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Research Paper

Lightweight Multi-PPE Detection for Edge-Based Industrial Safety Monitoring

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Abstract: Personal Protective Equipment (PPE) is a key safety issue in the workplace. These are settings that are usually accompanied with complicated back- grounds, occlusions and huge disparities in the object sizes and so detection is not an easy task. Conventional vision based PPE detection systems are often not very resilient in such dynamic conditions. To remedy these issues, this paper will suggest a high-performance PPE detection model using YOLOv8 in real-time industrial safety monitoring. A stimulated multi-class PPE dataset is trained in the proposed system within a supervised learning strategy. The model carries out precise localization and classification by modeling bounding box regression and classification. The training procedure reduces bounding box loss, classification loss and distribution focal loss in order to improve detection. Experimental findings illustrate that the model has a detection error of 96.2, which depicts a great potential of detecting and locating the PPE components with great precision.

Keywords- Personal Protective Equipment (PPE), YOLOv8, Multi-Class Object Detection, Computer Vision, Industrial Safety Monitoring, Deep Learning.

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1. Introduction

Construction sites, manufacturing facilities, and processing plants are all typical industrial settings, and highly dangerous working environments that demand the high compliance with the Personal Protective Equipment (PPE) requirements [1]. PPE materials such as helmets, safety vests, boots, gloves, masks, safety glasses, and ear protection are important in the reduction of injuries and deaths in work places [2]. But manual attention to PPE compliance cannot be effective and is too labor intensive and subject to human errors, particularly in a large or dynamic industrial environment [3]. Monitoring systems Computer vision based on automated monitoring systems have become a promising solution. However, the actual factory setting has a number of issues, such as background clutter, changes in lighting, partial obstructions, worker congestion, and changes in object size [4]. Most of the currently available PPE detection systems concentrate on a narrow range of PPEs including helmets and reflective vests, which leads to partial safety evaluation [5]. In order to overcome these difficulties, the given work suggests a lightweight multi-class PPE detection system, which is built on YOLOv8. The suggested model is trained with a publicly available multi-class dataset and implemented on the Flask based backend used to monitor the real-time industrial safety situation. The system provides enhanced scalability, reproducibility and wide covering of safety.

2. Related Work

The PPE detection methods were early and were based on the classical image processing methods like color segmentation, edge detection, and hand- crafted feature detection [6][7]. Such methods were very sensitive to the environmental changes and could not work in the complicated industrial scenes [8].

As deep learning was developed, object detection networks like Faster R-CNN, SSD, and different versions of YOLO became much more efficient and resistant to detection errors [9][10]. A deep learning approach that combined person detection, body pose estimation, and spatial attention mechanisms proved to be better in PPE classification through targeting the body parts of interest during training [11]. There was also an improvement in the robustness of the complex construction environments with features extraction modules being changed to build better YOLO-based frameworks to detect helmets [12].

Some of them used custom datasets, including the Color Helmet and Vest (CHV) dataset [13], to enhance performance. These datasets were, however, typically restricted to certain groups of PPE and were not multi-class based. Moreover, other studies pointed to the difficulty of head-body association and identity switching in busy place [14].

Newer developments in anchor-free based systems like YOLOv8 have better localization accuracy, higher inference speed, and multi-scale feature extraction, which is applicable in real-time industry.

3. Existing Model

The safety-wear detection systems currently in use generally identify the helmets, heads, and bodies and reflective vests as individual objects with typical object detection models [15] [16]. Even though some of the previously used methods were based on the publicly available datasets, these datasets lacked consistency in the association of the heads to the bodies [17] [18]. In order to address this problem, some studies created custom datasets of personal data, including head-body matching of each worker [19].

Although learning a set of associations was enhanced by the use of a personal dataset, the method posed bottlenecks. This was caused by the lack of an explicit head-body binding mechanism in most of the implementations resulting in inaccurate detection in crowded scenes [20]. Under occlusion; performance suffered and switching identities under tracking led to false alarms being repeated. Also, models, which were trained on a small number of PPE categories, offered partial analysis of safety compliance. The reliance on proprietary data also limited reproducibility and benchmarking in different industry environments [21].

