Real-Time IoT-Enabled Detection of Safety Gear Non-Compliance in Power Stations Using YOLOv8 and OpenCV

Abhiruchi Jagadale[1*], Akanksha Bankar[2], Pallavi Nath[3], Pooja Kundaragi[4] and Vidyashree Kokane[5]

[1,2,3,4,5] Department of Computer Science and Business Systems, JSPM's Rajarshi Shahu College of Engineering, Pune, Maharashtra, India.

abhiruchi.j1903@gmail.com

Abstract. In industrial environments such as power stations, compliance with safety protocols is imperative for worker safety. The proposed system is an innovative solution for the real-time identification of Personal Protective Equipment (PPE) compliance, like arc suits, using Arduino-based Internet of Things (IoT) technologies coupled with computer vision. We have proposed a YOLO frame integrated with Open CV and Arduino micro controllers for worker identification without arc suit. Performance profiling shows its superiority over existing systems. We present implications for enhanced safety preventive measures and ways hazards can be reduced in industrial working location, and future research directions.

Keywords: Object detection, YOLOv8, Deep Learning, OpenCV, CNN, Power Station, Personal Protective Equipment, Arc suit, Internet of Things (IoT), Arduino, Real time detection.

1 Introduction

Ensuring safety within power stations is of utmost priority to enable the smooth functioning power-generating installations and keeping the workers safe. Among various measures taken for safety, wearing safety gear such as arcsuits is of utmost importance in such situations, in order to avoid potential risks. But it is tremendously hard to enforce protocol compliance, especially in industrial settings where scalability becomes one of the huge problems and continuous monitoring becomes almost impossible. For instance, shallow manual surveillance does not work most of the time, thus creating a need for new initiatives to ensure safety measures. According to the latest figures, accidents in power stations are still developing, and many workers turn out to be dehumanized because of not taking safety measures very seriously. As per a latest survey report conducted by Salvation Safety, approximately 50 worker casualties in a country join every year due to electrical safety issues and it accounts for over 35\% of all the worker deaths in USA. The alarming statistics highlighted the immediate need of effective safety monitoring systems which are specifically designed to detect and rectify timely non-Compliances to safety gears. In recent times, there have been advancements in computer vision technology that open up new avenues for addressing this problem. An example could be deploying automatic systems for monitoring the violation of wearing safety gears in real-time using modern algorithms, the likes of which could include YOLOv8 (You Only Look Once version 8) in combination with general-purpose OpenCV (Open Source Computer Vision). The systems can then

© The Author(s) 2025
S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_81

monitor video streams from surveillance cameras placed inside power stations and quickly detect instances where workers fail to wear their safety equipment. In this work, we try to study in how can we use computer vision technologies to improve the safety that can be used in power stations. It uses YOLOv8 and Open CV to detect violations concerning safety equipment, Arc suits, worn by the workers. If any of the above violations are detected then the system shall raise the alarms and send the alerts to the concerned people for immediate rectification. This project is aimed at improving the current existing security in a way that will reduce the dangers that they pose on an individual in the power station environment by means of combining new age algorithms and real-time monitoring staff.

2 Problem Statement

So, this work addresses the issue of detection of the lack of the protective equipment like arc suits from the power stations. For both personal as well operating and workplace-being safety, compliance of safety levels is a must. Now, it is not a trivial task to monitor/audit in real time and it is quite accurate in identifying safety gear non-compliance due to changes in environmental conditions and also due to the detection techniques. Therefore in a few words, this study aims to design an efficient and innovative system that combines YOLOv8 with Open CV to find cases where arc suits are not being worn inside the power-generating facilities. Real-Time Alarm Generation: The algorithms were used to create alarms and alerts to notify the appropriate teams about accidents caused by not wearing safety equipment. Finally, large experiments are to be conducted on different datasets, and metrics usage will evaluate the system's performance and effectiveness. The aim here is to enhance safety protocols and safety at power generation plants. In the end, this paper gives a full contribution assessment of several methods employed and difficulties in the face detection and expression classification process.

