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Personal Protective Equipment Detection System for Workers

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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 photo popularity algorithms and device gaining knowledge of fashions to research video feeds from surveillance cameras strategically placed in the place of job. 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.

***IndexTerms* -. Image Recognition , PPE detection, imdustrial Safety, Real time detection.**

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.

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 mastering (DL) models, mainly Convolutional Neural Networks (CNNs), have come to be instrumental in item detection duties because of their high overall performance. CNN architectures, which include R-CNN, speedy R-CNN, quicker R-CNN, SSD, and YOLO, have been broadly adopted for item detection in business settings. [2] - "device studying for PPE Detection in commercial Environments": This paper might discuss the application of machine mastering and laptop imaginative and prescient techniques for detecting PPE usage in places of work. Those models had been notably implemented to put into effect place of business protection 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.

PROPOSED SYSTEM

System Overview

As the system is based on Yolov5s cutting-edge architecture, it can effectively train a neural network to recognize personal protective equipment in real time. A custom dataset is created using thorough image segmentation and data augmentation techniques to triple the number of frames to guarantee optimal performance. The trained model is then used to analyze images of webcam images, allowing it to easily detect the personal protective equipment (PPE) people are wearing in real time.

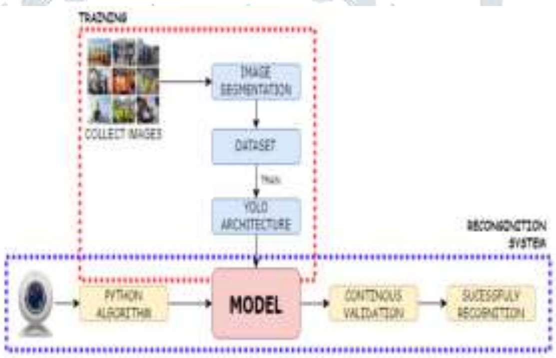


Fig.1. System Architecture

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 mentioned earlier, our PPE detection system aims to detect the presence of three PPE (hat, vest and gloves). As a result, the six classes shown in the images in the dataset are: hands without gloves, hands without gloves, chest without vest, chest with vest, and hands without helmet. For simplicity, we refer to these classes as head, helmet, chest, vest, hands, and gloves.

Yolo Network

After an extensive comparative analysis of different open access neural networks, the YOLO v8 neural network was chosen for its ease of training, direct compatibility with video and webcam sources, and light weight compared to previous versions of YOLO. However, there are many variations of YOLOv8, so when choosing a neural network variation, consider accuracy with respect to the Common Objects in Context (COCO) dataset and processing speed with respect to a fixed amount of images being processed. . Considered. When it has been noted that v5n is the ideal choice for systems that require ideal processing time and accuracy, but in this example, higher accuracy was desired at the cost of performance, so v8s was chosen.

Python was used for both implementation and training of the neural network because it is compatible with many existing Python libraries and is actively supported by the community. Since training is GPU intensive and can be expensive, a cloud service called Google Colab is used.

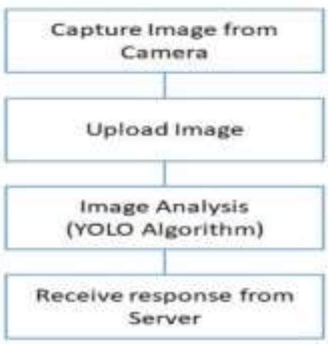


Fig.2. Yolo Procedure

PPE DETECTION TASK TRRAINING AND METHODOLOGY

DNN's for Detection Task

When developing predictive models such as deep neural networks (DNNs) for object recognition tasks in images, it is important to have a suitable set of labelled training examples. In this case, you need RGB images and information about the objects in each image, such as their position and label. An ideal training dataset for our purposes should include images from an industrial environment that represent various items of PPE for detection purposes, such as helmets, safety vests, and protective gloves. This dataset should also contain images taken in different environmental conditions with different backgrounds, distances and camera angles. This diversity is necessary to enable DNNs to effectively identify PPE in different scenarios.

