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CONSTRUCTION SITE LAYOUT PLANNING AND PROGRESS MONITORING USING COMPUTER VISION ON DRONE IMAGES

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Abstract

Recent advancements in construction methods necessitate automated technologies for designing, planning, and monitoring workplaces. Construction site layout planning and control is often manual and infrequent. This framework applies deep learning and computer vision techniques to automate continuous monitoring and inspection of protective safety barriers separating workers from vehicle traffic. Orthomosaic maps, generated from georeferenced aerial images, assist in training a deep learning model. Automatic barrier detection links to the original site layout baseline. A custom-built layout analysis algorithm identifies changes over time. This approach enables practitioners to assess site safety, track modifications, and implement necessary improvements effectively.

Introduction

Construction site monitoring plays a crucial role in ensuring that projects adhere to their planned schedules, budgets, and quality standards. The necessity of continuous and precise monitoring arises from the need to detect deviations between the "as-planned" and "as-built" states of construction projects, which can lead to cost overruns, delays, and compromised quality. As highlighted by Kopsida et al. (2015), significant discrepancies in project outcomes often emerge when comparing planned versus actual construction progress, emphasizing the importance of effective monitoring mechanisms to mitigate risks and ensure project success.

Initially, this study aimed to employ dense point clouds generated through photogrammetry techniques to monitor layout changes. However, due to the relatively small size and indistinct features of protective barrier and the poor segmentation results obtained from point cloud processing, an alternative approach was adopted. Instead, ortho-mosaic maps generated through similar photogrammetry techniques were chosen as the primary data source. This shift in methodology allows for better visibility and analysis of critical safety elements, such as the placement of guardrails or protective barriers, ensuring compliance with worksite safety regulations.

The automation of worksite progress monitoring using computer vision techniques is a key focus of this study. Automation offers significant advantages in improving the efficiency and accuracy of tracking project developments. Techniques such as feature matching, object recognition, and change detection are explored to streamline the monitoring process, aligning with the findings of Siebert and Teizer (2014). Moreover, this study delves into advanced methods for detecting layout changes over time and employing geo-transforms to accurately map these changes into geospatial images. This capability is essential for ensuring that spatial planning aligns with the evolving needs of the construction project, enabling better decision-making and proactive adjustments.

The primary research questions addressed in this study include:

1. Is the use of orthomosaic maps generated from aerial imagery a viable and reliable method for monitoring construction worksite layout changes?
2. Can the changes between two consecutive days be effectively detected, predicted, and mapped onto a geospatial image to support site management and planning?

To provide a structured and comprehensive discussion, the remainder of this paper is organized as follows. Section 2 presents a review of related work on layout monitoring and the integration of mapped metadata with Building Information Modeling (BIM) or CAD models. Section 3 details the methodology adopted for this study, including data acquisition, processing techniques, and analytical approaches. Section 4 illustrates the application of this methodology through a case study, demonstrating its effectiveness in a real-world construction environment. Finally, Section 5 summarizes key findings from the case study, discusses potential improvements, and outlines future research directions aimed at enhancing automated construction site monitoring.

This study contributes to the growing field of automated construction monitoring by leveraging drone imagery and computer vision techniques to improve safety, efficiency, and accuracy in worksite supervision. The insights gained from this research can be extended to broader applications in construction management, offering innovative solutions for real-time site analysis and decision-making.

Related Work

Several studies have explored layout monitoring in construction using advanced technologies, demonstrating the potential of various methods to improve accuracy, efficiency, and automation in tracking construction progress. Among these, Sacks et al. (2020) explored the synergy of Building Information Modelling (BIM) and Artificial Intelligence (AI) in advancing Construction Tech innovations. Their work highlights how BIM serves as an information backbone, enabling applications like automated code-compliance checking, construction layout, and project performance monitoring, while AI enhances data processing and semantic enrichment. This integration fosters the development of startup-driven solutions, addressing industry fragmentation and paving the way for digital twins in construction.

Teizer et al. (2024) introduced a Digital Twin for Construction Safety (DTCS) framework to enhance safety management on construction sites. This work outlines a system-based approach integrating Building Information Modeling (BIM), IoT, and AI to connect physical site conditions with digital models. Similarly, Speiser et al. (2025) has developed unified ontology for construction safety called UNOCS that shares safety knowledge between stakeholders during construction process. Such frameworks and ontologies could be more effective with digital safety information which could be readily shared and analyzed by safety managers or automated safety checks to better ensure safety norms.

