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Visualizing PPE Violation Risks in BIM: A Computer Vision-Based Spatial Approach for Construction Safety

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ABSTRACT

Ensuring worker safety is a critical priority in the construction industry. While Building Information Modeling (BIM) has advanced project management and visualization, its role in spatially-aware safety analysis, particularly for Personal Protective Equipment (PPE) violations, remains limited. Existing approaches often fail to capture insights into high-risk zones. This study proposes a framework for spatial risk categorization within BIM models, based on the frequency of PPE violations. Using a computer vision approach with the You Only Look Once (YOLO) model, PPE infractions involving hard hats and safety vests are automatically detected from site imagery and aggregated per spatial element. These violations are linked to the Revit model, incorporating camera positions to visualize high-risk zones as color gradients within the model. The evaluation demonstrates strong detection accuracy, with mean average precision (mAP) values of 0.823 for "Person," 0.819 for "Hat," and 0.567 for "Vest," yielding an overall mAP of 0.746. By highlighting spatial zones with elevated risk, the framework supports targeted deployment of safety measures where needed. It also enables tailored training programs for subcontractor crews in these zones, ensuring context-specific and effective safety management. This innovative approach introduces a new data layer to coordination models, derived from real-world safety performance, enabling stakeholders to spatially identify areas with high PPE non-compliance. This enables proactive monitoring and allows for the timely deployment of safety measures. Informed decision-making is thereby supported, leading to more effective safety interventions and a reduction in on-site hazards. The study's finding aligns with the perspectives of safety experts, validating a practical approach to hazard reduction.

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1. Introduction

1.1. Background and Context

The construction industry is a cornerstone of global economies, employing millions and significantly contributing to infrastructure development [1]. However, despite its vital role, it remains one of the most hazardous sectors worldwide, consistently reporting high rates of injuries and fatalities [2]. The inherent complexities of construction sites, including dynamic environments, concurrent operations, and a diverse workforce, pose persistent safety challenges. While extensive research and traditional safety protocols have been implemented over the years, their effectiveness is often limited by the sheer scale and ever-changing nature of projects. Traditional methods struggle to provide real-time insights and proactive hazard identification, underscoring an urgent need for innovative, technology-driven approaches to enhance worker safety [3,4]. The integration of advanced technologies, such as computer vision and BIM, can contribute significantly to overcoming these limitations and to establishing more robust safety management systems . Among these critical safety measures, the diligent use of Personal Protective Equipment (PPE) is recognized as a fundamental defense against occupational hazards, directly contributing to the reduction of injuries and fatalities on site [5].

1.2. Problem Statement

Previous research has widely explored the application of either computer vision or BIM for construction safety management [6–8]. Computer vision, while excellent for real-time monitoring and anomaly detection [9], often lacks a clear spatial context when visualizing safety incidents on traditional 2D plans. Conversely, BIM excels at providing rich spatial information and design context [10] but typically does not integrate real-time operational data, especially regarding dynamic safety compliance like PPE usage. Among the myriad of hazards prevalent on construction sites, falls from height and collisions are recognized as particularly dangerous risks, contributing significantly to severe injuries and fatalities [11]. Crucially, these risks are intrinsically linked to specific spatial areas within a construction site, and their mitigation is directly influenced by the proper use of PPE, such as hard hats and safety vests, which are fundamental in preventing impacts and enhancing visibility. This disconnect creates a critical gap: existing methods struggle to provide an integrated, spatially-aware overview of safety risks based on actual site performance. Therefore, a novel approach that seamlessly combines the strengths of computer vision for real-time monitoring with the robust spatial capabilities of BIM is essential for effective hazard identification.

1.3. Objectives

The primary objective of this paper is to present an integrated approach for real-time construction site safety analysis, specifically focusing on the spatial identification and categorization of safety risks within a BIM environment. This research aims to classify various PPE violation hotspots directly within the BIM model. By leveraging real-time data from site surveillance cameras, this approach provides a robust and documented process for integrating actual construction process data into the BIM platform. The spatial mapping of PPE non-compliance within the digital model will enable stakeholders to visually discern high-risk zones, thereby facilitating more informed decision-making and targeted interventions for improving overall site safety.

1.4. Paper Organization

The remainder of this paper is structured to present a comprehensive overview of the proposed system. Section 2 provides a thorough review of existing literature on computer vision applications in construction safety and the role of BIM in safety management, identifying key research gaps. Section 3 details the methodology, outlining the various steps involved in implementing the PPE violation detection and heat mapping framework, including data acquisition, processing, and visualization. Section 4 presents the results of the experimental implementation and discusses their implications for enhancing safety awareness and identification on construction sites. Finally, Section 5 concludes the paper by summarizing the main findings, discussing the practical impact, and outlining avenues for future research.

2. Literature Review

This section provides a comprehensive review of the existing literature pertinent to the integration of computer vision and Building Information Modeling (BIM) within construction safety management. Initial discussions are focused on advancements in computer vision applications for safety, followed by an examination of BIM's role in proactive safety planning. Finally, prior efforts and the identified gaps in combining these two powerful technologies for enhanced safety oversight are explored.

2.1. Computer Vision for Construction Safety

The application of computer vision in construction safety has seen rapid development, particularly since 2020, driven by advancements in deep learning [12]. A primary focus has been the automated detection of workers and their PPE, such as hard hats [13–16] and safety vests [17,18], which are fundamental to on-site safety. Many studies have effectively utilized highly efficient and accurate real-time object detection algorithms, such as the You Only Look Once (YOLO) series [17,19], to identify these safety elements. Researchers have developed various models to detect full sets of PPE [20], track workers over time to monitor compliance [21], and even use pose estimation to recognize unsafe postures and behaviors [22]. These systems effectively use surveillance camera footage to automatically flag non-compliance incidents.

However, as summarized in Table 1, a significant and pervasive limitation remains across the majority of these vision-based systems. While they are highly proficient at detecting violations within 2D image frames, they fundamentally fail to provide a spatial context or link the detected violation to a specific location or space within the construction site's digital twin. This deficiency means that safety managers receive alerts without knowing the precise area in the building where the risk is highest, which critically hinders targeted interventions and proper documentation [23]. The vast majority of these systems operate at a pixel level, lacking a meaningful connection to the physical site layout. Therefore, a major research gap exists in translating this rich 2D visual data into a spatial, 3D representation that can be used for informed decision-making and comprehensive safety analysis. There is a clear need for a system that not only detects violations but also maps them onto a 3D model, providing a color-coded visualization of risk hotspots.

Table 1. Summary of Computer Vision Applications for Construction Safety

Study	Primary Objective	Method/Algorithm Used	Key Strength	Research Gap/Limitation
[13]	Hard Hat Detection	YOLOv5	High accuracy in real-time detection	Lacks spatial context; provides only a 2D bounding box.
[18]	Safety Vest Detection	Faster R-CNN	High precision for PPE detection	Output is a 2D image alert; does not link to a physical location.
[21]	Worker & PPE Tracking	DeepSORT + YOLO	Ability to track individuals over time	Focuses on individual behavior, not on high-risk spatial zones.
[22]	Unsafe Behavior Detection	Pose Estimation	Recognizes unsafe postures	Cannot visualize the risk location within the building layout.
[23]	Real-time PPE Compliance	Custom CNN Model	Automated non-compliance flagging	Alerts are not integrated with a site's 3D spatial model.
Current Research	Integrated CV & BIM	Our Proposed Framework	Links 2D data to 3D space; identifies risk hotspots.	Addresses the spatial context gap of previous research.

2.2. BIM in Construction Safety

The role of BIM in enhancing construction safety has been a prominent research area, primarily focusing on proactive hazard identification during the design and planning phases [24]. Numerous studies have leveraged BIM to identify potential risks and clashes before construction even begins [25–27]. By integrating safety rules and checklists, BIM-based tools can automatically flag design elements that pose risks, such as unguarded openings or insufficient space for scaffolding [28,29]. Frameworks incorporating 4D BIM (BIM + time) have also been developed to visualize the construction sequence and identify potential spatiotemporal risks, such as crane operations near active work zones [30,31]. Researchers have also used BIM to assess and quantify risks in a detailed manner, often within software environments like Revit [32,33] and have also demonstrated its effectiveness for specific hazards like fall risk analysis during the design stage [34].

