Utilization of Big Data For PPE Detection Using Convolutional Neural Network And Yolov8

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Abstract - Indonesia holds a strategic position in the global manufacturing sector, with a manufacturing output of USD 228.32 billion in 2021, ranking 10th worldwide. In 2023, it ranked 12th globally by manufacturing value added, according to the World Bank's report. However, this growth is accompanied by 297,725 workplace accidents reported in Indonesia in 2022, marking a 27.03% increase from the previous year. This study aims to develop a Personal Protective Equipment (PPE) monitoring system using Big Data, employing Convolutional Neural Network (CNN) and You Only Look Once (YOLO) algorithms. The dataset consists of at least 1,000 images for each of four classes: Helmet, Vest, NoHelmet, and NoVest. Evaluation results show a mAP@50 of 83.1%, with the highest detection performance in Vest (0.90), followed by NoHelmet (0.88), Helmet (0.85), and NoVest (0.81). These findings demonstrate strong potential in supporting safety protocol compliance and reducing workplace accidents in high-risk industrial environments.

Keywords - Big Data, Convolutonal Neural Network, You Only Look Once

1. INTRODUCTION

Indonesia is one of the countries with a strategic position in the global manufacturing industry map. In 2021, Indonesia's manufacturing output was recorded at USD 228.32 billion, placing it as the 10th largest manufacturing country in the world and the highest in the Southeast Asian region [1]. This achievement is strengthened in 2023, where Indonesia ranks 12th globally in the category of manufacturing countries based on added value [2]. In addition, based on data from Trading Economics (2024), Indonesia's Gross Domestic Product (GDP) in the manufacturing sector reached a high value of IDR 672.14 trillion in the fourth quarter of 2024 [3]. However, the growth of the manufacturing industry is accompanied by a significant increase in the risk of work accidents. In 2022, there were 297,725 cases of work accidents in Indonesia, an increase of 27.03% compared to the previous year [4]. Work accidents, particularly in the manufacturing sector, are still a serious challenge due to the complexity of the work environment involving heavy equipment, hazardous chemicals, and other potential hazards [5]. The main causes of work accidents include unsafe actions, unsafe working conditions, and lack of training and supervision of safety procedures [6]. In addition, violations of the procedures for the use of personal protective equipment (PPE) also contribute significantly to the occurrence of work accidents [7].

The use of Personal Protective Equipment (PPE) is one of the crucial elements in an occupational safety system designed to minimize the risk of accidents in high-risk work environments, especially in the manufacturing sector. Various studies show a significant causal relationship between the level of compliance with the use of PPE and a decrease in the number of work accidents. When workers use PPE consistently and in accordance with procedures, the potential for injury due to direct contact with physical, chemical, or mechanical hazards can be substantially reduced. On the contrary, negligence in using PPE has been proven to increase the likelihood of accidents, both in the form of minor injuries, serious injuries, and death. A

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systematic review in the construction and industrial sectors by Rahma et al. also reported that adherence to safety procedures, including the use of PPE, contributed significantly to a decrease in both the number and severity of accident incidents [8]. In addition, a literature review by Khalisha et al. confirms that the consistent and appropriate application of PPE has been statistically proven to reduce the number of work accidents [9]. Therefore, the implementation of a monitoring system for compliance with the use of PPE is a strategic step in supporting the Occupational Health and Safety (K3) program and creating a safer and more productive work culture. In the realm of technology, this research is focused on the use of Big Data in creating datasets for automatic detection systems for PPE use, by applying Convolutional Neural Network (CNN) and You Only Look Once (YOLO) algorithms. CNN is a neural network architecture that is effective in processing visual data through convolution, pooling, and activation layers, allowing for automatic and hierarchical extraction of features from images. CNN is capable of transforming the representation of raw data into high-level features, enabling applications such as image classification, object detection, and video prediction [10]. YOLO is a real-time object detection algorithm that positions detection as a direct regression task, processing the entire image in a single forward pass [11].

