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Implementation of Personal Protective Equipment Detection Using Django and Yolo Web at Paiton Steam Power Plant (PLTU)

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ABSTRACT

Work accidents can occur at any time and unexpectedly, so work safety is associated with health because the work safety system in Indonesia is related to the K3 (Occupational Safety and Health) program. To create a safe and healthy work environment, occupational safety and health management are implemented to avoid work accidents by requiring every worker to use Personal Protective Equipment (PPE). This research aims to develop an immediate detection system for violations of Personal Protective Equipment (PPE) in the workplace using the Yolov8 Method and the Django web-based user interface framework. Yolov8 is one of the latest deep-learning object identification models while Django is the most popular Python developer framework. The system is designed to improve workplace safety and prevent accidents by monitoring compliance with PPE requirements. The research methodology involves literature study, image data collection, preprocessing, model training, and system deployment using the Django framework. There are four classes of detection based on the bounding box according to the specified color, the use of helmets and safety vests based on the red bounding box for helmets and blue for vests while when helmets and safety vests are not being used, based on green and yellow bounding boxes. The system successfully detected four PPE classes with an average accuracy of 82.3% from 230 test data, a mAP50 value of 81.6%, a precision value of 90.3%, and a recall value of 75.1%. The findings from this study indicate that the developed system can effectively improve occupational safety and health management. However, there is a detection error factor caused by the lighting and specifications of the camera used. Future research can focus on integrating the system with other work safety systems to provide a comprehensive solution for accident prevention.

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1. INTRODUCTION

Every employer wants the best for the company and its workforce to achieve their goals. Occupational Safety and Health (K3) is at the forefront of creating a healthy and safe work environment because the safety system in Indonesia is related to the K3 (Occupational Safety and Health) program [1], [2]. Because, work accidents can occur at any time and unexpected time starting from the tools used, machines, materials, or materials, even from the behavior of the workers themselves. To create a safe and healthy work environment, Occupational Safety and Health (K3) management is implemented to avoid work accidents that cause company and labor losses by requiring workers to use Personal Protective Equipment (PPE) [2], [4].

Indonesia has the largest power plant, the Paiton Steam Power Plant (PLTU) which has a high capacity of 4,600 megawatts (MW), located in Binor Village, Probolinggo Regency, East Java. In the process of a Steam Power Plant (PLTU) using a lot of fuel, machinery, and heavy equipment there are potential hazards that can cause work accidents. It is known that in 2018 in this company there was a work accident that fell from the 6th floor when dropping material. Personal Protective Equipment (PPE) is a form of protection in minimizing the possibility of work accidents and prioritizing safety at work [5], [6]. The company has a big responsibility to its workers for occupational safety and health by providing personal protective equipment following the requirements and standardization that have been determined [3], [8].

There are several studies related to the detection of the use of Personal Protective Equipment (PPE). In 2021 [9], The research focuses on the use of PPE Safety Helmets and Vest through videos using the You Only Look Once (YOLO) version 5 method with the best results at batch parameter 8 epoch 50 with an accuracy of 95% from a test of 12 image data. However, the object detection results of the YOLO method are in the form of a bounding box whose segmentation is not directly on the intended object [4], [8].

Researchers [11]. developed a method using Mask Region Convolutional Network (Mask R-CNN) by distinguishing four classes of objects, namely workers using personal protective equipment and hair (hair) or no_vest (not vested) and workers who do not use personal protective equipment. The best result is at parameter epoch 35 with a loss value of 0.1985 and val_loss value 0.1933 in 461s 922ms/step with 95% accuracy from 250 test images [5], [10].

The next research on the development of a system for PPE detection is using the Yolov2 method based on the Flask web [13]. Stages start from data collection, image annotation, modeling, and finally deployment using Flask which produces a system with a bounding box with an average accuracy of 81.60% [6], [12].

To improve the accuracy of PPE detection, this research proposes a new system using YOLOv8 and the Django Web user interface in real time. Yolov8 is one of the latest deep learning object identification models from Yolo which focuses on speed, size, and accuracy, in contrast to previous research which still uses yolov2 [7], [19]. While using Django Web to make it easier to create a system that uses Python language and the most popular framework [8]. Detection is done using a webcam or real-time which is then marked in the form of a bounding box according to the dataset of previous training results with high speed and accuracy. This research is also built using more than one camera that can be used at each corner of different workplaces that previously only displayed one camera [10], [16]. By using yolov8 and Django web, the system is expected to be able to produce more accurate detection than before. The purpose of developing this system is to facilitate monitoring and checking violations of the use of personal protective equipment.

2. METHODS

The research stage as shown in Fig. 1 starts from the literature study process based on books, research, and journals related to the topic of PPE detection, Yolo, and Django. Then formulate the problem, namely building a detection system using the latest methods to facilitate checking violations of PPE use. Followed by collecting datasets and processing data according to the plan, namely detection focusing on Safety Helmets and Vest. After that, modeling and deployment of the system, finally testing and analyzing the results of the system that has been made [9], [18].