Kim et al. (2011) introduced a fully automated method for registering 3D point cloud data to CAD models. This method is particularly significant for layout monitoring as it facilitates the alignment of actual site conditions with design models, ensuring that layouts are accurately implemented. In this study, the approach is extended to register changes and potential defects back to orthomosaic maps, which could be further developed to integrate with BIM or CAD models for enhanced visualization and tracking of worksite modifications.

Greeshma et al. (2022) developed a framework that integrates 4D BIM with image processing for automated construction progress monitoring. Their research directly applies to layout monitoring by using images to track changes in construction layouts over time, providing valuable insights into different project development stages. This study demonstrates that images alone can be a highly effective tool for layout monitoring, sometimes even more reliable than point cloud data, particularly when dealing with small-scale objects or challenging environmental conditions.

Initially, the approach planned for this study involved the use of point clouds to monitor worksite layouts. However, several limitations were identified in practice, leading to a shift towards orthomosaic maps as the primary data source. The decision to move away from point clouds was based on multiple factors, including challenges in achieving proper alignment between point clouds and reference models, as well as the relatively small scale of objects of interest, such as protective barrier, which resulted in suboptimal feature representation in point cloud data. This decision aligns with prior research that has explored alternative data sources to improve monitoring accuracy.

Additional studies related to mapping worksite changes back to BIM were also reviewed. Kavaliauskas et al. (2022) proposed a novel methodology for automated construction progress monitoring by integrating 3D point cloud data with IFC-based BIM models. Their approach focuses on aligning as-built point clouds with as-planned BIM data to detect completed objects, even in noisy and occluded environments, using point-to-plane distance estimation. This method enhances construction efficiency by automating object detection and providing visual progress reports, contributing to timely project management and decision-making.

Golparvar-Fard et al. (2012) developed methods for automated progress monitoring by integrating unordered construction photographs with IFC-based BIMs. Their approach illustrates how image data can be synchronized with BIM to facilitate effective layout tracking, enhancing the ability to assess discrepancies in construction progress and identify deviations that may affect project timelines. Braun et al. (2018) developed a BIM-based approach for automated construction progress monitoring using photogrammetric point clouds and 4D Building Information Models. Their method involves generating dense point clouds from semi-global-matching disparity maps and comparing them with the planned state to detect construction deviations. By integrating process dependencies and confidence-based component detection, this approach enhances the accuracy of progress tracking, supporting efficient construction management.

Finally, dataset availability plays a crucial role in advancing research on BIM applications and automated monitoring. Abreu et al. (2023) addressed this issue by introducing a labeled indoor point cloud dataset designed for training and testing algorithms in BIM-related applications. Their dataset provides a benchmark for the automatic detection of construction elements, layout changes, and safety hazards, offering valuable resources for the development of advanced monitoring systems. The integration of such datasets into machine learning models could further enhance the automation and accuracy of construction site monitoring techniques, presenting opportunities for future research and application.

Overall, these studies demonstrate the evolving landscape of construction site monitoring, where the integration of BIM, machine learning, image processing, and automation continues to enhance efficiency and accuracy. By leveraging the insights from previous research, this study aims to contribute to the field by demonstrating the viability of orthomosaic maps as an effective alternative to point cloud data for layout monitoring, with a particular focus on safety compliance and proactive site management.

Methodology

This study focuses on monitoring construction progress of the aforementioned utility tunnel. In this study a systematic approach utilizing time-lapse drone imagery for data collection has been used. The methodology, illustrated in Figure 1, outlines a linear process flow designed to capture, analyze, and interpret changes over time at the construction site. The detailed explanation about each step involved in methodology is explained below.

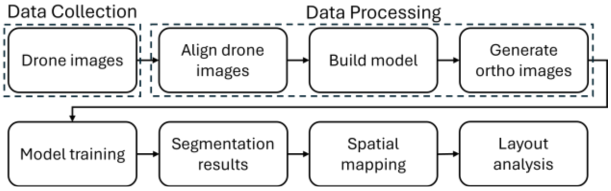

Figure 1: Methodology for this work.