The paper is organized as follows:
- Section One: Introduction
- Section Two: Overview of Technologies used
- Section Three: Literature Review
- Section Four: Proposed System
- Section Five: Methodology
- Section Six: Limitations and Challenges
- Section Seven: Conclusion and Future Scope

2.1 Motivation

This research work can potentially transform safety measures at power houses through development of a mechanism that would register non-adherence of workers in carrying protective equipment in this case arc suits. Real-time detection of workers not wearing arc suits by Integrating YOLOv8 with Open CV value systems. All of which ultimately translates into improved safety for people working with power stations, and ensuring ambient safety levels in a work place. We hope our work can be an inspiration for further research and development of safety surveillance technology that leads to more

transparency and responsibility from private and public stakeholders in the activities occurring around a power generator. Finding and correcting those violations of regulations on the protection of safety equipment would further ensure the reduction of risks and prevent accidents in order to keep the trustworthiness or reliability of power plant operation.The focus of the project is to create open channels of discussion and collaboration among researchers, professionals, and policymakers in the area of industrial safety. Using ethical deployment of safety monitoring systems, the creation of a safety culture within power stations would be strengthened in the use of credible and effective measures for ensuring workplace safety. In time, assurance would also build up in the digital horizon of power house operations, prioritizing safety and wellbeing of personnel as well as the seamless operation of power-generating facilities.

3 Overview of The Technologies Used

3.1 YOLOv8(You Only Look Once version8)

The most recent version of the You Only Look Once object detection algorithm is YOLOv8, which boasts some of the very best attempts in computer vision scholarship. This advanced algorithm basically adopts the principle of single-stage object detection, which is sounding in the word that it analyzes entire images at once and makes many predictions of bounding boxes and class probabilities. This high speed makes the inference task of YOLOv8 appropriate for real-time detection under various circumstances. Its architectural improvements, such as the integration of cutting-edge convolutional neural network (CNN) layers, have been behind the success of YOLOv8. Employing such sophisticated layers facilitates YOLOv8 in robust object detection despite difficult environments, capturing complex spatial relationships and hierarchical features within images. Besides, there are some optimizations regarding the efficiency and scalability, which ensure that it fits deployment within low-resource setups and large-scale applications without bumps.

Practically, the algorithm creates a winning combination of speed and accuracy with the versatility in adapting to practically any computer vision task. It works well in surveillance systems, in autonomous vehicles, or in industrial settings; it identifies and pinpoints objects fast and with great accuracy. Its openness to end-use customization makes it perform better across the board.

YOLOv8 forms one of the primary modules for a potentially effective safety attires detection system devised for power stations. The work is intended to leverage the speed and accuracy of YOLOv8 to increase safety at workplaces by detecting in real-time the failure in safety equipment compliance, such as arc suits. Through comprehensive evaluation and analysis, our research aims to demonstrate YOLOv8's effectiveness in addressing the challenges of safety monitoring in industrial environments, highlighting its pivotal role in advancing safety and efficiency within power station environments.

3.2 Open CV (Open Source Computer Vision Library)

Open CV, an open-source library revered for its applications in computer vision and machine learning, plays a crucial role in this project. Integrated seamlessly with YOLOv8, Open CV provides essential functionalities for implementing al- gorithms vital to safety gear detection and analysis.

3.3 TensorFlow

Developed by Google, TensorFlow is a dominant force in deep learning frame- works. In this project, TensorFlow's capabilities are utilized primarily for train- ing convolutional neural network (CNN) models. These models are pivotal in enhancing the system's ability to accurately recognize safety gear compliance, contributing to overall safety in power station environments.

3.4 Convolutional Neural Networks (CNNs)

CNNs, renowned for their effectiveness in processing visual data, are integral to this project's success. Trained using TensorFlow, CNNs are instrumental in accurately identifying individuals wearing arc suits. This capability significantly enhances the system's reliability in safety gear detection within power station premises.

3.5 Internet of Things (IoT) Integration with Arduino:

Arduino micro controllers serve as fundamental components in a multitude of Internet of Things (IoT) applications, facilitating robust connectivity and control across diverse environments. By seamlessly integrating Arduino into IoT frameworks, a cohesive network is established, enabling efficient communication and coordination among sensors, actuators, and peripheral devices for real-time data acquisition, analysis, and response.