4. Proposed Methodology

The suggested framework presents a multi-class PPE detection system that is lightweight and consists of a YOLOv8 model that is trained on a publicly available dataset. The methodology involves collection of data, pre-processing, model design and implementation in a Flask based API.

4.1 Data Collection

The suggested model uses the “PPE Dataset for Workplace Safety” that is provided in the Roboflow Universe. It has four PPE-related classes (Person, Helmet, Vest, and Boots) that are not only supported by this dataset but also support multi-class object detection. The annotations are all in the form of a bounding box and are compatible with the YOLO based models. In comparison to previous methods of using only helmet and vest detection, the provided dataset allows performing a comprehensive monitoring of safety compliance by considering various types of protective equipment. Reproducibility and ability to benchmark is guaranteed by the public availability of the dataset.

Table I. Dataset Overview

Attribute	Details
Dataset Name	PPE Dataset for Workplace Safety
Task Type	Multi-class Object Detection
No. of Classes	4
Classes	Person, Helmet, Vest, Boots
Annotation	Bounding Box Format
Platform	Roboflow Universe
Compatibility	YOLO-based Models
Training Use	PPE Compliance Detection

4.2 Image Preprocessing

Python, OpenCV, and NumPy are used as the modes of processing images. The uploaded images are translated into NumPy arrays and decoded to BGR format by converting the streams of bytes into NumPy arrays. YOLOv8 autonomously employs resizing, normalization and augmentation methods (scaling, horizontal flipping and mosaic augmentation) during training. These preprocessing methods enhance the resistance to the scale variation, changes in lighting, and partial blocking. The input images may be expressed in the form of a tensor.

$$I \in RH\times W\times 3 \tag{1}$$

Where H and W represent the height and width respectively. The processed images are passed to detection network where the features are extracted.

4.3 Model Architecture

The Safety Wear Detection System is suggested to be a complete end-to-end deep learning system of automated detection of Personal Protective Equipment (PPE) in the workplace. The system itself starts with the creation of an organized PPE data set that is being curated with the help of the Roboflow platform, which includes tagged images of objects, including helmets, safety vests, and people. Correct annotations of the bounding box make certain a high probability of multi-class object detection and allows the model to learn the specific visual features of each safety component. The correct data set preparation increases the performance of the model in terms of generalization and robust detection in conditions of different light and other work-related complexities.

The system is based on the main principle of the YOLOv8 optimization training framework that uses a pretrained model and fine-tunes it on the custom PPE dataset. The parameter of the model and the hyperparameters are optimally adjusted during training to reduce loss and maximize the ability to detect. The network acquires spatial and contextual characteristics that are necessary to detect safety equipment in real-time situations with precision. The performance metrics are constantly examined to make sure that there is balanced detection of all classes. The result of this process is an optimized YOLOv8 trained model that can produce fast and accurate object detection that can be used in industrial safety surveillance.

After training, the optimized model is implemented with a Flask based backend architecture to allow real time inference. The deployment layer input: Image or video input; process: Image or video input is processed, YOLOv8 predictions are made, and detections are produced in the form of bounding boxes and class labels. The inference server is developed to be efficient within real time conditions so that it has minimal latency, but high detection rates. A prediction reliability enhancement layer is again used to enhance accuracy to minimize false detection and enhance system stability.

The last phase of the system generates outputs of safety monitoring, such as real-time detection viewing and automatic alert options of safety violations. The system can send out alerts whenever any gaps in PPE have been detected so that supervisors or safety staff can be notified. By integrating both powerful deep learning tactics with scalable deployment infrastructure, this integrated architecture guarantees ongoing surveillance and better adherence at the workplace alongside the improved operational safety.

