Design of a Fire Spot Identification System in PT PAL Indonesia Work Area Using YOLOv5s

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***Abstract*— PT. PAL Indonesia is a company that operates in the field of national-scale ship production, which has the potential for fire hazards during the ship fabrication process. Therefore, a fire protection system must implemented. This research began with observation to determine the suitability of active and passive fire protection systems in the workplace based on several standards such as SNI 03-3985-2000, NFPA 13, Permenaker no. 04/1980, Permen PU no. 26/PRT/M/2008, and SNI 03-1745-2000. Observational data collection used a checklist with a cross-sectional research design. This production site has the potential for danger, causing fires in large areas, including Irian Dock and Sumatera Dock. Active fire protection has several types such as alarms, detectors, sprinklers, fire extinguishers, and hydrants. In passive fire protection, the assessment is based on the building structure. Field observations showed that active protection systems such as alarms were in the good category, detectors in the good category, sprinklers in the good category, light fire extinguishers (APAR) in the good category, hydrants in the good category, and passive fire protection systems in the good category. To support active and passive fire protection systems, this research proposes a fire spot recognition system based on YOLOv5s by utilizing CCTV facilities that are installed in the PT PAL work area. Dataset collection was carried out using image samples for each class, four classes were used in this research, including Repair, Maintenance, dan Overhaul (RMO) class (type of work that causes a combination of flash points and sparks such as grinding and welding work), spark class, fire spot class and finally the fire class. The research used 1971 training data, 515 validation data, and 262 testing data. The best results were obtained with an Intersection over Union (IoU) threshold value of 0.5 which had a Mean Average Precision (mAP) value during testing for all classes of 0.919. The accuracy produced through the confusion matrix is 0.755 or 75.5% with object detection testing on running videos showing a fairly high and stable accuracy value.**

Key Words — Fire detection, sparks, RMO, fire, image processing, YOLOv5s.

I. Introduction

Occupational safety and health (K3) is an effort made so that every worker or all people in the workplace are protected and do not suffer work accidents and increase production efficiency in the company. Work safety related to the raw materials for work equipment and the work environment [1]. The use of technology and the flammable materials used should accompanied by increasing protection for workers as regulated in Law no. 1 of 1970 concerning Work Safety. This means covering work safety guarantees from the dangers of fire, which states preventing, reducing and extinguishing fires. Until recent years, fire disasters have often occurred both abroad and within the country. The number of fire incidents in America is still high, namely 1,375,000 fire cases reported in 2012, resulting in 2,855 deaths, 16,500 injuries, and property losses of approximately $12,400,000. Fire incidents in the non-residential sector, in 2011 there were 85,400 fire cases with 80 fatalities, 1,100 injuries and financial losses amounting to $2,435,700,000 [2]. To deal with the increasing number of fire cases, an effective protection system is needed according to active and passive fire protection systems in the workplace based on several standards such as SNI 03-3985-2000, NFPA 13, Permenaker no. 04/1980, Permen PU no. 26/ PRT/M/2008, and SNI 03-1745-2000. PT. PAL Indonesia has carried out observational and periodic data collection using a checklist with a cross-sectional design. Based on the results of this data collection, production places that have the potential for serious dangers that can cause large area fires are in the Irian DOK and Sumatra DOK areas. Active fire protection owned by PT. PAL Indonesia based on several components such as alarms, detectors, sprinklers, light fire extinguishers, and hydrants. Meanwhile, for passive fire protection, the assessment carried out based on the building structure. Observations in the field obtained results showing that active protection systems such as alarms were in the good category, detectors in the good category, sprinklers in the good category, light fire extinguishers in the good category, hydrants in the good category, and passive fire protection systems in the good category. To support more efficient active and passive fire protection systems, this research proposes a fire spot recognition system based on YOLOv5s by utilizing CCTV facilities that installed in the PT PAL Indonesia work area. Dataset collection was carried out using image samples for each class, there are four classes used in this research, including: RMO class (type of work that causes a combination of flash points and sparks such as grinding and welding work), spark class, fire spot class and finally the fire class. With the hope that the image processing application in this research would help PT. PAL Indonesia minimizes the fire risk in the work area and is a novelty for implementing YOLOv5s in the work area in real time.