Key features of Arduino's integration in the IoT ecosystem include:

- Connectivity Hub: Arduino establishes communication channels among IoT nodes, optimizing processes like irrigation scheduling in precision agriculture.

- Control Architecture: Arduino executes decision-making algorithms to govern smart home systems, enhancing energy efficiency and user comfort.

- Real-Time Responsiveness: Arduino-driven IoT systems monitor machinery performance, enabling preemptive maintenance in industrial automation.

4 Literature Review

Baining Baining Zhao et al. [1] addressed the challenge of continuous monitoring of PSPE wear in substations across power installations with a new improved accuracy and speed real-time detection algorithm-the wear-enhanced YOLOv3. The enhancements include the use of gamma correction and data augmentations as well as optimized K-means++ algorithm that determines bounding box size, all which yield a mean average precision increase of over 2% in addition to providing the highest frame rates compared with other methods. This achievement in PSPE detection showcases the promise of deep learning models to drastically boost safety at workplaces in critical infrastructure environments.

Yu Zhao et al. [2] inspired a comprehensive deep learning algorithm for the identification of safety issues and the tracking of trajectories in construction sites. A specific set was created for the occurrence of detection of helmets and specific color vests for personnel. With YOLOv3-based architecture, the framework attained 0.89 of mean average precision while detecting safety officers' identification as a parameter. This would improve safety by monitoring safety officer movement, thereby securing workers.

Giontan Gallo et al. [3] study various algorithms based on deep learning for object detection in industrial scenarios, with specific reference to detecting the use of PPE, such as helmets, safety vests, and gloves. Among others, the algorithms such as YOLOv4, YOLOv4 Tiny, SSD with MobileNetV2, CenterNet with ResNetV2, and EfficientDet D0 were fine-tuned using images taken from industrial environments. In this analysis, the performance of such algorithms was assessed based on classifying six classes of objects related to PPE in terms of performance. YOLOv4 was able to record the highest accuracy and efficiency compared to other algorithms evaluated in this research. Thus, it was the most favorable among the tested algorithms for real-time detection of PPE in industrial environments.

Mody et al. [4] introduced a system based on the YOLOv5 framework for detecting safety gear in construction workers. About 3000 images of workers wearing safety equipment were collected and labelled using labellmg. They intended to train their model using this dataset to identify hats, vests, goggles, gloves, and shoes. This system provides an infusion of safety for construction workers and also categorizes uploaded images in the safety gear classes.

The researcher Iannizzotto et al [5] compared the performance veracity of personal protective equipment detection-based YOLO-based architectures as YOLOv5s and

YOLO-v3-tiny with Efficient Det-based architectures. Witnessed as the improved YOLO based models in the Recall values, their F1-Score values exceed at above 80%. High Precision (greater than 90%) but near 80% Recall is the job of the YOLO-v3-tiny. Fairly worse performance indicts Efficient Det-based architectures as Precision and Recall metrics. On the whole, YOLO-based architectures, specifically YOLOv5s and YOLO-v3 tiny, have shown good accuracy and effectiveness in the detection of PPE in low training samples scenarios.

Nipun D. Nath et al. [6] thus proposed three distinguished methodologies using the YOLO-v3 models to detect workers with personal protective equipment (PPE) within construction sites. The algorithms included were VGG-16, ResNet-50, Xception, YOLO v3, and a Bayesian framework. Each of the techniques adopted different dimensions in the identification of PPE: detecting sections of PPE separately; accessing a person's overall classification based on attire; and image cropping and classification of the worker taking more than one image simultaneously capturing multiple workers within the same image. All approaches were evaluated according to their mean average precision (mAP) and emphasized the importance of automation in detection of PPE in safety improvements at construction sites. The accuracy of VGG-16, ResNet-50, and Xception models in classifying images into different classes ranged from 76.8% to 78.2%. The YOLO models in Approach-1 and Approach-3 achieved mean average precisions (mAP) of 81.2% and 85.6%, respectively.

