A Robust Deep Learning Approach for PPE Detection Using Attention Mechanism and CIoU Loss Optimization

K. Baby Ramya[1], K. Pavani [2], K. Jahanavi[3]

#1 Assistant Professor in the Department of MCA, SRK Institute of Technology, Vijayawada.

#2. Assistant Professor & Head of Department of MCA, SRK Institute of Technology, Vijayawada

#3 Student in the Department of MCA, SRK Institute of Technology, Vijayawada.

Abstract: Construction sites are highly hazardous environments where improper use of Personal Protective Equipment (PPE) can lead to serious accidents. This paper presents an enhanced deep learning-based PPE detection system using a novel dataset and optimized YOLO models to address limitations in existing approaches, particularly in detecting reflective clothing and handling overlapping objects. The proposed AL-YOLOv5 model integrates an attention mechanism to improve feature extraction and replaces the traditional SEIoU loss with CIoU loss for better bounding box regression and localization accuracy.

Furthermore, advanced models such as YOLOv5x6, YOLOv8, and YOLOv9 are incorporated to improve detection performance and real-time efficiency. Experimental results demonstrate that the proposed system achieves over 90% mAP with an improvement of 0.4 in overall detection accuracy and approximately 0.9 AP gain in limited data categories. The system also achieves high-speed detection, making it suitable for real-time construction site monitoring. Overall, the proposed approach enhances PPE detection reliability and contributes to improved worker safety through intelligent automation.

Index terms - — *Personal Protective Equipment (PPE), Construction Site Safety, Object Detection, Deep Learning, YOLOv5, YOLOv8, YOLOv9, Attention Mechanism, CIoU Loss, Real-Time Detection, Computer Vision, Safety Monitoring*

1. INTRODUCTION

Construction sites are inherently hazardous environments where workers are exposed to various risks such as falling objects, heavy machinery, and unsafe working conditions. Personal Protective Equipment (PPE), including helmets and reflective clothing, plays a crucial role in minimizing injuries and ensuring worker safety. However, due to lack of awareness, discomfort, or negligence, workers often fail to wear proper PPE, leading to increased accident rates. Traditional safety monitoring methods rely heavily on manual supervision, which is time-consuming, error-prone, and inefficient in large-scale construction environments.

With the advancement of computer vision and deep learning, automated PPE detection systems have gained significant attention. Existing approaches, mainly based on object detection models, have shown promising results but suffer from limitations such as lack of diverse datasets, poor detection of reflective clothing, and reduced performance under challenging conditions like occlusion and varying illumination. Many models focus primarily on helmet detection and fail to generalize well across different real-world construction scenarios.

To address these challenges, this paper proposes an enhanced PPE detection framework using a novel dataset and optimized YOLO-based models. The proposed system incorporates an attention mechanism to improve feature extraction and replaces the traditional loss function with CIoU loss to enhance localization accuracy. Additionally, advanced YOLO variants are integrated to achieve high detection accuracy and real-time performance. The developed system aims to provide an intelligent and automated solution for improving safety compliance and reducing accidents at construction sites.

2. LITERATURE SURVEY

a) Vision-based monitoring of site safety compliance based on worker re-identification and personal protective equipment classification:

Because of the dynamic interaction between humans and moving machinery, construction sites are extremely dangerous. Collisions and falls from heights, among other things, have a high death rate. Therefore, monitoring employees' on-site mobility and personal protective equipment (PPE) is essential for improving site safety. On construction sites, vision-based video processing has been actively employed to automatically identify employees and their actions. Nevertheless, the majority of studies that are now available track employees using a single camera, which only records a limited portion of the area. More thorough behavioral analysis would be possible if workers' movements were continually monitored by several cameras, as they usually roam throughout rather big areas. Therefore, by integrating worker re-identification (ReID) with PPE categorization, this research suggests a methodology for tracking worker safety compliance. The difficulties for these two tasks are addressed by deep learning-based methods, respectively. In order to enable deep learning models to learn more discriminative human traits and achieve a more reliable monitoring of individual workers, ReID has developed a new loss function called similarity loss. A weighted-class approach is suggested for PPE status classification in order to reduce model bias when imbalanced data are provided among classes, resulting in better performance even with less training examples. A process is created to record every instance of employees failing to wear the required PPEs by merging the ReID and PPE categorization data. The suggested techniques increase worker ReID and PPE categorization accuracy by 4% and 13%, respectively, using a real construction site dataset. This will make site video analytics and worker safety compliance inspection easier.

