Utilization of Artificial Intelligence (AI) to Monitor PPE for Construction Safety

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Abstract

Construction safety continues to remain a dogged issue that threatens the lives and livelihood of construction personnel around the world. Despite extensive research in this area, statistics of accidents are a sobering reminder of the work ahead. There were 5,190 fatal work injuries recorded in the United States in 2021, an 8.9-percent increase from 4,764 in 2020. The majority of the construction-related fatalities were due to violations of OSHA safety standards. There has been a significant number of research to reduce the number of injuries and fatalities resulting from non-compliance with PPE standards. To automate the monitoring of PPE standards, the systems could be categorized into two major types: 1) Sensor-based and; 2) Vision-based. However, both of these methods do not provide real-time discoveries. Artificial Intelligence (AI) is being implemented in many different fields such as defense, security, healthcare, etc. to achieve the highest level of efficiency. In this paper, the authors have proposed the use of AI to monitor PPE compliance on construction sites. Authors have proposed the utilization of already built AI systems and robots that are used for person and object detection. The paper will explain the developmental phase of an automatic detection system for a) hard hats and b) vests. The results of experiments in a semi-controlled environment are presented in the paper.

Keywords

Construction Safety, Artificial Intelligence, Computer Vision.

1. Introduction

On a global scale, the construction industry is acknowledged as the most hazardous sector, with construction workers facing twice the risk of sustaining injuries compared to their counterparts in other occupational fields (Sehsah et al., 2020). Over time, regulatory authorities have devised and enforced multiple safety regulations and on-site inspections to establish a safer working environment. However, despite the implementation of these new regulations, the incidence of casualties continues to persist at elevated levels (Lo et al., 2023). Construction work is inherently dangerous, with workers facing a range of hazards from falls, material handling, being struck by objects, equipment failure, and more (Shamsuddin et al., 2015). Construction job sites have garnered significant attention related to the issue of health and safety on a global scale, emerging as a key point of discussion (Furci & Sunindijo, 2020). Ensuring proper use of Personal Protective Equipment (PPE) such as hard hats, safety glasses, high-visibility clothing, and fall protection is crucial for preventing injuries and fatalities on construction sites. Head injuries rank among the most grave forms of injury, underscoring the critical significance of helmets as essential PPE on construction sites (Li et al., 2017). Occupational health and safety represents both a legal and moral imperative, carrying significant economic ramifications (Umeokafor et al., 2022). Nonetheless, the construction industry continues to exhibit a substandard occupational health and safety record (Umeokafor et al., 2021). The continuing challenge of substandard safety performance within the construction industry persists as a longstanding issue, leading to a rising number of injuries and accidents observed on construction job sites (Elshafey et al., 2020).

Studies consistently show failure to properly use PPE is a major factor in construction injuries and deaths. According to the safety report conducted by the Occupational Safety and Health Administration (OSHA), construction sites worldwide experience a minimum of 60,000 fatal accidents annually (Ashuro et al., 2021). Safety experts emphasize the need for rigorous PPE compliance programs and oversight on job sites as it is one of the major factors in ensuring safety (Rafindadi et al., 2022). However, traditional methods of monitoring PPE are based on manual inspections and self-reporting of workers. Both methods have its limitations. To date, the present, manual visual inspections have been the primary method employed to regulate the utilization of PPE (Dong et al., 2018). It heavily relies on human observers, who cannot monitor all workers continuously. There are also issues like observer biases, intentional evasion of rules, and lack of motivation among workers.

In recent decades, notable technological advancements have been witnessed across various sectors. However, within the Architecture, Engineering, and Construction (AEC) sector, the integration of safety measures through the full implementation of new technologies in the design, planning, and construction phases has remained largely incomplete (Arezes et al., 2018). Recent advances in artificial intelligence (AI) present new opportunities for automatically monitoring PPE compliance to enhance construction safety. The advancements in AI and deep learning (DL) have led to the widespread adoption of image recognition in various domains. One promising application involves the analysis of images taken by surveillance cameras at construction sites to verify whether construction workers are following PPE protocols. By leveraging this technology, a faster, more precise, and all-encompassing assessment of construction site conditions can be achieved, mitigating the need for substantial supplementary expenses (Fang, Li, Luo, Ding, Luo, et al., 2018). This article discusses key applications of AI for PPE monitoring in construction and examines the technology, implementation challenges, and benefits of intelligent PPE systems.

