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Improving Resnet Model in Safety Gear Classification using Finest Optimizer

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Abstract

The Occupational accidents that occur in the work environment are increasing day by day. This is caused by workers' non-compliance with the established work safety equipment. Although the supervision of the use of work safety equipment has been carried out, it is still done manually involving less effective human resources. Therefore, it is necessary to develop an intelligent model that can classify the use of work safety equipment more accurately. This study uses the pre-trained ResNet50 model and is combined with the best optimization model to improve accuracy. The results of the study showed that the RMSProp optimization model has better performance with an accuracy value of 97.01% in the 17th epoch of 50 epochs of data training and with training loss and validation loss values of 0.3268 and 0.145, respectively. Testing of 20 images with each image, 10 images using safety equipment, and 10 images not using safety equipment can be classified correctly.

Keywords: *safety gear; classification; resnet; pre-trained; optimizer*

1. Introduction

According to Badan Penyelenggara Jaminan Sosial (BPJS) Ketenagakerjaan Indonesia data, work accidents have been increasingly common in the last five years. Although many factors cause an increase in work accidents, one of the main factors of work accidents is still dominated by the negligence of workers who ignore the Occupational Safety and Health or Kesehatan dan Keselamatan Kerja (K3) instructions from the company [1]. Safety equipment is one of the protection mechanisms for minimizing the possibility of work accidents. Therefore, companies need to implement a monitoring system for the use of work safety equipment by the requirements and standards set [2] [3].

To ensure that monitoring runs well, currently, the implementation of monitoring whether workers use safety equipment or not is still mostly done manually, meaning that manual monitoring still involves human labor which can sometimes be tiring, make mistakes, and is also a boring job [4]. Therefore, the situation demands the development of an intelligent monitoring system. The existence of an intelligent monitoring system will provide an economical, effective solution, and has real-time capabilities to ensure safety in the workplace [5].

Moreover, this is also supported by the emergence of big data and the significantly increased speed of Graphics Processing Units (GPUs), which make it possible to train Convolutional Neural Networks (CNN) in depth, so it becomes clear that deep learning has significant advantages in terms of efficiency and speed that can be used as a monitoring technique using computer vision for pattern and image recognition needs [6].

One example is AlexNet, a convolutional neural network whose architecture won the ImageNet Large Scale Visual Recognition Competition (ILSVRC) using a Deep Convolutional Neural Network (DCNN) where the architecture was able to extract features from images and also simultaneously classify 1000 object classes using 1.3 million images [7]. There are several related studies on classification methods using deep learning methods.

Li et al [8] to reduce labor costs and increase waste classification capacity tried to use the MobileNetV2 model. The results of the study showed that the average waste classification accuracy was 89.26%. The comparison of deep learning models for household waste classification was also carried out [9] by comparing the AlexNet, VGG16, VGG19, ResNet, and ResNext models. The comparison results show that the ResNet and ResNext models are better with an accuracy value of 100%.
Pothineni et al. [10] used the CNN model by modifying the architecture to improve accuracy in traffic sign classification, to reduce traffic accidents. To see the accuracy of the proposed model, the researcher compared the test results with the Le-Net 5 Standard model, where the accuracy of the CNN TrafficSign model reached 95.8%.

Sethi et al. [11] during the COVID-19 pandemic, an experiment was conducted comparing three classification models, namely ResNet50, AlexNet, and MobileNet to identify mask use. The results of the comparison of the three models showed that the ResNet50 model performed better with an accuracy of 98.2%.

Shomal Zadeh et al. [12] tried several deep learning models in their research to monitor and check the structural health of buildings. The use of several deep learning models is due to the subtle crack features, which can often be mistaken for background textures, or foreign objects. Therefore, in this study, the researchers applied fine-tuning techniques to pre-trained models on the VGG19, ResNet50, InceptionV3, and EfficientNetV2 architectures. The four models were chosen because of their better performance and good flexibility in image analysis. The comparison results of the four models show that the EfficientNetV2 model outperformed, which is then followed by the ResNet50 model.

