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Regular Research Article

Application of Automatic Detection of Personal Protective Equipment (PPE) for Loading and Unloading Workers at PT. Pelindo TPK Makassar

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Abstract: The purpose of this study is to apply the use of an automatic PPE (Personal Protective Equipment) detection system prototype in supporting the Health, Safety, Security, and Environment (HSSE) efforts of PT. Pelindo Terminal Peti Kemas Makassar also known as TPK Makassar to improve the effectiveness of supervision and reduce the risk of workplace accidents. Workplace accidents can be caused by various factors, ranging from worker negligence in not using PPE, lack of discipline, and carelessness. Safety and health are top priorities for workers and companies. Field testing results show that the system can consistently distinguish between workers who comply with and those who violate PPE usage rules, and send automatic alerts when violations occur. The YOLOv8-based detection model shows fairly good performance with a precision value of 0.7–0.9, recall of 0.5–0.6, and mAP50 reaching 0.7–0.8, which indicates that the system is capable of recognizing main objects with high accuracy.

Keywords: Work safety; Automatic detection; Personal Protective Equipment, PT. Pelindo TPK Makassar.

1. Introduction

Work accidents are unpredictable and unforeseeable situations because they are intentional, unplanned, and often result in material losses and suffering, ranging from minor to very serious [1], [2]. Accidents at work can be caused by various factors, ranging from worker negligence in not using PPE (Personal Protective Equipment), lack of discipline, and carelessness [3], [4]. Safety and health are top priorities for workers and companies [5]. The implementation of optimal safety and health measures will create a safe and comfortable working environment and conditions to increase labor productivity [6].

Loading and unloading workers are one group of workers who need attention because their work involves many risks of accidents [7]. According to the International Labor Organization (ILO), there are more than 250 million accidents in the workplace every year. Workplace accident cases in Indonesia tended to increase throughout 2017, with 123,000 cases of workplace accidents [8]. Workplace accidents in Indonesia continue to increase, requiring policies and actions to reduce the number of workplace accidents. Data on workplace accidents in Indonesia from the Social Security Administration Agency (BPJS) for Employment recorded 173,415 workplace accidents in 2016 and a total of 10,923 workplace accidents at the end of September 2019 [9], [10].

Not using Personal Protective Equipment (PPE) while working is an example of unsafe behavior. It can lead to death or injury. The lower the frequency of PPE use, the greater the

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chance of a workplace accident. The use of personal protective equipment is significantly related to workplace accidents. Lack of awareness of PPE use can be caused by low awareness, knowledge, and attitude of workers about safety techniques in the work environment. Makassar Container Terminal 1 is a terminal that operates 24 hours a day with a high level of operational activity. Loading and unloading activities at Terminal Peti Kemas 1 Makassar are carried out with the assistance of loading and unloading workers and loading and unloading equipment. Loading and unloading activities at Terminal Peti Kemas 1 Makassar are divided into three parts, consisting of Stevedoring (loading and unloading goods from ships to docks and vice versa), Corgodoring (the work of transporting goods from the dock to the warehouse and vice versa) and Receiving/delivery (the work of taking goods from the warehouse to vehicles and vice versa [11].

The importance of monitoring workers is a crucial factor in efforts to reduce workplace accidents [12]. Therefore, object detection of PPE, particularly vests, shoes, and safety helmets, is needed to minimize workplace accidents. Deep learning is widely used in computer vision activities. One algorithm that can be used to detect PPE is the You Only Look Once (YOLO) algorithm [13]. YOLO is an algorithm that can be used to detect and identify objects in images or videos quickly and efficiently. The YOLO algorithm was chosen as the method for creating the application in this study because it has the advantage of being able to classify objects directly in one inference step through a neural network. This makes it faster than some other object detection approaches that require multiple steps or more complex calculations. YOLO is also capable of real-time object detection [14]. Based on the above description, it is necessary to conduct research on the use of automatic detection of personal protective equipment (PPE) for loading and unloading workers at PT. Pelindo Terminal Peti Kemas New Makassar, with the aim of developing a real-time object detection system using the YOLOv8 algorithm [15], which is expected to facilitate the reduction of work accidents and increase the efficiency of controlling safety helmet violations for workers at PT. Pelindo Terminal Peti Kemas New Makassar.

