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Artificial Intelligence System Based Personal Protective Equipment Detection for Construction Site Safety using YOLOv8

Nirupama Malik[1], Amiyajyoti Nayak[2]
[1]M.Tech Student, Construction Technology and Management, GIFT Autonomous, Odisha, India
[2]Assistant Professor, Department of CSE, GIFT Autonomous, Odisha, India

Abstract: This paper addresses the limitations of current deep learning models for detecting Personal Protective Equipment (PPE) on construction sites, where performance enhancement is crucial. This paper use You Only Look Once (YOLO) architecture, focusing on ten categories: 'Hardhat', 'Mask', 'NO-Hardhat', 'NO-Mask', 'NO-Safety Vest', 'Person', 'Safety Cone', 'Safety Vest', 'machinery', 'vehicle'. A new high-quality dataset, named PPE dataset from Roboflow, was created, comprising 1,330 images that reflect real construction environments, various poses, angles, distances, and multiple PPE types. Among the evaluated models, YOLO v8 achieved the highest mean Average Precision (mAP) of 87.55%, while YOLO v8 demonstrated the fastest processing speed at 52 images per second on a GPU. The study involved training a model using 2,934 images and validating it with 816, resulting in a 95% mean Average Precision (mAP). It underscores the significant role of artificial intelligence in enhancing safety management and occupational health within the construction sector. This research serves as a foundation for future advancements in AI-driven safety measures, addressing the urgent need for innovative strategies to minimize workplace risks and elevate compliance standards in the industry.
Keywords: Protective Equipment (PPE), Artificial Intelligence (AI), YOLO (You Only Look Once), Computer Vision, Object Detection, Convolution Neural Networks(CNN).

I. INTRODUCTION

The construction sector, recognized as a key contributor to infrastructure development, has consistently been ranked among the most perilous industries globally, characterized by a high frequency of accidents and fatalities that render it one of the most hazardous fields (Lingard, 2013 [1]; Pinto et al., 2011 [2]; Waehrer et al., 2007 [3]). Reports indicate that elevated accident and fatality rates are often linked to failures in adhering to safety protocols, particularly regarding the use of Personal Protective Equipment (PPE) (Memon et al., 2023 [4]; Sehsah et al., 2020 [5]). In numerous cases, the absence of PPE or its improper usage—such as helmets, vests, and boots—has been a significant contributing factor. According to Kang (2018) [6], over 70% of fatal incidents involved some level of non-compliance with PPE regulations. The YOLO (You Only Look Once) time line shown in Figure1 framework has progressed through multiple iterations, each enhancing the previous version in terms of speed and precision. YOLOv1, released in 2016, introduced a grid-based methodology. This was succeeded by YOLOv2 in 2017, which incorporated anchor boxes. In 2018, YOLOv3 added multi-scale predictions, while YOLOv4 in 2020 focused on optimizing hyperparameters. The same year saw the release of YOLOv5, which emphasized architectural improvements. YOLOv6, launched in 2022, targeted industrial applications, and YOLOv7, also from 2022, achieved cutting-edge real-time object detection.