Silopung et al. [13] tried to classify 5 categories of work safety equipment and also performed binary classification on safety equipment using the CNN model. The results of the model showed better performance in binary classification. Where the final test results can reach 88%.

Based on the research study above, this study aims to use the pre-trained ResNet50 model [14] to perform binary classification on the dataset of work safety equipment usage. Meanwhile, to improve the accuracy of the model, the best optimizer is selected. The results of the model training are expected to be used to classify the use of work safety equipment with precise and accurate results so that it can be used in monitoring work areas that require its use [15].

2. Research Methods

Starting from writing with considering handles based on books, research, and journals related to the subject of recognizing work security equipment with the utilization of smart systems. Subsequently, at that point gather datasets and deal with the preprocessing image like resizing, and normalizing pixels before moving to the training process specifically the classification of workers who utilize security equipment or not. After that, the results of the classification show that the deep learning model used several optimizers and lastly testing. The stages are carried out as shown in Fig 1.

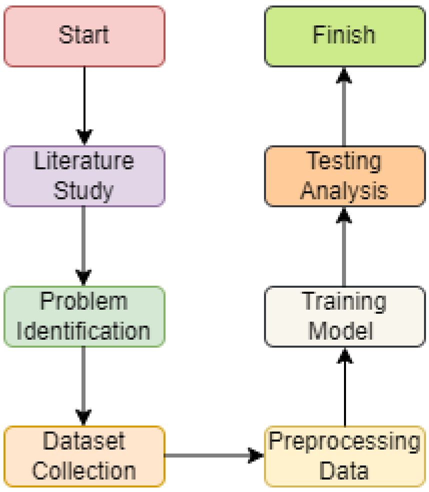

Fig. 1: Research Stages

a. Literature Review

At this stage, researchers collect information related to the problem to be studied, namely the classification of the use of work safety equipment using an intelligent system method, where researchers conduct literature studies from books, journals, and from previous research, namely regarding the classification models that are widely used in other fields, as well as those used in the classification of the use of work safety equipment.

b. Problem Identification

Work accidents often occur because workers are negligent in terms of occupational safety and security in using safety equipment while in the work environment. The use of deep learning models has been widely used to classify in other fields as well as in the classification of the use of work safety equipment, but the reason for this research is to analyze the accuracy of the ResNet50 model that has been combined with a leading optimizer.

c. Dataset Collection

In any experiment, information must be handled accordingly. This dataset contains a collection of images of workers using security equipment in the form of head security, vests, and workers not using security equipment. This dataset was obtained through a web dataset supplier source, to be precise https://kaggle.com/. And can be accessed through https://www.kaggle.com/datasets/khananikrahman/is-an-employee-wearing-safety-gear [16]. The dataset consists of two folders, where one subfolder contains images of people wearing safety helmets and vests with a total of 161 images, and the other subfolder contains general images of people with a total of 195 images. A sample of the dataset can be seen in Fig 2.

Fig. 2: Sample Dataset

d. Experiment Setup

The specifications hardware and software used in the research are shown in Table 1.

Table 1: Experiment Setup

Hardware/Software	Description
PC Intel Core I5-10400F 2.9 GHz	Computer Spesification
Microsoft Windows 10 Pro	Operating system
NVIDIA GeForce GTX 1650 4GB	Graphic Card Specification to Run Pytorch
16 GB DDR 4-3200 (1600MHz)	RAM Unit Specification
Pytorch 2.4.0	Software for Training and Testing the Images
Anaconda	Virtual Environment for Python Code

e. Data Preprocessing

Image data of workers using safety equipment in the form of head protectors and vests and image data not using safety equipment before being used for model training are divided into a train subfolder of 90%, and a test subfolder of 10%. After separating the dataset, the next step was to resize the images to 128x128 size and normalize the image pixel.

f. Model Training

In training, the model used is pre-trained ResNet50 sourced from the open-source software Pytorch by modifying the last layer to perform binary classification. In model training to reduce the amount of loss, experiments were carried out on several optimizer models such as Adam, AdaDelta, SGD, RAdam, AdamW, and RMSProp by applying early stopping to find out at which epoch the model did not experience an increase in validation accuracy. The training parameter configuration consists of 50 epochs, and a learning rate of 0.001 for all optimization models.

g. Model Testing

Model testing is conducted to determine the level of success of the model used. In this study, the success of the model is assessed based on the level of accuracy, and the value of detection errors (loss). The trial was conducted on each of the 10 images obtained from the internet for images that use safety equipment and those that do not.

