International Journal of Modern Engineering and Management
Volume 1, Issue 1,May 2024
ISSN No:XXXX-XXXX

Personal Protective Equipment Detection System for Workers

Dr. Yogendra V Patil[1], Aditya Aher[2], Dhanashri Dagade[3], Madhumita Mahata[4], Meghashree Pawar[5]
[1,2,3,4,5]Assoc.Prof, Computer Engineering, Marathwada Mitramandal's Institute of Technology[1]
patyogendra@gmail.com, [2] adityaaheir01@gmail.com, [3]dhanashridagade50@gmail.com, [4]mmahata422@gmail.com,
[5]megha.pawar2607@gmail.com

Abstract

The safety and well-being of workers in various industries are of paramount importance, and the use of Personal Protective Equipment (PPE) is a fundamental aspect of ensuring their protection. This abstract presents a novel approach to enhancing workplace safety through the development of a Personal Protective Equipment Detection System (PPEDS). The PPEDS is a computer vision-based solution designed to identify and monitor the correct usage of PPE among workers in real-time, thereby reducing workplace accidents and ensuring compliance with safety regulations. The PPEDS utilizes advanced image recognition algorithms and machine learning models to analyze video feeds from surveillance cameras strategically placed in the workplace. It can detect and track the presence of various types of PPE, including helmets, safety goggles, face masks, gloves, reflective vests, and ear protection devices. By identifying whether workers are wearing the appropriate PPE for their specific tasks, the system can raise alarms and notifications when violations are detected. Key features of the PPEDS include real-time detection, customizable rules and alerts, data logging and reporting, integration capabilities, worker education, and privacy considerations. The implementation of the Personal Protective Equipment Detection System aims to reduce workplace accidents, enhance safety compliance, and ultimately save lives by addressing the ever-increasing need for workplace safety and ensuring that employees are properly protected in hazardous environments.

Keyword: Image Recognition, PPE detection, industrial Safety, Real time detection.

I. INTRODUCTION

The Personal Protective Equipment (PPE) Detection System for Workers is an innovative and crucial technological solution designed to enhance workplace safety and mitigate occupational hazards. In industrial and construction settings, where employees face a wide range of potential risks, ensuring the proper utilization of PPE is paramount.

This system leverages advanced sensor technology, computer vision, and artificial intelligence to monitor and detect the correct usage of essential PPE components, such as helmets, safety goggles, masks, gloves, and protective clothing, among others. Through real-time monitoring and analysis, the system can not only identify instances of PPE non-compliance but also issue immediate alerts and warnings to both workers and supervisors, thereby preventing accidents and injuries. The system is equipped with machine learning algorithms capable of recognizing specific PPE items and their condition, ensuring that employees are not only wearing the necessary gear but that it is in good working order.

Furthermore, the system can generate comprehensive reports and data for management to analyze PPE compliance trends, enabling companies to refine safety protocols and reduce liability. With its potential to transform workplace safety practices, this PPE Detection System represents a critical advancement in safeguarding the health and well-being of workers across various industries.

II. RELATED WORK

Advancements in video surveillance technology and the availability of extensive image datasets from industrial areas have spurred the development of Computer Vision (CV) algorithms for critical area monitoring. These algorithms analyze visual features in images to accomplish various tasks, such as tracking workers, detecting defects in products, and identifying high-risk situations in industrial environments. [1] - "A Survey of Wearable Sensor Technologies for PPE Monitoring": This paper may provide an overview of various wearable sensor technologies used to monitor the usage of personal protective equipment by workers.

Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), have become instrumental in object detection tasks due to their high performance. Various CNN architectures, including R-CNN, Fast R-CNN, Faster R-CNN, SSD, and YOLO, have been widely adopted for object detection in industrial settings. [2] - "Machine Learning for PPE Detection in Industrial Environments": This paper might discuss the application of machine learning and computer vision techniques for detecting PPE usage in workplaces. These models have been extensively applied to enforce workplace safety compliance, such as predicting collisions, monitoring helmet usage, and identifying personal protective equipment (PPE) like vests and helmets.

Transfer learning techniques are commonly employed to adapt pre-trained object detectors for PPE recognition in images. Recent studies have compared different versions of YOLO detectors and explored various techniques, including machine learning classifiers and decision trees, for PPE identification. Some works have also integrated pose estimators into PPE detection systems to improve accuracy by identifying regions of interest on the human body.

