Industrial Safety Helmet Detection Using Single Shot Detectors Models and Transfer Learning

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Abstract. Personal safety is concerned to be as a crucial part for the industrial workers while working in an industrial environment. Industries provide personal protective equipment to their workers to ensure their safety, similarly the workers are also meant to wear and follow all the regulations regarding the personal protective equipment's (PPEs) provided to them. Our study provides the methodology to detect the industrial safety helmet using the surveillance cameras. In this study, we have trained two different single shot detector models i.e., Single Shot Detector (SSD) MobilenetV2 and Single Shot Detector (SSD) Resnet50 and used transfer learning methodology to detect the industrial safety helmet. We have utilized a publically available dataset from Kaggle website and utilized that dataset for the purpose of training the models. Furthermore, the models evaluation is done based on these parameters i.e., classification loss, localization loss, regularization loss and total loss. However, we concluded that the SSD Mobilenet V2 performs better than SSD Resnet50 model based on loss parameters. For SSD Mobilenet v2 we achieved a classification loss of 0.11, localization loss of 0.05, regularization loss of 0.15, and a total loss as 0.32 respectively. Moreover, the graphs for the loss of each model has also been studied.

Keywords: SSD Models · SSD Mobilenet V2 · SSD Resnet50 · Object detection · Safety helmet detection · Transfer learning

1 Introduction

Personal Safety is one of an important aspect for human being. Now a day, every organization ensure that it provides a safe environment for their workers [1, 2]. Industries emphasis on their safety protocols, using various methodologies, many safety protocols have been developed to improve the quality life of workers [3, 4]. Personal protective equipment (PPEs) are one of the necessary safety measures that workers are meant to wear while working in an industrial environment [5–7]. The main purpose of PPEs is that they provide the Head protection, Eye Protection, Hearing Protection, Foot protection and Hand protection by wearing safety helmet, Safety glasses, earmuffs, safety shoes and gloves.

However, it is the need of the industries that they want to ensure that their workers are not abiding the regulations and wearing all the necessary PPEs during work hours [8]. To

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automate this need, Artificial intelligence (AI) techniques are proving to be as a handy tool. As, by the evaluation of the technology, industries tend to adopt the modern world technology, and this has arisen an industry 4.0 concept [9]. There are various studies available which describes that for the revolution of industry 4.0 concepts [10–13].

However, the Single Shot Detector (SSD) in a realtime object detection speeds up the process by removing the need for the region based proposed network. Convolutional neural network (CNN) are the backbones of these SSD models and the features extraction are done by the CNN model. Moreover, Yolo models are also used for the object detection but in most of the Yolo models they possess high localization error and low recall and they also struggle to do the detection in a single frame with two close target objects.

In our study, we provided a methodology for the detection of hard hat safety helmet of the workers. For this purpose, we have utilized the Deep learning models and trained them on publically available dataset from Kaggle website [14, 15]. It is to be noted that the we have used 5000 images along with their annotated files. Moreover, we have done the training on the Google Colab notebook which provides a free GPU access to the user over a limited memory [16].

Moreover, in this paper, the Sect. 2 provides the related work, and Sect. 3 discuss about the experimental methodology and results. We have concluded our study in the Sect. 4.

2 Literature Review

The authors of [17] have done the study about the helmet detection by utilizing the SHEL5K dataset. They have used the state of the art object detection models of YOLO. Similarly, the authors of [18] have proposed a convolutional neural network based safety hat detection. They have used web crawling method and used 3500 images. They achieved 95% precision and 77% recall on their proposed framework. In this study [19], the authors proposed a methodology for helmet detection and used 10,000 images which were captured via 10 various surveillance cameras.

Moreover, in this study [20], the authors have proposed a classifier method called it as Color Feature Discrimination (CFD) and the ViBE algorithm. Along with this they have also utilized the HOG and SVM classifier too. They achieved an accuracy of 89.2% on HOG and SVM classifier and 94.13% accuracy on their proposed methodology. The authors of [21] proposed helmet detection method in a constructional site environment. Moreover, they have used 954 images among them 354 images were of human and 600 non-human images, moreover, they have achieved an accuracy of 79.10% for helmet class and for non-helmet class they achieved an accuracy of 84.34%.

Similarly, the authors of the [22] proposed a single shot detectors (SSD) methodology and used 5229 images. Their proposed methodology achieved 70.8% accuracy and an IoU of 0.5 on the test images.