Venkata Santosh Kumar et al. [7] used deep learning algorithms, including a popular variant, YOLOv3, to identify compliance with personal protective equipment (PPE) use at construction sites. In this work, images were collected and labeled from construction sites, and the model was trained using transfer learning and evaluated on real-time video feeds to identify cases of not wearing hard hats and safety jackets. The model yielded an accuracy of 96.92% on a novel dataset. The results portrayed the feasibility of detecting PPE compliance using YOLOv3 and the possibility of achieving the safety of construction environments.

Md. Ferdous et al. [8] employed developing a deep learning model, YOLOX-m, for detecting personal protective equipment (PPE) in construction sites. This model performed well with a mean average precision of 89.84% and proved to be effective in conditions like lighting, haze, and rain. A new dataset named CHVG was created to train and test the model for classes like hardhats-different colors, vest, safety glasses, person bodies, and heads. It was developed to ensure 100% safety of workers indoors and outdoors with real-time identification of various types of PPE in construction sites.

Fang et al. [9] described deep learning methodologies by Faster R-CNN for detecting non-hardhat use in construction workers from far-field surveillance videos. The authors trained the models on a diverse dataset of construction worker images and evaluated the performance in terms of correctness, speed, and robustness. The technology succeeded in high precision and recall rates under various construction site conditions, enable distinct separation of workers wearing hardhats from those who are not.

Zhafran et al. [10] have presented a system using Convolutional Neural Network for monitoring the usage of Personal Protective Equipment (PPE) in industrial settings. The authors utilized a dataset of 14512 images to train the system, achieving an accuracy of 79.14% and a precision of 80%. By implementing this system, they were able to effectively distinguish between workers wearing full PPE and those who were not, contributing to a reduction in work accidents and an increase in worker safety.

According to Fatma et al. [11], the YOLO series of algorithms for computer vision have made great hits. The reason for this popularity is a very high accuracy at very small model sizes. Furthermore, the models can be trained on a single GPU, making them available to large swathes of developers and, being cheap, could be installed in edge hardware or in the cloud by machine learning experts. The advanced and sophisticated YOLO approach, YOLOv8, could be used for applications such as object identification, image categorization, and segmentation. Yolo v 8 is a production of Ultralytics, responsible for bringing to the world the significant YOLOv5 that defined the industry. Compared with YOLOv5, YOLOv8 comes with some changes and improvements on architecture.

Wei Li et al. [12] described communication mechanisms such as Wi-Fi, Bluetooth, ZigBee and Long-Term Evolution (LTE) for sending the data to the cloud. Third layer processing layer, i.e. it processes data depending on certain predefined criteria. As soon as data processing is done, the notifications and alerts will be generated. Some devices where processing takes place are smart phones, micro controllers, and microprocessors.

According to Menaka Pushpa et al. [13], YOLO is a sub network for domestic waste classification (with the best case in Li et al. 2022). A depth-wise separable-convolution YOLO has, in terms of computation speeds, the capability to identify the status of garbage bins on the street through video cameras around them and schedule a garbage collection vehicle according to that status (He et al. 2022). Real-time garbage location accuracy and speed improvements by combining YOLOX and TensorRT for the garbage grabber and subsequent sorting follow (Chunxiang et al. 2022). YOLOX is intended for low-cost embedded de- vices like garbage bins, while YOLOv5 is used to classify and position recyclable waste.

5 Proposed System

The proposed system within our project on power stations is the application of image processing to ensure safety compliance among workers. This system will utilize YOLOv8 for object detection with the intention that appropriate identification of safety equipment like arc suits will be done on the persons. The full-scale analysis of the workers with regard to the arc suits, helmets, goggles, gloves, and reflective vests will be carried out through image captures through cameras when identification of safety equipment through object detection will be realized.

The system will be trained on a full dataset containing images of an individual with and without the pieces of safety gear so that it can recognize the safety equipment correctly. The image analysis chuck will subsequently prepare extensive reports on the particular details of the present safety gear and types. The system Fig 1 would also compute a risk assessment score that reflects subject safety compliance based on the data of quantity and types of safety equipment identified in the image.