2. Methods

Object detection is one of the domains that has seen great success in computer vision. Object detection is used not only to determine the presence of objects in an image or video, but also to find and classify objects into predetermined variables (categories). Several factors can influence detection results, including the object's background, position, and height or distance in the image. This process typically uses two methods: localization to determine the exact location of the object in the image. This is usually done by drawing a bounding box around the object, which will determine the position and size of the object in the image. Meanwhile, classification involves assigning localized objects to specific categories or classes. This involves identifying the type or class of each detected object, such as people, cars, or dogs, from a series of predetermined categories.

Every workplace that has a risk of accidents and occupational diseases must provide and use PPE. This is regulated in Law Number 1 of 1970 concerning Safety. According to Minister of Manpower Regulation No. 8 of 2010 concerning Personal Protective Equipment, PPE is defined as a device capable of protecting a person and functioning to protect part or all of the body from potential hazards in the workplace. PPE is the final stage in the hazard control hierarchy. The obligation to wear PPE in the workplace, especially in areas with potential hazards, applies not only to employees but also to managers, supervisors, and anyone else who enters the workplace. Companies are required to provide PPE free of charge and also ensure that the PPE provided is used properly, including providing training, instructions, and continuous supervision. Each workplace has different hazards depending on the type, materials, and production processes used.

YOLO (You Only Look Once) is a digital image algorithm (Object Detection) that runs using deep learning techniques. This algorithm works based on the single shot principle, meaning that the network architecture is arranged in such a way that in one frame pass, it can detect several objects simultaneously [12], [14]. Therefore, YOLO uses images or videos as input, which will then produce direct image detection predictions without the need to go through separate detection steps. YOLO is a single convolutional neural network that divides the input image into a set of grid cells, so unlike image classification or face detection, each grid cell in the YOLO algorithm will have a related vector in the output that tells us if there are objects in it. The YOLO model is very precise, enabling the model to detect objects within the image frame [16]. YOLO applies a neural network to the entire image to predict bounding boxes and their probabilities, as shown in the image below: Object Detection Architecture. This model is so advanced that YOLO will learn more over time and improve the accuracy of its predictions over time.

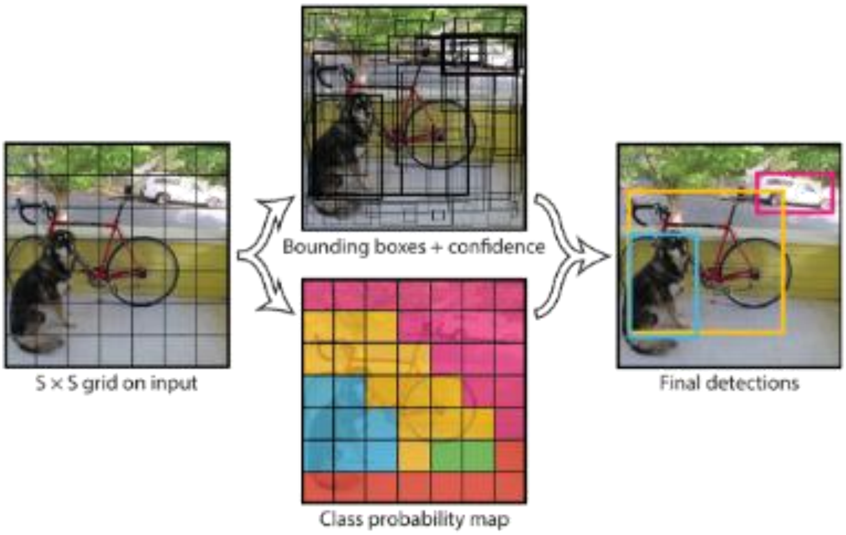

Figure 1. Illustration of YOLO (You Only Look Once)

