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# Generic compliance of industrial PPE by using deep learning techniques

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ABSTRACT

Inability of safety managers to timely detect misuse of Personal protective equipment (PPE) causes a number of injuries and financial losses. Considering sizes of industry halls and number of workers, there is an increasing demand for computerized tools that could help companies to enhance the implementation of strictinging workplace safety standards. As a solution, we propose a procedure that: 1) reduces the problem of PPE compliance to the binary classification, and 2) enables compliance of arbitrary type and number of PPE that could be mounted on various body parts. To prove this hypothesis, we studied 18 different PPE types used across various industries for protecting 5 physiological body parts/functions. The HigherHRNet pose estimator was used for defining the PPE regions of interest, while six different image classification architectures were assessed for the compliance/classification of the considered regions. All classifiers were pretrained on the ImageNet data set and fine-tuned using the dedicated data set developed during this study. Top-performing models were MobileNetV2, Dense-Net, and ResNet, while the MobileNetV2 was recommended as the most optimal choice considering its lower computation demands. Compared to previous studies, the proposed approach demonstrated competing performances with unique ability to be easily adopted for performing compliance of various PPE by slight editing of the predefined lists of PPE types and corresponding body parts. Considering the present data/privacy/computational constraints, the procedure is recommended as suited for the digitalization of PPE compliance in: 1) self-check points, and 2) safety-critical workplaces.

## 1. Introduction

Considering the nature and environment of the manufacturing halls, the existence of hazards cannot be completely avoided. Instead, regulatory bodies have enforced industry standards with obligations and recommendations on how to reduce employees' exposure to various types of hazards (e.g. chemical, radiological, physical, electrical, mechanical, cyber, etc.) (Occupational Safety and Health Administration (OSHA), U.S. Department of Labor, 2004). Occupational safety and health (OSH) is a sub-field of Safety science, that has emerged as an independent and multidisciplinary scientific field focused on improving the safety, health and well-being of people in the work environment (Bautista-Bernal et al., 2021). Over decades, goals and criteria of OSH have changed and increased – so that nowadays companies have the tendency to reduce the number of production injuries down to zero (Rajendran et al., 2021). In order to achieve the "zero-injuries" goal, companies tend to focus their attention and activities on the proactive identification of pre-accidents, which control and timely management should prevent the occurrence of accidents at work (Baldissone et al., 2019). The subject of this study is the compliance of personal protective equipment (PPE) (Proctor, 1993), which purpose is to reduce employee exposure to hazards when engineering controls (e.g. isolating people from hazards) and administrative controls (e.g. change the way how people work) are not feasible or effective to reduce risks down to acceptable levels (The National Institute for Occupational Safety and Health (NIOSH), 2015).

Despite efforts invested into the PPE standardization and use guidance, the practice has shown that misuse of PPE still represents a serious problem for companies that are facing consequences of occurred injuries. Liabilities and irreverence from PPE recommendations cause a number of injuries and large loss to national economies (i.e. 360B dollars annually to the US alone) (Bureau of Labor Statistics (BLS) et al., 2015).

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The reports from 2017 indicated that there were over 2.8 million nonfatal injuries, of which a large portion could be prevented through the proper use of PPE (Bureau of Labor Statistics (BLS) Employer-reported workplace injuries and illnesses, 2017). In general, availability and affordability of PPE are not considered as OSH's bottleneck nowadays (Boustras and Guldenmund, 2018). Instead, the bottleneck of OSH management is the assumption that a supervisor will notice PPE non-use, and timely warn employees – which is very difficult to be achieved manually, considering the size of halls and number of workers in industrial companies (Wong et al., 2020).

### 1.1. Types of PPE and the challenges of PPE compliance in industry practice

According to the degree of hazard that they aim to mitigate, PPEs are commonly stratified into four levels (A-D) (United States Environmental Protection Agency (USEPA), 2021). Briefly, A-level corresponds to the greatest potential for exposure to hazards, while D-level requests minimum protection of head, skin, respiratory, and eye protection. Following the OSHA recommendation (Occupational Safety and Health Administration (OSHA), U.S. Department of Labor, 2004), this study splits PPEs into the five groups with respect to the body parts and physiological functions that they aim to protect: 1) Head; 2) Body; 3) Hands; 4) Feet; and 5) Whole body. Typical examples of corresponding PPEs are safety glasses, high visibility vests (or yellow vests), gloves, hardhats/helmets, safety boots, face shields, sound reducing headphones and earmuffs, respirators, welding shields, etc. State of the art approaches for improving and ensuring the PPE compliance include: self-check of employees (through education and increasing employees' awareness about the importance of PPE); specially designed self-check points (where employees can use mirror to visually compare their PPEs with an image of proper use of PPE); internal inspection by supervisors and safety managers within the company; and external control by OSH representatives. Regarding the above mentioned, challenges of PPE compliance may be related to: large number of employees that circulate in a workspace; differences in safety recommendations among various workplaces; presence of visitors, interns and other persons that are not permanently employed in a company; movement of employees through different sectors of a company (which may have different safety recommendations); needs for removing PPE during execution of specific tasks; frequent change and fluctuation of PPE suppliers and types of PPE on the market; limited period of use of specific PPEs (e.g. respiratory masks). Accordingly, there are large practical needs for technologies that could help practitioners to improve and/or ensure PPE compliance. Although there were attempts to employ electronic circuits into PPE (Buchweiller et al., 2003) – a technology that could enable visual and contactless compliance of safety rules appears to be more generic and practical considering sizes of industry environments (Ayhan and Tokdemir, 2019). Particularly, artificial intelligence algorithms have demonstrated high potential for reducing risks related to human activities (Pustokhina et al., 2021). The detailed review on the topic of safety science showed that artificial neural networks are the most applied machine learning method to aid in engineering risk assessment – and the next step towards this direction is application of Deep learning (Hegde and Rokseth, 2020).