II. Materials and Methods

A. Fire and Image Processing

A fire in a work area presents a significant hazard with potential consequences ranging from property damage to injury or loss of life. In such a scenario, swift and organized response is crucial. Workplaces must have fire safety measures in place, including fire alarms, extinguishers, and evacuation plans. When a fire erupts, employees should immediately activate alarms, notify emergency services, and initiate evacuation procedures. Ensuring safety is paramount, and employees should avoid attempting to combat the fire themselves unless they have been trained to do so. Effective communication and adherence to evacuation routes are key to minimizing risks. Regular fire drills and training can help prepare personnel for such emergencies. Fire in the work area underscores the importance of a comprehensive fire safety strategy, quick response, and employee readiness to safeguard lives, property, and business continuity. Image processing technology plays a critical role in fire cases by enabling efficient prevention, detection, and response strategies. In the realm of fire detection, infrared imaging and smoke analysis using image-processing algorithms offer early warning systems, identifying temperature anomalies and smoke presence. Video surveillance equipped with image processing capabilities allows for real-time monitoring of high-risk areas, with computer vision algorithms able to detect fire and smoke patterns, aiding in rapid response. Additionally, flame detection algorithms can identify flames' characteristic features, aiding in automatic fire suppression activation. Image processing assists in fire monitoring and management, enabling real-time tracking of fire spread and guiding firefighting efforts. Moreover, it supports post-incident analysis by reconstructing events and identifying potential ignition sources. From building safety inspections to wildfire management and training simulations, image-processing technology enhances safety, resource allocation, and preparedness, ultimately reducing the impact of fires on lives and property

B. You Only Look Once (YOLO)

You Only Look Once (YOLO) is a model that uses Region-based convolutional neural network (R-CNN) to detect objects. This model can perform many object detections, predict the classes created, and identify the location of the object. YOLO claimed to be a very fast and accurate architecture. However, the accuracy of this architecture influenced by several variables [3]. YOLO has several versions including: YOLOv1 is the first version of the YOLO model. The input image only processed once, the convolution kernel parameters shared each time, and different features extracted through several convolution layers. This model has a very fast object detection speed. However, its weakness is that it cannot detect small objects and the position detection accuracy is low [4]. YOLOv2 improves YOLOv1. Backbone network improved. YOLOv2 uses average pooling, softmax classification and anchor prediction box, and combines classification and target training methods. Due to some of these improvements, the accuracy increases for small object detection [5]. YOLOv3 has several improvements over YOLOv2, the convolution layer improved 2.8 times over YOLOv2 and the softmax classifiers replaced with multiple logic classifiers. This increases the depth and thickness of the network so that model accuracy increases [6]. YOLOv4 appeared in 2019. Its main goal is to design a fast object detection system that can be implemented in real work environments and can be optimized in parallel. It uses increased data and some of the latest deep learning network tricks in recent years [7]. YOLOv5 is the latest version of YOLO. YOLOv5 has the same base as YOLOv4 with several improvements, the result is that running speed is greatly increased with a smaller size, and the file weight is almost 90% smaller than YOLOv4 [8]. YOLOv5 has three main components, namely: backbone, head, and detection. Backbone is a CNN whose job is to collect and form image features in different roles. Head is a series of layers whose job is to combine image features for the prediction process. Detection is a process that uses features from the head and predicts boxes and classes [9].