The authors of the [23] used SSD Mobilenet model for the helmet detection and they utilized a dataset of 3261 images. The authors of [24] proposed an HSV color space and morphological pre-processing and utilized an SSD based neural network for the detection of safety helmet. The authors of [25] used single shot multiple box detector CNN based model and used them to detect the helmet detection for the bikers.

The authors of the [26] used SSD Mobilenet v2 model for the different cases and used to detect the three classes i.e., vehicle, number plate of the vehicle and helmet detection. The authors of the [27], proposed SSD model for the safety helmet detection and improved the network, moreover, the also proposed a lightweight network structure and reduced the parameters. Their results show that their proposed lightweight network has achieved 295% higher detection speed and also up to 83 frame per second.

However, in this study we have used the Single Shot Multiple Box detectors models i.e., Mobilenet V2 and Resnet50 and applied the transfer learning methodology on them to detect the safety helmet that is used in the industrial sites. Moreover, we used a publicly available dataset form Kaggle website which consists of 5000 images [14]. We have then split the dataset into training and testing, thus 4000 images are used for the training and 1000 images are used for testing purposed. Moreover, we have used the Keras and Tensorflow libraries [28, 29].

3 Experiments and Results

This section provides all the discussion about the experimental procedure and the results that we achieved on them.

3.1 Dataset

The dataset used in this study is utilized from the Kaggle website which provides a publically available dataset. Thus for this study we have used the 5000 images [14, 15]. This dataset was already annotated in the PASCAL VOC format and possess 3 classes i.e., Helmet, Head and Person. Thus we then split this dataset into training and testing, thus 4000 images are used to train the model and 1000 images are used for the testing purposes. Figure 1 shows the sample of the images that are used for this study [14, 15].

3.2 Methodology

We have utilized the two pre-trained models from the Tensorflow model zoo [29]. The models are SSD Resnet50 with FPN 640 × 640 and SSD Mobilenet V2 FPN 320 × 320. Moreover, these pre trained models are already being trained for the COCO 2017 dataset, this dataset contains 90 different categories of images [30]. However, in our case we have used the transfer learning technique in which we have downloaded these trained best fit weights and utilized these models to do the training on our classes i.e., person, helmet and head. Moreover, Fig. 2 depicts the methodology that we have used in this study. We have used the dataset and then split into the train and test with 4:1 ratio and then applied the transfer learning technique and then the model evaluation was done based on the loss values obtained from the models. After then we have used the trained weights file to do the detection.

Fig. 1. Dataset image samples [14, 15].

3.3 Models

3.3.1 SSD Mobilenet V2

The SSD Mobilenet V2 models contain 28 layers, which are divided into depth wise and point wise convolutional layers. It is also referred to be as one-stage object detection model because of its lean network. This model is also being used for the classification, regression and object detection based application.

3.3.2 SSD Resnet50

In Resnet50 model it contains 48 number of convolutional layers. Moreover, the Resnet50 model is also be used for different classification, regression and object detection task. This SSD Resnet50 that we have utilized is trained on the COCO dataset as mentioned above and we have utilized these weights and then further done the training for only 3 classes in our case.

3.4 Models Evolution Graphs

After the training of the models the models were evaluated based on their loss graphs and results. For both models we have used the same training images and then both images also used the same testing dataset. Moreover, each model was trained on 3000 number of steps.

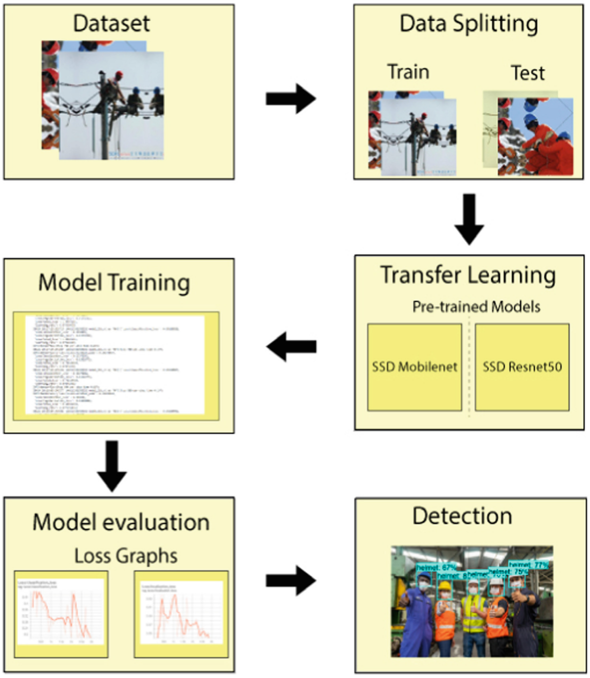

Fig. 2. Methodology used in this study.