### 1.2. Related studies on the topic of application of AI for improving PPE compliance

In the study from 2016, Rubaiyat et al. developed Computer vision (CV) methods for automatically detecting misses of construction helmets from the workspace images, which assumed the feature engineering approach based on combining the Histogram of Oriented Gradient and Circle Hough Transform algorithms (Rubaiyat et al., 2016). Li et al. proposed a radiomics-based approach for helmet wearing detection, reporting ~90% accuracy of helmet detection (Li et al., 2017). Mneymneh et al. proposed a solution that first detects motion, then workers and finally it detects hardhat in the identified region of interest using an object detection tool coupled with a color-based image classification (with ~93.1% accuracy in the best-case scenario) (Mneymneh et al., 2019). In a recent study, Wu et al. proposed convolutional neural networks for detecting hardhats of various colors worn by construction personnel (Wu et al., 2019). Moreover, the same authors made the developed models publicly available along with the dataset used[1]. Delhi et. al used transfer learning and YOLOv3 detector to develop a system that detects the presence of hardhat and safety jackets, and accordingly performs compliance by stratifying four categories such as NOT SAFE, SAFE, NoHardHat, and NoJacket (Delhi et al., 2020). Tran et al. also utilized the YOLOv3 detector for the compliance of hardhat, shirt, belt, gloves, pants, shoes with precision ranging from 0.95 to 0.98 (Tran et al., 2019). Zhafran et al. proposed usage of the Fast R-CNN deep learning architecture for compliance of various PPEs, with accuracies varying from 89% for helmets to 78% for masks, 67% for vests and 58% for gloves at one-meter distance (accuracies drastically decreased at the distance of five meters) (Zhafran et al., 2019). In the recent study from 2020, Nath et al. considered three various Deep learning - based approaches for detecting hardhats and safety vests (Nath et al., 2020). In general, all three approaches assume classifying cropped employees on predefined classes in a Pictor-v3[2] data set - and resulted with ~73–84% mean average precision (mAP). Although it was recommended as a generic and applicable for intersecting other PPE as well, this possibility has not been studied yet. Balakreshnan et al. tested the proof of concept platform for PPE compliance detection using low-power AI enabled cameras (Balakreshnan et al., 2020). Particularly, the system was designed to detect if persons are wearing safety glasses or not. The precision obtained using the web-mined images was 37.5%, and 50% for images acquired from the testing environment. It was concluded that future work should be regarded towards distinguishing safety glasses and regular glasses (Jing et al., 2000). Finally, Nagrath et al. demonstrated application of combining Single shot detector and MobileNetV2 classifier for real time Covid19 masks detection (Nagrath et al., 2021). Starting from the end of 2020, application of AI in OSH gained attention among industry as well. For example, Amazon proposed the Amazon Rekognition PPE detection system[3] – which currently provides AWS for recognizing if body parts (such hand, face and hands) are covered with corresponding PPEs.

As it may be noted, most of the previous studies were attracted by construction engineering needs - which is justified with facts that construction is still one of the least digitized industries, as well as that it records a largest number of fatal injuries and thus incurs safety improvements. As the compliance of various PPEs has been studied independently, studies were mostly focused on compliance of particular PPE (commonly helmets, vests, masks) – while needs of other industries (e.g. automotive, textile, energy, metal, food industry etc.) has remained uncovered. Thus, existing approaches for inspecting PPE remain to be assessed in other industries before being widely accepted. For example, approaches based on using PPE detectors (e.g. YOLO, SSD, or Faster R-CNN) for detecting hardhats would be challenging to adapt for compliance of earmuffs (as they may be present on the head, but not properly used). Furthermore, usage of detectors increases the complexity of developing generic purpose PPE compliance – as it is not efficient to develop and run multiple detectors for head, hands, legs, etc. Finally, conventional detectors could not separate the left and right part of the body – which disables one to provide employees with safety

[1] https://github.com/wujixiu/helmet-detection/tree/master/hardhat-wearing-detection

[2] https://github.com/ciber-lab/pictor-ppe

[3] https://aws.amazon.com/blogs/machine-learning/automatically-detecting-personal-protective-equipment-on-persons-in-images-using-amazon-rekognition/

guidance (OSHA, 2020). Having this in mind, the aim of this study was to propose a generic framework for the PPE compliance which should be modular and applicable for various PPEs and various body-parts on which they should be mounted - as described in the official OSHA guidelines (Occupational Safety and Health Administration (OSHA), U. S. Department of Labor, 2004).

