Aalborg Universitet

Enhancing Construction Site Safety Using AI

The Development of a Custom YOLOV8 Model for PPE Compliance Detection

Al-khiami, Mohamad Iyad; ElHadad, Mohamed M

Published in:
Proceedings of the 2024 European Conference on Computing in Construction

DOI (link to publication from Publisher):
10.35490/EC3.2024.307

Creative Commons License
CC BY-NC-ND 4.0

Publication date:
2024

Document Version
Publisher's PDF, also known as Version of record

Link to publication from Aalborg University

Citation for published version (APA):
Al-khiami, M. I., & ElHadad, M. M. (2024). Enhancing Construction Site Safety Using AI: The Development of a Custom YOLOV8 Model for PPE Compliance Detection. In M. Srećković, M. Kassem, R. Soman, & A. Chassiakos (Eds.), *Proceedings of the 2024 European Conference on Computing in Construction* (pp. 577-584). European Council on Computing in Construction. https://doi.org/10.35490/EC3.2024.307

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal -

Take down policy
If you believe that this document breaches copyright please contact us at vbn@aub.aau.dk providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from vbn.aau.dk on: October 21, 2025

ENHANCING CONSTRUCTION SITE SAFETY USING AI: THE DEVELOPMENT OF A CUSTOM YOLOV8 MODEL FOR PPE COMPLIANCE DETECTION

Mohamad Iyad Al-Khiami[1,2], Mohamed M ElHadad[3],
[1]Australian University - Kuwait, Mishref, Kuwait
[2]Aalborg University, Aalborg, Denmark
[3]Gulf University for Science & Technology, Mishref, Kuwait

Abstract

This study addresses construction safety by deploying computer vision techniques, specifically a YOLOv8 model by Ultralytics, to monitor PPE compliance. Targeting helmets, vests, and safety shoes, it aims to mitigate accident risks. The model was trained with 2934 images and validated with 816, achieved a 95% mAP. Emphasizing AI's potential in safety management and occupational health in the construction industry. This research lays groundwork for future AI-based safety enhancements in construction sector, highlighting the industry's pressing need for innovative approaches to reduce occupational hazards and improve compliance standards.

Introduction

The construction industry, known for being the primary driver to infrastructure development been consistently ranked among the most dangerous industries worldwide, with a high incidence of accidents and fatality rates making it one of the most hazardous sectors (Lingard, 2013; Pinto et al., 2011; Waehrer et al., 2007). High rates of accidents and fatalities have been consistently reported, many attributable to non-compliance with safety measures, particularly the use of Personal Protective Equipment (PPE) (Memon et al., 2023; Sehsah et al., 2020). In many incidents, the lack of PPE or improper use of safety gear such as helmets, vests, and boots has been a critical factor. (Kang, 2018) reported that more than 70% of all fatal accidents had some form of incompliance with PPE. This persistent challenge highlights a gap in safety protocols and enforcement on construction sites, highlighting the need for more stringent and effective monitoring tools to ensure worker safety and reduce the risk of accidents.

Given the high importance of maintaining safety standards and reducing injuries from accidents in construction sites along with the prevalent safety challenges, it is necessary to rethink traditional methods and employ innovative technologies to enhance safety compliance rates on sites (Zhang, 2021). Among these technologies, artificial intelligence (AI) takes the lead when it comes to the development of object detection systems specifically for PPE in the site (Abioye et al., 2021). On a site, monitoring systems using AI can assist safety engineers in achieving higher compliance of safety due to the fact that traditional human supervision can sometimes be expensive, prone to error and insufficient in maintaining safety standards (Yi and Wu, 2020). Such systems can aid in the detection of workers who are not complying with safety standards mainly, wearing proper PPE while working on sites. The necessity for improved safety compliance on construction sites, coupled with the inadequacies of traditional safety monitoring methods dictates the need to start integrating AI-driven object detection systems in construction sites. The integration of AI-driven systems in construction sites represents an important opportunity and a significant leap forward in terms of technology adoption within the construction industry.

This paper is part of a larger project that aims to utilize AI in the construction sector. The project is divided into several phases where the objective of this phase is to answer the following research question (RQ).

RQ – Are fine-tuned object detection models, specifically YOLOV8 efficient and effective in identifying safety helmets, safety shoes and vests in construction sites?

Literature Review

Safety risks in the construction sector

The construction engineering sector is a key driver of economic growth in both developed and developing nations (Sánchez et al., 2017). Despite advances in workplace safety within the construction sector, it still faces a greater risk of injuries and deaths than many other industries (Johansson et al., 2019). According to the US bureau of labor statistics (BLS), more than 1 in 5 deaths occurred in the workplace was within the construction industry in the year 2020 with a reported number of 1,008 construction workers that were killed on the job (A Look at Workplace Deaths, Injuries, and Illnesses on Workers' Memorial Day, 2022). Each year, more than 100,000 individuals suffer from fatal injuries each year within the construction industry as per the International Labor Organization (ILO) which alone, represents about 30% of all occupational fatal injuries ("Construction," 2015).

