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Personal Protective Equipment Detection for Grinding Machine Workers Based on Computer Vision

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Abstract:- Negligence in the use of Personal Protective Equipment for workers is one factor the occurrence of work accidents, especially in manufacturing industries such as grinding process. There has been research carried out to develop it Personal Protective Equipment detection system, but there is still no research specifically in the grinding machine area and there is no system that can take it. decisions from results that have been detected so that no action has been taken directly from worker negligence. In an effort to improve the safety of the workers and reduce the risk of work accidents, especially for workers grinding machine, the author in this final project created a Detection System Design Negligence in the Use of Personal Protective Equipment for Based Grinding Machine Workers Computer Vision using the You Only Look Once v5s detection model (YOLOv5s). This system is able to identify grinding machine workers wearing earmuffs, face shields, masks, gloves, and those who do not use or no earmuff, no face shield, no mask, and no gloves. From overall testing obtained (Frame Per Second) the highest FPS of 2.25 FPS from the image size 256, at an optimal distance of 3 meters with 88% accuracy and light intensity of 600 lux with 76% accuracy run using NVIDIA Jetson Nano 2GB and Logitech C270 webcam.

Keywords:- *Personal Protective Equipment Grinding, Work Accidents, Objects Detection.*

I. INTRODUCTION

Personal Protective Equipment (PPE) according to OSHA (Occupational Safety and Health Association) is equipment used to protect workers from injuries or illnesses caused by contact with workplace hazards, whether chemical, biological, radiation, physical, electrical, mechanical, or others [1]. According to the explanation outlined in the Regulation of the Minister of Public Works and Housing Number 10 of 2021 concerning the Construction Safety Management System (SMKK), PPE includes safety helmets, eye protection, face shields, diving masks, ear protection, gloves, safety shoes, full body harnesses, life jackets, safety vests, aprons, and fall protection [2].

Personal Protective Equipment is regulated under the Indonesian Minister of Manpower and Transmigration Regulation Number PER.08/MEN/VII/2010, where employers are required to provide PPE to workers free of charge. Employers are also obligated to post signs about the requirement to wear safety equipment while working for employees or anyone entering the workplace [3]. This equipment functions for both the safety and security of workers. Security in the production process is a crucial guarantee for the development of a high-quality industrial company. In the manufacturing industry, the factors influencing industrial company safety are increasing, and

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various potential hazards are interrelated and overlapping, often resulting in accidents [4].

Work accidents are unwanted incidents that occur in the workplace and result in injury or even death of workers [5]. The discipline of workers in using personal protective equipment is relatively low, increasing the risk of work accidents that can endanger workers [6]. In the manufacturing industry, one essential tool in the process is the grinding machine, which can pose potential hazards leading to work accidents. Such accidents often occur, including workers getting cut by the grinder, getting splashed by metal fragments, or hit by ejected steel pieces during grinding [7]. Additionally, grinder workers are at risk of occupational diseases due to frequent noise exposure during grinding. The factors causing work accidents and noise exposure among grinder workers are due to their lack of discipline in wearing personal protective equipment (PPE). Furthermore, accidents occur during grinding, such as an incident where "the victim was grinding a steel rod for a house's foundation using an electric grinder. However, an exposed electrical cable (roll cable) stuck to the iron rod being cut, causing the victim to get an electric shock," said AKP Rizky, Tuesday [8].

To reduce the number of work accidents, implementing an effective occupational safety and health management system is crucial. Organizations can identify and control risk factors that can cause accidents or injuries. Appropriate preventive measures can be taken to reduce the likelihood of accidents or injuries, such as equipping employees with suitable Personal Protective Equipment (PPE) [9]. To assist supervisors in conducting inspections, a tool that facilitates the detection of negligence in using personal protective equipment is necessary. Research has been conducted related to hazard and accident analysis in fabrication areas of industries and construction, addressing it by using personal protective equipment [10]. This research produced a tool that can detect workers using personal protective equipment, including face shields and masks [11]. However, this research could not detect earmuffs and gloves. Subsequent research could detect masks and gloves [12], but it could not detect face shields and earmuffs. Further research could detect personal protective equipment such as masks, gloves, and earmuffs [13], but it could not detect face shields. All these detection systems used the same platform, You Only Look Once (YOLO). However, these studies have shortcomings as the system only performs detection without any action based on detected objects. Subsequent research [14] used the YOLOv5s classification platform with detection results divided into nine classes and processed for actions such as capturing images when violations occur. Another study related to detecting personal protective equipment in welding areas used the YOLOv5s classification platform divided into seven classes, with detection results processed for actions such as capturing images when violations occur [15]. None of these studies, however, focused on detecting personal protective equipment specifically for grinding machine use.