## 2. Methods

### 2.1. Overview of the proposed approach

This study considers the misuse of PPE as an unsafe act (UA), which needs to be detected, reported and managed efficiently within a company. For these purposes, a company may use a dedicated web platform (Vukicevic et al., 2019) for real-time management of UA and unsafe conditions (UC) - in which PPE compliance module needs to be integrated. Following the graphical illustration in Fig. 1, we propose an intuitive four-step solution for the AI-based PPE compliance. The starting assumption is the fact that each PPE should be mounted on a corresponding part of employee' body. The first step is detection/identification of an employee in the workspace (Fig. 2a). For these purposes, we used 2D pose estimation algorithms as they enabled us to simultaneously detect body landmark points (Fig. 2b). By using the body landmark points, we defined the region of interest (ROI) that should be the subject of PPE compliance (Fig. 2c). Particularly, we divide PPE into five groups (following Fig. 2d): 1) head-mounted PPE (e.g. hardhats, glasses, earmuffs); 2) upper body PPE (e.g. wets); 3) Hands (e.g. Gloves); 4) Legs (e.g. boots, safety shoes); and 5) whole-body (i.e. work suit). It is assumed that the list of recommended PPE for each corresponding body part is defined with a company's safety regulations and industry standards[4], so that the PPE list in Fig. 2d may vary for different companies. For each body ROI (Fig. 2e), we developed dedicated deep learning classifiers (see Section 2.3) that consider PPE compliance as the binary classification problem (Fig. 2f). In the following paragraphs, we provide details about algorithms used for solving problems illustrated in Fig. 2.

### 2.2. Pose estimation and PPE ROI cropping

The pose estimation was done using the HigherHRNet[5] (Cheng, xxxx), which itself uses the HRNet (Sun et al., 2019) as the backbone to solve the problem of scale variation during the bottom-up pose estimation. The HigherHRNet outperforms state-of-the-art competitors on the COCO dataset (Lin et al., 2014) by outputting multi-resolution heatmaps and using the high resolution representation provided by the HRNet. In this study we used the HigherHRNet with the HRNet-W48 (input size 640) to obtain body landmark points shown in Fig. 2b. Regions of interests were predefined by using the detected landmark points, which absent from the pose estimator aware one skip occluded body parts – or to inform users to stand upfront to the camera in order to complete the PPE check. In this study, we defined the five regions of interest (ROI) illustrated in Fig. 2e around five types of body parts (head, hands, upper body, legs, and whole body).

### 2.3. Classification of PPE ROIs

The PPE compliance was considered as a classification problem, where the classification inputs are previously cropped ROIs. In this study we considered the following deep learning classifiers: MobileNetV2 (Sandler et al., 2018), VGG19 (Simonyan and Zisserman, 2014), Dense-Net (Huang et al., 2017), Squeeze-Net (Iandola et al., 2016), Inception_v3 (Szegedy et al., 2015), and ResNet (He et al., 2015). Chronologically, the VGG19 was introduced as the winning architecture at the 2014 ImageNet challenge – demonstrating the superiority of increasing an architecture depth with very small (3 × 3) convolution filters (Simonyan and Zisserman, 2014). Due to the efficiency of the VGG starting layers, they have been frequently adopted to serve as the encoder part of many top-performing deep learning architectures for solving various computer vision tasks such are FCN (Long et al., 2015), and U-Net (Ronneberger et al., 2015) architectures for semantic segmentation. While winning the 2015 COCO and ImageNet challenges, the ResNet introduced residual layers as learning residual functions with reference to the layer inputs (He et al., 2015) – which reduced the vanishing gradient problem while enabling efficient training of deeper networks (up to 152 layers, or 8x deeper than the VGG). The Inception_v3 was the first runner up at the 2015 ImageNet challenge. It is the most efficient variant of the inception family of architectures (the v1, named GoogLeNet, introduced the inception module (Szegedy et al., 2014), while the v2 introduced the batch normalization (Ioffe and Szegedy, 2015), which proposed the idea of factoring convolutions to reduce the number of trainable parameters. The Squeeze-Net was proposed in 2016 as a lightweight replacement for the AlexNet (Krizhevsky et al., 2017) (50x less trainable parameters) – which was achieved by proposing the usage of squeeze and expand layers, along with the decrease of filters size down to 1x1, decrease the number of input channels down to 3x3 filters and downsample late in the network (Iandola et al., 2016). The Dense-Net connects each layer to every other layer in a feed-forward fashion, which is (compared to the ResNet) a simplific connectivity pattern that reduces the vanishing of gradients during the training of very deep networks (Iandola et al., 2016). The MobileNetV2 was introduced in 2018 by Google, as an architecture that will enable usage of Deep learning techniques on mobile devices (Balakreshnan et al., 2020). It is based on an inverted residual structure, where the input and output of the residual block are thin bottleneck layers, while the intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity (Sandler et al., 2018).