A recent study (Memon et al., 2023) highlights that substandard quality of PPE is a leading cause of accidents in the construction industry. This study also found that the use of PPE can reduce accidents related to falls by 30%. Another study indicated that many accidents on construction sites occur due to the lack of PPE or failure to wear it properly (Ammad et al., 2021). Despite approximately 62% of construction workers being at risk of falls, only about half use PPE, as reported by the Bureau of Labor Statistics (BLS) (A Look at Workplace Deaths, Injuries, and Illnesses on Workers' Memorial Day, 2022). Furthermore, it was noted that over 70% of fatal fall accidents involved workers not wearing PPE (Kang, 2018). Additionally, according to the Health and

Safety Executive (HSE), there are more than 9,000 PPE-related accidents annually on construction sites in the United Kingdom. Understanding the frequency of these incidents underscores the need to educate employees on the importance of proper PPE usage (Martin et al., 2021). Severe brain injuries on construction sites, primarily caused by falls and falling objects, are a significant concern (Kamardeen and Hasan, 2022). Furthermore, the Centers for Disease Control and Prevention (CDC, 2011) estimates that almost half (49%) of all fatal injuries in this sector are due to head injuries (Occupational Ladder Fall Injuries — United States, 2011).

The concerning statistics and studies highlighted in this section emphasize the urgent need for more stringent and effective enforcement of PPE safety compliance in the construction industry (Ebekozien, 2021; Gattuso, 2021). It is imperative to develop and implement reliable strategies to ensure that workers are adequately protected, thereby reducing the high incidence of injuries and fatalities that currently plague this sector.

Technology adoption and integration in construction industry

The potential of Artificial Intelligence (AI) is increasingly being recognized across various sectors. However, its adoption and application in the construction industry are scarce compared to other industries. As a matter of fact, the construction industry ranks among the least digitized sectors globally, and a common misconception among stakeholder exists regarding the industry's longstanding culture of resistance to change (Young et al., 2021). Additionally, the lack of technology integration in the construction industry is often associated with health and safety concerns (Nikas et al., 2007). In an effort to address this slow growth in adoption, many companies are now turning to Artificial Intelligence (AI) as a means to streamline their processes and boost productivity within the working environment (Yigitcanlar, 2021; Yigitcanlar and Cugurullo, 2020). The adoption of AI technology grants a competitive edge in terms of automation when compared to conventional approaches (Chien et al., 2020). Within the wide variety of AI-Based technologies, the application of computer vision through deep learning has shown promising potential in construction safety management. The object detection capability of AI provides flexibility in terms of classifying and recognizing objects, which is something to be capitalized upon to improve safety compliance. This technology, serves a foundation to effectively substitute human vision for many tasks across the construction safety workflow (Abioye et al., 2021). This sets the stage for exploring advancements in AI for PPE compliance monitoring in the next section.

Advancement in AI for PPE compliance monitoring

In recent years, the construction industry has seen significant advancements in the application of Artificial Intelligence (AI) for safety management, particularly in monitoring Personal Protective Equipment (PPE) compliance. The effectiveness of AI, specifically deep learning, and computer vision, in real-time monitoring of safety helmets and PPE compliance, showing promise for enhanced on-site safety have been demonstrated in the literature (Delhi et al., 2020; Kisaezehra et al., 2023).

Recent advancements in the construction industry's approach to safety management have been significantly influenced by the application of Artificial Intelligence (AI). A focus on enhancing Personal Protective Equipment (PPE) compliance has been evident, with AI-driven systems, particularly those incorporating YOLO models for object detection, demonstrating notable accuracy and real-time capabilities. This shift towards AI-based methodologies for safety gear recognition, especially through the use of advanced YOLO v5 and v8 models, underscores a growing trend in leveraging technology to improve on-site safety measures (Chen et al., 2021; Kim et al., 2023; Wang et al., 2023).

The advancements in AI for construction safety have seen significant strides in the development of systems for detecting safety helmets and protective clothing. A notable approach involves the enhancement of YOLOv3 methods, specifically tailored to improve the detection of smaller-sized safety gear. This innovation, focusing on the addition of a large-size input layer for multi-scale prediction, represents a crucial step in fine-tuning AI models to meet the unique demands of construction site applications, underscoring the critical role of AI optimization in specific industrial contexts (Wang et al., 2020).