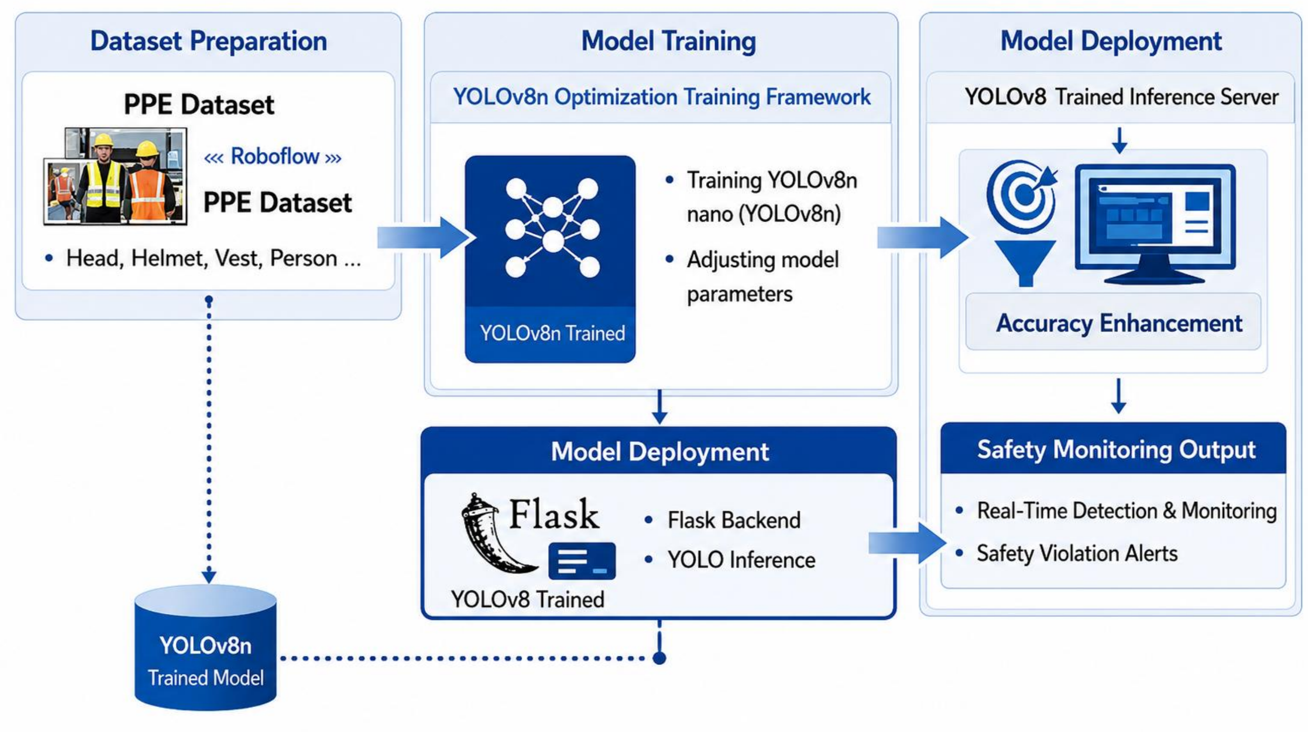

Fig.1. Proposed Safety Wear Detection System Architecture

4.4 Model Training

The suggested multi-PPE detection framework is based on the YOLOv8 object detection framework which is chosen because of lightweight architecture, anchor-free detection system, and real-time inferences. The eight object classes of the PPE Dataset that were fine-tuned to a pretrained YOLOv8 model are Person, Helmet, Vest, Boots, Mask, Gloves, Safety Glasses and Ear Protection. The dataset is annotated with bounding box labels which can be used in training pipelines based on YOLO.

Before the training, the dataset was stratified into training and validation subsets to have the right generalization and objective assessment. The optimization of the model parameters was done using supervised learning. The training process reduced three significant loss terms at once: bounding box regression loss used to ensure localization accuracy, classification loss used to ensure higher accuracy in multi-class prediction, and distribution focal loss used to get better bounding box refinement. The anchor-free approach to detection of YOLOv8 makes less computationally complex and more stable to detect variations in object sizes.

The YOLOv8 backbone and neck architecture allows the creation of multi-scale feature extraction to allow a model to recognize small-scale PPE objects (e.g., gloves, masks) and relatively large objects (e.g., persons, vests). Learning rate, batch size, and number of epochs were hyperparameters which were adjusted to find the best convergence without overfitting. Optimal weights of the models were chosen using validation performance measurements and are sent to be deployed. This training approach will guarantee the strong behavior in the problematic industrial conditions such as the presence of occlusion, scale variations, and cluttered backgrounds.