2. Literature Review

Among all economic sectors, the construction industry exhibits one of the highest rates of occupational accidents, thus emphasizing its prominent vulnerability in this regard (Rodrigues et al., 2022). The incidence of construction fatalities resulting from falls, slips, and trips exhibited a notable increase of 5.9 percent in the year 2021 (*U.S. Department of Labor*, 2023).

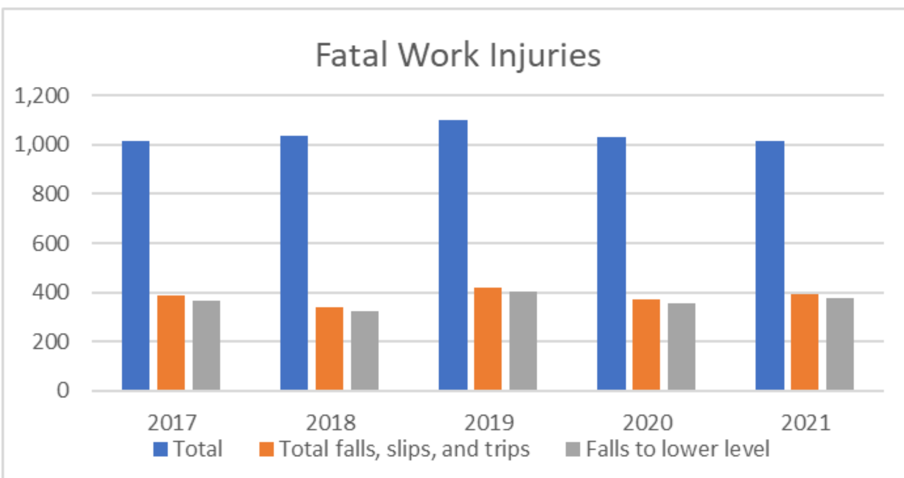

Fig. 1. Number of fatal work injuries in the construction industry by selected event or exposure, all ownerships, 2017–21. *(Bureau of Labor Statistics, U.S. Department of Labor, The Economics Daily, Construction deaths due to falls, slips, and trips increased 5.9 percent in 2021 at https://www.bls.gov/opub/ted/2023/construction-deaths-due-to-falls-slips-and-trips-increased-5-9-percent-in-2021.htm (visited July 14, 2023)).*

The construction industry is by far one of the most dangerous fields to work in. There were 5,190 fatal work injuries recorded in the United States in 2021, an 8.9-percent increase from 4,764 in 2020. Out of every 5,000 private-industry worker fatalities, 20 percent are in construction. Of the construction-related deaths 58.6% were due to the following four causes, which OSHA has named ‘The Fatal Four’: 1) Falls – 338 (33.5%); 2) Struck by Object – 112 (11.1%); 3) Electrocutions – 86 (8.5%) and; 4) Caught-in/between – 55 (5.5%). OSHA has also published the top 10 frequently cited violations: 1) Fall protection; 2) Hazard communication standard; 3) Scaffolding, general requirements; 4) Respiratory protection; 5) Control of hazardous energy (lockout/Tagout); 6) Ladders; 7) Powered industrial trucks; 8) Fall Protection–Training Requirements; 9) Machinery and Machine Guarding and; 10) Eye and Face Protection.

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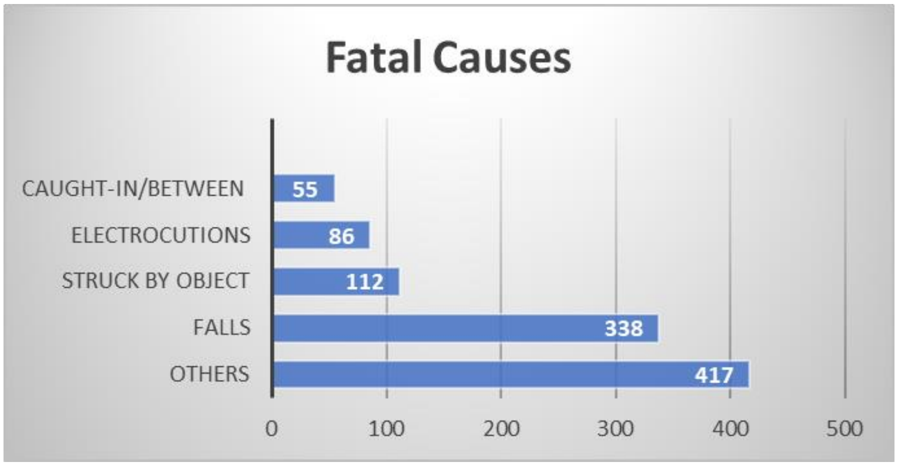