The exploration of AI in the construction industry has further expanded with the introduction of rapid PPE detection systems for actual construction sites, utilizing deep learning techniques. This advancement, as presented in the literature, signifies the practicality and effectiveness of AI in enhancing real-time safety management on construction sites. It addresses the critical requirement for advanced and efficient safety monitoring tools within the industry, showcasing the potential of AI to significantly improve construction safety practices (Wang et al., 2021).

Together, these studies underscore the potential of AI and machine learning, particularly YOLO models, in revolutionizing safety compliance in the construction industry. They highlight the technical feasibility and practical implications of deploying AI systems for real-time, accurate PPE monitoring, marking a significant step forward in occupational safety management.

Closing remarks

As indicated by the literature, to the best of the authors' knowledge, there has been limited empirical research examining the adoption of AI technologies in the construction industry. As such, this study aims to contribute to the growing body of knowledge surrounding the integration of artificial intelligence, namely, PPE compliance detection systems in the construction industry.

Methodology

Development of the PPE Compliance AI model – YOLOV8

You Only Look Once V8 (YOLOV8), developed by Ultralytics in January 2023, served as the foundation for our AI model. YOLOV8 is a convolutional neural network (CNN), that is a category of deep learning neural networks, commonly used in analyzing visual imagery. YOLO was trained and validated using a dataset, namely Common Objects in Context (COCO). The COCO dataset contains more than 330 thousand images of 80 different common objects, including but not limited to, humans, bicycles, cars and animals. A total of 118 thousand images were used for the training, 5000 for validation and 20 thousand for testing. The model was then benchmarked against the validation dataset using the mean average precision (mAP) which is basically a percentage precision of the number of detected objects correctly identified across multiple objects (Ultralytics, 2023a). YOLOV8 can be used for different purposes, including object detection, object tracking, object classification and segmentation. The project utilizes the object detection capabilities of YOLOV8.

Currently, there exists five YOLO models with varying sizes, (1) Nano, (2) Medium, (3) Large, (4) Extra Large. Simply put, smaller models compromise accuracy for speed, and are useful where computational power is limited and speed is a necessity. On the contrary, the larger models are the most accurate, but also the most resource intensive. According to Ultraltytics documentations, mAP is 37.3 and 53.9 for the Nano and Extra-large model respectively (Ultralytics, 2023b).

Based on the limited computational power available, and the fact that the model is aimed to run in real-time, the YOLOV8 (m) model was used, with a mAP of 50.2. The (m) model offers a middle ground between speed and accuracy with a good balance between performance and efficiency.

YOLOV8 (m) fine tuning

While COCO is a well-established dataset, it fails to serve the purpose of the project, therefore, a custom dataset was required. Following Ultralytics recommendations, two main folders were created, a folder dedicated specifically to the training dataset and a folder dedicated to the model validation. Within each directory, two subfolders were created, namely “Images” and “Labels”. All the training images that were collected were inserted in the “Images” subfolder under “Train” main folder. On the other hand, the images used for validations were inserted in “Images” subfolder under the “Validation” main folder. A total of 2934 images and 816 images were for training and validation respectively. Figure 1 shows the breakdown of the dataset organization.

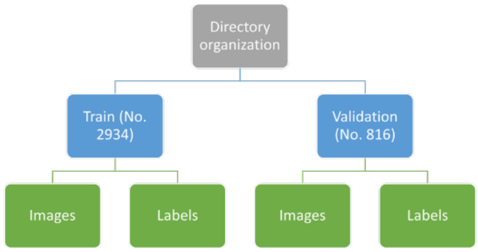

Figure 1: Directory organization for the customized training

The 2934 images collected were to fine tune the model to detect if a construction worker, within a construction site setting is adhering to the PPE requirements. The object detection model aims to detect if workers are wearing their safety helmets, vests, and safety shoes. The open-source images were collected in addition to taking photos using a phone camera in construction sites after taking consent from safety officers. To avoid bias in the image collection, the data collected was made sure to be as diverse as possible, encompassing different colors and shapes of helmets, vests, and safety shoes with varying backgrounds ensuring transferability of the model across different countries.

After the collection of the photos, the fine-tuning process begins. First, Conda, an open-source package management and environment management system was downloaded and installed in which all the machine learning is managed. A dedicated environment was created using Conda where all the packages required for YOLOV8 were installed. Using the command “pip install ultralytics” downloads all the packages and dependencies required to run YOLOV8. Prior to installing the packages concerning YOLOV8, it is necessary to annotate the images in the “Train” and “Validation” folders and save the output into the “Labels” subfolder of both “Train” and “Validation”. For that, “LabelImg”, an open-source graphical image annotation tool, was downloaded and installed. Labelling the images using “LabelImg” outputs a .txt file for each image with the location of the label within an image. Figure 2 shows the user interface and the labelling using “LabelImg".

