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IMPLEMENTATION OF DEEP LEARNING FOR PERSONAL PROTECTIVE EQUIPMENT (PPE) DETECTION IN WORKERS IN THE OIL INDUSTRY USING THE YOLOv5 ALGORITHM

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Abstract

Occupational accidents pose a significant challenge in the construction, manufacturing, and oil industries. This study aims to develop a deep learning model for real-time detection of personal protective equipment (PPE) usage utilizing the YOLOv5 algorithm. The dataset was collected from two primary sources: direct data acquisition at PT. Pertamina (Persero) Terminal BBM Sorong and open-source datasets from Roboflow and Google Images. It consists of 1,950 raw images in JPG, JPEG, and PNG formats, categorized into four classes (hardhat, no hardhat, coverall, and no coverall). The model was trained and evaluated using precision, recall, and mean Average Precision (mAP) metrics. Results demonstrated that the model achieved a high accuracy level with an mAP of 0.91 and stable performance. The model effectively and rapidly detects safety attributes even under complex working conditions, including varied lighting and multiple background objects. With a usability testing score of 85.35% and satisfactory black box testing outcomes, this study produced a prototype web-based application enabling efficient and effective PPE monitoring. The application is designed to facilitate workplace safety improvements across various industrial sectors, including the oil industry, in a practical and adaptive manner. It is expected to enhance PPE compliance, reduce accident risks, and contribute significantly to industrial workplace safety. In conclusion, the YOLOv5 algorithm holds great potential for implementation in technology-based safety monitoring systems and supports the advancement of safer and more modern industrial environments.

Keywords: Personal Protective Equipment, Object Detection, YOLO, Deep Learning, Oil Industry

INTRODUCTION

The construction, manufacturing, and oil industries are important sectors that contribute significantly to Indonesia's economy; however, these sectors also experience high rates of occupational accidents [1], [2]. Data from the Ministry of Manpower indicates that in 2021 there were more than 234,000 cases of workplace accidents, representing a 5.65% increase compared to the previous year [3]. Numerous studies emphasize that the proper use of personal protective equipment (PPE) can substantially reduce the risk of injury, but worker compliance remains low due to inadequate socialization and supervision [4], [5]. This issue is further exacerbated by the lack of automated monitoring systems at worksites to ensure adherence to occupational safety standards [6]. In Workers In The Oil Industry Using The Yolov5 Algorithm

The use of artificial intelligence technology based on deep learning, especially the YOLOv5 algorithm, has been demonstrated to be effective for real-time object detection, including the detection of PPE usage in industrial environments [7], [8]. YOLOv5 has been applied in various studies to detect safety helmets, vests, and gloves with high accuracy, even under challenging lighting and background conditions [9], [10]. Recent studies in Indonesia utilizing the YOLOv5

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model have shown improved detection efficiency as well as integration capability with web-based systems and mobile applications for safety monitoring [11], [12]. This approach reduces dependence on manual supervision prone to errors and delayed responses [13].

Other research reports that the development of PPE detection systems based on YOLOv5 not only enhances worker compliance but also assists proactive safety risk management through automatic notifications and reporting [14]. The integration of deep learning with IoT and cloud platforms further opens opportunities for more adaptive and scalable safety monitoring systems across various industrial sectors, including the oil industry [15]. Moreover, this system represents the first in Indonesia to offer a fully functional web interface that enables real-time and easy access by management and field supervisors. This innovative aspect underscores the significant contribution of this research in strengthening the implementation of occupational safety in the industry.

This study aims to develop and implement the YOLOv5 model for real-time detection of PPE usage and to integrate this model into a web-based application accessible by management and field supervisors with a user-friendly and fully featured interface. The system is expected to significantly improve worker compliance with PPE usage, reduce workplace accident rates, and decrease the burden of manual monitoring, thus enabling more efficient and safer industrial operations. The contribution of this research is anticipated to reinforce the foundation of occupational health and safety (OHS) in the construction, manufacturing, and oil industries in Indonesia.