Data Collection

The proposed process begins with the deployment of a drone to capture high-resolution images of the construction site at predetermined intervals. In total, 55 drone flights recorded 45 different states of the entire construction site in the timeframe June 2024 to December 2024. On average, the drone flights were 13 days apart from each other to capture enough progress. Manually supervised flights occurred in available time slots (e.g., considering security and privacy also on weekends) and during stabile weather conditions (above 0° Celsius, dry conditions, sunny or cloudy). We used commercially available drone (aka. Unmanned Aerial Vehicle, UAV) DJI mini4 Pro collects data at 4K resolution using a 12 MP camera, facing downwards. The temporal resolution for the drone to automatically capture individual photo images was set to be 2 seconds. Although feasible, autonomous flight path planning was not performed. Yet, the same routine and flight sequence was conducted every time. These steps are crucial for establishing a temporal sequence of visual data, which forms the foundation for analysis (post-processing). The Data collection acquired over a span of 6 months can be seen as shown in Figure 2. A closer look to the layout could be seen in Figure 3.

Figure 2: Orthomosaic maps over time.

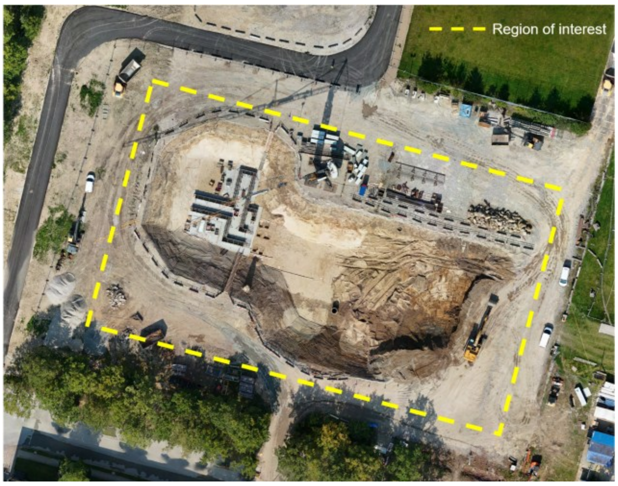

Figure 3: A closer look at the work site layout on 29-08-2024. The yellow highlighted boundary shows the area of interest for monitoring the construction site layout in this work.

Data Processing

The next critical phase in our project involves aligning the multitude of images captured by drones to construct an intricate three-dimensional (3-D) model. This task is executed through the application of Structure from Motion (SfM), a photogrammetric technique that reconstructs 3D scenes from a series of 2D images. The process begins with feature detection and matching, where distinctive points like corners or edges are identified in each image using algorithms such as SIFT or SURF. These points are matched across different images to establish spatial relationships.

Following feature detection, we calibrate the camera parameters. This calibration involves determining both intrinsic properties like focal length and distortion, and extrinsic ones concerning the camera's position and orientation for each shot. This calibration aids in understanding how the camera perceives the scene from various angles. Subsequently, a sparse point cloud is generated, which is a preliminary 3D model based on

matched features. However, this cloud has limited density, prompting the need for error reduction through methods like bundle adjustment, which simultaneously adjusts camera parameters and 3D points to minimize discrepancies.
To further refine our model, we integrate Ground Control Points (GCPs). These points, known for their precise geographic coordinates, are crucial for enhancing the model's accuracy, scale, and georeferencing. After incorporating GCPs, we transition from a sparse to a dense point cloud. This involves computing depth for every pixel across all images, resulting in a comprehensive 3D representation of the surveyed area.

The final step involves generating high-quality orthomosaic maps from the dense point cloud. An orthomosaic corrects for distortions caused by camera angles and terrain, providing a seamless, scale-accurate, and georeferenced image. These orthomosaic maps are saved in the “tif" format, which supports high-quality, lossless compression, ensuring the preservation of detail. The resolution of these images reaches approximately 19000x19000 pixels, offering exceptional clarity.

This entire process has been facilitated by "Agisoft Metashape, version 2.1.3" (Agisoft, 2023), software known for its robust capabilities in Structure from Motion (SfM), image alignment, and 3D modeling. For further processing and labeling, "QGIS, version 3.40" (QGIS Development Team, 2023) has been employed, providing additional GIS functionalities like annotation and integration with other geographic data.

Model training

In this study, we have employed the Deeplabv3 model, as proposed by Chen et al. (2017), for the specific task of segmenting protective barrier within high-resolution imagery. The first challenge encountered was the sheer size of the data; the resulting orthomosaic maps or orthophotos from our earlier processes have a resolution of 19.000 x 19.000 pixels, which are far too large for the model to process in one go. To circumvent this issue, both the images and their corresponding labels were segmented into smaller, manageable tiles, each measuring 512 x 512 pixels. These tiles were then organized into data loaders.

