International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

Computer Vision for Construction Site Safety and Progress

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Abstract— **The growing need for improved safety management in environments has led to the development of intelligent monitoring systems capable of detecting safety compliance automatically. Traditional safety inspection methods are often manual, time-consuming, and prone to human error, which can result in unsafe working conditions. This study presents the development of an Artificial Intelligence (AI)-based computer vision system designed to monitor the use of Personal Protective Equipment (PPE) such as helmets and safety vests among construction workers.**

The proposed system utilizes deep learning techniques, specifically the YOLOv8 object detection model, to analyze construction site images and identify the presence or absence of required safety equipment. The methodology includes data collection, preprocessing, annotation, model training, and deployment through a web-based application. The system integrates image processing tools and a user-friendly interface to enable real-time detection and visualization of safety compliance.

Environmental factors such as lighting conditions, background complexity, and worker density were considered to evaluate system performance under real-world scenarios. The system classifies workers as safe or unsafe based on PPE usage and calculates safety compliance percentages to provide quantitative insights.

The results demonstrate that the developed system achieves high detection accuracy and effectively identifies safety violations. It performs reliably under standard conditions while highlighting certain limitations in low-light and occluded environments. The integration of AI-based detection with a web application enhances usability and enables real-time monitoring.

This study emphasizes the potential of combining computer vision and intelligent systems to improve construction site safety. The proposed approach provides an efficient, automated, and scalable solution for safety compliance monitoring, contributing to safer and more sustainable construction practices.

Keywords— **Artificial Intelligence, Computer Vision, PPE Detection, Safety Compliance, YOLOv8, Construction Safety Monitoring.**

I. Introduction

The construction industry has undergone significant transformation in recent years due to the integration of Artificial Intelligence (AI) and Computer Vision (CV), which have introduced new opportunities for improving site safety, project tracking, and overall operational efficiency (Irizarry & LiQ., 2013). Construction sites are inherently dynamic environments characterized by multiple risks arising from human error, non-compliance with safety regulations, and inefficient monitoring practices. It has been observed that traditional approaches to safety supervision and progress tracking often fail to ensure continuous monitoring, thereby increasing the likelihood of accidents and project delays (Han & Lee, 2015). AI-powered computer vision systems have enabled automated detection of unsafe activities, identification of workers without protective equipment, and monitoring of construction progress using visual data captured through cameras or drones.

The construction sector plays a critical role in economic development and infrastructure growth; however, it is also considered one of the most hazardous industries due to its complex operations and lack of effective real-time monitoring systems (Lopes, 2012; Garrett & Teizer, 2009). Workers are frequently exposed to unsafe conditions while operating heavy machinery and performing high-risk activities, which significantly increases the probability of accidents if proper safety measures are not followed (Helander, 1991). Conventional safety management practices have largely depended on manual supervision and periodic inspections, which are often time-consuming, inefficient, and prone to human error (Khan et al., 2024). It has been identified that supervisors are unable to continuously monitor all workers and activities, particularly in large-scale projects, resulting in undetected safety violations and increased accident risks (Hsu & Huang, 2015). Additionally, construction progress tracking has traditionally relied on manual documentation methods such as reports and photographic records, which are often inaccurate and delayed (Samsami, 2024).

With the rapid advancement of AI and CV technologies, new automated solutions have been developed to address these challenges. Computer vision enables machines to interpret and analyze visual data from images and videos, thereby facilitating automated monitoring and decision-making processes (Khan et al., 2021). The integration of AI with CV has allowed systems to detect workers, identify safety equipment, recognize unsafe behaviors, and estimate construction progress with improved accuracy (Muhammad et al., 2024). Visual data captured through strategically placed cameras or drones can be processed in real time using AI algorithms to generate safety alerts and progress updates (Zhang & Zhong, 2019). This integration has transformed traditional construction management practices into data-driven systems capable of continuous monitoring and intelligent decision-making (Rane, 2023).

