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REAL-TIME PERSONAL PROTECTIVE EQUIPMENT AND WAREHOUSE SAFETY DETECTION WITH DEEP LEARNING-BASED WORKPLACE CAMERA

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ABSTRACT

The majority of work accidents can be prevented with simple precautions. The most important of these is the personal protective equipment that employees must use. In the study, personal protective equipment and warehouse security were detected in real time with images taken from a workplace camera. For this purpose, a data set was created from images taken from the workplace camera. This data set consists of 6125 photographs. Additionally, grayscale, tilt addition, blurring, variability addition, noise addition, image brightness change, color vibrancy change, perspective change, resizing and position change have been added to the photographs. With these additions, the error that may occur due to any distortion that may occur from the camera is minimized. With the changes made to the photographs, the number of photographs forming the data set increased to 21079. The created data set was run on YOLOv8 architecture. In the study, 9 types of personal protective equipment and warehouse safety were determined: helmet, shoes, vest, on the road, not on the road, without vest, without shoes, apron and without helmet. As a result of the study, average stability was 97.30%, mean average precision (mAP) was 93.80% and recall was 91.70%.

Keywords: Deep learning, Personal protective equipment, Real-time object detection, YOLO architecture, Warehouse security.

DERiN ÖĞRENME TABANLI İŞ YERi KAMERASI iLE GERÇEK ZAMANLI KiŞiSEL KORUYUCU EKiPMAN VE DEPO GÜVENLiĞi TESPiTi

ÖZET

İş kazalarının büyük bir çoğunluğu basit tedbirlerle önlenebilecek seviyededir. Bunların başında çalışanların kullanması gereken kişisel koruyucu ekipmanları gelmektedir. Yapılan çalışmada bir iş yeri kamerasından alınan görüntüler ile gerçek zamanlı olarak kişisel koruyucu ekipmanlarının tespiti gerçekleştirilmiştir. Bunun için iş yeri kamerasından alınan görüntülerden bir veri seti oluşturulmuştur. Bu veri seti 6125 tane fotoğraftan oluşmaktadır. Ayrıca fotoğraflar üzerinde gri tonlama, eğim eklenmesi, bulanıklaştırma, değişkenlik eklenmesi, gürültü eklenmesi, görüntü parlaklığı değişikliği, renk canlılığı değişikliği, perspektif değişikliği, boyutlandırma ve konum değişikliği eklenmiştir. Bu eklemeler ile kameradan meydana gelebilecek herhangi bir bozulmaya karşı oluşacak hata en aza indirilmiştir. Fotoğraflar üzerinde yapılan değişiklikler ile veri setini oluşturan fotoğraf sayısı 21079'a yükselmiştir. Oluşturulan veri seti YOLOv8 mimarisinde çalıştırılmıştır. Çalışmada kask, ayakkabı, yelek, yolda, yolda değil, yeleksiz, ayakkabısız, apron ve kasksız olmak üzere 9 çeşit kişisel koruyucu ekipmanın tespiti gerçekleştirilmiştir. Çalışma sonucunda ortalama doğruluk %97.30, kesinlik %93.80 ve duyarlılık %91.70'dir.

Anahtar Kelimeler: Derin öğrenme; Kişisel koruyucu ekipman; Gerçek zamanlı nesne algılama; YOLO mimarisi; Depo güvenliği.

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1. Introduction

There are many and different hazards in work environments. Employers and employees must act together to maintain a safe and healthy work environment. For this to happen, the employer must ensure the supply of personal protective equipment. The worker must use personal protective equipment [1].

The foundation of personal protective equipment dates back to the works of Hippocrates, who lived between 460-370 BC. Hippocrates revealed the harmful effects of lead in his studies. The studies carried out to avoid being affected by this have formed the basis of personal protective equipment studies. The most accepted approach in national and international research is considered to be the scientific studies on work and disease conducted by the Italian researcher Bernardino Ramazzini 1633-1714 in the 17th century. Agricola 1494-1555 was the first person in history to talk about personal protective equipment. He came up with the idea of protective equipment for mouth and nose. He explained that employees should protect their mouths and noses with cloths in the form of dust masks. Agricola has taken modern measures regarding worker health and protective equipment [2].

Work performance of employees cannot be increased by providing occupational health and protective equipment. In order for employees to increase their job performance, there must be appropriate working conditions [3]. Having a healthy, hygienic and safe environment in workplaces has a great impact on work quality [4, 5]. Laws on occupational health and safety are made in many countries around the world [6]. Regulations are being made on these laws every day [7]. Personal protective equipment forms the basis of occupational safety in workplaces. With the development of technology, personal protective equipment used is updated or changed.

Personal protective equipment provides a significant degree of safety in case of work accidents. For this reason, employees must wear it [8]. Employees do not pay attention to the use of personal protective equipment with various excuses. There is a lack of awareness of these in the press. In addition, personal protective equipment is not used during work due to discomfort and itching [9].

The control of personal protective equipment is mostly done by people. Observations made with people cause huge errors in very large workplaces and places with a large number of workers. There are studies on different methods to control the use of personal protective equipment by workers.