### 2.4. Transfer learning

All classification models were pretrained on the ImageNet data set (Russakovsky et al., 2015) and loaded into the PyTorch framework (Paszke et al., 2017) for the transfer learning. The impairment of already learned low-level features was prevented by frizzing the base layers of considered deep learning models. Then, new trainable layers were added and trained on the collected datasets to classify PPEs. During the training, we performed an online augmentation (with a probability of 20%), which means that various augmentation techniques were applied each iteration while the batches were passed into the training loop (instead of the traditional preprocessing approach). The considered augmentation techniques were: random rotation (±30∘), random flip, random crop, and Gaussian noise. For the training, each dataset was randomly split into training (70%), validation (15%), and test (15%) datasets. The learning of the considered architectures was performed using the Adam optimization algorithm (Kingma and Ba, 2014), with the cross-entropy loss function. The initial learning rate of the Adam was set to 1e-4, and it was decreased by a factor of 0.1 every 7 epochs. The training of the models on the developed data sets were automatized using the Python script, which varies number of epochs (5, 10, 15, 20, 30, 50, and 100) and batch sizes (1, 2, 4, 8, 16, 32, 40, and 50) – so that we afterwards could load and select the top-performing models.

### 2.5. Experiments and results

All the implementation was done by using the Python 3.7.4 programming language; along with the PyTorch 1.6.0 and torcvision 0.7.0 libraries with the cuda 10.2 GPU drivers. All the computations were done on the workstation with the AMD Threadripper 3970X (32 cores,

[4] Standard: OHSAS 18001, Occupational Health and Safety Assessment Series.