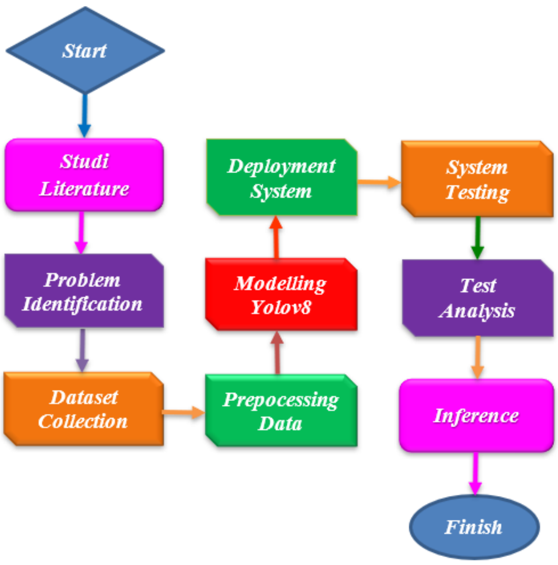

Fig. 1. Research Stages

2.1. Literature Study

Used to study theories and knowledge related to research problems. As a comparison to previous research and a reference in improving or completing research used as a solution to previously identified problems. Literature studies come from books, journals, and previous research, namely the detection of the use of personal protective equipment for the safety and health of the workforce. This is needed so that workers are aware of their discipline and obligations while in the work environment. And system development is carried out to create a user interface to make it easier to check workers' violations [10], [22].

2.2. Problem Identification

Work accidents often occur because workers are negligent about their safety and are not disciplined in using personal protective equipment while in the work environment. The detection of personal protective equipment has been done many times before with different methods and systems such as detection using Yolo based on flask web. From the results of identifying these problems, it becomes a reference or description for developing a new system using the yolov8 method and the Django web user interface with higher speed and accuracy than before. The purpose of developing this system, namely to facilitate monitoring and checking violations of the use of personal protective equipment, and does not take a long time [11], [21].

2.3. Dataset Collection

In every research, data is needed to process as needed. The dataset contains a set of images of workers in the construction sector who use PPE in the form of helmets (head protectors), vests (vests), and workers who do not use PPE [12], [26]. Datasets are obtained through an online-based dataset provider source, namely https://roboflow.com/. And can be accessed via the following link https://public.roboflow/object-detection/hard-hatworkers by downloading the Pascal VOC (Visual Object Classes) dataset format so that the downloaded annotation format is *.xml.

This system development uses roboflow to collect datasets as shown in Fig. 2. The main page of roboflow, an online-based dataset provider source can be accessed through the following page https://roboflow.com/ . There are various kinds of datasets on roboflow, while this research focuses on safety helmets and vests. This dataset contains a random set of images of workers involved in construction that will be reprocessed according to research needs [13], [28].

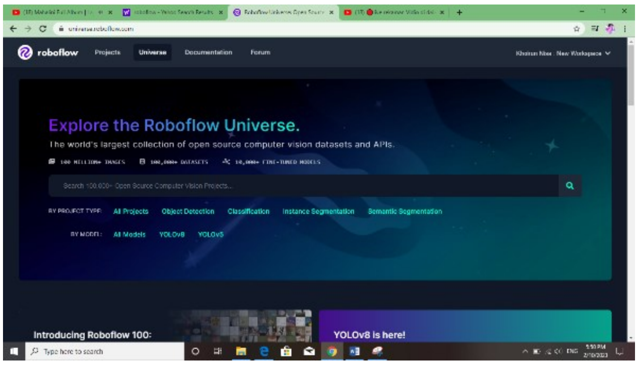

Fig. 2. Roboflow Main Page

Roboflow provides a hard hat worker dataset of 7,041 image data accompanied by annotations or labeling which is then downloaded in yolov8 format to facilitate the detection process. In Fig. 3 the dataset is downloaded in yolov8 format but there are only 3 classes in the form of heads, helmets, and people. While this research focuses on safety helmets and vests that use four classes in the form of helmet, vest, no-helmet, and no-vest. The dataset will be annotated according to the specified class.

The previously downloaded dataset is a ZIP file in yolov8 format consisting of test data, training data, val data, and yaml data as shown in Fig. 4. Of the 7,041 images, it has several image sizes from 179×270 pixels to 640×959 pixels stored in *.jpg format. Each data consists of images and annotations in the form of bounding boxes according to their respective classes, namely head, helmet, and person stored in *.txt format. Furthermore, image data is taken randomly for training data and research validation with the annotation process on roboflow according to the specified class.