The dataset was partitioned into training and validation sets with a ratio of 4:1, ensuring that there is adequate data for both training the model and validating its performance. The Deeplabv3 model was trained over 250 epochs, utilizing a learning rate of 1e-05 to finely tune the network's weights.

One significant challenge in this segmentation task was the class imbalance; the areas covered by protective barrier are notably smaller than the surrounding background, leading to skewed representation in the data. To address this issue, we opted for the focal loss function, which is particularly effective in handling imbalanced datasets by focusing learning on hard, misclassified examples. This approach was paired with the Adam optimizer, known for its adaptive learning rate capabilities, enhancing convergence speed and stability in training.

The training process yielded promising results with the model achieving a validation loss of 0.1351, which indicates a high level of accuracy in predicting the segmentation masks. Furthermore, the Intersection over Union (IoU) metric, a key indicator for segmentation tasks, reached a value of 0.7588 for validation data, demonstrating that the model has a reasonable overlap between predicted and actual segmentations.

Overall, by breaking down the large images into smaller tiles, employing focal loss to mitigate class imbalance, and using the Adam optimizer alongside a meticulously set learning rate, we were able to train Deeplabv3 effectively for the precise segmentation of protective barrier in our high-resolution orthophotos.

Spatial mapping

In this study to geo-reference objects and to retrieve data from “.tif” files python library called “Rasterio” proposed by Gillies et al., (2019) has been used. This step involves extracting not only the pixel data but also metadata like the coordinate reference system (CRS), geo-transform, and other information for geo-spatial analysis. Geo-transform refers to the process of mapping pixel coordinates to geographic coordinates. Here the segmentation result received from the trained model is taken as references to associate each instance of object with its corresponding geo-location. For this the segmentation masks of the images are converted into bounding boxes with corresponding 4-pixel coordinates. This step is needed as it makes the process of extracting location data from “.tif” files more efficient. Each bounding box with its corresponding coordinates is in turn used to query the “.tif”. Now each bounding box has its equivalent geolocations in the form of latitude and longitude tagged to it. Using the bounding box tagged with locations data, the site layout manager could use this data to visualize these objects on real earth images or even in the Georeferenced BIM models.

Layout analysis

In the layout analysis we compare changes between two consecutive or non-consecutive images to monitor the changes. This is done by checking if the bounding box of objects detected in the former image are present in the same or similar locations in the latter image within a certain tolerance. The bounding box prediction in the images has the corresponding geo-spatial locations for its four corners which have been retrieved in the previous step. Then we use the technique of IOU between predictions of 2 images to detect if the objects have been removed or newly added between the images. The threshold for this work has been set to 0.85 IOU meaning if the overlap of a single protective barrier between 2 consecutive days is over 85 percent, then it is considered as not modified. In Ideal scenario, the IOU must be 1 but in order to account for some error or deviation in the geospatial information between images an optimal threshold of 0.85 was used. These changes are then mapped back to the later image highlighting the new blocks with a different color code.

Table 1: Construction site layout change analysis algorithm.

```
Algorithm 1: Layout change analysis
Input: Bounding Box (BB) predictions of protective barrier
(2 images), d - day
Output: Bounding Box on image2 with colour codes
for all BB on d:
    if IOU (BB at d, BB at d-1) > threshold then
        Status of object = "Not modified - Red"
    else
        Status of object = "Added - Green"
    end if
for all remaining BB on d-1:
    if IOU (BB at d-1, BB at d) > threshold then
        Status of object = "Not modified - Red"
    else
        Status of object = "Removed - Yellow"
    end if
```

For the purpose of analyzing the work site layout to the as-built site layout, the replica of as-planned site layout plan is needed which was created for this work in Revit 2024.

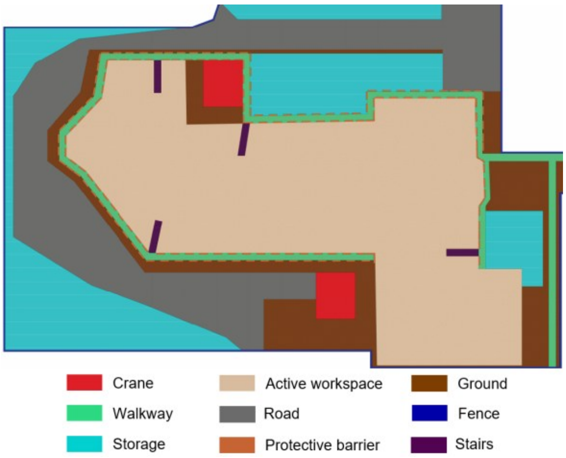

Figure 4: Replica of original construction site layout plan.