Table II. YOLOv8 Training Configuration

Parameter	**Value**
Optimizer	SGD (Momentum)
Learning Rate	0.01
Batch Size	16
Epochs	20
Loss	Box + Cls + DFL
Metrics	Precision, Recall, mAP

5. Results and Analysis

5.1 Experimental Setup

The training framework of the Roboflow-hosted PPE Dataset of Workplace Safety was used as an experimental evaluation with the YOLOv8 training framework. It is a multi-object detection dataset consisting of multi-class annotations of objects. The experiments were conducted through supervised learning with an annotated image train where the model was trained and a validation split was used to test the model.

Training and inference are done efficiently, and the deployment pipeline was deployed based on a Flask-based backend server. The trained YOLOv8 model was built into the inference server, which allows processing real-time images and detecting PPE. The deployment system takes uploaded images, does a certain object detection inference and produces visual output in form of bounding boxes, labels and confidence scores. This configuration has low latency and scalability, which makes the system applicable in edge based industrial safety monitoring applications.

5.2 Evaluation Metrics

To measure the localization accuracy and classification performance of the proposed YOLOv8-based multi-PPE detection model, the standard object detection metrics were used to ensure that all the aspects are covered. This assessment is consisting of Precision, Recall, F1-Score, Mean Average Precision (mAP), and Intersection over Union (IoU), and Confusion Matrix evaluation.

Precision: The precision is used to determine the rate of positive detection predictions made correctly against the total number of predictions made. It indicates how the model is able to prevent false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

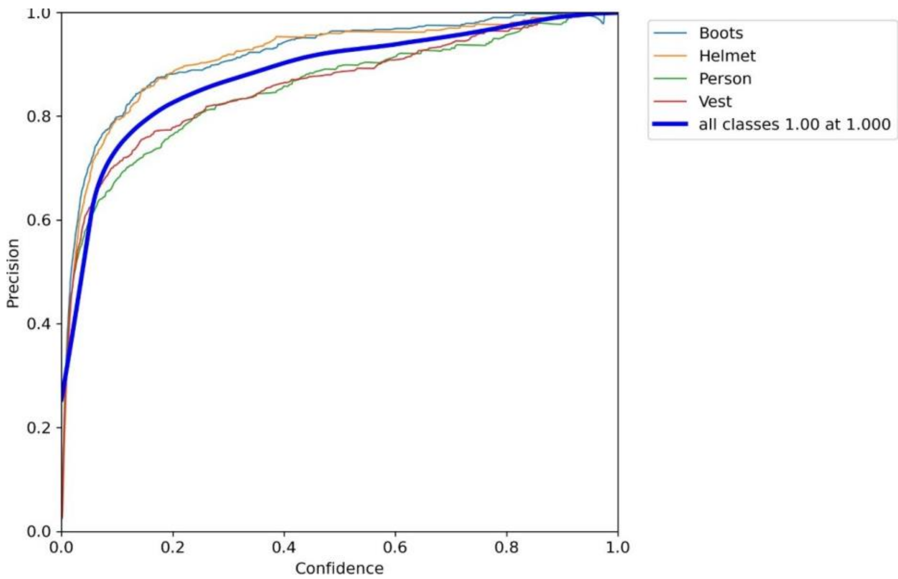

Fig. 2. Precision-Confidence Curve

Recall: The recall is a ratio of the number of correct instances of positives that were detected by the model. It determines how the model can reduce false negatives.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

FN being the false negatives.

Recall-Confidence curve shows that recall is the highest at the lower confidence threshold and how- ever decreases with the increase in the confidence threshold. This trade-off brings out the aspects of detection completeness and detection certainty.