Numerous prior studies have explored PPE detection using various techniques. For instance, Vukicevic et al. [12] reviewed computer vision-based PPE monitoring across industries. Guney et al. [13] implemented YOLO for real-time PPE compliance and Delhi et al. [14] developed a CNN-based system for construction safety. However, most studies either focus on a single PPE type, lack a balanced dataset, or ignore real-time deployment. This research fills the gap by using YOLOv8, the latest in YOLO evolution, trained with balanced big data from four PPE classes, and deployed on a real-time webcam system, forming a strong contribution to both practical safety systems and the AI research domain. The purpose of this study is to gain a comprehensive understanding of the procedure for developing a compliance monitoring model for the use of Personal Protective Equipment (PPE) by workers. This research also aims to design and implement a detection model that has a high level of accuracy, so that it can support increased efficiency and operational safety in the industrial environment. In addition, this study is directed to analyze the contribution of the use of Big Data in providing large-scale and real-time datasets, in order to increase the effectiveness and accuracy of the monitoring system for the use of PPE in a sustainable manner. The development of this system is expected to support the implementation of the Healthy and Safety protocol more optimally, especially in high-risk work areas. In addition to contributing to efforts to prevent work accidents, this research is also a representation of the application of fields in industrial engineering, such as artificial intelligence, data analysis, information systems engineering, and occupational safety. Thus, this research not only has practical urgency, but also academic value in supporting the development of technology-based occupational safety systems in the Indonesian manufacturing industry sector.

2. RESEARCH METHOD

2.1 Research Tools and Materials

The research material utilized in this study comprises a collection of photographic images that capture the real-world usage of personal protective equipment (PPE) by workers in various operational environments. These images serve as visual data to train and evaluate the detection model, ensuring that it reflects actual conditions in the field. The research instruments employed are categorized into two main types: hardware and software

Table 1. Hardware Used in the Research

No.	Component	Specification
1	Brand/Processor	Acer/ AMD Ryzen 5 (Hexa-core)
2	Clock Speed	~3.0 GHz (boost up to 4.0 GHz)
3	Core/Thread	6 Cores / 12 Threads
4	RAM/Storage	8GB or more / 512GB SSD or 1TB HDD
5	GPU / Operating System	Radeon Vega IG or Discrete GPU / Windows 11

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Table 2. Software Used in the Research

No.	Software	Unit	Specificaion
1.	Operating System	1	Windows 11
2.	Text Editor	1	Visual Studio Code
3.	Programming Language	1	*Python*

2.2 Method Selection

In general, there are currently two main approaches to the automatic monitoring of compliance with Personal Protective Equipment (PPE) usage: sensor-based monitoring and vision-based monitoring [15]. The sensor-based approach, for example, utilizes Radio Frequency Identification (RFID) technology, which is attached to each component of the Personal Protective Equipment (PPE). This system enables the automatic identification process through scanners to determine whether workers are wearing the appropriate PPE. Although effective in ensuring compliance, the implementation of this method requires a high investment cost, including expenses for hardware procurement, system installation, and ongoing maintenance [16].

As an alternative, the vision-based approach employs cameras to capture images or videos in the workplace environment, which are then analyzed using computer vision algorithms. This method is increasingly being adopted due to its ability to perform self-learning from large-scale datasets and its flexibility in being implemented across various operational conditions [17]. Based on this potential, this study is directed toward the development of a computer vision-based personal protective equipment (PPE) monitoring system to support real-time efficiency and workplace safety [18].

This research primarily employs Convolutional Neural Networks (CNNs) and YOLOv8 for object detection. The CNN architecture facilitates hierarchical feature extraction through layers like convolution, pooling, and activation. YOLOv8, as the core object detection framework, directly predicts bounding boxes and class probabilities in a single inference pass, ensuring real-time detection capabilities. Among five YOLOv8 variants (n, s, m, l, x), YOLOv8s was selected for its balance between computational efficiency and detection accuracy, especially suitable for limited GPU environments like Google Colab.

2.3 Data Processing Stage

Data processing in this study was conducted systematically through two main stages: pre-processing and model development, prior to integration into the machine learning-based object detection system.

1. Pre-Processing

The initial pre-processing stage begins with data selection and reduction, including the removal of duplicate images to prevent bias during model training. The process includes the following steps:

a. Image Labelling/Annotation, At this stage, bounding box labels are applied to objects within images to identify classes such as Helmet, Vest, No Helmet, and No Vest. This enables the model to detect and learn from predefined inputs. Several datasets sourced from Roboflow and Kaggle already contain annotations; however, for manually collected data (e.g., from Google Images), annotations were conducted manually.
b. Image Transformation, Annotated images are standardized in terms of resolution, aspect ratio, or file format to reduce irrelevant variations. This step helps the model recognize patterns more consistently.
c. Data Augmentation, Augmentation techniques are applied to increase dataset diversity, especially when the original data volume is limited. These techniques include rotation, flipping, lighting adjustments, and noise addition, which improve the model's robustness under complex visual conditions such as occlusion, blur, or underexposure.

