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AI BASED PPE DETECTION UTILIZING COMPUTER VISION AND DEEP LEARNING TECHNIQUES

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ABSTRACT

Ensuring the proper use of Personal Protective Equipment (PPE) is essential for maintaining safety standards in industrial and construction environments. Manual monitoring of PPE compliance is often time-consuming, prone to human errors, and difficult to scale. This project proposes an AI-based PPE Detection System that leverages computer vision and deep learning techniques to automatically identify whether workers are wearing required safety gear such as helmets, masks, gloves, vests, and safety shoes The system uses a trained deep learning model such as YOLO or SSD for real time object detection and classification of PPE elements from video feeds or images. Preprocessing, data augmentation, and model optimization techniques are employed to improve accuracy, robustness, and performance under verying lighting, angles, and environmental conditions. The output provides instant alerts when PPE violations are detected, enabling faster decision-making and reducing workplace risks. The proposed system enhances safety compliance, minimizes accidents, and offers a scalable, automated solution that can be interated into existing surveillance infrastructures.

KEYWORDS: Personal Protective Equipment (PPE),Computer Vision, Deep Learning, Object Detection,YOLO, SSD, Convolutional Neural Networks (CNN), Real-Time Surveillance, Safety Compliance Monitoring, Workplace Safety Automation, Video Analytics, Industrial Safety, Image Processing, PPE Violation Detection.

I.INTRODUCTION

In industrial and construction environments, ensuring the safety of workers is a top priority. Personal Protective Equipment (PPE) such as helmets, safety vests, gloves, and masks play a vital role in minimizing the risk of injuries and accidents. However, manual monitoring of PPE compliance is often timeconsuming, error-prone, and inefficient, especially in large-scale operations, To overcome these challenges, recent advancements in Artificial Intelligence (AI) and Computer Vision have enabled the development of automated systems capable of detecting PPE usage in real time. This project focuses on building an AI-based PPE Detection System that leverages Computer Vision and Deep Learning techniques to automatically identify whether individuals are wearing the required safety equipment. By using object detection algorithms such as YOLO (You Only Look Once) or Faster RCNN the system can analyze images or video streams, detect workers, and determine the presence or absence of specific PPE items. The output can then be used to alert supervisors or log compliance data for further analysis. The proposed system not only enhances workplace safety but also helps organizations comply with safety regulations by providing continuous and reliable monitoring. Moreover, it reduces human workload, increases efficiency, and can be deployed on both edge devices and cloud based platforms for real time applications. This integration of AI with safety management demonstrates the platforms for real time applications. automation in improving occupational safety standards in Improving occupational safety standards across industries

