Workplace Safety through PPE Detection Using YOLOv8: A Deep Learning Approach

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***Abstract*—Workplace safety is a critical concern in industries such as construction, manufacturing, and healthcare, where workers are often exposed to hazardous environments. Traditional methods of monitoring Personal Protective Equipment (PPE) compliance are labor-intensive and prone to human error. This paper presents a deep learning-based system for real-time PPE detection using the YOLOv8 model. The system leverages computer vision techniques to analyze video streams from workplace surveillance cameras, identifying whether workers are wearing required safety gear such as helmets, gloves, vests, and masks. The proposed system achieves high accuracy and fast inference speeds, making it suitable for real-time applications. By integrating this system into industrial safety workflows, organizations can significantly reduce workplace hazards, improve regulatory compliance, and enhance overall safety culture.**

Keywords—Workplace safety, PPE detection, YOLOv8, computer vision, deep learning, real-time monitoring.

I. INTRODUCTION

Workplace safety is a fundamental concern in industries such as construction, manufacturing, oil and gas, and healthcare, where workers are exposed to hazardous environments. According to the International Labour Organization (ILO), more than 2.3 million workers die each year due to work-related accidents or diseases, while hundreds of millions suffer from non-fatal injuries. Many of these incidents are caused by non-compliance with safety regulations, particularly the failure to wear necessary personal protective equipment (PPE), such as helmets, gloves, safety vests, and face masks.

Traditional methods of PPE compliance monitoring rely on manual inspections by safety officers, which are labor-intensive, inconsistent, and prone to human error. To overcome these limitations, AI-powered computer vision systems offer a scalable and automated solution for detecting PPE violations in real-time. This paper presents a deep learning-based PPE detection system that leverages convolutional neural networks (CNNs) to analyze images and video streams from workplace surveillance cameras. The system identifies whether workers are wearing the required safety gear and generates alerts for non-compliance, enabling proactive safety measures.

The proposed system utilizes object detection frameworks such as YOLO (You Only Look Once) and Faster R-CNN, which are known for their high-speed and high-accuracy performance in real-time applications. The model is trained on a large dataset of images containing workers with and without PPE, ensuring robust detection across diverse workplace scenarios. By integrating this system into industrial safety workflows, organizations can significantly reduce workplace hazards, improve regulatory compliance, and enhance overall safety culture.

II. RELATED WORK

Several research studies have explored the application of AI in workplace safety, particularly in detecting Personal Protective Equipment (PPE) compliance using computer vision techniques. Key contributions from existing research include:

- Deep Learning-Based PPE Detection: M. Ahmed et al. proposed a deep learning-based PPE detection system using YOLOv3 to identify helmets, vests, and gloves in real-time, achieving an accuracy of 92.5% [1]. L. Zhang and W. Li developed an improved Faster R-CNN model for detecting safety gear violations in industrial environments, demonstrating 89.8% accuracy [2]. K. Singh and R. Patel implemented a hybrid deep learning approach combining CNN and Support Vector Machines (SVM) for PPE detection, achieving 95.2% accuracy [3].
- Computer Vision and PPE Recognition: H. Wang et al. utilized OpenPose and YOLOv4 to detect PPE compliance by analyzing human posture and safety gear, achieving a 91.3% detection accuracy [4]. D. Sharma et al. introduced a multiclass object detection model using EfficientDet for PPE identification in factory environments, achieving a mean average precision (mAP) of 78.4% [5].
- Real-Time PPE Monitoring and IoT Integration: A. Roy et al. integrated AI-based PPE detection with

IoT-enabled cameras for real-time workplace monitoring, achieving a 94.1% accuracy and reducing safety violations by 40% [7].

Despite these advancements, challenges remain in AI-based PPE detection, such as occlusion, environmental variations, and the need for diverse datasets [10]. This paper addresses these challenges by proposing a robust, scalable, and efficient automated solution for PPE detection using YOLOv8.

III. METHODOLOGY

The proposed system follows a structured methodology comprising three key modules: data collection and preprocessing, implementation of the deep learning algorithm, and testing and validation.