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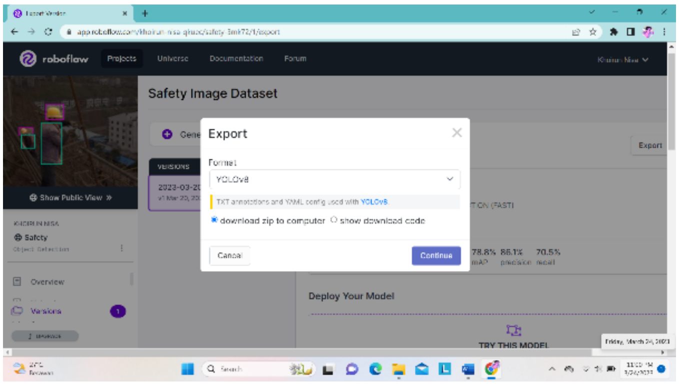
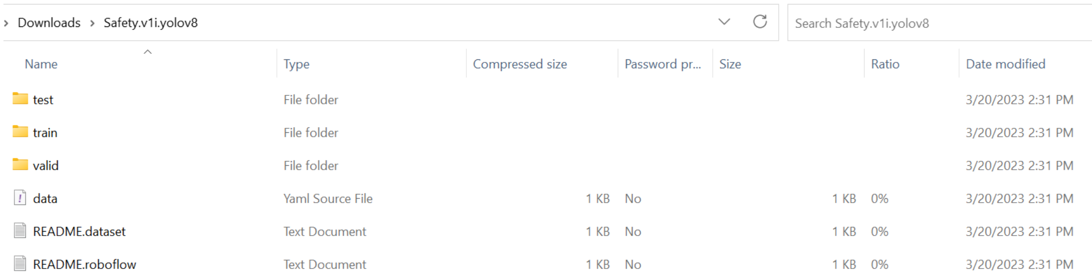


Fig. 3. Format Download Yolov8



Name	Type	Compressed size	Password pr...	Size	Ratio	Date modified
test	File folder					3/20/2023 2:31 PM
train	File folder					3/20/2023 2:31 PM
valid	File folder					3/20/2023 2:31 PM
data	Yaml Source File	1 KB	No	1 KB	0%	3/20/2023 2:31 PM
README.dataset	Text Document	1 KB	No	1 KB	0%	3/20/2023 2:31 PM
README.roboflow	Text Document	1 KB	No	1 KB	0%	3/20/2023 2:31 PM

Fig. 4. Raw Dataset

2.4. Preprocessing Data

Image data of workers who use PPE in the form of helmets and vests as well as image data that does not use PPE will be annotated according to certain classes. Previous research has different classes but the annotation process uses the Labelling Img application [14], [28]. Furthermore, the annotation results will be saved in *.txt format which will be used in the specified data processing process.

Fig. 5 represents the classes used in the dataset, clearly showing the difference between workers who use complete PPE and do not use PPE [15], [26]. Image data obtained through roboflow will previously be annotated through the roboflow page according to the specified class. This research is categorized into 4 parts, namely helmet, no_helmet, vest, and no_vest which are marked with a bounding box. From 7,041 image data, 2,300 image data are randomly taken which will be used as training data and research validation, then annotate or label each image data according to the class.

Helmet and Vest　　No_Vest and No_Helmet

Fig. 5. Class Representation

Roboflow develops computer vision services to run AI projects. The first thing to do is upload data on the roboflow platform and then it will be organized to improve the automatic model of analyzing images to make it easier when doing bounding boxes and labeling, annotations on images are integrated and simplified directly with the roboflow model by labeling each object needed and the data will be input to the trained model. The model can be deployed so that the detection results of the trained model can be seen. Roboflow workflow is very easy as shown in Fig. 6.

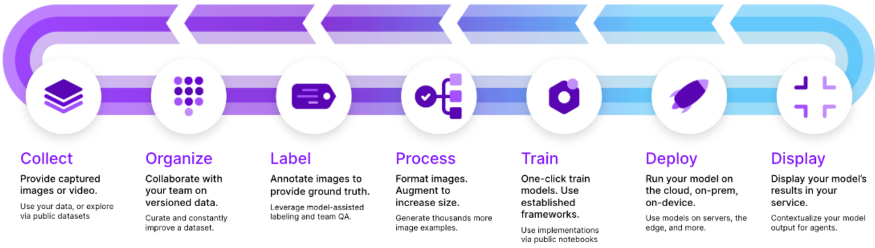


Fig. 6. Roboflow Workflow

Fig. 7 is a sample dataset of 7,041 images containing image data of workers involved in construction from several job positions. In this research, the dataset and annotation process use roboflow based on predetermined classes, namely helmet, no_helmet, vest, and no_vest. The annotation results are divided into three parts in the form of training data, testing data, and validation data accompanied by yaml data. There are 230 test data, 1,610 training data, and 460 valid data, each of which already has a label. Image data that has been annotated will be used to create a detection model using Google Collaboratory by calling the data. It can be downloaded first or called directly using the link provided.

Fig. 7. Samples Dataset

Fig. 8 is the process of annotating or labeling image data according to the class used. Image annotations are marked with a color bounding box for each class, the helmet bounding box is red while the vest bounding box is blue. The no-helmet bounding box is green and the no-vest bounding box is yellow. The image labeling process is following the needs of the classes that will be used in the study consisting of helmets, vests, no_helm, and no_vest. The helmet and vest classes represent workers who use Personal Protective Equipment (PPE), while the no_helmet and no_vest classes represent workers who do not use Personal Protective Equipment (PPE) so that the class of people previously available from Roboflow can be eliminated [16], [28]. The annotations made are saved in *.txt format.