b) Standardized use inspection of workers' personal protective equipment based on deep learning:

(FFH) and object strikes (OS) are common on construction sites, endangering worker safety and lowering building quality. Personal protective equipment (PPE) is the easiest measure to implement in the hierarchy of controls. However, PPE is the least effective control method due to the existence of dangers and the variation in subjective protection awareness. Therefore, in order to satisfy the criteria from the standpoint of administrative control, it is essential to encourage appropriate and uniform usage of PPE. This paper suggests a deep-learning-based inspection technique employing two behaviors—loosening the hardhat and not using the safety harness's hook—that can result in OS and FFH accidents as a research case. First, we developed a hardhat and hook detection model based on You Only Look Once v5. Following that, 1200 video clips with three risky behaviors and one safe behavior were identified using the object-detection model and Openpose method, which produced 1200 data files that varied over time. Ultimately, 600 films were used to train a one-dimensional convolutional neural network (1D-CNN) model, which was then used to evaluate the remaining 600 videos. In the experimental case, the accuracy reached was 0.9467. The suggested approach can increase the effectiveness of safety management by identifying inappropriate PPE use without interfering with people's regular activity.

c) 100+ FPS detector of personal protective equipment for worker safety: A deep learning approach for green edge computing

Personal protection equipment (PPE) shields workers from unintentional injury in industrial manufacturing. However, for a variety of reasons, workers are not necessarily required to wear PPE. Designing an automated PPE detection system is crucial to improving worker monitoring and preventing safety incidents. For our analysis in this work, we created a dataset called FZU-PPE, which includes four different kinds of personal protective equipment (PPE): gloves, masks, safety vests, and helmets. We provide a lightweight object identification technique based on deep learning for ultrafast detection of whether or not workers are wearing personal protective equipment (PPE) in order to minimize the model size and resource usage. In order to minimize accuracy loss while reducing the computing effort and detection model parameters by 32% and 25%, respectively, we employ two lightweight techniques to improve the network topology of the object detection algorithm. To further minimize the size of the detection model, we provide a channel pruning approach based on the BN layer scaling factor γ. Experiments demonstrate that our lightweight item detection system can identify PPE automatically at a speed of 105 frames per second (FPS) in just 9.5 ms. With a minimal size of 1.82 MB and a model size reduction rate of 86.7%, our detection model can satisfy the stringent memory occupancy and computational resource requirements for mobile and embedded devices. Our method is a green edge computing speedy detection technique.

d) Personal Protection Equipment detection system for embedded devices based on DNN and Fuzzy Logic:

It is frequently impractical or inconvenient for human operators to continuously assess every employee to identify individuals who are not wearing their Personal Protection Equipment (PPE) devices due to the vast scope and intricate structure of most industrial and construction sectors. However, in order to lower the amount of worker injuries, such identification is crucial. Therefore, it is a desirable choice to implement a computer vision system based on Deep Neural Networks (DNNs) that detects PPE by analyzing the video feeds from security cameras. When smart video cameras are installed in the workplace, for example, they may evaluate the video frames at run-time and sound an alert if they find that employees are not properly donning personal protective equipment (PPE). However, DNN-based object identification needs a lot of processing power to be accurate, which is challenging to integrate into cameras. Furthermore, the development of a tailored DNN to identify unique PPE devices necessitates a significant amount of labor in locating and categorizing pictures to train the network because DNN training must be done on a sizable dataset with thousands of annotated image examples. This research presents a PPE detection framework that uses fuzzy logic filtering to integrate human judgment with DNN-based item recognition. On embedded devices, the suggested framework operates in almost real-time and can be trained using a small number of images—a few hundred—while still yielding results with excellent accuracy.

e) Detecting safety helmet wearing on construction sites with bounding-box regression and deep transfer learning:

For safety management, regulatory compliance, and lowering the fatality rate from construction industry accidents, it is crucial to identify the use of safety helmets in surveillance footage. Interocclusion, size variations, perspective distortion, tiny object detection, and safety helmet carrier recognition are some of the issues that make it extremely difficult. They are a problem for conventional image-based techniques. This paper presents a novel approach to safety helmet recognition using bounding-box regression and convolutional neural network-based face detection. On the one hand, the technique can assist in identifying the safety helmet's bearer and identifying a tiny, multiscale safety helmet. Conversely, two distinct approaches—object feature extractor and fine-tuning for safety helmet recognition—are used to introduce and implement deep transfer learning based on DenseNet. The network model with two peer DenseNet networks is trained by mutual distillation to further increase the recognition accuracy. Compared to existing cutting-edge models, the unique technique offers significant benefits in identifying safety helmet usage, according to extensive study and trials. 96.2% recall, 96.2% precision, and 94.47% average detection accuracy have been attained by the suggested model. These findings, along with the receiver operating characteristic (ROC) curve and precision-recall (PR) curve, show that the proposed model is feasible.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on developing an intelligent PPE detection system for construction workers using a novel dataset and enhanced deep learning models. A comprehensive dataset is created using semi-automatic labeling techniques, covering four major PPE categories, including hard helmets and reflective clothing, to better represent real-world construction site conditions. This dataset improves diversity by incorporating variations in lighting, angles, occlusion, and worker positions, thereby addressing the limitations of existing small and less representative datasets.

To improve detection performance, the YOLOv5 model is enhanced by integrating an attention mechanism that enables the model to focus on important regions and effectively handle overlapping objects. Additionally, the traditional SEIoU loss function is replaced with the CIoU loss function to improve bounding box regression and localization accuracy. The proposed system is further extended by incorporating advanced models such as YOLOv5x6, YOLOv8, and YOLOv9 to achieve higher accuracy and real-time performance. This integrated approach ensures robust PPE detection, reduces false positives, and enhances safety monitoring in dynamic construction environments..

ii) System Architecture:

The system architecture consists of a sequential pipeline that begins with dataset collection and preprocessing, followed by image processing and model training, and finally PPE detection with performance evaluation. Initially, a construction site dataset is collected and passed through a preprocessing stage where images are cleaned, resized, and normalized. Data augmentation techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and improve model generalization. This processed data is then fed into the image processing module for feature extraction and preparation for training.

The trained models include multiple YOLO variants such as YOLOv5, A-YOLOv5, I-YOLOv5, AL-YOLOv5, YOLOv8, and YOLOv5x6, which are used to detect PPE items like helmets and reflective clothing. The detection module identifies PPE in real-time and outputs bounding boxes with class labels. Finally, a performance evaluation module analyzes the results using metrics such as accuracy and mAP to compare model performance. This architecture ensures efficient data flow, accurate detection, and reliable safety monitoring in construction environments.

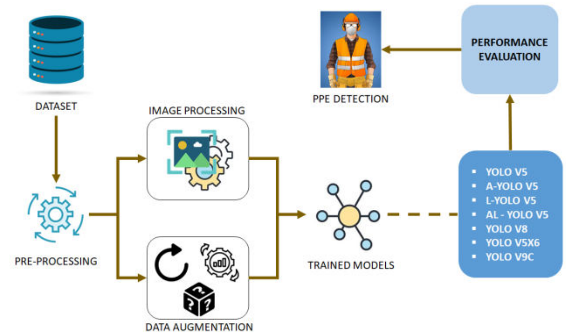

Fig1 proposed architecture

iii) Modules:

1. Dataset Collection

- Collects real-time construction site images
- Includes PPE categories like helmets and reflective clothing
- Ensures diversity in lighting, angles, and environments

2. Pre-processing

- Image resizing and normalization
- Noise removal and quality enhancement
- Prepares data for efficient model training

3. Data Augmentation

- Applies flipping, rotation, scaling, and brightness changes
- Increases dataset size and diversity
- Reduces overfitting and improves generalization

4. Image Processing

- Extracts important visual features from images
- Enhances object visibility
- Prepares data for deep learning models

5. Model Training

- Uses YOLOv5, A-YOLOv5, I-YOLOv5, AL-YOLOv5
- Extended with YOLOv8 and YOLOv5x6
- Trains models using labeled dataset

6. Attention Mechanism Integration

- Focuses on important regions in images
- Handles overlapping PPE objects
- Improves detection accuracy

7. PPE Detection

- Detects helmets and reflective clothing
- Generates bounding boxes and class labels
- Supports real-time monitoring

8. Performance Evaluation

- Evaluates models using accuracy and mAP
- Compares different YOLO variants
- Measures detection speed and efficiency

9. User Interface (Flask)

- Provides web-based interaction
- Displays detection results
- Ensures secure access with authentication

iv) Algorithms:

1. YOLOv5 Algorithm

YOLOv5 is employed for real-time object detection of Personal Protective Equipment (PPE) on construction sites. It processes images in a single stage, enabling fast and accurate detection of multiple PPE types such as helmets and reflective clothing. Its efficiency ensures timely identification and helps maintain safety compliance while enhancing worker protection in dynamic environments.