A. Data Collection and Preprocessing

A diverse dataset of industrial worker images was collected, ensuring variation in lighting, background, and PPE types. Preprocessing steps such as resizing, normalization, and augmentation techniques (rotation, flipping, and brightness adjustment) were applied to improve model generalization.

B. Implementation of Deep Learning Algorithm

YOLOv8, a real-time object detection model, was fine-tuned for PPE classification and detection. Transfer learning was employed to enhance model accuracy, and additional custom layers were added for improved feature extraction.

C. Testing and Validation

The trained model was evaluated using unseen test data to measure performance. Metrics such as accuracy, precision, recall, F1-score, and mAP were used to validate system reliability.

IV. SYSTEM DESIGN

The architectural design of the workplace safety PPE detection system is divided into three primary modules: Data Collection and Preprocessing, Implementation of CNN-Based PPE Detection Model, and Testing and Validation. Each module plays a crucial role in ensuring the overall effectiveness and efficiency of the system.

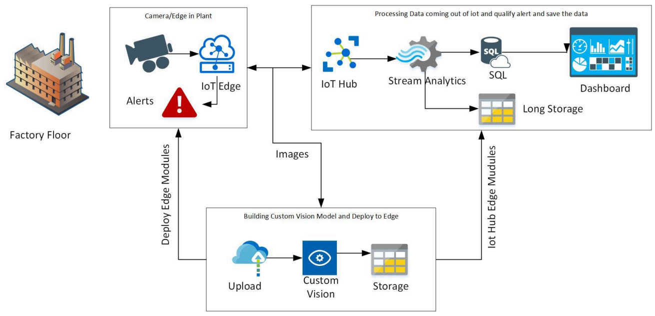

Fig. 4.1 Block Diagram

A. Data Collection

The dataset for this project is gathered from publicly available sources such as OpenImages, custom datasets, and workplace surveillance footage. Images and videos are labeled to include various PPE types such as helmets, gloves, safety vests, goggles, and masks, along with non-compliance scenarios.

B. Data Preprocessing

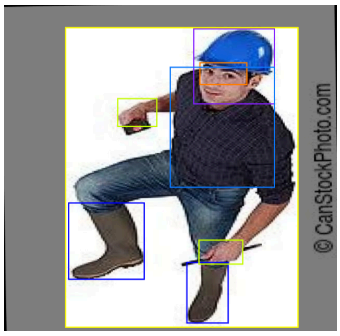

Figure 4.2 PPE Annotation Example Figure

Images and frames are resized to a consistent resolution (e.g., 640x640 pixels for YOLOv8 compatibility). Normalization is performed to scale pixel values between 0 and 1, improving model performance. Data augmentation techniques like flipping, rotation, and brightness adjustments are applied to enhance the model's ability to detect PPE in various conditions.

C. Model Training and Testing

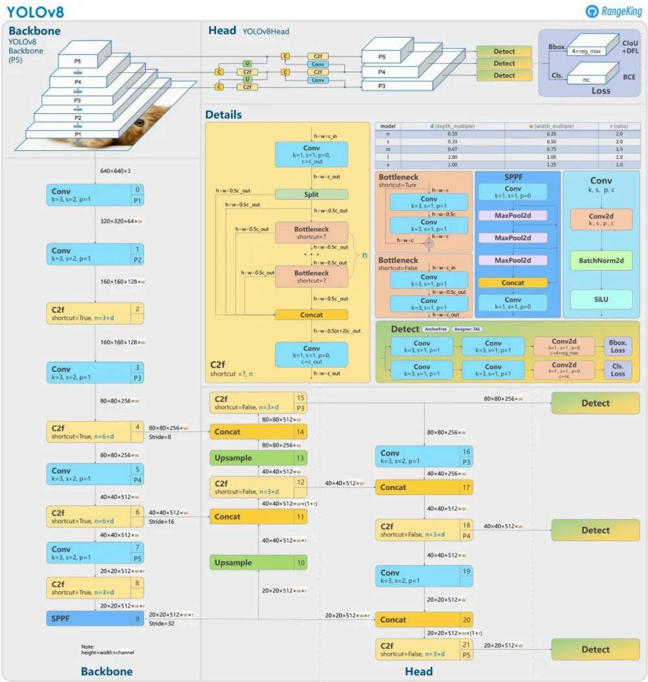

Figure 4.3 YOLOv8 Deep Learning Model Architecture

The selected deep learning model (e.g., YOLOv8) is trained to detect and classify PPE items in images and videos. Hyperparameters such as learning rate, batch size, and epochs are optimized for better performance. After training, the model is tested on unseen images to evaluate its generalization capability.