[3]"IoT-Based Systems for Real-Time PPE Monitoring": Research in this area may focus on IoT (Internet of Things) solutions for real-time monitoring of PPE usage, with sensors and data analysis. [4]"Worker Safety and PPE Compliance: A Review of Recent Studies": This paper may summarize recent studies and findings related to worker safety and PPE compliance, highlighting the importance of PPE detection systems. Real-time video analysis for PPE detection typically demands significant computational resources, prompting exploration into edge computing solutions. Edge AI systems, deployed close to data-generating devices, offer potential for real-time analysis with low latency and high privacy. While many existing approaches focus on cloud-based solutions, this paper proposes a PPE detection system based on edge computing, tailored for deployment on embedded systems near surveillance cameras in industrial environments. The study evaluates different DL techniques for model accuracy and latency to enable real-time analysis of video streams.[5]"Challenges and Opportunities in PPE Detection Systems": This paper could provide insights into the challenges faced in developing PPE detection systems and the opportunities for improvement.

III. PROPOSED SYSTEM

A. *System Overview*

Since the system is based on the cutting-edge Yolov5s architecture, it can effectively train a neural network to recognize personal protective equipment in real time. A custom dataset is created, utilizing thorough image segmentation and data augmentation techniques to triple the amount of images, in order to guarantee optimal performance. The trained model is then used to analyze webcam frame captures, allowing it to detect personal protective equipment (PPE) worn by people in real time with ease.

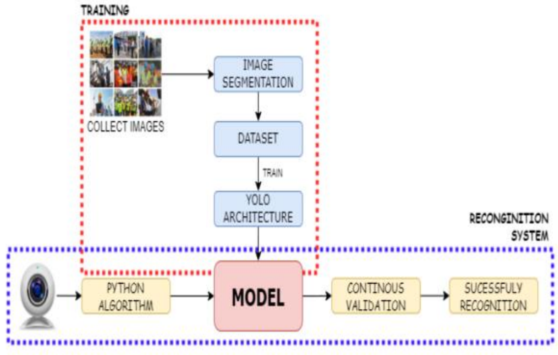


Fig.1. System Architecture

B. Dataset

Large labeled dataset creation typically takes a lot of time: first, it's necessary to identify the set of images that are appropriate for a given task, and then those images need to be labeled. The latter is typically done by hand, which could lead to mistakes as well.

As previously indicated, the goal of our PPE detection system is to identify whether or not three PPEs—helmets, vests, and gloves—are present. As a result, the six classes represented in the dataset's images are: hand without glove, hand with glove, chest without vest, chest with vest, and head without helmet. These classes will be referred to as head, helmet, chest, vest, hand, and glove, respectively, for the purpose of simplicity.

C. Yolo Network

Following an extensive comparative analysis of various open-access neural networks, the YOLO v8 neural network was selected due to its ease of training, direct compatibility with video and webcam sources, and reduced weight compared to previous YOLO versions. However, there are some variations in YOLOv8, so two factors were taken into account when choosing the neural network variant: the accuracy with reference to the Common Objects in Context (COCO) dataset and the processing speed in terms of images processed in a given amount of time.

Although it has been noted that v5n is the ideal choice for a system when an ideal processing time and accuracy are required, v8s was employed in this instance because greater accuracy was desired at the expense of some performance.

Because it is compatible with a large number of existing Python libraries and has active community support, Python was used for both the neural network's implementation and training. Due to the intensive GPU usage required for training, which can be costly, a cloud service called Google Colab is used.

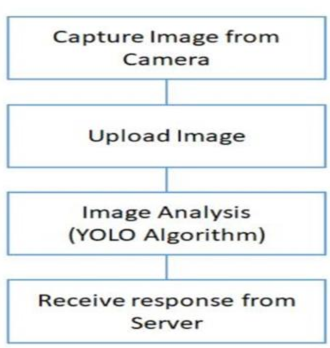


Fig.2. Yolo Procedure

IV. PPE DETECTION TASK TRRAINING AND METHODOLOGY

A. DNN's for Detection Task

When developing a predictive model like Deep Neural Networks (DNNs) for the task of object detection in images, it's crucial to have an appropriate set of labelled training samples. In our case, we require RGB images along with information about the objects within each image, including their position and label. An ideal training dataset for our purpose should consist of images from industrial settings, showcasing a diverse range of the PPE items we aim to detect, such as hard hats, safety vests, and protective gloves. This dataset should also encompass images captured under various ambient conditions, with different backgrounds, distances, and angles from the camera. This diversity is essential to ensure that the DNNs can effectively recognize PPE in different and varied scenarios.