[5] https://github.com/leoxiaobin/deep-high-resolution-net.pytorch

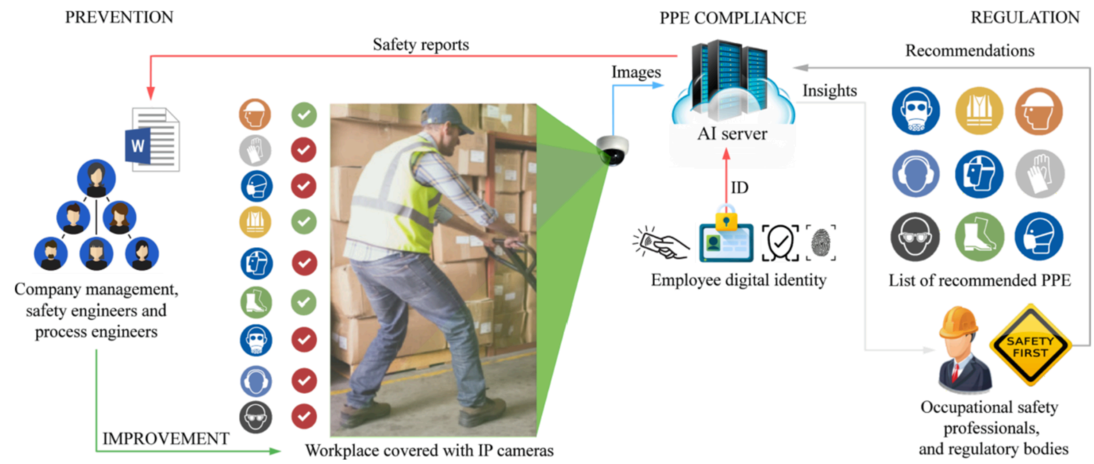


**Fig. 1.** The concept of AI-driven PPE compliance.

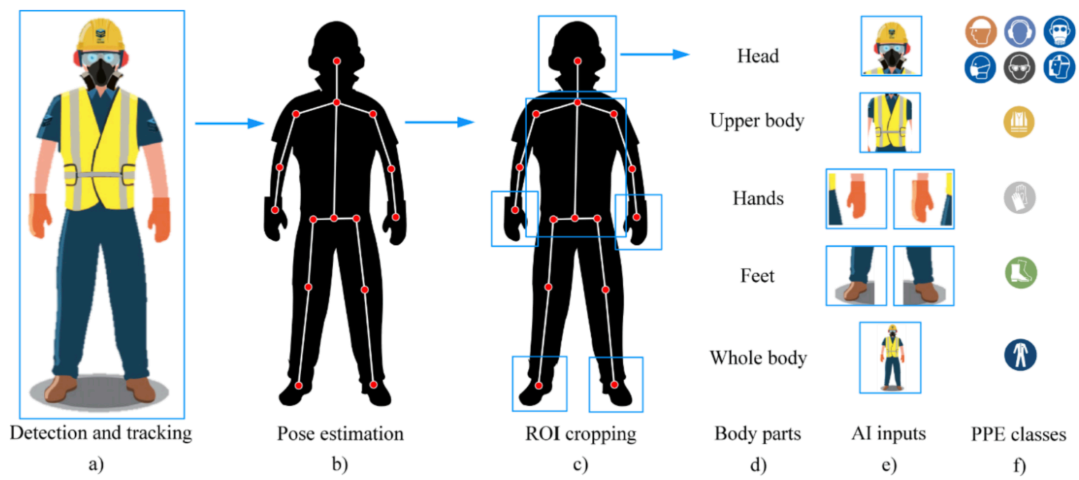


**Fig. 2.** Workflow of the proposed pose-aware PPE compliance.

3.79 GHz processor), 128 GB RAM and two Titan RTX (24 GB) + NVLink GPUs.

Data set used in this study was developed by combining web-mined images and public PPE datasets (5200 images from the Roboflow hardhat train data set[6] , and 400 images from the Pictor PPE data set[7]). Because a portion of images contained multiple persons, we were able to crop a total 15,728 images of people (without and with various types of PPE) from the collected 12,893 images. The ROI cropping was performed following Fig. 2, and it was done by using in-house Python scripts and the LabelMe annotation tool (Wada, 2016). After cropping PPE-related ROIs, we developed datasets described in Table 1. As it may be noted, this study covers nine different PPE compliance topics: a) Protection of respiratory system (face mask, and respiratory mask); b) Noise removal and hearing protection (earmuffs); c) Face protection (face shield, and welding shields); d) Eyes protection (various types of glasses/goggles); e) Head protection (various types of caps, hardhat, and head covers); f) Visibility (safety vests, and suits with reflective tracks); g) Hands protection (Covid19 and industry gloves); h) Feet protection (various shoes, and feet covers); and i) Coveralls and protective cloths.

Because datasets were imbalanced, we developed dedicated data loaders that for each epoch load the same amount of images from each class. Particularly, the per-class number of images is determined with the target class, while other classes are randomly loaded for each epoch. In this way, we ensured that the data is balanced while keeping benefits of increased variability of over-sampled classes.

The metrics selected for the evaluation and comparison of developed models included: $Accuracy = \frac{Tp+Tn}{(Tp+Fp+Fn+Tn)}$, $Precision = \frac{Tp}{(Tp+Fp)}$, $Recal = \frac{Tp}{(Tp+Fn)}$ and $f1\ score = 2\frac{Recal*Precision}{(Recal+Precision)}$, - where $Tp$ are true positive, $Tn$ are true negative, $Fp$ are false positive, $Fn$ are false negative classifications. The obtained results are given in Table 2.

## 3. Discussion

The obtained performances in Table 2 indicate that MobileNetV2, Dense-Net, and ResNet are top-performing classificators. As all three models achieved comparable performances – we recommend the use of MobileNetV2 as it is least computationally expensive. We also emphasize that during the transfer learning of the pretrained models we have experimented with freezing various numbers of initial layers (as there is no recommendation on how many layers to fine-tune) – which may affect ranking of the considered models. As there are 18 developed PPE classificators, for the purpose of consistency, we will discuss them with respect to corresponding body parts. Moreover, we report that we preferred to exclude noisy or extremely low-quality images in our data set – which may be a distinction and one of reason why we outperformed some studies discussed in the rest of this section (some of which may include e.g. images with poor lighting conditions, or extremely low

[6] https://public.roboflow.ai/object-detection/hard-hat-workers
[7] https://github.com/ciber-lab/pictor-ppe

**Table 1**
Considered PPE compliance problems and class-distribution in our data set.

| Body part or physiological function | PPE classes | | | | |
|---|---|---|---|---|---|
| Respiratory system | No protection (5231) | Face mask (4107) | Respiratory mask (608) | | |
| Hearing system | No protection (6280) | Earmuffs (3664) | | | |
| Face protection | No protection (3375) | Face shields (1386) | Welding mask (826) | | |
| Eyes protection | No protection (4673) | Glasses (1058) | Sunglasses (483) | Safety glasses (2799) | Face shields (1386) |
| Head protection | No protection (3506) | Winter cap (384) | Hardhat (3640) | Cap (572) | Head cover (602) |
| Visibility | No protection (8460) | Yellow vests (3500) | Suits with reflective tracks (1248) | | |
| Hands protection | No protection (5602) | Exam gloves (2410) | Industry gloves (4309) | | |
| Feet protection | No protection (2300) | Sandals (1200) | Industry shoes (1700) | Boots (935) | Shoe covers (520) |
| Skin protection | No protection (4800) | Overalls (2500) | Protective cloth (970) | | |

resolution images). For these reasons, we will base our discussion on comparing both performances and approaches with alternatives in literature.