2. Model Development

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Following pre-processing, the data is ready for model development, which consists of three main stages:

a. Model Training, This is the core of machine learning, where the model is trained to recognize patterns, relationships, and features from the prepared dataset.
b. Model Validation, Validation assesses the model's performance during training and ensures that overfitting does not occur. Model parameters are adjusted based on validation outcomes to improve generalization.
c. Model Testing, The final stage evaluates the model's performance objectively using a test set that has not been previously seen by the model. The testing results serve as a comprehensive indicator of model accuracy.

After completing the training, validation, and testing stages, the model is ready for implementation. Data processing is conducted using open-source frameworks based on the Python programming language, such as Ultralytics YOLO, executed on cloud computing via the Google Colaboratory (Colab) platform, which provides free access to GPU (Graphics Processing Unit) resources to accelerate the model training process.

2.4 Research Procedure

To achieve the objectives of this research, a structured series of stages was conducted, each designed to ensure a systematic and comprehensive approach. The research methodology was meticulously developed to align with the aim of enhancing workplace safety and operational efficiency through real-time detection and analysis.

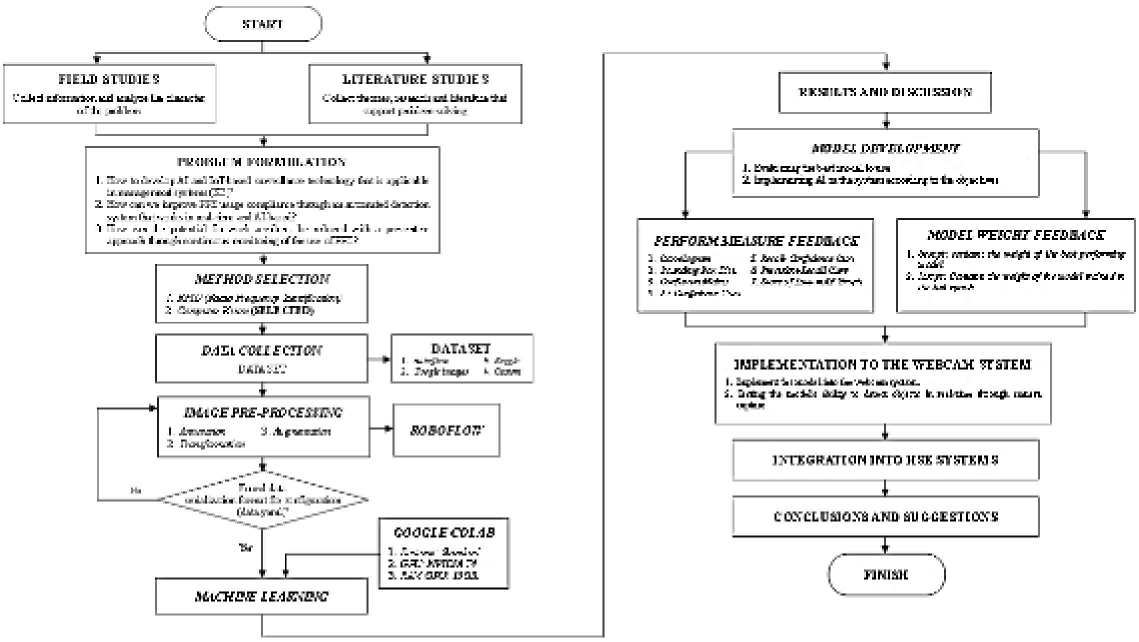

Figure 1. Research and Work Flow Scheme of Computer Vision-Based PPE Detection System

3. RESULTS AND DISCUSSION

3.1 Data Requirements Analysis

1. Field Studies

Field studies were conducted to investigate the current conditions of Personal Protective Equipment (PPE) compliance in real-world manufacturing environments. The researchers visited several industrial sites located in East Java, Indonesia, where daily operations involve high-risk activities such as welding, heavy lifting, chemical exposure, and machine operation. These field

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observations aimed to assess not only the availability of PPE but also how consistently workers utilized it and how compliance was being monitored by safety personnel.