Based on the issues described, this thesis proposes designing a system to detect negligence in using Personal Protective Equipment for grinding machine workers based on Computer Vision. The system will be created to identify the completeness of personal protective equipment used by grinder workers using Computer Vision. This method is chosen because Computer Vision is a computer science field focused on creating digital systems that can process, analyze, and understand visual data in the same way humans do [16]. The objective of this Computer Vision method in this thesis is to recognize objects, specifically Personal Protective Equipment. The research includes several stages: collecting images as a dataset, labeling and annotating the data, augmenting the dataset to create additional variations, training the data using the You Only Look Once (YOLO) model, and equipping the detection model with features to capture images (screenshots) when a worker is incomplete in using personal protective equipment. The data will be sent to a cloud server and stored in a database server as violation data accessible via a website. Additionally, notifications of PPE negligence will be sent through Telegram, allowing supervisors to take immediate action. The system will also include real-time monitoring features, enabling supervisors to oversee workers outside the work location. This tool aims to ensure continuous, real-time supervision of personal protective equipment usage among grinder workers, thereby minimizing the risk of work accidents due to negligence in using personal protective equipment.

II. PROPOSED METHODS

This section will explain the method, block diagram for personal protective equiment detection dan monitoring.

A. Proposed System

In Figure 1 a block diagram of personal protective equiment detection system.

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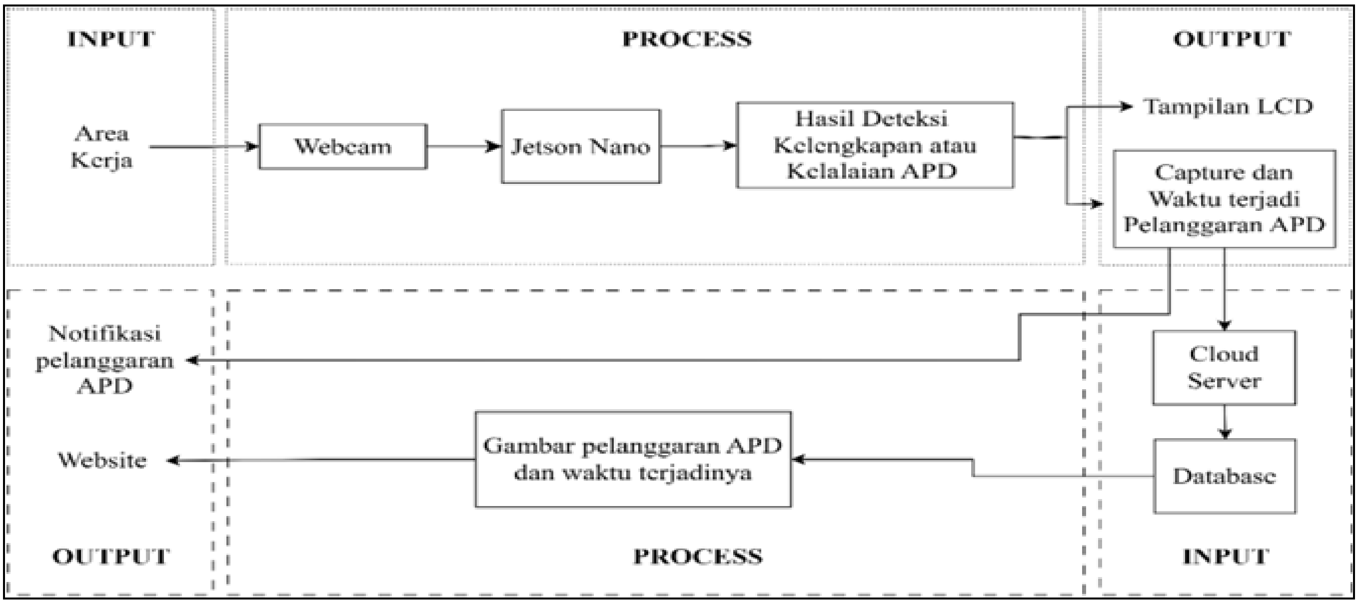

