Chapter 1

Book Chapter

Advanced Safety Helmet Detection: Enhancing Industrial Site Safety with AI

Sheela S Maharajpet *[1], Deepa Mugad †[2], and Nagaraj C ‡[3]

[1]Assistant Professor, Department of MCA, Acharya Institute of Technology, Bangalore
[2]Department of MCA, Acharya Institute of Technology, Bangalore
[3]Assistant Professor, School of CSA, REVA University, Bangalore

Abstract

Employees who work in industrial and construction environments prioritize safety above all else. In an industrial setting, real-time object detection is a crucial method for identifying safety compliance infractions. Workers may be put in danger if safety helmets are not worn properly, thus it is crucial that an automatic surveillance system be in place to identify those who are not wearing them. This will lessen the amount of labor-intensive work that needs to be done to keep an eye out for infractions. Several techniques for image processing are applied to each video clip that is collected from the manufacturing plant. CNN has released a novel and practical safety detection framework that entails first identifying individuals from the camera footage and then determining whether or not they are wearing safety helmets.

Keywords: Multiple disease. CNN. Object Detection. Safety Helmet. Industrial Site. YOLOv.

*Email: sheelamaharajpet4@gmail.com Corresponding Author
†Email: deepac.22.mcav@acharya.ac.in
‡Email: nagaraj.c@reva.edu.in

1 Introduction

With the increasing significance of supply chain finance and corporate strategies in industrial settings as mentioned by Jain, Kaur, and Mittal's (2023), Workers in the high-risk sector of construction frequently suffer accidents. Deaths from severe head traumas happen often. Accident records from 2015 to 2018 were made available by the state administration of work safety. Of the 78 construction accidents that were recorded, 53 (or 67.95% of all incidents) were related to workers not wearing safety helmets as required. This highlights the need for a greater emphasis on sustainable human resource management, which, if it encourages equitable treatment and happiness for workers and supports pro-ecological activities within the industry. (Okr glicka, Mittal, & Navickas, 2023).

In industrial, construction and mining sectors, maintaining strict safety regulations is essential to shielding employees from possible risks and averting incidents that can cause critical injuries or even fatalities. The regular use of protective gear, including as helmets, jackets, and masks, is one of the most important safety precautions for reducing hazards and guaranteeing worker wellbeing. For safety staff and supervisors, however, enforcing compliance with safety procedures over large work sites presents logistical obstacles.

Artificial intelligence and Machine Learning algorithms not only help in increasing sales, understand consumer behaviour, education , fraud detection but also in maintaining health, particularly in the industrial sector.(Gautam & Mittal, 2022). To address these challenges, This project presents a web application that automatically detects safety Helmet in industrial settings by using deep learning technology. The tool facilitates quick identification of helmets, safety jackets, and masks in photographs and videos by utilizing the YOLOv8 model, which is widely recognized for its precision and instantaneous detection abilities. Workers and safety personnel can quickly upload media files for examination through an easy-to-use interface created with Flask, which streamlines the safety monitoring procedure.

2 Literature Review

H. Wang et al.'s (2020) a modified backbone network with Cross Stage Partial Network (CSPNet) and a Spatial Pyramid Pooling (SPP) structure for feature enhancement was used to increase computational efficiency and training speed.(C. Y. Wang et al., 2020). Ten thousand photos from cameras on construction sites were collected to create a dataset dedicated to safety helmet detection. The results of the experiments showed that CSYOLOv3 performed much better than YOLOv3, attaining a 28% improvement in mean average precision (mAP) and a 6 frames per second increase in processing speed. Workers in the high-risk industry of construction frequently suffer accidents. Deaths from severe head traumas happen often. According to accident statistics given by the state office of work

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safety between 2015 and 2018, workers' failure to correctly wear safety helmets resulted in 53 of the 78 construction accidents that were reported, or 67.95% of all incidents.(Saniya et al., 2022). Monitoring the state in which construction workers are donning their safety protective equipment is crucial to safety management at the site. Safety helmets can lessen the damage caused by employees falling from heights and can absorb and distribute the impact of falling objects. Safety helmets are often disregarded by construction workers due to a lack of knowledge regarding safety.

