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A Survey: Personal Protective Equipment Detection

Vedant Borgaonkar [1], Mahadev Dudhat [2], Prasad Misal [3], Priyanka Kinage [4]
Department of Computer Engineering, (SKNCOE- Vadgaon), SPPU Pune Pune, India.

Abstract: In industrial environments, real-time object identification has become crucial for automating various tasks, including the monitoring of Personal Protective Equipment (PPE) usage. Ensuring the proper application of PPE in hazardous areas is essential for enhancing worker safety. Typically, PPE usage is monitored through video streams from security cameras, and when an employee is detected without the required PPE, automatic visual or auditory warnings are triggered to raise awareness. However, most existing solutions rely on cloud-based systems, which require substantial network bandwidth and a reliable internet connection to transmit video data for analysis. This centralized architecture introduces challenges related to network reliability, bandwidth consumption, and privacy.This paper proposes a real-time PPE detection system based on deep learning and edge computing to overcome these limitations. By leveraging Convolutional Neural Networks (CNNs) and deploying the system on low-cost hardware, such as Raspberry Pi and Intel Neural Compute Stick, PPE detection can be conducted locally, reducing bandwidth usage and enhancing system reliability and worker privacy. The proposed system is tested with various deep learning models, evaluating the trade-offs between detection accuracy and processing speed, leading to practical recommendations for real-time deployment in industrial environments.

Keywords: Personal Protective Equipment, PPE detection, Deep Learning, Edge Computing, Worker Safety, CNN, YOLO, Raspberry Pi.

I. INTRODUCTION

Worker safety is a top priority in industrial environments, particularly in high-risk sectors such as manufacturing, construction, and chemical processing. These environments are often fraught with hazards ranging from falling objects to dangerous machinery and toxic substances. To mitigate these risks, the use of Personal Protective Equipment (PPE) such as helmets, vests, gloves, and masks is not only recommended but often mandatory. PPE plays a critical role in preventing injuries and saving lives by providing a physical barrier between workers and potential hazards.

Despite the critical importance of PPE, ensuring its consistent and proper use by workers remains a significant challenge. In fast-paced or large-scale industrial settings, manual monitoring of PPE compliance can be both inefficient and prone to error. Human supervisors may not always be able to detect every instance of non-compliance, especially in crowded areas or during peak work hours when the flow of workers is high. This leads to lapses in safety enforcement and increases the risk of accidents.

To address these challenges, industrial environments are increasingly adopting real-time object identification systems to automate the monitoring of PPE compliance. These systems are typically integrated with surveillance cameras that continuously capture video footage of the worksite. The footage is then analyzed in real time to detect whether workers are wearing the appropriate PPE. When a worker is detected without the necessary safety gear, the system automatically triggers an alert, such as a visual or auditory warning, to raise awareness and prompt immediate corrective action. This automated monitoring approach enhances vigilance and ensures a more consistent application of safety protocols, thereby reducing the risk of workplace accidents.

However, the majority of the PPE detection solutions currently in use rely on cloud-based systems. In these setups, video footage is continuously transmitted from the worksite to cloud servers, where it is processed using machine learning algorithms. While cloud-based systems offer powerful computational resources, they come with several inherent drawbacks. First, they require a substantial amount of network bandwidth to transmit high-resolution video streams for real-time analysis. In environments with limited or unstable internet connectivity, this can lead to significant delays in processing or, worse, a complete breakdown of the system. Second, cloud-based systems introduce potential privacy concerns as sensitive video data is transmitted to and processed by external servers, often owned and managed by third parties. This creates vulnerabilities, especially in industries where worker privacy is a key concern. Lastly, the reliance on cloud infrastructure means that any network disruption or outage can result in critical gaps in PPE monitoring, compromising worker safety.

Given these challenges, there is a growing need for an alternative solution that can perform real-time PPE detection without depending on cloud infrastructure. Edge computing offers a promising solution to this problem. Edge computing involves processing data closer to the source of data generation (i.e., at the "edge" of the network), such as on local devices rather than on remote cloud servers. By processing video streams locally, an edge computing-based system can significantly reduce bandwidth usage, enhance system reliability, and maintain data privacy since the video data never leaves the local network.

