ISSN: 2633-4828 Vol. 6 No.4, December, 2024

International Journal of Applied Engineering & Technology

AI-BASED RISK MANAGEMENT AND SAFETY IN CONSTRUCTION PROJECTS: A CASE STUDY OF PUNE CITY, MAHARASHTRA

Prof. A. N. Bhirud [1] and Ms. Sayali Chandrashekhar Chaudhari [2]

[1]Assistant Professor, Department of Civil Engineering, Imperial College of Engineering and Research, Wagholi, Pune-412207

[2]PG Student (ME- Construction Management), Department of Civil Engineering , JSPM'S Imperial College of Engineering and Research, Wagholi, Pune-412207

ABSTRACT

The construction industry is inherently prone to risks due to its dynamic, labor-intensive, and complex nature, particularly in rapidly urbanizing regions like Pune City, Maharashtra. Despite the implementation of traditional safety protocols, construction sites continue to witness frequent accidents, delays, and financial losses. This study explores the application of Artificial Intelligence (AI) in enhancing risk management and safety outcomes in civil engineering construction projects within Pune. The research adopts a mixed-method approach, combining primary data collection through surveys and expert interviews with AI-based modeling techniques such as Artificial Neural Networks (ANN) and decision tree algorithms. Key construction-related risks were identified, ranked, and predicted using AI tools to assess potential hazards and mitigate them in advance. The study found that AI integration significantly improved the prediction accuracy of accident-prone scenarios, enabled proactive decision-making, and reduced response time in risk mitigation. The results highlight the potential of AI to transform traditional risk management frameworks into intelligent, adaptive systems. This paper contributes to the growing body of knowledge on smart construction practices in India and offers actionable recommendations for policymakers, contractors, and engineers to adopt AI-driven safety mechanisms. The findings underscore the need for digital transformation in the construction sector to meet future urban infrastructure demands safely and efficiently.

Keywords: *AI in construction, risk management, safety systems, construction safety, civil engineering, predictive analytics, Pune construction industry, accident prevention, artificial intelligence, ANN, Maharashtra infrastructure.*

1. INTRODUCTION

1.1 Background of Construction Industry Risk Factors

The construction industry is globally recognized for its high-risk environment due to its complex, dynamic, and labor-intensive nature (Zhou et al., 2012). Projects often face unpredictable challenges such as design errors, poor site management, equipment failures, and unsafe work practices. In India, the construction sector accounts for a significant proportion of occupational accidents and fatalities, second only to the manufacturing industry (National Crime Records Bureau, 2020). The unorganized nature of small- and medium-scale construction enterprises exacerbates these issues, leading to ineffective safety enforcement (Jadhav & Bhirud, 2015).

1.2 Significance of Risk Management in Urban Construction (Pune as a Case)

Urban centers like Pune, Maharashtra, are undergoing rapid infrastructure development, including high-rise buildings, metro rail projects, and road networks. This surge in construction activity increases the exposure to safety hazards due to congested workspaces, labor migration, and environmental constraints (Bansal & Agrawal, 2019). Effective risk management is thus essential not only to reduce accidents but also to ensure timely project delivery and cost efficiency (Bhirud & Revatkar, 2016). Traditional risk management tools such as hazard identification and control checklists are often reactive rather than predictive (Kale & Patil, 2021).

1.3 Emergence of Artificial Intelligence in Safety Management

Recent advances in Artificial Intelligence (AI) have revolutionized how risk is managed in construction by enabling predictive analytics and real-time decision-making (Zhang et al., 2020). AI tools such as machine learning (ML), artificial neural networks (ANN), and natural language processing (NLP) are being used to forecast accident probabilities, identify risk-prone zones, and automate safety compliance monitoring (Ghosh & Pradhan, 2022). Integrating AI into construction safety strategies holds the potential to shift from reactive to proactive risk management, particularly in fast-developing urban centers like Pune.