Figure 2: LabelIMG annotation user interface

The annotation process involved six classes:

- Class 0 – “Helmets”

- Class 1 – “Vests”
- Class 2 – “Safety shoes”
- Class 3 - "No vests”
- Class 4 - "No helmets”
- Class 5 - "No safety shoes”

Upon annotating all the images collected, a “.yaml” file was prepared where the train and validation directory were set, the number of classes and the names of each class in order. This file is necessary as it contains all the necessary information required to override the existing trained YOLOV8.

An important parameter to consider before initiating the training, is the number of epochs required, that is basically one complete pass of the entire training dataset through the algorithm. Zhang et al., (2019) underscores the importance of setting the number of epochs to an acceptable and reasonable number. For example, a very small number of epochs can result in an underfitted model, meaning that the model has not been trained enough on the trained data, thus resulting in a poor performance against validation or testing data. Conversely, overfitting phenomena can occur in the cases of an exaggerated number of epochs. In such cases, the model memorizes the training set rather than generalizing. The model would ultimately perform well on the trained data but poorly on unseen data.

Selecting the appropriate number of epochs is an iterative process requiring several trials. The number of epochs for the project was set to 100 and the performance was constantly checked against the validation dataset setting an early stopping parameter in case there is no improvement in the performance as the number of epochs continues to increase. The command used in the Conda environment to conduct the training was as follows “yolo task=detect mode=train epochs=100 data=data_custom.yaml model=yolov8m.pt imgsz=640”.

Figure 3 summarizes the whole processes followed to create the custom model.

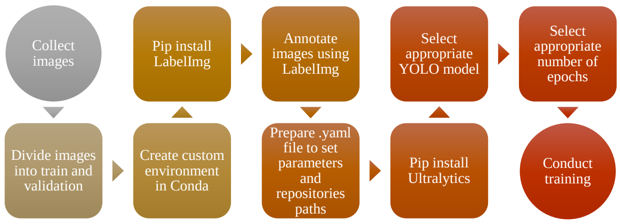

Figure 3: Summary of the fine-tuning on custom dataset.

Results and Discussion

The results and discussion section summarizes the findings of the methodological approach conducted.

YOLOV8 (m) was selected as the foundation for the fine-tuning process. A total of 2934 and 816 photos were used for the training and validation respectively. A processor of Intel® Core (TM) i9-9980HK CPU @ 2.40GHZ (16CPUs), with a dedicated graphics card of NVIDIA RTX 2060 and 32 GB RAM served as the training hardware.

By default, a patience value = 50 is set, where the numerical value represents the number of epochs. The patience parameter simply means that while the training is in process, the model shall check its performance against the validation dataset, in any case where no improvement is perceived in the last 50 completed epochs, an early stop is employed. As a result, the YOLOV8 fine-tuning process took 23.33 hours and had an early stop at 96 epochs, as there was no improvement seen beyond 46 epochs.