3. Results and Discussion

a. Training

When performing the data training process using the pre-trained ResNet50 model, several optimizers were tested, as well as parameter determination to obtain the desired accuracy value. The parameters used include the epoch used and the learning rate. The results of model training are in the form of a comparison of Train Loss, and Val Loss Values and Accuracy which can be seen in Table 2.

Table 2: Comparison of Optimization Model Combined with ResNet50

NO	Model	Train Loss	Val Loss	Early Stop Epochs	Accuracy
1	ResNet50+Adam	0.0232	0.2168	16	0.9403
2	ResNet50+AdaDelta	0.1414	0.2854	48	0.8955
3	ResNet50+SGD	0.1315	0.282584	22	0.8657
4	ResNet50+RAdam	0.0061	0.2174	17	0.9403
5	ResNet50+AdamW	0.0096	0.2440	12	0.9701
6	ResNet50+RMSProp	**0.3268**	**0.1453**	17	**0.9701**

The results of the comparison of the best optimization models can be seen in graphical form in Fig 3.

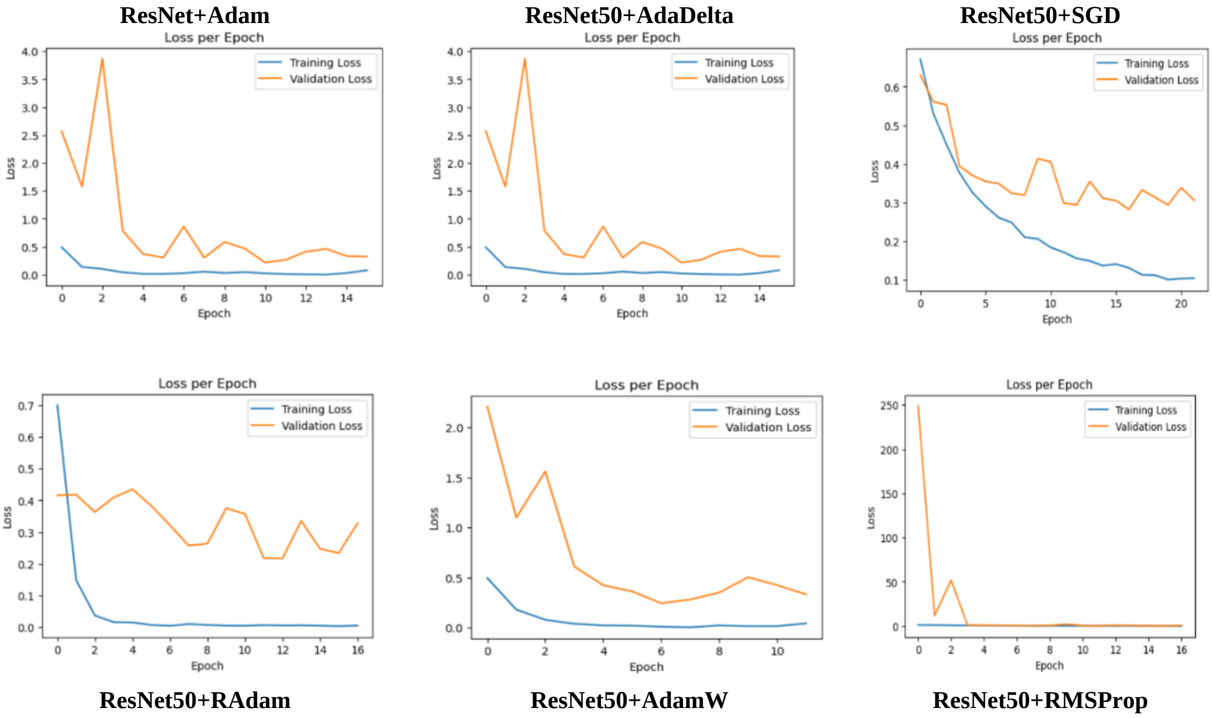

Fig. 3: Comparison of the Best Optimization Models Combined with Pre-trained ResNet50