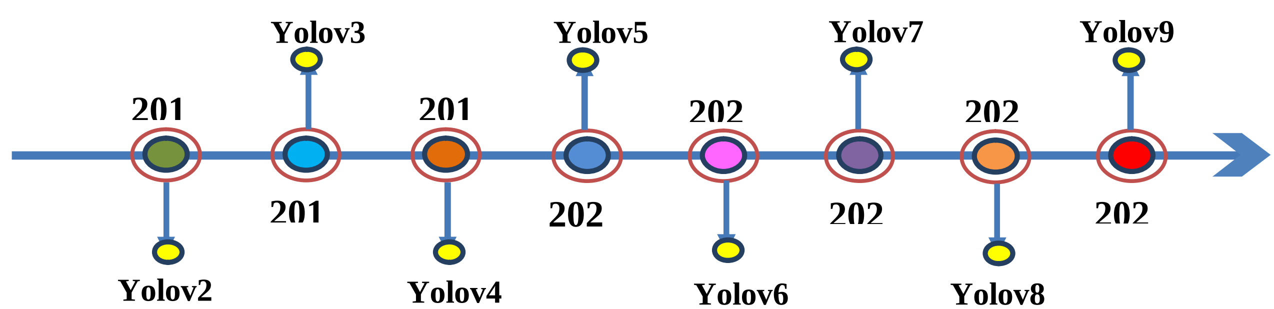

Fig. 1:-Time Line of Yolo version

A. Problem Statement

To address the growing need for dependable computer vision solutions across various fields, develop a precise and efficient object detection system utilizing YOLOv8, OpenCV, and TensorFlow. The goal is to create a system capable of recognizing and locating objects of interest in both still images and live video feeds, with an emphasis on speed, accuracy, and scalability. The system should be adaptable enough to manage different object categories and adjust to changing lighting conditions and environments. Additionally, it should prioritize optimization techniques to ensure optimal performance on devices with limited resources, such as edge devices or embedded systems. The proposed solution must feature a user-friendly interface that allows both developers and end users to easily implement and operate it, and it should seamlessly integrate with existing frameworks or applications. Ultimately, the aim is to leverage the strengths of YOLOv8, OpenCV, and TensorFlow to deliver a state-of-the-art object detection system that meets the demands of modern computer vision applications.

B. Motivation

To There are numerous compelling reasons to embark on a YOLOv8 object detection project. To begin with, the significance of such initiatives in real-world applications is substantial. Their applications are vast, ranging from enhancing surveillance systems to improving the efficiency of autonomous vehicles and facilitating medical imaging. By leveraging YOLOv8's cutting-edge technology, developers can delve into the intricacies of neural networks and machine learning, positioning themselves at the leading edge of advancements in computer vision. This presents an excellent opportunity for skill development, allowing individuals to tackle complex challenges while honing their expertise. Additionally, the flexibility of object detection models enables customization for various industries and applications, fostering innovation and creativity. Engaging with the vibrant community focused on computer vision and deep learning opens doors for collaboration and knowledge exchange, enriching the overall experience. Mastery of YOLOv8 and object detection can also pave the way for exciting career prospects in fields such as computer vision engineering, data science, and artificial intelligence. Ultimately, the satisfaction derived from witnessing a YOLOv8-based model accurately identify and localize objects serves as a powerful motivator, inspiring enthusiasts to overcome challenges and advance the frontiers of computer vision technology.

C. Objective

This project is designed to develop a dependable and efficient object detection system utilizing TensorFlow, OpenCV, and YOLOv8. Our primary objective is to emphasize speed and scalability while ensuring high accuracy in real-time object detection within static images. We plan to achieve this by implementing the YOLOv3 architecture, training the model with specialized datasets using TensorFlow, and incorporating OpenCV for preprocessing, post-processing, and visualization tasks. To ensure real-time performance, we will focus on reducing latency and improving throughput. Additionally, we aim to enhance the system's robustness to various conditions, such as background clutter, occlusions, varying lighting, and different object sizes. The system will feature a user-friendly interface that facilitates seamless integration with existing frameworks, simplifying deployment for both developers and end users.

The key goals of PPE detection include:

1) Safety Compliance: Ensuring that workers adhere to safety regulations and standards, thereby reducing the risk of accidents and injuries in hazardous environments.
2) Risk Mitigation: Identifying non-compliance with PPE requirements in real-time to prevent potential injuries or health risks associated with exposure to hazardous materials or environments.
3) Monitoring and Reporting: Providing data and analytics on PPE usage to help organizations track compliance, identify trends, and improve safety protocols.
4) Automation: Utilizing technology, such as computer vision and machine learning, to automate the detection of PPE, which can enhance efficiency and reduce the need for manual monitoring.
5) Training and Awareness: Raising awareness about the importance of PPE and ensuring that workers understand the necessity of wearing the correct equipment for their specific tasks.
6) Emergency Response: Facilitating quicker responses in emergency situations by ensuring that all personnel are properly equipped before entering hazardous areas.