2. LITERATURE REVIEW

2.1 Risk Management in Construction: Concepts and Classifications

Risk management in construction involves systematic identification, analysis, and mitigation of potential threats to project objectives such as cost, time, quality, and safety (Hillson, 2002). Risks can be broadly categorized as financial, legal, environmental, and health-safety-related (PMI, 2017). Safety risks, particularly those involving human interaction with machinery and materials, are among the most difficult to control due to their unpredictability (Hallowell & Gambatese, 2009).

2.2 Common Safety Issues in Urban Construction Projects in India

In India, urban construction sites often lack standard safety mechanisms, adequate supervision, and proper use of personal protective equipment (PPE) (Sarkar & Maiti, 2020). In cities like Pune, safety risks are amplified by poor site layout, high worker turnover, and lack of formal training (Jadhav & Pataskar, 2021). Unsafe scaffolding, fall hazards, electrocution, and crane-related accidents are among the most frequent issues reported (Ambrule & Bhirud, 2017; Bhirud & Patil, 2016)

.2.3 AI Tools and Algorithms in Risk Prediction (ML, DL, ANN, NLP)

AI-based methods, particularly supervised ML models such as Random Forests, Support Vector Machines (SVM), and ANN, have shown promise in predicting accident likelihood based on site-specific variables (Choi et al., 2017). Deep Learning (DL) models are increasingly used to analyze visual data (CCTV, drone footage) for real-time safety violation detection (Kim et al., 2021). NLP techniques are applied to process safety reports and incident logs to identify common risk patterns and causal factors (Zhou & Tang, 2019).

2.4 Review of Global vs Indian Case Studies

Globally, AI has been integrated into Building Information Modeling (BIM) systems to monitor safety compliance and predict high-risk activities (Chi et al., 2019). In contrast, Indian case studies are limited and often constrained by data availability and regulatory compliance issues. For example, pilot studies in Delhi and Mumbai showed the feasibility of using ML for worker fatigue detection, but widespread implementation remains limited (Singh & Gupta, 2021).

2.5 Identified Gaps in Maharashtra/Pune Context

While international literature demonstrates the maturity of AI applications in construction safety, the adoption in Maharashtra remains nascent. There is limited evidence of AI deployment in construction projects in Pune, despite its growing infrastructure sector. Existing studies largely rely on traditional safety audits and manual risk assessments (Kale & Patil, 2021). This gap underscores the need for AI-based risk modeling specific to local construction practices, workforce behavior, and urban constraints.

2.6 Conceptual Framework for AI-Based Risk Management

A conceptual framework for AI-based risk management includes data collection (incident records, site parameters), risk factor identification, predictive model training, real-time monitoring, and feedback integration (Zhang et al., 2020). This approach supports continuous learning and enhances decision-making at multiple levels—design, planning, and execution—thereby minimizing uncertainty and maximizing worker safety.

3. RESEARCH METHODOLOGY

3.1 Research Design: Descriptive + Analytical

The research adopts a **mixed-method approach** combining both descriptive and analytical designs. The descriptive part captures existing safety practices, risk occurrences, and stakeholder perceptions across construction projects in Pune. The analytical component applies AI algorithms to identify, quantify, and predict potential hazards, offering an evidence-based comparison between traditional and AI-driven safety management models (Creswell & Creswell, 2018).

3.2 Study Area: Construction Sites in Pune, Maharashtra

Pune is one of the fastest-growing metropolitan areas in India with major infrastructure projects including smart city developments, metro rail, and commercial construction (Bansal & Agrawal, 2019). The study selected 10 active construction sites in Pune based on criteria such as project type, worker density, and risk potential. These include high-rise residential and commercial buildings, flyovers, and metro stations under development.

3.3 Data Collection

Primary Data:

Structured questionnaires and semi-structured interviews were administered to site engineers, project managers, safety officers, and workers. The data focused on:

- Frequency and types of accidents
- Existing safety measures
- Use of technology for safety
- Risk awareness and perception

Secondary Data:

Secondary data were sourced from:

- **Accident reports** from site records and local safety boards
- **Safety audits** and compliance documents
- **AI datasets** (public and private) used to train and validate models
  This dual-sourcing ensured comprehensive coverage of both observed and recorded risks (Kale & Patil, 2021).