The studies revealed several significant insights. First, it was observed that PPE compliance—particularly for helmets and safety vests—was often inconsistent, especially in informal or poorly supervised work shifts. Second, current monitoring systems largely relied on manual inspections by safety officers, which were found to be time-consuming, prone to oversight, and inconsistent in documentation. Lastly, safety supervisors expressed the need for more efficient and automated monitoring systems that could help reduce the burden of human surveillance while improving detection accuracy.

These findings affirmed the practical urgency of developing a real-time, AI-based system capable of automatically detecting PPE compliance using computer vision technologies. They also informed the technical specifications for the model, such as the types of PPE to be detected and the environmental conditions in which the system would be deployed.

2. *Literature Studies*

The development of a PPE detection system using computer vision requires a comprehensive understanding of the existing research landscape. Therefore, a literature review was conducted to identify current advancements and limitations in the field of PPE detection, real-time object recognition, and deep learning applications in workplace safety.

3. *Problem Formulation*

Based on insights from field observations and findings from previous studies, this research formulates how can an AI-based system utilizing Convolutional Neural Networks (CNN) and YOLOv8 be developed to detect multiple types of PPE in real time using large-scale image data, and how can this system be effectively integrated into workplace safety monitoring.

This core question encompasses several sub-problems. First, the system must be trained on a balanced and diverse dataset that includes different PPE categories such as Helmet, NoHelmet, Vest, and NoVest. Second, the model must be optimized to run in real time without sacrificing detection accuracy—requiring careful selection and configuration of the YOLOv8 architecture. Third, the deployment must include webcam-based live detection, capable of working in dynamic lighting and crowded industrial environments. Finally, the output of the detection system must be integrated into HSE protocols, contributing not only to passive monitoring but also to active compliance enforcement.

This formulation ensures that the research addresses not just theoretical and algorithmic innovation, but also operational feasibility and relevance to the safety management practices currently employed in Indonesia's industrial sector.

4. *Data Collection*

The data collection process began with determining the types of PPE to be used in the development of the object detection model. This study focuses on two main types of PPE: helmets and safety vests. The researchers established that each class must include a minimum of 1,000 images to ensure sufficient data diversity for effective model training.

The researchers explored publicly available datasets through Roboflow Universe, a platform that shares datasets and models. Roboflow allows access to pre-annotated images, significantly reducing the time required for initial data processing. However, for certain classes such as "Helmet," a large number of duplicate images were found. Therefore, additional data was sourced from other platforms to enhance dataset diversity and completeness. The Roboflow 3.0 model, trained on the "ppe-tqmos" dataset with the COCO checkpoint, demonstrated a reasonably good performance, achieving a precision of 80.1% and a recall of 77.6%. Real-time detection successfully identified objects such as "person" (96%) and "vest" (87%), along with other attributes like work boots, with varying accuracy ranging from 56% to 64%.

To address the limitations of the images available from Roboflow, the researcher supplemented the dataset with additional images from Kaggle, resulting in a total of 2,825 images covering two main classes and two negative classes ("NoHelmet" and "NoVest"). Final validation

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confirmed that the class distribution was balanced without significant disparity, making the dataset suitable for direct use in model development.

5. *Data Processing*

This stage consists of two main phases: pre-processing and machine learning-based model development. The purpose of this process is to prepare an optimized dataset for training the object detection model using the YOLO framework.

a. *Pra-Processing Data*, The images are collected from various sources and then processed through several stages as follows:
   1) *Re – Sizing,* All images are tuned to 640×640 pixel resolution to ensure consistency and efficiency in the training process, according to YOLO's architecture optimized for 32-fold multiples [11].
   2) *Transformation,* This stage was carried out to standardize labels from various sources, where images containing the "Helmet" object were annotated differently (e.g., one source might label it as "Helmet", while another as "Safety Helmet"). In this study, all labels were remapped to a unified set of classes originally included in the PPE dataset, namely "Helmet", "Vest", and the negative classes "NoHelmet" and "NoVest". The remapping process involved discarding negative samples outside of these detection classes, as such samples were deemed unnecessary. This is because the object detection model automatically treats the background (areas not marked with bounding boxes) as negative samples. Consequently, this process reduces the complexity of training, resulting in faster and more efficient model training.
   3) *Augmentation,* This stage was conducted to enhance data diversity and improve the model's robustness in real-world scenarios. Several augmentation techniques were applied, including converting 15% of the images to grayscale, randomly rotating images within a range of -15° to +15°, adjusting brightness levels between -20% and +20%, and adding 1% random noise. These augmentations help simulate various environmental conditions such as lighting changes, different viewing angles, and visual disturbances, thereby enabling the object detection model to generalize better and perform more reliably across diverse inputs.