2. A-YOLOv5 Algorithm

A-YOLOv5 extends the standard YOLOv5 by integrating an attention mechanism that focuses on the most relevant regions of an image. This improves feature extraction and increases detection precision, especially for small or partially occluded PPE items. It performs effectively in complex construction environments with varying lighting conditions and overlapping objects.

3. L-YOLOv5 Algorithm

L-YOLOv5 is a lightweight version of YOLOv5 designed to reduce computational complexity and improve inference speed. It consumes fewer resources while maintaining acceptable detection accuracy, making it suitable for deployment on mobile devices and edge computing systems. This ensures efficient PPE detection in real-time scenarios with limited hardware capacity.

4. AL-YOLOv5 Algorithm

AL-YOLOv5 enhances detection performance by combining attention mechanisms with advanced loss functions such as CIoU. It focuses on difficult training samples and improves the model's robustness in detecting PPE under challenging conditions like occlusion, varying distances, and complex backgrounds. This results in higher accuracy and reduced false detections.

5. YOLOv8 Algorithm

YOLOv8 introduces advanced architectural improvements, including better feature extraction and anchor-free detection. It provides higher accuracy and efficiency compared to previous versions, making it suitable for complex PPE detection scenarios. The model maintains real-time performance while handling diverse construction site conditions effectively.

6. YOLOv5x6 Algorithm

YOLOv5x6 is an enhanced version of YOLOv5 with increased model capacity and deeper layers. It improves the detection of smaller and partially hidden PPE objects by capturing more detailed features. This makes it highly effective for monitoring safety in complex construction environments with multiple overlapping elements.

7. YOLOv9 Algorithm

YOLOv9 represents the latest advancements in the YOLO series, focusing on improving both detection speed and accuracy. It incorporates optimized learning strategies and architectural enhancements, enabling high-performance PPE detection. This model ensures reliable real-time monitoring and supports better safety compliance on construction sites.

4. EXPERIMENTAL RESULTS

The custom-built dataset, which included photos of construction sites with various PPE categories, such as helmets and reflective apparel, was used to assess the suggested PPE detection method. To increase variety and resilience, the dataset underwent preprocessing and augmentation. To guarantee fair comparison, a number of models, including YOLOv5, A-YOLOv5, L-YOLOv5, AL-YOLOv5, YOLOv8, YOLOv5x6, and YOLOv9, were trained and evaluated under identical settings. Standard criteria including Mean Average Precision (mAP), precision, recall, and detection speed (FPS) were used to assess each model's performance.

According to experimental results, the suggested AL-YOLOv5 model achieves an improvement of almost 0.4 in total mAP and nearly 0.9 AP gain in data-limited categories, especially for reflecting garment detection, outperforming baseline models. When it comes to handling occlusion, overlapping objects, and different lighting situations, the model exhibits remarkable resilience. Additionally, the system may be used in real-world construction scenarios because to its excellent real-time performance, which includes a detection speed of up to 172.4 FPS. Comparing the suggested method to more sophisticated models like YOLOv8 and YOLOv9 shows that it strikes a balance between speed and accuracy while drastically lowering missed and false detections.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

Accuracy = TP + TN /(TP + TN + FP + FN)

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

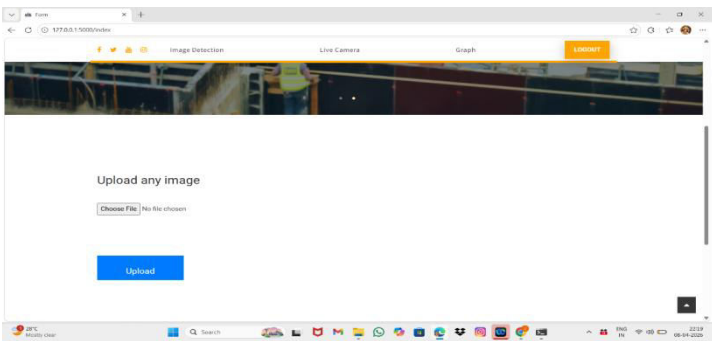

Fig 2:In above screen dashboard is displayed after successful login. The dashboard contains modules such as Image Detection, Live Camera, and Graph. In above screen user can upload construction worker image for PPE detection. User need to click on “Choose File” option and select required image from system. After selecting image, user can click on “Upload” button to process image using YOLOv5 model.

