

An Investigation of the Use of Personal Protective Equipment on the Jobsite using Transfer Learning Approach

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Abstract

Practicing engineers throughout the globe are very concerned about the safety at the construction sites. There are still dangers in construction workplaces and thus requires suitable detection and risk assessment. This research establishes a framework for real-time monitoring of Personal Protective Equipment (PPE) compliance by construction workers, which is meant to be incorporated into an organization's safety workflow. Using the Convolutional Neural Network (CNN) model which has been constructed using multiple transfer learning approaches, this inquiry study takes the existence of hard helmets and safety feature jackets as a part of its analysis. Four types of compliances are predicted by the model, including;

1. Red Sign (NOT SAFE)
2. Green Sign (SAFE)
3. Yellow Sign (No Hard Hat or Gloves and something missing)
4. Dark Yellow (No Jacket and many protectives missing).

Overall, the research shows that computer vision-based approaches through transfer learning may be used to automate safety-related compliance procedures at construction sites. It is also clear that real-time performance is better, with a higher accuracy rate after review and study of the obtained consequences by different transfer learning approaches.

Keywords: Transfer learning, Construction safety, safety hazards, MobileNet, DarkNet, YOLO, Protective Equipment

1. Introduction

Recently, contrary to other sectors, the construction industries have a long and high prevalence of workplace accidents. For a long time, project managers have made worker

safety as a top priority. The building industry in India employs about million people, and the safety features of civil works are frightening. With 15.8 accidents per 1,000 employees per year, most of the developed countries have highest accident rates in the world recently, because of no good maintenance conditions. When it comes to ensuring construction site safety, proper data collection methods and monitoring procedures are not in place, making this issue even more difficult to deal with. This industry has a significant problem in ensuring the safety of its employees, both internationally and in India.

Wearing appropriate PPE such as helmets and safety glasses may prevent most injuries, illnesses and deaths [1-3]. The safety helmet is a crucial component of PPE that protects construction workers from direct impacts to the head by entities, by repelling items and absorbing shock. Wearing a helmet minimises the risk of fracturing the skull, spraining the neck, and suffering a concussion when one falls from a great height [4]. The likelihood of a serious head injury from a concrete block might be reduced by up to 95 percent with the use of helmets [5].



Figure 1. Know our PPE

The primary objective of PPE detection is to assess worker adherence to health and safety regulations in order to raise the level of construction site safety. In the event of an accident, wearing a helmet would lessen the severity of injuries and possibly death. In addition, construction workers must wear a vest to boost their visibility. Using a reflective vest with flash lines would make it easier for people to spot construction workers and reduce accidents, especially in wet and foggy weather. Understanding the actions of work and improving management is another goal. Variations in colour scheme symbolise various social

classes across the world. Wearing a black helmet is the norm for site supervisors in many places. An orange one might be worn by slingers and signallers. Wearing a blue helmet indicates that the wearer is inexperienced or is visiting [6]. Figure 1 shows some important PPE elements.

It is a common practise for the manager, the customer, and a competent operator to wear a white helmet; real time measurement of risk parameter for helmet and its colour is useful in analysing whole conditions of PPE components after usage from the construction work. Due to its capacity to self-learn relevant features from large-scale annotated training data, deep learning approaches have gained substantial interest in computer vision in recent years. Images and objects may be classified and detected using convolutional neural networks. On building sites, precise safety monitoring may be achieved via the use of computer vision and machine intelligence. Artificial intelligence and machine learning are being used more often in construction safety. Deep learning-enabled computer vision-based methods are used in this study to construct a framework for the identification and monitoring of preventive measures' compliance [7-9].

The remaining section is as follows: background research works are described in section 2. Section 3 gives an investigation of personal protective equipment systems. Section 4 discusses the relative challenges of personal protective equipment on the jobsite using the Transfer Learning approach. Conclusion and possible future enhancements are described in section 5.