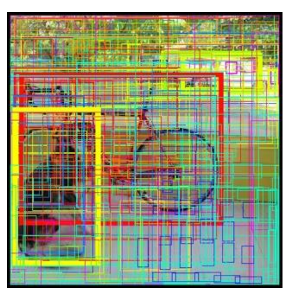
Fig. 2. The Fatal Four

To reduce the number of fatalities and injuries resulting from a violation of proper PPE compliance, there has been a significant number of research to automate the monitoring of PPE. They can be categorized into two major types: 1) Sensor-based and; 2) Vision-based. Sensors or Short-range respondents are wireless systems/sensors attached to PPE which verifies if the worker is complying with the regulations (Nath et al., 2020). An example of sensor-based is installing RFID tags on PPE components that continuously monitor PPE compliance, while the employees are working (Nath et.al, 2020). On the contrary, Vision-based approaches use cameras to record images and videos and analyze them to verify the compliance of PPE at a later stage (Nath et.al, 2020). Both of these methods work similarly and require a significant investment in purchasing, installing, and maintaining complicated sensor networks. There is also no video option in either of the methods, therefore in case of an accident, one can only listen to people who witnessed the event. AI refers to human-like intelligence exhibited by a computer, robot, or other machine. It is being used in many different fields and can be used to identify speech, and images, make real-time recommendations, and much more (D. Lee et al., 2020). Recent breakthroughs in AI with computer vision and deep learning technologies have enabled reliable automatic detection of PPE use. The main approaches include:

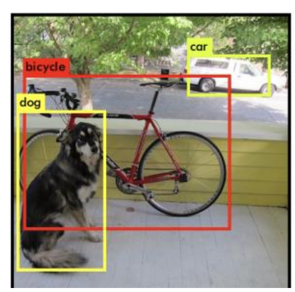
Object detection: This involves predicting bounding boxes around PPE items present in an image and classifying the detected object. Object detection models like Faster Convolutional Neural Networks (CNN) and You-Only-Look-Once (YOLO) are commonly used for PPE detection. The models can be trained on labeled datasets of construction images to identify items including hardhats, safety vests, protective glasses, face masks, and harnesses (K. Lee et al., 2023). Currently, to achieve real-time object detection, Artificial Intelligence/ Deep Learning/Machine Learning (AI/DL/ML) is being used in many different industries like defense, healthcare, safety, security, etc. Particularly, CNN and YOLO are being widely used for image classification and detection. YOLO is an object detection system targeted for real-time processing. It divides the input image into a 13x13 grid. Each grid cell is capable of predicting one object. For example, in the picture below, input was given to detect a bicycle, a car, and a dog with different output colors to identify the differences.

YOLO divides up the image into a grid of 13x13 cells

Each cell predicts a class which is based on the input given to the system



YOLO predicts the region of interests



The final Prediction

Fig. 3 How AI works (Kramer, 2021)

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Pose estimation: Detecting the pose of workers can indicate if they are wearing expected PPE elements. For example, pose estimation models like OpenPose can analyze body joint coordinates to detect the presence or absence of a hard on a worker's head. The expected pose of a worker wearing a harness can also be encoded to identify fall protection equipment (Noori et al., 2019).

Anomaly detection*:* PPE compliance can also be monitored by training models to learn normal PPE use. Deviations from expected norms are flagged as anomalies indicative of missing PPE elements. This approach helps detect violations even with diverse apparel worn on sites (Kamoona et al., 2019). ***Segmentation***: Semantic and instance segmentation models like Mask R-CNN can precisely segment PPE items from image backgrounds. This enables detailed analysis of PPE use across each worker based on the segmented outputs (Mathur & Jain, 2023).

Image recognition and data recognition is also being used in the construction industry and there have been many studies in the last decade to reduce construction-related accident by automating the monitoring of PPE compliance according to OSHA regulations. To implement an AI PPE monitoring system, the first requirement is gathering training data. This involves capturing construction site images covering diverse worker appearances, poses, camera angles, lighting conditions, and backgrounds. However, creating a high-quality training dataset is essential for the system's accuracy. There are also several options for developing the AI models:

Using pre-trained models*:* Many open-source object detection and pose estimation models can be used off-the-shelf or be fine-tuned on construction data. This approach is significantly faster (Sanchez et al., 2020).