When dealing with DNNs, especially for image object detection, the quality of the trained model improves as the number of labelled training samples increases. This is because DNNs have numerous parameters to optimize. Therefore, having a large set of labelled images is crucial for training a DNN from scratch. However, gathering and labelling a large number of images is a time-consuming process. Therefore, researchers and practitioners often employ transfer learning, where pre-trained models designed for general tasks, such as object detection, are selected and fine-tuned for a more specific task, like recognizing specific PPE items in our case. For the pre-training stage of DNNs in image object detection, there are datasets containing millions of labeled images across thousands of categories that are recognized as effective. Several highly accurate pre-trained DNNs, including those for object detection, are available in AI and ML software libraries and online repositories. In our study, we assessed the effectiveness of five well-known DNNs for object detection, including YOLOv8 and its lightweight YOLOv8-Tiny version, SSD MobileNet V2, CenterNet V2, and Efficient Det D0. For each of these networks, we initially downloaded the pre-trained model generated using the COCO dataset from specific public code repositories. The pre-trained YOLOv8 and YOLOv8-Tiny models can be found in Alexey's GitHub repository, while the others are available in the TensorFlow official repository. We then fine-tuned each pre-trained network to adapt it to our specific PPE detection task. To do this, we used three different datasets. Below, we describe these datasets and the process of fine-tuning and comparing the performance of the five deep learning networks.

B. Detection Scenario

Personal protective equipment is often required to ensure the safety of workers and prevent serious injuries. Different parts of the body need specific protection measures. Additionally, hearing protection and safety goggles can protect the ears and eyes from loud machinery and flying debris. The chest area can be made more visible with safety vests, and stability can be ensured with harnesses. For the limbs, gloves and safety shoes are necessary to prevent burns and scratches.

In our study, we have chosen one specific type of PPE for each body area. Safety helmets are selected for head protection, safety vests for the upper body, and gloves for the arms and hands since these are commonly used in industrial settings.

The workspace consists of both low-risk and high-risk areas. In the high-risk zones, workers are required to wear PPE, including helmets, vests, and gloves to ensure their safety. Our proposed system's objective is to analyze real-time images captured by surveillance cameras to identify workers who are not wearing the required PPE. If a worker enters a high-risk area without the necessary protection, the system will issue visual or audible alerts to notify the worker. Specifically, an alert will be raised for each type of PPE that is not worn. Additionally, the system could be linked to a control mechanism that can shut down potentially hazardous machinery in the high-risk area, thus preventing accidents and enhancing overall safety.

Fig.3. Detection webapplication

V. EVALUATION AND RESULT

A. *Performance on Image Datasets*

The processing speed for each image ranged from 2 images per second to 1 image per second, regardless of the number of classes or bounding boxes detected in the image. To evaluate the performance of the trained model, a confusion matrix was utilized, marking human interpretations and model predictions on a table. The model's accuracy and F1 score were the primary metrics for performance assessment. To calculate accuracy, True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each class were tabulated. Accuracy was determined by summing up TP over the total number of data points. Precision, indicating the likelihood of correct predictions for a given class, was computed as TP over the sum of TP and FP. Recall, indicating the classifier model's ability to detect a particular class, was calculated as TP over the sum of TP and FN. The F1 score, representing the balance between precision and recall, was calculated as the harmonic mean of precision and recall. It was computed as twice the product of precision and recall over the sum of precision and recall. These metrics provided a comprehensive understanding of the model's performance in accurately identifying different classes in the dataset.