For the head-mounted PPE, MobileNetV2 and ResNet classificators showed superior performances, with average 95% accuracy over eight considered PPE types. So far, there have been a series of studies focused on developing AI for detecting face masks and hardhats. In the recent study, Nagrath et al. proposed the usage of SSDMNV2 (SSD and MobileNetV2) for the real-time face masks compliance – reaching 92% accuracy on their data set. Compared to the proposed study, limitation of the SSDMNV2 is the fact that such approach is not sufficiently generic to be applied for e.g. compliance of hands-mounded or legs-mounted PPEs. The similar approach is also proposed by Loey et al. (2021), which combined YOLO-v2 object detector and ResNet-50 classifier. Both mentioned studies would most likely need additional training of the SSD/YOLO-v2 part to accurately detect various types of PPEs that cover other body parts. More importantly, object-detection approaches suffer to distinguish wearing PPE from holding it (e.g. gloves at Fig. 3). Only a recent study by Chen and Demachi studied the possibility of combining object and individual detection for PPE compliance (Chen and Demachi, 2021). Particularly, they proposed a hierarchical scene graph structure that enables the conditional reasoning for automated hazards identification to address different requirements in each zone of construction sites. AI-based compliance of hardhats has also been the subject of studies in the domain of construction engineering (Rubaiyat et al., 2016; Li et al., 2017; Mneymneh et al., 2019; Wu et al., 2019; Nath et al., 2020) – which are all based on using object detection principle and achieved lower performances compared to the proposed approach. To the best of our knowledge, Balakreshnan et al. are only those who considered safety glasses – reporting lower performances compared to ours (with the note that their assessment was focused on analyzing the performance drop with variations in distance and image quality) (Balakreshnan et al., 2020). Therefore, compared to previous studies, our study is more comprehensive as we covered eight most frequently used head-mounted PPEs.

Regarding the visibility vests and tracks that are mounted on the upper body, there is a significant difference in obtained performances because we considered suits with reflective tracks as separate class – which additionally was underestimated class (1248 samples, compared to the vests 3500, and no protection samples 8460). Compared to previous study that achieved lower (~84%) accuracy in vests compliance on the Pictor-v3 dataset, we emphasize that our performances were assessed on the cropped images – while authors of the mentioned study used object detection approach (YOLO-v3) and analyzed whole images. This indicates that the proposed approach of combining pose estimation, ROI cropping and ROI classification increases the overall PPE compliance accuracy.

Regarding the AI-based compliance of hands, legs and whole-body PPE, we found that our study is the first who considered this problem. We report that improving compliance of this type of PPE is very important for e.g. healthcare (feet covers) or chemical industry (which has some specific requirements, such as preventing entry of people with footwear that does not cover feet - e.g. sandals). In terms of accuracy, we report that legs-related PPE was the most challenging task, as we reached 0.92, 0.84, 0.92, and 0.95 accuracy for compliance of sandals, industry shoes, boots, and feet covers, respectively. Similarly, there is a practical need to timely detect and protect people who do not wear gloves for protecting hands - especially in the lumber industry (which records a large number of finger injuries due to the misuse of PPE), along with the recent recommendations to wear exam gloves during the Covid19 pandemic.

To summarize, in terms of accuracy, the proposed study showed increased performances compared to approaches based on using object detectors and combining object detectors with classifiers. More