Training custom models: For optimal accuracy, custom models can be trained on the construction dataset from scratch. However, this requires significant data volumes and computing resources (Toğan et al., 2022).

Using active learning: With limited data, active learning techniques can augment training data by identifying useful new examples for labeling. This concentrates manual effort on images that maximize model improvements.

Fang et. al, 2018, developed a system to make sure workers are doing the work they are certified for. They proposed a novel framework to check whether a site worker is working within the constraints of their certification. The researchers developed a deep learning algorithm to detect certified personnel on job sites. The study found that the requirement for worker certification led to an 80% decrease in fatalities from crane accidents (Fang, Li, Luo, Ding, Rose, et al., 2018). Another study by Nath et al, 2020, presents three Deep Learning (DL) models using different AI software like YOLO, and Python language, and built a system architecture to verify the PPE compliance of workers; i.e., if a worker is wearing a hard hat, vest, or both, from image/video in real-time (Nath et al., 2020). The algorithm developed detected workers, hats, and vests, and then, a machine learning model verified if each detected worker was properly wearing a hat or vest. For example, the model was making sure that the worker was wearing the hard hat on his head and not holding it in his hand.

Adopting AI PPE monitoring provides multifaceted benefits for improving worksite safety: (1) AI allows constant hands-free assessment of all workers as opposed to periodic manual inspections. (2) PPE use can be tracked across the entire site over time, removing the need to manually verify PPE compliance and freeing up safety managers for proactive harm prevention and engagement with workers. (3) AI provides objective PPE use data, unlike biased or arbitrary human observations. (4) The intelligent systems collect granular data like PPE use per worker, trends over time, problem areas, and types of violations. This will enable proactive and targeted interventions. (5) Instant notifications on PPE violations allow rapid corrective action to avoid accidents and fatalities. (7) Lastly, it'll reduce injuries and disruptions from accidents increase active man-hours, and improve schedules.

Research Gap**:** The previous research about non-hardhat-use (NHU) detection methods, has yet to attain practical applicability. After a detailed literature review, the authors decided to test to use of the pretrained models to detect the compliance of PPE on a construction site. This approach was chosen based on the insights gathered from the literature, which indicated the potential efficacy of pre-trained models in accurately identifying PPE compliance. By integrating these models, the authors aimed to enhance the accuracy and efficiency of the construction sites.

3. Methodology

The authors used a newly launched product and services that became available for commercial use in 2020. The Amazon Web Services (AWS) DeepLens camera is used for object detection. AWS Deeplens camera can be used by developers to build an application that identifies if a worker is wearing a hard hat and a vest (*AWS DeepLens – Deep Learning Enabled Video Camera for Developers - AWS*, 2020). Provectus is a service provided by Amazon Marketplace, where many developers exhibit their services (*Provectus — AI-First Consultancy and Solutions Provider*, 2020). The platform has developed an ML algorithm to detect hard hats and vests; however, the model needs to be trained on a large data set to give accurate results.

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Fig. 4. Amazon Web Services (AWS) DeepLens camera (*AWS DeepLens – Deep Learning Enabled Video Camera for Developers - AWS*, 2020)

The researchers used Amazon Marketplace services to create the ML model. "Amazon Rekognition" was used to achieve the algorithm to detect PPE and "Amazon Web Service (AWS)" was used for cloud storage. The "Hard Hat Detector" ML model is based on computer vision applications. The ML model was designed to detect PPE compliance/non-compliance at the construction site in real time. The system can analyze video footage of a construction site, identify workers, and check if they are complying with safety regulations. Safety managers are notified on-site if any piece of equipment is missing to enforce safety compliance (*Provectus — AI-First Consultancy and Solutions Provider*, 2020).

The camera on a construction site along with high-speed internet service is set to work on site. Image recognition and classification systems assess video data from cameras; identify unsafe worker behavior in real-time and send alerts to safety supervisors. As shown in Figure 5, the camera captures the footage and sends it to the system. The video is then analyzed through the ML model to ensure PPE compliance and send the result to an Amazon app. The app sends the video to be stored in AWS cloud storage and also sends information to the safety manager.