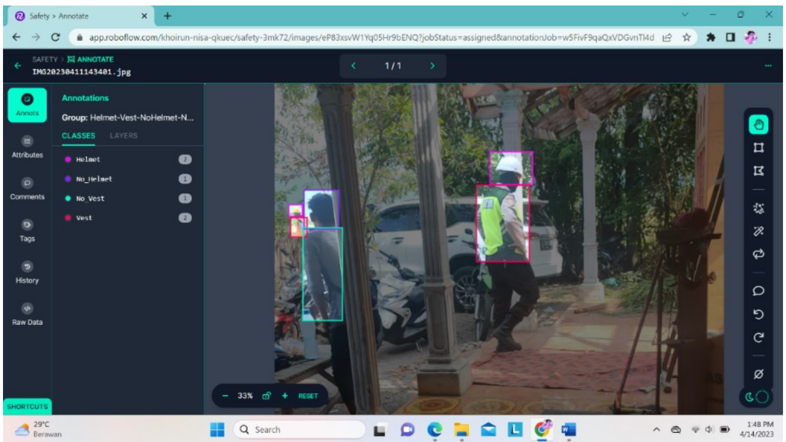


Fig. 8. Class and Image Annotations

2.5. Modeling

The pre-processed data is used as training and testing of the data recording process. There are two files used as the basis for training the system, namely training data and testing data. The model uses the Yolov2 algorithm with the training process at Google Collaboratory. The testing process is directly webcam-based or in real-time using the Flask web browser framework.

Yolov8 is the latest version of an object detection and image segmentation model designed with a strong focus on speed, size, and accuracy, making it an attractive choice for a wide range of vision AI tasks. YOLOv8 outperforms previous versions by incorporating innovations such as a new backbone network, a new anchor-free split head, and new loss functions. These improvements enable YOLOv8 to deliver superior results, while maintaining a compact size and exceptional speed [17], [30].

Fig. 9 is a Yolov8 workflow using the latest version of Ultralytics. The yolov8 workflow involves collecting datasets from online dataset providers such as roboflow or a collection of custom datasets. Next, prediction and training of previously annotated data is carried out. Finally, the system is modeled and deployed as desired [32], [33].

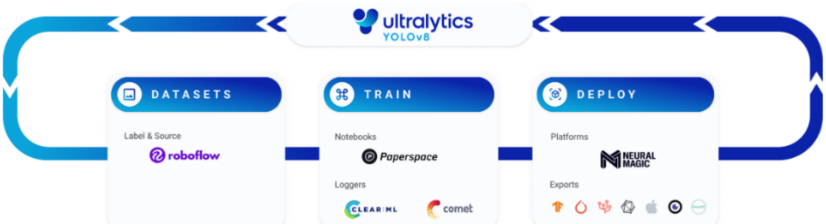


Fig. 9. Yolov8 Workflow

Fig. 10 is the data training process using 40 epochs completed in 0.693 hours. Each result of the data training process is automatically stored in the runs/detect/train file, the learning model will automatically be stored in the best.pt format and the model will be used in the trial process. The yolov8 training process includes testing and determining parameters to get the desired accuracy value in the research. The parameters used are batch and epoch, batch itself as a determinant of the data division process during the training process, and epoch as a determinant of how many times the learning method is carried out.

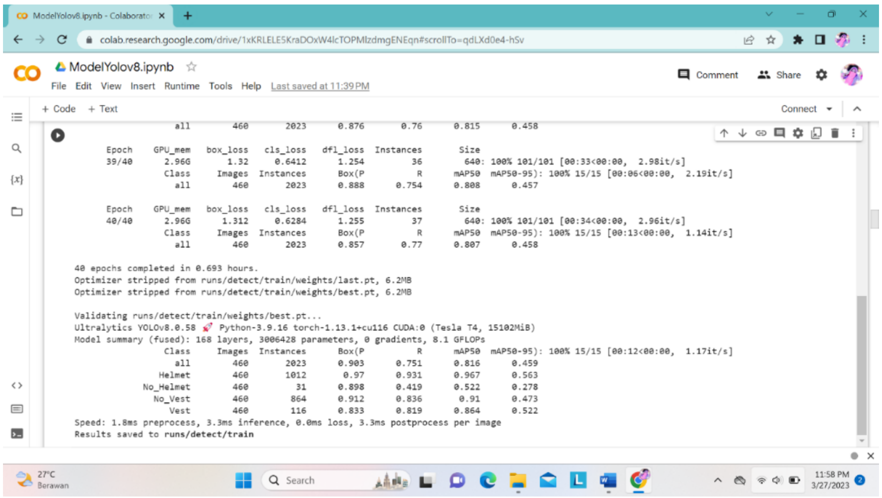


Fig. 10. Training Process

After the development is complete, the system takes real-time images and sends them for analysis. Confusion matrix as an accuracy analysis in determining the number of classes in the calculation round. The following is a picture of the confusion matrix used in this study. System accuracy is needed to find out how accurate the system that has been made by relying on the prediction and recall values. Precision is calculated to establish the amount of accuracy between the requested information and the response of the system while recall is the ability of the system to find information and accuracy is the degree of closeness between the predicted value and the accuracy value using the confusion matrix. Two columns of information about the calculation of the confusion matrix are contained in Table 1.