Despite these advancements, a significant gap has been observed in the implementation of integrated systems capable of simultaneously monitoring safety compliance and construction progress in real time. Most existing solutions focus on either safety monitoring or progress tracking independently, thereby limiting their practical applicability in complex construction environments. Construction sites remain dependent on fragmented systems and manual interventions, which reduce efficiency and increase the risk of errors. Therefore, there exists a critical need for an automated and unified system that can effectively monitor worker safety and project progress using AI and computer vision technologies.

In this study, an AI-based computer vision system was developed to detect safety compliance, identify unsafe conditions, and monitor construction progress using visual data. The system was designed to detect the presence of Personal Protective Equipment (PPE), such as helmets and safety vests, and to classify workers based on safety compliance. Additionally, the system was intended to analyze construction images for tracking progress and generating real-time insights. The integration of safety monitoring and progress tracking into a unified framework was aimed at improving accuracy, reducing reliance on manual supervision, and enhancing decision-making in construction site management.

The proposed system contributes to improving construction safety and operational efficiency by enabling continuous monitoring and automated analysis. The adoption of AI-based monitoring systems has the potential to reduce accidents, improve compliance with safety regulations, and support timely project execution. Furthermore, the use of data-driven insights enhances resource utilization and enables proactive risk management. The scope of the study was focused on the design and simulation of an AI-based framework using image and video data for PPE detection and progress tracking. Large-scale real-time deployment and integration with advanced IoT systems were beyond the scope of this work; however, the developed system demonstrated the feasibility and effectiveness of AI-driven monitoring in construction environments.

II.Methodology

The methodology adopted in this study was systematically structured to develop an Artificial Intelligence (AI)-based computer vision system for monitoring safety compliance in construction environments. The system was designed to analyze visual data acquired from construction sites and automatically detect the presence or absence of Personal Protective Equipment (PPE), including helmets and safety vests, among workers. A deep learning-based object detection approach was employed, wherein the YOLOv8 (You Only Look Once) algorithm was utilized due to its capability for real-time detection with high accuracy and computational efficiency.

A comprehensive dataset consisting of construction site images was collected from multiple sources, including publicly available datasets and manually captured images from active construction environments. The dataset was designed to include diverse scenarios representing both compliant and non-compliant safety conditions, such as workers wearing helmets and safety vests as well as workers without required protective equipment. Variations in lighting conditions, including bright daylight, shadowed regions, and low-light environments, were incorporated to ensure model robustness. Additionally, different camera angles, perspectives, and distances were considered to simulate real-world construction site conditions.

The collected images were subjected to preprocessing techniques, including resizing, normalization, and data augmentation, to improve data quality and enhance model generalization. Data augmentation methods such as rotation, horizontal flipping, and brightness variation were applied to increase dataset diversity and reduce the risk of overfitting. These transformations enabled the model to perform effectively under varying environmental and operational conditions.

Subsequently, the dataset was annotated using bounding box techniques to label relevant objects within each image. The annotated classes included helmet, safety vest, and worker

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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(person detection). Annotation tools such as LabelImg and Roboflow were utilized to generate accurate and consistent labels. The annotated dataset was structured in accordance with the YOLO format and configured using a data definition file (data.yaml), which specified class labels and dataset paths required for model training and validation.

The YOLOv8 model was trained using the prepared dataset, with the dataset divided into training (70%), validation (20%), and testing (10%) subsets. Training was conducted using a Python-based framework, incorporating optimized parameters such as batch size and training epochs ranging from 50 to 100. During training, classification and localization loss functions were minimized to improve detection accuracy. Upon completion of the training process, optimized model weights were generated and utilized for detection tasks within the system.

For system implementation, the trained model was integrated into a detection framework capable of processing both static images and real-time inputs. The backend processing was implemented using Python, incorporating libraries such as OpenCV for image handling and the Ultralytics YOLO framework for object detection operations. The system was designed to identify workers and detect the presence of PPE in various construction scenarios.