Fig 1 Mapping System Diagram

From the block diagram in Figure 1, the researcher worked on the yellow-colored block, which is "Designing a System to Detect Negligence in the Use of Personal Protective Equipment by Grinding Machine Workers Based on Computer Vision." The work area serves as the input to be processed, where grinding machine workers are either using personal protective equipment or not. A webcam is used to capture images in the work area. These images are then processed by the Jetson Nano using the Deep Learning YOLOv5s method to identify workers and the personal protective equipment being used, such as masks, face shields, earmuffs, and gloves. The identification results from the Jetson Nano are displayed on the LCD screen. When there is a violation of the completeness of personal protective equipment, the system captures the image and saves the violation information in the violations folder on the Jetson Nano.

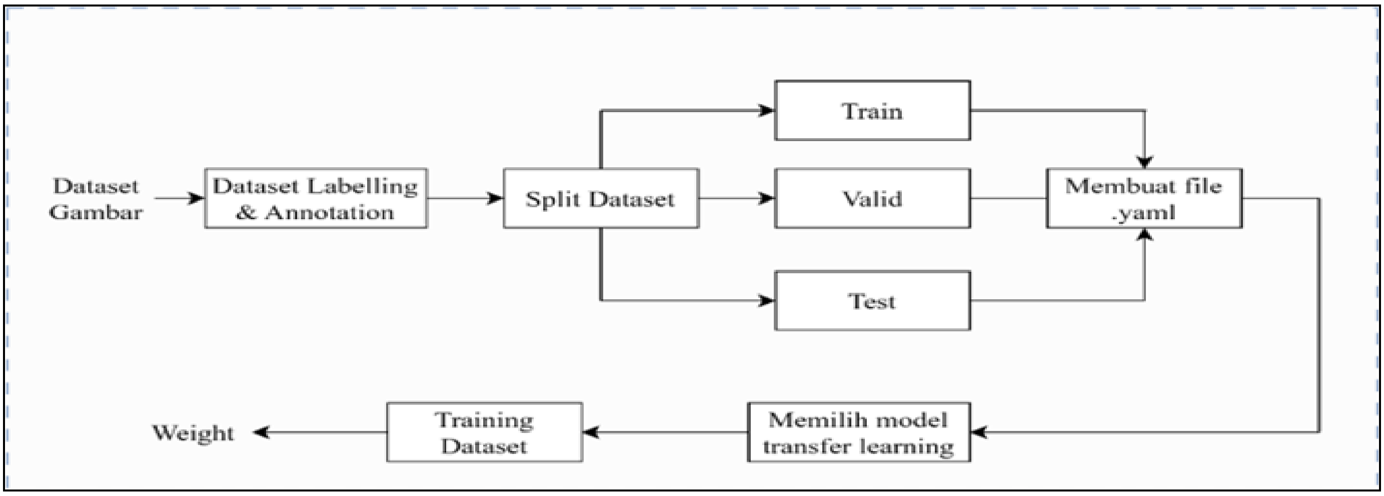

Fig 2 Block Diagram of Data training

Here is an explanation of the data training block diagram shown in Figure 2. First, a dataset was created by collecting images containing the objects to be detected. These images were sourced from Google Images, Roboflow, and personal documentation. The dataset for this system design consists of 4,032 images, with the following class breakdown: 1,580 images of persons, 715 images of masks, 527 images of no masks, 407 images of face shields, 766 images of no face shields, 460 images of earmuffs, 601 images of no earmuffs, 1,318 images of gloves, and 1,195 images of no gloves. Next, the dataset underwent labeling for nine classes: person, mask, face shield, earmuff, gloves, no mask, no face shield, no earmuff, and no gloves. After labeling, the dataset was augmented using the roboflow.ai platform. The augmentation aimed to improve detection accuracy under certain conditions with the following details: horizontal and vertical flips for inverted or mirrored objects, 90º rotation for detecting tilted objects, and cropping to ensure detection even if the object is partially visible, with a 25% tolerance. The dataset was tripled on the roboflow.ai platform, increasing to 9,916 images, thereby enhancing the training set. After labeling and annotation, the dataset was split into three parts: 89% for training, 7% for validation, and 4% for testing.