METHODS

This study was conducted systematically through four main stages, namely problem identification, data collection, deep learning model development, and software development [16]. Each stage was designed to produce valid and relevant results aligned with the research objectives. The research stages began with designing a research workflow that encompasses the entire process from start to finish. These stages include problem identification, data collection, data processing, model training, model evaluation, software development, testing, and application deployment. In Figure 1, the research flow diagram is designed to clearly and systematically visualize the work process, thereby facilitating the management of each step in the research.

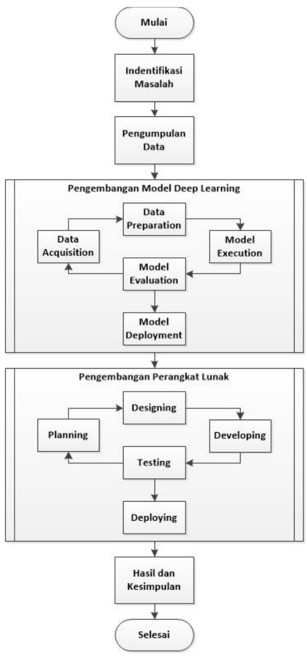

Fig. 1. Research Flow

Problem Identification
The researcher conducted a literature review to understand issues related to occupational accidents in the construction and manufacturing sectors, as well as the importance of using personal protective equipment (PPE) [17]. Based on this analysis, the researcher identified the need for a technology-based PPE detection system to address the limitations of manual monitoring. The main problem formulated was how to build a deep learning model capable of detecting PPE in real-time with high accuracy. From this formulation, the research objective was set to develop a web-based application implementing the YOLOv5 algorithm.

Data Collection
Data collection was conducted through a literature study related to the YOLO algorithm and object detection, observation, and interviews to obtain information about compliance with personal protective equipment usage [18], as well as dataset collection from two primary sources: direct data acquisition at PT. Pertamina (Persero) Terminal BBM Sorong and open-source datasets from Roboflow and Google Images.

Deep Learning Model Development
The development of a deep learning model for detecting personal protective equipment (PPE) was carried out through several main stages, starting with data acquisition, which involved collecting a dataset consisting of four classes: hardhat, no hardhat, coverall, and no coverall, obtained from the research site as well as open sources such as Roboflow and Google Images [19]. The next stage was data preparation, where the dataset was processed through exploration, preprocessing, augmentation, and splitting into train, validation, and test sets [20]. Subsequently, in the model execution stage, the deep learning model was built using the YOLOv5 architecture by integrating the dataset, installing requirements, and performing configuration such as model parameters, image size, batch size, epochs, weights, and training processes. After training was completed, model evaluation was conducted using metrics such as precision, recall, and mean Average Precision (mAP), accompanied by direct detection trials for verification. Finally, the tested model showing satisfactory results was saved in PyTorch (.pt) format and prepared for implementation into software, such as a web-based application, in the model deployment stage.

Software Development
The software development in this study employed the agile software development method, consisting of five main stages as show in Figure 2. The first stage, planning, involved setting application objectives and analyzing hardware and software requirements [21]. The second stage, designing, included creating use case diagrams, flowcharts, and user interface designs [22]. The flowchart illustrated the system workflow, starting from image acquisition, image processing by the object detection module, detection validation, boundary box creation, object tracking, to result display [23]. The developing stage involved application development using Python, Flask, and Anaconda Distribution, followed by local testing. The fourth stage, testing, encompassed black box testing for input-output validation and usability testing to evaluate the user experience [24]. Finally, in the deploying stage, the tested application was uploaded to the server for flexible use according to needs [25].