The YOLO algorithm predicts objects in the form of bounding boxes B with confidence scores C and divides the input image or video into an S x S grid. The confidence score reflects how confident the model is that the box contains an object and shows how accurately the model estimates the predicted box. The confidence score can be defined as equation (1) below:

$$\text{Confidance} = \Pr(\text{Object}) \times \text{IoU} \tag{1}$$

Pr() is the value of objectivity in a cell. Object means that when there is an object in a cell, the value is 0, and when there is an object in a cell, the value is 1. IoU is the ratio between the ground truth box and the prediction box. If there is no object in the cell, the confidence value will be zero. Otherwise, the confidence value is equal to the intersection over union (IoU) between the predicted box and the ground truth. Small grid cells are responsible for making predictions if the center point of an object falls on the grid. The bounding box contains 5 prediction elements, namely x, y, w, h, and confidence score. The x and y coordinates represent the center point of the box relative to the grid cell. The w (width) and h (height) elements are considered relative to the entire image. Based on Figure 1, the system will divide the image with grid dimensions S × S, and each grid cell will predict B bounding boxes, the confidence value for each box, and the class probability map for class C. This prediction is formulated as a tensor into $S \times S \times (B * 5 + C)$. In general, the YOLO architecture will be described in layers, commonly referred to as convolution layers.

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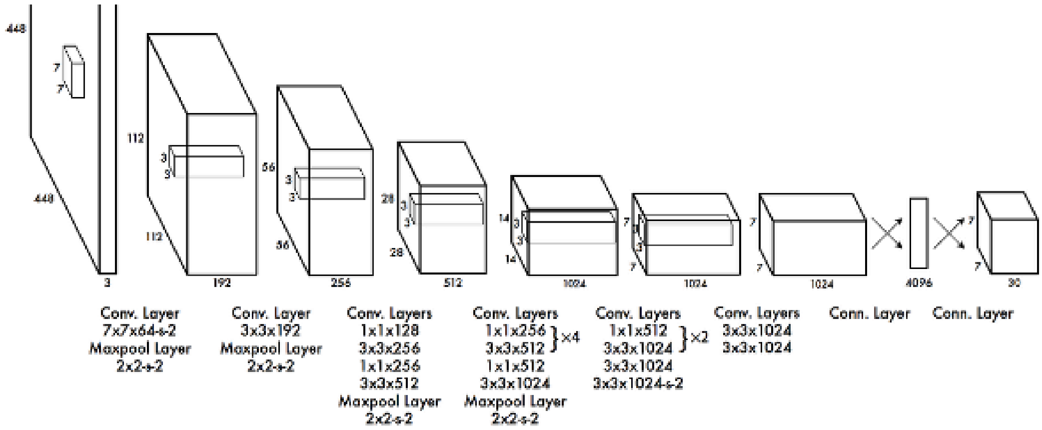

Figure 2. *Architecture* YOLO

The YOLO network architecture is inspired by the GoogLeNet model for image classification. YOLO has 24 convolutional layers followed by 2 fully connected layers. In Figure 2.6, the YOLO detection network has 24 convolutional layers followed by 2 fully connected layers. The 1 × 1 convolutional layer reduces the space in the features from the previous layer. The convolution layer is trained with ImageNet classification at half resolution (input image 224 × 224) and then doubles the resolution for 448 × 448 detection. YOLOv8 is a state-of-the-art real-time object detector that surpasses all known object detectors in terms of speed and accuracy in the range of 5 FPS to 160 FPS. The design of the prototype automatic APD violation detection system consists of several main hardware and software components. The hardware includes a Raspberry Pi 5 as the processing center, a camera as a visual sensor to capture images of workers in the field, a speaker to provide direct audio warnings, and a portable screen, keyboard, and mouse as interface devices to manage the system. Meanwhile, on the software side, the Telegram application is used as a medium for receiving real-time violation notifications.

With the integration of all these components, the system can detect worker compliance with PPE use, provide warnings via speakers and screen displays, and send automatic notifications to the Telegram application. This design aims to improve the

Table 1. Performance metrics for the YOLOv8 detection model on the system

Metric	Value Range	Description
Precision	0.7–0.9	Most predictions are correct (minimal false positives).
Recall	0.5–0.6	The model is quite good at finding existing objects, though some are missed.
mAP50	0.7–0.8	Good detection performance at an IoU threshold of 0.5.
mAP50-95	0.3–0.4	Still quite good for field applications, covering various IoU thresholds (0.5-0.95).
Violation Detection Duration	3.4 seconds	The time it took the system to detect a specific violation (in one scenario).

effectiveness of work safety supervision at the Container Terminal by utilizing artificial intelligence-based visual detection technology. The design can be seen in Figure 3.

Researchers conducted direct observations in the dock area, container yard, and operating terminals. Based on the observations, workers were still found to be undisciplined in using PPE, particularly safety helmets and reflective safety vests, especially during peak loading and unloading hours.