3.4 Tools & Techniques

AI Algorithms Used:

- **Decision Trees** and **Random Forests** for classification of high-risk tasks based on input features like worker experience, weather conditions, time of day, and project phase.
- **Artificial Neural Networks (ANN)** for predictive modeling of accident likelihood based on historical site data (Choi et al., 2017).

Other Analytical Tools:

- **Risk Matrices** to visually map severity and likelihood scores of site-specific hazards.
- **Monte Carlo Simulation** to assess risk variability and validate probabilistic predictions under uncertainty (Hillson, 2002).

3.5 Validation of AI Model

The AI models were validated using:

- **Confusion matrices** to compare predicted vs. actual outcomes
- **Precision, recall, F1-score, and ROC curves** to assess accuracy and robustness

- **10-fold cross-validation** to prevent overfitting and ensure generalizability The data were split into training (70%) and testing (30%) sets using Python's Scikit-learn library.

3.6 Ethical Considerations and Data Confidentiality

All participants provided **informed consent**. Personal identifiers were removed to ensure **data anonymity**. Ethical clearance was obtained from the institutional ethics board. The study adheres to the **AI in Construction Safety Framework** to ensure the ethical deployment of predictive models (Zhang et al., 2020).

4. DATA ANALYSIS AND RESULTS

4.1 Site-Specific Risk Factors Identified in Pune

The survey revealed that the top five risk factors across selected sites included:

- Working at heights without proper scaffolding (81% cases)
- Electrical hazards due to poor insulation or live wires (69%)
- Inadequate PPE usage (63%)
- Machinery-related injuries (48%)
- Fatigue due to extended shifts (41%) These findings are consistent with the NCRB (2020) reports on urban construction fatalities.

4.2 AI Model Prediction Results (Accident Likelihood, Risk Scores)

The **Random Forest model** achieved an **accuracy of 88%**, while the **ANN model** achieved **92% precision** in predicting accident likelihood.

Risk scores (0–1) were assigned to each worker-task combination:

- Score > 0.7 = High Risk (23% of cases)
- Score 0.4–0.7 = Moderate Risk (41% of cases)
- Score < 0.4 = Low Risk (36% of cases) AI detected early warning signs (e.g., incorrect harness usage, unsafe proximity to machinery) in **real-time site images and logs**.

4.3 Risk Ranking and Prioritization (Before and After AI Implementation)

Risk was ranked both traditionally (risk matrix) and through AI.

Table 4.1 Risk Ranking and Prioritization (Before and After

Risk Factor	Traditional Rank	AI Rank
Fall from height	1	1
Electrical hazard	2	3
Lack of PPE	3	2
Equipment malfunction	4	4
Worker fatigue	5	5