Furthermore, tools utilizing BIM for the measurement of safety leading indicators have been explored, providing proactive insights into safety performance [35]. Automated approaches leveraging BIM and system dynamics have also been developed to assess these leading indicators, offering dynamic tools for proactive safety assessment [36]. As detailed in Table 2, while these contributions have been significant, they are largely confined to the static planning and design stages. This highlights a pressing need for more robust BIM applications tailored for the active construction phase. The dynamic nature of construction projects, where work zones, equipment, and personnel are constantly in motion, necessitates the use of real-time, operational data from the site for effective safety management. The static nature of BIM models in many of these applications fails to capture this fluid reality. Therefore, a clear gap exists in integrating BIM with real-time, as-built data to create a dynamic safety monitoring system. Without live data feeds, BIM's potential as a proactive safety management tool during the construction phase remains largely untapped. Our research seeks to bridge this gap by injecting real-time site data into the BIM environment to reflect the ever-changing project reality.

Table 2. Summary of BIM Applications for Construction Safety

Study	Primary Objective	Method/Tool Used	Key Strength	Research Gap/Limitation
[26]	Clash detection for safety planning	Navisworks	Identifies design-related safety clashes	Confined to the design phase; static analysis.
[28]	Automated safety rule checking	Dynamo script in Revit	Flags potential safety risks in the model	Static approach; does not account for real-time site changes.
[30]	4D visualization of spatiotemporal risks	4D BIM	Visualizes hazards over time (e.g., crane path)	Based on a static schedule; lacks integration with live site data.
[34]	Automated fall hazard analysis	BIM-based method	Highly effective at identifying and assessing fall risks during design	Static approach; focuses on the design phase and does not use real-time data from the construction site.
[35]	Measuring safety leading indicators	BIM-based dashboard	Provides proactive insights	Relies on manual data input; not a dynamic, real-time system.
[36]	System dynamics for safety assessment	BIM + SD Model	Assesses leading indicators dynamically	Uses simulated data; does not integrate with real-time, as-built information.
Current Research	Integrated CV & BIM	Our Proposed Framework	Links BIM to image data; provides dynamic risk visualization.	Addresses the gap in dynamic BIM applications for the active construction phase.

2.3. The integration of BIM and computer vision in safety management

While significant advancements have been achieved through the integration of BIM and computer vision in other construction management domains, such as project control [37,38], their comprehensive combined application specifically for safety management has been scarcely explored. As noted in Table 3, while some advancements have been made in workforce safety monitoring using this integrated approach [39], the focus was primarily directed towards the positions of individuals rather than comprehensive work front analysis. This focus on individual locations, without explicit reference to work fronts within the BIM model, can inherently lead to increased computational costs and lacks a holistic view of site safety. Consequently, in light of these specific limitations, research focusing on a novel integrated approach that is computationally appropriate for implementation in the safety domain is necessary.

Recognizing the limitations of relying on either computer vision or BIM in isolation, this research proposes a novel integrated approach. By combining the real-time detection capabilities of computer vision with the rich spatial context of BIM, a dynamic and spatially aware safety monitoring system is created. This integration allows us to overcome the existing research gaps and offers several key innovations. First, we move beyond simple 2D image alerts by spatially mapping PPE violations directly onto the BIM model, providing a clear visual representation of risk zones. Next, this framework enables the creation of a new, data-driven layer in the coordination model, where spaces are color-coded based on real-world violation frequencies, which is a significant advancement over static design-stage analysis. Finally, by linking site camera locations to the BIM model, violations can be accurately attributed to specific rooms, corridors, or ramps, providing a level of spatial granularity previously unavailable. This integrated approach not only identifies risks but also provides the necessary spatial context to facilitate targeted safety management. The detailed framework will be presented in subsequent sections.

Table 3. Summary of Integrated BIM and Computer Vision Applications in Construction

Study	Primary Objective	Method/Tool Used	Key Strength	Research Gap/Limitation
[37]	Project Progress Tracking	Photogrammetry + BIM	Automates progress monitoring	Focuses on progress, not safety; no risk analysis.
[38]	Worker Location Tracking	Computer Vision + BIM	Tracks worker position on site	Focuses on individuals; not integrated with safety rules or hotspots.
[39]	Comprehensive Safety Monitoring	CV + BIM	Tracks individuals for safety compliance	Lacks "work front analysis"; high computational cost due to individual focus.
Current Research	Dynamic Safety Hotspot Analysis	Our Proposed Framework	Links PPE violations to specific BIM spaces; provides spatial granularity for risk analysis.	Addresses the lack of risk hotspot analysis and improves computational efficiency by focusing on zones.

3. Methodology

The comprehensive methodology for the spatial identification and visualization of PPE violation risks within BIM is structured into a systematic operational workflow. This end-to-end process, depicted in Figure 1

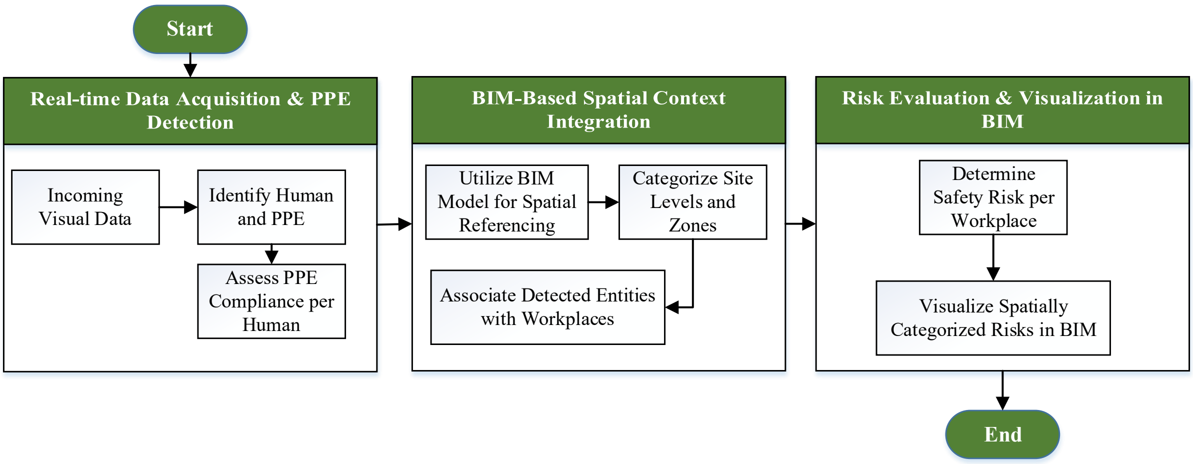

Figure 1, integrates advanced computer vision capabilities with BIM's robust spatial intelligence through three interconnected main phases. These phases are designed to transform raw visual data into actionable safety insights, culminating in a clear, spatial representation of risk levels across a construction site.

The initial phase, "Real-time Data Acquisition and PPE Detection," commences with the ingestion of incoming visual data from site surveillance. Within this stage, human presence and PPE are identified through automated detection processes. Subsequently, the compliance status regarding PPE usage is meticulously assessed for each identified individual, forming the foundational layer of safety information.

Following the detection, the data progresses to the "BIM-Based Spatial Context Integration" phase. Here, the BIM model is utilized for its precise spatial referencing capabilities, allowing for the categorization of site levels and zones. Detected entities (humans and their PPE compliance status) are then accurately associated with their corresponding workplaces or spatial elements within the BIM environment, thereby contextualizing the detected safety data.

Finally, the "Risk Evaluation & Visualization in BIM" phase is executed. In this stage, safety risks are systematically determined for each defined workplace based on the aggregated PPE compliance data associated with it. The calculated risks are then visually communicated by spatially categorizing and rendering them within the BIM model, typically through color-coding, providing an immediate and intuitive overview of safety performance across the construction site.