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Figure 3. Design Prototype for PPE Violation Detection

This condition confirms the need for automated system-based monitoring to support HSSE efforts. Figure 4 shows a map of the Makassar Container Terminal (TPK Makassar) area marked as "PPE REQUIRED AREA," which is a zone where all workers are required to wear Personal Protective Equipment (PPE) while working. This map was compiled by Pelindo Container Terminal and refers to the ISPS Code safety standards applicable at international ports.

Figure 4. Mandatory PPE Area at PT. Pelindo Terminal Peti Kemas Makassar

3. Results

3.1 Training Model YOLOv8

Train Loss shows the decrease in model error values during the YOLOv8 training process, which consists of box_loss, cls_loss, and dfl_loss. The box_loss value describes the accuracy of bounding box predictions, cls_loss shows the error rate in object classification, while dfl_loss relates to the accuracy of box boundary distribution. All three curves decline consistently as the epoch increases, indicating that the model can learn well, is more accurate in recognizing object positions, and is more precise in distinguishing the classes of PPE detected in the train loss image, as shown in Figure 5.

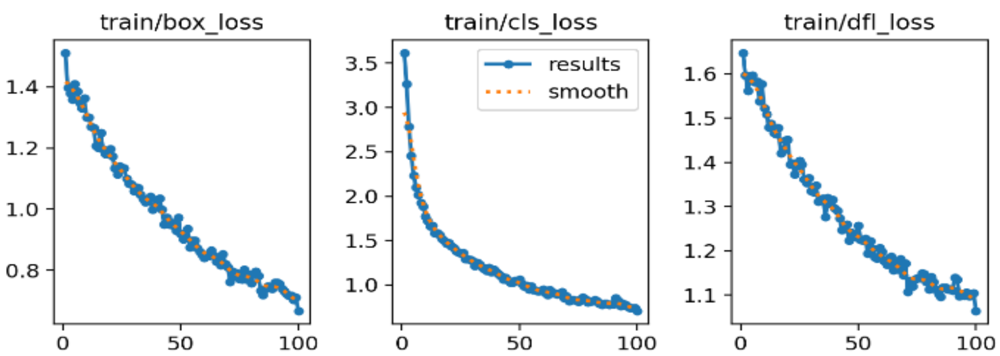

Figure 5. Train Loss

The Validation Loss graph shows the performance of the YOLOv8 model on validation data, consisting of val/box_loss, val/cls_loss, and val/dfl_loss. In general, all three curves show a downward trend as the number of epochs increases, although there are higher fluctuations compared to train loss. This is normal because validation data is independent and reflects more diverse conditions. The val/box_loss value tends to decrease although it is unstable, val/cls_loss shows a consistent decrease from start to finish, while val/dfl_loss also fluctuates but continues to move downward. This trend indicates that the model can generalize well on data that has not been trained, although there is still room for improvement, especially in the stability of bounding box predictions. Metrics display the performance evaluation of the YOLOv8 model using four main metrics: Precision, Recall, mAP50, and mAP50-95.