Table 1. Confusion Matrix

Predict	**Actual Values**	
	Positif	**Negative**
Positif	TP	FP
Negatives	FN	TN
	True	

The type of data used and the result of the categorization, if a helmet and safety vest are found and the system can correctly identify both then the finding is classified as True Positive (TP). A detection finding is considered a False Positive (FP) if the item is not a helmet and safety vest but is identified as such by the system. When the object of the helmet and safety vest is detected as not helmet and safety vest, it will be classified as False Negative (FN). And if the non-helmet and safety vest object is detected as not a helmet and safety vest, it will be classified as True Negative (TN). To get an accurate result, the accumulation will be calculated using the following formula as follows:

To calculate Accuracy, the formula is used:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

To calculate Precision, the formula is used:

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

To calculate Recall, the formula is used:

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

2.6. Deployment System

In this process, namely creating a user interface using the Django framework which is built using the Python language after getting the right and accurate model. Django itself is used as a web deployment prototype that can recognize workers who use safety helmets and safety vests and do not use them. Django is a Python-based framework, which has advantages in terms of functionality and can speed up the process of creating an application or website. This is because Django includes Python code that is already written and ready to use. The Django framework includes a set of fully functional classes, libraries, and modules to create powerful websites and applications [18], [43].

Fig. 11 is the flow of the system deployment process, the Django framework runs on top of the Python program, so before installing Django, make sure you have successfully installed Python first and activated the Python Pip package to facilitate development. After successfully installing Python and the Python Pip package open CMD or use the Git Bash plugin to open the folder that will be used to deploy the system. then create a virtual environment so that the project created is isolated. Then enter the virtual environment to install the Django framework and the plugins needed for the system. After the needs are met, make the design as desired and finally proceed with testing the system that has been created.

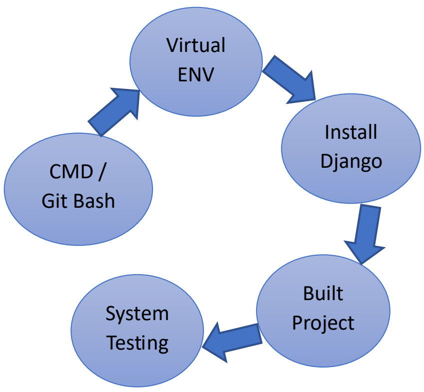


Fig. 11. Deployment System Process

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Previous research has made web deployment using Flask with the yolov2 method. Flask is a web microframework built with Python which is categorized as a web framework. The user interface design is made with a simple "real-time safety detection" page that contains Navigation Bar, Running Text, and real-time detection results. A simple user interface design that only displays one navigation bar with one camera.

Fig. 12 shows an illustration of the User Interface design of this development system. The simple User Interface has two navigator bars and a detection page that can use more than one camera. Detection takes place if the camera is active on an available camera when the system is running. Detection results will continue to run while the system is still active on the detection page. The system can use one or more cameras as needed.

