Detection of elements of personal safety for the prevention of accidents at work with convolutional neural networks

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ABSTRACT

The task of recognizing personal protective elements in workplace environments in real time is fundamental to protecting the employees in case of any accidents. This can be achieved by deploying a convolutional neural network (CNN) algorithm that can efficiently detect protective elements through surveillance devices. Therefore, this work proposes the construction of a model, implementing the you only look once (YOLO) detector, whose architecture has been one of the most tested according to literature review. YOLOv5 and YOLOv7 versions were used and a dataset of 2,000 images for four classes considered. This dataset was collection from various sources and labelled by the authors, of which 80% was used for training, 15% for testing and 5% for model validation. The most important metrics are presented, making a comparison between the models, and finally it was identified that YOLOv7 achieved a higher success rate, which could be considered a more complete solution for occupational health and safety management in companies.

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1. INTRODUCTION

Those responsible for health and safety in the workplace face the challenge of observing, reporting and assessing the hazards existing in workplaces and their impact on the company, while at the same time promptly perceiving the lack of use of personal protective equipment (PPE), which can have repercussions in the appearance of diseases, reduced production time or unfortunate injuries in the worker that diminish their quality of life and well-being. Consequently, there is a growing demand for computational tools based on convolutional neural networks (CNNs) that can learn from accident records in industrial sectors [1], to facilitate decision-making that contributes to improve the enforcement of strict rules and constant monitoring in workplaces [2]. This is because CNNs have made significant advances in the field of facial recognition, fatigue detection [3], image classification and real-time visual weapon detection in crime and surveillance [4], and even in the transportation sector [5]. In sectors such as construction, deep learning techniques allow equipment tracking and crack detection [6], based on an object dataset that serves as a basis for training object detection models and testing their performance [7].

In recent years, object detection has been a popular topic among studies and research aiming to create object detection models that are capable of performing useful tasks of area selection, feature extraction as a key attribute and categorization in images and videos, based on training a suitably labelled dataset [8].

Thus, using the deep learning (DL) approach and hand in hand with computer vision, studies have been conducted to identify and locate objects of certain classes in images and videos in real time, for an accurate assessment of PPE work environments [9].

CNN-based algorithms outperform other techniques in feature extraction, so they are the most used method [10]. Generic object detectors present two categories: two-shot and single-shot [11]. The first achieves the goal in two steps: region proposal followed by the classification of those regions and refinement of the location prediction. Region proposal network can predict the object's bounding box and class confidence scores simultaneously using fully connected layers at each position [12]. The second detectors are capable of analyzing an image with a single network assessment, these focus on all spatial region proposals for object detection through a relatively simpler architecture, examples of this type is you only look once (YOLO) [13]. One-stage algorithms are faster, but less precise, while two-stage object detection algorithms are slower, but more accurate. In addition to the above classification, multi-stage method detectors [14] are included, which are mainly focused on the selective region proposal strategy through a very complex architecture.

The performance of these algorithms are compared using known datasets [15], [16] and metrics such as precision, recall, F1-score, Intersection over Union (IoU), which allows to combine the measures of exhaustiveness and precision in a single value. Another evaluation metric used is average precision (AP) which is the area under the curve, that is, under the graph generated by the metrics axis y = precision and axis x = recall, given by the expression (1).

$$IoU = (intersection\ area)/(total\ area\ of\ the\ union) \quad (1)$$

The mean average precision (mAP) metric is also used, which calculates the average value of the average precision (AP) in all classes, it is given by expression (2).

$$mAP = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{APi} \quad (2)$$

In review of previous work, we identified that YOLO popularized the one-stage approach by demonstrating real-time predictions and achieving remarkable detection speed. The network divides an image into a grid of size G×G, and each grid generates N predictions for bounding boxes. Each bounding box is limited to having only one class during prediction. This has been optimized in different versions, YOLOv2 [17] is named after the improvement that includes batch normalization, high-resolution classifier and anchor frames [18].

Later, YOLOv3 was proposed based on Residual Blocks [19], which are employed in feature learning and are composed of convolutional connections, providing the ability to detect its distinguishing feature at three different levels, thus making objects of various sizes more correctly recognized. The last layer of the YOLO-v3 models can be modified to accommodate object classes of interest such as helmet and/or safety waistcoat in construction environments [20]. A real application of this detector is its integration into the SafeFac intelligent system [21], designed for safety management in manufacturing environments. This system uses a set of installed cameras to capture images of workers approaching machinery in dangerous situations. The system analyses these images in real time and alerts managers when it detects unsafe behavior or lack of PPE use.