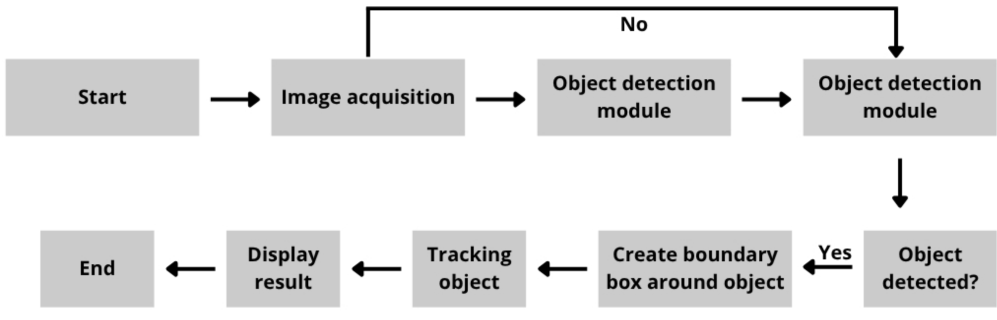

Fig. 2. Flowchart System

RESULT AND DISCUSSIONS

This study utilized a dataset consisting of images of personal protective equipment (PPE) on workers, captured directly at the research site as well as from open-source dataset providers. The collected image dataset comprises raw data amounting to 1,950 images in jpg, jpeg, or png formats.

Deep Learning Model Development

In this study, a deep learning model based on YOLOv5 was developed to detect compliance with personal protective equipment (PPE) usage in the workplace. The model development process involved several stages, namely data acquisition, data preparation, model execution, model evaluation, and model deployment. Each stage is explained as follows,

- **Data Acquisition**
  The data acquisition process began with gathering a dataset consisting of 1,950 raw images in JPG, JPEG, or PNG formats. The data originated from two primary sources: direct field collection and open datasets from data provider platforms. The raw datasets were then combined to produce data ready for annotation. The subsequent stage involved labeling and annotation using the image management software Roboflow. The labels applied consisted of four main classes: hardhat, no hardhat, coverall, and no coverall. The annotation process yielded 6,320 bounding boxes, with a balanced distribution of annotated data: 1,660 annotations for the hardhat and coverall classes, and 1,500 annotations for the no hardhat and no coverall classes. The average image size was 0.35 megapixels, with an image ratio of 500×700 pixels.
- **Data Preparation**
  The data preparation stage was conducted to ensure data quality before model training. The labeled and annotated dataset was then split into training, validation, and testing datasets through a train/valid/test split process with proportions of 80% training, 10% validation, and 10% testing datasets. Subsequently, the data underwent preprocessing, applying auto orientation to maintain the bounding boxes in accurate positions and resizing the images to 640×640 pixels to standardize the image size, thereby improving the model training performance, as illustrated in Figure 3.

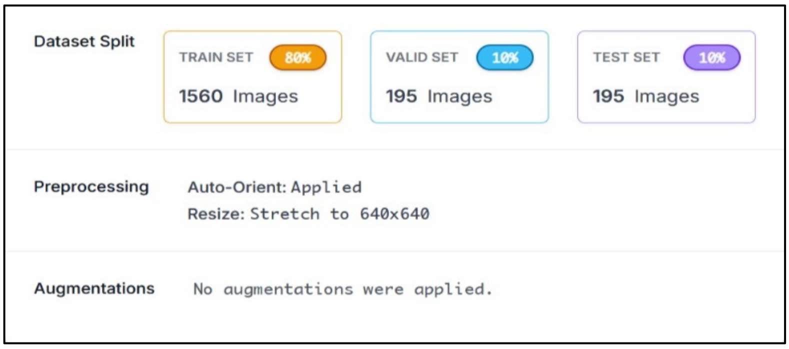

Fig. 3. Data Preparation

- **Model Execution**
  The model execution stage began with the setup of the training environment, including the installation of dependencies and model configuration. Installing dependencies or requirements was the first step to ensure that the necessary libraries or packages were available so that the command codes could be executed properly within the environment. Next, the dataset assembly was performed to connect the preprocessed dataset from Roboflow to the Colaboratory notebook for processing and training. Once the dataset was connected, the model architecture was configured using the YOLOv5s model configuration. After determining the configuration, the model was trained using the prepared dataset with the command !python train.py, alongside additional arguments such as an image size ratio of 640, a batch size of 16, and 100 training epochs.

- **Model Evaluation**

At this stage, the model was evaluated to assess metrics such as precision, recall, mean Average Precision (mAP), and the confusion matrix, which provide an overview of the model training outcomes. Subsequently, the model testing was conducted to validate the model's capability in detecting the relevant objects.