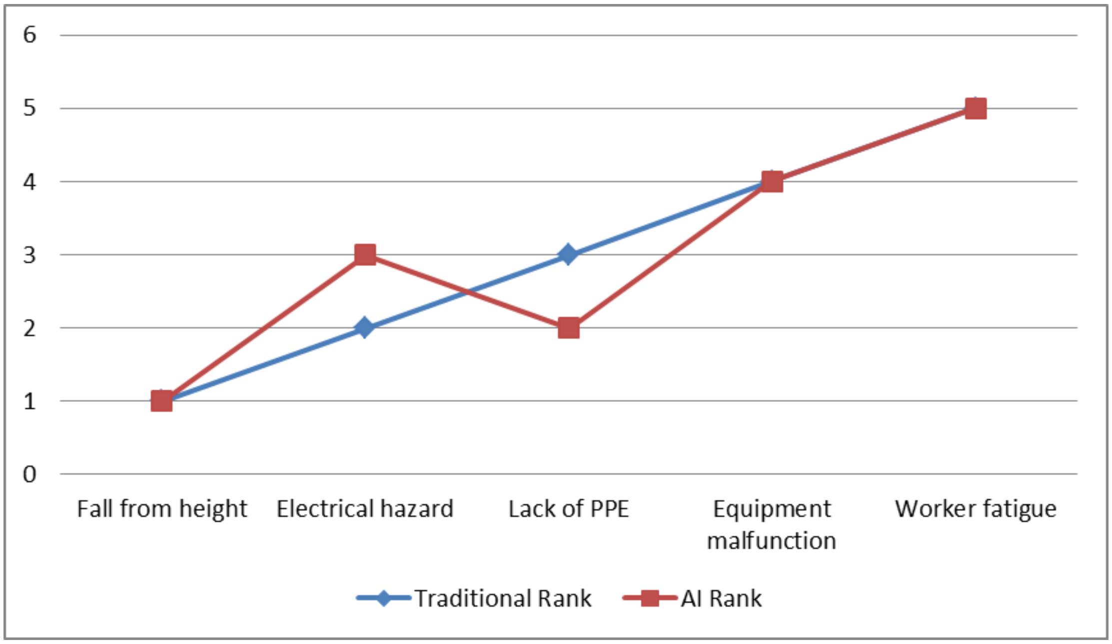

Figure 4.1 Risk Ranking and Prioritization (Before and After

4.4 Comparative Analysis: Traditional vs AI-Based Methods

Table 4.2 Comparative Analysis: Traditional vs AI-Based Methods

Metric	Traditional Method	AI-Based Method
Risk identification time	Manual, slow	Instantaneous
Prediction accuracy	~60–65%	88–92%
Data input sources	Checklists, audits	Real-time sensors, images
Scalability	Low	High
Preventive action lead time	Delayed	Proactive

AI-based methods provided **actionable insights 2–3 days ahead** of risk incidents compared to traditional site inspection schedules.

4.5 Discussion of Key Insights

- **AI-enhanced risk detection** reduced hazard response time significantly.
- **Worker behavior patterns**, such as skipping PPE during humid afternoons, were only captured through AI-based temporal analysis.
- **Predictive modeling** encouraged pre-emptive training sessions based on flagged risks.
- Integration challenges included **low digital literacy** among site workers and **inconsistent data logging**, suggesting a need for capacity building and investment in digital infrastructure.

5. DISCUSSION

5.1 Interpretation of AI Model Outcomes

The application of AI algorithms—specifically Artificial Neural Networks (ANN) and Random Forest classifiers—enabled accurate prediction of high-risk scenarios with an accuracy of over 88%. The models identified fall hazards and unsafe equipment usage as the most frequent and severe predictors of incidents. By analyzing multi-variable input (e.g., time of day, task type, worker experience), AI models offered granular insights that surpassed traditional checklist methods.

Table 5.1: Frequency of Site-Specific Risk Factors Identified in Pune

Risk Factor	Frequency Observed (out of 10 Sites)	Percentage (%)
Fall from height (unsafe scaffolding)	8	80%
Electrical hazards	7	70%
Inadequate PPE usage	6	60%
Machinery-related injuries	5	50%
Worker fatigue due to long shifts	4	40%