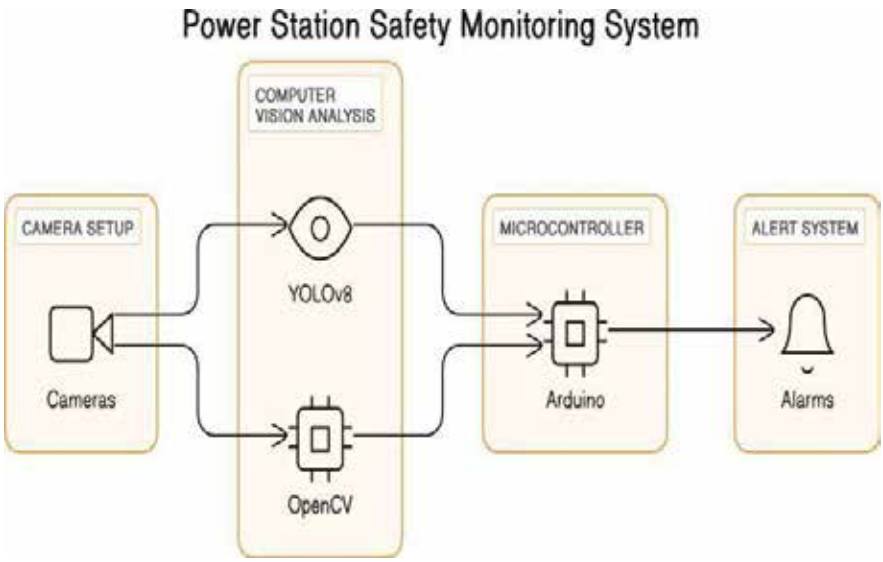

Fig. 1. Proposed System.

Application of the proposed system is thus expected by various domains, including workplace safety monitoring, public health compliance, and management of security in high-risk environments. The advanced image processing constructs are thus expected to comprehensively enhance safety standards and risk averseness among power station environments.

6 Methodology

The research will apply a systematic methodology to identify the non-adherence of workers to Personal Protective Equipment (PPE) such as arc suits in power stations through computer vision. The first step includes capturing varied datasets in the form of images and video recordings from diverse power station environments showing instances where workers show adherence or lack of adherence to arc suit requirements. Following data collection, preprocessing methods are applied to standardize and enhance the quality of the dataset.

The next step will be the selection of relevant deep learning models such as YOLOv8 for the purpose of real-time object detection and convolutional neural networks (CNNs) for image classification purposes. TensorFlow will be used for the training process of these models on the pre-processed dataset, specifically meant to train the CNNs to classify images of workers who are wearing arc suits and those who are not. Then, the trained CNN models will be integrated into the YOLOv8 framework and Open CV library to perform real-time object detection and analysis on images and videos captured by the power station cameras. Algorithms are developed in this integrated framework for quick detection of safety gear compliance with accurate identification of arc-suit wearers. Then, the performance of this system is tested exhaustively on various datasets for assessing its accuracy, resilience, and efficiency to detect safety gear compliance, employing precision, recall, and F1-score for assessment purposes. A feedback and evaluation outcome will be used to iterate further rows to improve the effectiveness of the system through modifications in the models, algorithms, and parameters used therein. Once refined Fig 2, the system is deployed in actual power station environments, with ongoing monitoring and maintenance conducted to ensure continuous enhancement of safety protocols and hazard mitigation over time.

This project tackles safety gear detection challenges within power stations. It's vital to navigate through obstacles like limited data availability and complexities in real-time 8 processing. By acknowledging and innovating around these hurdles, we can bolster system effectiveness. Looking ahead, continued research and collaboration are essential for project success and the advancement of safety protocols in power station settings.