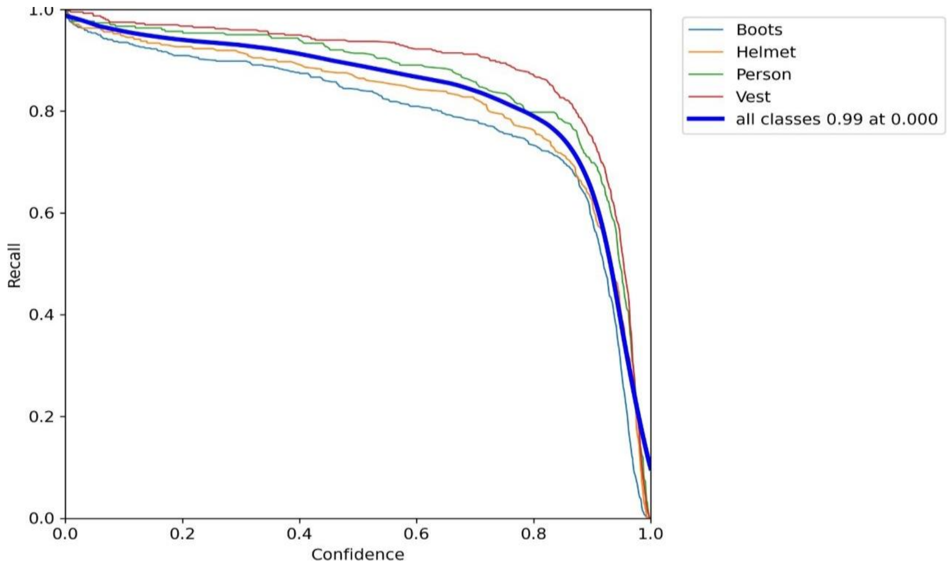

Fig. 3. Recall-Confidence Curve

F1-Score: It is the harmonic mean of Precision and Recall and is a more balanced measure of evaluation when it is important to both minimize false positives and false negatives.

$$F1 = \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Based on the F1- Confidence curve, the maximum F1-score of the overall model is about 0.91 with a confidence value of 0.437. This shows a good trade- off between accuracy and the recall at that working point.

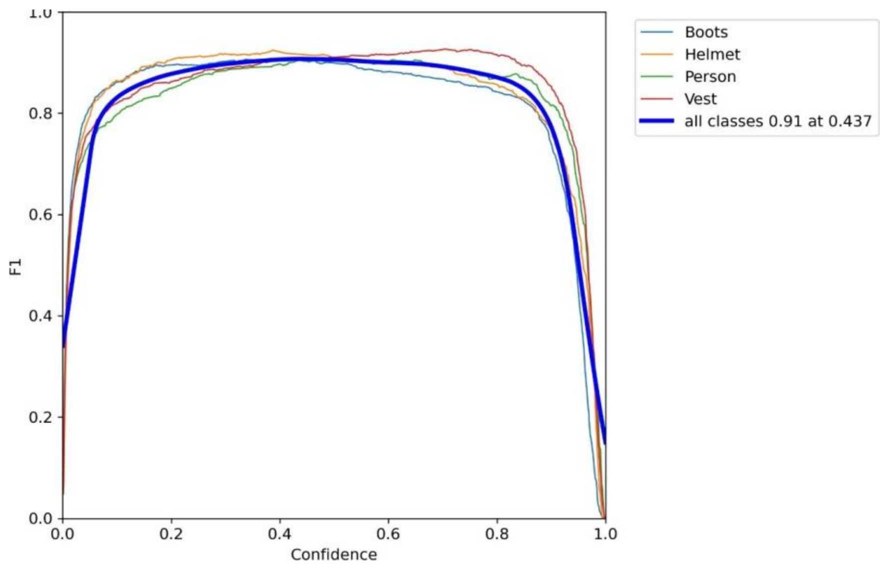

Fig. 4. F1-Confidence Curve for Multi-PPE Detection

Mean Average Precision (mAP): The major performance measure of the object detection models is mean average precision (mAP). It is used to compare the average precision of all the classes and over a variety of Intersection over Union (IoU) thresholds. mAP = 0.5 is the evaluation of detection performance with IoU=0.5 and mAP0.5:0.95 is the aver- age performance of detection with an IoU between 0.5 and 0.95.

The proposed model exhibits high multi-class detection, which proves a good localization and classification performance when it comes to the PPE types.

Confusion Matrix Analysis: Both the confu- sion matrix and the performance analysis give a detailed performance analysis on a per-class basis. It shows the right classifications along the diagonal and improper classifications in off-diagonal factors.