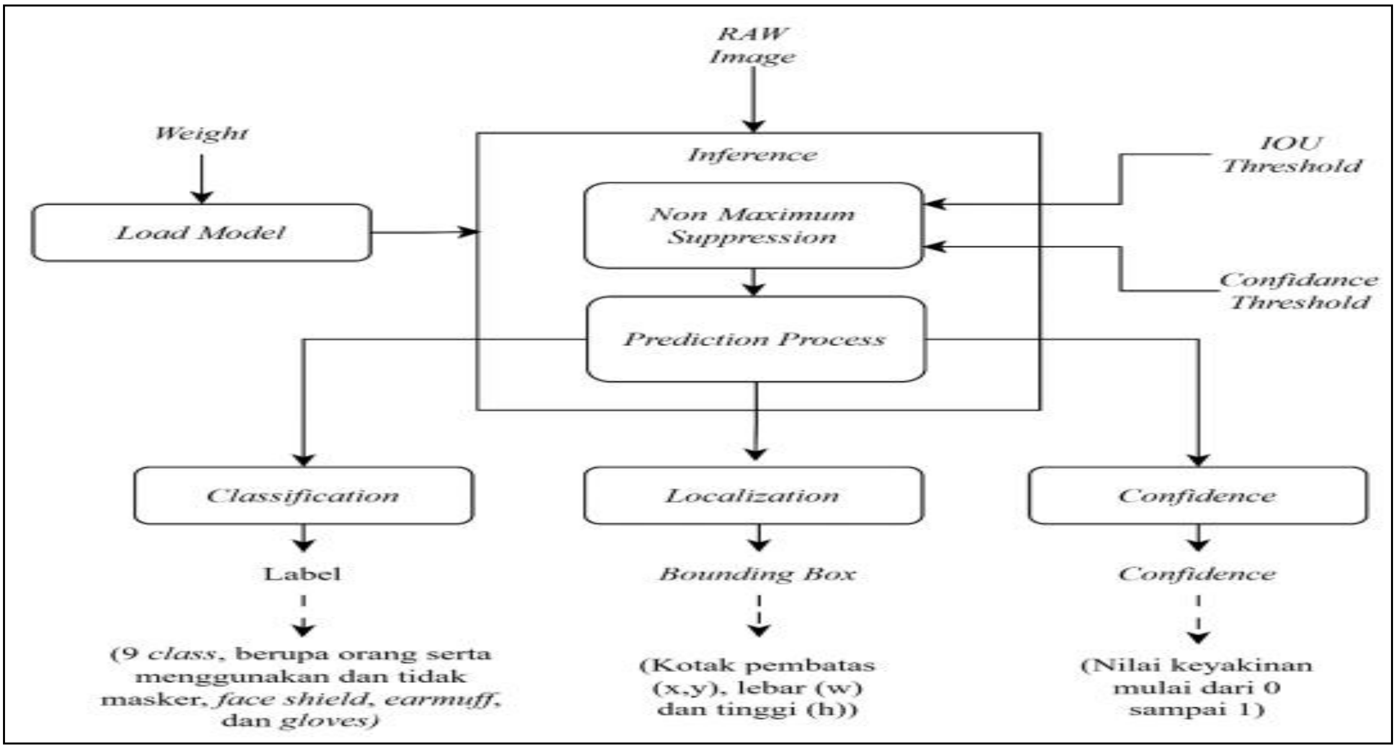

Fig 3 Block Diagram of Object Detection

From the block diagram of object detection in Figure 3, the following can be explained:First, the load model process functions to input the training dataset results, i.e., the weights, into the inference process. Next, in the inference process, there are two inputs: the load model results and RAW images. The inference process consists of two steps. The first step is non-maximum suppression, which uses inputs from the intersection of unity threshold and confidence threshold, each ranging from 0 to 1. The intersection of unity threshold increases the predicted bounding boxes on the image, while the confidence threshold reduces multiple bounding boxes that do not match the prediction model.