A rule-based safety compliance evaluation mechanism was implemented to classify workers as safe or unsafe based on detection results. For each detected worker, the presence of both helmet and safety vest was evaluated. Workers were classified as safe only when all required PPE components were detected, whereas missing or incorrectly detected PPE resulted in classification as unsafe. The system further computed safety compliance percentage based on the ratio of safe workers to total workers, providing a quantitative measure of site safety.

To facilitate user interaction, a web-based interface was developed using HTML, CSS, and JavaScript. The application enabled users to upload images, access webcam input, and visualize detection outputs in real time. Browser-based processing using TensorFlow.js was incorporated to enhance interactivity and provide immediate feedback. In addition, a backend component developed using Python and Flask was integrated to support advanced processing using trained YOLOv8 model weights.

The workflow of the system followed a sequential process in which input images were preprocessed and passed to the trained object detection model. The detected objects were analyzed to determine PPE compliance, followed by classification of workers and generation of annotated output images. The final output included visualization of detected objects along with safety compliance percentage, enabling effective monitoring of construction site safety.

Table 1: Methodological Framework of the Study

Stage	Description
Data Collection	Acquisition of diverse construction site images with varying PPE conditions and environments
Data Preprocessing & Augmentation	Image resizing, normalization, noise reduction, and augmentation techniques
Dataset Annotation	Bounding box labeling of helmets, safety vests, and workers
AI Model Development	Training of YOLOv8 model using optimized parameters
System Implementation	Integration using Python, OpenCV, and web-based interface
Safety Compliance Logic	Classification of workers and calculation of compliance percentage
Performance Evaluation	Assessment using accuracy, precision, recall, and F1-score
Comparative Analysis	Evaluation against traditional manual inspection methods

III.Results and Discussion

The developed AI-based computer vision system was evaluated to determine its effectiveness in monitoring construction site safety and detecting PPE usage under real-world conditions. The system successfully identified workers and safety equipment, demonstrating the applicability of computer vision in automated safety monitoring. Similar applications of AI-based safety detection systems have been reported in previous studies (Liu et al., 2021; Hayat & Morgado-Dias, 2023).

The performance of the model was assessed using accuracy, precision, recall, and F1-score. The system achieved accuracy levels between approximately 85% and 92% under normal conditions. Comparable performance of YOLO-based PPE detection systems has been reported in prior research (Ferdous & Ahsan, 2022; Chen & Wang, 2025). Precision was higher for

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 05 , May - 2026

helmet detection due to its distinct features, whereas vest detection showed slight variation due to background similarity, which is consistent with findings in existing literature (Chaudhary & Das, 2023; Liu et al., 2023).

The recall performance was slightly affected by occlusion, poor lighting, and object overlap. These limitations align with previously reported challenges in construction site monitoring using computer vision (Bonyani et al., 2024; Liu et al., 2023). The F1-score indicated a balanced performance, confirming the reliability of the system.

The detection results showed that helmets were detected more accurately compared to safety vests due to their distinct shape and positioning. Similar observations have been reported in deep learning-based PPE detection studies (Li et al., 2020; Wei et al., 2024). Minor detection errors were observed in complex scenes involving occlusion and lighting variations.

The system effectively performed safety compliance analysis by classifying workers as safe or unsafe based on PPE usage. Compliance levels ranged from 80%–95% in well-managed environments and below 50% in unsafe conditions. The capability of AI systems to automatically evaluate PPE compliance has been validated in previous studies (Ahmed et al., 2023; Al-Khiami & ElHadad, 2024).

A detailed evaluation of PPE detection performance is presented below:

Detection Class	Total Workers	Workers with PPE	Safety Compliance (%)
Helmet	100	96	96.0
Vest	100	95	95.0
Goggles	100	92	92.0
Overall PPE	300	283	94.3

The web application demonstrated efficient performance with response times of approximately 1–3 seconds. The system supported image upload and real-time webcam monitoring, providing immediate detection results. Similar real-time monitoring systems have been developed for construction safety applications (Machfudiyanto & Park, 2024; Rahman et al., 2023).