Further on, YOLOv4 emerges with the ability to recognize multiple objects in a single frame [22]. YOLOv4-Tiny [23] is lighter and designed to reduce the time for object detection. Its supports real-time image analysis also when running on embedded systems or devices [24]. An improved SCM-YOLO helmet detection is proposed [25]. This version is optimized by integrating a spatial pyramid pooling (SPP) module [26]. Similarly, SAI-YOLO [27] reduces the number of parameters and computational difficulty and increases the network detection speed while maintaining certain recognition accuracy [28].

Next, YOLOv5 [29] is used to train a dataset of face mask. Also, FD-YOLOv5 [30] integrates a fuzzy-based image module, which allows differentiating between various types of helmets training a 764 image dataset. It optimizes YOLOv5 [31] to address low accuracy and robustness problems for small objects in complex natural environments and integrates the Ghost module [32] which requires fewer parameters and less computational complexity.

Similarly, training of different versions YOLOv5 is done using a dataset of 1.485 images, comprising four PPE in educational laboratories, The YOLOv5n approach achieved the highest mAP of 77.40% for small and large instances [33]. Regarding related work involving an enhancement of existing datasets, in study [34] presents a case detection model with 5,000 images, The dataset was trained with the YOLOv3, YOLOv4, YOLOv5, obtaining better results for YOLOR. Also, a comparison of the performance of YOLOv7 with others models is made [35], its can detect the absence of safety helmets on dark-skinned people in low light conditions, this is because its architecture consists of three important parts: the spine, the neck and the head. The backbone is responsible for extracting features from the given input images, the neck mainly generates feature pyramids, and the head performs the final detection as output. Its design is based on efficient layer aggregation network (ELAN), which makes use of expansion, shuffling and cardinality fusion to increase the learning capacity of the network without compromising the original gradient path. Other models with the objects of interest of this study employing YOLOv5 have been done in [36]–[38].

However, these previous researches only build the models with a single type of object; this work proposes the detection of elements such as industrial helmets and face masks in image, making use of a dataset of 2,000 images of people with and without these protective elements collected from different sources and labeling several classes in one image. The selection of images covering a wide variety of scenarios, from crowds to more focused situations and varying the distance between people to achieve the generality of the model. Although YOLO has been optimized in different versions, the experiment is performed only with YOLOv5 and YOLOv7, the latter being the most recent at the time of the development of this work, we present the parameterization and analysis of the results of the two trained models.

2. METHOD

Model building for endpoint protection platform (EPP) detection relies on several critical phases: data collection, data pre-processing, data partitioning and model training [39]. Each of these phases is essential to ensure the performance and accuracy of the final model. In the following, we explain in detail the tasks performed, the source and size of the dataset, tools used, training parameters, and the products obtained in each phase.

2.1. Data collection

For this study, the labeled dataset was assembled by collecting 2,000 images obtained freely online, both from Kaggle and other internet sources, including those captured by the authors themselves. In the labeling process, the tool *https://www.makesense.ai/* was used, specifying the class as shown in Table 1 and coordinates. The dataset is available in *https://www.kaggle.com/datasets/ivanhernandezruiz/safety-helmet-and-mask*, where it has been duly published. Another aspect to consider is that all images must have the same pixel size in height and width (640 pp).

Table 1. Definition of classes

Class	Description
0	with helmet - with mask
1	with helmet - without mask
2	without helmet - with mask
3	without helmet - without mask

2.2. Division of data

The labelled images were randomly divided into the following percentage distribution, 80% training, 15% testing and the remaining 5% for validation. The training sample is composed of 25% for each class, so it can be stated that it is a balanced sample, the same proportion was used in testing and validation. Each class is represented uniformly in the subsets, which is crucial to avoid biases in the model. Random partitioning and class balancing help ensure that the model generalizes well and is not overly dependent on a specific class.

2.3. Training the detection model

The hyperparameters used in the training process were selected considering the recommendation found in the literature review [30], in terms of epochs and batch were adjusted in our experiment on a trial-and-error basis. A batch size of 16, the selected optimizer is stochastic gradient descent (SGD), with logistic regression (Lr = 0.01) that provided an appropriate balance between convergence speed and training stability. In addition, other important parameters were considered to optimize the training process, which are detailed in Table 2. These adjustments allowed the model not only to learn effectively, but also to generalize well on unseen data, and the assurance of obtaining a robust and efficient model, suitable for the required classification tasks.