Helmet is one of the most important personal protective equipment [10, 11]. They used a mobile Radio Frequency Identification (RFID) card for helmet detection. They placed an RFID card inside the helmet. Entrance to the construction site is from a single point and through a turnstile. RFID card readers have been placed at the entrance point to the construction site. In this way, everyone was ensured to wear a helmet when entering the construction site [12]. Helmet detection method with RFID card has been developed. In this method, they placed an RFID card, RFID card reader, zigbee transmitter and a speaker on the construction worker. When the helmet is not worn, the signal received from the RFID card reader is transferred to the centre via a zigbee transmitter. Transactions are made on the control card at the centre. The result is transferred again via the zigbee transmitter. Then, information is given via loudspeaker [13, 14]. These studies are insufficient for continuous monitoring. At the same time, carrying devices on people is both costly and undesirable. For this reason, studies have been conducted on non-device methods to detect personal protective equipment. The most important of these are camera-based methods.

Wuand and Zhao used convolutional neural networks (CNN) for helmet detection. First, it scans whether there are people in the photo. In case of a human, it works to detect the head area. After detecting the head area, it is determined whether there is a helmet or not. In their study, they achieved an accuracy of 98.80% [15]. Li and his colleagues used the SSD-MobileNet architecture in the CNN algorithm in their study. The dataset was created from images taken from the internet and videos at work. The data set was created from 3261 helmet images. As a result of the study, an accuracy of 78% was obtained [16]. The accuracy rates of studies conducted with machine learning have not increased to very high levels. At the same time, the detection process takes a lot of time. For real-time detection, the frame rate per second (FPS) must be very high. Otherwise, the image disappears from the screen before detection can be done. For this reason, detection cannot be made. Since machine learning processes are done one by one, FPS rates remain very low.

Fangbo and his colleagues used the YOLOv5 architecture, a deep learning network, for helmet detection. They prepared a data set consisting of 6045 photographs for helmet detection. As a result of the study, the highest accuracy of 94.70% was achieved [19]. Fan and his colleagues used YOLOv3 and YOLO-Dense backbone architectures in their studies on caste detection. They detected helmets in two different studies. In their study, they achieved an accuracy of 95.15% with YOLOv3 and 97.59% with YOLO-Dense backbone architecture. Accuracy was increased by 2.44% in the YOLO-Dense backbone architecture [20]. Madhuchhanda and his friends worked on determining whether a helmet was worn on a motorcycle. They used YOLOv3 architecture in their work. As a result of their study, an accuracy of 96.23% was achieved [21]. Wei and colleagues used YOLOv5 architecture for helmet detection. They preferred to use the ready data set as the data set. They tried to increase efficiency by using soft Non-Maximum Suppression (NMS) instead of NMS in the YOLOv5 architecture. As a result of their studies, they increased the accuracy rate to 97.70% [22]. Shilei and colleagues have made fundamental improvements to the YOLOv5 architecture for helmet detection. In the YOLOv5 architecture, they added functionality that tries to find small targets such as helmets. They also used DloU-NMS instead of NMS in the YOLOv5 architecture. An accuracy of 92.12% was achieved in the YOLOv5 architecture. In the improved YOLOv5 architecture, the accuracy rate was increased by 3.56% to 95.68% [23]. Rui and his colleagues investigated the effects of data preparation on accuracy in helmet detection. They used the Gaussian fuzzy method in the data set. Thanks to this method, the accuracy rate improved by 0.01-0.02 [24]. The leading causes of construction fatalities include falling, electrocution, or being struck by objects. As a preventative step, it is highly preventative that workers always wear appropriate personal protective equipment such as hard hats and vests. Nath and his colleagues studied whether workers were wearing hats and vests. In their study, they presented three deep learning models based on YOLO architecture on the image in real time. 1500 labels were made in the data set used in their study. They used CNN-based architectures such as VGG-16, ResNet-50 and Xception in his studies. When applied to real life in their studies, the highest accuracy rate of 72.30% was achieved in the ResNet-50 architecture. The frame per second rate remained at 11 frames. For this reason, the detection speed remained very low. When the FPS rate is increased to 13 frames, accuracy rates decrease. The highest accuracy rate was 67.93% when the FPS rate was 13 frames [25].

The study determined whether employees in a warehouse use personal protective equipment. The study also determined whether employees use walking paths for warehouse safety. Normally, people are assigned to detect this. In this method, huge human errors occur. In the literature studies, mostly helmet detection has been studied. RFID card readers and extra electronic circuits were used in these studies. These are also very costly. Detection is only done at the entrance of the workplace. Very high accuracy rates could not be achieved in detection processes made with machine learning. High accuracy rates were achieved in deep learning detection processes. It is made only for helmet detection among personal protective equipment. In this study, a total of 6 pieces of personal protective equipment were identified: helmet, shoes, vest, without vest, without shoes and without helmet. At the same time, 3 different situations of the employee have been determined for warehouse security: on the apron, on the road, and not on the road. A total of 9 different situation determinations were carried out in the study. A data set consisting of 6125 photographs was prepared for this detection process. In this data, greyscale, slope addition, blurring, variability addition, noise addition, image brightness change, colour vividness change, perspective change, sizing and position changes have been made. With these changes, the error that may occur due to any distortion that may occur from the camera has been minimized. With the changes made to the photographs, the number of photographs forming the data set increased to 21079. The created data set was run on YOLOv8 architecture. As a result of the study, average stability was 97.30%, mAP was 93.80% and recall was 91.70%.