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II. RELATED WORK

Ensuring the proper use of Personal Protective Equipment (PPE) in industrial and construction environments is a crucial factor in maintaining workplace safety. Traditional manual inspection methods are inefficient, subjective, and prone to human error. Recent advancements in Artificial intelligence (AI), Computer Vision, and Deep Learning have paved the way for intelligent systems that can automatically detect and monitor PPE compliance in real time. This section presents a review of existing research and developments related to AI based PPE detection Early developments in PPE detection Initial attempts at PPE detection used classical image processing techniques such as color segmentation, contour detection, and edge-based recognition to identify safety helmets or vests. Zhao et al.(2017) developed an image processing method using color thresholding to detect safety helmets on construction siges. However, the systems accurancy was affected by lighting and background variations. · Huang et al. (2018) used Histogram of Oriented Gradients (HOG) features combined with Support Vector Machines (SVM) for helmet detection but struggled with complex and cluttered backgrounds. These early methods lacked robustness and could not generalize well to different real world conditions. Emergence of deep learning techniques With the rise of Convolution Neural Networks (CNNs), researchers began 8 applying deep learning for feature extraction and object detection. · Redmon et al. (2016) introduced the YOLO (You Only Look Once) framework, which revolutionized object detection with its real time performance. · Ren et al. (2017) Presented Faster R-CNN, which achieved higher accuracy but required more computation power. These architectures laid the foundation for modern PPE detection systems. Application of yolo models in ppe detection Several studies have applied YOLO variants for detecting helmets, vests, and other PPE items: · Chaudhary et al. (2020) implemented YOLOv3 for helmet and vest detection on construction workers, achieving an accuracy of over 92% · Kumar et al. (2021) used YOLOv4 to detect helmets and safety jackets, demonstrating robust performance in complex environments. · Rahman et al. (2023) employed YOLOv8 for detecting multiple PPE items including masks and gloves, shows improved detection speed and precision over earlier versions Deep learning for mask covid 19 safety monitoring During the COVID-19 pandemic, PE detection research expanded to include mask detection: · Loey et al. (2021) used a modified ResNet50 + SSD architecture for face mask detection, achieving 98% accuracy. · Chowdhury et al. (2022) combined MobileNetV2 with transfer learning to detect masks efficiently on edge devices. These works demonstrated the adaptability of deep learning models for various PPE related applications. 2.5Advanced architectures and multi-ppe detection Recent studies focus on multi class PPE detection and compliance verification: · Ahmed et al.(2023) developed a system using YOLOv5 to detect multiple PPE items such as helmets, gloves, and safety vests simultaneously. Wang et al. (2023) introduced a hybrid YOLOv7 + DeepSORT tracking model to monitor PPE compliance in live video streams. · Singh and Gupta (2024) used Mask R-CNN for instance segmentation, allowing the system to assess whether PPE was worn correctly. Such advancements move beyond mere detection to real time compliance assessment and behavioral safety monitoring. Datasets used in PPE research Reliable datasets are essential for effective model training. Common datasets include: · PictorPPE Dataset (2021): Contains images of workers wearing helmets, vests, gloves, and boots. · Construction-PPE Dataset (2022): Focuses on detection of multiple PPE types and missing PPE cases. · SH17 Dataset (2024): A large scale dataset covering carious PPE items across different environments, designed for benchmarking AI safety systems. Researchers also often create custom datasets by annotating site specific images using tools like Labelling,

CVAT, or Label Studio. Evaluation metrics and performance PPE detection models are commonly evaluated using: · Mean Average Precision (mAP) · Precision, Recall, and F1-score · Frame Rate (FPS) for real time performance For instance, YOLOv8 based systems typically achieve mAP>90% with real time inference speeds of >30 FPS on modern GPUs, making them suitable form industrial monitoring. 2.8 Challenges identified in previous research Despite significant progress, existing studies highlight several challenges: · Dataset Limitations: Many datasets are limited to helmets or vests, with insufficient diversing in lighting, angles, and worker types. Occlusion and Crowding: PPE may be partially hidden or overlapping in dense work environments, reducing detection accurancy. Edge Deployment

Constraints: High computational demand limits deployment on low cost embedded systems. · Person PPE Association: Determining whether detected PPE belongs to the correct person remains challenging in multi person scenes. · Wearing Correctness: Detecting improperly worn PPE (e.g.,unbuckled helmet)is still an open research area. 2.9 Recent trends and research directions · Lightweight models(e.g., YOLOv8n, MobileNet, NanoDet) for real time edge deployment. · Pose Estimation Integration to link PPE with human keypoints (head, torso, hands). · Transformer Based Architectures (e.g.,DETR, Vision Transformers) for improved feature learning. · Explainable AI (XAI) to interpret model decisions and increase safety audit transparency. · Hybrid Edge Cloud Systems combining local detection with centralized monitoring dashboards. 2.10 Summary of literature findings The literature review reveals that integrading Computer Vision and Deep Learning has significantly enhanced PPE detection capabilities, moving from simple color based detection to intelligent, real time safety monitoring systems. However, challenges such as data diversity, real time performance on edge devices, and correct PPE association remain open areas for improvement. The proposed system aims to address this gap by developing a real time multi class PPE detection system using the YOLOv8 architecture with optimized accuracy and speed.

III.PROBLEM STATEMENT

Ensuring that workers consistently wear Personal Protective Equipment (PPE) is a major challenge in industries such as construction, manufacturing, mining,
and chemical processing. Traditional monitoring methods rely heavily on human supervision or basic CCTV systems, which ae often inefficient, time-consuming, and prone to human error. Supervisors cannot continuously observe every worker, especially in large or complex environments, which results in missed violations and increased risk of workplace accidents. Additionally, existing surveillance system lack intelligent capabilities to automatically detect PPE compliance in real time.