Figure 5: Installation of protective barrier to separate pedestrian worker walkway from vehicle traffic.

The layoutof the construction site mainly consists of areas such as crane, protective barrier, walkway, storage, road, active workspace, office containers, road, etc. as shown in Figure 4. The protective barrier area is the region for placement of guardrails. In this work we monitor the protective barrier (protective barrier for guardrail installation on worksite as seen in Figure 5) instead of guardrail. The reason being the guardrails are not seen clearly from the top-down aerial view and that they occupy only very few pixels which results in difficulties in mapping them back with the geo locations. The As-planned worksite layout shown in Figure 4 is not the same as the As-built worksite layout. This calls for monitoring of the as-built worksite layout by a safety manager inspecting the site in person. This process of manual monitoring could be automated by using the methods shown in the previous sections. As seen in the As-planned worksite layout the placement of a protective barrier is very important as it separates walkways from the road with frequent movement of heavy equipment and workspace below ground level (approx. 20 feet.) Hence by automating the process of monitoring the placement of protective barrier and analyzing change in layout over time will significantly benefit the site managers and other practitioners.

Results

The methodology outlined in Section 3 of this study has been employed to monitor the layout of protective barrier at a construction site, specifically under two distinct scenarios illustrated in Figure 6. In the first scenario, the layout of the protective barrier shows minimal variation, with only one block missing on the previous day, which was correctly replaced by the following day, indicating a time difference of just one day. This missing block, highlighted by a red circle in the figure, plays a pivotal role as it delineates the boundary between the walkway and the active workspace, where its absence could lead to a dangerous 20-foot drop to the ground below.

In contrast, Scenario 2 reflects a significant progression of work over a week (a time difference of 7 days), leading to a noticeable transformation in the layout. Here, multiple protective barriers have been added, while others have either been modified or entirely removed, demonstrating the dynamic nature of construction activities.

To delve into these scenarios with greater detail, the first step involves extracting the bounding boxes of the detected protective barrier from the images. Each image is fed through our trained deep learning model, Deeplabv3, which performs pixel-wise segmentation, distinguishing between protective barrier and the background. However, due to the model being trained on a relatively sparse dataset, the initial segmentation results are not optimal. To enhance these results, we apply various computer vision techniques like dilation and erosion, which improve the segmentation masks by filling gaps and smoothing edges.

Once we have refined segmentation masks, the next phase involves identifying the contours of each detected block. Using the contours and the convex hull method, we derive precise bounding boxes for each protective barrier. These bounding boxes, which initially contain pixel coordinates, are then correlated with the geo-spatial coordinates extracted from the metadata of the corresponding ".tif" files. This step allows us to map each block's position in real-world coordinates, facilitating a detailed analysis of their placement within the construction site.

Following this, we utilize the algorithm described in Table 1 to determine if the blocks have remained unchanged, been added, or removed. The outcomes of this analysis for both scenarios are visually represented in Figure 6, providing a clear comparison of block layouts over time.

Additionally, our analysis quantifies the changes in the number of protective barrier; we document how many have been added, how many have been removed, and how many have remained unmodified. These detailed statistics are organized and presented in Table 2, offering a comprehensive overview of the construction site's evolution over the observed period.

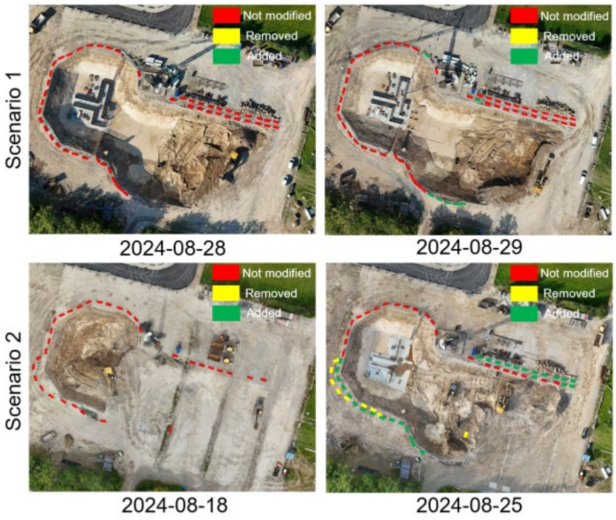

Figure 6: Side-by-side comparison of two consecutive workdays showing change in protective barrier.