2. Materials and Methods

The majority of work accidents can be prevented with simple precautions. The most important of these is the personal protective equipment that employees must use. In the study, a model was developed for personal protective equipment and warehouse security. The study was carried out in three stages. First stage; data set was prepared. For this purpose, the security camera in the warehouse was used. Thus, when the study was implemented, a higher rate of compliance was achieved in real life. In the second stage; Data set duplication was applied. As the data set increased, the accuracy of the system also increased. The highest accuracy was achieved by using the created data set in YOLOv8 architecture. Since the work will be real-time, the FPS rate must also be very good. In the last stage; applied in real life. Figure 1 shows the general structure of the study carried out for the determination of personal protective equipment.

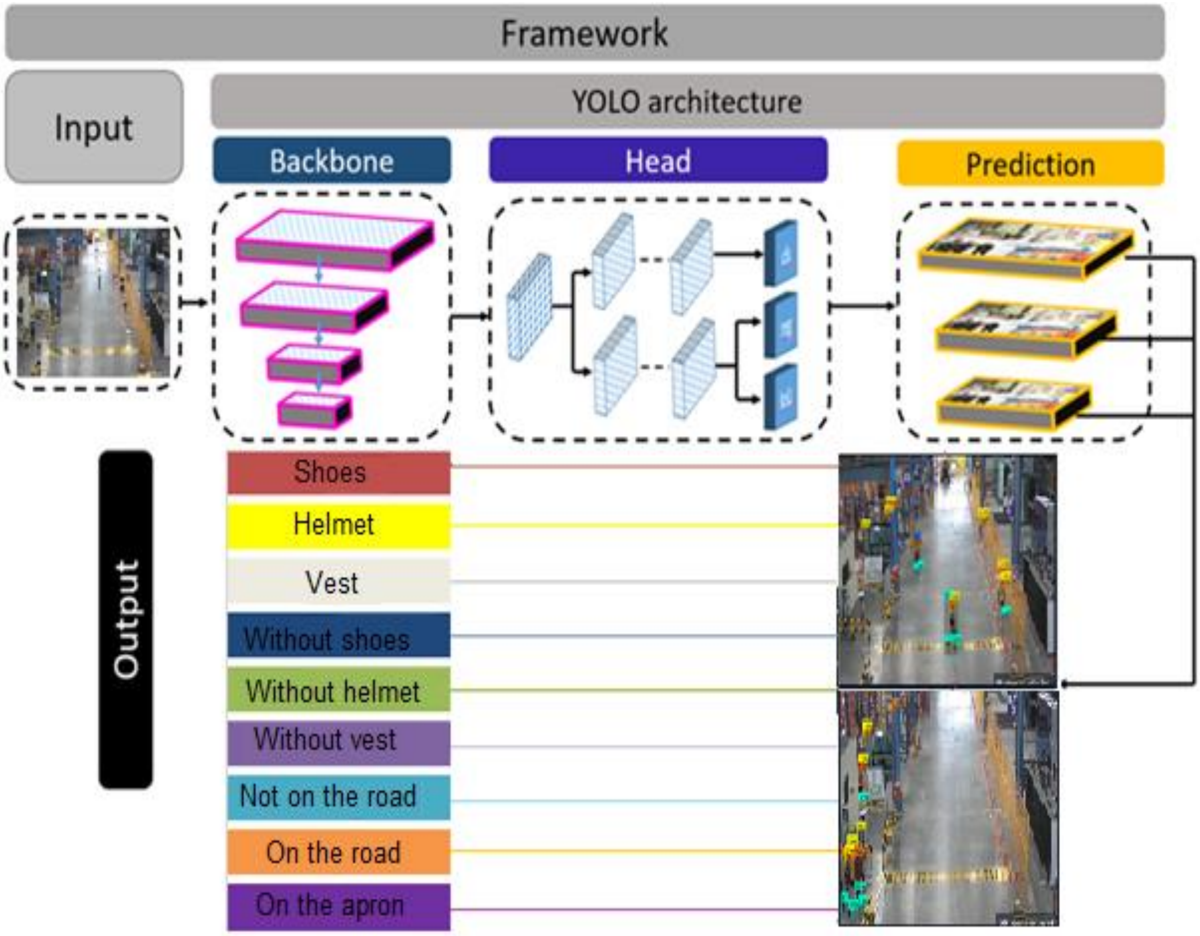

Figure 1 General structure of the study carried out for the determination of personal protective equipment.