There is a markedly increased risk of harm for workers at construction sites who wear safety helmets incorrectly. Traditional safety helmet supervision of construction site workers sometimes requires manual labor. (Hayat & Morgado-Dias, 2022). Research by Cheng et al.'s (2021) suggested to replace the original model in YOLOv3-tiny with a better one by creating a depthwise separable convolution and directing the light sandglass-residual (SR) module of the channel attention mechanism. To improve the helmet's detection accuracy, the enhanced spatial pyramid pooling (SPP) module was added to the feature extraction network. Additionally, the convolutional layer was used to substitute three-scale feature prediction for the two-scale feature prediction. Geng, Ma, and Huang's (2021) and Yan and Wang's (2021) presented an enhanced method based on YOLOv3 for detecting safety helmet use. Further, Han and Zeng's (2022) explains the method improves the speed and accuracy of wearing helmet recognition by enlarging the input image, using multi-scale feature fusion structure, depth wise separable convolution instead of Darknet53's traditional convolution, and other techniques.

Zhang, Xiao, and Lu's (2022) proposed a YOLOv5-based technique to improve helmet recognition speed and accuracy. This method utilizes an attention mechanism in the backbone network, adds a fourth scale to forecast the bounding boxes of smaller objects, and applies additional techniques. It starts with YOLOv5 as the baseline. The literature does not contain any study on dense object occlusion detection. In the published works of Dong et al.'s (2015), Kelm et al.'s (2013), and Kim et al.'s (2018) Several sensors were used for the safety helmet that we wore. A range of sensors, including pressure, RFID, three-axis accelerometers, and chinstrap sensors, were employed to identify whether or not a safety helmet was being worn. However, these methods raise the expense of detection and may be viewed as worker invasions.

Workers are typically reluctant to wear safety helmets with the aforementioned sensors due to concerns about their privacy and health.(Shen et al., 2021).Background subtraction is used for moving object recognition in an effort to extract moving objects and categorize them as motorcycling or not depending on the parameters extracted from their region properties. The average colors, average intensity, and circularity of each head quadrant are the features that are taken into account here. The proposed method employs KNN to classify people according to features extracted from 4 segments of the segmented head area

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regarding helmet use.(Waranusast et al., 2013).The study by Silva et al.'s (2013) mentioned two ways to look at the system that this study suggests. To identify the moving items, the photos are first split and classed. This is accomplished by having the user define the CL (Cross Line), after which the system classifies the detected system as a motorcycle or not based on features extracted from the system using LBP (Local Binary Pattern).

The next step involves looking at the helmet recognition component. Here, visual features are extracted using methods like hybrid descriptors, and an SVM classifier is used to assess whether or not the image of interest is a helmet.Segmenting moving objects allows for the evaluation of just the image's interesting objects. (Silva, Aires, & Veras, 2014) .After that, attributes of the image were extracted using descriptors. The term "feature vector" refers to this extracted set of data. To determine if an image is of a motorcycle or not, feature vector classifiers such as multilayer Perceptron's are used to classify the photos. Helmet detection follows the identification of motor vehicles and is accomplished in four steps: ROI extraction, sub window computation, characteristics extraction, and image categorization. ROI is mostly used for classifier-based helmet search; a second sub-window computation is performed by focusing only on the head portion to ascertain whether or not the subject is wearing a helmet. (Liang & Seo, 2022).

3 Proposed System

By automatically identifying safety equipment, the suggested system is a feature-rich web application that aims to transform safety monitoring procedures in industrial, construction, and mining settings. Cutting-edge deep learning technology—specifically, the YOLOv8 model—is used by the system to detect protective gear, such as masks, jackets, and helmets, in real-time from pictures and videos.

The primary characteristic of the system is its user-friendly interface, which was designed using the Flask framework and enables employees and security staff to upload media assets for review. Using a high-quality dataset from Robo flow, a platform that specializes in dataset maintenance and augmentation, is essential to the system's effectiveness. This dataset, which has been carefully chosen and annotated to span a wide range of environmental settings and variations in the appearance of safety gear, is used to train the YOLOv8 model. With the help of this large dataset, the model is able to train to achieve remarkable accuracy and generalization, enabling it to reliably detect safety gear in a range of real-world scenarios.

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4 Methodology

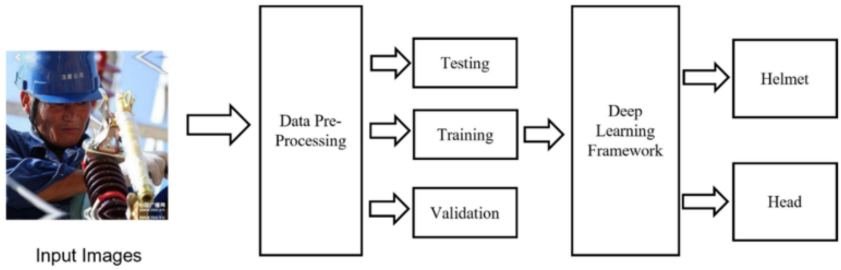

Figure 1. General Architecture for Worker Safety Helmet Detection using Deep Learning Framework