b. Testing

Testing was conducted to measure the success of the pre-trained ResNet50 model with the best optimizer in classifying based on the accuracy and validation loss value obtained from each class of classified objects. The trial was conducted on 20 images with 10 images each for images Wear Safety Gear (WSG), and 10 images for images Not Wear Safety Gear (NWSG). To determine the best optimization model combined with the pre-trained ResNet50, testing was carried out by calculating the most appropriate probability in classifying. The test results can be seen in Table 3.

Table 3: Probability of Classification Prediction Results

No	Model	Class	Img1	Img2	Img3	Img4	Img5	Img6	Img7	Img8	Img9	Img10
1	ResNet50	WSG	**0.9998**	0.1711	**1.0000**	**0.9745**	**1.0000**	**1.0000**	0.1638	**0.9956**	**0.9865**	**0.9954**
	+Adam	NWSG	0.2259	0.4627	0.1921	0.2406	**0.9689**	0.1497	0.0986	0.0169	**0.8613**	0.0441
2	ResNet50	WSG	**0.9115**	**0.7561**	**0.8484**	**0.8850**	**0.8969**	**0.9251**	**0.7990**	**0.9415**	**0.6674**	**0.8584**
	+AdaDelta	NWSG	**0.6013**	0.3868	0.3731	0.1273	**0.6318**	0.3665	0.3069	0.1392	**0.9406**	0.1213
3	ResNet50	WSG	**0.9665**	**0.6379**	**0.5821**	**0.8545**	**0.8387**	**0.9435**	**0.6452**	**0.8242**	**0.9026**	0.4542
	+SGD	NWSG	**0.7091**	0.2820	**0.8737**	0.2515	0.3105	**0.8148**	0.2767	0.2687	**0.7280**	0.1802
4	ResNet50	WSG	**0.9593**	**0.8473**	**0.9334**	**0.9985**	**0.9922**	**0.9984**	**0.9608**	**0.9886**	**0.9951**	**0.9828**
	+RAdam	NWSG	**0.9249**	0.2447	**0.9159**	0.0358	0.3651	**0.9734**	0.4986	0.0750	**0.9974**	0.0101
5	ResNet50	WSG	**1.0000**	0.0096	**0.9277**	**0.9829**	**0.9975**	**1.0000**	**0.8447**	**0.9999**	**1.0000**	**0.9965**
	+AdamW	NWSG	**1.0000**	**0.9971**	**0.9999**	**0.9234**	**0.9999**	**0.9962**	**0.9983**	**0.9420**	**0.9989**	**0.9459**
6	**ResNet50**	WSG	**0.9841**	**0.7636**	**0.9954**	**0.9950**	**0.9968**	**0.9323**	**0.7137**	**0.9845**	**0.9475**	**0.6446**
	+RMSProp	NWSG	**0.9653**	**0.8906**	**0.9578**	**0.9520**	**0.9962**	**0.9880**	**0.9092**	**0.5774**	**0.9737**	**0.9171**

Based on the test results above, it can be seen that the ResNet50+RMSProp model can perform accurate classification for 20 images.

4. Conclusion

This study was conducted with the hope of utilizing artificial intelligence technology, especially in the field of computer vision, to assist in monitoring the use of safety equipment to reduce the risk of work accidents. In the proposed study, the classification of the use of safety equipment or not using the CNN model with the ResNet50 architecture and optimized with the RMSProp model was able to achieve an accuracy of 97.01% and was able to accurately classify 20 images. And for the second-best optimization model, namely ResNet50 + AdamW.

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