IV.PROPOSED SYSTEM

The proposed system aims to develop an AI-based automated PPE detection model using computer Vision and Deep Learning techniques to monitor and ensure worker safety in real time. Unlike traditional manual or rule-based approaches this system leverages intelligent object detection algorithm to identify wherther workers are wearing essential PPE such as helmets, safety vests, gloves,masks, and boots in live video streams or surveillance footage. The system can automatically analyze input images or video feeds, detect multiple PPE item Simultaneously, andgenerate real-time alerts when any worker is found not wearing the required protective equipment. This significantly reduces the risk of workplace injuries and enhances safety compliance monitoring efficiency. Working process:Video is captured from CCTV/IP cameras. Frames are preprocessed for model input (resized, normalized). YOLOv5 model detects PPE objects(helmet, gloves, etc.) Detection results are analyzed for compliance. Alerts are generated for missing PPE items Data is stored for future analysis and reporting. Advantages Real – time detection and monitoring. Automated alerts and reports. Higher accuracy and reduced false positives. Minimal human involvement. Scalability across multiple locations. Compliance tracking over time. When adapting a model for a new purpose, the lower layers are usually kept intact, while only the upper layers are retrained to extract features specific to the new task. This approach really speeds up the training can be applied to another related task, optimizing the process.

V.IMPLEMENTATION

Python was chosen as the primary development language because of its rich ecosystem and ease of integration with artificial intelligence frameworks. It provides a simple, readable syntax that allows developers to focus on the logic rather than the complexity of syntax rules. Python supports various machine learning libraries such as TensorFlow, Keras, PyTOrch, and Scikit_learn, which makes it highly. Suitable for AI – based applications. Moreover, Python offers seamless integration with GPU-based computing, enabling faster model training and inference. Its cross-platform compatibility allows deployment on multiple environments, including Windows, Linux, and cloud-based platforms. Another major advantage of Python is its large and active developer community, which ensures continuous updates, documentation, and troubleshooting support. Overall, Python's modularity, flexibility, and comprehensive support make it the most appropriate choice for developing an intelligent PPE detection system process. Processing the Images to enhance training speed while keeping the fine details of the images intact, we resized them to 64 by 64 pixels. To tackle the common both. Exploding gradients issue found in CNNs and transfer learning the data was scaled down to values between 0 and 1 after being loaded into the NumPy array.

The model used for convertin sign language to text is based on transfer learning. A pre-trained model serves as the foundation for a new model in this approach. In simple terms, a model developed for one taskrimary reasons for choosing Python include: · Wide availability of AI and machine learning libraries such as TensorFlow, Keras, PyTorch, Scikit-learn, and Numpy. · Cross-platform compatibility, allowing, deployment on Windows, Linux or cloud environments. · Strong community support with abundant online resources and active developer forums. · Ability to handle large datasets and high speed computations with the help of optimized libraries. · Integration with GPU-based processing using CUDA, which accelerates deep learning training and inference.

1.Problem identification and requirement analysis: The first step in the project was to identify the real-world problem of ensuring safety compliance in industrial environments. Manual monitoring of PPE compliance is often time-consuming and error-prone. Thus, the need for an intelligent automated system arises to detect PPE usage efficiently and accurately. The system requirements were defined based on hardware, software, and performance needs such as high accuracy, low latency and real time detection

2. Data collection and dataset preparation: The dataset was divided into multiple categories such as helmet, no helmet, vest, no vest, mask, and no mask. Prober labeling was done using annotation tools such as Labeling and Roboflow Annotator, generating XML or YOLO compatible text files containing bounding box coordinates and class names. 6.3 Data preprocessing and augmentation Data preprocessing ensures that all input images are in a standardized format for model training. This involves resizing images to a fixed resolution, converting color formats, and normalizing pixel values between 0 and 1.

3.Data Annotation

After collecting the dataset, annotation is performed o label the objects within the images. This is done using annotation tools such as Labelling, where bounding boxes are drawn around the PPE items. Each object is assigned a specific class label, and the annotations are saved in YOLO format. Proper annotation is essential as it directly affects the accurancy and performance of the trained model.

4.Data Preprocessing

Before training the model, the dataset undergoes preprocessing to ensure consistency and improve performance. The images are resized to a fixed dimension, typically 640:640 pixels, to match the input requirements of the YOLO model. Data augmentation techniques such as flipping, rotation, and brightness adjustment are applied to increase dataset diversity. The dataset is then divided into training and validation sets, usually in an 80:20 ratio.