2.1. Dataset

In the study, a total of 6 personal protection equipment were identified: helmet, shoes, vest, without vest, without shoes and without helmet. At the same time, 3 different situations of the employee have been determined for warehouse security: on the apron, on the road, and not on the road. Security camera footage was used to detect these. The data set consists of 6125 photographs. The data set consists of photographs collected from real environments and websites. Figure 2 shows examples of the photographs that created the data set.

For the detection process, first the data set is labelled. Labelling is done for 9 different situations in the photographs that generated the data set. For this reason, a different number of tags are applied to each photo. In the study, approximately one hundred thousand tags were made. Figure 3 shows the number of labels made for each case in the data set.

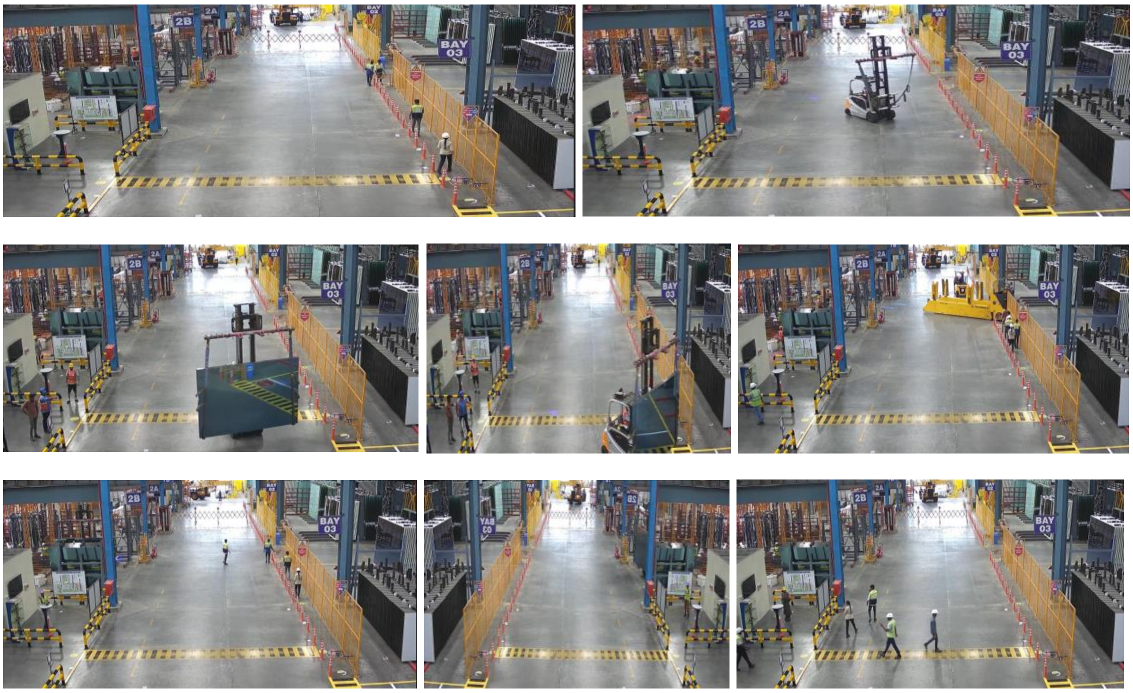

Figure 2. Some sample photos from the dataset.

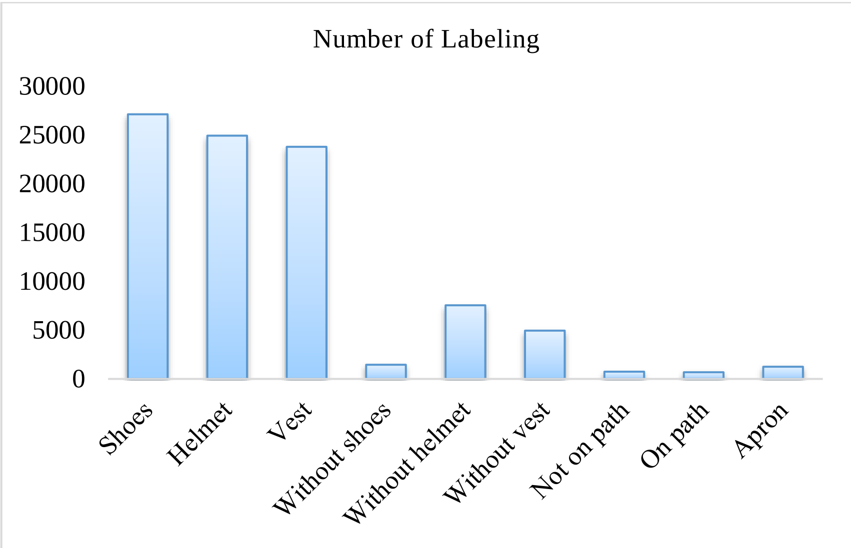

Figure 3. Labelling numbers used from the data set.

Personal protective equipment such as shoes, helmet and vest are used for each worker. For this reason, the number of labels for shoes, helmets and vests is very high. In particular, tagging without shoes is very rare. Because it is very difficult to find an employee without shoes.