The precision graph shown in Figure 4 illustrates the progression of the precision metric of the trained YOLOv5 model, with each training step measured from 0 to 99. The Y-axis represents the precision value ranging from 0 to 1, while the X-axis represents the training steps from 0 to 99. During the early stages of training, approximately steps 0 to 10, the precision experienced significant fluctuations due to the model still being in the learning and adjustment phase with the data. After step 10, precision increased steadily until about step 40. From step 40 onward, the precision began to stabilize, remaining above 0.8 and showing slight improvements. At the end of training (step 99), the model's precision reached a value of 0.867. The smoothed average precision was approximately 0.8658.

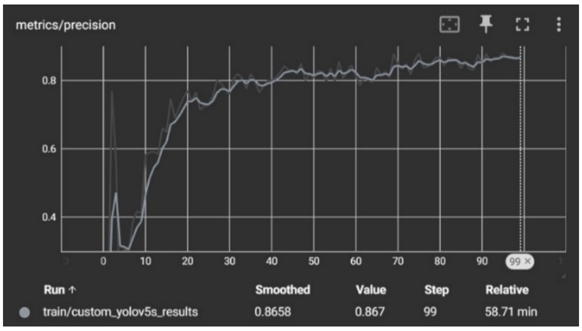

Fig. 4. Precision Grafic

The mAP graph in Figure 5 depicts the mAP value of the YOLOv5 model at a threshold of 0.5 during training. From step 0 to around step 20, there was a sharp increase from almost 0 to approximately 0.8, indicating that the model quickly learned the basic data patterns. Afterward, the mAP increase slowed down, rising gradually to about 0.9 by step 70, then plateaued, indicating stable performance. At step 99, the mAP reached 0.9104 with a smoothed value of 0.9101, and the training time was 58.71 minutes. These results demonstrate that the model has good detection capability, with high precision at the 0.5 threshold.

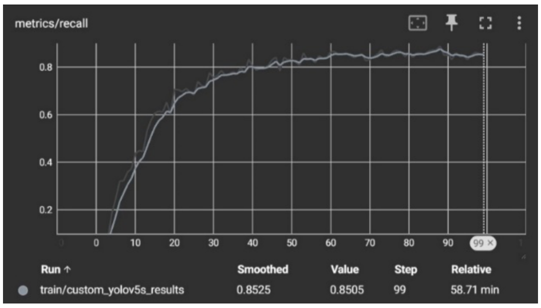

Fig. 5. mAP (mean Average Precision)

Figure 6 presents the confusion matrix of the model for detecting the classes coverall, hardhat, no-coverall, no-hardhat, and background. The model achieved the highest accuracy for the hardhat class (96%) and no-hardhat class (94%), while coverall and no-coverall were detected with accuracies of 88% and 76%, respectively. The largest error occurred when hardhat predictions were mistaken for background (47%), indicating difficulty in distinguishing workers wearing helmets from the background. Overall, the model performs well, especially on the hardhat and no-hardhat classes, but improvements are needed to increase accuracy for the no-coverall, background classes, and in differentiating hardhat from background.

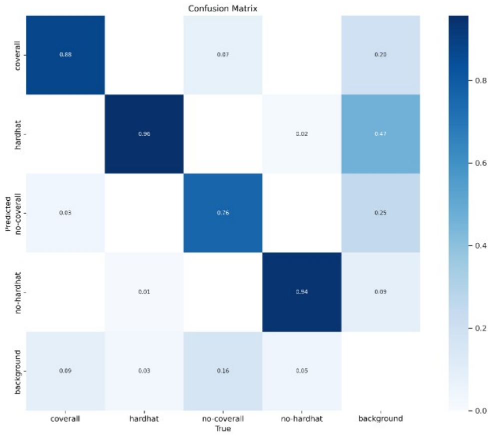

Fig. 6. Confusion Matrix

Based on the detection results shown in Figure 7, the YOLOv5 model demonstrates good performance in detecting safety attributes such as hardhat and coverall, both in outdoor and indoor environments. The model successfully recognizes workers with safety attributes (indicated by red and pink bounding boxes) with high confidence levels, and distinguishes between workers who are wearing and not wearing safety attributes. Nevertheless, there is potential for improvement in detecting attributes against complex or crowded backgrounds.