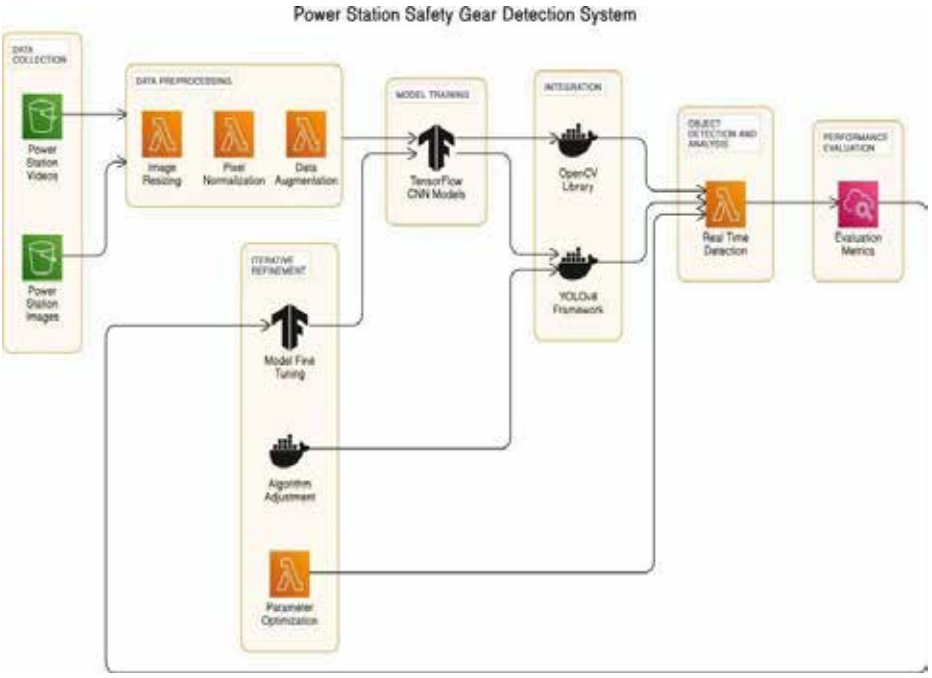

Fig. 2. Methodology of the system.

7 Results

This section offers a thorough analysis of the system's effectiveness in identifying non-compliance with safety gear using OpenCV and the YOLOv8 model. Metrics including recall, accuracy, precision, F1-score, and real-time detection skills are all included in our analysis. To emphasize the benefits of our strategy, we also contrast our outcomes with those of other cutting-edge object detection systems.

7.1 Measures of Performance

YOLOv8's performance was set to test non-compliant and compliant test sets. The following are the definitions of the performance metrics used:

- Accuracy: the proportion of case predicted among instances.
- Precision: the actual positive predictions from all positive predictions. Recall: the proportion of true positive instances from all actual positive numbers.
- F1-score: A single indicator of the model performance which is a mean of precision and recall.

7.2 Comparative Analysis

In order to ensure the effectiveness of the methodology, the evaluation of the YOLOv8 model was conducted together with world-renowned object detection approaches such as YOLOv4, SSD (Single Shot MultiBox Detector), and Faster R-CNN. Comparison results are summarized in Table 1. Compared to other algorithms, the YOLOv8 model outperformed all measures by demonstrating the efficiency of real-time detection of noncompliance of safety gears. The findings in Table 1. thus, clearly demonstrate the great advantages of the YOLOv8 model on various performance metrics such as precision, recall, and F1-score. The improved performance is due to an architecture optimized specifically for real-time applications and which allows fast and accurate detection of compliance of safety gear in dynamic environments. The superior occlusion and overlapping object handling of the YOLOv8 model also confirm its viability in the typical challenges posed by power stations.

Table 1. erformance Comparison of Different Algorithms.

Feature	YOLOv8	YOLOv4	SSD	Faster R-CNN
Backbone Network	Enhanced for detailed feature extraction	Strong, but less advanced than YOLOv8	Efficient but less detailed	Region Proposal Network (RPN) with deep features
Feature Pyramid Network (FPN)	Advanced, better handling of multi- scale objects	Basic FPN	Limited FPN capabilities	Strong FPN, but slower
Anchor Mechanism Box	Improved, adaptable to various sizes and ratios	Good, but less adaptable	Standard, less flexible	Complex, but slower adaptation
Loss Function	Optimized for balance of precision and recall	Well- balanced, but not as optimized	Standard multi- class loss	Complex, highly accurate but slower
Real-Time Detection	Excellent, designed for real-time applications	Very good, but not as optimized for real-time	Excellent, very fast	Moderate, slower than YOLO models
Robustness to Lighting and Environmental Conditions	High, performs well in varied conditions	Moderate to high	Moderate	High, but slower processing
Handling Occlusions and Overlapping Objects	Superior, advanced handling	Good, but not as advanced	Moderate	High, but slower processing