Real-time detection will be made in the study. This will be done with images taken from the security camera. Errors that may occur in the camera will either greatly reduce the accuracy rate in the detection process or the detection process will not occur. For this reason, changes were made to the data set to prevent errors that may occur from the camera. Figure 4 shows the changes made to the samples used in the data set. A computer was used to prepare the data set. The computer used in the study has an AMD Ryzen 1500X 3.5 GHz processor. The graphics card is NVIDIA GeForce GTX 1050 Ti 4GB GDDR5. Memory speed is 16 GB 3000 MHz.

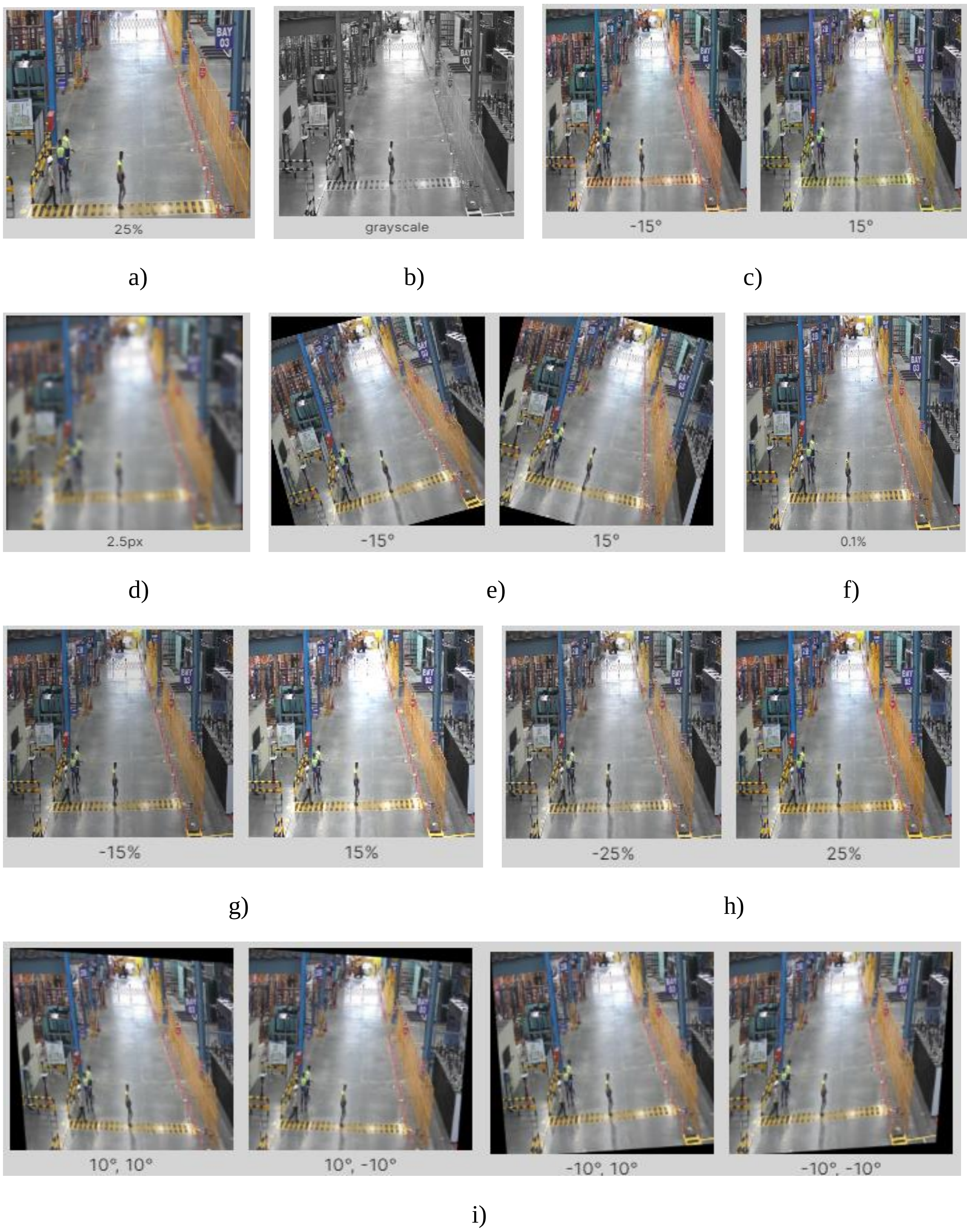

Figure 4 a) Sizing and position change, **b)**Grayscale, **c)**Adding slope, **d)**Blurring, **e)**Adding variability, **f)** Adding noise, **g)**Image brightness change, **h)**Color vividness change, **i)**Perspective change.

In Figure 4a, 25% variability has been added to the positioning and sizing of the images that created the database. Thus, this process was done with the help of the model being more durable depending on the camera position. In Figure 4b, the images in the database are grayscale. In Figure 4c, +15% and -15% slope has been added to the images. In Figure 4d, random Gaussian blurring was performed to be more resistant to camera focus. In Figure 4e, +15% and -15% variability has been added to the rotations to be more resistant to camera roll. In Figure 4f, noise has been added to make it more robust to camera artifacts. In order for the Figure 4 model to be resistant to lighting and camera changes, the image brightness was changed by +15% and -15%. In Figure 4h, the vividness of the colours in the images is randomly adjusted. In Figure 4i, variability has been added to the perspective to be more robust to camera, subject pitch, and aberration. With these changes made from the photographs that generate the data set, the error rate in real-time helmet detection has been minimized.