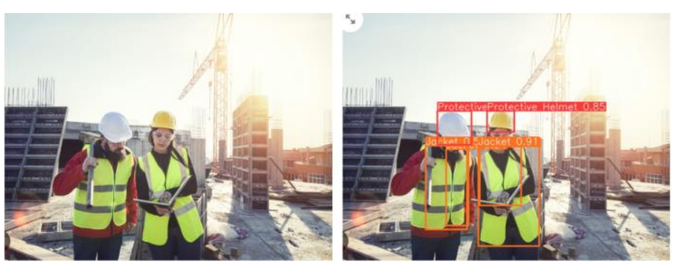


Fig.4. Performance of image dataset

B. *Training Dataset*

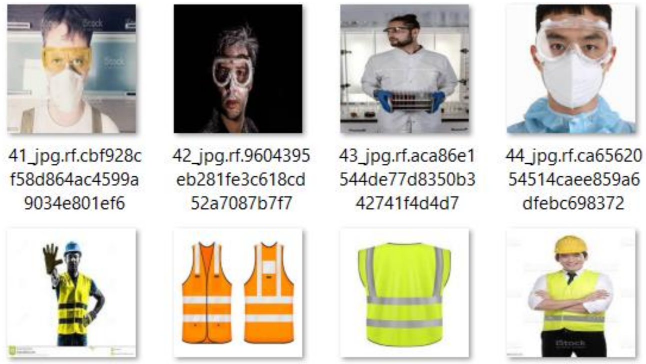


Fig.4. Train Dataset

The junctions that are not included in the training dataset are used only for validation of the network. Moreover, the images are resized to 416×416 pixels. The network was trained on a workstation equipped with an Nvidia GPU with mini-batch size of 10, maximum number epochs of 60, a selected initial learning rate of 10−4 and solved by the stochastic gradient descent [32] with momentum optimizer. The trained network provides an accuracy of 100% and 89.2% on training and validation datasets, respectively.

C. *Test Dataset*

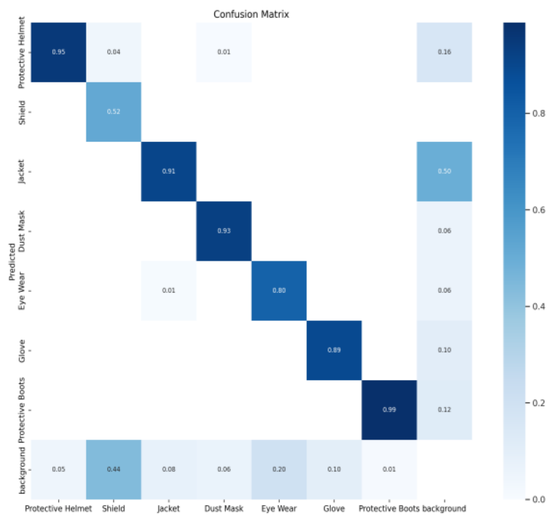
Fig. Test Dataset

The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset. The Test dataset provides the gold standard used to evaluate the model. It is only used once a model is completely trained(using the train and validation sets). For example,the validation set is released initially along with the training set and the actual test set is only released when the competition is about to close, and it is the result of the the model on the Test set that decides the winner). Many a times the validation set is used as the test set, but it is not good practice. The test set is generally well curated. It contains carefully sampled data that spans the various classes that the model would face, when used in the real world.

D. Validation Dataset

The model's performance on the validation dataset indicates strong predictive capability, as evidenced by an impressive overall accuracy of 96.27%. Notably, cells marked in green, representing the maximum number of detections, consistently align with the ground truth, further validating the model's efficacy. In addition to accuracy, a comprehensive evaluation of the model's performance is provided through a classification report. This report includes metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each class. These metrics allow for a deeper understanding of the model's precision, recall, and F1 score across various classes, providing insights into its predictive strengths and weaknesses. Overall, the results underscore the model's robustness and reliability in accurately predicting classifications within the validation dataset, showcasing its potential for real-world application with high confidence.

Confusion Matrix:



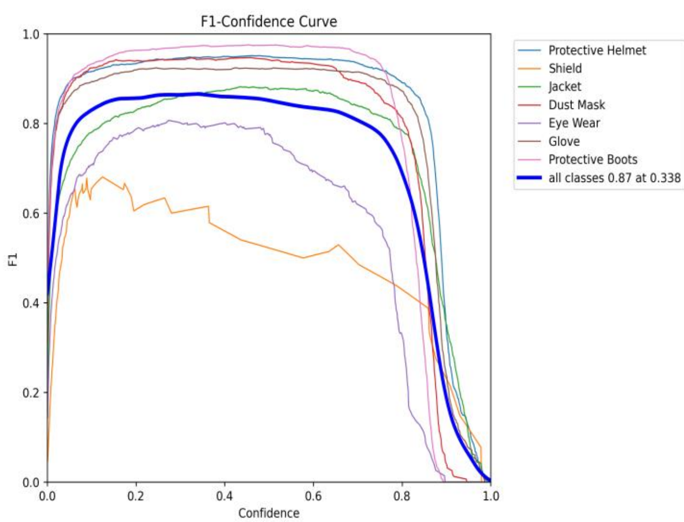


Fig.4. F1 confidence Curve

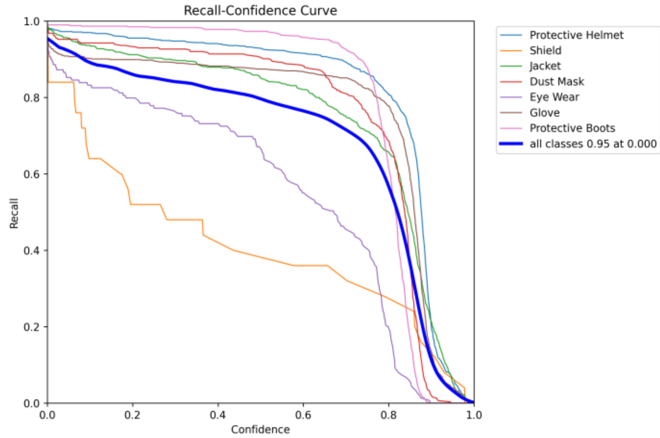


Fig.5. Recall confidence Curve

E. Performance of the Video File

To assess the trained model's robustness, it was employed to predict a video file generated from CCTV footage in mp4 format, processed at a rate of 2 frames per second due to limited computational resources. Despite the reduced speed, the model exhibited proficient performance in detecting individuals across frames. Notably, the algorithm accurately classified individuals as unsafe when there was a modification in their personal protective equipment (PPE), such as the removal of a hard hat or jacket. Conversely, individuals initially labeled as unsafe were promptly reclassified as SAFE upon restoring PPE compliance. This dynamic showcases the model's adaptability and reliability in real-world scenarios, where changes in safety equipment usage can impact risk assessment.

Fig.6. Video detection output

VI. CONCLUSION

The development and implementation of a personal protective equipment (PPE) detection system for workers represents a critical step forward in ensuring the safety and well-being of employees across various industries. This innovative technology not only helps in identifying and monitoring the proper usage of PPE but also serves as a proactive measure to prevent accidents and injuries. By leveraging advanced sensors, data analysis, and real-time alerts, this system not only enhances workplace safety but also fosters a culture of responsibility and compliance among workers. Moreover, the PPE detection system plays a pivotal role in mitigating health and safety risks, reducing liability, and enhancing overall productivity and efficiency. It is a testament to our commitment to safeguarding the workforce, and its implementation is a significant stride towards creating a safer, more secure, and sustainable work environment for all.

ACKNOWLEDGMENT

We invested a lot of time and energy into this project. However, a lot of people contributed to and encouraged us as we finished our tasks. We want to express our sincere gratitude to each one of them. We are grateful to Dr. Yogendra V Patil for acting as our mentor and for always being available to supervise us and provide the project with the information and insights we needed. We are appreciative of his guidance. We would like to express our gratitude to our parents and friends at Marathwada Mitra mandal's Institute of Technology for their support and cooperation in helping us finish this job.

REFERENCES

[1] C.-C. Hung, G. Ananthanarayanan, P. Bodik, L. Golubchik, M. Yu,P. Bahl, and M.Philipose,''VideoEdge:Processingcamerastreamsusinghierarchicalclusters,''inProc.IEEE/ACMSymp.EdgeComputing.(SEC),Oct.2018,pp.115–131.

[2] L.Ciampi,C.Gennaro,F.Carrara,F.Falchi,C.Vairo,andG.Amato,''Multi-cameravehiclecounting using edge-AI,'' Expert Syst.Appl.,vol. 207,Nov.2022,Art.no.117929B. Smith, "An approach to graphs of linear forms (Unpublished work style)," unpublished.

[3] R.Rajavel,S.K.Ravichandran,K.Harimoorthy,P.Nagappan,andK.R.Gobichettipalayam,''IoT-basedsmarthealthcarevideosurveillancesystemusingedgecomputing,'' J. Ambient Intel. Hum. Compute., vol. 13,no. 6, pp. 3195–3207, Jun.2022.

[4] S.Liu,L.Liu,J.Tang,B.Yu,andW.Shi,''Edgecomputingforautonomousdriving:Opportunitiesandchallenges,''Proc.IEEE,vol.107,no.8,pp.1697–1716,Jun.2019.

[5] A. Ndikumana, N. H. Tran, D. H. Kim, K. T. Kim, and C. S. Hong, ''Deep learningbased caching for self-driving cars in multi-access edge computing,'' IEEE Trans. Intel.Transp.Syst.,vol.22,no.5,pp.2862–2877,May2020.

[6] The Potential of Artificial Intelligence for Tourism: A Review of the Literature by Buhalis and Foerste (2020)

[7] The Impact of Artificial Intelligence on Tourist Behavior: A Case Study of Online Travel Agencies by Xiang et al.