This paper proposes a novel real-time PPE detection system that leverages deep learning algorithms and edge computing to monitor worker safety. The system is designed to detect the presence of essential PPE, such as helmets, vests, and gloves, using Convolutional Neural Networks (CNNs). By deploying the system on low-cost, portable hardware devices, such as Raspberry Pi and Intel Neural Compute Stick, the detection process can be performed locally without requiring continuous internet connectivity or expensive cloud infrastructure. This edge-based approach ensures that the system remains operational even in the absence of a reliable network connection, thereby offering a robust and scalable solution for industrial environments.

The proposed system is also cost-effective, making it an accessible option for small to medium-sized industries that may not have the resources to implement high-end cloud-based solutions. The use of Raspberry Pi and Intel Neural Compute Stick provides the necessary computational power to run deep learning models efficiently, while keeping the hardware costs manageable. Additionally, the system's local processing capability enhances worker privacy by eliminating the need to transmit sensitive video footage to external servers.

In this study, several deep learning models, including variations of CNNs, are tested to evaluate their performance in detecting different types of PPE. The models are assessed based on key metrics such as detection accuracy, inference time, and their ability to process video streams in real time. One of the key findings of this research is the trade-off between accuracy and processing speed. While more complex models may offer higher accuracy in detecting PPE, they often require more computational power and result in slower processing times. On the other hand, lighter models provide faster processing but may sacrifice some level of accuracy, especially in detecting smaller items like gloves. These trade-offs are carefully analyzed to provide practical recommendations for selecting the most suitable model for different industrial scenarios.

The contributions of this paper are twofold: first, it introduces a practical and scalable solution for real-time PPE detection using edge computing, and second, it offers a comprehensive evaluation of various deep learning models, balancing accuracy and speed for real-time industrial applications. By implementing such a system, industrial environments can significantly enhance their safety protocols, ensuring that workers are protected at all times without the need for constant human supervision or high-cost cloud infrastructure.

II. RELATED WORK

The field of PPE detection has witnessed significant advancements in recent years, with deep learning models emerging as the dominant approach. Convolutional Neural Networks (CNNs), particularly object detection architectures like YOLO (You Only Look Once), have demonstrated remarkable performance in accurately identifying PPE items within video streams.

Early PPE detection systems relied on traditional image processing techniques, such as Support Vector Machines (SVM) and Haar cascades, which often struggled with complex backgrounds, occlusions, and variations in PPE appearance. The introduction of deep learning, and specifically CNNs, revolutionized PPE detection. CNNs are adept at extracting meaningful features from images, making them well-suited for tasks like object detection and classification. While early deep learning-based PPE detection systems utilized Faster R-CNN and SSD (Single Shot Detector), the YOLO family of algorithms has gained widespread popularity due to its speed and accuracy. YOLOv3 and YOLOv5, in particular, have been effective in PPE detection, employing a single-stage detector architecture for efficient real-time predictions.

Although deep learning models have significantly improved PPE detection, their computational demands can still be challenging for deployment in resource-constrained environments. Edge computing offers a promising solution to address this issue. By processing video streams locally on edge devices, such as Raspberry Pi or Intel Neural Compute Sticks, PPE detection systems can reduce latency, enhance privacy, and minimize bandwidth requirements.

Recent research has focused on further improving PPE detection accuracy and efficiency through techniques like transfer learning, data augmentation, and model quantization. Additionally, there is ongoing work to develop models that can handle multiple PPE items simultaneously and adapt to different lighting conditions and camera perspectives.

The proposed research paper aligns with the current state of the art in PPE detection by leveraging the YOLO architecture and exploring its integration with edge computing. It contributes to the field by providing a comprehensive evaluation of YOLO variants for PPE detection and offering practical recommendations for real-time deployment.

