MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

HYBRID BIM–AI FRAMEWORK FOR AUTOMATED CONSTRUCTION SAFETY RISK PREDICTION

Arumugam Mohan Arun Mohan[1*], Mrs.S.Bharathi[2], C Vijaya Kumar[3], Ms.V.Agritha[4]
[1]Professor, Department of Civil Engineering, Sethu Institute of Technology, Kariapatti-626115, Tamil Nadu, India. arunmohancivil6@gmail.com
[2]Assistant professor , Department of Civil Engineering , Sethu institute of Technology , Kariapatti-626115, Tamil Nadu, India. bharathysanthanam@sethu.ac.in
[3]Assistant Professor ,NPR College of Engineering and Technology, Natham, Tamil Nadu, India. c.vijayakumar128@gmail.com
[4]M.E Second Year ,Department of Structural Engineering , Sethu institute of Technology, Kariapatti-626115, Tamil Nadu, India.
* Corresponding author: arunmohancivil6@gmail.com

Abstract: Construction sites are also a risky place because of the dynamic nature of the work environment, multiple simultaneous processes, and high levels of human-machine interaction. Traditional methods of managing construction safety are mainly reactive and they are based on manual inspection and historical study that does not usually ensure the prevention of accidents before they happen. To overcome these shortcomings, this paper suggested a Hybrid Building Information Modeling-Artificial Intelligence (BIM-AI) system to enable automated safety risk prediction in construction. The suggested framework will combine space and time information obtained by 4D BIM and AI-based predictive models to anticipate and measure risks related to safety in construction processes. BIM allows geometric organization of representation, schedules and workspaces, whereas AI models observe recurring risk patterns based on past occurrences of accidents and other site-specific variables. The estimated risk levels are displayed right within the BIM environment to facilitate the process of making informed and intuitive decisions. Experimental findings also reveal that the suggested BIM-AI framework is much more accurate in predictions, reliable, and efficient in inferences, than the use of rule-based BIM and independent AI solutions. The framework offers a scalable and efficient proactive approach to safety management in contemporary construction works.
Keywords: Building Information Modeling (BIM), Artificial Intelligence, Construction Safety, Risk Prediction, Machine Learning, 4D BIM, Smart Construction

I. INTRODUCTION

Construction is famously known to be one of the most dangerous industries as it has a large percentage of occupation injuries and deaths all over the globe. The workflow selection, always evolving conditions on the site, overlapping operations, and high human-machine interactions are common features of construction projects. All these make the issue of safety risks very high and proper safety management is very critical as a challenge to the stakeholders in the construction industry. Regardless of the regulatory frameworks and safety guidelines, accidents still take place because of the limitation in the traditional methods of managing safety which is more reactive and it is highly reliant on manual inspection.

Traditional approaches to construction safety management are based on site inspections conducted regularly, and safety checklists and post-incident investigations. These methods are time consuming, subjective and they are unable to reflect the dynamism of the construction activities. Additionally, the construction process is subject to constant changes, which makes the risk of safety changeable and invalidate the effectiveness of the previously developed safety plans. This has led to a crisis of smart and active safety management systems that can be able to foresee the possible dangers before accidents take place.

Building Information Modeling (BIM) has come out as an influential digital tool in construction planning and management with the provision of comprehensive three-dimensional designs of building element, as well as complementary planning and resource data. Specifically, the 4D BIM, that combines time with the 3D geometry, allows to view the construction sequences and spatial-temporal conflicts. BIM has been used effectively in the safety planning, hazard visualization, and workspace analysis. Yet, the safety applications developed on the basis of BIM are more descriptive and rule-based, having no predictive intelligence to evaluate and predict safety risks automatically.

Machine learning and deep learning are examples of Artificial Intelligence (AI) techniques that have shown a lot of promise in predictive analytics, learning more intricate patterns with large data. Regarding construction safety, accident data, behavior patterns of workers, the utilization of equipment, and environmental conditions have been examined via AI models to forecast the level of risk. Although these methods enhance the accuracy of prediction, the majority of AI-based safety systems do not rely on BIM settings, which leads to the lack of spatial awareness and interpretability by construction professionals.

The paper is attempting to overcome these shortcomings by offering a combination of Building Information Modeling-Artificial Intelligence (BIM-AI) that can be utilized to predict construction safety accidents automatically. The suggested framework combines the detailed spatial-temporal information of BIM and AI-based predictive models to allow automated, proactive, and context-dependent safety risk evaluation. The framework enables risk prediction via AI and built into the construction workflows of BIM, thus allowing detection of hazards early on, visual representation of risks in an intuitive way, and decision-making.