2.2. YOLOv8

YOLO was first introduced in 2015 in the article "You Only Look Once: Unified, Real-Time Object Detection," published by Joseph Redmon. The YOLO algorithm has shown more successful results than many object detection algorithms used in real-time object tracking. Many different models of YOLO have been released since 2015. The YOLOv1 model was first released in 2015. YOLOv2 was released in 2016, YOLOv3 in 2018, YOLOv4 and YOLOv5 in 2020, YOLOX in 2021, YOLOv6 and YOLOv7 in 2022, and finally YOLOv8 in 2023. As of January 2023, Ultralytics has released perhaps the best YOLO model to date, YOLOv8, under the ultralytics repository.

YOLOv8 is an open source object detection algorithm based on deep learning, specifically Convolutional Neural Networks (CNNs). It is part of the YOLO (You Only Look Only Once) family of object detection algorithms, known for their speed and accuracy in detecting objects in real time.

Leveraging previous YOLO versions, the YOLOv8 model is faster and more accurate while providing a unified framework for training models for performance.

YOLOv8 is a state-of-the-art object detection algorithm that outperforms many other object detection algorithms in terms of both speed and accuracy. It is an improvement over previous YOLO versions such as YOLOv3 by incorporating new techniques in deep learning and computer vision. Figure 5 shows the general structure of the YOLOv8 architecture.

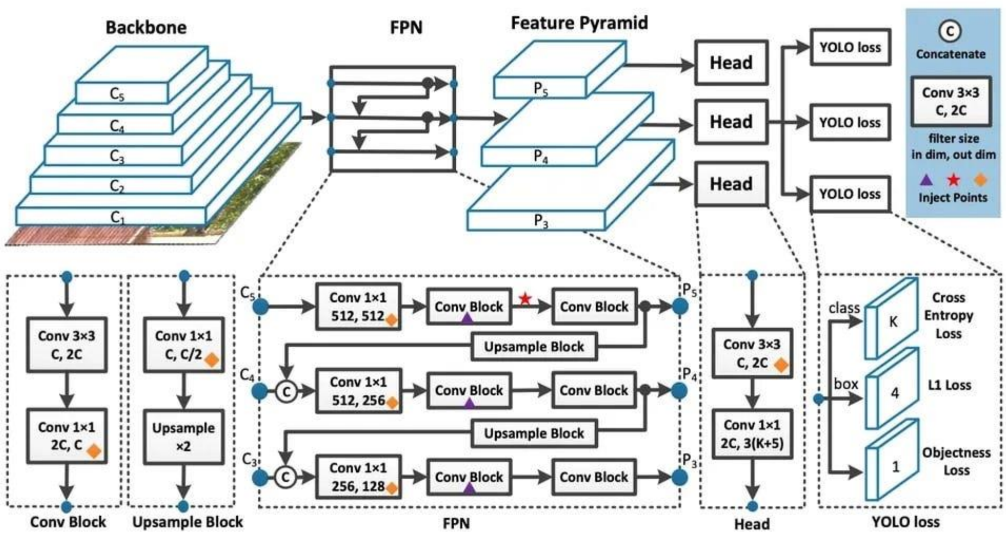

Figure 5. General structure of YOLOv8 architecture

3. Results and Discussion

YOLOv8 dataset architecture was used in the study. In the YOLOv8 architecture study, a total of 6 personal protective equipment was identified: helmet, shoes, vest, without vest, without shoes and without helmet. At the same time, 3 different situations of the employee have been determined for warehouse security: on the apron, on the road, and not on the road. A total of 9 different situation determinations were carried out in the study. Figure 6 shows the ROC curve resulting from the study.