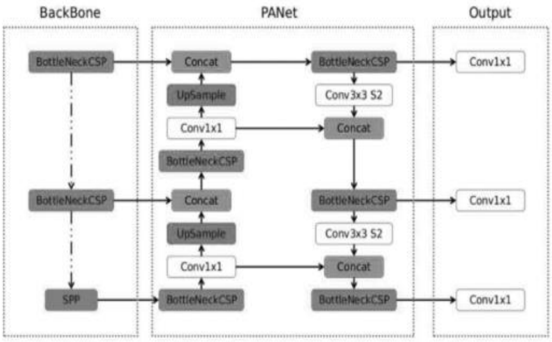

Figure. 1. YOLOv5s Architecture

YOLOv5 has several models, namely: YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. For mobile use it is recommended to use YOLOv5s or YOLOv5m and for cloud use it is recommended to use YOLOv5l or YOLOv5x [10]. YOLOv5 uses the Sigmoid-weighted Linear Units (SiLU) activation function in the following equation:

$$ak(z) = zk \cdot \sigma(zk) \tag{1}$$

$$Z_k = \sum_i \omega_{ik} S_i + b_k \tag{2}$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

ak(z): The output of the activation function for the k-th neuron or unit. This is the activated value after applying the SiLU function.
zk: The input to the activation function for the k-th neuron. It is the linear combination of inputs and weights plus bias (defined in Equation 2).
σ(zk): The sigmoid function applied to zk. It produces a value between 0 and 1, acting as a smooth gating mechanism.
zk: The weighted sum input to the k-th neuron before activation.
∑i: Summation over all input indices i.
ω_{ik}: The weight connecting the i-th input Si to the k-th neuron. It represents how strongly input i influences neuron k.
S_i: The i-th input signal or feature value coming into the neuron. This could be raw input data or output from a previous layer.
b_k: The bias term for the k-th neuron. It allows the activation function to be shifted left or right, providing flexibility in learning.
σ(x): The sigmoid function, a common activation function in neural networks.
x: The input to the sigmoid function (in this context, x is typically zk).
e: The base of the natural logarithm, approximately equal to 2.71828.

The sigmoid function outputs values between 0 and 1, smoothly mapping any real-valued number into this range.

C. Intersection Over Union (IoU)

Intersection Over Union (IoU) is a value based on the similarity and diversity statistics of the sample set which aims to evaluate the overlap area (intersecting area) between two bounding boxes, namely the model predicted bounding box and the model predicted bounding box and the original data bounding box.

$$\mathrm{IOU} = \frac{\text{Area of Intersection of two boxes}}{\text{Area of Union of two boxes}} \tag{4}$$

IoU has a minimum value so that the prediction result is considered truly positive, which is called the IoU threshold.

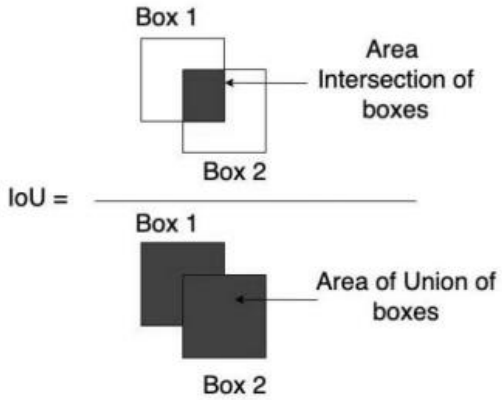

Figure. 2. IoU Equation

IoU threshold is the threshold value of the IoU value of an image that is successfully detected by the model which is used to determine, whether the bounding box is a true positive or false positive. The IoU threshold value can affect the mAP value. The IoU threshold has a value between zero and one. If you use a low IoU threshold value, the model will have a large number of false positives. On the other hand, if you use a higher threshold value, it can cause a very significant reduction in true positives during the training process [11]. Reducing the threshold value appropriately can improve detection performance [12-18]. If the reduction in the IoU threshold value is too large it can cause a significant reduction in false positives [19][20], the following is an illustration of the IoU threshold:

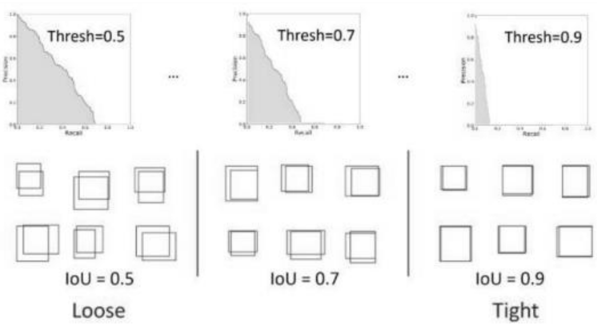

Figure. 3. IoU threshold

III. Result and Discussion

A. Preprocessing

This research uses a dataset with a total dataset of 2748 image data. The dataset divided into four classes, namely RMO, spark, hotspot and fire. The images in the dataset have already been annotated so there is no need to annotate them first. Examples of images in the dataset that used in this research are in Figure 4 below:

Figure. 4. (From top left to bottom right) RMO image, spark image, hotspot image, and fire image

In this study, researchers used a combined dataset taken personally (primary data) on the majority of RMO, spark and hot spot images. As well as some images downloaded from the internet (secondary data) for the majority of fire images. The dataset collected by researchers was 2748 images consisting of 1971 image train data, 515 image validation data and 262 image test data.

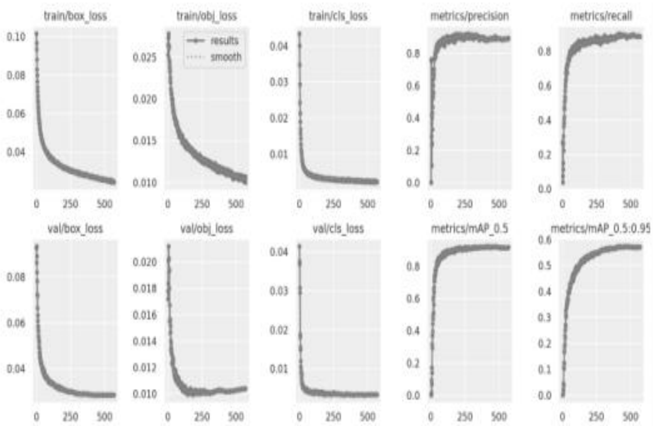

Figure. 5. Training Data Evaluation Results

The results of training on the fire detection system obtained a precision value of 0.919 relative to the recall value. The peak average recall value was 0.97 at a confidence value of 0.00.