Table 2: Details to protective barriers over entire observation.

Date of	Change from previous observation time		
observation	Not modified	Removed	Added
2024-06-28	-	-	28
2024-07-21	0	28	1
2024-08-10	1	0	38
2024-08-15	28	11	5
2024-08-18	33	0	0
2024-08-25	24	9	39
2024-08-26	61	3	2
2024-08-27	63	0	2
2024-08-28	63	0	0
2024-08-29	62	1	0
2024-09-02	62	0	1
2024-09-03	63	0	8
2024-09-04	71	0	0
2024-09-14	71	0	0
2024-10-26	69	2	1
2024-12-03	60	10	14

Conclusion

This study introduces a robust methodology for monitoring construction site layouts, particularly focusing on the detection and tracking of protective barrier. By employing the Deeplabv3 model, we have successfully reduced the reliance on time-consuming and potentially dangerous manual site inspections. Our method allows for the analysis of high-resolution orthophotos to observe layout changes over time, under different scenarios as detailed in our research.

Despite these advancements, our approach is not without its challenges. The accuracy of object detection can sometimes be compromised by elements such as shadows, overlapping objects, or low-resolution images, which can lead to missed or incorrect predictions of protective barrier locations. This underscores the need for collecting and training our model with more diverse and comprehensive data, encompassing various lighting conditions, angles, and construction phases.

Looking ahead, the integration of other high-benchmarked segmentation models could significantly enhance our methodology. A model like the Segment Anything Model (SAM) by Meta AI (Kirillov et al., 2023) has demonstrated exceptional zero-shot segmentation capabilities, which could be advantageous for our application due to its ability to segment objects without specific training on construction imagery. Another model to consider is SegFormer3D (Perera et al., 2024), which harnesses a lightweight hierarchical Vision Transformer architecture to achieve exceptional accuracy and efficiency in 3D segmentation tasks. Its efficient self-attention mechanisms and multi-scale feature processing enable precise segmentation of complex 3D environments, making it highly suitable for construction site monitoring. The model's compact design, with 34× fewer parameters and 13× lower computational complexity than state-of-the-art models, ensures accessibility for on-site deployment with limited computational resources, potentially elevating the precision and adaptability of automated construction site analysis.

The current study has successfully mapped detected protective barriers back to their geo-spatial coordinates on orthophotos, providing real-time monitoring capabilities. This work can be easily extended to monitor other layout critical elements such as other safety barriers, containers, vehicles, equipment, etc., providing more detailed site layout analysis. However, the potential of this work extends far beyond just monitoring. By integrating these detections into Building Information Modeling (BIM) systems, we could automate the comparison of as-built versus as-planned site layouts, enhancing safety assessments and contributing to the creation of a digital twin of the construction site. This leads to a significant potential for extending this work into the realm of 4D Safe BIM comparison, where time is incorporated as a fourth dimension. This would enable dynamic, real-time safety evaluations throughout the construction timeline, leading to what could be termed 'Safe BIM'. Such an approach would not only monitor but also predict safety concerns by comparing the current state of the site with planned progress.

Lastly, we envision the creation of real-time worker safety zones, as explored in the work by Hong and Teizer (2024). Here, the layout data detected by our model could be used along with RTK-GNSS for precise tracking of equipment and personnel, dynamically establishing safety zones around active work areas. By leveraging this approach, algorithms could be developed to not only monitor but also manage safety zones in response to the changing conditions of the construction site. This could be integrated with wearable technology to alert workers when they approach or enter potentially hazardous areas, enhancing personal safety on the job site. The methodology presented for identifying static and dynamic hazard zones could be extended to incorporate real-time data from our segmentation models, allowing for a proactive approach to safety management. This integration could lead to systems that automatically adjust safety zones based on the movement of equipment, workers, and materials, thereby reducing the risk of accidents and improving overall site safety.

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Declaration of Generative AI in the writing process

During the preparation of this work, the authors used Grok 3 and Grammarly to improve readability and language of the writing process. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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