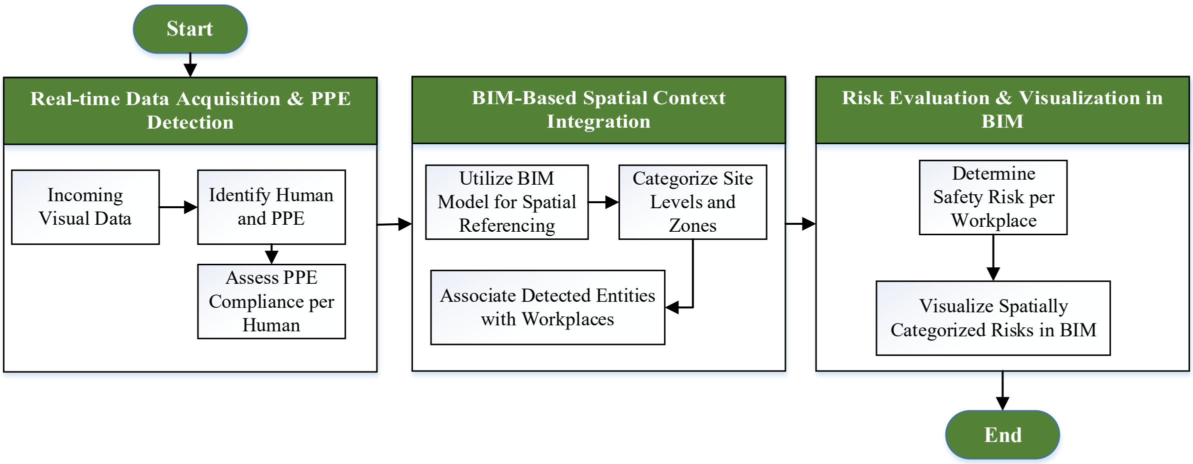

Figure 1. Overall Framework of the Proposed Methodology for Spatial Risk Classification in BIM Models

3.1. Real-time Data Acquisition & PPE Detection

The detection of PPE non-compliance is foundational to the proposed framework. For this critical task, YOLOv11 [40] is leveraged, being recognized for its exceptional balance of high accuracy and rapid processing speed, thus uniquely suited for real-time analysis within dynamic construction environments. This advanced object detection algorithm allows for the precise identification of individuals and various types of PPE, such as hard hats and safety vests. As conceptually illustrated in Figure 2, the workflow involves visual data being processed through the model's architectural design (comprising a backbone for feature extraction, a neck for multi-scale feature amalgamation, and a head for generating precise predictions) contributing significantly to its high precision and efficiency [41].

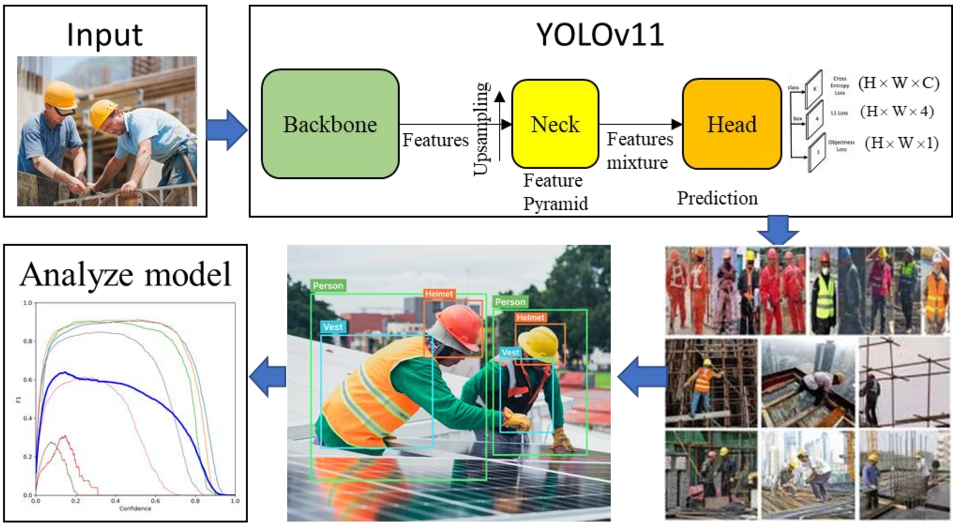

Figure 2. A graphical representation of image based YOLOv11

To rigorously evaluate the efficacy of the detection algorithm, predicted outputs are systematically compared against ground truth annotations. A key metric employed for this comparison is Intersection over Union (IoU), by which the spatial overlap between a predicted bounding box and its corresponding ground truth box is quantified (Eq. (1)). An IoU threshold, commonly set at 50%, is used to determine whether a detection is considered correct. Detections exceeding this threshold are classified as True Positives (TP), with accurate identification and localization being indicated. Conversely, incorrectly identified objects are termed False Positives (FP), while instances where an object was present but not detected are categorized as False Negatives (FN). This clear distinction between detection outcomes is critical for understanding model performance, and is conceptually illustrated in Figure 3, where the relationship between actual and predicted object instances is outlined.

Furthermore, the overall performance of the object detection model is comprehensively assessed using a suite of standard metrics. The accuracy of positive predictions is measured by Precision (Eq. (2)), with the proportion of correctly identified objects among all objects detected by the model being represented. Recall, on the other hand, is quantified for the model's completeness (Eq. (3)), with the proportion of actual objects in the dataset that were successfully detected being indicated. A balanced evaluation is provided by the F1-score through the calculation of the harmonic mean of precision and recall (Eq. (4)(5)), with a single metric that reflects both aspects of performance being offered. For a more holistic assessment across various confidence thresholds and object classes, Mean Average Precision (mAP) is utilized (Eq. (5)). A robust summary of the model's detection capabilities across a range of operational conditions is provided by this metric. The dynamic process whereby initially misclassified detections (FPs) can be refined into correct ones (TPs) through improved model performance or adjusted parameters is considered a critical aspect of optimization, and is conceptually outlined in Figure 3.

$$IOU = \frac{A_p \cap A_g}{A_p \cup A_g} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

$$mAP = \frac{1}{c}\sum_{i=1}^{N} P_i \Delta R_i \quad (5)$$

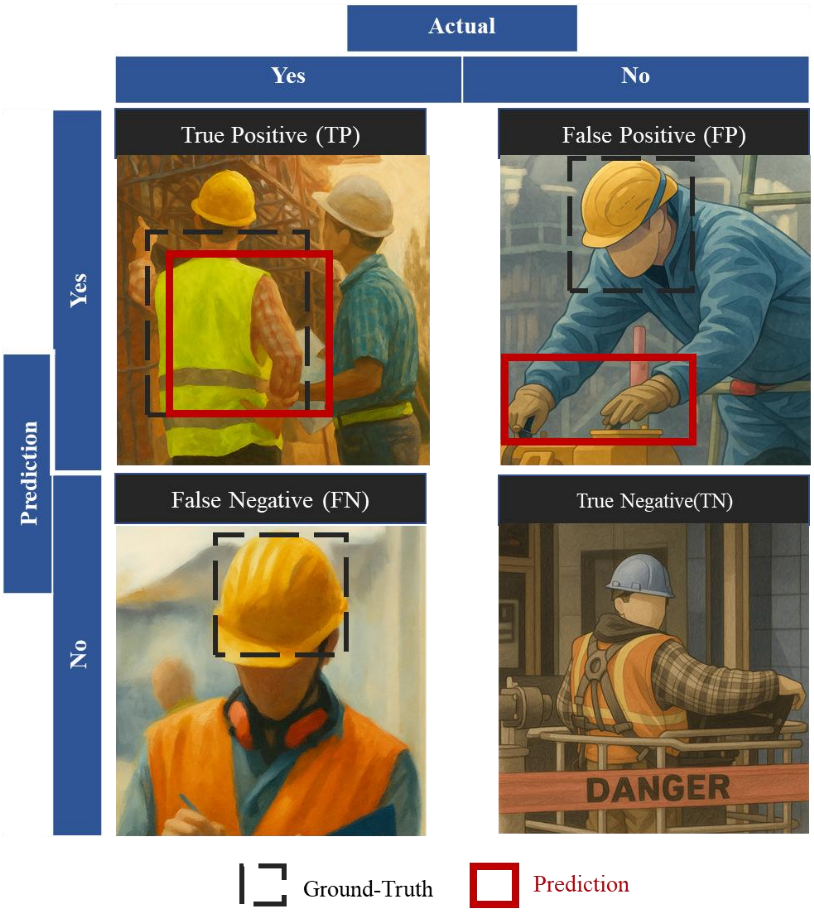

Figure 3. Example of the change of FP into TP

The accurate association of detected PPE with individual workers in real-time is a critical step in the proposed framework. This process typically involves several stages:

- **Detection:** Initially, individual workers and various PPE items (e.g., hard hats, safety vests) are precisely identified within video frames by the **YOLOv11** algorithm, resulting in distinct bounding boxes for each entity.
- **Spatial Proximity Quantification:** Subsequently, the spatial relationship between each detected worker and each detected PPE item is meticulously quantified. This is commonly achieved by calculating the Mahalanobis distance between the centroids of their respective bounding boxes. This distance serves as

a robust measure of spatial proximity, reflecting the likelihood of a given PPE item belonging to a specific worker.