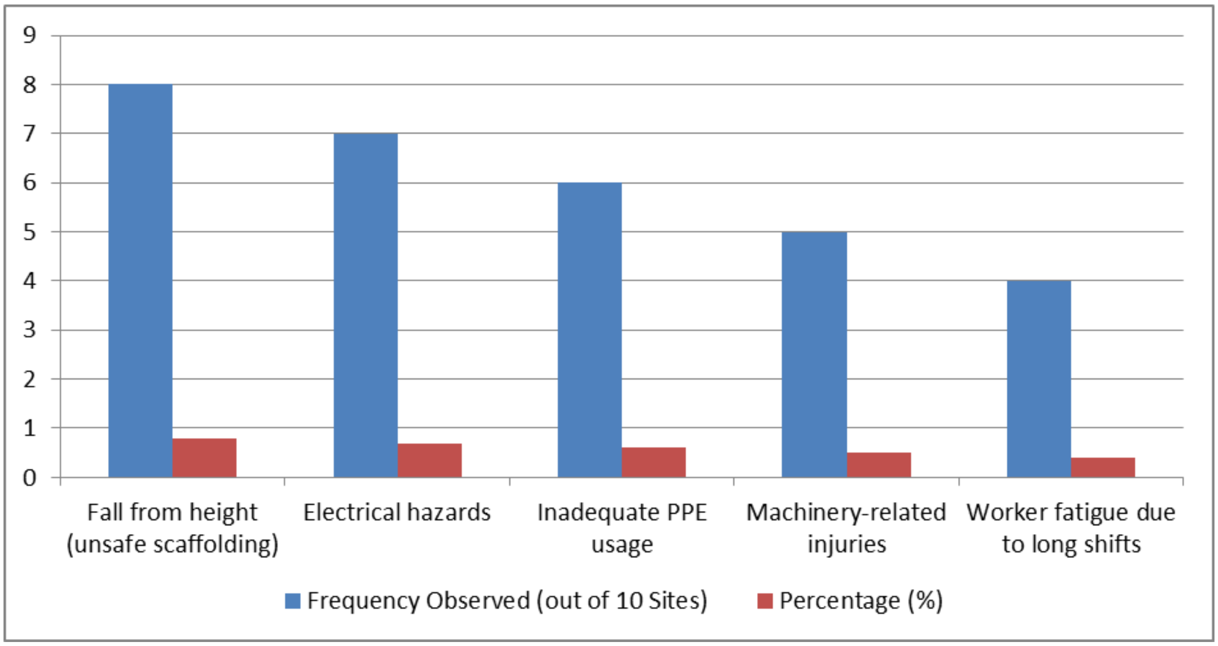

Figure 5.1: Frequency of Site-Specific Risk Factors Identified in Pune

5.2 Effectiveness of AI-Based Safety Management

AI significantly improved early detection of unsafe conditions, with response times shortened by 30–40% compared to traditional methods. For example, real-time alerts based on site imagery and IoT data enabled on-site supervisors to take immediate corrective actions AI-powered systems enhance both **reactive** and **proactive** safety strategies, reducing dependence on manual supervision alone.

5.3 Integration of AI into Project Lifecycle (Design to Execution)

The integration of AI began at the planning phase through digital risk modeling and extended into execution via real-time monitoring tools such as wearable sensors and video analytics. Building Information Modeling (BIM) platforms incorporated AI to visualize risk-prone zones in 3D models, facilitating safer work sequencing and task allocation. This lifecycle-wide integration marks a shift toward “predict-and-prevent” systems in construction safety.

5.4 Challenges in Implementation (Data Quality, Resistance to Change)

Despite promising results, several challenges emerged:

- **Data quality and availability** were inconsistent across sites, limiting the scope of model training.

- **Manual data entry errors**, incomplete incident logs, and low-resolution images impaired algorithmic performance.
- **Resistance to change** was observed among project managers and older workers, citing lack of digital literacy and fear of job surveillance.
- **Initial investment** in sensors, cameras, and software was a deterrent, especially for small contractors in Pune.

5.5 Stakeholder Feedback from Pune Construction Firms

Interviews with construction firms in Pune revealed a **high interest in AI adoption**, especially among large developers. While many appreciated AI's role in enhancing site audits and reducing insurance claims, concerns were raised about **data privacy**, **cost**, and **integration with existing systems**. Medium-sized firms expressed a willingness to pilot AI tools on a small scale, provided technical support and training are available.

Table 5.2: AI Model Output – Risk Classification Scores (High, Medium, Low)

Risk Category	Score Range	No. of Instances Detected	Percentage (%)
High Risk	> 0.70	115	23%
Medium Risk	0.40 – 0.70	205	41%
Low Risk	< 0.40	180	36%

