PERSONAL PROTECTIVE EQUIPMENT DETECTION AND MACHINE POWER CONTROL USING IMAGE PROCESSING

Bharani T[1], Jishin Jayan T[2], Vadivel S[3]

[1]Bharani T, PG Student, Department of Mechanical Engineering, Bannari amman Institue of Technology, Tamil Nadu, India
[2]Jishin Jayan T, Asst. Professor, Department of Mechanical Engineering, Bannari amman Institue of Technology, Tamil Nadu, India
[3]Vadivel S, PG Student, Department of Mechanical Engineering, Bannari amman Institue of Technology, Tamil Nadu, India

---***---

Abstract - *Safety is defined as the act of protecting oneself from injury or, in other words, being aware of the presence of danger. In the new era of technology development and automation, Image Processing has shown tremendous growth in the 21st century making a better future for society and for human beings. The incorporation of Image processing in safety is one of the fast growing and promising methods in promoting safety in industries as well as in protecting human lives. PPEs are important is any industry as they help to protect personnel from injury when all other lines of defense (engineering controls, administrative controls) fail. The aim of incorporating Image processing in PPE detection is to provide protection to the person operating machines like cutter or grinders. Personal Protective Equipment is must for an operator but usually in the hurry of work some operator forgot to wear the safety equipment and right away they start to operate the machine which is completely not a safe process of working. This may lead or cause anything to the operator. With the help of image processing technique, the Personal Protective Equipment is monitored for every operator when they try to work in the machine, it will not work unless they wear PPE. The device works by detecting Protective equipment with image processing technique and allows access to the machine by closing the circuit. This helps to rectify the major danger before occurring itself, proving a better solution to the safety of workers. To sum up PPE detection to avoid accidents using Image Processing is a great initiative to provide safety to workers in industries.*

***Key Words*: Personal Protective Equipment, safety, image processing, access to machine.**

1.INTRODUCTION

Despite development of science and technology, statistics from the International Labour Organization (ILO) show that workplace environments in many countries (e.g., the European Union) have not improved to the point where the problem of occupational injuries has been significantly reduced. As a result, every effort should be made to reduce the number of accidents or, at the at least, keep the rate within an acceptable range, which can be achieved through organizational actions, collective training, or individual safeguards. Establishing barriers, which plays a key part in accident prevention, is the traditional strategy to avoiding loss. Safety barriers are characterized as "physical and/or non-physical measures meant to deter, control, or mitigate undesired events or accidents”. There are major opportunities before it becomes a loss, to prevent or change an accident sequence of events. The first solution is to alter the necessary conditions for an event to happen by eliminating or adjusting the energy characteristics of the hazard.

1.1 Objective

The objective is to prevent danger before it occurs when operator operates any machine without proper protective equipment. With the help of image processing technique, the Personal Protective Equipment is monitored for every operator once it is available then only the operator can perform operations in the machine.

1.2 Methodology

The process for automatically identifying proper PPE use is outlined, and the steps are as follows:

1. Individuals are discovered, together with their key point coordinates, in each image captured by an on-site cctv system using an individual detection model.

2. Using an object detection model, the PPE(s) are identified and located.

3. Proper PPE identification is accomplished by studying the geometric correlations between the individual's key points and the PPE that has been identified.

2. Image Processing and Computer Vision

Current automated PPE compliance monitoring techniques can be divided into two categories: sensor-based and vision-based. The majority of existing vision-based PPE compliance monitoring systems are limited to spotting hard hats, employed Region-based CNNs (R-CNNs) to detect whether or not a worker was wearing a hard hat. The image processing-based protective eyewear detection system makes use of widely accessible hardware and software components for ease of use, as well as cloud computing support for scalability on-demand. Raspberry Pi, Webcam module, wires, and a relay are among the hardware components. A Raspberry Pi is a credit card-sized computer that is primarily used for projects. The webcam module is used to record video or photos, with the obtained images being compared to pre-set data to provide a result. Power supply, camera, and display cables are all linked to the Raspberry Pi board, which offers a variety of peripherals for connections. Other electronic devices are connected to GPIO pins. Relays are commonly used to manage the power as well as switch the smaller current values in a control circuit in control panels, manufacturing, and building automation. However, because a low voltage is given to the relay coil, a big voltage can be switched by the contacts, the supply of amplifying effect can help regulate huge amperes and voltages.