Overall, PPE detection aims to create a safer work environment, enhance compliance with safety regulations, and ultimately protect the health and well-being of workers.

II. LITERATURE REVIEW

Ahmed et al. (2023) [6] Main Findings: The study presents a deep learning-based approach for detecting personal protective equipment (PPE) using advanced computer vision techniques. The authors emphasize the importance of PPE in ensuring safety in various industries and propose a sustainable method for real-time detection. The proposed model demonstrates high accuracy and efficiency in identifying different types of PPE, contributing to workplace safety.
Kumar et al. (2023) [7] Main Findings: - This paper discusses the use of Single Shot MultiBox Detector (SSD) for object detection, highlighting its speed and accuracy in real-time applications. The authors provide a comparative analysis of SSD with other object detection frameworks, showcasing its effectiveness in various scenarios.
Ferdous& Ahsan (2022) [8] Main Findings:- The authors propose a YOLO-based architecture specifically designed for detecting PPE in construction sites, emphasizing the importance of safety in hazardous environments. The model achieves high precision and recall rates, demonstrating its potential for real-world applications in monitoring compliance with safety regulations.
Afandi& Isa (2021) [9] Main Findings:- This research focuses on detecting harmful weapons using the YOLOv4 framework, highlighting its application in security and surveillance. The authors report significant improvements in detection accuracy and speed compared to previous models, making it suitable for real-time monitoring.

III. METHODOLOGY

You Only Look Once V8 (YOLOV8), created by Ultralytics in January 2023, served as the basis for our AI model. YOLOV8 is a type of convolutional neural network (CNN), which falls under the umbrella of deep learning neural networks and is frequently employed for visual analysis. The model was trained and validated using the Roboflow PPE dataset, which includes over 330,000 images featuring 80 different everyday objects, such as humans, bicycles, cars, and animals. For training, 118,000 images were utilized, along with 5,000 for validation and 20,000 for testing. The model's performance was evaluated against the validation dataset using mean average precision (mAP), which measures the percentage of correctly identified objects across various categories (Ultralytics, 2023a). YOLOV8 is versatile and can be applied to tasks like object detection, tracking, classification, and segmentation. Our project specifically leverages the object detection features of YOLOV8.