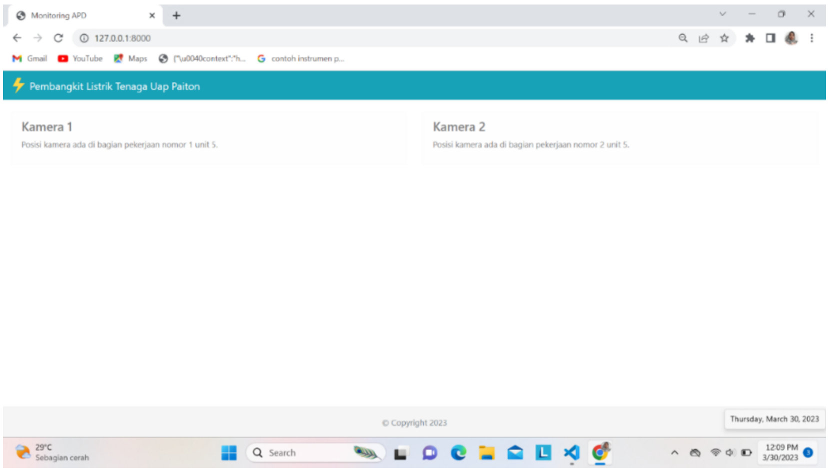

Fig. 12. User Interface Design

3. RESULTS AND DISCUSSION

3.1. Results

This research produces a web-based detection system using the Yolov8 algorithm in real-time. The dataset used is 2,300 image data divided into 3 parts, namely training data of as many as 1,610 images, testing data of as many as 230 images, and validation data of as many as 460 images consisting of 4 classes namely helmet, vest, not_helm, not_rompi. The accuracy of helmet and safety vest detection is reported to achieve maximum accuracy at an accuracy level of 95%, with an average Average Precision (mAP) value of 78.8%, a precision value of 86.1%, and a recall value of 70.5%. Tests were conducted on 230 test data images, and the system was able to detect the use of helmets and safety vests based on the red bounding box for helmets and the blue color for vests. The system can also detect when helmets and safety vests are not in use, based on the green and yellow bounding boxes. The detection results are presented in real time on both the front and rear views. However, the accuracy of detection is affected by factors such as lighting, object distance, camera specifications, and internet lag. Detection can also use more than one camera such as CCTV placed in every corner of the room or workplace.

Fig. 13 is the result of the model training graph with an epoch of 50 on Google Collaboratory. The results of precision with epoch 40 have produced quite high precision, the greater the result of the precision level in object detection, the lower the error rate of each object detection performed.

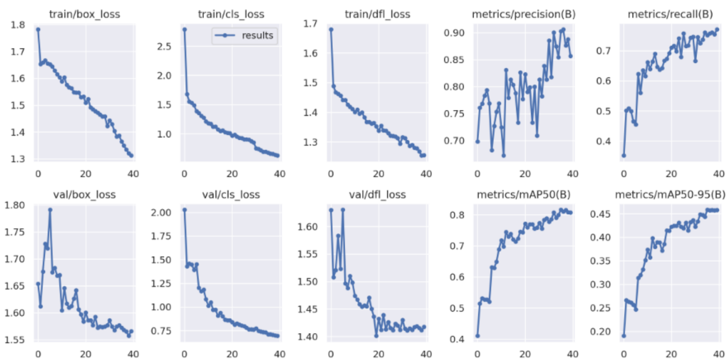

Fig. 13. Training Result

3.1.1. Detection page using safety helmet and vest from a front view

From the detection results in real-time or live streaming on Fig. 14 with front-facing, the test successfully detects using a safety helmet and vest based on the bounding box of red color using a helmet with a helmet description and blue color using a vest with a vest description. However, the accuracy of each detection will change according to the position and lighting at the time of detection.

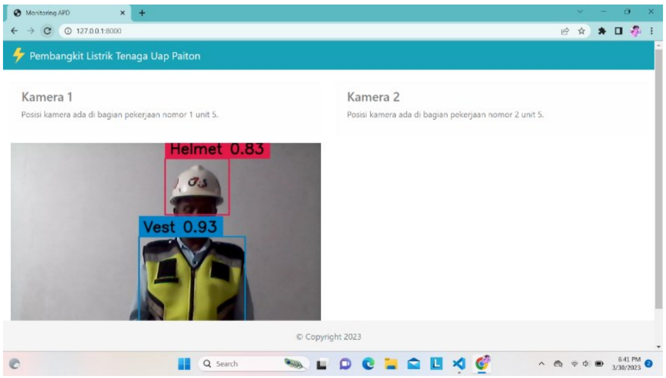

Fig. 14. Front view detection result

3.1.2. Detection page using safety helmet and vest from at back view

From the detection results in real-time or live streaming on Fig. 15 with rear facing, the test successfully detects using a safety helmet and vest based on the bounding box of red color using a helmet with a helmet description and blue color using a vest with a vest description.

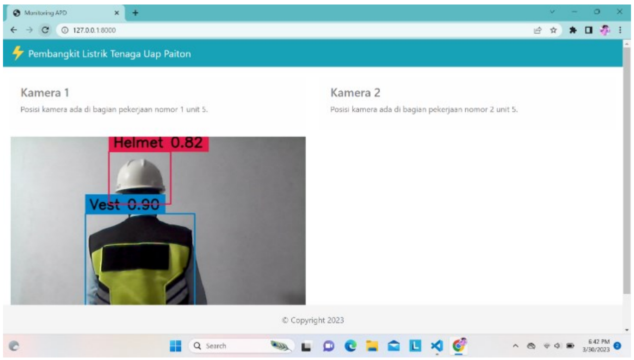

Fig. 15. Rearview detection result

3.1.3. Detection page not using safety helmet and vest from a front view

From the detection results in real-time or live streaming on Fig. 16 with front-facing, the test successfully detects not using safety helmets and vests based on the bounding box of green color not using a helmet with the description no_helmet and yellow color not using a vest with the description no_vest.