**Table 2**
Performances of the developed deep learning models for PPE compliance.

| | MobileNetV2 | VGG19 | Dense-Net | Squeeze-Net | ResNet | Inception_v3 |
|---|---|---|---|---|---|---|
| Face mask | **0.97**, 0.97, 0.96, 0.96 | 0.92, 0.92, 0.93, 0.92 | 0.96, 0.95, 0.96, 0.96 | 0.91, 0.91, 0.9, 0.90 | 0.95, 0.94, 0.96, 0.95 | 0.93, 0.93, 0.92, 0.93 |
| Respirator | 0.95, 0.95, 0.94, 0.94 | 0.93, 0.91, 0.93, 0.94 | 0.94, 0.94, 0.96, 0.95 | 0.93, 0.92, 0.94, 0.93 | **0.96**, 0.97, 0.96, 0.96 | 0.88, 0.89, 0.87, 0.88 |
| Earmuffs | 0.93, 0.94, 0.92, 0.93 | 0.90, 0.89, 0.91, 0.90 | 0.93, 0.95, 0.92, 0.93 | 0.86, 0.87, 0.85, 0.86 | **0.94**, 0.95, 0.93, 0.94 | 0.92, 0.93, 0.91, 0.92 |
| Welding mask | **0.96**, 0.97, 0.95, 0.96 | 0.93, 0.95, 0.92, 0.93 | 0.92, 0.93, 0.92, 0.92 | 0.85, 0.86, 0.84, 0.85 | **0.96**, 0.95, 0.97, 0.96 | 0.91, 0.91, 0.92, 0.91 |
| Face shields | **0.95**, 0.94, 0.96, 0.95 | 0.91, 0.89, 0.93, 0.91 | 0.93, 0.91, 0.96, 0.93 | 0.90, 0.87, 0.94, 0.91 | **0.95**, 0.94, 0.96, 0.95 | 0.91, 0.90, 0.92, 0.91 |
| Safety glasses | 0.93, 0.92, 0.94, 0.93 | 0.90, 0.88, 0.92, 0.90 | 0.89, 0.88, 0.90, 0.89 | 0.87, 0.87, 0.86, 0.86 | **0.94**, 0.92, 0.96, 0.94 | 0.91, 0.88, 0.93, 0.91 |
| Hardhat | **0.97**, 0.96, 0.98, 0.97 | 0.93, 0.91, 0.94, 0.93 | 0.96, 0.96, 0.96, 0.96 | 0.94, 0.93, 0.95, 0.94 | 0.94, 0.94, 0.95, 0.94 | 0.95, 0.95, 0.94, 0.94 |
| Head cover | **0.95**, 0.93, 0.96, 0.95 | 0.91, 0.90, 0.93, 0.92 | 0.94, 0.92, 0.95, 0.93 | 0.90, 0.91, 0.90, 0.90 | 0.93, 0.92, 0.93, 0.93 | 0.94, 0.93, 0.95, 0.94 |
| Yellow vests | **0.98**, 0.98, 0.97, 0.98 | 0.94, 0.93, 0.94, 0.94 | 0.96, 0.97, 0.96, 0.96 | 0.93, 0.92, 0.95, 0.93 | 0.96, 0.96, 0.97, 0.96 | 0.95, 0.95, 0.94, 0.94 |
| Visibility tracks | 0.90, 0.90, 0.89, 0.90 | 0.87, 0.87, 0.86, 0.86 | **0.91**, 0.92, 0.90, 0.91 | 0.80, 0.79, 0.81, 0.80 | 0.86, 0.85, 0.87, 0.86 | 0.87, 0.87, 0.85, 0.86 |
| Exam gloves | 0.92, 0.91, 0.93, 0.92 | 0.89, 0.89, 0.88, 0.88 | **0.94**, 0.95, 0.92, 0.93 | 0.84, 0.82, 0.86, 0.84 | 0.91, 0.90, 0.92, 0.91 | 0.86, 0.86, 0.87, 0.87 |
| Industry gloves | 0.92, 0.91, 0.93, 0.92 | 0.86, 0.87, 0.84, 0.85 | **0.95**, 0.95, 0.94, 0.94 | 0.87, 0.87, 0.86, 0.86 | 0.92, 0.90, 0.94, 0.92 | 0.89, 0.88, 0.88, 0.86 |
| Sandals | **0.92**, 0.91, 0.94, 0.92 | 0.87, 0.86, 0.87, 0.86 | 0.87, 0.89, 0.85, 0.86 | 0.81, 0.83, 0.79, 0.81 | 0.90, 0.91, 0.89, 0.90 | 0.91, 0.90, 0.91, 0.90 |
| Industry shoes | **0.84**, 0.84, 0.83, 0.84 | 0.83, 0.83, 0.81, 0.82 | **0.84**, 0.85, 0.82, 0.83 | 0.80, 0.81, 0.78, 0.79 | **0.84**, 0.85, 0.84, 0.84 | 0.82, 0.80, 0.84, 0.82 |
| Boots | **0.92**, 0.90, 0.94, 0.92 | 0.89, 0.86, 0.92, 0.89 | **0.92**, 0.89, 0.95, 0.92 | 0.90, 0.88, 0.92, 0.90 | **0.92**, 0.91, 0.93, 0.92 | 0.84, 0.86, 0.81, 0.83 |
| Feet covers | **0.95**, 0.93, 0.97, 0.95 | 0.93, 0.91, 0.95, 0.93 | **0.95**, 0.94, 0.96, 0.95 | 0.87, 0.86, 0.87, 0.87 | 0.94, 0.92, 0.96, 0.93 | 0.84, 0.82, 0.86, 0.84 |
| Overall | **0.95**, 0.94, 0.96, 0.95 | 0.93, 0.92, 0.94, 0.93 | **0.95**, 0.95, 0.94, 0.94 | 0.87, 0.86, 0.88 0.87 | **0.95**, 0.95, 0.94, 0.94 | 0.92. 0.91, 0.93, 0.92 |
| Protective cloth | **0.98**, 0.98, 0.97, 0.97 | 0.95, 0.95, 0.94, 0.94 | **0.98**, 0.96, 1.00, 0.98 | 0.91, 0.90, 0.91, 0.91 | 0.97, 0.96, 0.98, 0.97 | 0.96, 0.94, 0.98, 0.96 |

Values in cells are: Accuracy / Precision / Recall / F1 score.