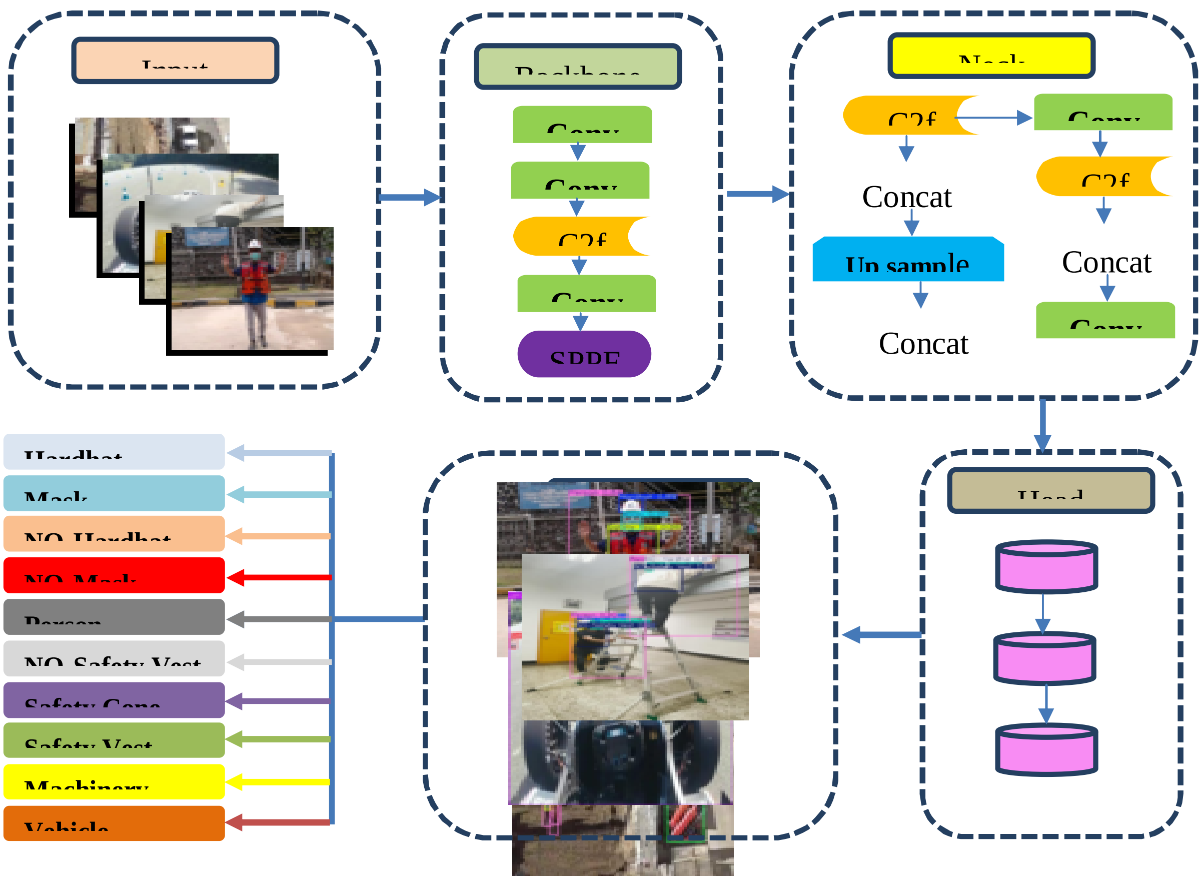

Fig. 2:- Proposed Flow Chart

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A. Data Collection

Data Collection with Roboflow: Roboflow is a web-based platform that streamlines the data collection and labeling process for machine learning applications. It facilitates the gathering and annotation of images or videos of individuals wearing PPE. Users can upload their own media or utilize publicly accessible datasets. After the data is uploaded, Roboflow can automatically identify and label objects within the images or videos, significantly enhancing the speed and efficiency of compiling and annotating extensive datasets.

B. Data Pre-Processing

Image Resizing and Cropping: Images often need to be resized and cropped to a specific dimension to align with the requirements of the training algorithm. Additionally, cropping may be necessary to concentrate on the areas where the PPE is present. Data Splitting: The dataset shown in Figure 3 can be divided into training, validation, and testing subsets. The training set is utilized for model training, the validation set is used for fine-tuning the model's hyperparameters, and the testing set assesses the model's effectiveness on unseen data.