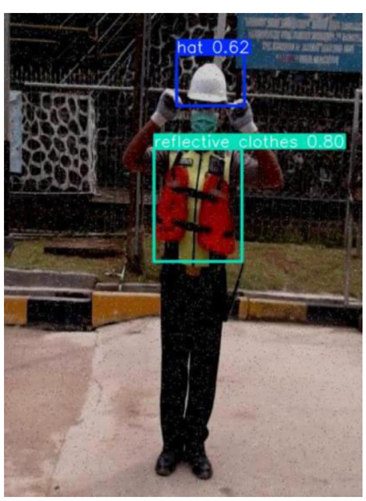

Fig 3:In above screen system successfully detected multiple personal protective equipments from construction worker image. The YOLOv5 model identified safety helmet and reflective clothes using bounding boxes with confidence scores.

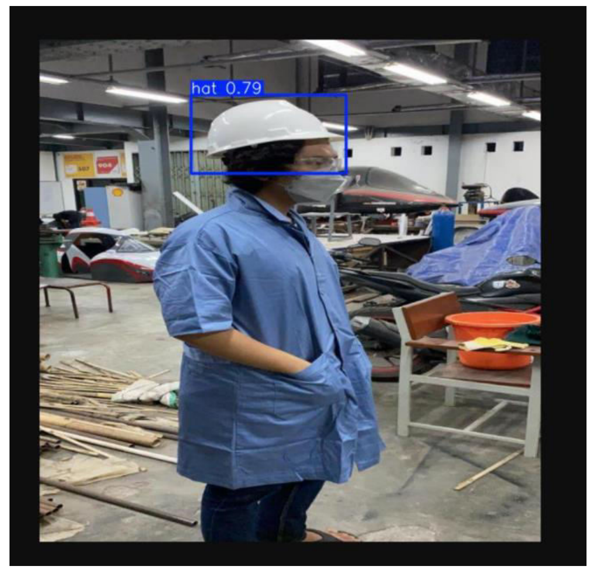

Fig 4:In above screen system successfully detected safety helmet from uploaded image. The YOLOv5 model identifies PPE equipment and displays detected object using bounding box with confidence score. This detection result helps to monitor worker safety.

5. CONCLUSION

This paper presented an enhanced deep learning-based PPE detection system for construction sites using a novel dataset and optimized YOLO models. The proposed AL-YOLOv5 model integrates an attention mechanism and CIoU loss function to improve detection accuracy, particularly for reflective clothing and overlapping objects. Experimental results demonstrate that the model achieves higher performance compared to baseline approaches, with improved mAP, reduced false detections, and effective handling of complex real-world scenarios.

Furthermore, the system achieves real-time detection speed, making it suitable for practical deployment in construction environments. The integration of advanced models such as YOLOv8 and YOLOv9 further enhances detection capability and robustness. Overall, the proposed approach provides an efficient and reliable solution for automated PPE monitoring, contributing to improved worker safety and better compliance with safety regulations on construction sites.

6. FUTURE SCOPE

- Improve detection of highly occluded and deformable PPE items such as partially visible reflective clothing using advanced feature extraction techniques.
- Integrate Transformer-based architectures and hybrid deep learning models to further enhance detection accuracy and robustness in complex environments.
- Deploy the system on edge devices and IoT-enabled smart cameras for real-time, on-site safety monitoring with low latency.
- Expand the dataset to include additional PPE categories such as gloves, safety boots, and goggles to improve system scalability and coverage.
- Incorporate real-time alert and notification systems to automatically warn workers and supervisors about safety violations.
- Enhance the web-based interface with advanced analytics, reporting dashboards, and cloud integration for better safety management.

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Author Profiles

Ms. K. Baby Ramya is working as an Assistant Professor in the Department of MCA at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. She completed her MCA from Krishna University. She has nearly 3 years of teaching experience at SRK Institute of Technology. Her areas of interest include Machine Learning, Data Science, and Computer Applications.

Ms. K. Pavani is working as an Assistant and Head of Department of MCA, in SRK Institute of technology in Vijayawada. She completed her MCA and M.Tech in Computer Science. She has 10 years of teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her areas of interest include AI and ML, etc.

Ms. K. Jahanavi is an MCA student in the Department of Computer Applications at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. She completed her degree in B.Sc.(Computers and Electronics) from P.B. Siddhartha College of Arts and Science Vijayawada. Her areas of interest are DBMS and Machine Learning.