From the confusion matrix:

- High degree of diagonal dominance indicates high level of classification.
- Little confusion is noted between the similar classes in terms of their visual appearances.
- False detections are minimal because the back- ground misclassifications are minimal.
- This discussion indicates that the proposed model ensures the stable multi-class discrimination be- tween the types of PPE.

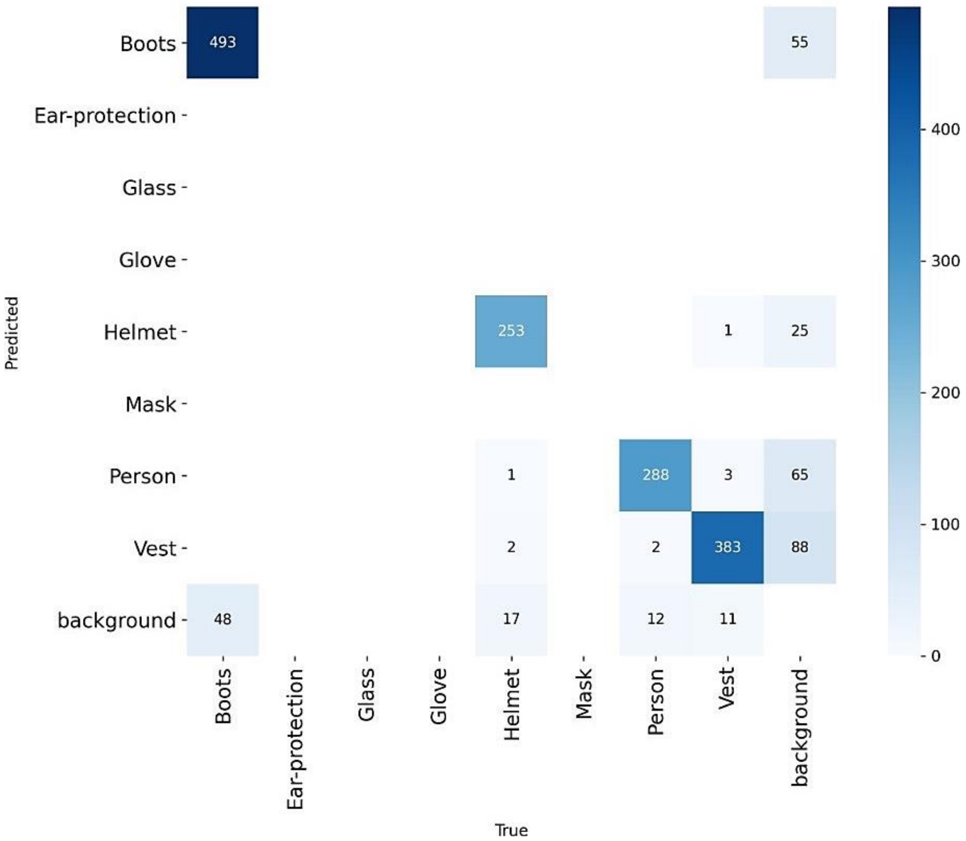

Fig. 5. Confusion Matrix for Multi-Class PPE Detection

5.3 Model Demonstration

The trained YOLOv8 model was implemented into a web application based on Flask to test the viability of the practical use. The system provides the option to upload images to check the PPE and then the inference engine is used, whereby the PPE components are detectable in real time. All the identified objects are presented in the form of a bounding box, corresponding class label, and a confidence score.

The demonstration attests that the model is effective to identify several PPE items related to individual workers in one frame. The system works well in changing light conditions and with the partial occlusions. It is lightweight which makes its architecture minimal in terms of computational overhead and it can be deployed on edge devices and industrial surveillance systems.

The automatic compliance in safety is facilitated by the real-time monitoring capability. In case a worker is found without necessary protection gears, the system can be expanded to raise violation notifications. This will increase the level of safety enforcement in the workplace and also decrease reliance on manual control.

Web-Based Deployment Interface: The graphical user interface of the deployed PPE Industrial Safety Detection system is given in below figure. The interface is built on a Flask based backend along with the trained YOLOv8 inference engine. The web application offers the interactive and user-friendly interface to monitor the real-time PPE.