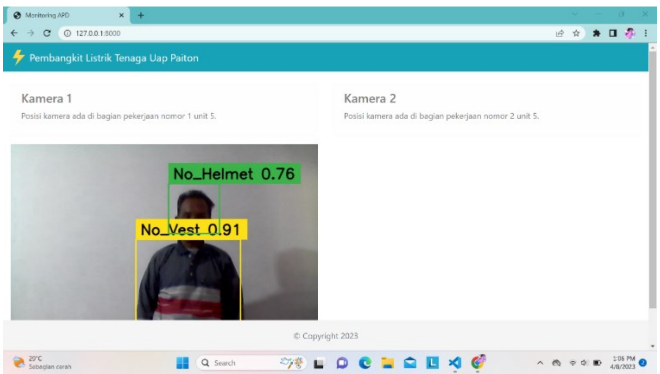

Fig. 16. Front view detection result

3.1.4. Detection page not using safety helmet and vest from at back view

From the detection results in real-time or live streaming on Fig. 17 with rear facing, the test successfully detects not using safety helmets and vests based on the bounding box of green color not using a helmet with the description no_helmet and yellow color not using a vest with the description no_vest.

Fig. 17. Rearview detection result

However, there are errors in detection due to lighting, internet slowness, camera specifications, and also pre-made models. This happens because there are similarities in the intended object and the image is not legible. For example, in Fig. 18, the detection does not match the model that has been made before.

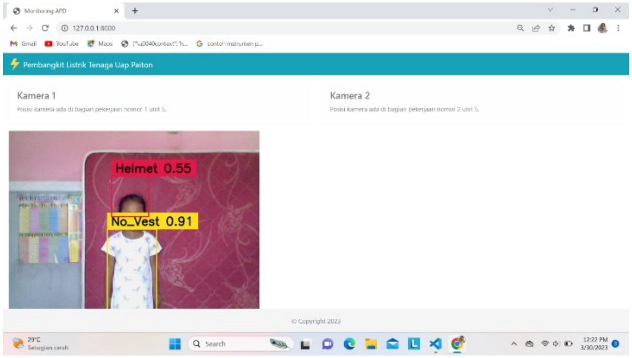

Fig. 18. Detection results are not suitable

3.1.5. Safety no helmet and vest detection page

From the detection results in real-time or live streaming in the image, the test successfully detects the use of a safety helmet and vest based on the bounding box of each color according to the previous annotation. The system can distinguish between a safety helmet and a vest as shown in the picture. Fig. 19 shows that the system can detect objects not wearing a helmet and using a vest with an accuracy that continues to run as long as the object is detected by the camera marked by the bounding box.

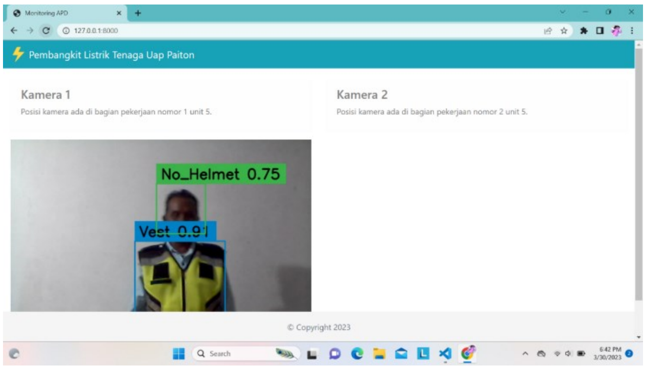

Fig. 19. Detection of no_helmet (head) and vest

Fig. 20 shows that the system can detect objects not wearing a helmet but wearing a kopyah and not using a vest with an accuracy that continues to run as long as the object is detected by the camera marked by the bounding box.

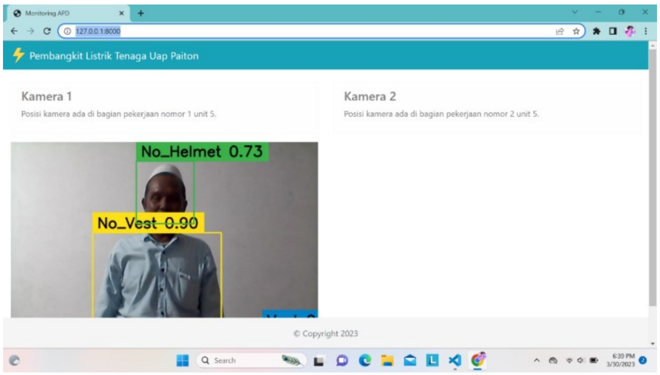

Fig. 20. Detection of no_helmet (skullcap) and no_vest (shirt)

3.2. Discussion

Detection of the use of personal protective equipment has been carried out but has not been able to determine the number of each class that has been successfully detected. Furthermore, it has successfully built a flask web-based real-time safety helmet and vest detection system but several factors affect the detection results. It is necessary to estimate the time calculation of the accuracy of the method in detecting so that it can determine the number of objects detected. Some factors that affect the detection results are lighting, camera object position, and height/distance of the object. implementation is carried out to update the system with the latest version in overcoming violations of personal protective equipment.

Previous research has been able to detect personal protective equipment and there is a system that uses one camera. In the development of this system, it can use more than one camera so that it can monitor violations from every corner of the workplace as needed. The system can detect the use of helmets and safety vests based on the bounding box in real-time and the accuracy obtained is higher than before. The purpose of this system is to facilitate monitoring and checking violations of the use of personal protective equipment and does not take a long time.