Table 2. Configuration parameters of the algorithms

Parameter value	YOLOv5	YOLOv7
Época	170	70
Batch	16	16
Box loss gain	0.01951	0.02403
Class loss gain	0.000388	0.001092
Object loss gain	0.01857	0.009501
Learning rate	0.01	0.01
Warmup momentum	0.8	0.8
Warmup epochs	3.0	3.0
Optimizer weight decay	0.0005	0.0005
Warmup bias	0.1	0.1

3. RESULTS AND DISCUSSION

Figure 1 shows the confusion matrix of the YOLOv5 model. It summarizes the performance of the trained model when performing the object detection task for the four defined classes. When analyzing the confusion matrix, the trained model can detect all classes above 80%.

In Figure 2, the plot of F1 against confidence shows that the model trained with YOLOv5 achieves an F1-score of 0.88 across all classes (blue curve). The F1-score is a value that represents a trade-off between the accuracy rate and the recall rate of the model. Referring to the graphs plotted precision versus confidence is 1.00 to 0.94, and recall versus confidence of all classes is 0.95, and the metric mAP@0.5 is 0.87. The metrics are shown in Table 3. Figure 3 show the confusion matrix of YOLOv7, where the trained model can detect classes equal to or greater than 85%.

Figure 4 shows the YOLOv7 performance plots: F1 vs confidence from 0.89, Precision vs. confidence from 1.00 to 0.93, recall vs confidence of 0.98 and mAP@0.5 is 0.89. In terms of the F1-score metric, YOLOv5 obtained a score of 0.88 while YOLOv7 obtained 0.89. This indicates that YOLOv7 has a better balance between accuracy rate and recall rate than YOLOv5. On the other hand, the accuracy vs confidence graphs show that both models have a very high accuracy rate, YOLOv5 scored 0.95 in all classes while YOLOv7 scored 0.98. Regarding the metric mAP@0.5, YOLOv5 scored 0.87 while YOLOv7 scored 0.89. The performance metrics for each class are shown in Table 4.