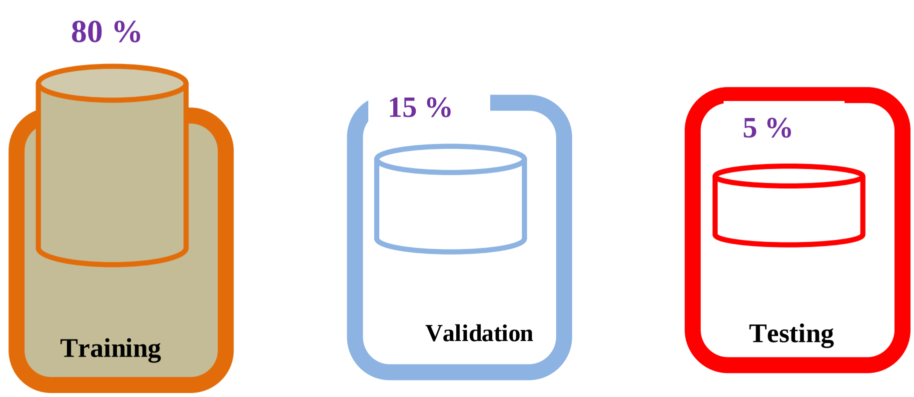

Figure 3:- Dataset Split for PPE Detection

A. Training a PPE detection model using YOLOv8

1) Install YOLOv8: Begin by installing the YOLOv8 framework on your machine. You can do this via pip with the following command: `pip install -q ultralytics`
2) Prepare the dataset: Prior to training the model, it's essential to prepare your dataset. This includes resizing and augmenting images, labeling the objects within them, and dividing the dataset into training, validation, and testing sets as part of the data pre-processing step. After completing the pre-processing, execute the following command.
3) Create a configuration file: You will need to create a configuration file that outlines the model architecture, training hyper parameters, and the paths for the training, validation, and testing datasets.
4) Train the model: After setting up the configuration file, you can initiate the training process using the YOLOv8 framework. This involves feeding the model batches of images and adjusting its parameters to reduce the loss function.

B. Validating the Model:

Validation plays a crucial role in the PPE detection process when using YOLOv8. It ensures that the model is both accurate and dependable in identifying PPE in new, previously unseen images. Here are the steps to validate the model for PPE detection with YOLOv8:

1) Prepare the validation dataset: Create a distinct validation dataset that includes a selection of images from the original dataset, ensuring these images were not utilized during the model's training.
2) Run the validation script: YOLOv8 includes a validation script designed to assess the model's performance on the validation dataset. Execute the following command to evaluate the model.
3) Analyze the results: Review the output from the validation script to gauge the model's effectiveness on the validation set. Pay attention to the precision, recall, and mAP scores to evaluate how accurately the model detects PPE.

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4) Fine-tune the model: If the model's performance on the validation set is lacking, consider fine-tuning it by modifying hyperparameters or training it on a more extensive dataset.
5) Repeat the validation: After making adjustments to the model, conduct the validation step once more to reassess its performance. Continue this cycle until the model achieves satisfactory results on the validation set.

C. Software Configuration:

STEP 1:- YOLOv8: The YOLOv8 object detection model and its necessary dependencies must be installed on the system for personal protective equipment (PPE) detection.

STEP 2:- Python: A compatible Python environment is required to execute the YOLOv8 model and its associated scripts, as it is implemented in Python Google Colab.

STEP 3:- Deep Learning Framework: PyTorch, the deep learning framework utilized by YOLOv8, must be installed to support the model's training and inference functions.

STEP 4:- Image Processing Libraries: Libraries like OpenCV are essential for image manipulation, resizing, and pre-processing, which are crucial for preparing images for the model.

IV. RESULTS AND DISCUSSION

The Table 1 presents a comparative analysis of various object detection models, specifically focusing on their performance metrics: precision, recall, and mean Average Precision at IoU threshold 0.5 (mAP0.5). Precision measures the accuracy of the positive predictions made by the model, while recall indicates the model's ability to identify all relevant instances within the dataset. The mean Average Precision provides a comprehensive evaluation of the model's performance across different confidence thresholds, reflecting both precision and recall.

TABLE I

Comparison of Different Algorithm

SN.	Model	Precision	Recall	mAP0.5
1	Faster R-CNN	0.82	0.82	0.78
2	SSD	0.89	0.80	0.73
3	YOLOv5s	0.88	0.78	0.76
4	YOLOv7	0.91	0.82	0.74
5	YOLOv8	0.923	0.87	0.822

A. Precision Recall Curve

The PR curve is plotted with Recall on the x-axis and Precision on the y-axis. Each point on the curve represents a different threshold for classifying a positive instance. As the threshold changes, both precision and recall will change, leading to different points on the curve. The curve typically starts at (0,1) (when the threshold is very low, leading to high recall but low precision) and ends at (1,0) (when the threshold is very high, leading to high precision but low recall).

Particularly useful in cases where the positive class is rare (e.g., object detection, fraud detection, disease diagnosis) because it focuses on the performance of the positive class rather than the overall accuracy, which can be misleading in imbalanced datasets.