When working with DNNs, especially for image object recognition, the quality of the trained model increases as the number of labeled training samples increases. This is because DNNs have many parameters to optimize. Therefore, to train a DNN from scratch, it is important to have a large collection of labeled images. However, collecting and labeling a large number of images is a time-consuming process. Therefore, researchers and practitioners often adopt transfer learning. Transfer learning takes a pre-trained model designed for a common task, such as object recognition, and adapts it to a more specific task, in this case, recognizing a specific item of PPE. The pre-training phase of a DNN in image object recognition has a dataset containing millions of labeled images in thousands of categories that are known to be effective. Several high-accuracy pre-trained DNNs are available in AI and ML software libraries and online repositories, including DNNs for object detection. In our study, we evaluated the object detection effectiveness of five well-known DNNs, including YOLOv8 and its lightweight version YOLOv8-Tiny, SSD MobileNet V2, CenterNet V2, and Efficient Det D0. For each of these networks, we first downloaded a pre-trained model generated using the COCO dataset from a specific public code repository. The pre-trained YOLOv8 and YOLOv8-Tiny models are available in Alexi's GitHub repository, and other models are available in the official TensorFlow repository. We then tuned each pre-trained network to adapt it to a specific PPE detection task. For this purpose, we used three different data sets. Below, we describe this dataset and the process of fine-tuning and comparing the performance of five deep learning networks.

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 and high risk areas. In high-risk zones, workers are required to wear PPE, including helmets, vests and gloves, to ensure their safety. The goal of our proposed system is to analyze real-time images captured by security cameras and 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 a visual or audible warning to alert the worker. Specifically, each type of PPE that is not worn will be noted. In addition, the system could be linked to a control mechanism that can shut down potentially dangerous machinery in a high-risk area, preventing accidents and increasing overall safety.

Fig.3. Detection webapplication

EVALUATION AND RESULT

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 positive (TP), true negative (TN), false positive (FP) and false negative (FN) were tabulated for each class. Accuracy was determined by summing TP over the total number of data points. Accuracy, which represents the probability of correct prediction for a particular class, was calculated as TP over the sum of TP and FP. Recall, which represents the ability of a classifier model to recognize a particular class, was calculated as TP over the sum of TP and FN. The F1 score, which represents the balance between precision and recall, was calculated as the harmonic mean of precision and recall. This was calculated as twice the product of precision and recall over the sum of precision and recall. These metrics now provide a comprehensive understanding of model performance. in accurately identifying different classes in the dataset.

Fig.4. Performance of image dataset

Training Dataset

Fig.4. Train Dataset

Connections not included in the training dataset are only used for network validation. The image size will also change to 416x416 pixels. The network was trained on a workstation with an GPU with a small batch size of 10, a maximum number of epochs of 60, and a chosen initial learning rate of 10-4 and solved by stochastic gradient descent with a motion optimizer [32]. The trained network provides 100% and 89.2% accuracy in the training and validation datasets, respectively.