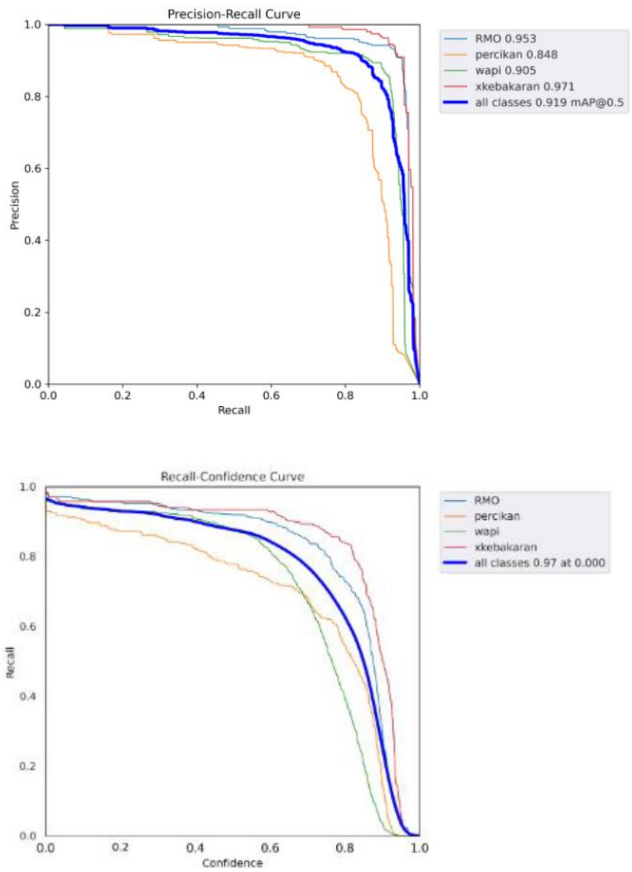

Figure. 6. Recall Value

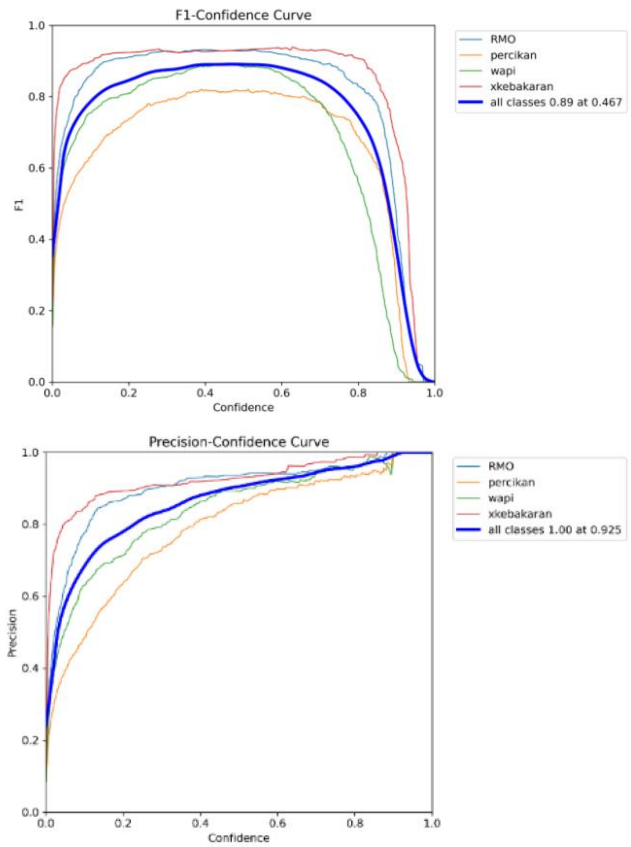

Figure. 7 Curve of F1 and precision values against confidence values.

In Figure 7 above, the F1 value gets an average peak value of 0.89 against a confidence value of 0.467. The precision value gets anaverage value of 1.00 with a confidence value of 0.925. To calculate the accuracy value of the confusion matrix, it can be found using the following equation, with the variables True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN):

$Accuracy = TP + TN\ TP + FP + FN + TN$
$Accuracy$ = 3.72 + 0.04 3.72 + 0.99 + 0.23 + 0.04
$Accuracy$ = 75.5%

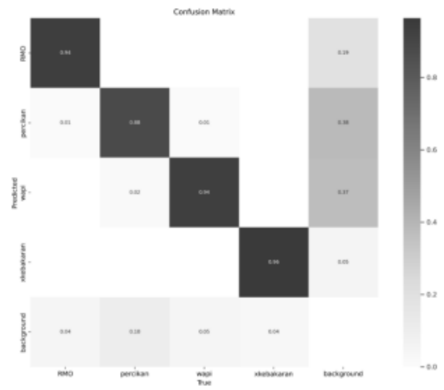

Figure. 8. Confusion Matrix

Therefore, in this research, the fire detection system got a moderate accuracy value, namely 0.755 or 75.5%. Vehicle type detection using the YOLOv5s method runs well and the accuracy value is sufficient. The following is a class detection image:

Figure 9. Hot spot detection

Even though it has a medium level accuracy value, in the object detection test in the video taken, the accuracy value is quite high and objects can be detected stably. The following is an image of object detection testing on a running video

Figure 10. Fire spot object detection testing in the work area

IV. CONCLUSION

Based on the tests carried out in this research, the YOLOv5s method can detect RMO activity by utilizing images from the hotspot dataset as training, validation and test data. The model that has the best results uses the original dataset with an IoU threshold value of 0.5 with an mAP value during testing for each class of 0.919. The variation and amount of data greatly influences the IoU threshold value used. Meanwhile, the accuracy value produced through the confusion matrix is 0.755 or 75.5%. The object detection test on running videos shows a fairly high and stable accuracy value

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