The final dataset was divided into three subsets: a training set comprising 93% (2,640 images), a validation set comprising 6% (160 images), and a test set comprising 1% (25 images). To enhance data diversity and improve model robustness in real-world conditions, data augmentation techniques were applied. These techniques included object rotation between -15° and +15°, 1% noise addition to simulate blur conditions, grayscale conversion applied to 15% of the images, and brightness adjustment ranging from -20% to +20%. This process aimed to enable the model to recognize objects more accurately despite variations in visual conditions.

b. *Machine Learning*
   1) *Preparation of the Computing Environment,* The development was carried out on the Google Colab platform, which supports Python code execution and GPU-based processing. Google Colab provides a runtime environment with an NVIDIA T4 GPU, 15GB of GPU RAM, 12.7GB of system RAM, and 112GB of disk storage.
   2) *Model Architecture Selection,* The YOLOv8 architecture was used because it supports real-time object detection with high accuracy. Among the five YOLOv8 variants (n, s, m, l, x), the YOLOv8s model was chosen as it offers the most optimal balance between precision and speed, based on benchmarks provided by Ultralytics.
   3) *Library Installation and Integration,* The Ultralytics and Roboflow libraries were installed to load the model and dataset. Google Drive was mounted to allow direct access to the dataset from Google Colab.
   4) *Dataset Configuration (Data.yaml file),* The data.yaml configuration file was prepared, containing the dataset directory paths, the number of classes, and the name of each class used in model training.

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5) *Model Initialization and Training,* Once the environment was set up, the model was trained for 100 epochs. During training, metrics such as box_loss, cls_loss, and dfl_loss were monitored.

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances
100/100	2.75G	0.6997	0.4795	0.9249	18
	Class	Images	Instances	Box(P	R
	all	642	1752	0.736	0.781

Figure 2. *Feedback Training Model Google Colab*

3.2 Model Development

1. *Model Weight Feedback*

File weights are the result of training the model based on the data that has been used, and it greatly determines the quality of detection when the model is used.

a. *Best.pt,* It is the weight of the best-performing model based on evaluation metrics (such as mAP50). It is used as the final result as it shows the highest accuracy during training.

b. *Last.pt,* Save the weight from the last epoch of training. This file is used if the training model is to be continued or for final performance analysis.

2. *Perform Measure Feedback*

a. *Xy-wh Bounding Boxes Correlogram and Bounding Box Distribution,* According to **Figure 11.** The bounding box distribution graph shows that the Helmet class appears the most in the dataset and the No-Vest the least. Overall, the bounding boxes are evenly distributed in various positions and sizes, following a similar distribution pattern on the previous corroboration chart. Beside that, according to **Figure 12.** The bounding box distribution graph shows that the Helmet class appears the most in the dataset and the No-Vest the least. Overall, the bounding boxes are evenly distributed in various positions and sizes, following a similar distribution pattern on the previous corroboration chart.

