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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 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.

KEYWORDS: Image Recognition, surveillance cameras

I. Introduction

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. NEED OF THE STUDY.

The development of a Personal Protective Equipment (PPE) detection system for workplaces is imperative in ensuring the safety and well-being of workers. With the increasing complexity of work environments and the diverse range of tasks performed, accurately identifying and monitoring the usage of PPE is crucial to prevent accidents and minimize occupational hazards. A dedicated PPE detection system can significantly reduce the risk of injuries and exposure to harmful substances by promptly detecting instances of non-compliance with safety protocols. This technology not only enhances workplace safety but also streamlines monitoring processes, enabling timely intervention and corrective actions. Ultimately, the implementation of a robust PPE detection system is essential for fostering a secure and healthy work environment, promoting occupational safety.

III. PROPOSED SYSTEM

3.1. 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.

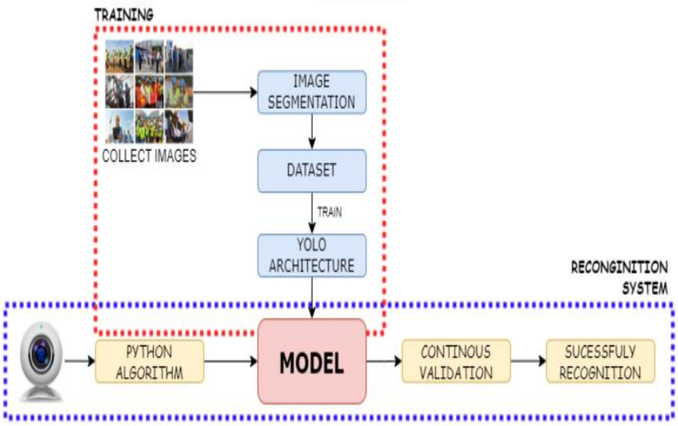

Fig. 1. System architecture

3.2 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.

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3.3 YOLO NETWORK

Following an extensive comparative analysis of various open-access neural networks, the YOLO v5 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 YOLOv5, 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, v5s was employed in this instance because greater accuracy was desired at the expense of some performance.

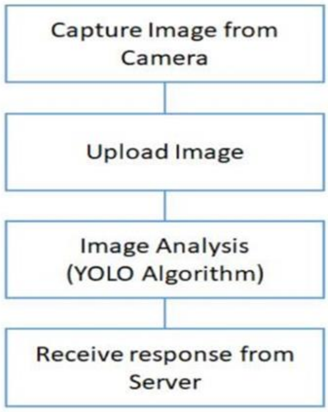

Fig. 2. Data Flow

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.

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 offive well-known DNNs for object detection, including YOLOv4 and its lightweight YOLOv4-Tiny version, SSD MobileNet V2, CenterNet V2, and EfficientDet 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 YOLOv4 and YOLOv4-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.

IV. TRAINNING AND METHODOLOGY

4.1 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 offive well-known DNNs for object detection, including YOLOv4 and its lightweight YOLOv4-Tiny version, SSD MobileNet V2, CenterNet V2, and EfficientDet 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 YOLOv4 and YOLOv4-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.

4.2 DETECTION SCENARIO

In industrial environments, the use of various types of 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.

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.

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