The system has several functional modules:

- Image Upload Module: Allows users to attach PPE inspection images.
- Webcam Module: Allows the real-time detection with a live camera feed.
- Detection Processing Module: This run inference with the trained YOLOv8 model.
- Captured Output Display: Shows processed images with bounding boxes and confidence scores marked.

The modular structure guarantees scalability and flexibility, which can be used either to study the static images or to monitor the real-time with the integration of the webcams. The web deployment is an indication of the feasibility of the proposed model to the industrial setting. The lightweight architecture offers low latency thus it can be used on edge deployment scenarios.

The usability and operational efficiency of the interface design are considered its priority because it allows the supervisors and the safety personnel to easily evaluate the compliance with PPE and do so without the technical skills.

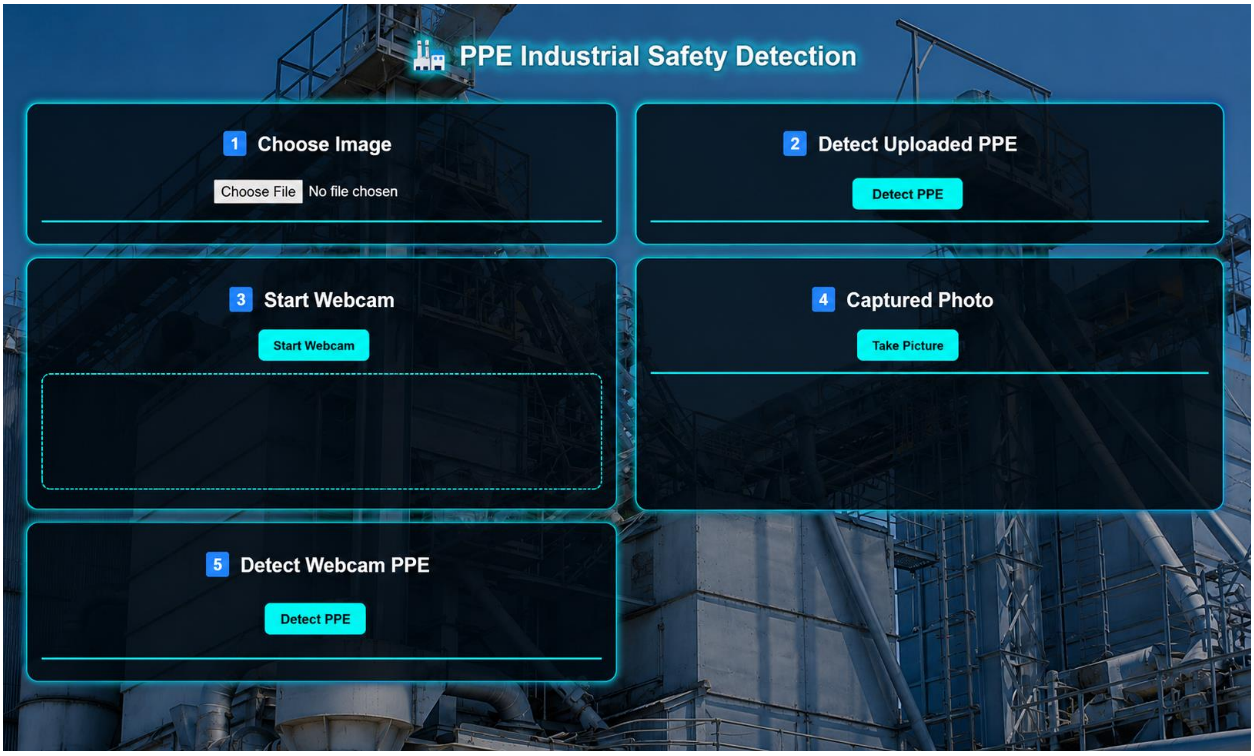

Fig. 6. Flask-Based Web Interface for PPE Industrial Safety Detection System

Detection Output Visualization: The below figure illustrates the detection output generated by the proposed YOLOv8-based multi-PPE detection model in a real industrial environment. The system successfully identifies multiple workers and detects various personal protective equipment components, including helmets, reflective vests, and safety boots. Each detected object is represented using color-coded bounding boxes along with confidence scores.