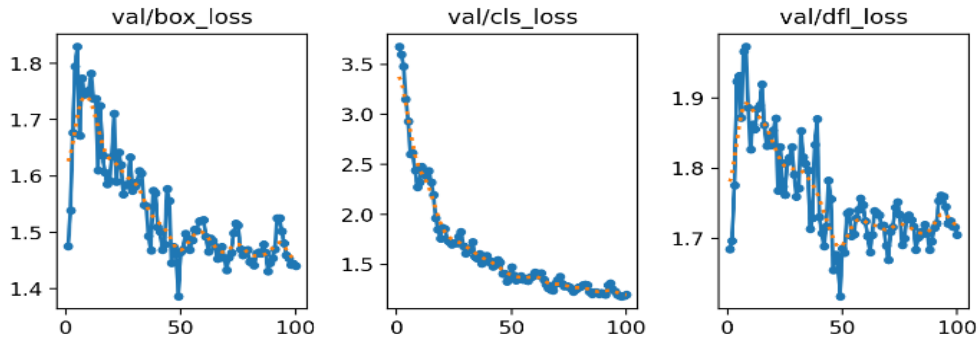

Figure 6. Validation Loss

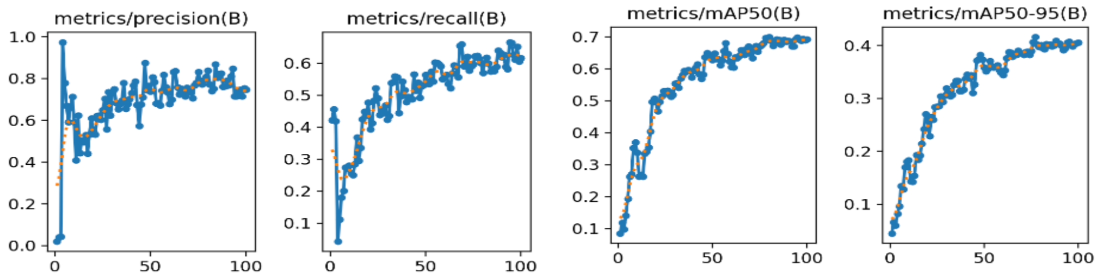

Figure 7. Metrics evaluation

The metrics/precision(B) graph shows an increasing trend until it stabilizes in the range of 0.7–0.9. This means that most of the predictions made by the model are correct (minimal false positive errors). The metrics/recall(B) graph also rises consistently, although it is more volatile, and remains in the range of 0.5–0.6. This shows that the model is quite good at finding existing objects, although some are still missed. The metrics/mAP50(B) graph shows a steady increase to around 0.7–0.8. This value indicates good detection performance at an IoU threshold of 0.5, where the model is able to distinguish objects with high accuracy which is in accordance with some previous studies [17], [18], [19]. The metrics/mAP50-95(B) graph, which is more stringent because it covers various IoU thresholds (0.5–0.95), shows results in the range of 0.3–0.4. This value is still quite good for field applications, although it is lower than mAP50 because the requirements are higher.

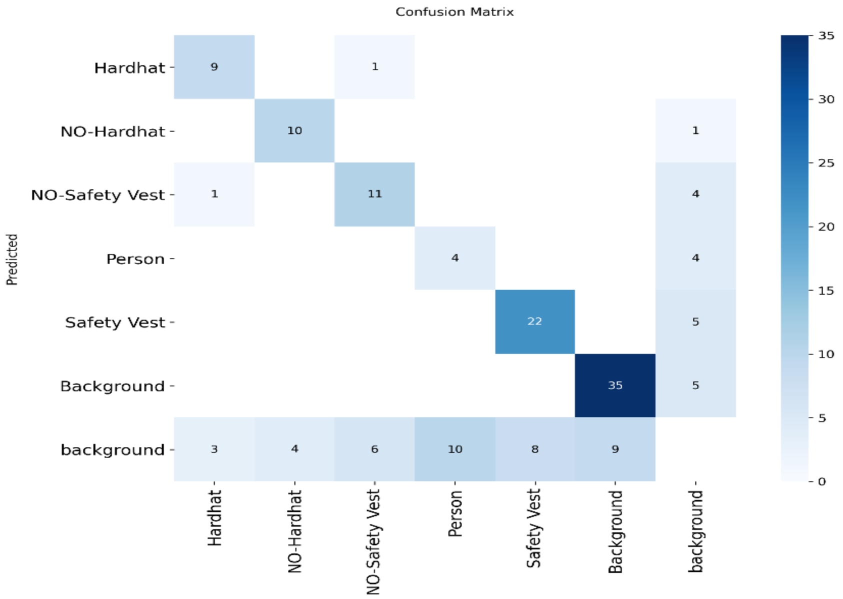

Figure 8. Confusion Matrix

The confusion matrix in Figure 8 is used to evaluate the classification performance of the model in the main classes, namely Hardhat, NO-Hardhat, NO-Safety Vest, Person, and Safety Vest, by comparing the true label with the predicted label. The test results show that the model is able to recognize several classes quite well, although there are still classification errors in certain classes. In the Safety Vest class, the model showed the best performance with 22 data points successfully detected correctly. This shows that safety attributes in the form of vests are relatively easier to recognize because they have contrasting visual characteristics compared to other objects around them. Furthermore, the Hardhat and NO-Hardhat classes were also identified quite well, with 9 and 10 correct predictions, respectively. However, errors were still found in some of the data that were predicted to be in other classes, such as Hardhat being incorrectly predicted as NO-Safety Vest, and NO-Hardhat being partially misidentified as other classes.