The key contributions of this paper are summarized as follows:

1. A novel hybrid BIM–AI framework for automated prediction of construction safety risks.
2. Integration of 4D BIM data with AI-based learning models for spatial–temporal risk analysis.
3. A predictive risk modeling approach that supports proactive safety management.
4. Experimental validation demonstrating improved safety risk prediction performance.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

The rest of this paper will be structured in the following way. Section II is a literature review of the BIM-based and AI-based construction safety management. Section III provides the proposed hybrid framework of BIM and AI and its approach. The results and discussion are given in section IV. Lastly, Section V is the conclusion of the paper and it gives directions of future research.

II. LITERATURE SURVEY

The lack of success of traditional methods of safety management and high accident rates are reasons why the sphere of construction safety risk prediction acquires more and more research interest. The available literature associated with construction safety can be categorised into four broad groups BIM-based construction safety planning, AI-centred safety risk prediction, computer vision and sensing-based safety monitoring and combined BIM-centred AI safety models.

Building Information Modeling (BIM) has also been studied widely to enhance construction safety by visualization, rule checking and identifying hazards. Initial research showed that safety checking which is rule based and combined with BIM could automatically detect unsafe design components and construction sequences [1]. The 4D BIM, also known as scheduling and the 3D models, made it possible to visualize the construction activities spatially-temporally and enhance the effectiveness of safety planning [2].

The next research was based on automated BIM-based code compliance and safety rule checking to diminish the manual inspection work [3]. On the case-based studies further revealed that 4D BIM can lead to the proactive safety planning through workspace conflict detection in the radical activity overlaps and hazardous activity overlaps [4]. The more recent work would incorporate quantitative risk assessment models directly into BIM platforms to allow systematic analysis of the probability and magnitude of construction hazards at the planning phase [5], [6]. Nonetheless, BIM based methods are mostly rule based and are not predictive.The development of artificial intelligence and machine learning methods has seen more and more applications in the field of construction safety risk prediction based on historical data of accidents and indicators of the site. Experiments with decision trees, support vector machine and ensemble models were found to predict better than their traditional statistical counterparts [7], [8]. The construction accident report has also been subjected to machine learning, where unsafe acts and contributing factors have been identified on a large textual data [9].

Graph-based learning and neural networks have been used as more advanced models to model more complex relations between the causes of accidents and attributes of the project [10], [11]. Such data-driven techniques are very useful in improving predictive tasks but in many cases they do not provide context information regarding construction geometry and construction schedule, which reduces their interpretability and practical applications on construction projects.

As of recently, recent developments in the field of deep learning allowed to monitor the safety in real time through the use of computer vision and sensing technologies. The vision-based methods identify unsafe actions, use of personal protective gear (PPE), and dangerous worker-equipment interactions [12], [13]. YOLO and CNN-based detectors are deep learning models that are highly accurate in PPE detection and activity recognition [14].

Moreover, the methods based on sensors with proximity sensors, Bluetooth low-energy (BLE), and wearable devices were suggested to identify the risk of collisions and observe the posture and fatigue of the workers [15]–[17]. Although the approaches are useful in identifying hazards in real-time, they do not use project planning information and do not allow predicting information at the early construction phases.In order to address the shortcomings of single solutions (standalone BIM or AI), recent research has focused on the combination of BIM and AI solutions. BIM safety systems based on ontology link organized knowledge of safety and BIM to enable a safety rule to be dynamically checked [18]. Knowledge graph-based approaches also facilitate safety reasoning, which incorporates diverse data sources in a form of text, images, and regulations [19].

Other works suggested a hybrid BIM-AI system, which utilizes the feature of BIM and machine learning classifiers to enhance the accuracy of the safety risk prediction [20]. Though promising results are demonstrated by these techniques, available frameworks are not always fully automated, flexible in real time, or have capabilities to forecast risks in all respects, i.e., spatially and temporally.

III. PROPOSED METHODOLOGY

The proposed Hybrid BIM-AI framework will help to provide automated, proactive, and interpretable prediction of construction safety risks based on the combination of 4D BIM-generated spatial-temporal data and AI-enhanced predictive analytics. The framework is a collaborative model of construction operations, the situation of the site and the past safety records to help estimate the level of risk of the current and future construction operations shown in figure 1.