The blue bounding boxes correspond to detected persons, while green, red, and cyan boxes represent helmets, vests, and boots respectively. The confidence values displayed above each bounding box indicate the probability of correct classification. The model demonstrates strong multi-class detection capability by simultaneously identifying PPE items associated with multiple individuals within the same frame.

The detection results highlight the robustness of the proposed framework in handling complex industrial scenes involving multiple workers, varying object scales, and partial occlusions. The model effectively localizes small objects such as boots while maintaining high confidence in larger objects such as helmets and vests. This demonstrates the capability of multi-scale feature extraction in YOLOv8 to capture both fine-grained and large- scale PPE components.

Overall, the detection output confirms that the system provides accurate localization and classification, supporting real-time industrial safety monitoring and compliance verification.

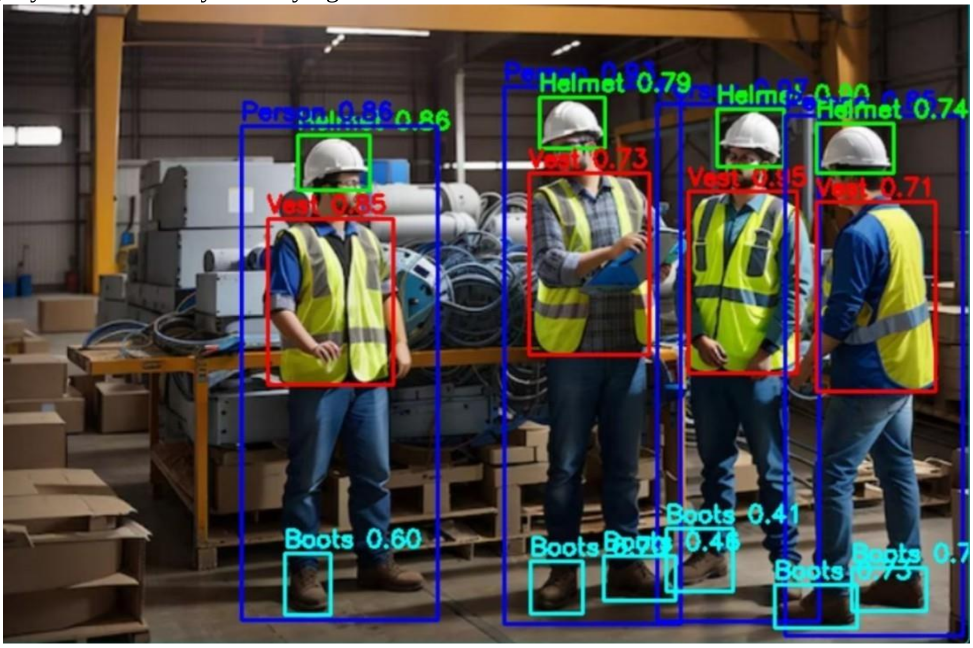

Fig. 7. Multi-PPE Detection Output Showing Person, Helmet, Vest, and Boots with Confidence Scores

6. Conclusion

This paper describes a small multi-PPE detector that is used to monitor the safety of the edges in the industry. With the help of the YOLOv8 architecture and a large multi-class PPE dataset, the proposed framework provides accurate and real-time detection of various safety equipment parts. There are the anchor-free detector mechanism, the multi-scale extraction of features, and the optimization of loss functions, which facilitates a better localization and classification.

The effect of the proposed model is justified as the experimental results prove its mAP: 0.5:0.95 of about 0.73. The fact that the trained model is integrated into a Flask-based deployment framework is another step to prove the need to implement the model in a real-life industrial setting. The system proposed has a high degree of safety coverage, better robustness, and scalability compared to the traditional safety detection systems that only con- sider limited categories of PPE.

The possible future work would involve the addition of time tracking functionalities, a better consistency of head and body associations, and the optimization of the framework to be used on low-power embedded edge devices. Altogether, the suggested system offers a powerful and scalable automated system of safety compliance monitoring in industries

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