Fig. 21 is the result of a confusion matrix that has been created using Google Collaboratory with an mAP of 86.1%, a precision value of 90.3%, and a recall value of 75.1%. From these results, the image can be detected correctly and accurately according to the model that has been made. The precision and recall values are calculated using the confusion matrix, and the average accuracy is calculated based on the detection of the four classes (helmet, no_helmet, vest, no_vest). The highest accuracy was achieved for the helmet object, with a value of 95%. The average accuracy (precision) was reported as 90.3%, while the average accuracy (recall) was not explicitly stated.

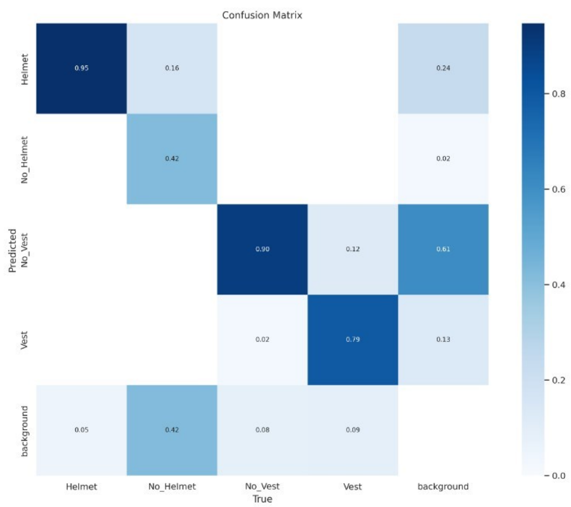

Fig. 21. Confusion Matrix Results

The matrix calculation can be seen in Fig. 21 where the highest accuracy is achieved for the helmet object, with a value of 95%. Apart from the four predetermined classes, to find out the accuracy, precision, and sensitivity values of the model generated from each of the previous parameter trials, it can use the Confusion Matrix calculation based on Table 1. From the results of the confusion, the matrix can also calculate the average accuracy of this research based on Table 2.

Table 2. Average Accuracy

Predict Class	**Actual Value**				
	Images	**Instances**	**Box (P)**	**Box (R)**	**mAP50**
All	460	2023	0.903	0.751	0.816
Helmet	460	1012	0.97	0.931	0.967
No_Helmet	460	31	0.898	0.419	0.522
No_Vest	460	864	0.912	0.86	0.91
Vest	460	116	0.833	0.819	0.522

$$Average\ Accuracy\ (Precision) = \frac{\mathrm{H + NH + NV + V}}{\mathrm{Object}} = \frac{97 + 89.8 + 91.2 + 83.3}{4} = 90.3$$

$$Average\ Accuracy\ (Recall) = \frac{\mathrm{H + NH + NV + V}}{\mathrm{Object}} = \frac{93.1 + 41.9 + 86 + 81.9}{4} = 75.1$$

$$Average\ Accuracy\ (mAP50) = \frac{\mathrm{H + NH + NV + V}}{\mathrm{Object}} = \frac{96.7 + 52.2 + 91 + 52.2}{4} = 81.6$$

$$Average\ Accuracy = \frac{\mathrm{AP + AR + AmAP50}}{\mathrm{Object}} = \frac{90.3+75.1+81.6}{3} = 82.3$$

Some images are not read due to distance or lighting during live-streaming detection which causes the results to be incorrect. To reduce the occurrence of errors during detection by increasing the image data used in modeling. Taking datasets is attempted to pay more attention to the distance and clarity of the image to match the specified class. The addition of a more varied dataset both from the situation (morning and night) or various directions of data collection so that it can distinguish from each camera point of view.

The findings of this study show that the developed system can effectively improve occupational safety and health management. However, there is a factor of detection error caused by the lighting and specifications of the camera used. Future research can focus on integrating the system with other work safety systems to provide a comprehensive solution for accident prevention.

4. CONCLUSION

A web-based detection system using the Yolov8 algorithm with the Django web user interface in real time has successfully detected properly and correctly. The dataset used is 2,300 image data divided into 3 parts, namely training data of 1,610 images, testing data of 230 images, and validation data of 460 images consisting of 4 classes namely helmet, vest, not_helm, and not_rompi. The accuracy of helmet and safety vest detection is reported to achieve maximum accuracy at an accuracy level of 95%, with an average Average Precision (mAP) value of 78.8%, a precision value of 86.1%, and a recall value of 70.5%.

Tests were conducted on 230 test data images, and the system was able to detect the use of helmets and safety vests based on the red bounding box for helmets and the blue color for vests. The system can also detect when helmets and safety vests are not in use, based on the green and yellow bounding boxes. The detection results are presented in real time, both on the front and back views. The developed system can effectively improve occupational safety and health management. However, there is a detection error factor caused by the lighting and specifications of the camera used. Future research can focus on integrating the system with other work safety systems to provide a comprehensive solution for accident prevention.

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