Test Dataset

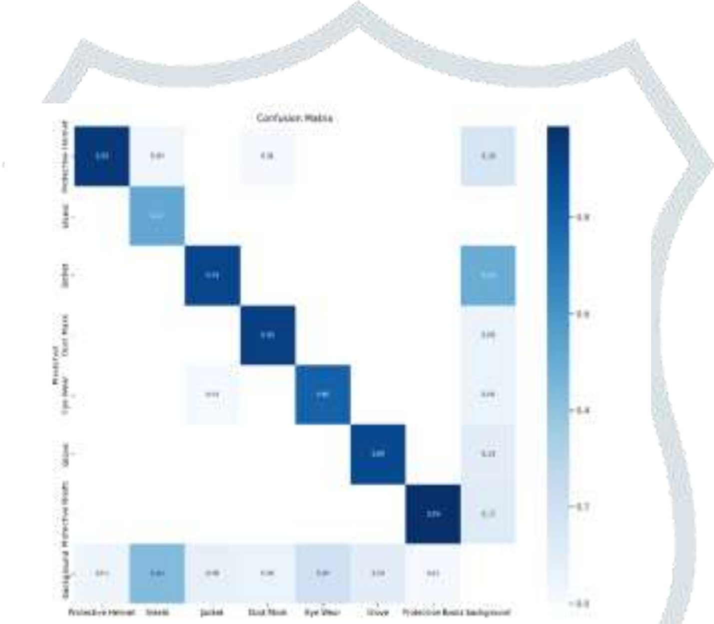
Fig. Test Dataset

A sample of data is used to provide an unbiased estimate of the final model fit to the training data set. It provides the gold standard test dataset used to evaluate the model. This is only used when the model is fully trained (using training and validation sets). For example, the validation set is published first together with the training set, the actual test set is published only before the end of the competition, and it is the model results in the test set that determine the winner. Often validation sets are used as test sets, but this is not a good practice. The collections are usually well organized. Contains carefully sampled data in different classes that the model will encounter when used in the real world.

Validation Dataset

The performance of the model on the validation dataset shows strong predictive ability, as evidenced by an excellent overall accuracy of 96.27%. In particular, the cells marked in green, which represent the maximum number of detections, consistently correspond to the ground truth, further confirming the model's efficiency. In addition to accuracy, comprehensive evaluation of model performance is provided through classification reports. This report includes metrics such as true positive (TP), true negative (TN), false positive (FP) and false negative (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:



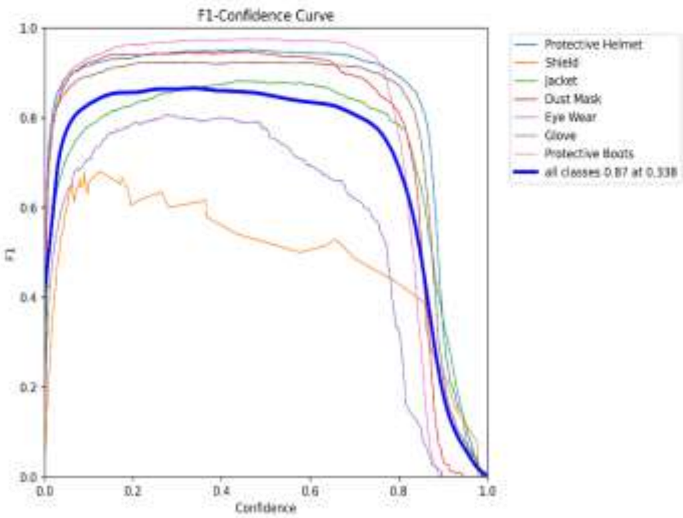


Fig.4. F1 confidence Curve

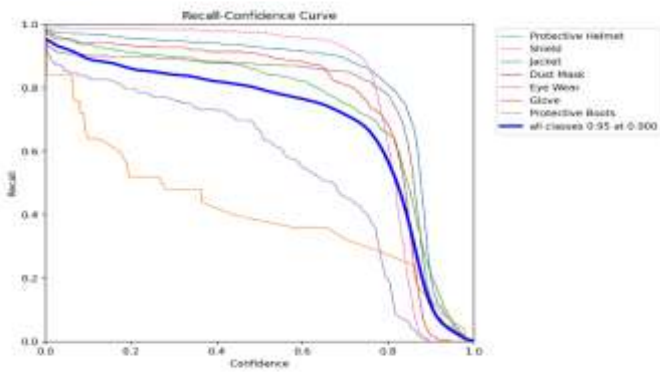


Fig.5. Recall confidence Curve

Performance of the Video File

To assess the robustness of the trained model, it was used to predict a video file generated from CCTV footage in mp4 format, processed at 2 frames per second due to limited computing 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

CONCLUSION

The development and implementation of a personal protective equipment (PPE) detection system for workers represents a major step forward in ensuring the safety and well-being of employees in 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.

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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.