3.4.1 SSD Mobilenet V2

For the SSD Mobilenet V2 model we have achieved a minimum classification loss on the testing dataset is of 0.11, a minimum localization loss of 0.05, a minimum regularization loss value of 0.15 and a total loss of 0.32. Moreover, the Fig. 3 depicts the classification loss for this model, Fig. 4 depicts the localization loss and then the Fig. 5 depicts the regularization loss for this model.

3.4.2 SSD Resnet50

For the SSD Resnet50 model we have achieved a minimum classification loss on the testing dataset is of 5.72, a minimum localization loss of 0.60, minimum regularization loss value of 57x106 and a minimum total loss of 31x1010. Moreover, the Fig. 6 depicts the classification loss for this model, Fig. 7 depicts the localization loss and then the Fig. 8 depicts the regularization loss for this model.

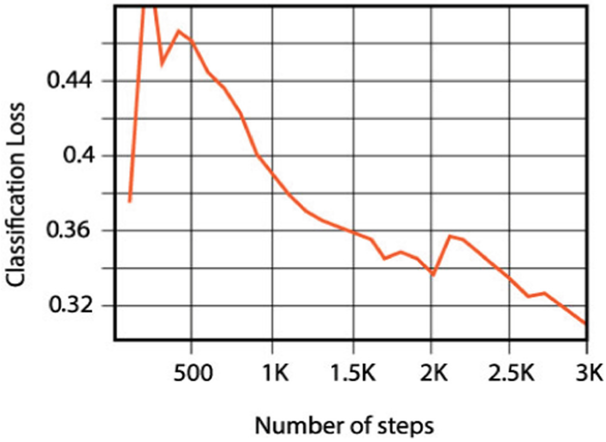

Fig. 3. Classification loss over number of steps for SSD Mobilenet.

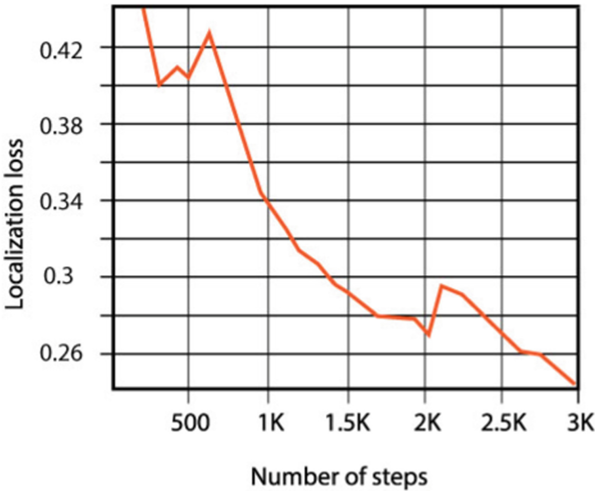

Fig. 4. Localization loss over number of steps SSD Mobilenet.

3.4.3 Comparison of Results

It is to be noteworthy that the SSD Resnet50 model is doing under fitting and the loss values for this model is in increasing trend, that shows that this model's performance is worse on the testing dataset. However, if we observe the graphs of the SSD Mobilenet model, then we can observe that the graphs are decreasing and loss values are still

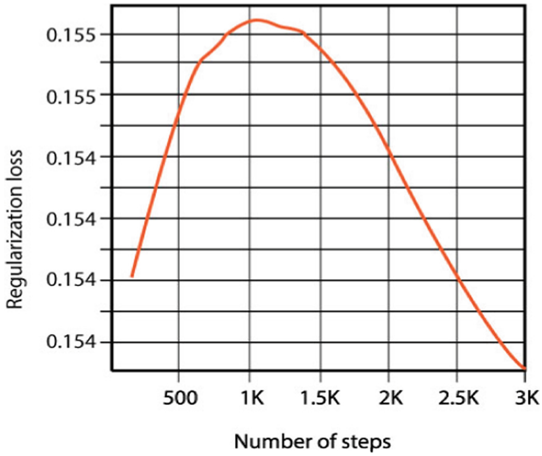

Fig. 5. Regularization loss over number of steps SSD Mobilenet.