TABLE I. SUMMARY OF RELATED WORK/GAP ANALYSIS

Content	Parameters	Algorithms/Techniques	Limitations and Future Work
Study 1: Smart system for PPE detection in industrial area	- Personal Protective Equipment types : Helmets,Vests, Gloves	- Convolutional Neural Networks (CNNs) YOLOv4	High latency for complex models like YOLOv4.
Study 2 :YOLOv8n-ASF-DH model for improved safety helmet detection, focusing on small objects and complex scenes.	Triplet Attention for small target focus - ASF for multi-scale feature fusion - DyHead for spatial, scale, and task awareness	Triplet Attention, ASF, DyHead, and Focal-EIoU for improved accuracy.	Slower inference speed; future work on speed optimization and applying to other object detection tasks.
Study 3: Real-time PPE compliance analysis system using edge computing and pose estimation for underground mines.	- YOLO Pose v8 for pose estimation - Edge computing for real-time processing - PPE detection for helmets, gloves, vests, and boots	YOLOv8 for real-time detection and pose estimation, keypoint validation for PPE compliance, and edge computing for fast, decentralized analysis.	Issues with low-light conditions and occlusions; future work focuses on improving image quality and expanding application to more mine sites.
Study 4: MARA-YOLO model for efficient multi-class PPE detection, balancing speed and accuracy in complex environments.	- MobileOne-S0 backbone - Attentional Space-to-Depth Block - R-C2F module for feature fusion	Built on YOLOv8 with improvements like AS-Block, R-C2F, and RASFF to enhance detection accuracy in industrial scenarios.	- Challenges with low-light conditions and occlusions; future work includes improving real-time processing speed and expanding to larger datasets.
Study 5: YOLO-ESCA model for detecting proper helmet-wearing in real-time using UAVs and video systems.	- Dataset: 4400 images - mAP: 94.7% - FPS: 65.3 - Model Size: 4.47MB	- Based on YOLOv5n - EIOU-loss for better accuracy - Soft-NMS for overlap handling - CBAM for feature enhancement	- Difficulty detecting small targets in complex environments - Future: expand dataset, reduce model complexity, real-world testing, deploy on edge devices (e.g., drones)
Study 6: SuPEr-SAM:	- Datasets: Helmets, Boots, and Surgical Masks - Helmet dataset: 13,481 images (people with helmets), 4,170	- SuPEr-SAM: Uses a person detector, pose estimator, and classifier with spatial attention module - Pose Estimator: Used during training to generate attention masks for guiding the spatial attention module	Tested only on a few types of PPE (helmets, boots, masks) - Potential expansion to more types of PPE

A deep learning model for detecting personal protective equipment (PPE) using a pose estimator during training to enhance spatial attention module performance.	(without helmets) - Boots dataset: 4,784 (with boots), 988 (without)		in future - Plan to apply the approach to other neural architectures beyond PPE
Study 7: Implementation of Convolutional Neural Networks (CNN) for image detection and recognition on MNIST (handwritten digits)	- MNIST Dataset: 70,000 images, 28x28 pixels, 10 output labels - CIFAR-10 Dataset: 60,000 images, 32x32 pixels, 10 object classes	CNN with Relu activation - Dropout for reducing overfitting - Data augmentation (rotation, mirroring) for CIFAR-10 dataset	CIFAR-10 accuracy could improve with more hidden layers and training on a GPU - Future work could focus on larger models and integration with GPU to enhance performance

III. OBSERVATIONS AND FINDING

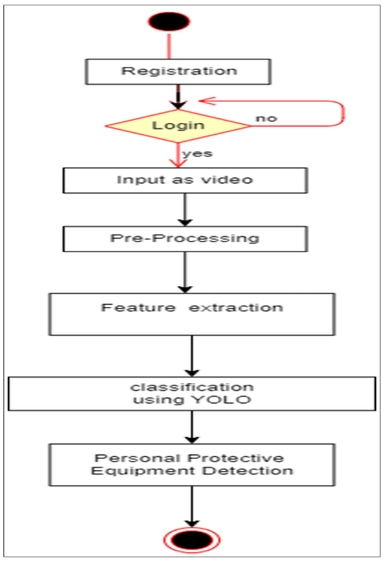

Fig. Activity Diagram

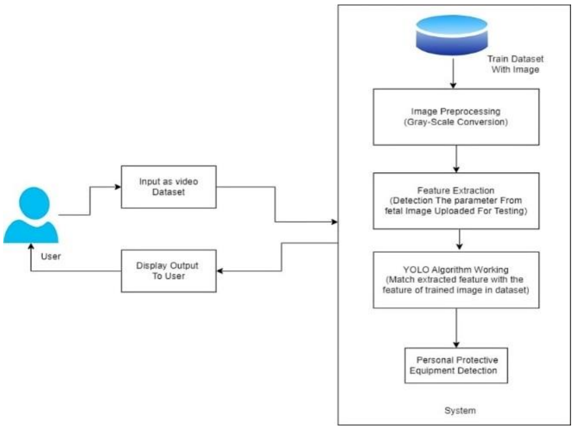

Fig. Overview of PPE Detection

(A) Key Issues:

Significant progress has been made in PPE detection using deep learning and edge computing; however, several key challenges remain. One of the primary difficulties lies in handling occlusions and complex backgrounds, as PPE items can often be partially obscured by other objects or the worker's body, making accurate detection challenging. Additionally, cluttered industrial environments introduce noise that hinders the detection process. Lighting conditions also pose a significant challenge, with variations such as shadows, glare, and low-light situations greatly impacting the performance of PPE detection systems. Therefore, models need to be robust against different lighting scenarios to ensure reliable detection.Furthermore, the diversity of PPE types, styles, and colors complicates the creation of a single model that can accurately detect all variations. Generalization to unseen PPE types remains an ongoing issue. Real-time performance is another critical consideration; PPE detection systems must operate in real time to provide timely alerts and prevent accidents. Balancing detection accuracy with processing speed is essential for practical deployment, particularly on edge devices like Raspberry Pi or Intel Neural Compute Sticks, which have limited computational resources and necessitate careful optimization of deep learning models for efficient performance.Data privacy and security are also crucial concerns, as processing video data on edge devices can raise privacy issues, especially in sensitive industries. Additionally, PPE detection models should be resilient against adversarial attacks, which can manipulate images to deceive the system, making techniques to enhance model robustness against such examples essential. Lastly, scalability is a critical factor; as the number of workers and cameras in industrial environments increases, PPE detection systems must be scalable to manage large-scale deployments effectively. Efficient distributed processing and data management are necessary to accommodate growing demands. Addressing these key challenges will contribute to the development of more reliable and robust PPE detection systems, ultimately enhancing worker safety in industrial settings.

(B) Key Insights:

The research paper on PPE detection unveils several significant insights, particularly regarding the efficacy of deep learning models like YOLO in real-time PPE item detection. By implementing the system on edge devices, the study illustrates key advantages, including reduced bandwidth requirements, heightened privacy, and increased reliability. Achieving an optimal balance between detection accuracy and processing speed is essential for effective real-time deployment, and the paper offers tailored recommendations for selecting the most suitable model to meet specific operational needs.Furthermore, tackling challenges such as occlusions, variations in lighting, and the diversity of PPE types is vital for the creation of robust detection systems. The research underscores the importance of advancing techniques for managing complex backgrounds, enhancing model resilience, and developing strategies for detecting multiple PPE items simultaneously. The implications of these findings extend into practical applications within industrial settings. By adopting effective PPE detection systems, organizations can significantly improve worker safety and minimize the risk of accidents. Overall, the paper not only sheds light on the current state of PPE detection technology but also lays the groundwork for future research and applications in this critical area.

IV. RESULTS AND FUTURE WORK

The research paper on PPE detection reveals several significant findings. Deep learning models, especially YOLO, demonstrate a remarkable improvement over traditional techniques, achieving superior accuracy and speed in detecting PPE. Implementing the system on edge devices brings several benefits, including lower bandwidth consumption, greater privacy, and enhanced reliability. The study emphasizes the critical balance between detection accuracy and processing speed, offering insights into how to choose the right model based on specific operational needs.Overcoming challenges such as occlusions, variations in lighting, and the diversity of PPE is crucial for building resilient detection systems. Future research could focus on advancing the system's capability to navigate complex backgrounds, perform well under varying lighting conditions, and effectively identify a wide range of PPE types.To optimize the system further, upcoming work may explore innovative techniques for improving real-time performance, particularly on resource-limited edge devices. Additionally, investigating methods for detecting multiple types of PPE simultaneously, integrating the detection system with other safety protocols, and conducting extensive evaluations in actual industrial settings present promising avenues for future inquiry. By targeting these areas, subsequent research can enhance the development of even more effective PPE detection systems, ultimately bolstering worker safety in various industrial contexts.

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