- **Assignment Logic:** Following distance calculation, the assignment of PPE to workers is performed. This is often accomplished using algorithms such as K-nearest neighbors (KNN), where PPE bounding boxes are assigned to the closest worker bounding boxes based on the computed Mahalanobis distances.
- **Temporal Refinement:** To enhance the robustness and reliability of these assignments, the confidence of PPE association is continuously updated and refined across subsequent frames, leveraging temporal information to confirm or adjust initial pairings.

The methodology aims to accurately determine the specific PPE used by each worker in real-time, which forms a crucial link between object detection and worker-specific safety compliance assessment. A sample output illustrating the detection and assignment capabilities of the proposed framework is shown in Figure 4. In this figure, individual workers and their corresponding PPE items are presented with bounding boxes and confidence scores, exemplifying the final result of a multi-stage process. The visual representation demonstrates how specific PPE items are accurately attributed to each worker, laying the groundwork for a robust compliance assessment.

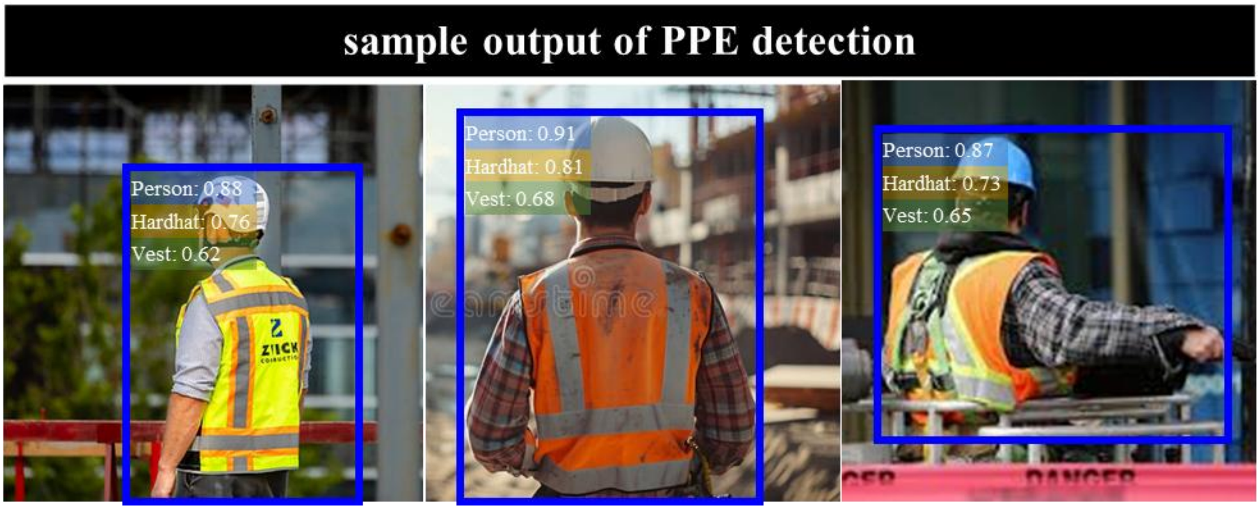

Figure 4. Sample Output of PPE Detection and Assignment

3.2. BIM-Based Spatial Context Integration

Following the accurate detection of human and PPE compliance status, the subsequent crucial step involves spatially mapping these observations into the BIM. This process is essential for associating detected violations with their specific locations within the construction site and for quantifying the risk level of each designated space.

For the purpose of illustrating this spatial integration, a hypothetical multi-story construction project is considered, as depicted in Figure 5. In a real-world implementation, effective risk categorization within different areas necessitates the availability of a comprehensive BIM model of the project, along with detailed information regarding the number and precise locations of surveillance cameras deployed across the site. The positioning of these cameras is paramount, as their fields of view directly determine the observable areas for automated safety monitoring. Therefore, for any project seeking to adopt this methodology, a detailed digital representation of the facility and an accurate record of camera placements are indispensable for subsequent spatial risk classification.

Upon the establishment of the BIM environment and camera placements, the visual data captured by the cameras are utilized to determine worker presence and PPE compliance within their respective fields of view. As conceptually shown in Figure 6, a specific floor area is depicted, with a highlighted zone indicating the approximate coverage area of a surveillance camera. Within such coverage zones, the movement and activities of workers are continuously monitored. The frequency of detected PPE non-compliance incidents within these camera-observed areas then serves as a direct indicator of the relative safety risk. Consequently, areas with higher concentrations of detected violations, which often correspond to zones of frequent worker traffic or specific task performance, are systematically identified as higher-risk locations. This spatial correlation between detected non-compliance and specific BIM-defined areas is fundamental to the proposed risk visualization approach.