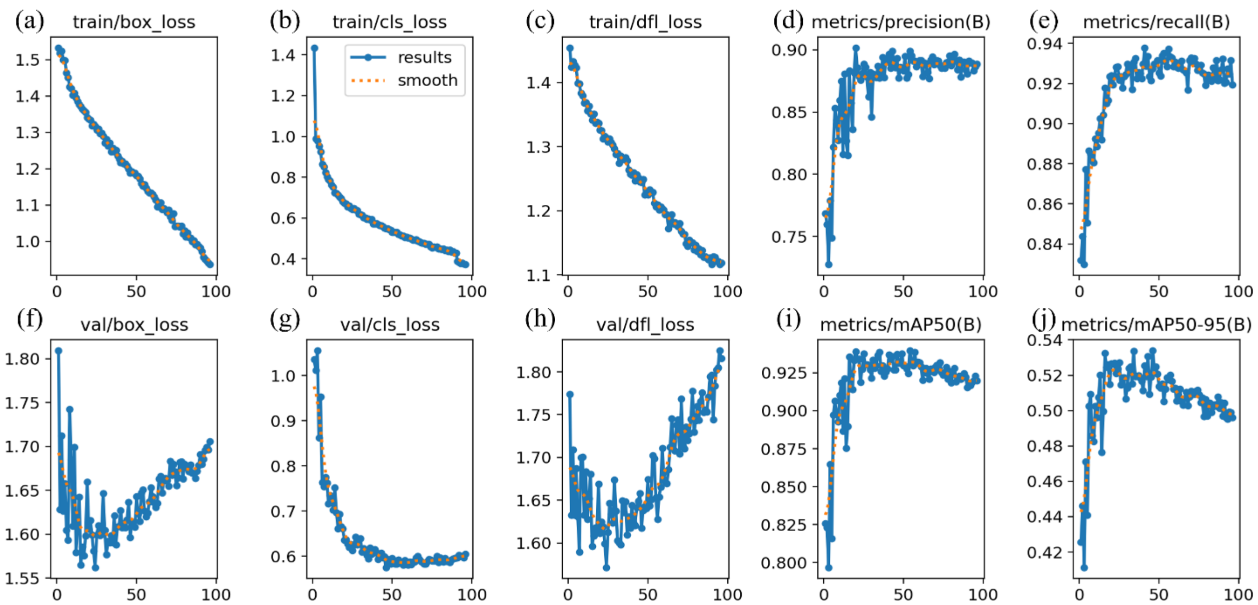

Figure 4: Training dashboard against the validation dataset

Figure 4. illustrates the results of the custom trained model from the validation dataset. The x-axis represents the number of epochs, while the y-axis varies depending on the graph it represents.

A total of 10 graphs (a) – (j) are shown in Figure 4. Figure 4 (a) – (c) and Figure 4 (f) – (h) shows the “box loss”, “cls_loss” and “dfl_loss” that correspond to box loss, classification loss, and directional focal loss on the training and validation dataset respectively. Box loss measures how well the model is predicting the bounding box coordinates for each detected object. It can be seen as the number of epochs increases, Figure 4 (a) – (c) decreases illustrating a downwards trend. This means that the model gets better at defining the coordinates of the binding boxes, improving its ability to detect the orientation of the objects along with their presence. Though, when considering Figure 4 (f) – (h) it can be seen that all three figures see improvement in the box_loss, cls_loss, and dfl_loss up to the 46th epochs. This confirms the early stop and patience parameter were beyond the 46th epochs, there was no improvement seen. The change in the figures trend indicates a sign of overfitting. When the validation loss starts to increase while the training loss continues to decrease, it means that the improvements in the model are specific to the training data and are not improving the model’s predictive ability for new, unseen data.

Figure 4 (d) – (e) shows the precision and recall changes through 96 epochs for the validation dataset. Both Figures (d) and (e) show a positive and linear trend against the epochs. Once the training hits the 46th epochs mark, the precision reaches its highest value of 0.89/1 and 0.92/1 for the recall. The training continues all the way to the 96th epochs where the value of the precision and recall falls to 0.88/1 and 0.91/1 respectively. The precision level shows that the model, at the 46th epochs is precisely detection the correct object 89% of the time. On the other hand, a recall of 92% indicates that the model is able to recall 92% of the objects.

Figure 4 (i) – (j) shows the mean average precision and the mean average precision at 95% at Intersection over Union (IoU). Similar to Figure 3 (d) – (e), the figures here look at the average precision per class. In addition, IoU of 95% is considered a very stringent threshold, it means that for a detection to be considered to be a true positive, the predicting bounding box must overlap with the ground truth bounding by at least 95%. Only detections that satisfy this threshold is considered true positive. On the 46th epochs, the mean average precision at 95 % IoU is 0.53/1.

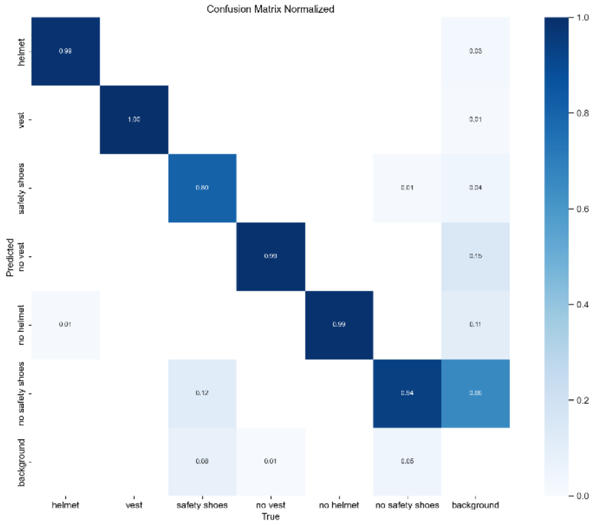

Figure 5: Normalized confusion matrix

To further understand the model reliability, and to visualize the performance of the algorithm, a normalized confusion matrix is shown in Figure 5. The matrix shows that the model predicted 'helmet' with 99% accuracy indicating true positive. Moreover, the 'vest' class has been predicted by the model with high accuracy. As for 'safety shoes', the true positives were 80%, but there were some instances where it predicted 'safety shoes' when there were none indicating false positives, and some instances where it failed to predict 'safety shoes' when there were some (false negatives). This can be due to the fact that normal shoes may emulate the look of safety shoes designs which can lead to false positives. It can also be mentioned that there are very few cases where the model indicated a 1% of false positives in helmets. While this result indicates high precision, it is limited to the used dataset.

