediction, occupational safety.

1. Introduction

Industrial construction projects involve complex work environments where changing site conditions, multiple contractors, equipment movement, and simultaneous operations create significant occupational safety challenges. Activities such as crane operations, scaffolding, hot work, excavation, electrical installation, and confined-space entry require continuous hazard identification and effective risk control.

Traditional safety management approaches include inspections, toolbox talks, permit-to-work systems, incident investigations, and risk matrices. Although these methods are essential, they often focus on existing hazards or incidents that have already occurred. The increasing availability of digital safety records provides an opportunity to develop predictive approaches that identify emerging risks before an accident takes place.

Near-miss reports are particularly valuable because they document events that could have caused injury or damage but did not result in an adverse outcome. When analysed alongside incident records and safety observations, these reports may reveal recurring hazards, ineffective controls, and unsafe work patterns.

Artificial intelligence offers techniques for extracting information from large datasets and identifying complex relationships between operational conditions and safety outcomes. Tixier et al. (2016) demonstrated the potential of machine learning for predicting construction injury outcomes using attributes extracted from injury reports. Baker et

al. (2020a, 2020b) further investigated machine learning and natural language processing for predicting safety outcomes and identifying injury precursors.

Despite these developments, practical implementation requires careful attention to data quality, underreporting, class imbalance, model interpretability, and validation across different projects. This paper proposes an integrated framework for addressing these challenges in industrial construction safety.

1.1 Research Aim and Objectives

The primary aim is to develop an AI-based predictive risk assessment framework using near-miss and incident data to support proactive safety management in industrial construction projects.

The objectives are to:

1. Identify important safety risk indicators from near-miss reports, incident records, and safety observations.
2. Develop a structured dataset integrating safety and project-related variables.
3. Compare machine learning algorithms for predicting future incidents.
4. Identify influential risk factors using explainable AI.
5. Propose a decision-support mechanism for prioritising inspections and preventive measures.

2. Literature Review

Traditional construction risk assessment commonly uses qualitative or semi-quantitative methods based on hazard severity and likelihood. Although these approaches are useful for workplace planning, their outcomes may depend on expert judgement and the quality of available information.

Tixier et al. (2016) applied random forest and stochastic gradient tree boosting to construction injury reports and demonstrated that machine learning can predict several injury-related outcomes. Their research established the potential of data-driven safety analysis.

Baker et al. (2020a) investigated the automatic identification of injury precursors from unstructured construction accident reports using natural language processing and machine learning. Their work demonstrated that textual safety narratives can contain predictive information about accident-related outcomes.

Baker et al. (2020b) examined the prediction of independent construction safety outcomes using attributes extracted from injury reports. The study compared random forest, XGBoost, and linear support vector machines, highlighting the value of structured attributes and comparative model evaluation.

These studies support the application of AI to construction safety; however, industrial construction presents specific challenges involving multiple contractors, complex work packages, and changing operational conditions. Near-miss data may provide additional leading indicators, but their usefulness depends on consistent reporting practices and appropriate interpretation.

A further challenge is that severe incidents are relatively uncommon, which can make model training difficult. In addition, a model must be interpretable enough to support safety professionals in deciding which hazards require immediate attention.

The proposed research addresses these issues by integrating near-miss information, incident records, predictive modelling, probability calibration, and explainable AI within a single methodological framework.

3. Research Methodology

3.1 Research Design and Data Collection

The proposed study will use a quantitative, data-driven research design based on historical safety records from industrial construction projects. Data may be collected from contractors, project safety departments, incident registers, inspection reports, and digital safety-management systems, subject to organisational permission.

The dataset should include the following categories:

- **Near-miss data:** Event type, date, location, hazard category, and potential consequence.
- **Incident data:** Incident type, injury severity, event mechanism, and investigation findings.
- **Safety observations:** Unsafe acts, unsafe conditions, inspection findings, and corrective actions.
- **Project characteristics:** Project phase, contractor, workforce size, work zone, and work hours.
- **Operational variables:** Lifting operations, work at height, electrical activities, confined-space work, and equipment use.
- **Environmental variables:** Weather, visibility, and relevant site conditions, where available.

Personal identifiers should be removed or pseudonymised before analysis.

3.2 Data Preprocessing and Feature Engineering

The collected records will be cleaned and standardised to establish consistent event categories and variable definitions. Missing values, duplicate reports, inconsistent timestamps, and incorrect entries will be examined.

Feature engineering will generate variables that represent the safety conditions preceding a potential incident. Examples include the number of recent near misses, frequency of repeated hazards, unresolved safety observations, time since the previous incident, corrective-action closure rates, and worker-hours.

Where safety reports contain unstructured text, natural language processing can extract information about hazard types, unsafe conditions, equipment involvement, and contributing factors. Text processing may begin with term-frequency and inverse-document-frequency features before considering more advanced language models.