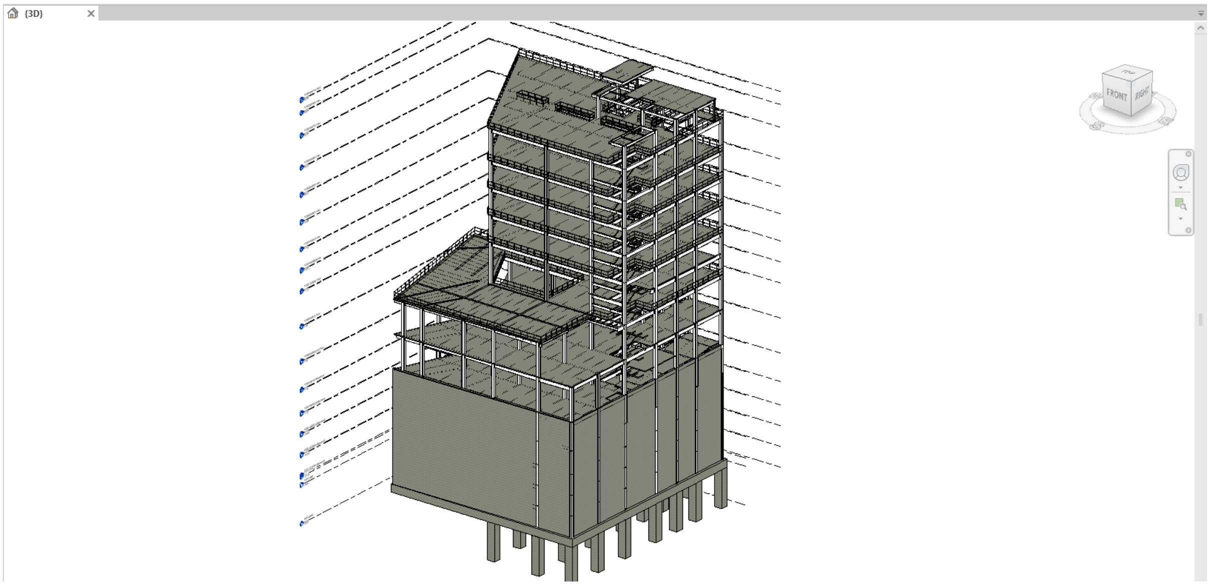

Figure 5. Overall BIM Model of the Illustrative Construction Project

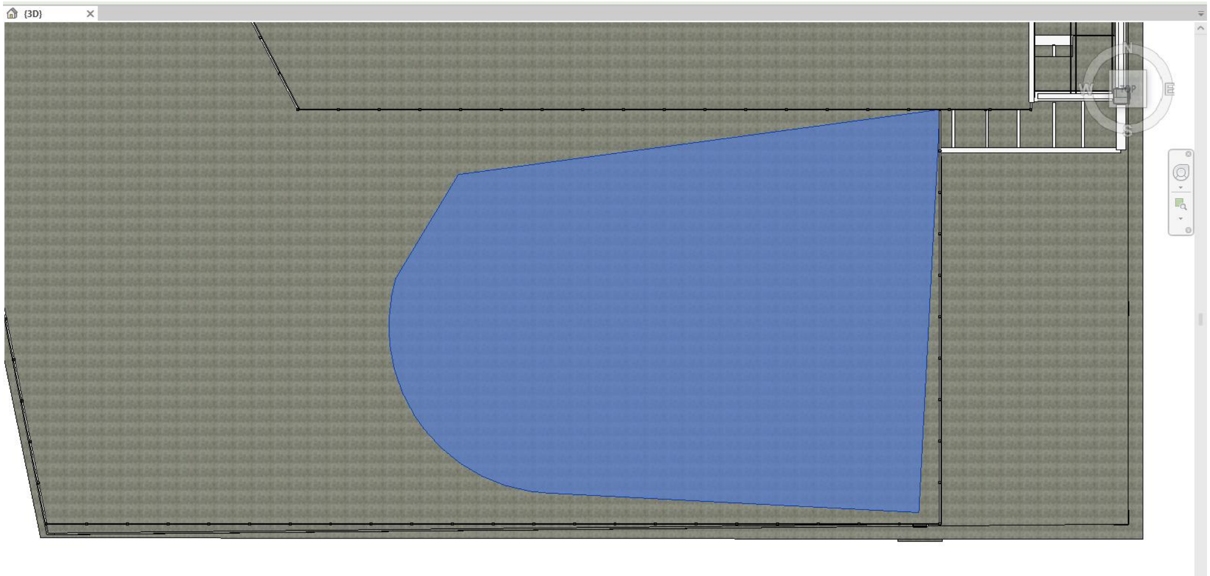

Figure 6. Illustrative Camera Coverage Area within a BIM Floor Level

3.3. Risk Evaluation & Visualization in BIM

Following the spatial mapping of camera coverage, the detected PPE compliance data is integrated into the BIM environment to facilitate risk calculation and visualization for each defined zone. This process involves a series of sequential steps:

- **Individual Detection and Attribute Assignment:** Within each specific zone under camera surveillance, a number of individuals are identified by the detection system. It is recognized that individuals are dynamic entities; thus, attribute assignment for PPE compliance is performed based on their state as observed within their current spatial location, rather than continuous tracking across the entire construction site. For each identified individual, properties relating to the probability of hard hat presence and safety vest presence are directly obtained from the YOLOv11 output. These probabilities are subsequently assigned as custom attributes to the corresponding individual elements within the Revit model. An illustrative representation of an individual element in Revit, along with its associated PPE compliance attributes, is provided in Figure 7**.**

- **Individual Risk Calculation:** The risk level for each individual is then computed based on their assigned PPE compliance probabilities. This is achieved by subtracting the minimum confidence score of both hard hat and safety vest presence from 1. For instance, if an individual's hard hat confidence is 0.9 and vest confidence is 0.8, their minimum confidence is 0.8, and their individual risk is calculated as 1 - 0.8 = 0.2. These calculated risk values are also stored as attributes within the Revit element representing each individual.
- **Zone Risk Aggregation:** To determine the overall risk level of each designated zone within the BIM model, the maximum of all individual risk values present within that specific zone is computed. This aggregated risk value then represents the hazardousness of that particular zone, providing a consolidated indicator of safety performance for the area.
- **Spatial Risk Categorization and Visualization:** Based on the calculated average risk level for each zone, a discrete categorization scheme is applied for visualization purposes. Each zone can be divided into up to four distinct risk categories. Correspondingly, these categories are represented by specific colors. As detailed in Table 4, zones are assigned colors such as green, blue, yellow, and red, providing an immediate visual cue regarding their safety status. This color-coding allows for intuitive and rapid identification of higher-risk areas within the BIM environment.

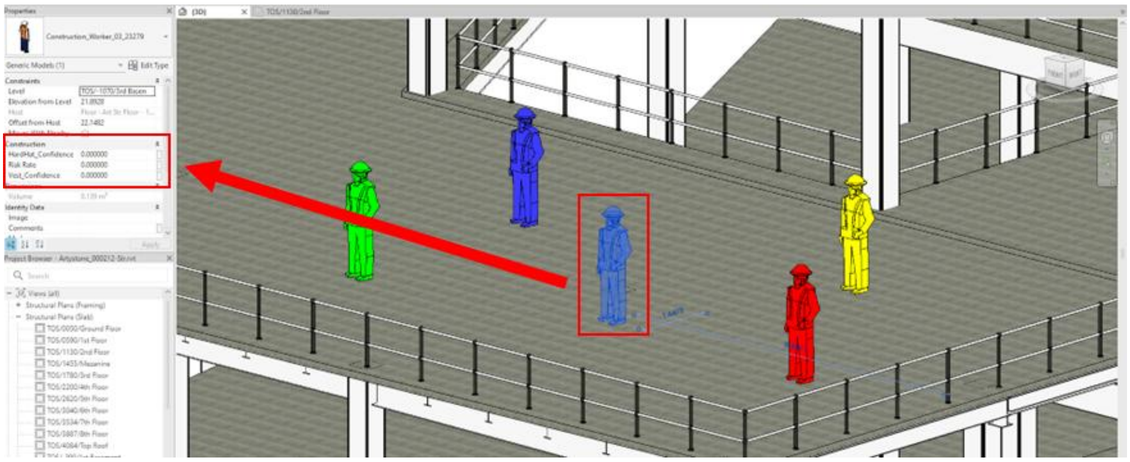

Figure 7. Revit Representation of a Detected Worker with Assigned PPE Compliance Attributes

Table 4. Risk Level Categorization and Corresponding Color Codes for BIM Zones

Risk Level	Color
0 - 0.25	green
0.25 - 0.5	blue
0.5 - 0.75	yellow
0.75 - 1	Red

An example of this process is graphically demonstrated through the visualization of calculated safety risk levels within the BIM model. The green-colored zone is assigned to areas where the calculated risk level is very low (0 to 0.25), signifying high compliance with PPE regulations. Individuals within such zones are detected to be consistently wearing all required personal protective equipment. Subsequently, zones are categorized into higher risk levels as follows: areas with a low risk (0.25 to 0.5) are represented by a blue color, while high-risk zones (0.5 to 0.75) are designated with a yellow color. Finally, areas where the calculated risk level is very high (0.75 to 1) are depicted in red. These precise visual representations are directly tied to the risk categorization scheme, providing an intuitive and immediate means for stakeholders to grasp the safety status of different operational areas within the BIM environment. Some examples of this illustrative visualization are shown in Figure 8.

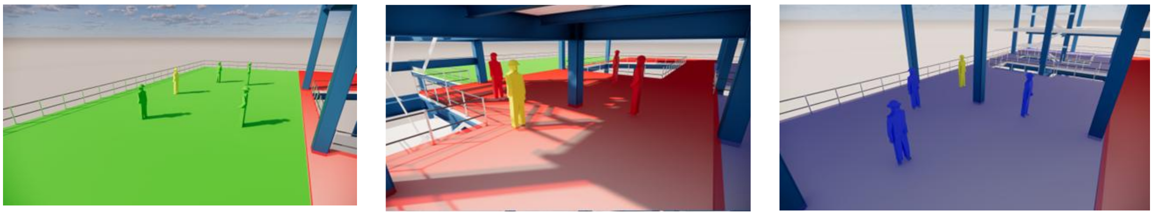

Figure 8. Illustrative Visualization of Spatially Categorized Risk Zones in the BIM Model based on PPE Compliance

A more comprehensive view of this spatial risk visualization on a full floor level is provided in Figure 9. This figure demonstrates how a complete floor plan is segmented into distinct zones, each assigned a color according to its aggregated risk score. This approach allows project stakeholders to immediately identify and understand safety hotspots at a glance.

It's important to note that both Figure 8 and Figure 9 are schematic representations that serve as illustrative examples of the system's capabilities. They demonstrate how the methodology's output would appear in practice, translating complex data into a clear and intuitive visual language for safety managers and other project personnel. This visual communication is a key innovation, as it moves beyond traditional textual reports to provide a powerful tool for proactive hazard identification and targeted intervention.