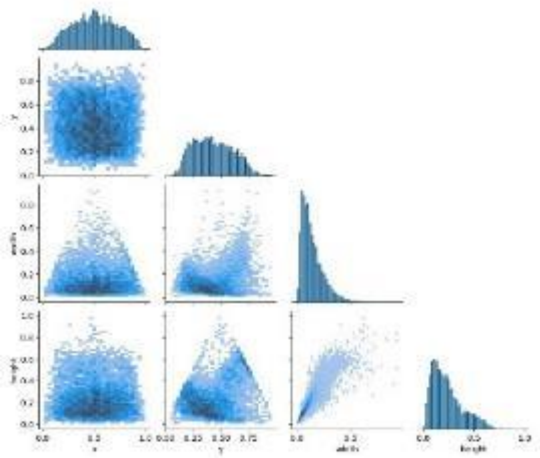

Figure 3. *Bounding Box Distribution*

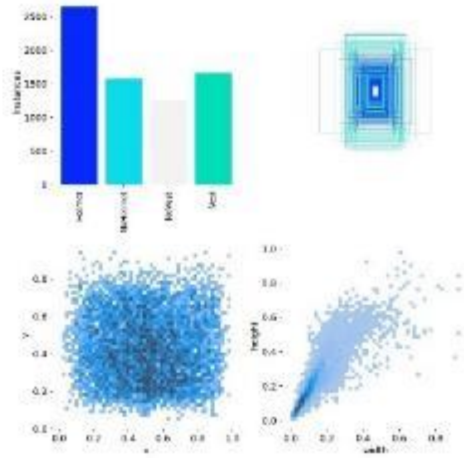

Figure 4. *Normalized Confusion Matrix*

b. *Normalized Confusion Matrix,* Normalized The confusion matrix indicates that the model has high accuracy in detecting objects, as shown by the dark blue color on the diagonal of the heatmap. The Vest class has the highest accuracy at 0.90, followed by NoHelmet (0.88), Helmet (0.85), and NoVest (0.81). Prediction errors such as false positives and false negatives still occur but remain relatively small in proportion. Moreover, the model has proven effective in distinguishing objects from the background.

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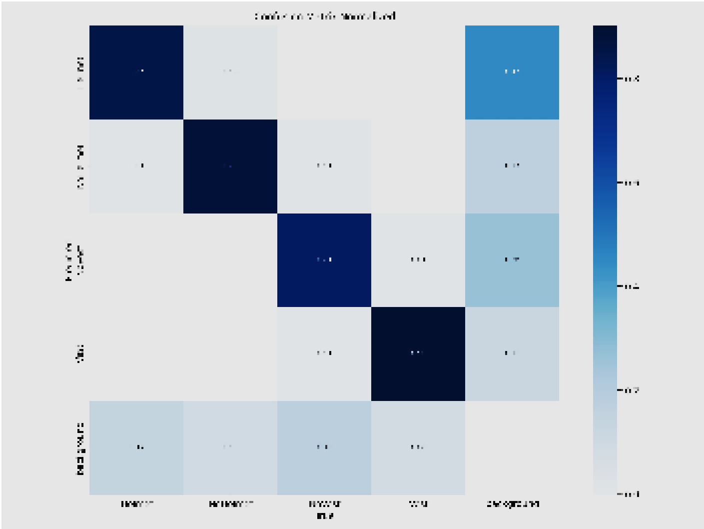

Figure 5. Normalized Confusion Matrix

c. *F1 Confidence Curv and Precision-Confidence Curv,* Based on Figure 14, the F1-Confidence curve demonstrates the model's performance in balancing precision and recall. The analysis shows that the highest F1 score of 0.76 is achieved at a confidence threshold of 0.405. This means the model only accepts or displays predictions with a confidence score greater than 40.5%. In other words, the model provides the most balanced detection results, being fairly accurate (with minimal false positives) and sufficiently sensitive (with minimal false negatives). Meanwhile, based on Figure 15, the Precision-Confidence curve indicates that the highest precision of 1.00 (100%) is achieved at a confidence threshold of 0.987. This means that at this confidence threshold, all detections made by the model are correct, with no false positives (incorrect predictions for non-existent objects). In other words, at a confidence level of 98.7%, the model only outputs highly reliable predictions.