Only information available before the prediction date will be used. This restriction is necessary to prevent data leakage from investigation conclusions or corrective actions recorded after an incident.

3.3 Development of Machine Learning Models

Three principal algorithms will be evaluated.

Logistic regression: This will provide an interpretable baseline for estimating incident probabilities and identifying associations between predictors and outcomes.

Random forest: This ensemble method can capture nonlinear relationships and interactions among safety variables and can accommodate complex patterns in structured datasets.

Gradient boosting: Algorithms such as XGBoost will be investigated for their ability to model interactions and achieve strong predictive performance in structured data.

The primary prediction task will estimate whether a qualifying incident occurs within a predefined future period, such as the next seven days, for a given project work zone. The forecast horizon will be determined before model training.

The predicted probability is expressed as:

$$P(Y_{i,t}=1 \mid X_{i,t})$$

where $Y_{i,t}$ indicates whether an incident occurs during the defined future period, and $X_{i,t}$ represents the safety and operational information available at prediction time.

3.4 Risk Assessment Framework

The proposed framework will convert predicted incident probabilities into information that can support safety decisions. An illustrative risk index is:

$$R_{i,t}=P(Y_{i,t}=1 \mid X_{i,t}) \times C_{i,t}$$

where $C_{i,t}$ is a predefined consequence-weighting score.

The resulting index may help prioritise work zones for additional inspections or safety reviews. Risk categories will be defined according to validated probability thresholds, consequence levels, and organisational requirements.

This index is a proposed decision-support measure, not a substitute for formal risk assessment or mandatory safety controls. Even a low predicted probability must not be used to justify unsafe work or reduce required precautions.

3.5 Model Validation and Evaluation

The dataset will be separated chronologically into training, validation, and testing periods. Where sufficient data are available, validation across separate projects will also be undertaken to assess generalisability.

Performance will be assessed using:

- **Precision:** The proportion of predicted incident cases that are actual incident cases.
- **Recall:** The proportion of actual incident cases identified by the model.
- **F1-score:** The harmonic mean of precision and recall.
- **ROC-AUC:** The ability to distinguish incident from non-incident cases across classification thresholds.
- **PR-AUC:** The quality of predictions when incident cases are relatively rare.
- **Brier score:** The accuracy of predicted probabilities relative to observed outcomes.

Class weighting or resampling may be considered if the dataset is imbalanced, but these techniques will be applied only within the training process. Probability calibration and false-alert burden will also be examined.

3.6 Explainable AI and Decision Support

Explainable AI techniques, such as SHAP, will be used to identify features contributing to predicted risk. These may include recurring near misses, unresolved observations, hazardous work activities, and workforce exposure.

The explanations will be reviewed by safety professionals to assess their practical relevance. Feature importance will not be interpreted as proof of causation.

A prototype dashboard could display risk estimates, trends across work zones, recurring hazards, and recommended inspection priorities. Safety personnel would retain responsibility for evaluating alerts and implementing appropriate controls.

4. Expected Results and Discussion

The proposed framework is expected to provide a structured approach for transforming historical safety information into predictive risk indicators. The integration of near-miss records and incident data may help identify recurring hazards and operational conditions associated with subsequent incidents.

Comparative model evaluation is expected to establish which algorithms provide the most useful balance between recall, precision, probability calibration, and interpretability. Natural language processing may provide additional value by extracting hazard information from narrative safety reports.

Explainable AI may help identify the principal factors contributing to elevated risk estimates, allowing safety managers to prioritise inspections and review existing controls. The framework may also improve the consistency of risk monitoring across project phases and work zones.

However, these benefits remain hypotheses until the models are trained and evaluated using actual data. Underreporting of near misses, differences in contractor reporting practices, missing records, and changes in site conditions may affect predictive reliability. Rare severe incidents may also limit the model's ability to estimate severity accurately.

The proposed approach should therefore complement established safety procedures rather than replace them. A prospective pilot would be required to assess alert usefulness, user acceptance, and operational feasibility. Demonstrating a reduction in accidents would require a separate evaluation of the interventions informed by the model.

5. Conclusion

This paper proposes an AI-based predictive risk assessment framework for industrial construction safety using near-miss reports, incident records, safety observations, and project characteristics. The methodology integrates data preprocessing, feature engineering, machine learning, probability estimation, explainable AI, and decision support.

The framework aims to support proactive safety management by identifying recurring hazards, estimating future incident likelihood, and prioritising preventive interventions. Its effectiveness will depend on data quality, consistent reporting, appropriate validation, and the interpretation of predictions within established safety-management practices.

Future research should implement the proposed framework using real industrial construction datasets, compare the predictive performance of candidate algorithms, and validate the resulting model across independent projects. Further prospective evaluation should determine whether model-informed interventions produce measurable improvements in workplace safety.

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