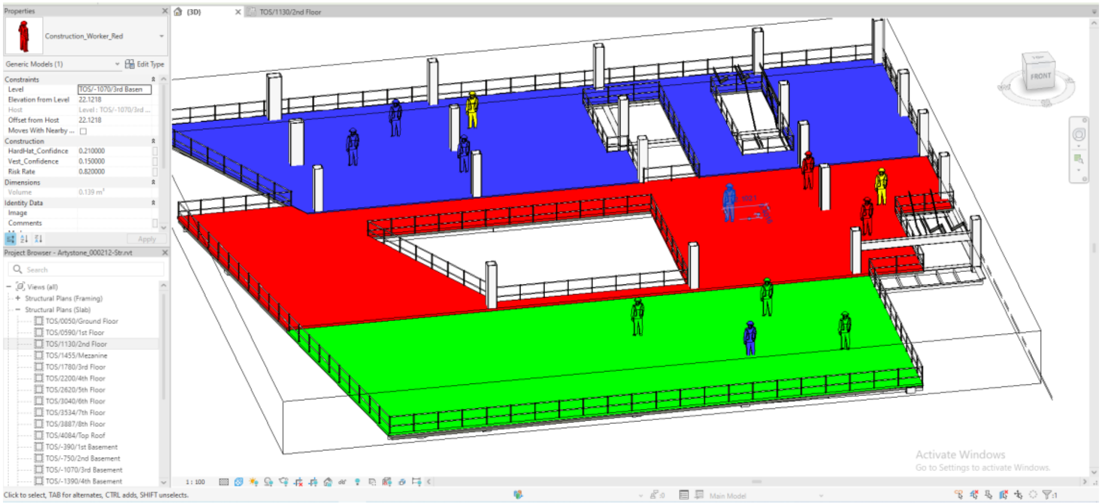

Figure 9. BIM Floor Level with Color-Coded PPE Violation Risk Zones

3.4. Tools and Setup

The proposed framework was implemented across distinct computational environments to leverage their specialized capabilities. For the computer vision component, including YOLOv11 model training and inference, the cloud-based Google Colab environment was primarily utilized. Conversely, BIM model development and data integration tasks, such as mapping detection results to BIM elements, were performed on a local system. The detailed specifications of these computational resources are comprehensively summarized in Table 5.

Table 5. Computational Environment Specifications

Component	Google Colab Environment	Local System Environment
GPU	NVIDIA Tesla T4 or A100 (Cloud Allocated)	NVIDIA GeForce RTX 3060
CPU	Intel Xeon E5 or AMD EPYC (Cloud Allocated)	Intel Core i7-8700K
RAM	Typically 12GB - 25GB (Dynamic)	16 GB
Operating System	Ubuntu (Linux Distribution)	Windows
Core Technologies	Python, TensorFlow/PyTorch, YOLOv11 Framework	Autodesk Revit, Microsoft Excel

4. Results and Discussion

This section is dedicated to presenting and discussing the key findings derived from the implemented methodology. Initially, the performance of the computer vision model in detecting humans and PPE is evaluated, including details on data partitioning for training and testing. Subsequently, the spatial categorization of PPE violation risks within the BIM model is demonstrated and analyzed. Furthermore, the implications of the proposed data framework for safety management strategies are explored, leading into a broader discussion on the overall contributions and impact of this research on construction safety practices.

4.1. Human and PPE detection using computer vision

The effectiveness of object detection models hinges significantly on the quality and diversity of the training data. For the purposes of both training and rigorous evaluation within this study, the GDUT-HWD dataset [42] was meticulously selected. This dataset is particularly well-suited for the current research due to its comprehensive array of environmental variables, including varied landscapes, diverse lighting conditions, and a wide spectrum of human postures and levels of occlusion. From this extensive dataset, a total of 1,400 images were randomly chosen, meticulously annotated with bounding boxes for three distinct categories: Human (5,696 instances), Hat (4,321 instances), and Vest (1,124 instances). For model training and evaluation, the dataset was rigorously partitioned, with 64% of the images allocated for training, 22% for validation, and 14% for testing. This rich and varied collection of worker scenarios proved instrumental in facilitating a thorough investigation and comprehensive assessment of the YOLOv11 algorithm for accurate PPE detection. In the first row of Figure 11, the raw output of the computer vision model is shown, where individuals and PPE are identified. In the second row, the process of assigning each PPE item to its corresponding person is depicted.

An initial evaluation of the YOLOv11 model's performance in a controlled setting indicated generally satisfactory results across most detection categories. While metrics such as precision and recall are fundamental for assessing the correctness and comprehensiveness of the model's outputs respectively, the mean Average Precision (mAP) is recognized as a more encompassing metric for a holistic evaluation of overall model efficacy. A comprehensive overview of the model's performance, including various evaluation curves and the normalized confusion matrix, is presented in Figure 10.

The mAP values obtained during this evaluation demonstrate strong performance for 'Person' (0.823) and 'Hat' (0.819) classes. For the 'Vest' class, an mAP of 0.567 was achieved, with the overall mAP across all classes being 0.746. Further insights into classification accuracy and misclassifications are provided by the normalized confusion matrix (bottom-left panel of Figure 10), where high diagonal values indicate correct predictions (e.g., 'Person' at 0.88, 'Hat' at 0.90, 'Vest' at 0.57). Conversely, challenges in differentiating 'Vest' from 'Background' (0.41) or 'Hat' (0.10) are also revealed.

It was observed that, in certain categories, human perception of PPE surpasses the model's current detection capabilities. Notably, the identification of hard hats demonstrated exceptional performance, largely attributable to their distinct geometric shape and consistently contrasting colors, which simplify their recognition. Conversely, detection accuracy for safety vests was comparatively lower, introducing a degree of potential instability into the automated warning system. Further analysis revealed specific challenges contributing to the reduced accuracy in the "vest" class. These difficulties are primarily associated with the inherent visual complexities involved in differentiating between various colors and styles of safety vests present in the dataset, particularly when attempting to distinguish a vest from ordinary clothing of similar hue, such as a blue vest versus a blue shirt. Such intrinsic ambiguities in the visual characteristics necessitate the incorporation of more granular distinctions within the training data to enhance the system's discerning capabilities. The Recall-Confidence and F1-Confidence curves, also shown in Figure 10, provide additional understanding of the model's behavior across different confidence thresholds.

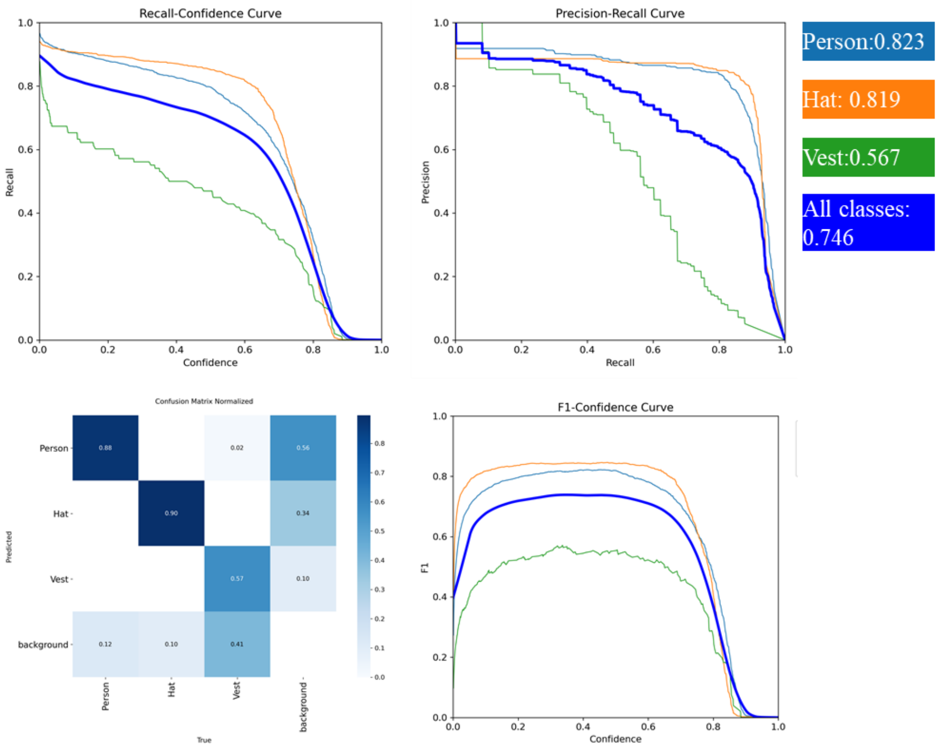

Figure 10. The model’s performance for each class

4.2. Spatial Violation Analysis

To demonstrate the system's effectiveness in a realistic setting, a building in Tehran, Iran with an area of approximately 1400 square meters was considered as a case study. A set of video clips from various parts of the building were recorded and selected frames were processed to analyze safety conditions. The results of this analysis are presented in Figure 11, which clearly shows the three key stages of the proposed methodology. This approach transforms raw visual data into targeted safety insights and showcases the system's efficiency in a practical scenario.