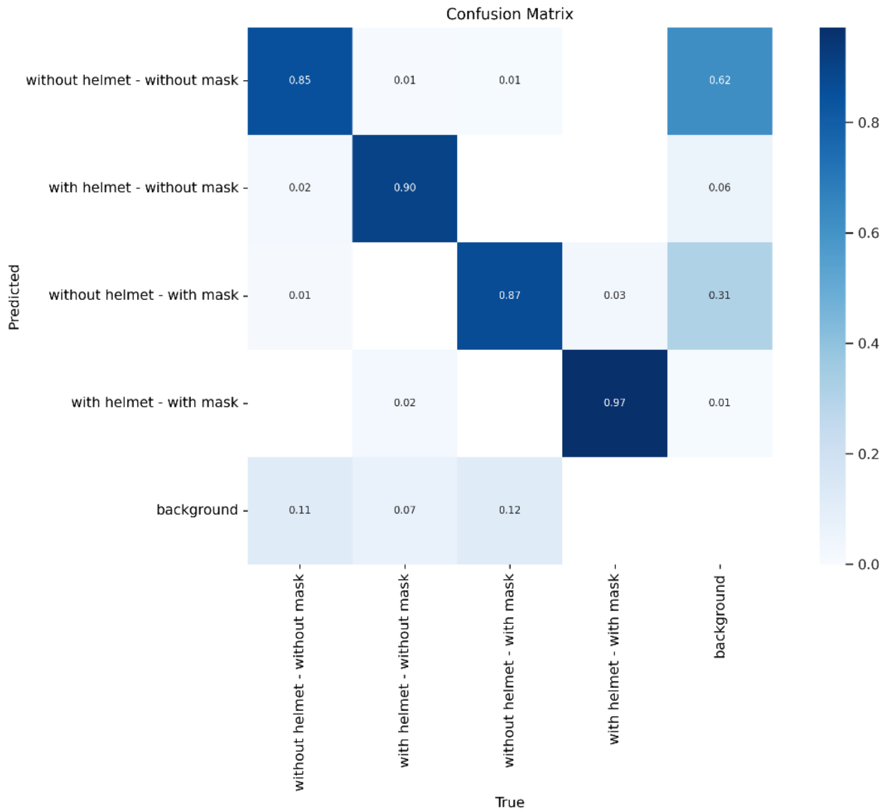


Figure 1. Confusion matrix of the YOLOv5 model

Figure 5 shows the validation of both trained models. In Figure 5(a), YOLOv5 shows the results of image preprocessing with edge detection for people wearing PPE. This approach allows to clearly identify the contours of workers and their protective equipment, highlighting its effectiveness in situations where the elements are clearly visible. On the other hand, Figure 5(b) presents the results obtained with YOLOv7, demonstrating a greater ability to detect small objects, even when they are partially hidden by other elements and are in various positions. YOLOv7 manages to correctly identify PPE despite the added difficulties due to obstructions and variability in object positions. Comparison of features between YOLOv5 and YOLOv7 can be seen in Table 5.

Compared to other works, our experiment used superior versions of YOLO used in [34] to detect PPE. Compared to other related [29]–[31] and [35], our experiment achieved a mAP@0.5 of 0.87 and a mAP@0.5:0.95 of 0.64 in the overall class ranking. If we compare the results with the paper [35] which employ YOLOv7, ours achieved a mAP@0.5 of 0.89 and a mAP@0.5:0.95 of 0.66, in both experiments a dataset significant compared to the image set used in the studies [29], [30], [33] which are smaller and this does not guarantee an accuracy in the validation. In contrast, our trained model can perfectly identify features in video streams together with still images. Different from other works that present a comparison of different versions of YOLO in classification systems of a single class, in our work a comparison between two versions of YOLO for a multiclass system is carried out and hyperparameters have been used that optimize the use of computational resources.

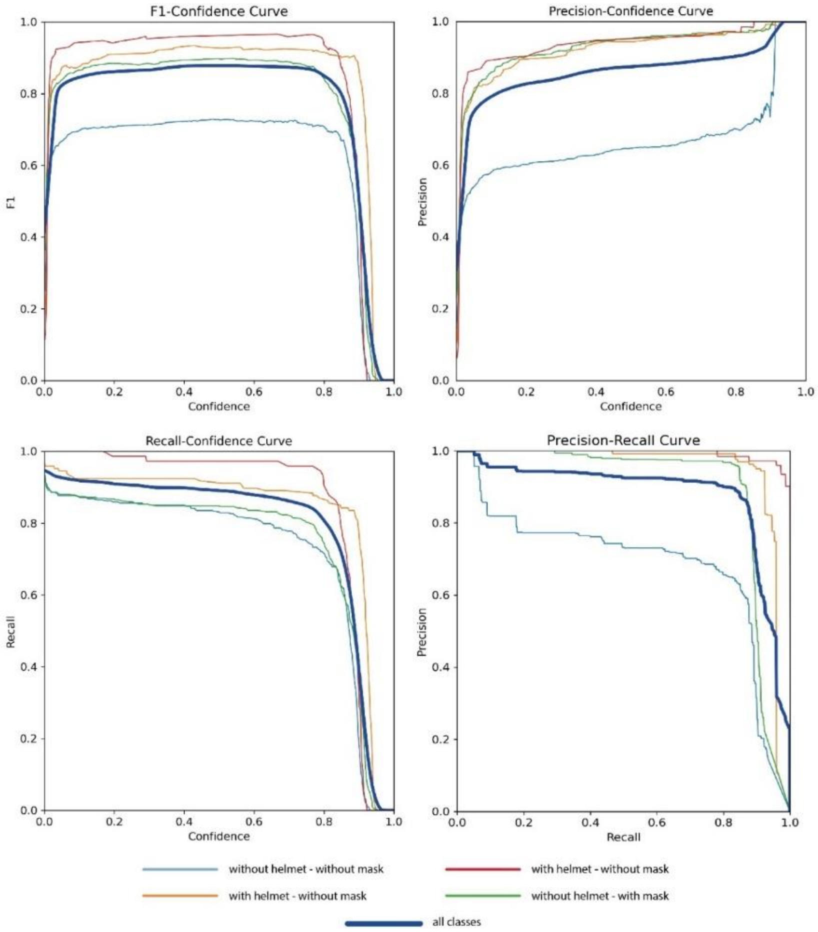


Figure 2. YOLOv5 performance metrics

Table 3. YOLOv5 performance metrics

Class	Precision	Recall	Map@.5	Map@0.5:0.95
0	0.64	0.82	0.68	0.36
1	0.94	0.91	0.94	0.78
2	0.95	0.84	0.89	0.58
3	0.95	0.97	0.98	0.85