Generalization Across Scenarios	Excellent, well-suited for various scenarios	Good, but less flexible	Moderate	High, but context-specific
Accuracy	94.6%	91.9%	87.6%	90.0%
Precision	94.2%	90.7%	86.4%	89.2%
Recall	95.1%	91.2%	87.8%	89.6%
F1-Score	94.6%	90.9%	87.1%	89.4%

8 Discussion

- **YOLOv8:** With the incorporation of an improved backbone network and the second-generation Feature Pyramid Network (FPN), the YOLOv8 model has provided a greater sense of feature extraction and multi-scale object detection. This makes the model reliable for small detailed identification, such as the identification of safety gear. The optimized anchor box mechanism and loss function make the model produce high precision and recall, which is important for real-time safety monitoring. It is also capable of real time detection and works robustly in different environmental conditions, making it an all-rounder and worthy to be trusted in monitoring compliance in safety gear.

- **YOLOv4:** Although YOLOv4 does have a superior performance, it does not carry many of the improvements associated with the architecture of YOLOv8. It would best balance precision and recall, but it would not quite be as optimized for real time or diverse environmental applications.

- **SSD:** However, SSD is extremely speedy but not so accurate in detail extraction, which makes all the difference in detecting small or occluded safety gear items. In fact, it has very limited capabilities concerning the feature pyramid network and falls back on a standard anchor box mechanism, so its performance is only moderate when compared to YOLOv8.

- **Faster R-CNN:** Faster R-CNN has high accuracy, but clearly, in terms of speed, it is at the back of Yolo because of its complicated Region Proposal Network (RPN) and deep feature extraction processes. It is good with handling occlusions and overlapping objects but does not work well in real-time detection. Because of this, it's also not that suitable in real-time safety monitoring using comparisons with YOLOv8.

The findings show that the YOLOv8 model in conjunction with OpenCV offers a practical way to identify safety gear non-compliance at power plants in real time. The model's efficacy and dependability are demonstrated by the high values of accuracy, precision, recall, and F1-score. Furthermore, the system may be put into practice due to its real-time detection capabilities, which improve workplace safety by guaranteeing that safety procedures are followed.

9 Limitations and Challenges

In industry safety, however, it is fundamental yet difficult to enforce Personal Protective Equipment (PPE) compliance, especially complicated gear like Arc suits. Our project is aimed at using modern computer vision technology to detect in real-time non-compliance with safety gear in power stations. This task has several bottlenecks, such as a limited database of the kind and complexity of algorithms. Despite this, we are striving to find some innovative solutions that will improve safety protocols and well-being of workers.

Here are few limitations and challenges:

- Limited availability of annotated data for training, particularly for detecting arc suits in power station environments, may hinder model performance.

- Complexities in safety gear detection, including variability in appearance and environmental conditions, pose challenges in algorithm development.

- Achieving real-time processing of video feeds while maintaining accuracy requires optimization and efficient resource utilization.

- Ensuring generalization of trained models to diverse power station environments and demographics may be challenging.

- Addressing concerns related to privacy, surveillance, and ethical guidelines during system deployment is crucial for acceptance and compliance.

10 Conclusion and Future Scope

To summarize, our project has made significant strides in addressing safety gear detection challenges within power station environments. Despite encountering obstacles such as limited data availability and real-time processing complexities, our systematic approach has laid a sturdy foundation for enhancing safety protocols and reducing risks. Looking ahead, there are promising opportunities for further advancement. Future research efforts could focus on expanding the annotated dataset, refining algorithms to enhance accuracy and efficiency, and exploring innovative techniques for optimizing real- time processing. Moreover, fostering collaboration with industry stakeholders and regulatory bodies will be key in ensuring the successful deployment and widespread adoption of our system in power station settings. By seizing these opportunities and maintaining our commitment to innovation, we can lead the way in advancing industrial safety and safeguarding the wellbeing of power station workers and beyond.