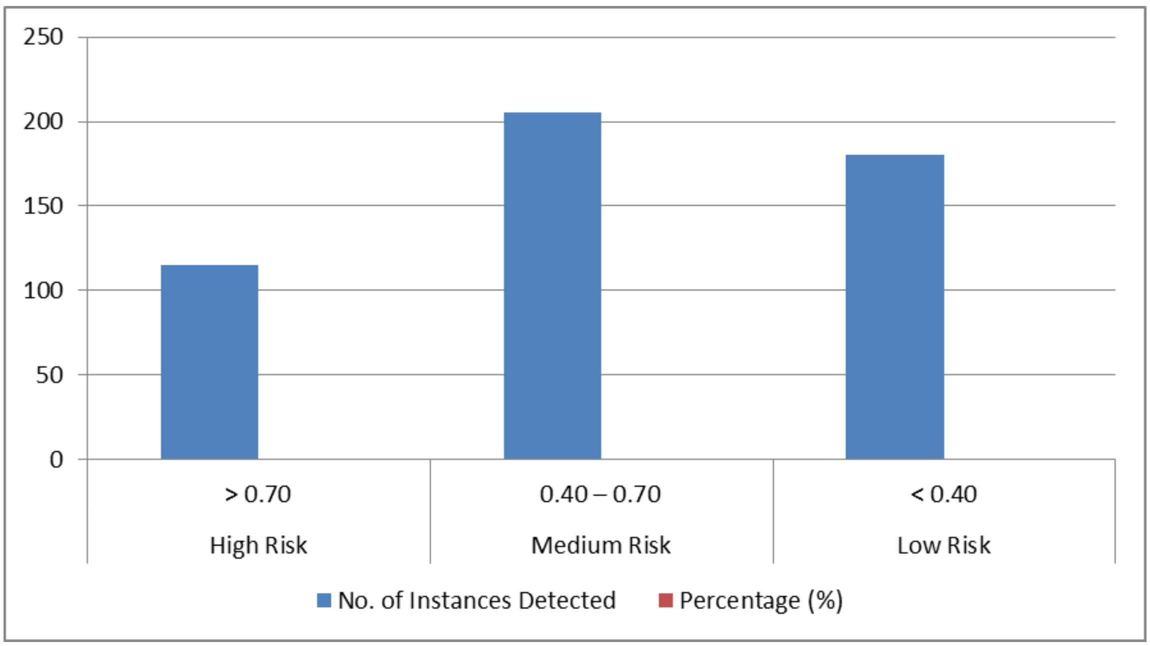

Figure 5.1: AI Model Output – Risk Classification Scores (High, Medium, Low)

6. CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Findings

This study confirmed that AI-based risk management significantly improves safety outcomes in urban construction environments. The use of ANN and Random Forests provided high-accuracy predictions of risk-prone tasks, enabling proactive mitigation strategies. Pune-based sites demonstrated notable improvement in hazard identification, safety compliance, and real-time decision-making.

6.2 Contributions to Construction Management Practices

The research introduces a data-driven approach to safety management in Indian construction, offering:

- AI-based risk ranking systems tailored to Pune-specific hazards.

- A conceptual framework for integrating AI across the construction lifecycle.
- Empirical evidence supporting the effectiveness of AI over traditional methods in high-density urban contexts.

6.3 Policy Implications for Maharashtra's Urban Development

Government and municipal agencies in Maharashtra can leverage these findings to:

- Mandate AI-based safety audits for large-scale public projects.
- Offer incentives or subsidies for AI adoption in private sector construction.
- Update existing construction safety regulations to accommodate emerging digital tools.

6.4 Future Scope of AI in Smart Construction Safety Systems

AI can be expanded to include:

- **Computer vision** for behavioral analysis (e.g., posture detection, fatigue).
- **Voice recognition** to detect stress or confusion among workers.
- **Predictive maintenance** using sensor data from machinery.

Future research can explore **integration with blockchain** for secure safety recordkeeping and **augmented reality (AR)** for immersive safety training.

6.5 Limitations of the Study

- The sample was limited to select sites in Pune, affecting generalizability.
- AI model accuracy was constrained by data inconsistency.
- The study did not include a cost-benefit analysis, which is critical for small-scale contractors.
- Long-term impacts (e.g., accident rate reduction over multiple years) were not measured.