In the NO-Safety Vest class, there were 11 data points that were predicted correctly, although there were still classification errors in some data points in other classes. This indicates that the model is quite capable of distinguishing objects that do not use safety vests, albeit with less-than-optimal accuracy. Conversely, the lowest performance was obtained in the Person class, where only 4 data points were correctly recognized. Most of the data in this class was incorrectly predicted as another class, indicating that the model had difficulty in consistently detecting human objects, especially when they were not accompanied by clear protective attributes. Overall, this confusion matrix shows that the model was able to recognize key safety attributes such as Safety Vest, Hardhat, and NO-Safety Vest with a fairly good level of accuracy. However, weaknesses are still evident in the detection of the Person class, which is often misclassified, so there is a need to improve the quality of the dataset, particularly by adding more varied images of humans in more diverse conditions. Thus, the model is expected to be more balanced in detecting all object classes in future research.

3.2. APD Violation Detection System Testing Scenario

To test the reliability and accuracy of the developed automatic Personal Protective Equipment (PPE) violation detection system, a series of scenario-based tests were conducted under several real-life conditions in the field. The system was designed using the YOLOv8 object detection model and implemented in a website-based application connected to a Telegram notification channel. The focus of this system is to detect two main types of PPE that are mandatory in the loading and unloading area of the Makassar Container Terminal, namely:

1. Safety helmet
2. Safety vest

Testing was conducted through four scenarios representing variations in PPE usage and violations. Each scenario was analyzed to determine worker safety status and system output in the form of violation notifications.

Table 2. Testing Scenario

No.	Detected Conditions	PPE Detected by the System		Security Status	Notification
		Helmet	Vest		
1	Not wearing a helmet and vest	×	×	Not Safe	Sent
2	Wearing a helmet but not wearing a vest	✓	×	Not Safe	Sent
3	Not wearing a helmet and vest	✓	✓	Safe	Not Sent
4	Wearing Helmets and Vests	✓	✓	Safe	Not Sent

Test results show that the YOLOv8-based detection system is able to identify PPE attributes quite well in favorable lighting and visual conditions. In scenarios 1–3, the system consistently classified the workers' status as Unsafe, due to the incomplete use of PPE detected by the model. In all three cases, the system automatically sent notifications to the configured Telegram channel. Conversely, in the fourth scenario, when workers wore helmets and vests completely and correctly, the system recognized the condition as Safe and did not send a warning. These results show that the system was able to perform its function in accordance with the research objective, which was to detect minimum violations of PPE use in the work area with a real-time automatic response.

3.3. Dashboard Aplikasi

The following is a display showing the application when a PPE violation is detected. The system detects a worker not wearing a helmet, resulting in the safety status being changed to “NOT SAFE”. The monitoring panel displays the number of workers detected, which is one person, and records the violation that occurred, which is not wearing a helmet (NO-Hardhat: 1), while safety vests are not detected as a violation (NO-Safety Vest: 0). The safety status displayed in red indicates a violation. The violation detection duration is recorded as 3.4 seconds, indicating how long the system detected the violation. On the right side, real-time statistics show the number of workers detected and violations that occurred, with the detection graph at the bottom showing the number of objects detected per category (person, helmet, vest) in the form of a histogram. This display provides a clear picture of the safety conditions in the work area and provides instant feedback to supervisors to take immediate action.

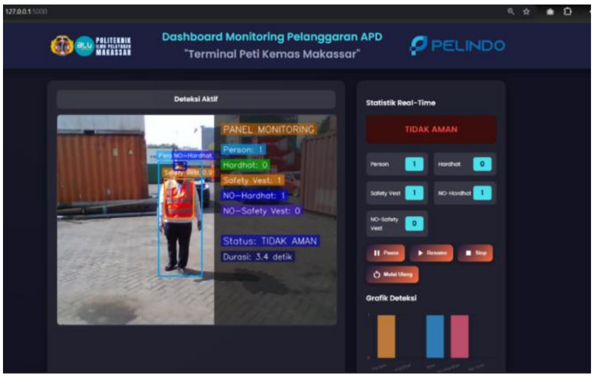

Figure 9. Application Display when a Violation Occurs

Figure 9 shows the application dashboard when the system detects that all individuals in the camera frame are wearing complete PPE, namely helmets (hard hats) and safety vests. The system gives a “SAFE” classification, which is displayed visually in the statistics panel on the right side of the interface. The following are the important elements that appear in the application display:

a. Bounding Box on individuals with detected PPE attribute labels (helmets, vests).