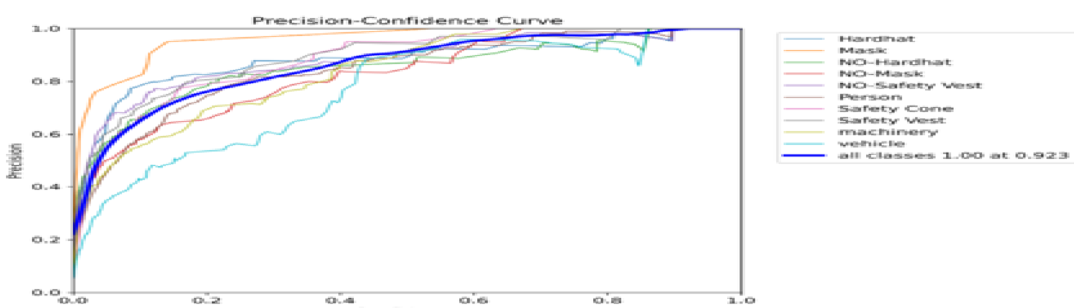

Fig. 4:- Precision Curve.

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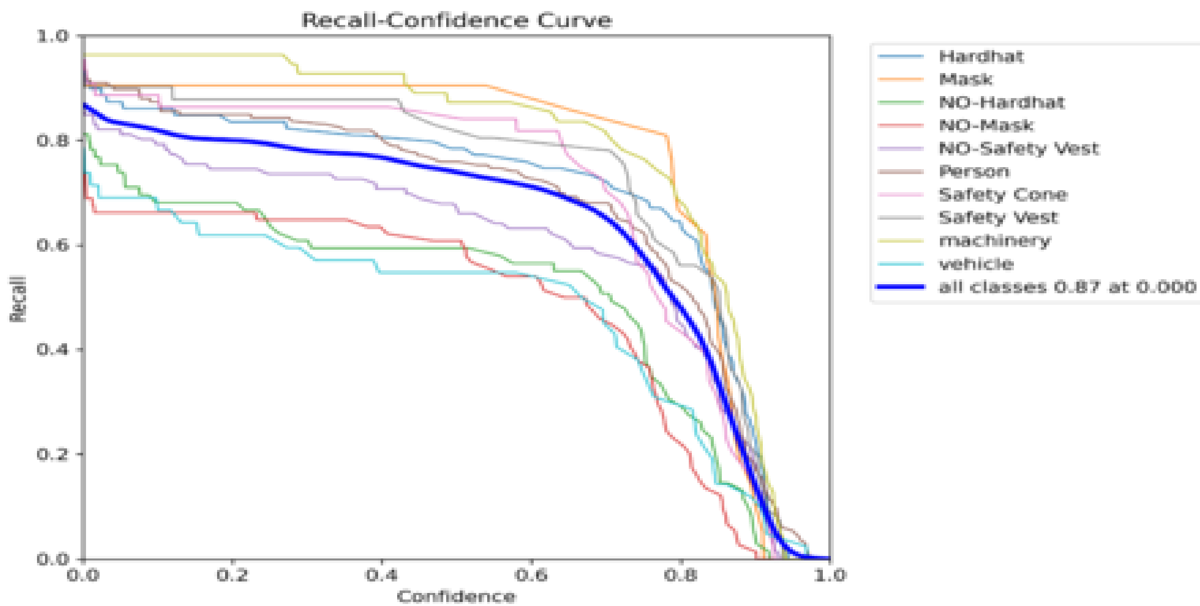


Fig. 5:- Recall Curve.