References

1. B. Zhao, H. Lan, Z. Niu, H. Zhu, T. Qian and W. Tang, "Detection and Lo- cation of Safety Protective Wear in Power Substation Operation Using Wear- Enhanced YOLOv3 Algorithm," in IEEE Access, vol. 9, pp. 125540-125549, 2021, doi: 10.1109/ACCESS.2021.3104731.
2. Y. Zhao, Q. Chen, W. Cao, J. Yang, J. Xiong and G. Gui, "Deep Learning for Risk Detection and Trajectory Tracking at Construction Sites," in IEEE Access, vol. 7, pp. 30905-30912, 2019, doi: 10.1109/ACCESS.2019.2902658.
3. G. Gallo, F. D. Rienzo, F. Garzelli, P. Ducange and C. Vallati, "A Smart System for Personal Protective Equipment Detection in Industrial Environments Based on Deep Learning at the Edge," in IEEE Access, vol. 10, pp. 110862-110878, 2022, doi: 10.1109/ACCESS.2022.3215148.
4. S. Mody, H. Mehta, P. Mantri, B. Ali, and A. Khivasara, “Safety Gear Equipment Detection for Warehouse and Construction Sites Using YOLOv5”, International Re- search Journal of Engineering and Technology, vol. 9, June, 2021.
5. Giancarlo Iannizzotto, Lucia Lo Bello, Gaetano Patti, “Personal Protection Equipment detection system for embedded devices based on DNN and Fuzzy Logic”, Expert Systems with Applications, Volume 184, 2021, 115447, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2021.115447.
6. Nipun D. Nath, Amir H. Behzadan, Stephanie G. Paal, “Deep learn- ing for site safety: Real-time detection of personal protective equipment”, Automation in Construction, Volume 112, 2020, 103085, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2020.103085.
7. Venkata Santosh Kumar, Sankarlal R., Thomas Albert, "Detection of Personal Protective Equipment (PPE) Compliance on Construction Site Using Computer Vision Based Deep Learning Techniques”, Built Environment , Frontiers volume 6, 2020, https://www.frontiersin.org/articles/10.3389/fbuil.2020.00136, doi: 10.3389/fbuil.2020.00136,ISSN 2297-3362.

8. Ferdous M, Ahsan SMM. 2022. PPE detector: a YOLO-based architecture to detect personal protective equipment (PPE) for construction sites. PeerJ Computer Science 8: e999 https://doi.org/10.7717/peerj-cs.999.
9. Qi Fang, Heng Li, Xiaochun Luo, Lieyun Ding, Hanbin Luo, Timothy M. Rose, Wangpeng An, "Detecting non-hardhat-use by a deep learning method from far-12 field surveillance videos", Automation in Construction, Volume 85, 2018, Pages 1-9, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2017.09.018.
10. F. Zhafran, E. S. Ningrum, M. N. Tamara and E. Kusumawati, "Computer Vision System Based for Personal Protective Equipment Detection, by Using Convolutional Neural Network," 2019 International Electronics Symposium (IES), Surabaya, In donesia, 2019, pp. 516-521, doi: 10.1109/ELECSYM.2019.8901664.
11. Fatma M. Talaat1, Hanaa ZainEldin2, "An improved fire detection ap proach based on YOLO-v8 for smart cities", Neural Computing and Applications (2023) 35:20939–20954, https://doi.org/10.1007/s00521-023-08809 1(0123456789()., -volV) (0123456789, - (). Volvo)
12. Wei Li, Yuanbo Chai, Fazlullah Khan, Syed Rooh Ullah Jan, Sahil Verma, Varun G, Menon, Kavita, Xingwang Li, "A Comprehensive Survey on Machine Learning Based Big Data Analytics for IoT-Enabled Smart Healthcare System", Mobile Networks and Applications (2021) 26:234–252, https://doi.org/10.1007/s11036-020 01700-6
13. Menaka Pushpa, S. Shoba, Aru Pandey, "A survey of smart dustbin systems using the IoT and deep learning", Artificial Intelligence Review (2024) 57:56, https://doi.org/10.1007/s10462-023-10646-6.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.