Practical observations indicated that detection accuracy decreased slightly in crowded scenes due to overlapping objects. Lighting conditions also influenced system performance, particularly in low-light environments. These challenges are consistent with real-world limitations reported in computer vision-based safety systems (Liu et al., 2021; Bonyani et al., 2024).

A comparative analysis showed that the developed system provides higher automation, consistency, and real-time monitoring capability compared to traditional manual inspection methods. Manual inspection is often limited by human error and lack of continuous monitoring, whereas AI-based systems enable efficient and scalable safety evaluation (Samsami, 2024; Singh & Rivera, 2024).

Despite its effectiveness, the system exhibited limitations related to lighting sensitivity, occlusion, and dataset dependency. Similar limitations have been identified in existing research, indicating the need for improved datasets and model optimization (Hayat & Morgado-Dias, 2023; Liu et al., 2023).

Table 3: Comparison Between Manual Inspection and AI-Based System

Parameter	Manual Inspection	AI-Based System
Accuracy	Moderate	High
Monitoring	Periodic	Continuous (Real-Time)
Speed	Slow	Fast
Consistency	Variable	Consistent
Human Effort	High	Reduced
Scalability	Limited	High

Overall, the results confirm that the developed AI-based system is effective for construction site safety monitoring, providing accurate detection, real-time analysis, and improved safety compliance evaluation.

IV.Conclusion

The present study demonstrated the development and evaluation of an Artificial Intelligence (AI)-based computer vision system for construction site safety monitoring and progress assessment. The proposed framework was designed to automate the detection of Personal Protective Equipment (PPE), identify unsafe conditions, and provide real-time insights into construction site operations. The integration of deep learning techniques, particularly the YOLOv8 model, enabled accurate detection of workers and safety equipment under varying environmental conditions.

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The system was trained and evaluated using a diverse dataset of construction site images, resulting in high detection performance with accuracy levels generally ranging between approximately 85% and 92%. The model exhibited strong precision, particularly in helmet detection, while slight variations were observed in safety vest detection due to environmental and visual complexities. The results confirmed that the developed system was capable of effectively classifying workers as safe or unsafe and computing safety compliance levels, thereby providing a quantitative assessment of site safety conditions.

The implementation of a web-based interface further enhanced the usability and accessibility of the system by enabling real-time interaction through image upload and webcam-based monitoring. The system demonstrated near real-time performance, with response times typically within a few seconds, thereby supporting practical deployment scenarios. The integration of browser-based processing improved system scalability and reduced dependency on centralized computational resources.

A significant contribution of this study lies in the integration of safety monitoring and compliance evaluation within a unified automated framework. Unlike traditional approaches that rely on manual inspection, the proposed system enabled continuous, consistent, and objective monitoring of construction site activities. This automation reduced the likelihood of human error, improved operational efficiency, and provided data-driven insights to support decision-making in safety management.

Despite the promising results, certain limitations were identified, including sensitivity to lighting conditions, challenges associated with occlusion in crowded environments, and dependency on dataset diversity for accurate detection. Additionally, the system was primarily evaluated using image-based inputs, which may limit its capability to capture dynamic activities over time.

Future enhancements of the system may include integration with real-time video surveillance systems, expansion of the dataset to include diverse construction scenarios, and implementation of advanced detection techniques for improved accuracy under challenging conditions. The incorporation of Internet of Things (IoT) devices, edge computing, and predictive analytics may further enhance system capabilities by enabling proactive risk assessment and real-time alert generation. Large-scale deployment across multiple construction sites can provide broader validation and contribute to the development of intelligent and automated construction management systems.

In conclusion, the developed AI-based computer vision system demonstrated strong potential for improving construction site safety and monitoring practices. By enabling automated detection, real-time analysis, and data-driven insights, the system contributes to reducing workplace hazards, enhancing compliance with safety regulations, and supporting efficient project management. The findings of this study highlight the importance of integrating intelligent technologies into construction workflows to achieve safer, smarter, and more sustainable infrastructure development.

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