2. Literature Survey

Worker and helmet locations were pinpointed by Zhang et al., [10] using the Global Positioning System (GPS). The existing work with Radio Frequency Identification (RFID) site for verifying PPE agreement was developed by Kelme et al. [11]. Workers who wear RFID PPE may be tracked as they enter and exit checkpoints. Zhuang and his colleagues also integrated RFID technology through recent developed methods where collected datasets were tested and trained through neural networks in the big cloud storage [12]. In order to use this method, employees must wear an additional device to transmit and receive data. Equipment that is not impacted by external elements like as weather, light, humidity, and so on is used in sensor-based helmet detection techniques. It is because of this, that they may be used on a wide range of building projects. Such method relies on sensors, but it's expensive, time-consuming, and requires a lot of upkeep. Installing sensors on every piece of PPE

components demands a significant investment that contains limited capacity to scale. In addition, existing RFID systems [13] need employees to take safer helmet or jacket for the end user to connect to the complex system, which adds weight and discomfort.

Support Vector Machine (SVM) was used to determine whether one individual is wearing or not wearing a helmet, based on Histograms of Orientation Gradient (HOG) extracted from head characteristics. HOG and SVM were used by Rubaiya et al., [14] to recognise humans, followed by the various Hough transform to identify headgear. Aside from that, Shrestha et al., [15] integrated many operators for edge identification as well as the head and face identification. Instead of identifying forms, Du et al., [16] proposed a color-based recognition approach. Distinct things, such as the face and helmet, have different colour thresholds specified. The detection results might be produced according to the colour value by the system.

Using deep learning approaches, researchers have developed automatic and efficient PPE detection systems [17]. Chinese researchers Wu et al., [18] used the K-Nearest Neighbors algorithm that were subsequently used in intelligent neural network models to categorise pedestrian, head and helmet, to extract moving features from the movie. Another example of this is the work of Pradana et al., [19] who utilised CNNs to identify twelve different PPE combinations, including glasses and helmets. As a result, it is possible that the photos could not be used in an outside context since they were only evaluated on a colourless interior backdrop. Akbarzade et al., [20] used two faster intelligent neural network models to identify protection breaches, the leading of which detected the presence of people on the building site as well as a helmet and vest. In the last step, Wu et al., [21] used the Single Shot Multibox Detector (SSMD) to determine if the building civil workers were wearing safety helmets or jackets with the matching colours.

3. Investigation procedures with detection

3.1 MobileNet extracting data from many sources

Despite the overall trend toward deeper models in the architecture of deep learning networks, these models are not optimised for speed and cannot be employed for applications that demand real-time performance because of computationally restricted hardware. MobileNets and their derivatives, on the other hand, are offered as a speedy alternative. Convolutions are the primary building pieces of this kind of network. Two different

procedures are factored out of the usual convolution in depth-wise separable convolution. A convolution kernel is formed for each input channel in the first step, which is also known as depth-wise convolution. Once the first step is complete, point wise convolution is used to merge the data. The conventional, point wise, and depth wise convolutions are shown and compared in Figure 2. Depth-separable convolutions have fewer parameters and processing costs more than normal convolutions, as may be shown mathematically.

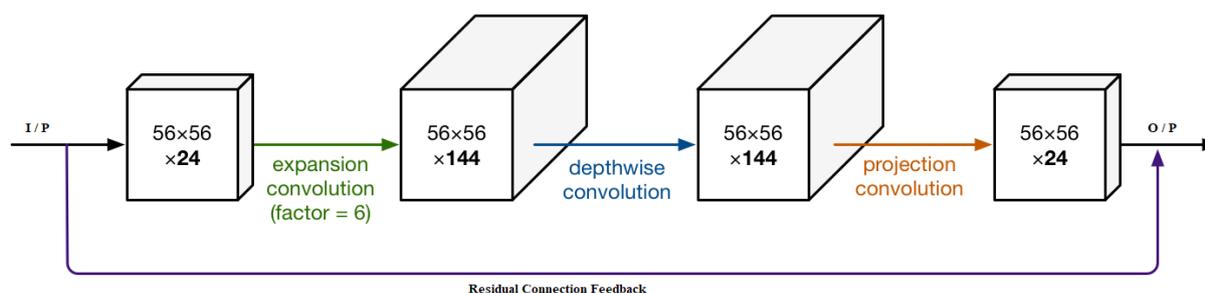


Figure 2. MobileNet Framework

3.2 SSD is the detector of objects

The detector in this investigation is a Single Shot Detector (SSD). One-stage and two-stage object detectors are the two most common types of detectors. The first step in the two-stage object detectors is to suggest the number of places that have a high likelihood of containing objects. Each suggestion is then be subjected to a convolutional classifier. However, despite their high accuracy, these object detectors cannot be employed in embedded systems or real-time applications due to their high computing requirements. The combining classification and localisation into a single network is what one-stage detectors do instead. One-stage detectors provide the benefits of end-to-end learning and model simplicity. A base network, or auxiliary network, is also used for feature extraction in this approach.