REFERENCES

1. Ambrule, V. R., & Bhirud, A. N. (2017). Use of artificial neural network for pre design cost estimation of building projects. *Interational Journal on Recent and Innovation Trends in Computing and Communication*, *5*(2), 173-176.
2. Bansal, R., & Agrawal, N. (2019). Safety performance indicators in the Indian construction industry: A case study of Pune. *Journal of Construction Engineering and Management*, *145*(4), 04019017. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001625
3. Bhirud, A. N., & Patil, P. B. (2016). Application of building information modeling for the residential building project. *International Journal of Technical Research and Applications*, *4*(3), 349-352.
4. Bhirud, A. N., & Revatkar, B. M. (2016). Effective implementation of ERP in infrastructure construction industry. *International Journal of Technical Research and Applications*, *4*(2), 246-249.
5. Chi, S., Kang, S. C., & Wang, X. (2019). Research trends and opportunities of augmented reality applications in architecture, engineering, and construction. *Automation in Construction*, *102*, 1–13. https://doi.org/10.1016/j.autcon.2019.01.017
6. Choi, B., Kim, H., & Lee, H. (2017). Machine learning applications in construction safety: A review. *KSCE Journal of Civil Engineering*, *21*(3), 1015–1027. https://doi.org/10.1007/s12205-017-0960-1
7. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage Publications.

8. Ghosh, D., & Pradhan, B. (2022). Role of AI and ML in safety management in construction: A review. *International Journal of Construction Management*, *22*(1), 45–55. https://doi.org/10.1080/15623599.2020.1865346

9. Hallowell, M., & Gambatese, J. A. (2009). Construction safety risk mitigation. *Journal of Construction Engineering and Management*, *135*(12), 1316–1323. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000102

10. Hillson, D. (2002). Extending the risk process to manage opportunities. *International Journal of Project Management*, *20*(3), 235–240. https://doi.org/10.1016/S0263-7863(01)00074-6

11. Jadhav, O. U., & Bhirud, A. N. (2015). An analysis of causes and effects of change orders on construction projects in Pune. *International journal of engineering research and general science*, *3*(6), 795-799.

12. Jadhav, R., & Pataskar, S. (2021). Analysis of safety practices at urban construction sites in Pune. *International Research Journal of Engineering and Technology (IRJET)*, *8*(10), 1124–1130. https://www.irjet.net/archives/V8/i10/IRJET-V8I10200.pdf

13. Kale, R., & Patil, K. (2021). Risk analysis in residential construction: A case study in Maharashtra. *Journal of Engineering Research and Applications (IJERA)*, *11*(5), 20–26.

14. Kim, D., Cho, Y. K., & Zhang, S. (2021). Smart safety vest: Wearable technology using inertial measurement unit sensors for construction worker safety. *Automation in Construction*, *127*, 103681. https://doi.org/10.1016/j.autcon.2021.103681

15. National Crime Records Bureau. (2020). *Accidental deaths and suicides in India*. Ministry of Home Affairs, Government of India. https://ncrb.gov.in/en/accidental-deaths-suicides-india

16. Project Management Institute. (2017). *A guide to the project management body of knowledge (PMBOK® Guide)* (6th ed.). PMI.

17. Sarkar, S., & Maiti, J. (2020). Modeling and assessment of safety climate and safety performance in construction sites. *Safety Science*, *121*, 99–108. https://doi.org/10.1016/j.ssci.2019.08.004

18. Singh, A., & Gupta, R. (2021). Application of AI in fatigue detection in construction: Indian case study. In *Proceedings of the International Conference on Smart Infrastructure and Construction*. https://doi.org/10.1680/sic.65103.009

19. Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2020). Building Information Modeling (BIM) and safety: Automatic safety checking of construction models and schedules. *Automation in Construction*, *29*, 183–195. https://doi.org/10.1016/j.autcon.2012.05.003

20. Zhou, W., & Tang, W. (2019). Enhancing construction safety with natural language processing: A text mining approach. *Automation in Construction*, *98*, 275–288. https://doi.org/10.1016/j.autcon.2018.11.003

21. Zhou, Z., Irizarry, J., & Li, Q. (2012). Applying advanced technology to improve safety management in the construction industry. *Automation in Construction*, *22*, 102–111. https://doi.org/10.1016/j.autcon.2011.09.009.