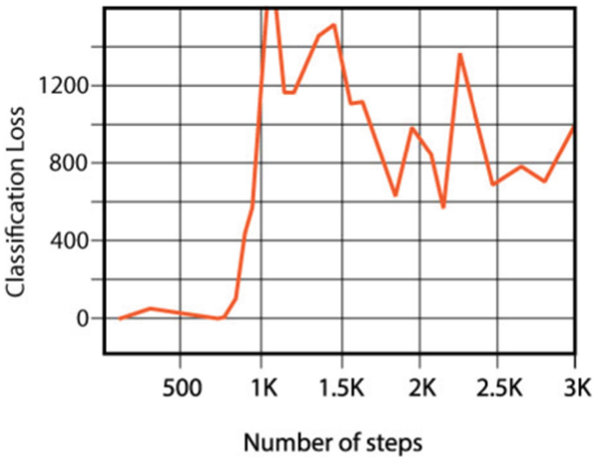

Fig. 6. Classification loss over number of steps for SSD Resnet50.

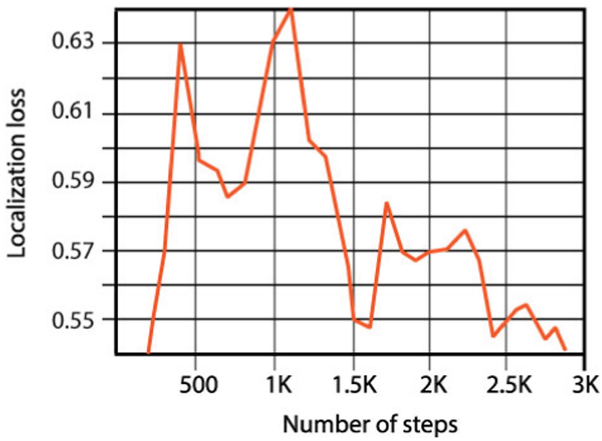

Fig. 7. Localization loss over number of steps SSD Resnet50.

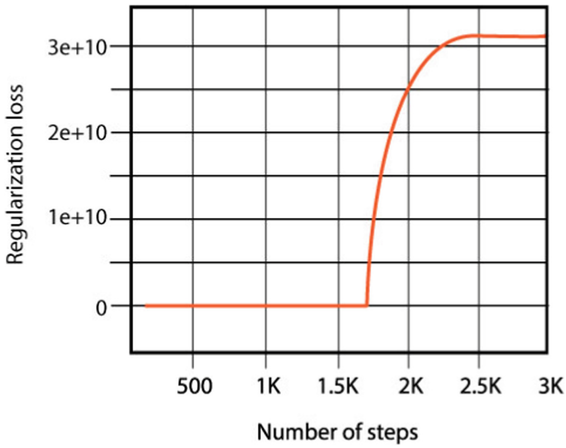

Fig. 8. Regularization loss over number of steps SSD Resnet50.

reducing. Moreover, if we trained this SSD Mobilenet for more than 3000 number of steps, the loss values will still decrease and the model performance will increase. However, as mentioned earlier that we have used the Google Colab notebook which provides a free access of GPU over a limited time, due to this it was not possible for us to train the model for more than 3000 steps. Figure 9 depicts the output image [14] on which model has done the detection.

Fig. 9. Detection of helmet on the image [14] from trained SSD Mobilenet model.

4 Conclusion

In our study, we provided a methodology for the detection of hard hat safety helmet of the workers. For this purpose, we have utilized the Deep learning models and trained them on publically available dataset from Kaggle website [14, 15]. It is to be noted that we have used 5000 images along with their annotated files. Moreover, we have done the training on the google colab notebook which provides a free GPU access to the user over a limited memory [16]. We have used the SSD Mobilenet V2 and SSD Resnet50 model. And this after the evaluation of the models we concluded that the SSD Mobilnet v2 model performed better compared to the SSD Resnet 50 model. For SSD Mobilenet v2 we achieved a classification loss of 0.11, localization loss of 0.05, regularization loss of 0.15, and a total loss as 0.32 respectively.

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