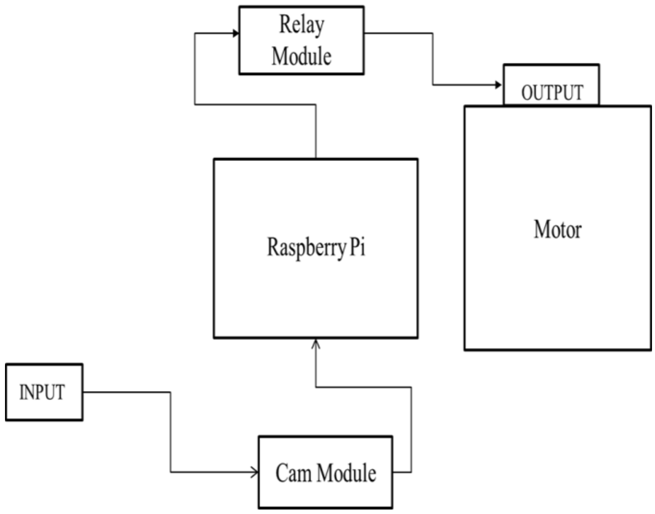

Fig -1: System Architecture

2.1 Computer Vision

Computer Vision (CV) is the study of automatic information extraction from images and movies. 3D models, camera location, object detection and recognition, as well as categorizing and searching visual material are all examples of information. CV combines knowledge from a variety of domains, including image processing, pattern recognition, mathematics, and AI. One of the project's key goals is to enable computers to mimic core human vision functions like motion perception and scene interpretation. As a result, visual object tracking has been extensively researched, and it involves three critical phases in video analysis: detecting object movement, tracking such objects from frame to frame, and analyzing object tracks to recognize their behaviour. Visual object tracking is essentially based on reliably estimating the motion status (i.e., location, orientation, size, etc.) of a target object in each frame of an input image sequence. Every system is designed to compensate for human operators' limitations in monitoring a large number of cameras at the same time. Exploring similar tools and problems to identify the use of PPE in order to prevent accidents in the workplace is an intriguing case.

2.2 You Only Look Once (YOLO)

A type of convolutional neural network is a multilayer neural network known as a convolutional neural network (CNN). It's a deep learning technique that recognizes and categorizes photos. It can solve problems like many parameters and difficult neural network-based training, resulting in better classification results. An input layer, a convolutional layer (Conv layer), a transfer functions, a pooling layer, and a fully connected layer are all common features of CNNs (FC layer). Local connection and parameter sharing are two key aspects of CNNs, which limit the number of factors while enhancing detection efficiency. Object identification algorithms based on classification, such as R-CNN as well as other categorization CNN object identification algorithms, are frequently used. The detecting speed, on the other hand, is slow and cannot be done in real time. Although the SSD algorithm does not have the maximum accuracy, it becomes much fast and equivalent to the YOLO algorithm in terms of detection speed, and its accuracy can be higher than the YOLO algorithm when the input image sizes are lower. Whereas the Faster R-CNN algorithm produces more accurate estimates, it is significantly slower, taking at least 100 milliseconds per image. As a result, the SSD algorithm was used in the study because of the real-time detection requirements.

2.3 Experiment

The computer vision equipped camera is used in the laboratory for two purposes: evaluating how successfully the camera and model recognize protective eyewear, and collecting image information for learning the Custom Vision train model. The image analysis model is trained with internet photographs of persons wearing safety glasses and then deployed to the camera using the method described in the previous section. The model is then tested to see if it can distinguish between people who are wearing PPE and those who aren't. The collecting of picture data and tagging of pictures for learning the custom vision model is the first stage of development. Three of the co-authors worked as lab employees for this experiment, recording their photos with and without safety glasses. VLC media player is used to capture the camera's live stream, which is then parsed into images. The Custom Vision model is built using the parsed images collected from the video feed in the second stage. Selecting a square border area around objects in photographs and applying tags is how imaging tagging is done. The Custom Vision model is trained with the tagged photos and the model's anticipated output, which is computed and recorded, after all of the images have now been tagged. The training set is then obtained from the Custom Vision tool and attached to the camera's cloud-based digital twin, which is then deployed to the on-premises camera. Finally, the new model is tested to see if it can accurately detect persons, faces, and PPEs. The next section contains the results of the performance.

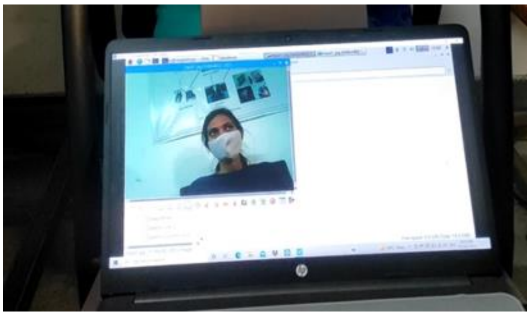

Fig -2: Sample recorded image with Mask (PPE)

The precision and recall of the experimental models were assessed. Precision refers to the percentage of correctly detected classes. For example, if the model identified 100 photos as dogs and 99 of them were indeed dogs, the precision would be 100%. The percentage of actual classes accurately identified is referred to as recall. If there were 100 photos of apples and the model correctly classified 80 of them as apples, the retention would've been 80%. Finally, mean Average Precision (mAP) represents the overall performance of the detector across all tags. When using a high probability threshold to interpret prediction calls, the system tends to produce findings with high accuracy at the cost of recall—the detected categories are correct, but many are missed. A small chance threshold had the reverse effect: most of the true classifications were discovered, but there were more false positives. With all that in mind, the likelihood of establishing whether or not the person is wearing PPE before starting work is increased.