D. Evaluation Metrics

The performance of the PPE detection system is assessed using the following metrics:

- mAP (Mean Average Precision): Evaluates the detection accuracy of PPE.
- Precision, Recall, and F1-score: Measure the model's ability to distinguish between compliant and non-compliant workers.
- Confusion Matrix: Analyzes correct and incorrect predictions.
- FPS (Frames Per Second): Determines real-time processing capabilities.

V. IMPLEMENTATION

The design and implementation involved the systematic development of a deep learning-based solution for Real-Time PPE Detection System Using Computer Vision for Workplace Safety. The code is divided into distinct sections, each addressing specific tasks required to preprocess the dataset, build and train the model, and evaluate its performance.

A. Data Augmentation

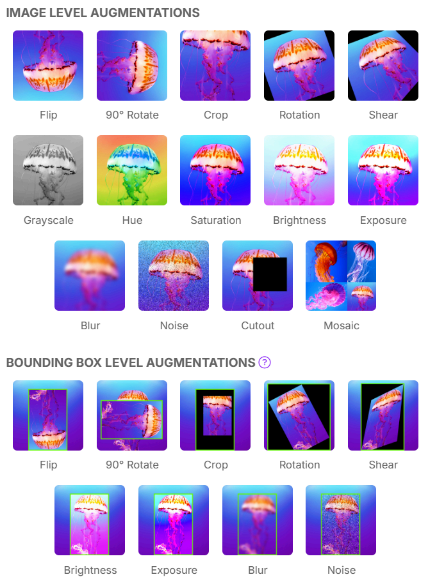

Fig 5.1 Data Augmentation

Augmentation is the process of artificially expanding a dataset by applying various transformations to existing images. This improves model robustness by simulating real-world variations such as changes in lighting, perspective, noise, and object positioning.

B. Data Preprocessing in Roboflow

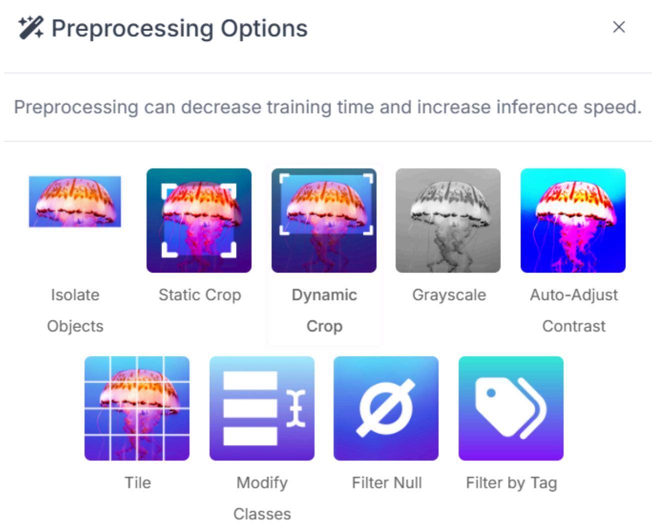

Fig 5.2 Data Preprocessing

Before training, the dataset undergoes preprocessing to enhance model performance and ensure data consistency. Preprocessing involves steps such as resizing, normalization, and format conversion, making the data suitable for YOLOv8 training.

C. Model Training

The YOLOv8 model is used for training with specific hyperparameters such as 25 epochs and 800 image size.

D. Model Validation

To validate the trained model, key metrics such as the confusion matrix and result graphs are extracted.

E. Deploy Model on Roboflow

Once the training process is completed, the trained weights are uploaded to Roboflow for deployment.