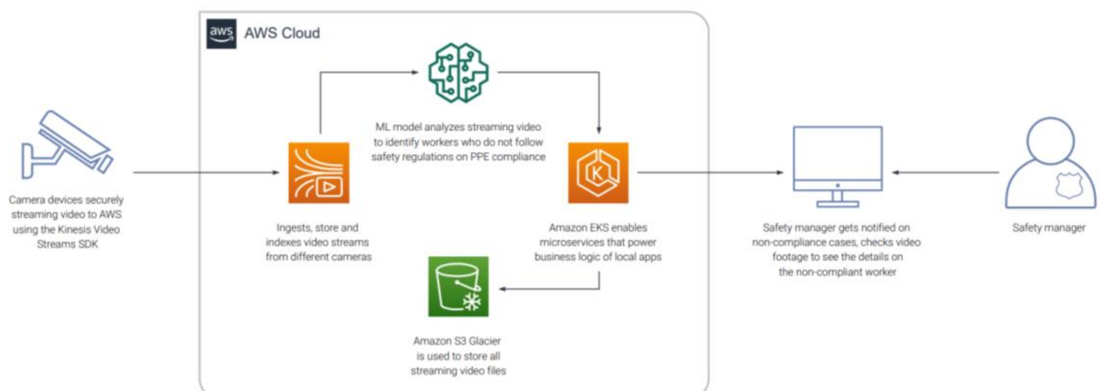

Fig. 5. System Architecture for PPE Compliance on a Construction Site

4. Results

The ML model was used on different images from the service-learning classes at the McWhorter School of Building Science, Auburn University, USA. It can be seen in the figures below that the ML model has identified most of the hard hats/no hard hats on workers on site. A detailed response can also be seen, showing the accuracy of the detection. However, Figure 7, does not detect any hard hat on the person on the right-hand side. Therefore, some irregularities exist, which need to be resolved. This ML model works on the provided data and it trains itself on it. The more data that we provide the more accurate it will get with time. Hence, this model needs to be trained on a larger data set for accurate and precise results.

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Fig. 6. Detection of hard hats through ML model

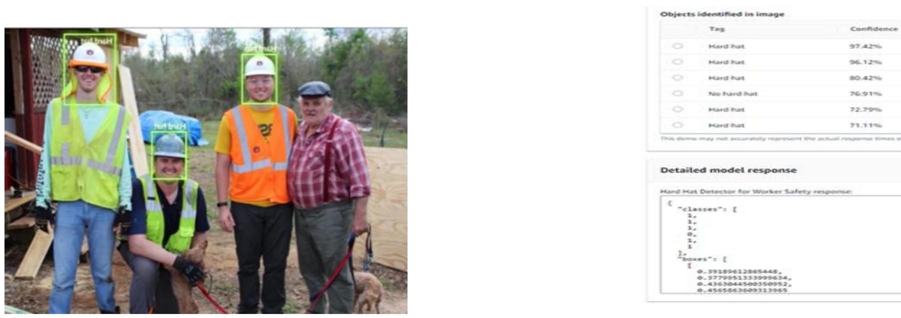

Fig. 7. Detection of hard hats through ML model

Fig. 8. Detection of hard hats through ML model

5. Discussion & Conclusions

AI/DL/ML is associated with creating intelligent machines that can do different manual processes in a much more efficient and effective manner. It is playing a major role in the era of construction 4.0 and is transforming the AEC industry. It provides advantages to deal with a diversity of difficult, complex construction engineering and management problems that defy conventional computational methods-based solutions. This research has applied the ML model to detect PPE compliance on a construction site utilizing the already-built AI systems and robots that are used for person and object detection. The pre-built machine-learning model has been trained to detect PPE compliance/non-compliance on a construction site in real time. The model was tested on the BSCI service-learning classes which assured promising results. It is a well-known fact that non-compliance with PPE on construction sites is one of the leading sources of construction workplace injuries. Hence, the developed system will play an integral role in ensuring workplace safety at construction sites by intelligently monitoring workers' PPE leading to a substantial decrease in workplace injuries and fatalities.

Future research will focus on installing cameras in all BSCI service-learning classes to achieve real-time safety data. To achieve this, a camera along with high-speed internet is needed to be deployed on-site. The camera will be connected to the Amazon service to analyze and store the incoming data. This application will give real-time information about PPE compliance. The generated data can be analyzed for future training and education. Preventing hazardous PPE non-compliance on construction projects is crucial for protecting worker health and safety. With thoughtful implementation accounting for technical and human challenges, AI PPE compliance systems offer invaluable benefits for reducing preventable construction injuries and deaths. They also provide objective verification of safety standards and strengthened assurance for project owners, regulators, and insurers. As the technology continues to grow, AI is poised to become an indispensable digital safety manager on construction sites of the future. The promise of safer workplaces and reduced risk makes adopting intelligent PPE monitoring systems a compelling imperative for the industry.

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