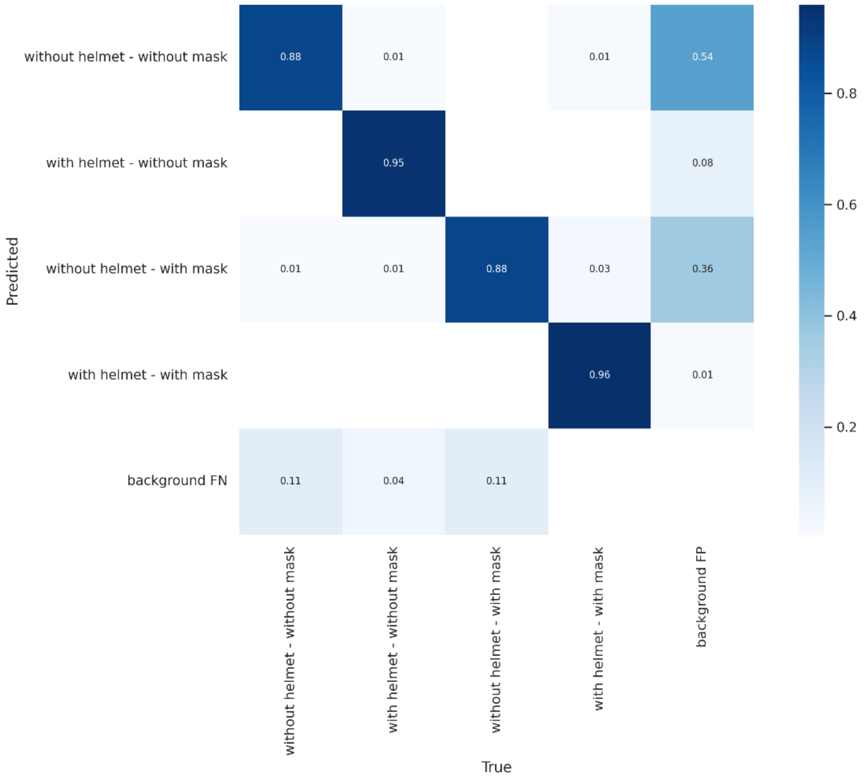


Figure 3. Confusion matrix of the YOLOv7 model

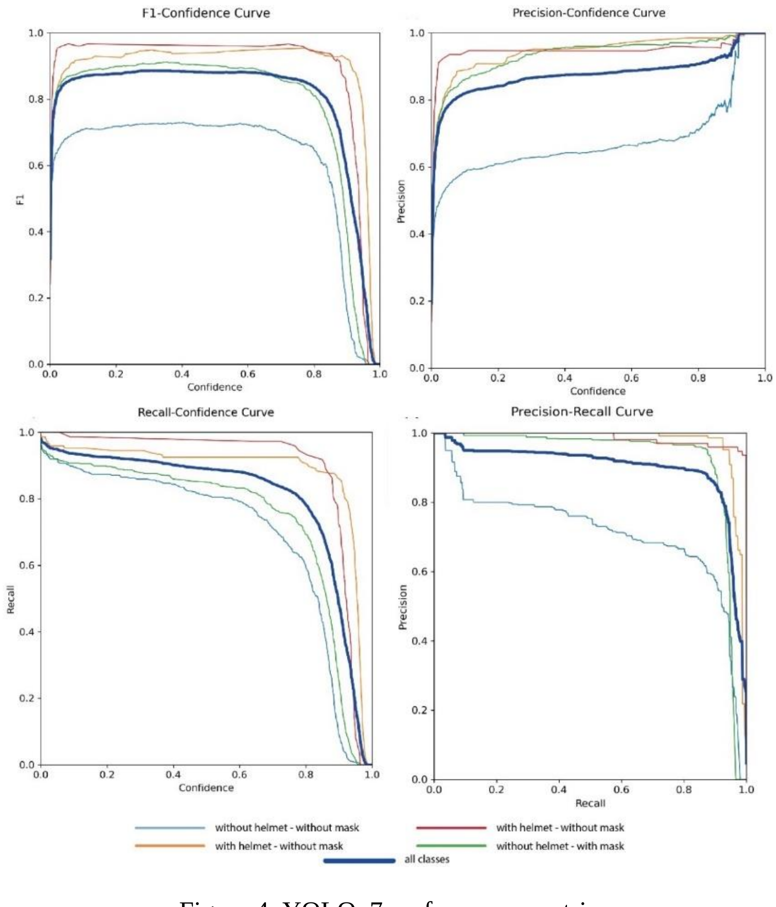
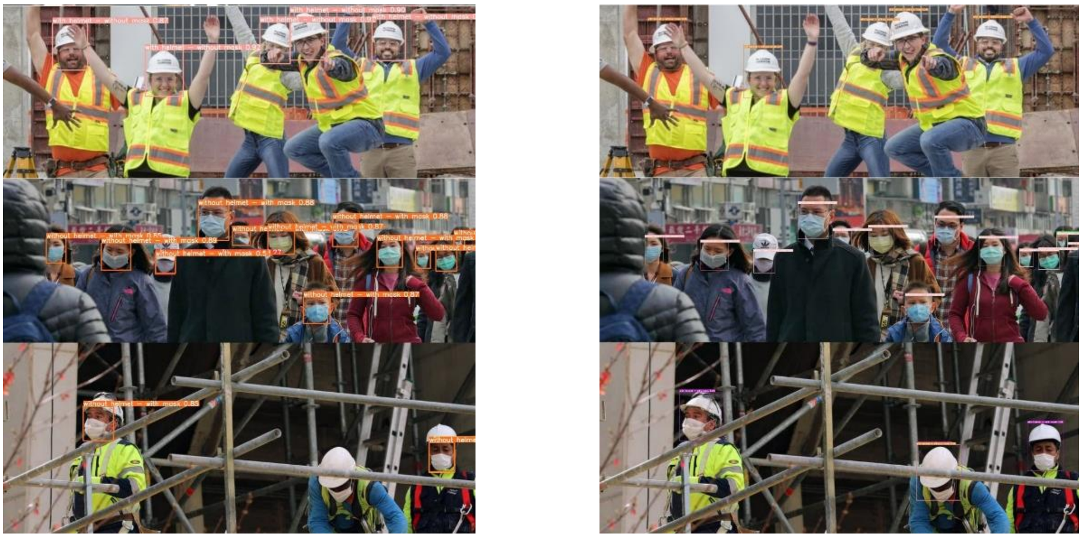


Figure 4. YOLOv7 performance metrics

Table 4. YOLOv7 performance metrics

Class	Precision	Recall	Map@.5	Map@0.5:0.95
0	0.62	0.85	0.71	0.38
1	0.95	0.94	0.97	0.83
2	0.93	0.87	0.92	0.58
3	0.94	0.98	0.98	0.85



(a) (b)

Figure 5. Validation of the models: (a) YOLOv5 and (b) YOLOv7

Table 5. Comparison of features between YOLOv5 and YOLOv7

Features	YOLOv5	YOLOv7
mAP@0.5	lower	Higher
Epochs	higher	Lower
Training process	lower	Higher
Trained model size	higher	Lower
Inference in CPU systems	Faster	Slower
Use of memory in training	Stable	Unstable
Backbone (computational Block) architecture	Darknet with cross stage partial network (CSPNet)	Extended efficient layer aggregation network (E-ELAN)
Floating point operations	lower	Higher
response time (test or inference)	higher	Lower

4. CONCLUSION

A substantial contribution of our work lies in the collection of images representing various situations, all accurately labeled and assigned to specific classes. Several factors were considered in determining the quality and diversity of the data to achieve a highly generalized model. Key considerations included: i) The inclusion of images captured under various lighting conditions, allowing the model to effectively adapt to real-world situations. This is essential to ensure that the model can perform optimally in environments with changing light levels. ii) The incorporation of images that represent both indoor and outdoor environments, extending the applicability of the algorithm to a wide range of real-world situations and offering versatility in its performance. And iii) The consideration the presence of complex objects or backgrounds, variations in people's clothing, and different times of day. This approach not only ensures the quality and diversity of the dataset used in training, but also strengthens the model's ability to generalize and perform efficiently in a wide variety of situations.

In future work, modifications will be made to the dataset by adding classes of other PPE such as: waistcoats, gloves, and boots. In addition, the possibility of using new versions of YOLO could be explored, since it is evident that the field of object detectors is improving, and new proposals are constantly appearing, so it could be considered a more complete solution for the management of health and safety at work in companies.

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