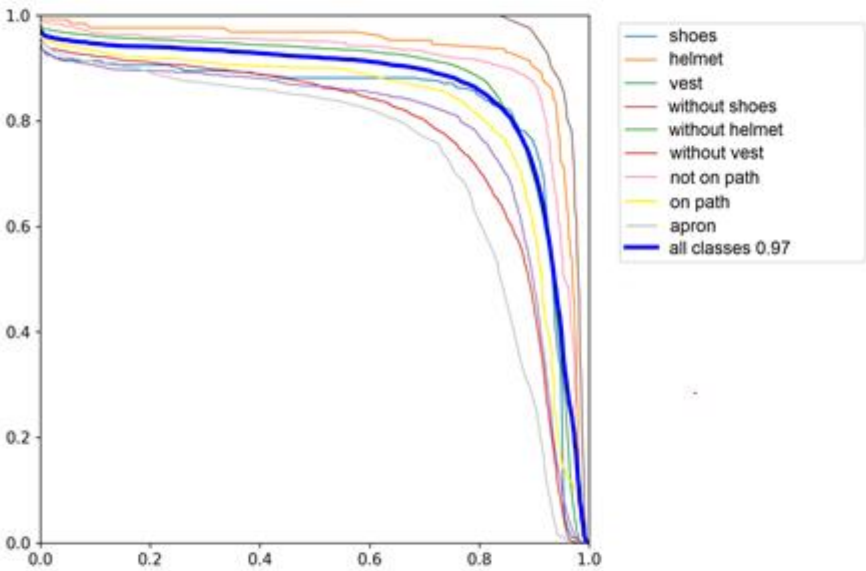

Figure 6. ROC curve

In the study, the training period for determining personal protective equipment and warehouse security lasted 87 hours, 25 minutes and 13 seconds. As a result of the study, the average accuracy rate was 97.30%, mAP@5 was 93.80% and recall was 91.70%. Figure 7 shows the experimental study analysis graphically.

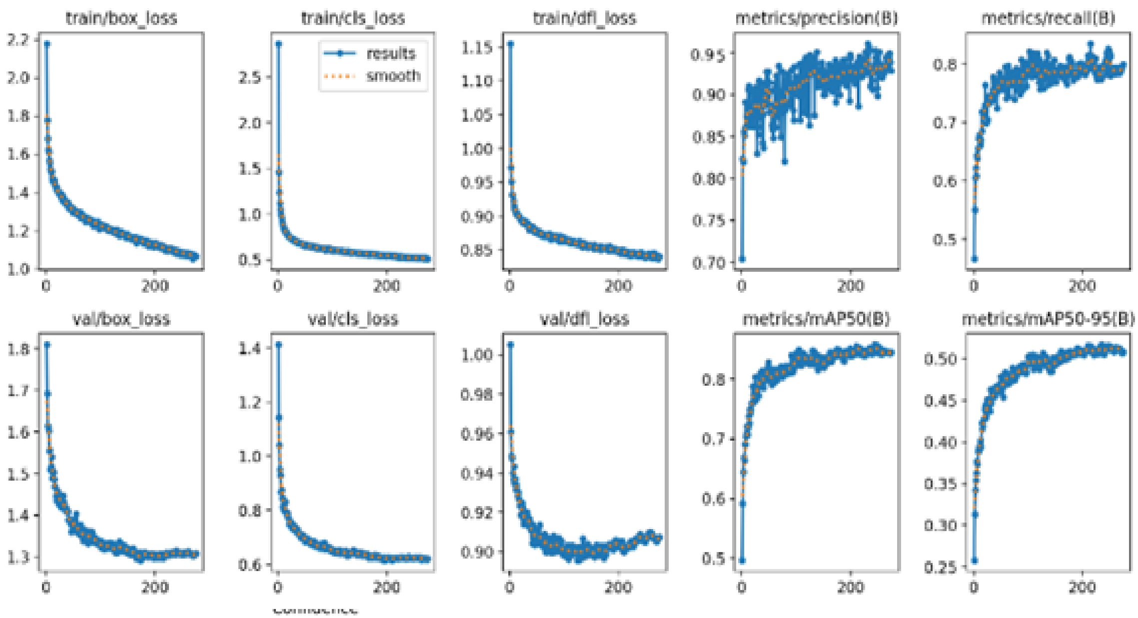

Figure 7. Graphical Representation of Experimental Study Analysis.

9 different detection procedures were performed in the study. But the sampling numbers used for each detection process were different. For this reason, accuracy rates were different for each group. Figure 8 shows the accuracy rates for each group.

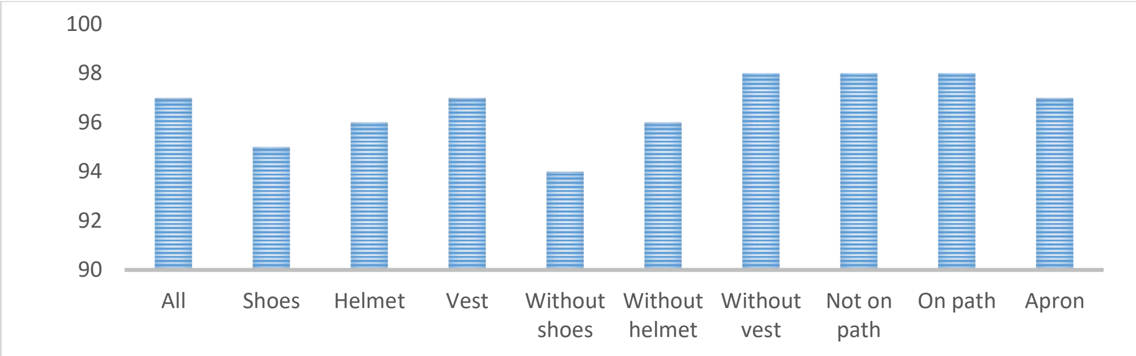

Figure 8. In the detection process, the accuracy rates of each group are determined.