The results from non-maximum suppression become the input for the second step, which is the prediction process. This process includes three sub-processes: classification, localization, and confidence. The classification process assigns prediction labels to the bounding boxes. In this study, the classification is divided into nine classes: person, mask, face shield, earmuff, gloves, no mask, no face shield, no earmuff, and no gloves. Figure 3.8 shows an example of the classification process for earmuffs and gloves.

The localization process assigns coordinates (x, y, w, and h) to generate a bounding box around the detected object. The confidence process provides a confidence score for the prediction, ranging from 0 to 1.

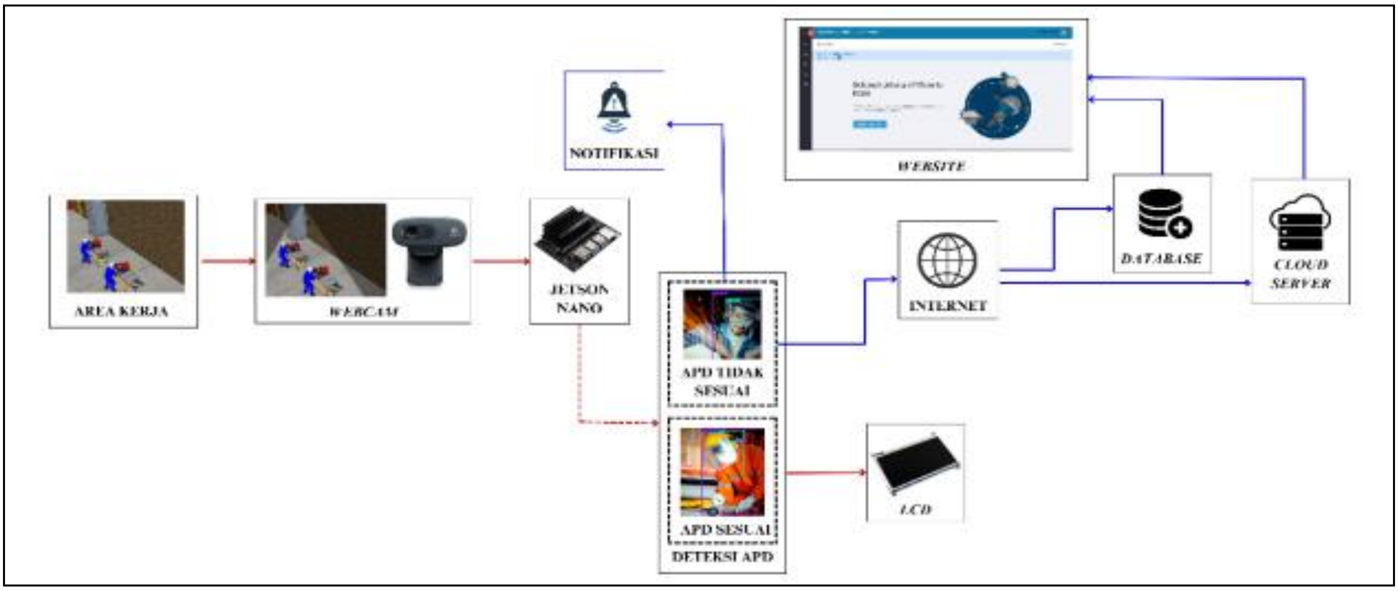

Fig 4 Working Principle of the Tool

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Here is an explanation of the working principle of the device shown in Figure 4: First, workers in the grinding machine work area will be monitored using a webcam. The webcam captures images of the work area and sends the image data directly to the Jetson Nano via a USB cable, without requiring a local network or WiFi for operation. The monitoring results from the webcam will undergo a classification process using the YOLOv5 detection platform on the Jetson Nano, resulting in classifications of workers either correctly or incorrectly using personal protective equipment. In this study, the classification is divided into nine classes: person, mask, face shield, earmuff, gloves, no mask, no face shield, no earmuff, and no gloves.

The detection results, whether the personal protective equipment is used correctly or not, can be viewed on the device's LCD monitor. If the classification results show improper use of personal protective equipment, the system will capture the image, and the results will be sent to a cloud server and stored in a database server via the internet. Once the captured data is stored in the database, it can be viewed and displayed on a website. A Telegram notification will be sent to the supervisor when there is a violation of the use of personal protective equipment, prompting immediate and quick action.