- Data processing: Collecting and annotating a variety of images, augmenting data for variability, normalizing pixel values, dividing the data into training, validation, and test sets, and effectively loading data during training are all part of the data processing for worker safety helmet detection. This ensures a reliable and accurate model.
- Testing: Testing a deep learning helmet detection model involves evaluating its performance on a separate test dataset, using metrics like precision, recall, and mean Average Precision (mAP) to ensure accuracy and robustness.
- Training: Training a deep learning helmet detection model involves feeding annotated images through the model, optimizing with loss functions and an optimizer like Adam, validating performance, and iterating to minimize errors and improve accuracy.
- Validation: Validation in deep learning helmet detection involves using a separate validation dataset to tune hyperparameters, monitor model performance during training, prevent overfitting, and ensure the model generalizes well to new, unseen data.
- Deep Learning Framework: Gathering and annotating data, preprocessing with augmentation and normalization, choosing and training a model, assessing performance, and deploying with continuous monitoring are all steps in a deep learning system for helmet detection. (see figure 1)

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5 Flow Chart

The following diagram illustrates the working of the proposed model:(see figure 2)

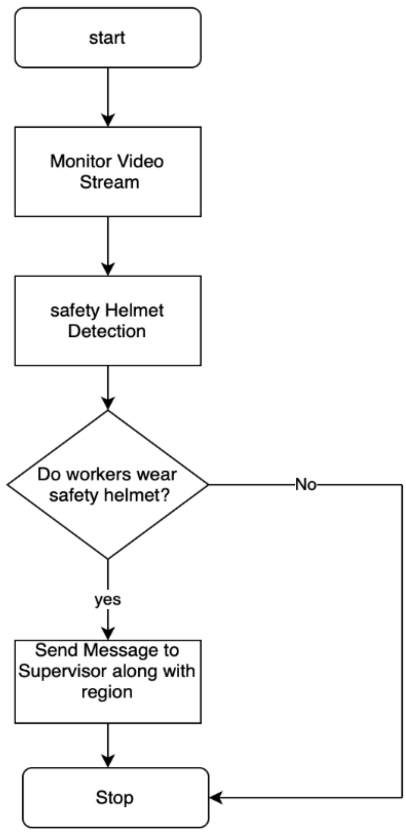

Figure 2. Flowchart

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6 Result

Since the safety gear identification system can precisely identify persons, helmets, jackets, and masks, it has demonstrated to be a very effective way to improve workplace safety. (see figure 3). Workers and safety personnel can upload photographs or videos with ease and obtain real-time detection results with clear visual signs thanks to the user-friendly interface that was designed using Flask.(see figure 4)

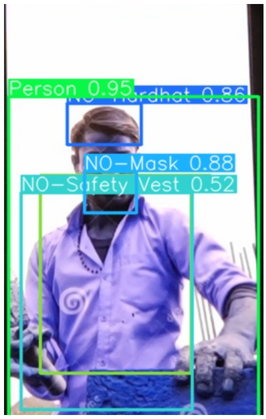

Figure 3. The person is detected without a Helmet, Mask or Safety Jacket.

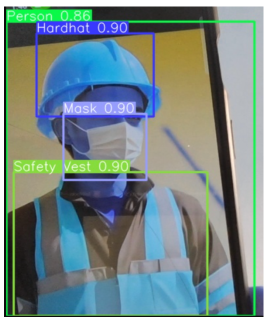

Figure 4. The person is detected with a Helmet, Mask and Safety Jacket.

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7 Conclusion

In conclusion, the safety gear detection project marks a significant stride forward in safety management practices across industrial, construction, and mining sectors. By using of web development frameworks and deep learning, two cutting-edge technologies, the project offers a potent tool for automatically identifying safety gear in photos and videos. YOLOv7 object detection model powers an advanced web application at its heart that provides both workers and safety personnel with an easy-to-use interface. Its user-friendly interface makes it simple for users to upload media assets and get rapid detection results, which improves compliance efforts and streamlines safety monitoring processes.

This project stands as a testament to the transformative potential of innovation in workplace safety. The safety gear detection system transforms the way that safety management is approached while also raising safety standards by utilizing cutting-edge methods. Because of its real-time detection capabilities, safety staff may quickly spot safety gear violations and take preventative action to reduce hazards, which makes the workplace safer for everyone involved.

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