In the first step, the top row of Figure 11 shows the raw output of the computer vision model, in which individuals and PPE are identified and labeled with confidence scores. In the next stage, the middle row of the image depicts the process of assigning each PPE to the corresponding individual, which enables a detailed safety analysis at the worker level. This two-stage approach transforms raw detection data into practical and understandable information for safety analysis.

Finally, the third row of Figure 11 addresses risk visualization in the BIM environment. Based on the location of the processed frames, floors and different areas are color-coded according to the aggregated confidence scores. This color-coding, which is directly linked to the risk categorization scheme in Table 4, provides a clear visual representation of risk levels in each area. This visualization allows safety managers to quickly identify high-risk areas and apply effective preventive measures to improve project site safety.

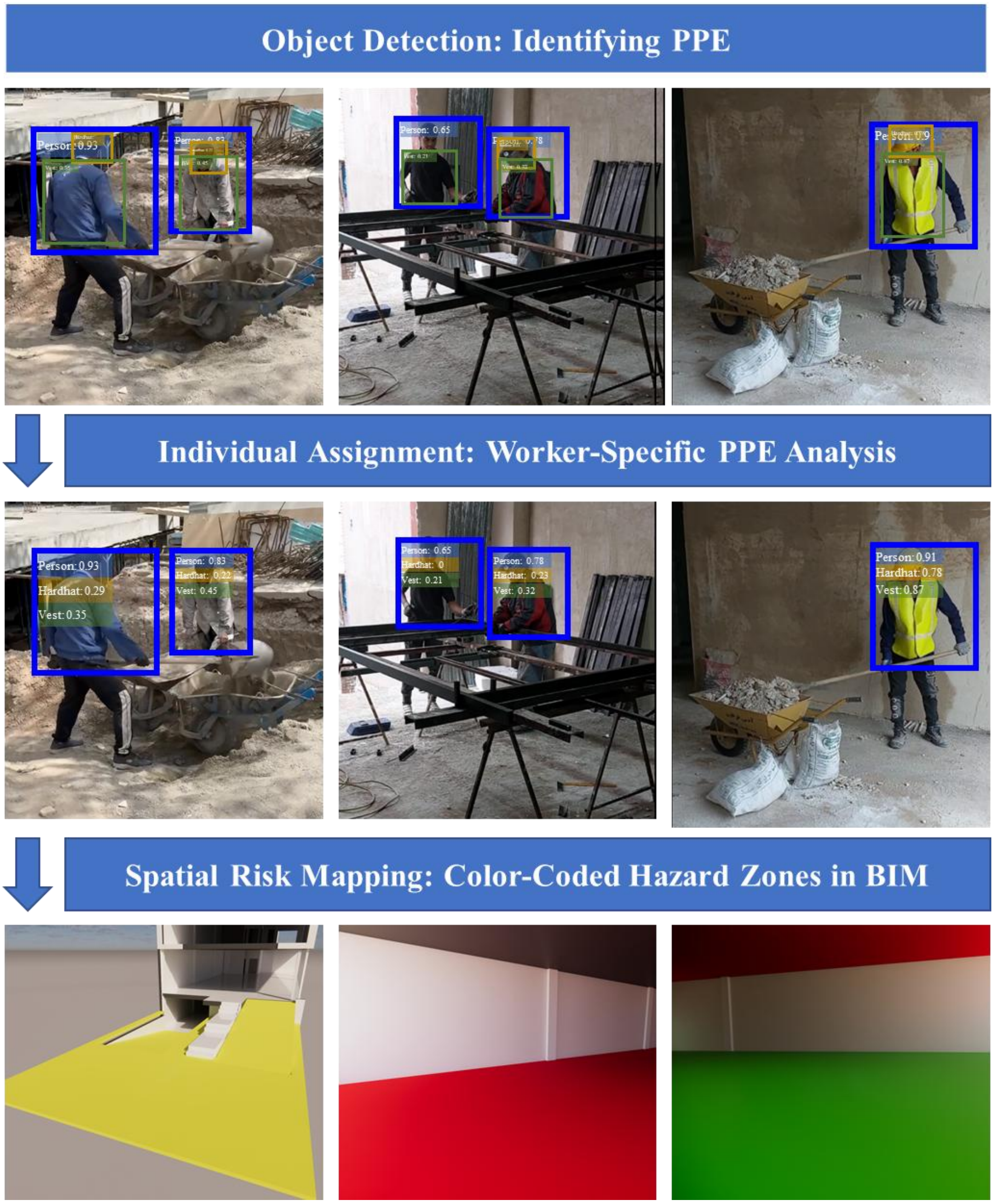

Figure 11. **An illustrative case showing the three key stages of the proposed methodology on a construction site**

4.3. Heat Map Visualization

The ultimate objective of integrating computer vision-based PPE violation detection with BIM is achieved through the spatial visualization of determined risk levels. This phase is critical, as it translates complex analytical findings into an intuitive and actionable visual output directly within the BIM environment, allowing for immediate understanding of safety performance across the construction site. A comprehensive overview of the illustrative case is provided in Figure 12, which displays various floors and areas of the BIM model with distinct features and color-coded risk zones. These identified zones correspond to approximate areas covered by one or more surveillance cameras, from which the PPE compliance data is aggregated.

As established in the methodology, these zones are assigned colors based on their aggregated PPE violation risk levels. For instance, green-colored areas denote zones with a very low risk (0 to 0.25), indicating high compliance. Conversely, red-colored zones represent areas of very high risk (0.75 to 1), where violation frequencies are highest. Additionally, blue-colored zones signify low-risk areas (0.25 to 0.5), while high-risk areas (0.5 to 0.75) are represented with a yellow color, as per the categorization in Table 4. This multi-layered visual feedback mechanism allows for rapid identification of problematic areas, enabling immediate and targeted safety interventions.

This comprehensive approach has been greatly welcomed by safety experts, who have affirmed its utility in rapidly detecting hazardous areas and identifying subcontractors that may not be taking safety policies seriously. By providing these detailed insights, the system allows for specific training courses to be customized and assigned to the workers of each subcontractor, leading to targeted improvements. The ability to visualize these discrete risk levels directly on the digital twin of the construction site greatly enhances situational awareness for safety managers and project stakeholders, facilitating more informed decision-making and efficient resource allocation towards improving overall site safety.

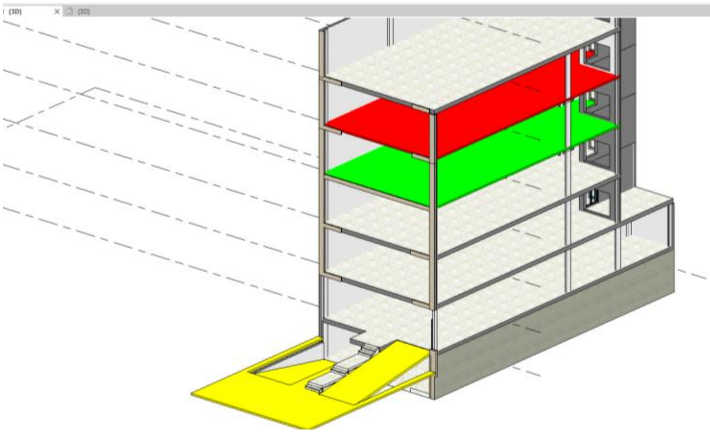

Figure 12. BIM Floor Level with Color-Coded PPE Violation Risk Zones

4.4. Implications and the risk mitigation strategy

Beyond the immediate visualization of PPE violation risk levels, the profound implications of this research lie in the generation and structured management of comprehensive safety data. For effective proactive safety management and the development of targeted risk mitigation strategies, it is imperative that the insights derived from automated detection and spatial mapping be organized within a coherent data framework. The data captured by the proposed system offers a rich source of information that, when structured appropriately, can significantly enhance decision-making processes. A conceptual framework for the integration and utilization of this data, enabling a more systematic approach to safety, is presented in Table 6.