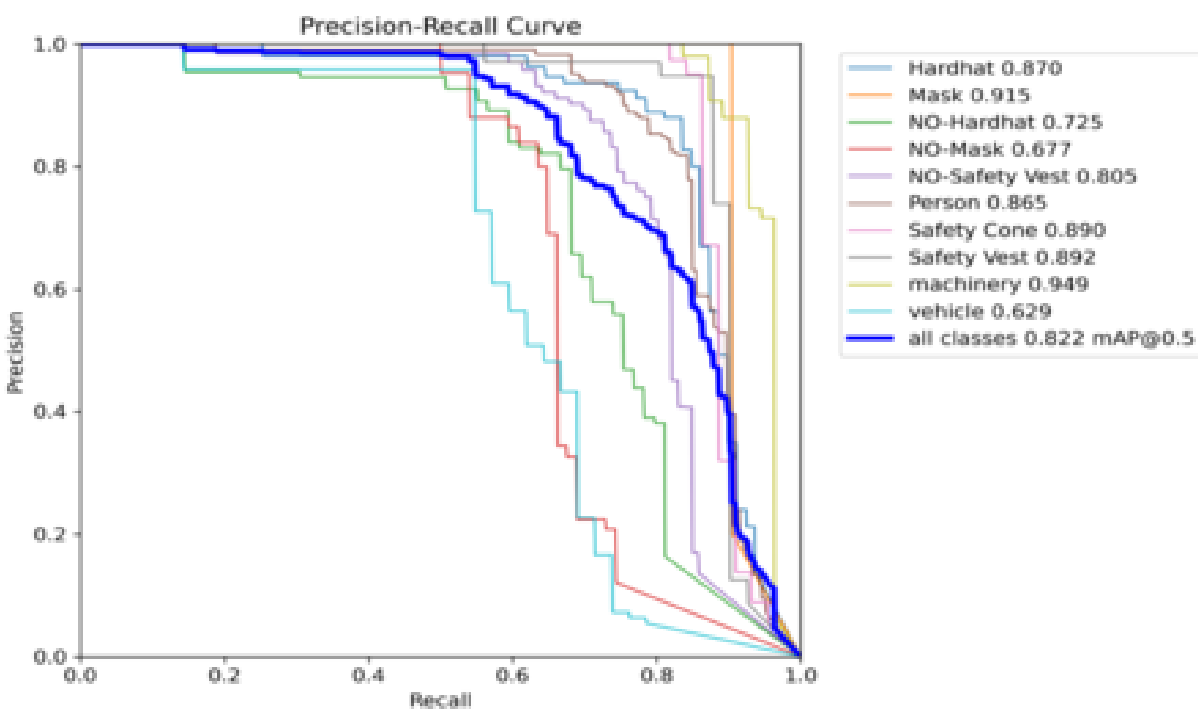
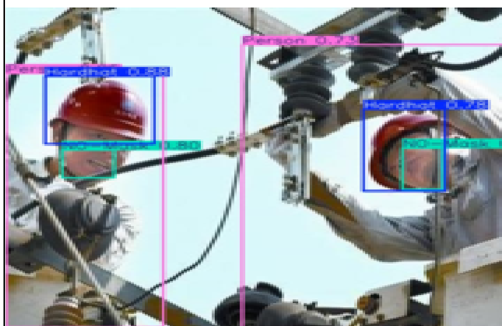
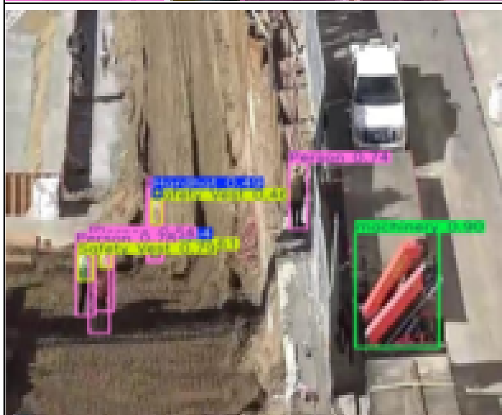
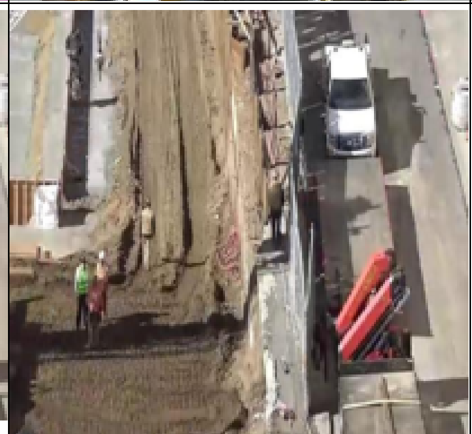