b. Monitoring Panel summarizing the number of people, helmets, vests, and violations (NO-Hardhat: 0, NO-Safety Vest: 0)
c. Safety Status with a green "SAFE" label, indicating no violations.
d. Real-time statistics showing automatic calculations based on frame analysis.
e. Detection graph showing the number of objects detected per type (person, helmet, vest) in the form of a histogram.

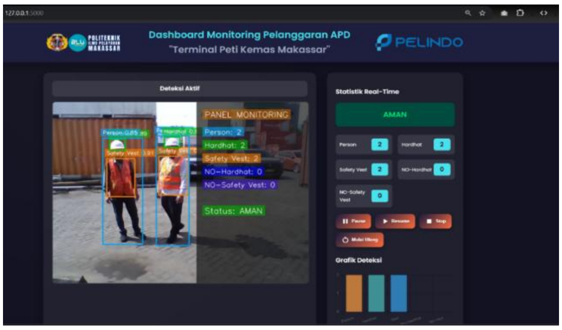

Figure 10. Application when no violation occurs

This display shows the system's success in detecting compliance with PPE usage and provides quick visual feedback to field operators. The system will automatically update the status and graphics dynamically based on real-time video input from surveillance cameras.

4. Discussion

Based on the results of research conducted on the automatic detection of Personal Protective Equipment (PPE) for loading and unloading workers at PT. Pelindo Terminal Peti Kemas Makassar using a Deep Learning approach, it can be concluded that the research has successfully developed a prototype automatic PPE detection system (safety helmets and reflective vests) that is integrated with a monitoring dashboard and real-time notifications. The YOLOv8-based detection model showed fairly good performance with precision values of 0.7–0.9, recall values of 0.5–0.6, and mAP50 reaching 0.7–0.8, indicating that the system is capable of recognizing main objects with high accuracy.

Field scenario testing results show that the system can consistently distinguish between workers who comply with and violate PPE usage rules, and send automatic warnings when violations occur. 4. This prototype supports PT. Pelindo Terminal Peti Kemas Makassar's Health, Safety, Security, and Environment (HSSE) efforts in improving surveillance effectiveness and reducing the risk of workplace accidents due to negligence in PPE use. Overall, this research shows that the application of Computer Vision technology with the YOLOv8 algorithm can be an innovative solution in workplace safety monitoring systems in port areas, particularly in the loading and unloading area of the Makassar Container Terminal.

5. Conclusions

Based on the results of research and system implementation, several recommendations can be made, namely System Development in a Real Environment. System implementation needs to be further tested on a broader operational scale, with surveillance cameras placed at various strategic points in the terminal. This will test the system's ability to deal with complex and dynamic field conditions. Integration with the HSSE Management System. The automatic PPE detection system can be integrated with PT. Pelindo's Health, Safety, Security, and Environment (HSSE) management system so that notifications of violations can be immediately followed up by the supervisory team, making the safety control process more responsive.

Expansion of Detectable PPE Types: Further research is recommended to add other categories of PPE such as safety shoes, gloves, and protective eyewear. This is important to expand the scope of the system so that it can provide more comprehensive protection. Development of Real-Time Monitoring Technology: The system needs to be optimized to run in real-time by utilizing edge computing technology or devices such as Jetson Nano, so that processing can be done directly on site without relying entirely on a central server. Improvement of Socialization and Compliance Aspects: In addition to technological aspects, companies need to strengthen the socialization of the importance of PPE use to workers. The automatic detection system should be positioned as a monitoring tool, not as a substitute for workers' awareness of occupational safety.

The deployment of this automatic detection system for Personal Protective Equipment (PPE) must be accompanied by ethical considerations, particularly regarding worker privacy. The system's use for monitoring should be transparent, clearly communicated to all personnel, and strictly limited to improving occupational safety and health (OSH) compliance. Data collected should be anonymized where possible, securely stored, and only used for the intended purpose of reducing workplace accidents. Furthermore, the detection system should serve as a supportive tool and not replace a culture of worker safety awareness and active supervision.

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