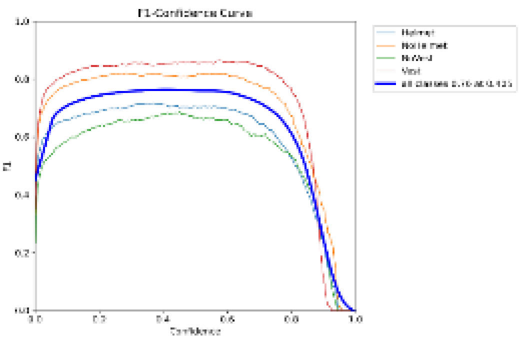

Figure 6. *F1 Confidence Curv*

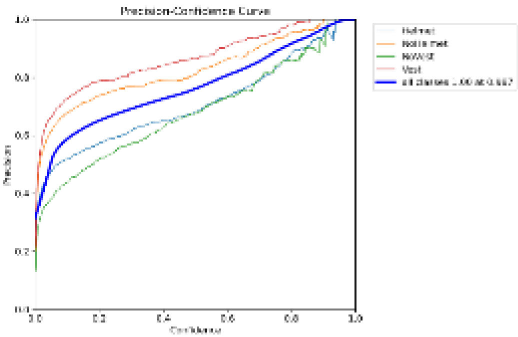

Figure 7. *Precision-Confidence Curv*

d. *Recall-Confidence Curv and Precision Recall Curv,* Based on Figure 16, the Recall-Confidence curve shows that the highest recall of 0.97 is achieved at a confidence threshold of 0.000, meaning all predictions are accepted (including low-confidence predictions). However, recall drops sharply after the threshold reaches 0.8, indicating that the model begins to ignore many objects considered to have low confidence (low-confidence detections are filtered out). Meanwhile, according to Figure 17, the Precision-Recall curve indicates detection performance with a mAP@0.5 of 83.1%, meaning the model is capable of detecting objects with 83.1% accuracy when the predicted bounding boxes have at least 50% overlap with the ground truth. This value reflects the model's strong ability to maintain a balance between precision and recall in real-world applications such as automated personal protective equipment (PPE) monitoring.

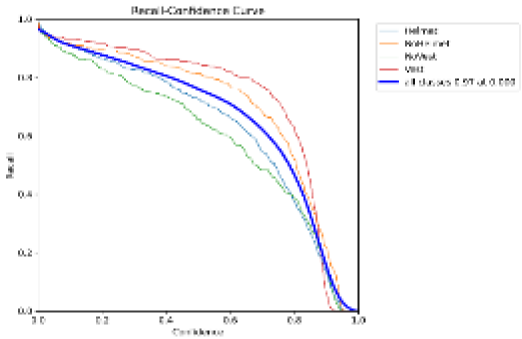

Figure 8. *Recall-Confidence Curv*

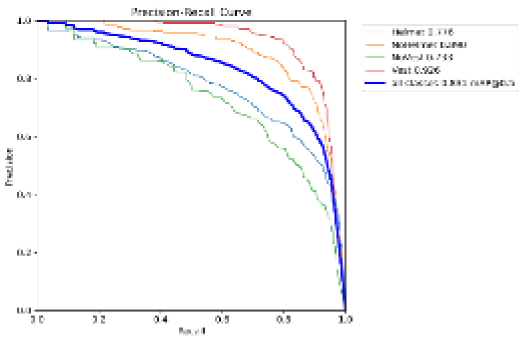

Figure 9. *Precision Recall Curv*

e. *Score of Loss-mAP training-validation-testing,* The training process involved 100 epochs, with performance visualized through loss and metric graphs. The left side displays localization, classification, and distribution focal losses during training (top) and validation/testing (bottom). The right side shows precision, recall, mAP@0.5, and mAP@0.5–0.95 scores. During training, localization and distribution focal losses consistently decreased, while classification loss decreased more slowly. In contrast, validation losses flattened around epoch 50, as did the precision, recall, and mAP scores. This indicates model convergence and potential overfitting if training continues. The model achieved a mAP@0.5 of 0.831, meaning it correctly detected around 831 of 1000 objects at 0.5 IoU threshold. Meanwhile, a mAP@0.5–0.95 of 0.627 reflects an average correct detection of 627 objects across a range of IoU thresholds. However, the model still struggles with occasional false positives and missed detections of personal protective equipment.