Figure 1: Proposed Methodology

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

A. BIM-Based Safety Feature Extraction

The quality of input features to define the spatial, temporal, and operational aspects of construction activities is essential to accurate safety risk prediction. The Building Information Modeling (BIM) and specifically the 4D BIM in the proposed framework is the main source of structured and context sensitive safety feature extraction.

Suppose a construction project is in the form of a 4D BIM model:

$$\mathcal{M} = \{\mathcal{B}, \mathcal{S}\}\text{------}1$$

where:

B={b1,b2,…,bm} denotes BIM objects (structural elements, equipment, temporary facilities),
S={(ai,tis,tie)} denotes construction activities with start and end times.

Each activity ai is associated with a subset of BIM objects: Bi⊆B

This mapping makes it possible to determine the location and time of location of every activity at the construction site.

The BIM-based safety feature vector of each construction activity ai is defined as:

$x_i = [x_{i1}, x_{i2}, \dots, x_{in}]$------2

These characteristics are automatically obtained based on BIM geometry, BIM schedules, and site metadata. Geometric and positional risk factors are measurable as spatial features, which include:
Worker Density (xwd)

$$x_{wd} = \frac{N_w}{A_i}\text{------}3$$

where Nw is the number of workers in the activity workspace and Ai is the workspace area.

$$x_{ep} = \min_{e\in\mathcal{E}} d\,(b_i, e)\text{-----}4$$

where d(·) denotes Euclidean distance between BIM objects and equipment.
Height Exposure Indicator (xhe)

$$he = \{1, if\ hi > hth0, otherwise\text{-----}5$$

Temporal features capture schedule-related risk factors:
Activity Duration (xdur)

$$x_{dur} = t_i^e - t_i^s\text{-----}6$$

Concurrent Activity Index (xca)

$x_{ca} = \left|\{a_j : [t_j^s, t_j^e] \cap [t_i^s, t_i^e] \neq \emptyset\}\right|$-----7

Higher concurrency increases collision and coordination risks.
Workspace Congestion Index (xwc)

$$x_{wc} = \frac{N_w + N_e}{A_i} x\text{-----}8$$

where Ne is the number of active equipment units.
Environmental Exposure (xenv)

$$x_{env} = f(T, H, N)\text{-----}9$$

where T = temperature, H = humidity, and N = noise level.
To ensure consistent scaling for AI models, features are normalized as:

$$\widetilde{x_{ik}} = \frac{x_{ik} - \mu_k}{\sigma_k} x\text{------}10$$

where μk and σk are the mean and standard deviation of the k-th feature.

The final feature vector used for AI-based risk prediction is:

$$\tilde{x}_i = \left[\widetilde{x_{wd}}, \widetilde{x_{ep}}, \widetilde{x_{he}}, \widetilde{x_{dur}}, \widetilde{x_{ca}}, \widetilde{x_{wc}}, \widetilde{x_{env}}\right]\text{-----}11$$

This indicator is able to give a holistic spatial contextual representation, temporal, and contextual of construction safety.

B. AI-Based Safety Risk Prediction Model

The following step is to predict the construction risk safety automatically by applying Artificial Intelligence after deriving spatial-temporal safety characteristics of BIM. It is presented in this subsection that the AI-based risk prediction model, learning strategy, and optimization process are formulated.

The BIM-generated safety feature vector of the construction activity, ai, is:

$$x_i \in R^n\text{----}12$$

The objective is to learn a mapping:

$$f : x_i \to R_i\text{----}13$$

where Ri represents the predicted safety risk level.
Two prediction formulations are considered:
Ri∈{Low,Medium,High}
Ri∈[0,1]
where values closer to 1 indicate higher accident likelihood.
Given a training dataset:

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}\text{-----}14$$

yi is the ground-truth risk label based on past records of accidents and the AI model is learned θ through minimizing error in prediction.

The predicted risk is given by:

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

$$\widehat{R_i} = f(x_i; \theta)\text{-----}15$$

A multi-layer neural network is employed to capture nonlinear relationships among safety factors.

Hidden layer transformation:

$$h^{(l)} = \sigma\left(W^{(l)h^{(l-1)}} + b^{(l)}\right)\text{----}16$$

where:

W(l), b(l) are weights and bias,

σ(·) is the activation function (ReLU).