The confusion matrix suggests that the model is quite effective at predicting 'helmet' and 'vest' classes, is fairly good at predicting 'safety shoes', and generally does not confuse items with the background. However, there are some areas where the model can generate false predictions, particularly with the 'safety shoes'. This information can be used to refine the model further, potentially by providing it with more training data for the classes where it is less accurate or adjusting the model's parameters.

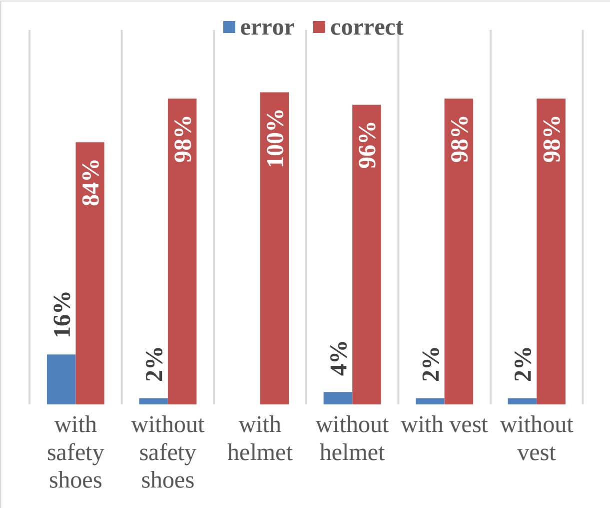

Figure 6: Results of YOLOV8 (m) "Best.pt" model against testing dataset

Figure 6 presents the performance results of the YOLOV8 (m) "Best.pt" model when evaluated against a testing dataset to detect various types of PPE. The figure illustrates and compares the percentage of correct identifications against the percentage of error across the six classes discussed before across 300 photos of workers complying or not in construction sites. All the 300 photos used for testing were exclusive to the testing dataset and were not used in the training nor the validation dataset.

The model clearly demonstrates high levels of accuracy in detecting the presence of a helmet, with a score of 100% and no perceived errors. Similarly, detecting vests achieved a 98% accuracy and success rate. The 'without helmet' category shows a slight decrease in accuracy of 4% error rate only which could be improved by further training the model. However, the model's performance exhibits a notable decline in the 'with safety shoes' category, with a correct identification rate of 84% and a corresponding error rate of 16%. This suggests that while the model is highly effective at identifying vests and helmets, it finds safety shoes more challenging, which may indicate a need for further model training or data augmentation in this category specially since safety shoes can exhibit a diverse number of models, colours and shapes.

The mAP for the testing dataset can be calculated by finding the average of all the precision from the 6 classes. A percentage of 95.6 was obtained, indicating a similar mAP to the validation dataset.

The error rates presented in the graph are essential for understanding the model's limitations and guide future improvements to enhance its predictive capabilities for PPE compliance on construction sites. It is important to note that since the testing data was only from 300 photos, the results cannot be considered reliable. Furthermore, construction sites are dynamic with variations in settings, lighting conditions and working environment. This illustrates the need to diversify the collected data to cover wider landscapes of conditions. A possible solution is using data augmentation techniques to transform images and simulate different lighting conditions.

Figure 7: PPE detection of sample in-test photo

Figure 7 demonstrates the PPE detection model's output when using the YOLOV8 (m) fine-tuned model. Each class is bounded by a box which states the confidence level of the PPE detection. The confidence level represents how accurately is the model detecting and determining the class of the PPE in use within the detection frame. While the testing was only conducted on images, the model can be utilized with a high-resolution camera to be tested and implemented in real-time scenarios.

Conclusion and Limitations

This research endeavor has illustrated the core hazards within the construction industry, examining the critical concerns concerning Personal Protective Equipment (PPE) safety standards. It highlights the necessity of upholding stringent safety compliance on construction sites to mitigate the risk of accidents and enhance worker protection.

Additionally, this study has detailed the capabilities of object detection technologies, namely, YOLO technique's robust framework. The analysis revealed that the YOLOV8 is balanced between precision and computational efficiency, particularly when utilizing a dataset of medium size to fine-tune the trade-off between speed and accuracy. The model's effectiveness at identifying compliance with helmet, vest, and safety shoes requirements in PPE protocols was notable, although it did exhibit a potential for enhancement in detecting 'safety shoes' class type.

The model is limited to the collected dataset which illustrates a need to increase the size of the training data, specifically, safety shoes. In addition, it is worth noting that the testing data was limited to 300 images which does not necessarily cover all real-world scenarios. Data augmentation techniques can further enhance the collected dataset to cover wider working conditions in construction sites. These insights not only validate YOLOV8's utility in practical applications but also identify specific possibilities for refining the model to achieve even higher levels of accuracy in PPE detection in future phases.