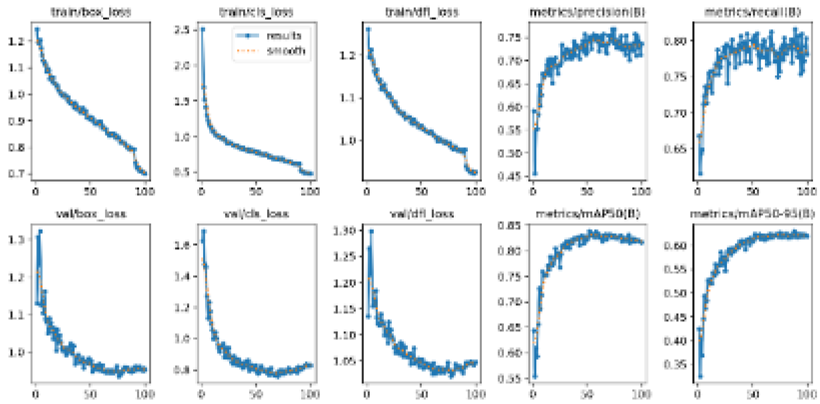

Figure 10. Score of Loss-mAP training-validation-testing

The model demonstrates difficulty in detecting "NoVest" due to background blending and class imbalance in certain scenes. False positives primarily occurred in complex lighting or crowded environments. The Precision-Recall curve suggests optimal performance at a confidence threshold of 0.4, balancing false alarms and missed detections effectively.

3.3 Implementation to the Webcam System

After the model detection development and training process is completed, the next step is to implement the model into the webcam system directly

1. Environment Setup

In this study, the process was conducted using Google Colab, a cloud-based platform that provides GPU support for executing Python-based programs. The environment setup involved several key steps. First, a virtual environment was created and activated using the command `python -m venv env`, with activation depending on the terminal used either via Command Prompt (`env\Scripts\activate`) or PowerShell in Visual Studio Code

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(`.\env\Scripts\Activate.ps1`). Next, the main libraries required for the model were installed. These included `ultralytics` for loading and running the YOLOv8 object detection model, `opencv-python` for capturing and processing webcam input in real-time, and supporting libraries such as `torch` and `numpy`. Additional libraries such as `matplotlib` were also installed to support visualization and data handling. The installation was performed using the following pip commands: `pip install ultralytics opencv-python` and `pip install numpy matplotlib`. To ensure GPU functionality, a verification step was carried out using the command `torch.cuda.is_available()` to confirm CUDA availability. Lastly, the best model checkpoint (`best.pt`) resulting from training was saved into the local working directory to be used during the detection process.

2. *Program Code Writing*

The second stage of this research involved writing the program code necessary to implement the object detection system. This phase focused on developing and structuring the Python scripts required to load the trained model, process input data, and display detection results in real-time.

3.4 Integration to the HSE System

This stage involves the integration of field installation data into the Health, Safety, and Environment (HSE) system to ensure that all operational activities comply with safety standards and company regulations.

Figure 11. Workflow of Integration to the HSE System

Installation work consists of three main phases: preparation, installation, reporting. The preparation phase includes planning, checking tools and materials, and preparing PPE. After that, the team went to the

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location, inspected the area, installed the device according to the design, and documented the process. The final stage includes area cleaning, testing results, and submitting reports to client and supervisor applications. The application of the PPE detection model is focused on the documentation stage during installation and report preparation, so researchers need to review the information flow and the role of personnel thoroughly.

Figure 12. PPE detection in technicians/operators by Model

Based on the example in Figure 4.20, the model can detect the presence of workers and their use of PPE, identifying classes such as Vest and Helmet (positive) and No_Vest and No_Helmet (negative). Previously, supervisors and team managers manually reviewed each report to assess PPE compliance, a repetitive and inefficient process, especially given the high volume and frequency of submissions. This often caused bottlenecks and risked inaccurate assessments.

4. CONCLUSION

The PPE detection model was developed using a pre-trained YOLOv8 architecture and trained on a dataset of 2,825 PPE usage images covering four distinct classes (Helmet, Vest, No Helmet, and No Vest). The training-validation-testing process was conducted over 100 epochs using a T4 GPU provided by Google Colab to generate model weights for deployment. This development process resulted in a model that achieved a mAP50 score of 0.831 and a mAP50-95 score of 0.627, with an inference time of 2.8 milliseconds per image demonstrating significant performance across its training-validation-testing phases. Furthermore, the implementation of this model is expected to reduce the workload of supervisors or team managers by automating the review process, thereby lowering the risk of human error and improving efficiency by approximately 9.38%. The model also serves as a positive feedback loop among technicians, supervisors, and the model itself, through reinforced learning enabled by user feedback, appeals, and revisions. In addition, the utilization of Big Data comprising both public datasets and real-time data significantly enhances the model's accuracy. The availability of diverse and extensive data allows the model to learn from various real-world conditions, improving its effectiveness in continuously monitoring PPE compliance.

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