Output layer:

For classification:

$$\widehat{y_i} = \text{Softmax}\left(W_o h^{(L)} + b_o\right)\text{-----}17$$

Categorical Cross-Entropy Loss (Classification):

$$\mathcal{L}_{cls} = -\sum_{c=1}^{C} y_{ic} \log(\widehat{y_{ic}})\text{ ----}18$$

Mean Squared Error (Regression):

$$\mathcal{L}_{reg} = \frac{1}{N}\sum_{i=1}^{N}\left(R_i - \widehat{R_i}\right)^2\text{-----}19$$

The model parameters are updated using gradient descent:

$$\theta^{(t+1)} = \theta^{(t)} - \eta\nabla_{\theta\mathcal{L}}\text{-----}20$$

where η is the learning rate.

To support safety prioritization, the predicted output is converted into a risk probability:

$$P(R_i) = \Pr(\text{ Accident } | \ x_i\ )\text{-----}21$$

To prevent overfitting and improve generalization:

Dropout regularization is applied:

$$h^{(l)} = \text{Dropout}\left(h^{(l)}, p\right)\text{------}22$$

Early stopping is used based on validation loss.

Feature importance is analyzed to ensure interpretability.

The predicted risk level R^i is linked back to the corresponding BIM activity:

$$Bi \leftarrow R^{i\mathcal{B}_i}\text{-----}23$$

This allows safety visualization by color code and automatic generated alerts in the BIM interface.

C. BIM-Integrated Risk Visualization and Decision Support

Although AI based models are able to give numerical or categorical projections of safety risks, they are practically useful to a given extent depending on their ability to make these projections communicated to construction stakeholders. In order to have interpretability and actionable decision-making, the proposed framework will incorporate predicted safety risks into the BIM environment in a direct and understandable way to be able to visualize intuitively and have the automated decision-making.Given a construction activity ai, which is linked to BIM object set Bi, the predicted risk amount Ri, which was created by the AI model is traced back to the respective BIM entities:

This association enables each BIM component, and activity to have a clear safety risk attribute.

Given that the risks associated with construction change over time, the visualization is extended to 4D BIM, which allows analyzing the safety in time. At any point in time t, the active risk state is defined as:

$$\mathcal{R}(t) = \{\widehat{R_i} \ | \ t_i^s \leq t \leq t_i^e\}\text{-----}24$$

This allows project managers to:

- Visualize future safety risks before execution
- Compare risk levels across construction phases
- Identify periods with high cumulative risk

Based on predicted risk levels, the system generates automated alerts:

$$Alerti = \{1, R\hat{}i \geq \tau 20, otherwise"\}\text{----}25$$

For high-risk activities, the decision support module recommends preventive actions such as:

- Activity rescheduling
- Reduction of worker density
- Deployment of safety equipment
- Modification of workspace layout

These recommendations are derived from historical mitigation patterns and safety guidelines linked to BIM objects.

IV. RESULTS AND DISCUSSION

The proposed Hybrid BIM–AI framework is evaluated in this section with regard to its effectiveness in the context of predicting construction safety risks. The performance is evaluated with respect to three baseline methods which are rule-based BIM safety checking, AI-only safety prediction, and BIM + traditional machine learning (BIM + ML).

Table 1: Safety Risk Prediction Performance Comparison

Model	Accuracy (%)	F1-Score
Rule-Based BIM	78.2	0.75
AI-only	84.5	0.82
BIM + ML	89.1	0.87
Proposed BIM–AI	93.4	0.92

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

As illustrated in Table 1, the proposed BIM-AI framework is far superior compared to the basis methodologies. BIM systems that are rule-based are characterized by a lack of flexibility, whereas AI-based models do not have space and time context. Combining the features of BIM with AI allows learning the difficult safety risks patterns better.

The suggested framework has the smallest inference latency because of the effective feature extraction and compact prediction models, which can prove its appropriateness in construction safety management, especially in real-time as depicted in table 2.