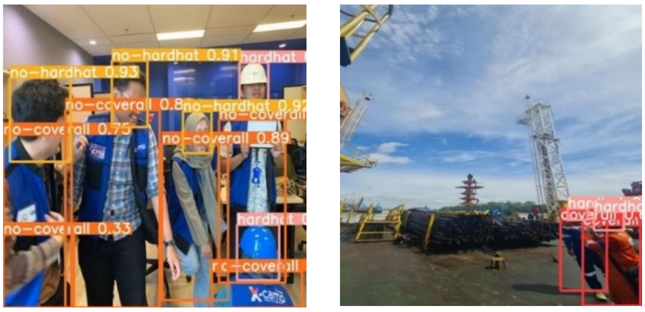

Fig. 7. Confusion Matrix

- **Model Deployment**
  The next stage involves model deployment, where the model is prepared and distributed for further development. This includes archiving the model and the files resulting from training and testing. After the evaluation results and model files are archived, these files are then downloaded to local storage on the computer using the file.download command. The downloaded files are subsequently separated; the YOLOv5 model will be integrated into software for easier application use, while the evaluation result files will be utilized to create a report summarizing the performance of the developed YOLOv5 model.

Software Development

The software development is carried out to implement the YOLOv5 model into a practical system that can be easily used by the end-users. This software development process consists of four main stages: Planning, Designing, Developing, and Testing.

- **Planning**
  Based on observations, interviews, and literature studies, several issues have been identified regarding compliance with the use of Personal Protective Equipment (PPE) among workers. Therefore, the objective of this application development is to optimize the monitoring of PPE compliance using a deep learning algorithm based on YOLOv5, implemented within a web-based application. The application development will involve

several supporting resources, including hardware, software, and programming languages to facilitate the detection of PPE objects on workers.

- **Designing**

This stage explains the final results of the implementation of the application's user interface based on the initial design or layout plan of the software user interface for the monitoring application of Personal Protective Equipment (PPE) usage among workers as show in Figure 8.

Fig. 8. Home Page View

Figure 8 illustrates the homepage interface of the web application "PPE Compliance Monitor," designed to monitor compliance with the use of Personal Protective Equipment (PPE) among workers. On the left side, the application title, a brief description, and an orange action button labeled "Run" provide access to the main feature. The right side displays a modern, technology-themed illustration, while the navigation menu at the top right includes "Home" and "Monitor" for easy page transitions. The purple and orange color scheme creates an elegant and interactive impression. This interface design is intuitive and visually appealing, emphasizing ease of access to the primary functions as show in Figure 9.

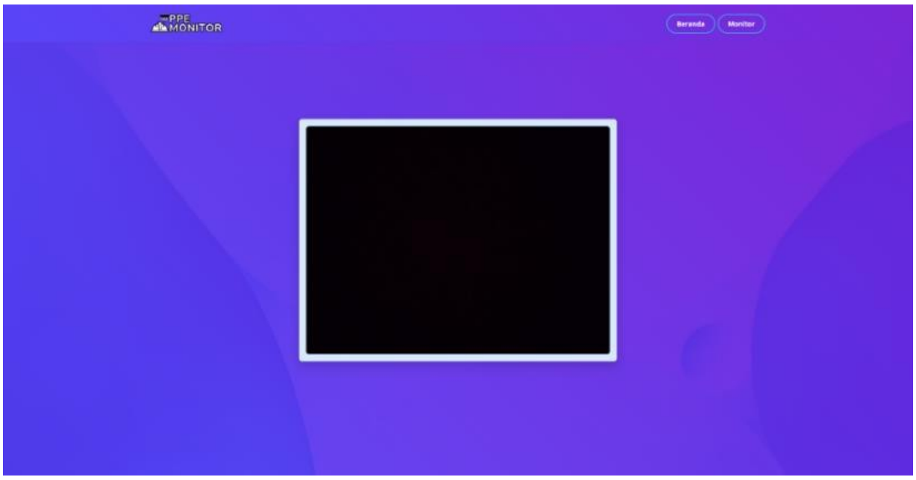

Fig. 9. Detection Page View

Figure 9 depicts the Personal Protective Equipment (PPE) detection page in the "PPE Compliance Monitor" application, featuring the application logo and name at the top left corner, with navigation buttons "Home" and "Monitor" located at the top right corner. The main area of the page displays the visual detection results within a white frame, set against a black background for real-time output. The consistent purple color scheme, matching the homepage, conveys a modern appearance and focuses attention on the detection area. This minimalist design highlights the PPE detection feature to facilitate ease of monitoring.