This stage of the conducted research was limited to the development of the AI-based PPE detection system. In the forthcoming stage of our research, a case study approach can be implemented to further investigate the model reliability. The focus will be on evaluating the impact of deploying the AI-based PPE compliance monitoring system within construction environments in real time. This assessment will illustrate the system's efficacy in reinforcing adherence to PPE usage standards and protocols. Moreover, we intend to conduct a thorough investigation into the sector's behavior in response to the system's implementation and acceptance.

While AI-based PPE compliance monitoring comprises privacy, it is essential to consider an ethical framework. Construction companies willing to implement this technology must obtain consent of workers being surveilled and implement anonymity approaches such as face blur techniques to preserve the privacy of workers. In addition, the reports generated by the AI model should be inspected against bias. Decision makers within the construction industry must be aware that the intention of such systems is to augment manual inspection and not replace it.

Acknowledgment

The authors would like to express their sincere gratitude to the Australian University – Kuwait for their support of the ongoing research. Special thanks are extended to Abdullah Jalal Jamal, Zainab Hani Jamal, Sherifa Meshal Borhamah, and Noryah Saeed Alqabadni for their exceptional efforts, without which this project would not have been possible.

References

A look at workplace deaths, injuries, and illnesses on Workers' Memorial Day : The Economics Daily: U.S. Bureau of Labor Statistics [WWW Document], 2022. URL https://www.bls.gov/opub/ted/2022/a-look-at-workplace-deaths-injuries-and-illnesses-on-workers-memorial-day.htm (accessed 1.6.24).

Abioye, S.O., Oyedele, L.O., Akanbi, L., Ajayi, A., Davila Delgado, J.M., Bilal, M., Akinade, O.O., Ahmed, A., 2021. Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. J. Build. Eng. 44, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Ammad, S., Alaloul, W.S., Saad, S., Qureshi, A.H., 2021. Personal protective equipment (PPE) usage in construction projects: A scientometric approach. J. Build. Eng. 35, 102086. https://doi.org/10.1016/j.jobe.2020.102086

Chen, B., Wang, X., Huang, G., Li, G., 2021. Detection of violations in construction site based on YOLO algorithm, in: 2021 2nd International Conference on Artificial Intelligence and Computer Engineering (ICAICE). Presented at the 2021 2nd International Conference on Artificial Intelligence and Computer Engineering (ICAICE), pp. 251–255. https://doi.org/10.1109/ICAICE54393.2021.00057

Chien, C.-F., Dauzère-Pérès, S., Huh, W.T., Jang, Y.J., Morrison, J.R., 2020. Artificial intelligence in manufacturing and logistics systems: algorithms, applications, and case studies. Int. J. Prod. Res. 58, 2730–2731. https://doi.org/10.1080/00207543.2020.1752488

Construction: a hazardous work [WWW Document], 2015. URL http://www.ilo.org/safework/areasofwork/hazardous-work/WCMS_356576/lang--en/index.htm (accessed 1.6.24).

Delhi, V.S.K., Sankarlal, R., Thomas, A., 2020. Detection of Personal Protective Equipment (PPE) Compliance on Construction Site Using Computer Vision Based Deep Learning Techniques. Front. Built Environ. 6.

Ebekozien, A., 2021. Construction companies' compliance to personal protective equipment on junior staff in Nigeria: issues and solutions. Int. J. Build. Pathol. Adapt. 40, 481–498. https://doi.org/10.1108/IJBPA-08-2020-0067

Gattuso, A., 2021. Common Issues of Compliance with Personal Protective Equipment for Construction Workers. Constr. Manag.

Johansson, J., Berglund, L., Johansson, M., Nygren, M., Rask, K., Samuelson, B., Stenberg, M., 2019. Occupational safety in the construction industry. Work 64, 21–32. https://doi.org/10.3233/WOR-192976

Kamardeen, I., Hasan, A., 2022. Occupational Health and Safety Challenges for Sustaining Construction Apprentice Programs. J. Manag. Eng. 38, 04022042. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001059

Kang, Y., 2018. Use of Fall Protection in the US Construction Industry. J. Manag. Eng. 34, 04018045. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000655

Kim, Kyunghwan, Kim, Kangeun, Jeong, S., 2023. Application of YOLO v5 and v8 for Recognition of Safety Risk Factors at Construction Sites. Sustainability 15, 15179. https://doi.org/10.3390/su152015179

Kisaezehra, Farooq, M.U., Bhutto, M.A., Kazi, A.K., 2023. Real-Time Safety Helmet Detection Using Yolov5 at Construction Sites. Intell. Autom. Soft Comput. 36, 911–927. https://doi.org/10.32604/iasc.2023.031359