III. EXPERIMENTAL RESULTS

This stage is tool testing carried out on creation of it. The results of this test are to determine the results of planning, analyzing system weaknesses, compare the accuracy and results of the test with thoseplanned. The tests carried out are as follows:

B. *Training Dataset on Completeness of Personal Protective Equipment in the Grinding Machine Worker Area*

In the training process, the dataset is divided into three parts: training, validation, and testing. The training dataset is a set of data used to train or build the model. The validation dataset is a set of data used to optimize the model during training. Once the model has been well-trained and can recognize patterns generally through a high accuracy score, the next step is to use the testing dataset. The testing dataset is a set of data used to test the model after the training process is complete. This is unseen data, meaning that neither the model nor humans should see these samples during the training process.

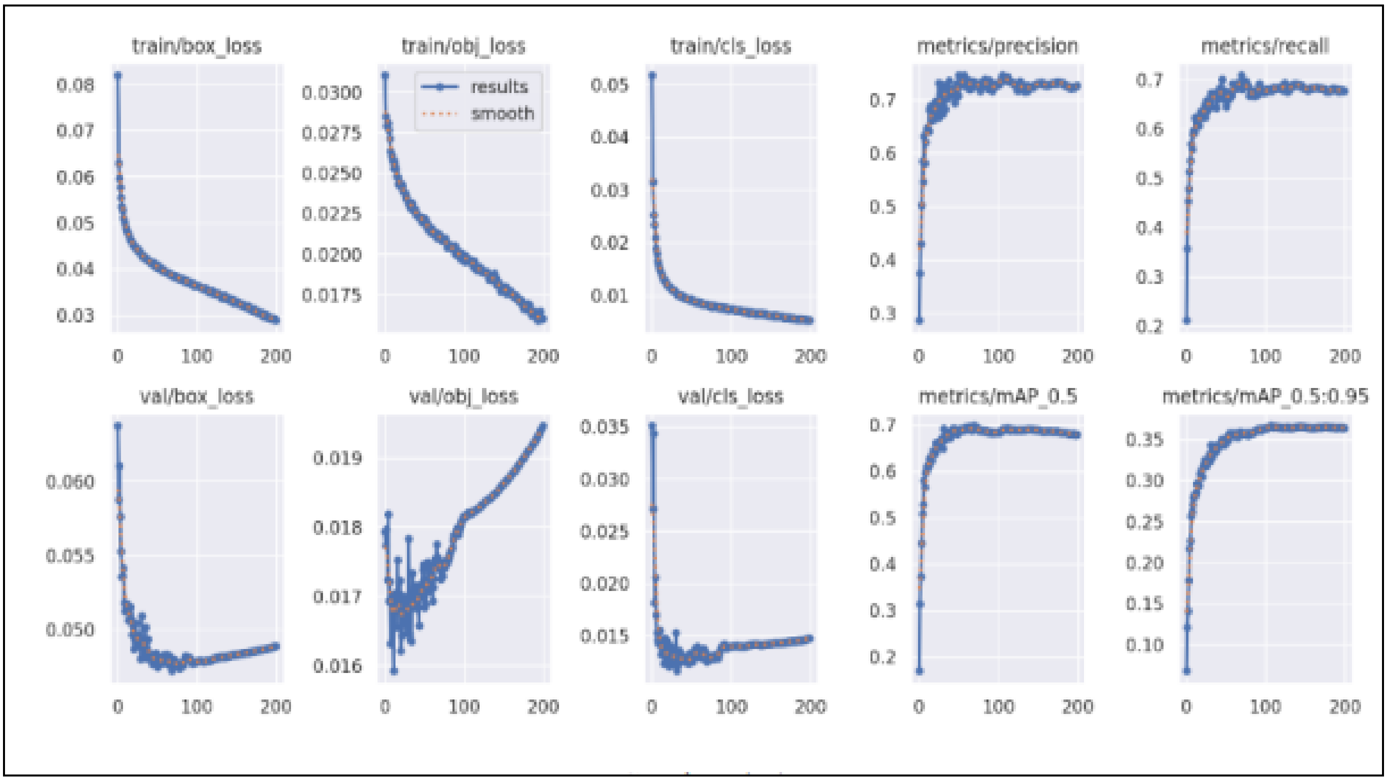

Fig 5 Result of Data Training

There are three types of loss data (indicators of poor model prediction) shown in Figure 5: Box loss, Objectness loss, and Classification loss. Box loss is used to measure how well the bounding box produced by the object detection model matches the ground truth. Objectness loss is used in object detection to assess how accurately a bounding box contains the correct object. Classification loss is used to evaluate how well the object detection model can classify objects correctly.