In the study, 9 different detection processes were performed. A different number of photographs and tags were taken for each detection process. As a result of the study, accuracy rate of 95% with shoes, 96% with a helmet, 97% with a vest, 94% without shoes, 96% without a helmet, 98% without a vest, 98% off the road, 98% on the road and 97% on the apron were obtained. As a result of the study, the average accuracy rate was 97.30%. The study was run from the workplace camera located in the warehouse. Figure 9 shows the detection processes carried out by the study at different times.

Figure 9. Detection processes carried out by the study at different times.

K-Fold Cross Validation method; It divides the data set into "k" equal parts and creates validation data for each part one by one. Thus, each data point is used as validation data at least once. In this way, the overall performance of the model is evaluated more accurately. There are 21709 samples in the data set of the study. Here, the number k is determined as 5. In other words, the data set is divided into 5. There are 4216 samples in each dataset. Their distribution is distributed in the same proportions as in the general data set. Table 1 shows the results after the K-Fold Cross Validation method.

Table 1: Results after K-Fold Cross Validation method

Model	Precision %	Accuracy %
k1	97.30	97.40
k2	97.10	97.25
k3	97.35	97.10
k4	97.25	97.50
k5	97.40	97.15

The average accuracy rate of the results obtained after the K-Fold Cross Validation method was 97.30. With this result, the overall result of the system is equal to the two results checked. Thus, it is understood that the overall performance of the model is good.

When the literature studies are examined, many studies have been done on helmet detection. Different methods, algorithms and architectures were used in the studies. Table 2 shows the comparative results of the studies conducted on the detection of personal protective equipment.

Table 2: Literature study

Author	Model	Precision
Huand et all.2021 [25]	YOLOv3, Improved YOLOv3, Faster R-CNN	0.93
Li et all. 2020 [26]	SSD	0.36
Kamboj et all [27]	SSD	0.96
Long et all 2019 [28]	SSD	0.69
Zhou et all 2021 [29]	YOLOv5s, YOLOv5m and YOLOv5l	0.95
Tan et all 2021 [30]	YOLOv5 and Improved YOLOv5	0.96
Yung et all 2022 [31]	YOLOv5s, YOLOv6s and YOLOv7	0.90
Korkmaz et all [32]	YOLOv8	0.97
Türkdamar et all 2023 [33]	YOLOv4, YOLOv5 and Faster R-CNN	0.98
Wu et all 2019 [34]	YOLOv3 and YOLO-Dense backbone	0.98
Jia et all 2021 [35]	YOLOv5	0.98
Nath et all 2020 [36]	VGG16, ResNet-50	0.67

The data sets and algorithms used in literature studies are different. For these reasons, the accuracy rates obtained as a result of the studies are different. In literature studies, architectures from YOLOv3 to YOLOv8 have been used in many studies. There is an increase in accuracy rates in studies from YOLOv3 to YOLOv8 architecture. The highest accuracy rate was in the YOLOv8 architecture. It is understood that the other results of the YOLOv8 architecture, especially the accuracy rates, are better than other models of the YOLO architecture.

As a result of the literature review, it is understood that the use of previous systems in daily life is quite difficult. These difficulties are that they have low FPS. For this reason, the systems cannot be used in real time. YOLOv8, the latest version of the YOLO architecture, was used in the study. In this way, the highest accuracy rate and FPS rate were determined by comparison. Since YOLO architectures perceive the image with a single glance, FPS rates are very good. A speed of 60 FPS was achieved in the YOLOv8 algorithm. In this way, detection can be carried out very easily in real time.

4. Conclusion

Many accidents occur in workplaces. If protective equipment is used, the vast majority of these accidents will cause little or no harm. Employees do not want to wear personal protective equipment for various excuses. In workplaces, control of these is left to people. This is costly and always very difficult to do. With the developing technology, RFID card, machine learning and most recently deep learning methods have been used for personal protectors. The controls made with the RFID card were insufficient because they were made only from a single point at the entrances. Very high accuracy has not been achieved in machine learning. Different architectures have been used in deep learning. The study must achieve very high accuracy as well as a fast detection time. In literature studies, studies have mostly focused on the detection of a single protective equipment. In this study, a total of 6 pieces of personal protective equipment were identified: helmet, shoes, vest, without vest, without shoes and without helmet. At the same time, 3 different situations of the employee have been determined for warehouse security: on the apron, on the road, and not on the road. A total of 9 different situation determinations were carried out in the study. In the study, YOLOv8 architecture, the latest YOLO architecture, was used. With this architecture, an accuracy rate of 97.3% was achieved. At the same time the land speed per second (FPS) increased to 60. In this way, real-time detection takes place on the screen. A large data set was prepared for the study to yield such good results. A data set consisting of 6125 photographs was prepared for this detection process. In this data, greyscale, slope addition, blurring, variability addition, noise addition, image brightness change, color vividness change, perspective change, sizing and position changes have been made. With these changes, the error that may occur due to any distortion that may occur from the camera has been minimized.

A high level of accuracy is achieved in detecting protective equipment. But during detection, the person's identity information cannot be determined. Adding facial recognition to the system will take the work one step further. If a mobile application is added to the system, people who do not wear protective equipment can receive instant warnings.

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