3. Result

The model draws a bounding box around each identified object from a list of predefined classes and generates an expected output in a controlled environment, but when we tested this model in a real-world setting, it failed to recognize safety mask. This model's performance was weak, and it was completely inappropriate for use in a safety system. This base model has considerable problems detecting various types of PPEs in general, and is unable to detect safety helmets in particular.

4. CONCLUSIONS

Using object detection with YOLO, this paper proposed a method for automatically identifying PPE consumption in a controlled environment. This method achieves a decent balance between speed and confidence by exploiting YOLO, which runs in real time and uses relatively few computer resources. Furthermore, the model can be adjusted to different scenarios based on specific requirements. Because the detection is fully automated and does not require continual human attention, this could have a positive impact on safety engineering. Our ongoing study is to enhance this model so that it may be used in a broader range of circumstances. For example, YOLO may be trained to recognize other types of PPEs so that it can be used to track the use of many PPEs at the same time. Additionally, the alert script might be improved, allowing this method to cover a broader range of cases. Future studies will be focused on defining these operating limits and investigating appropriate applications, including using genuine surveillance films as input, detecting the use of PPE in a realistic setting, averting accidents, and improving industry safety monitoring systems.

REFERENCES

[1] Allen, M.W., Coopman, S.J., Hart, J.L. and Walker, K.L. (2015) 'Workplace Surveillance and Managing Privacy Boundaries', Labor History, 51(1), pp. 172–200.

[2] Barnich, O. and Van Droogenbroeck, M. (2011) 'ViBe: A universal background subtraction algorithm for video sequences', IEEE Transactions on Image Processing, 20(6), pp. 1709–1724. doi: 10.1109/TIP.2010.2101613.

[3] Cavazza, N. and Serpe, A. (2009) 'Effects of safety climate on safety norm violations: exploring the mediating role of attitudinal ambivalence toward personal protective equipment', Journal of Safety Research, 40(4), pp. 277–283. doi: 10.1016/j.jsr.2009.06.002.

[4] Egmont-Petersen, M., de Ridder, D. and Handels, H. (2002) 'Image processing with neural networks—a review', Pattern Recognition, 35(10), pp. 2279–2301. doi: 10.1016/S0031–3203(01)00178–9.

[5] Enzweiler, M. and Gavrila, D.M. (2009) 'Monocular pedestrian detection: Survey and experiments', in IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 2179–2195. doi: 10.1109/TPAMI.2008.260.

[6] Guo, X., Chen, L. and Shen, C. (2016) 'Hierarchical adaptive deep convolution neural network and its application to bearing fault diagnosis', Measurement: Journal of the International Measurement Confederation, 93, pp. 490–502. doi: 10.1016/j.measurement.2016.07.054.

[7] Haritaoglu, I., Harwood, D. and Davis, L.S. (2000) 'W4: Real-time surveillance of people and their activities', IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(8), pp. 809–830. doi: 10.1109/34.868683.

[8] Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2012) 'ImageNet Classification with Deep Convolutional Neural Networks', Advances In Neural Information Processing Systems, pp. 1–9. doi:http://dx.doi.org/10.1016/j.protcy.2014.09.007.

[9] Newman, J.A., Beusenberg, M.C., Shewchenko, N., Withnall, C. and Fournier, E. (2005) 'Verification of biomechanical methods employed in a comprehensive

study of mild traumatic brain injury and the effectiveness of American football helmets', Journal of Biomechanics, 38(7), pp. 1469–1481. doi: 10.1016/j. jbiomech.2004.06.025.

[10] Redmon, J. and Farhadi, A. (2017) 'YOLO9000: Better, Faster, Stronger', Conference on Computer Vision and Pattern Recognition, 7(3). doi: 10.1142/9789812771728_0012.

[11] Valera, M. and Velastin, S.A. (2005) 'Intelligent distributed surveillance systems: a review', IEE Proceedings—Vision, Image, and Signal Processing, 152(2), p. 192. doi: 10.1049/ip-vis:20041147.