- **Developing**
  The development of this web application employs Python with the Flask framework for the backend, alongside HTML, CSS, JavaScript, and Bootstrap for the frontend. The project's structure follows the Flask framework conventions, including folders such as model, static, templates, and main files like app.py, model.py, and requirements.txt. Anaconda Distribution is used for package management and virtual environment maintenance, ensuring compatibility with libraries like Flask, PyTorch, and OpenCV. The backend manages the application logic and integration of the PPE detection model, while the frontend provides a responsive and interactive user interface. This structured approach supports effective development of a system for monitoring the usage of Personal Protective Equipment (PPE).
- **Testing**
  The testing phase in this software development process will be conducted using two testing methods: black box testing and usability testing. These methods employ different approaches but complement each other to thoroughly evaluate both the functionality and user experience aspects. Black box testing is a software testing method that focuses on testing the functionality without considering the internal structure or source code. In this method, the tester only observes the system's inputs and outputs to verify whether the application operates according to the specified requirements. The objective of black box testing is to identify any errors or bugs in every function and feature of the application, including interface testing, input validation, and process flow within the application. The results of the black box testing are documented in Table 1.

Table 1. Black Box Test Results

Test Case	Test Scenario	Expected results	Description
Testing running the personal protective equipment detection application	Open and run the personal protective equipment detection application	Applications can be opened and run smoothly	As expected
Testing detection features	Press the detection feature button	The application can capture and display objects on the detection screen.	As expected
Personal protective equipment detection testing	Displaying personal protective equipment objects	The application displays the object detection results on the detection screen.	As expected
Non-personal protective equipment detection testing	Displaying non-personal protective equipment objects	The application does not display object detection results on the detection screen.	As expected

Overall, all testing yielded results in line with expectations. The test results demonstrate that the application can effectively detect Personal Protective Equipment (PPE) and distinguish PPE from other objects, indicating the effectiveness and reliability of the detection feature in supporting monitoring of PPE compliance among workers. The usability testing results show that the PPE Compliance Monitor application has a very high user satisfaction rate, with an average usability score of 85.35%, calculated using formula (1). Testing involved five key aspects: learnability, memorability, efficiency, effectiveness, and satisfaction. The results show that the application is easy to understand (learnability at 86.03%), easy to remember (memorability at 84.52%), operationally efficient (efficiency at 84.15%), effective in enhancing work productivity (effectiveness at 87.92%), and overall satisfying (satisfaction at 84.15%). With a total percentage index across these five aspects of 426.77%, the average score is 85.35%, which falls within the "very satisfactory" category. The application proves to be intuitive, efficient, and supportive of the goal to monitor compliance with PPE usage in the workplace.

CONCLUSIONS

Based on the research and testing conducted on the implementation of deep learning for detecting Personal Protective Equipment (PPE) on workers using the YOLO algorithm, the developed YOLOv5 model demonstrates strong performance in detecting safety attributes such as hard hats and coveralls, with a mean Average Precision (mAP) value of 0.9104 at a threshold of 0.5, indicating high detection capability and precision on the test dataset as well as stable optimal performance after training. The model is adaptable to various lighting conditions and backgrounds, making it effective for PPE compliance monitoring systems. Black box and usability testing confirm that all features of the developed web application function as expected, with user satisfaction reaching 85.35%, interpreted as “very satisfactory.” The application accurately detects and differentiates PPE from other objects, demonstrating good effectiveness and reliability to support the monitoring system. For future development, improvements are needed to enhance detection capabilities in dense and complex work environments, as well as to implement the system on mobile platforms to expand scalability and ease of access for field users.

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