Lingard, H., 2013. Occupational health and safety in the construction industry. Constr. Manag. Econ. 31, 505–514. https://doi.org/10.1080/01446193.2013.816435

Martin, H., Mohan, N., Ellis, L., Dunne, S., 2021. Exploring the Role of PPE Knowledge, Attitude, and Correct Practices in Safety Outcomes on Construction Sites. J. Archit. Eng. 27, 05021011. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000501

Memon, M.H., Abas, N.H., Sohu, S., 2023. Ranking the critical causes of accidents in construction projects of Sindh: Perspective of safety professionals. IOP Conf. Ser. Earth Environ. Sci. 1205, 012035. https://doi.org/10.1088/1755-1315/1205/1/012035

Nikas, A., Poulymenakou, A., Kriaris, P., 2007. Investigating antecedents and drivers affecting the adoption of collaboration technologies in the construction industry. Autom. Constr. 16, 632–641.

Occupational Ladder Fall Injuries — United States, [WWW Document], 2011. URL https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6316a2.htm (accessed 1.6.24).

Pinto, A., Nunes, I.L., Ribeiro, R.A., 2011. Occupational risk assessment in construction industry – Overview and reflection. Saf. Sci. 49, 616–624. https://doi.org/10.1016/j.ssci.2011.01.003

Sánchez, F.A.S., Peláez, G.I.C., Alís, J.C., 2017. Occupational safety and health in construction: a review of applications and trends. Ind. Health 55, 210–218. https://doi.org/10.2486/indhealth.2016-0108

Sehsah, R., El-Gilany, A.-H., Ibrahim, A.M., 2020. Personal protective equipment (PPE) use and its relation to accidents among construction workers. Med. Lav. 111, 285–295. https://doi.org/10.23749/mdl.v111i4.9398

Ultralytics, 2023a. COCO [WWW Document]. URL https://docs.ultralytics.com/datasets/detect/coco (accessed 12.18.23).

Ultralytics, 2023b. Home [WWW Document]. URL https://docs.ultralytics.com/ (accessed 12.18.23).

Waehrer, G.M., Dong, X.S., Miller, T., Haile, E., Men, Y., 2007. Costs of occupational injuries in construction in the United States. Accid. Anal. Prev. 39, 1258–1266. https://doi.org/10.1016/j.aap.2007.03.012

Wang, L., Zhang, X., Yang, H., 2023. Safety Helmet Wearing Detection Model Based on Improved YOLO-M. IEEE Access 11, 26247–26257. https://doi.org/10.1109/ACCESS.2023.3257183

Wang, X., Niu, D., Luo, P., Zhu, C., Ding, L., Huang, K., 2020. A Safety Helmet and Protective Clothing Detection Method based on Improved-Yolo V 3, in: 2020 Chinese Automation Congress (CAC). Presented at the 2020 Chinese Automation Congress (CAC), pp. 5437–5441. https://doi.org/10.1109/CAC51589.2020.9327187

Wang, Z., Wu, Y., Yang, L., Thirunavukarasu, A., Evison, C., Zhao, Y., 2021. Fast Personal Protective Equipment Detection for Real Construction Sites Using Deep Learning Approaches. Sensors 21, 3478. https://doi.org/10.3390/s21103478

Yi, X., Wu, J., 2020. Research on Safety Management of Construction Engineering Personnel under “Big Data + Artificial Intelligence.” Open J. Bus. Manag. 8, 1059–1075. https://doi.org/10.4236/ojbm.2020.83067

Yigitcanlar, T., 2021. Greening the Artificial Intelligence for a Sustainable Planet: An Editorial Commentary. Sustainability 13, 13508. https://doi.org/10.3390/su132413508

Yigitcanlar, T., Cugurullo, F., 2020. The Sustainability of Artificial Intelligence: An Urbanistic Viewpoint from the Lens of Smart and Sustainable Cities. Sustainability 12, 8548. https://doi.org/10.3390/su12208548

Young, D., Panthi, K., Noor, O., 2021. Challenges involved in adopting BIM on the construction jobsite. EPiC Ser. Built Environ. 2, 302–310.

Zhang, H., Zhang, L., Jiang, Y., 2019. Overfitting and Underfitting Analysis for Deep Learning Based End-to-end Communication Systems, in: 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP). Presented at the 2019 11th International Conference on Wireless Communications and Signal Processing (WCSP), pp. 1–6. https://doi.org/10.1109/WCSP.2019.8927876

Zhang, Y., 2021. Safety Management of Civil Engineering Construction Based on Artificial Intelligence and Machine Vision Technology. Adv. Civ. Eng. 2021, e3769634. https://doi.org/10.1155/2021/3769634