The value or range of these losses is 0-1, with smaller values indicating a better model. According to Figure 5, the classification loss is close to or below 0.01, the box loss is below 0.03, and the objectness loss is below 0.0175, approaching 0.

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Fig 6 Result of Data Training

Figure 6 shows the experimental results of the training data in the image test set in the dataset. The results of the model training are shown. The system has been able to detect workers' personal protective equipment well.

C. Testing the Personal Protective Equipment Completeness Detection System for Grinding Machine Workers on Jetson Nano

After conducting independent testing by detecting based on class, distance, light intensity, and integrating with the Jetson Nano to test the autorun feature, capture/screenshot program, FPS, and webcam delay, direct testing will be conducted in the work area.

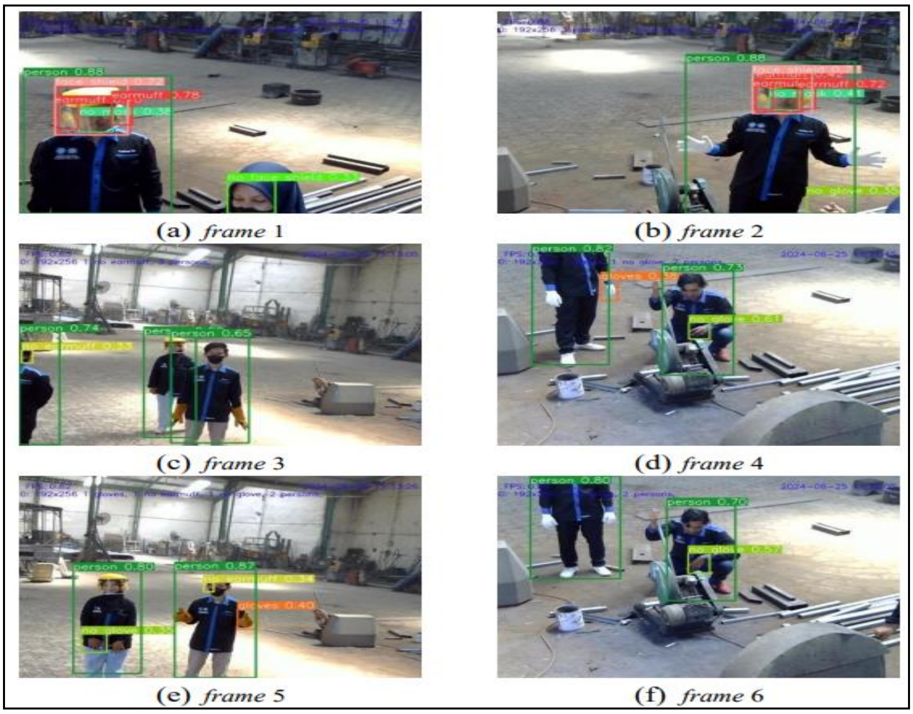

Fig 7 Result of Data Training in PT Rekaindo Global Jasa

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IV. CONCLUSIONS

Based on the design and testing results of the final project titled "Design of a Personal Protective Equipment Negligence Detection System for Grinding Machine Workers Based on Computer Vision," the following conclusions can be drawn:

First, the training dataset consisted of 4,032 images, including 1,580 images of persons, 715 images of masks, 527 images of no masks, 407 images of face shields, 766 images of no face shields, 460 images of earmuffs, 601 images of no earmuffs, 1,318 images of gloves, and 1,195 images of no gloves. The training was performed using Google Colab with the YoloV5s model, resulting in an F1 curve for all classes of 0.72, a precision curve for all classes of 0.74, a recall curve for all classes of 0.68, and a precision-recall curve for all classes of 0.69 mAP @ 0.5.

Second, the system can capture images and save them in the "tidaksesuai" folder, achieving a maximum FPS of 2.25 FPS from an image size of 256, at an optimal distance of 3 meters with 88% accuracy, and at a light intensity of 600 lux with 76% accuracy.

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