**Fig. 3.** Sample results of using the developed procedure.

importantly, in terms of methodological novelty, we demonstrated that the proposed approach is generic and applicable for inspecting all types of PPEs that may be used in various industries and mounted on various body parts. To prove this statement, we considered eighteen different PPEs that are proposed to protect various body parts. Technological advantage of the proposed approach is flexibility and extensibility of the PPE classifiers list – as we considered compliance of a particular PPE type as the binary classification problem. This means that if one wants to remove or add a new PPE class, this will not affect performance of the rest of PPE compliance classifiers. This is important distinction from the previous approaches, which developed multi-class detectors and classificators – e.g. for simultaneous inspecting use of hardhats and masks, which means that if one considers to fine-tune such model for another type of masks - the transfer learning may negatively affect the hardhat compliance.

### *3.1. Barriers of using AI for PPE compliance*

So far, Computer vision has shown promising great potential to replace or assist human experts' in making decisions that rely on analyzing visual data; ranging from biomedical (Vukicevic et al., 2021), industrial engineering (Vukicevic et al., 2019) to workplace safety (Min et al., 2019; Boustras et al., 2020; Vukicevic et al., 2021). Although previous studies demonstrated applicability of AI-driven PPE compliance in construction engineering, the usage of surveillance technology to cover larger areas and multiple workers at once makes it challenging for such technologies to find place in the industry practice. Furthermore, the current privacy regulations (Ring, 2016; Patil et al., 2014; Sullivan, 2017) and costs/complexity of using AI for 24/7 surveillance of whole industry halls are also barriers for approaches that recommended real-time tracking of employees. Instead, we recommend the proposed approach as suited for the use in controlled conditions, such are: 1) self-check points (when users are asked to confirm their identity by using e.g. RFID card, while AI is used solely for the PPE compliance but not for the purpose of identification and tracking), and on 2) monitoring of particular workplaces/machines with high risk from injuries (so that AI could ensure timely detection and mitigation of occurred risks). We report that one-shoot (single-frame) PPE compliance AI solutions will most likely suffer from effects illustrated in Fig. 3 - bottom row (white arrows). Thus, the reliability could be significantly increased if a sequence of frames is analyzed before making the decision. This issue is less relevant for the compliance of e.g. yellow vests, hardhats, covid masks, protective cloths, or hair cover - as there is no big variability among their design and colors. However, there is a significant number of less studied PPE types (e.g. industry gloves, industry masks, industry shoes, overalls, safety glasses, face shields etc.) whose appearance and design may be very different across different companies/industries - which make it a challenge for the community to develop AI solutions that will generalize well in practice.

## 4. Conclusion

The ongoing technological progress and strictinging of industrial safety standards have initiated the trend of developing computerized systems for improving workplace safety through automation of PPE compliance. Although the previous studies proved the potential of AI to solve the considered problem, their applicability in the industry practice remains limited. Identified barriers of using AI-based PPE compliance systems are: large computational costs needed to monitor whole manufacturing halls in real-time, privacy issues and regulations related to restricted usage of surveillance technology in workplaces, the lack of generic procedure that could be applied across various industries (e.g. construction, manufacturing, healthcare, chemical industry etc.).

In this study, we proposed a four-step procedure that reduces the problem of PPE compliance to the binary classification problem, while ensuring its genericity and ability to perform compliance of arbitrary types/number of PPE that protect various body parts. In the first step, the HigherHRNet pose estimator simultaneously detects body landmark points - which were used for defining the PPE regions of interest. The obtained performances indicated that MobileNetV2, Dense-Net, and ResNet are top-performing classificators, while the MobileNetV2 was recommended as the most optimal considering its lower computationally complexity. In comparison to previous studies (based on using multi-class object detectors, or combining object detectors with classificators), the proposed approach demonstrated improved performances while ensuring the ability for compliance of PPE mounted on various body parts (head, hands, feet, upper body, or whole body). To prove this hypothesis, the procedure was extensively assessed on the 18 different types of PPEs. Another contribution of this study is the demonstrated user-friendly adaptability, which is achieved by linking the lists of considered PPE (classifiers) and corresponding body parts. By editing these lists, one could easily adapt and use the proposed procedure for an arbitrary type of PPE or industry (including manufacturing, healthcare, military/security, food, lumber, construction engineering, etc.).

Considering the constraints present in the nowadays industry practice, we recommend the proposed approach as suited for the following use-cases: 1) self-check points (when users are asked to confirm its identity while AI is used solely for the PPE compliance), and on 2) monitoring of particular workplaces/machines with high risk from injuries (so that AI could ensure timely detection and mitigation of occurred risks under reasonable costs).

### *CRediT authorship contribution statement*

**Arso M. Vukicevic:** Conceptualization, Methodology, Software, Data curation, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Marko Djapan:** Data curation, Visualization, Writing – review & editing. **Velibor Isailovic:** Data curation, Visualization. **Danko Milasinovic:** Data curation. **Marija Savkovic:** Data curation. **Pavle Milosevic:** Data curation.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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