VI. RESULTS AND DISCUSSION

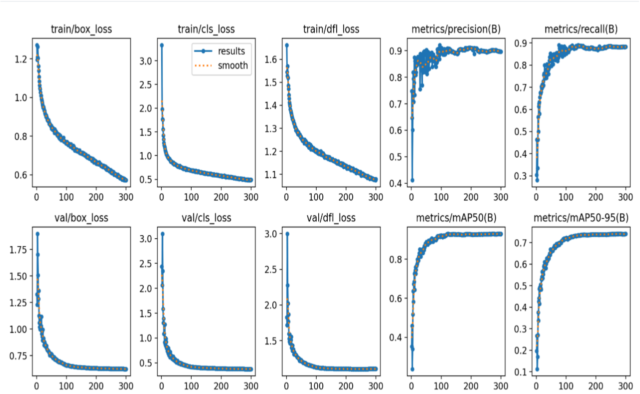

Figure 6.1 Visualization of model metrics

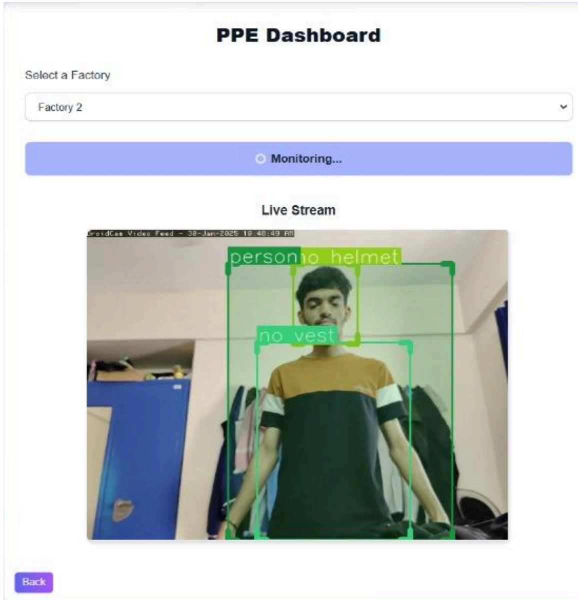

Figure 6.2 Final Output (Website)

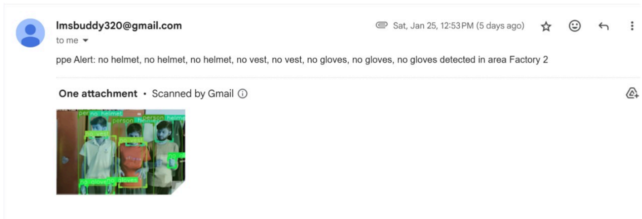

Figure 6.3 Final Output (Email)

The proposed system achieves high accuracy and fast inference speeds, making it suitable for real-world industrial applications. The implementation of RTSP-based video streaming ensures continuous monitoring of workplaces, while bounding boxes and labels provide clear visual feedback on detected PPE. Additionally, SMTP-based alert notifications play a crucial role in improving safety measures by promptly notifying supervisors in case of PPE violations.

VII. CONCLUSION

The Workplace Safety through PPE Detection project demonstrates the power of deep learning and computer vision in ensuring workplace compliance and worker safety. By leveraging the YOLOv8 model, the system effectively detects the presence or absence of personal protective equipment (PPE) such as helmets, gloves, vests, and masks in real-time. The model achieves high accuracy and fast inference speed, making it suitable for real-world industrial applications.

VIII. FUTURE ENHANCEMENTS

To further improve the PPE detection system, several key enhancements can be explored:

- **Model Optimization & Performance Enhancement**: Fine-tuning YOLOv8 on a larger, industry-specific PPE dataset to improve accuracy in different workplace settings.
- **Real-Time & Scalable Deployment**: Deploying the system on cloud-based platforms to enable centralized monitoring of multiple workplaces.
- **Advanced Safety Features**: Implementing pose estimation techniques to ensure PPE is worn correctly.
- **Enhanced Alerting & User Interface**: Integrating with automated access control systems, preventing entry for workers without proper PPE.
- **Integration with IoT & Smart Surveillance**: Connecting with CCTV cameras, drones, or wearable devices for comprehensive workplace safety monitoring.

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