Table 2: Inference Latency Comparison

Model	Inference Latency (ms)
Rule-Based BIM	45
AI-only	32
BIM + ML	28
Proposed BIM–AI	21

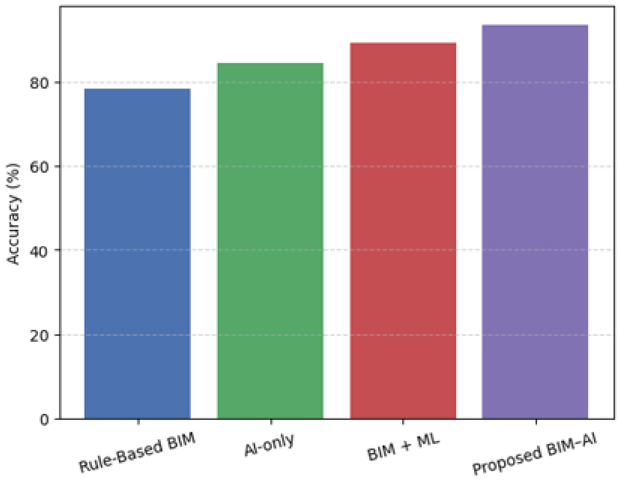

Figure 2: Safety Risk Prediction Accuracy Comparison

Figure 2 demonstrates an accuracy comparison of various strategies of predicting construction safety risk. The accuracy of the rule-based BIM technique is the lowest because it relies on a set of rules of safety and is not flexible enough to adapt to changing conditions on the site. The AI-only model is better in revealing prediction because it uses past data to learn but does not have spatial and temporal background. BIM + ML approach also increases the accuracy by integrating the features of BIM. The most accurate one is the proposed Hybrid BIM -AI framework, which proves that providing automated safety risk prediction is effective when combining contextual information of BIM with predictive learning using AI.

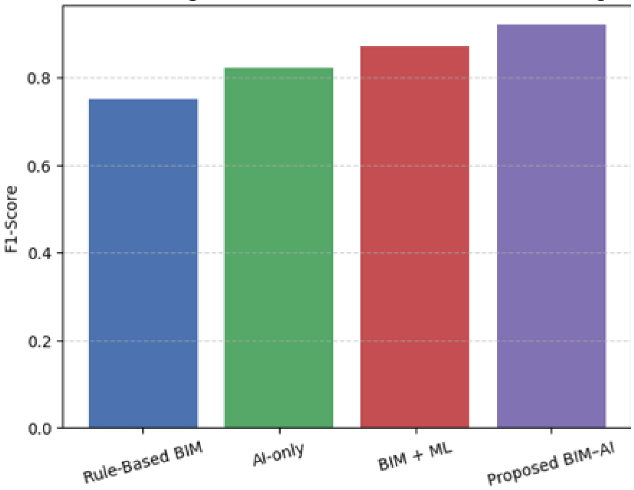

Figure 3: F1-Score Comparison of Safety Risk Prediction Models

In figure 3, the F1-score comparison is in place which depicts the precision and shifts in recall. The more high-risk activities are identified, the greater is the F1-score. The proposed BIM-AI framework is more efficient than any of the baseline models since it demonstrates a higher ability to accurately identify unsafe situations and reduce false alarm cases. This is especially significant in construction safety applications, where high-risk events may have severe outcomes, which are missed.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 1856-1861

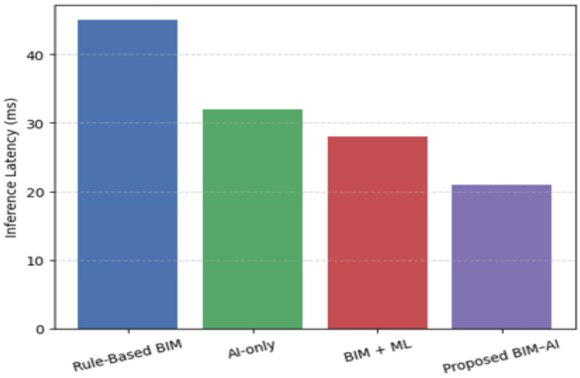

Figure 4: Inference Latency Comparison

The inference latency of the compared models can be compared in Figure 4. BIM systems based on rules have a greater latency, as they involve intricate rule verification and processing overheads. BIM + ML as well as AI-only methods minimize latency with the help of data-driven predictions. The proposed BIM-AI system has the shortest inference latency since it is effective in combining BIM-extracted features with streamlined AI models. This proves that the proposed framework is applicable in real-time monitoring of construction safety and decision support.