3.3 YOLO

It uses the concepts of CNN to recognise objects in real-time, the You Only Look Once (YOLO) method is a cutting-edge algorithm for object detection perfectly. In order to create a matrix grid from the input picture, the YOLO does this. These selected items are specified number of border boxes that may be predicted in each grid cell. As a result, there is a box confidence score for every grid cell. A single item is detected through number of layers with specified features that are present in the area. Finally, it forecasts the likelihood of each object class in terms of various layers through probabilities, one for each class [22]. There are

five components (x , y , w , h and object score) through the confusion matrix mark in each border box. According to the YOLO writers' definition of "object", the confidence score is a measure of how probable the package comprises an object. Finally, the image's width and height are used to normalise the blocks activity in the framework. Figure 3 shows YOLO framework for object detection.

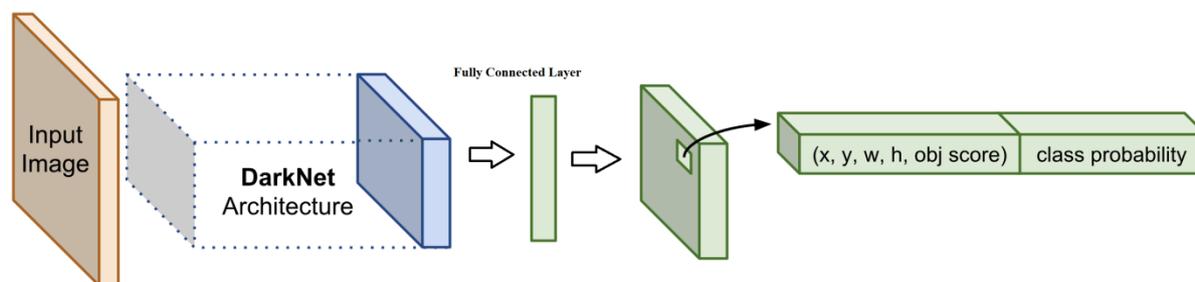


Figure 3. YOLO framework

It employs various activation functions such as Relu or softmax-based forecast that allows for multi-level and multi label arrangement using YOLOv3. It employs higher layer of Darknet, architecture for extracting features from photos. To put it another way, it is quicker than competing algorithms like faster neural networks domain through various transfer learning that can maintain the same levels of accuracy and precision as other similar designs. Multiple employees may be detected on construction sites using YOLOv3. This study's CNN architecture is based on YOLOv3, which is a natural choice.

3.3.1 Database description

Collecting and preparing data to help in model validation is a critical step in training the machine learning algorithm. Data preparation is the most important preliminary work for any classification domain research activities since it allows fast feeder algorithm identification. Both manual data collection and picture scraping are used to get data online [23].

3.3.2 Handling of dataset

Analysing a new dataset with the model's performance offers insight to how it performs in the real world. As an example, a new data collection is constructed to include photographs of people wearing various types of safety jackets or hard helmets. After the three phases of training, the network's ultimate loss is 12.06. For validation and testing purposes, a

confusion matrix is built, and accuracy is measured by dividing the number of correct guesses by total predictions [24].

3.3.3 Performance measures

It also produced a completely new dataset utilising video footage of persons wearing PPE in different circumstances and surroundings. Images and videos are used to evaluate the algorithm's performance once the model is trained. Overall, the results demonstrate a 96.27 percent accuracy rate. The most detections have been in the green cells. As can be observed, the model performed well on the validation dataset, as seen by the large number of outcomes that match [25].

4. Conclusion

This work addresses various investigation procedures by deep learning-based approach for the identification of construction equipment. The solution's implementation is the primary emphasis of this project, although it also includes sections on the solution's creation. During the early stages of development, data is gathered using the earliest accessible labelled datasets and web crawling tools. This study's findings may be put to a variety of practical uses, including:

1. Monitoring the situation
2. Effort evaluations
3. Decisions made by managers

Various algorithms are addressed in this work that have significant drawbacks that might get good advancement with accurate predictions possible. To improve the accuracy of the forecasts, an approach is being pursued to reduce the time it takes to run the algorithm.

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Author's biography

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