The proposed data framework, as outlined in Table 6 below, is structured to provide a holistic view of safety performance by categorizing key information generated by the system. Columns within such a framework typically include Data Source, identifying the origin of information (e.g., computer vision system, BIM model); Data Element, specifying the particular piece of safety-relevant information captured (e.g., Worker ID, PPE Compliance Status, Detected Violation Type, Location ID, Timestamp); and BIM Integration Point, indicating where this specific data is linked within the Building Information Model (e.g., as a property of a worker element, or an attribute of a specific room/zone). Additionally, a crucial column for Strategic Implication is included, detailing how each piece of data can be directly utilized for safety planning, intervention, and continuous improvement. This structured approach ensures that raw detections are transformed into actionable intelligence, facilitating a clear pathway from data acquisition to informed safety interventions.

Table 6. Conceptual Data Framework for BIM-Integrated Safety Information

Data Source	Data Element	BIM Integration Point	Strategic Implication
Computer Vision System	Worker ID	Worker Element Property	Targeted Training
Computer Vision System	PPE Compliance Status	Worker Element Property	Real-time Alerts
Computer Vision System	Detected Violation Type	Worker Element Property	Root Cause Analysis
Computer Vision System	Timestamp	Project Schedule/Log	Trend Analysis, Incident Logging
BIM Model	Location ID (Room/Zone)	Room/Zone Attribute	Spatial Risk Assessment
BIM Model	Element/Component ID	Element/Component Property	Design-for-Safety Revisions
BIM Model	Project Timeline	Project Timeline	Predictive Modeling
User Input	Hazard Report/Near-Miss	Location/Timestamp	Incident Investigation, Lesson Learned

The comprehensive data framework presented herein has direct and significant implications for the formulation and execution of risk mitigation strategies. By providing structured, spatially-referenced, and time-stamped information on PPE violations, highly detailed analyses of safety hotspots and trends are enabled. This provides specific, data-driven solutions for enhanced safety. The following key strategies are enabled by our approach:

- Targeted Training and Intervention: The system's ability to identify specific high-risk zones and the types of violations occurring allows for the development and implementation of focused worker training programs. For instance, if a specific area consistently shows a high frequency of hard hat non-compliance, safety managers can schedule targeted toolbox talks or training sessions for workers operating in that zone, instead of conducting general, less effective site-wide training.
- Efficient Resource Allocation: The color-coded risk visualization facilitates a more efficient allocation of safety resources, such as safety officers, barriers, or signage. Managers can prioritize their attention and resources on the red and yellow zones, ensuring that critical areas receive immediate oversight and mitigation efforts.
- Proactive and Predictive Safety Management: By analyzing trend data (e.g., violations over time or during specific tasks), safety managers can transition from a reactive to a proactive safety paradigm. The system helps anticipate potential future risks and develop preventative measures before accidents occur, thereby moving beyond traditional, often reactive, safety measures.

Ultimately, through the systematic organization and utilization of this rich dataset, a robust foundation for proactive risk management and continuous enhancement of construction site safety is established.

4.5. Discussion

The findings presented in this research significantly advance the field of construction safety management, directly addressing the identified gap concerning the limited availability of spatially-aware safety analysis within dynamic construction environments. This is achieved by successfully developing a novel framework that, unlike previous research relying solely on either computer vision or BIM, seamlessly integrates the real-time detection capabilities of computer vision (specifically utilizing YOLOv11) with the rich spatial context provided by the BIM model. This integration enables the transformation of raw PPE violation detection data into actionable, location-specific safety intelligence.

A primary contribution lies in the move beyond generic, non-spatial safety alerts and static design-stage analysis. Our framework enables the visualization of discrete risk levels directly within the BIM model, where areas are color-coded (green, blue, yellow, red) based on aggregated PPE non-compliance, offering a granular understanding of hazardous zones. The reliability of these visualized risks and their conformance to real-world conditions are underpinned by the robust performance of the underlying computer vision model, which is rigorously evaluated against diverse site imagery. The inherent design of the framework, enabling granular detection of PPE compliance directly from actual camera feeds, ensures that the generated insights are highly reflective of site-specific operational realities. This approach provides more comprehensive and dynamic information within the BIM model, which was previously unavailable, and its efficiency has been affirmed by domain experts, given the richer data available across different zones.

The practical implications of the proposed system are substantial for construction safety practices. Beyond the immediate visualization benefits, the comprehensive data framework and spatial mapping capability offer several key advantages that translate directly into operational gains for project stakeholders:

- Data-Informed Decision-Making: The system provides project managers with a clear, data-driven picture of safety performance, allowing for evidence-based decisions regarding safety protocols, worker training, and site logistics. This moves away from relying on anecdotal observations or periodic manual inspections.
- Enhanced Communication and Collaboration: By providing a shared, visual understanding of safety performance in the digital twin, the system improves communication and collaboration among all project stakeholders, including designers, managers, and site personnel. The color-coded zones act as a common visual language for discussing and addressing safety concerns.
- Fostering a Proactive Safety Culture: The continuous, automated monitoring and immediate feedback loop help to foster a culture of proactive safety. Workers and managers become more aware of and accountable for safety, as performance is continuously measured and visualized in a transparent manner.

5. Conclusion

This research successfully developed and demonstrated a novel heat mapping system that integrates computer vision with BIM model for enhanced construction safety identification. Addressing the critical gap in spatially-aware safety analysis, the proposed framework effectively leverages YOLO-based detection to identify PPE violations, specifically hard hats and safety vests, from site imagery. A key achievement lies in the seamless integration of this real-time violation data into the BIM environment. This process transformed raw detection counts into meaningful spatial heat maps, visualizing high-frequency non-compliance zones using intuitive color gradients.

The primary novelty of this work lies in its ability to overcome the limitations of previous studies that either lacked spatial context (in vision-based methods) or relied on static, design-stage data (in BIM-based methods). Our system not only automates the detection of safety breaches but crucially maps these incidents onto the actual 3D layout of the construction site, providing a level of granular spatial context previously unattainable in both traditional 2D reporting and static BIM applications. This novel data layer offers a powerful tool for understanding where safety risks are most prevalent.

The proposed heat mapping system holds significant potential to revolutionize safety identification practices in the construction industry. By providing a clear, visual representation of PPE violation hotspots directly within the BIM model, safety managers can proactively identify high-risk areas at an unprecedented level of detail. This facilitates targeted safety interventions, allowing resources to be allocated more efficiently to specific zones or tasks where non-compliance is frequent. Ultimately, this data-driven approach offers clear, actionable solutions for improving safety, including the ability to conduct targeted training, enhance resource allocation, and foster a more proactive and preventative safety culture across all project stakeholders. By improving the precision of hazard identification, a reduction in accidents and injuries can be contributed to, leading to safer working environments and improved project outcomes.

Despite its significant contributions, this research acknowledges certain limitations that pave the way for future advancements. First, it is recognized that the scalability of the current vision system for extremely large or highly complex construction sites might be faced with significant integration and computational challenges, particularly in managing data from hundreds of concurrent camera feeds. Second, the critical need to address ethical considerations regarding worker privacy has been acknowledged. As the system relies on continuous surveillance, practical deployments must be carefully designed to ensure data is handled responsibly, potentially through the anonymization of individual data or by reporting only aggregated, location-based safety metrics. These limitations, while present, define a clear and valuable roadmap for future research.

Future research avenues include integrating other forms of safety-related data, such as near-miss reports, accident logs, or sensor data (e.g., from IoT wearables), to provide a more holistic safety overview. Developing predictive models that anticipate potential violations based on historical patterns and environmental factors could transform the system from a reactive identification tool into a truly proactive risk forecasting platform. Further enhancing the user interface and interactivity of the heat mapping tool within BIM software would also improve its practical usability.

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