5.Model Selection and Architecture

The YOLOv5 model is selected for this project due to its efficiency in real-time object detection. It is a single-stage detector that processes the entire image in one pass, making it faster compared to traditional methods. The model divides the image into grids and predicts bounding boxes along with class probabilities. Its architecture enables accurate detection of multiple objects in a single frame.

6.Model Training

The model is trained using the prepared dataset and pre-trained weights to improve learning efficiency. During training, the model learns to identify patterns and features associated with PPE items. Important parameters such as epochs, batch size, and learning rate are adjusted to optimized performance. The training process involves minimizing loss functions related to classification, localization, and confidence. After multiple iterations, the model achieves improved accuracy in detecting PPE.

7. Model Evalution

Once the training is completed, the model is evaluated using various performance metric such as precision, recell, and mean average precision (mAP). Precision measures the accuracy of positive predictions, while recall indicates the model's ability to detect all relevant objects. A higher mAP value signifies better overall performace. Evaluation helps in identifying areas for improvement and ensure the reliability of the system.

8.Detection Implemention

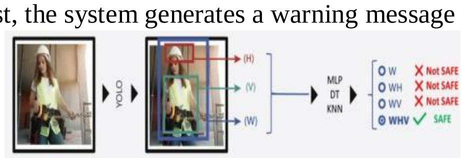
The trained model is then used to perform project detection on new images and video inputs. The system captures input data, processes it through the trained model, and generates output in the form of bounding boxes and labels. Each detected object is classified as helmet, vest, or no helmet. The results are displayed visually, making it easy to understand and interpret.

9.Real-time Detection

The system is capable of performing real-time detection using a webcam or CCTV feed. Video frames are continuously captured and passed to the model for processing. The detection results are displayed instantly, allowing continuous monitoring of workers. This real-time capability is crucial for ensuring immediate identification of safety violations in industrial environments.

10.Alert System

An alert mechanism is integrated into the system to notify users when safety violations are detected. If a worker is found without a helmet or safety vest, the system generates a warning message and



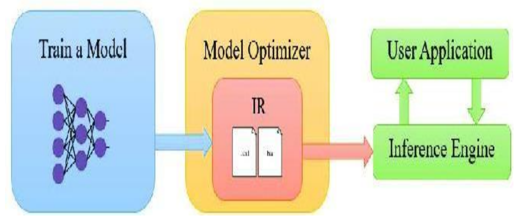
highlights the violation using colored bounding boxes. Optional features such as sound alerts or notifications can also be implemented to enhance responsiveness.

11.Output Generation

The system generates multiple forms of output, including processed images, real-time video streams, and detection reports. These outputs provide visual evidence of safety compliance and violations. The results can be stored for further analysis and documentation purpose, making the system useful for monitoring and reporting.

12.Challenges and Solutions

During implementation, several challenges were encountered, such as limited dataset size, variations in lighting conditions, and overlapping objects. These issues were addressed by applying data augmentation techniques, using pre-trained models, and optimizing parameters. Such improvements helped enhance the overall accuracy and performance of the system.



VI.RESULT

We used the AI-based PPE Detection System was successfully developed and tested using a combination of computer visiontechniques and deep learning-based object detection algorithms.

The system was evaluated on a dataset containg images and video frames of workers with and without Personal Protective Equipmemt (PPE), including helmets, safety vests, gloves, and masks. The experimental results show that the proposed system provides high accuracy in detecting PPE components and identifying safety violations. in real time.Using YOLO/SSD models, the system

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Achieved: Accurate detection o fmultiple workers simultaneously. Reliable identification of PPE items under varying lighting and background conditions.

Fast processing speed, making it suitable for real-time surveillance. Low false positive and false negatives, indicating stable and consistent performance

VI. CONCLUSION

In this paper, we introduced the Ai –Based PPE Detection system effectively demonstrates how computer vision and deep learning can be leveraged to enhance workplace safety in industrial environments. By integrating real-time video processing with advanced processing with advanced object detection algorithms such as YOLO and SSD, the system successfully identifies workers and verifies the presence of essential Personal Protective Equipment. The automated approach significantly reduces the dependency on manual monitoring, minimizes human error, and ensures continuous safety compliance across various work zones. The experimental results indicate that the proposed system offers high accuracy, ,and accuracy and robust performance under different lighting and background conditions.

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