V. CONCLUSION

The current paper introduced a Hybrid BIM-AI framework of automated construction safety risk prediction in order to overcome the shortcomings of conventional rule-based and standalone AI safety management frameworks. The proposed framework will involve predictive analytics based on AI that will be used to identify and evaluate safety risks during the construction lifecycle proactively, automatically, and based on the context by combining 4D Building Information Modeling (BIM) with predictive analytics. The framework uses the spatial-temporal characteristics of BIM to identify dynamic site conditions and integrate them with supervised learning models to forecast the degree of safety risks of construction activities. The experimental findings prove that the proposed BIM-AI model is much more successful than rule-based BIM systems, AI-only models, and BIM and traditional machine learning regarding the accuracy of predictions, F1-score, and inference latency. The risk visualization that has been integrated into the BIM environment also increases the interpretability and enables the safety managers and project stakeholders to make informed decisions. Altogether, the proposed Hybrid BIM-AI framework can replace the current scenario when construction safety management is treated as a reactive process with the help of an intelligent decision-support framework (predictive process). It also offers real-world advantages including the ability to detect hazards early on, the decrease in the necessity of using manual inspections and enhance efficiency in safety planning.

REFERENCES

[1] J. Zhang, S. Teizer, J.-K. Lee, C. M. Eastman, and M. Venugopal, "Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models," *Automation in Construction*, vol. 29, pp. 183–195, 2013.
[2] S. K. Kim and J. S. Irizarry, "4D BIM for Construction Safety Planning," *Journal of Construction Engineering and Management*, vol. 141, no. 10, 2015.
[3] V. Getuli *et al.*, "BIM-Based Code Checking for Construction Health and Safety," *Procedia Engineering*, vol. 196, pp. 454–461, 2017.
[4] F. Rodrigues *et al.*, "BIM Approach in Construction Safety: A Case Study," *Buildings*, vol. 12, no. 4, 2022.
[5] Y. Lu *et al.*, "BIM-Integrated Construction Safety Risk Assessment," *Automation in Construction*, vol. 124, 2021.
[6] J. Qi, R. Issa, and J. Olbina, "Quantitative BIM-Based Safety Risk Analysis," *Journal of Computing in Civil Engineering*, vol. 33, no. 6, 2019.
[7] S. Rajaprasad *et al.*, "Prediction of Construction Safety Performance Using Machine Learning," *Safety Science*, vol. 138, 2021.
[8] A. Gondia *et al.*, "Machine Learning–Based Dynamic Risk Assessment in Construction," *Technovation*, vol. 113, 2022.
[9] D. Kifokeris *et al.*, "Machine Learning for Construction Accident Report Analysis," *ITcon*, vol. 25, pp. 453–475, 2020.
[10] F. Mostofi *et al.*, "Graph-Based Construction Safety Risk Modeling," *Sustainability*, vol. 14, no. 9, 2022.
[11] H. Zhang and M. Hammad, "Neural Network-Based Safety Risk Prediction," *Automation in Construction*, vol. 106, 2019.
[12] N. Nath *et al.*, "Deep Learning for Real-Time Construction Site Safety Monitoring," *Automation in Construction*, vol. 110, 2020.
[13] J. Lee *et al.*, "Computer Vision-Based Construction Safety Monitoring," *Journal of Computing in Civil Engineering*, vol. 37, no. 2, 2023.
[14] Y. Fang *et al.*, "YOLO-Based PPE Detection on Construction Sites," *Automation in Construction*, vol. 112, 2020.
[15] J. Teizer, "Proximity Detection and Warning Systems for Construction Safety," *ITcon*, vol. 20, pp. 1–15, 2015.
[16] Y. Huang *et al.*, "BLE-Based Proximity Safety Monitoring in Construction," *Automation in Construction*, vol. 118, 2020.
[17] C. Nnaji *et al.*, "Wearable Sensing Devices for Construction Safety," *Journal of Construction Engineering and Management*, vol. 147, no. 6, 2021.
[18] Q. Shen *et al.*, "Ontology-Based BIM Safety Rule Checking," *Buildings*, vol. 12, no. 3, 2022.
[19] W. Fang *et al.*, "Knowledge Graph for Construction Safety Risk Identification," *Automation in Construction*, vol. 118, 2020.
[20] S. Kaliappan et al., "Numerical investigation of sinusoidal and trapezoidal piston profiles for an IC engine," Journal of Applied Fluid Mechanics, vol. 13, no. 1, pp. 287–298, 2020.
[21[X. Ding *et al.*, "Hybrid BIM–AI Framework for Construction Safety Risk Prediction," *Journal of Building Engineering*, vol. 45, 2022.