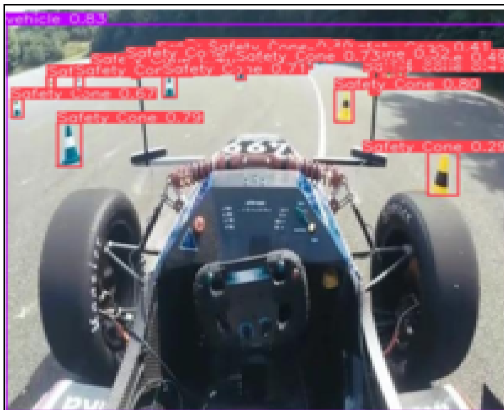
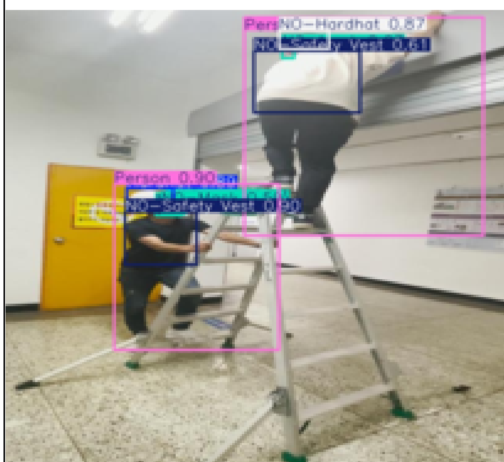
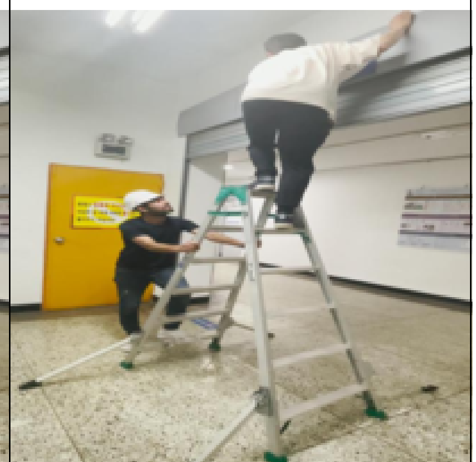
Fig. 6:- Precision Recall Curve

V. DETECTED OUTPUTS

The table 2 presents a series of input images alongside their corresponding output images and the detected objects within each image. The input images depict various scenarios involving individuals and safety equipment, which are critical for assessing compliance with safety regulations in industrial settings.

TABLE II
Input images their corresponding output images and detected objects

Input Image	**Output Image**	**Detected**
		'Hardhat', 'NO-Mask', 'Person',.
		'Hardhat', Safety Vest', 'Person', 'machinery',
		'Hardhat', 'Mask', 'Person', 'Safety Vest',

		'Safety Cone', 'vehicle'.
		'NO-Hardhat', 'NO-Mask', 'NO-Safety Vest', 'Person',

VI. CONCLUSIONS

The research indicates that the current dataset is limited, suggesting a need for a larger training set, particularly for safety shoes. Additionally, the testing phase was constrained to just 300 images, which may not represent all real-world scenarios. Employing data augmentation techniques could broaden the dataset to better reflect various construction site conditions. These findings not only confirm the practical utility of YOLOV8 but also point out areas for future enhancements to improve PPE detection accuracy.

Among the models evaluated, YOLOv8 demonstrates the highest precision at 0.923, indicating that it has the most accurate positive predictions compared to the other models. This is complemented by a recall of 0.87, suggesting that YOLOv8 effectively identifies a significant proportion of true positive instances. Consequently, its mAP0.5 score of 0.822 is the highest in the table, underscoring its overall superior performance in object detection tasks.

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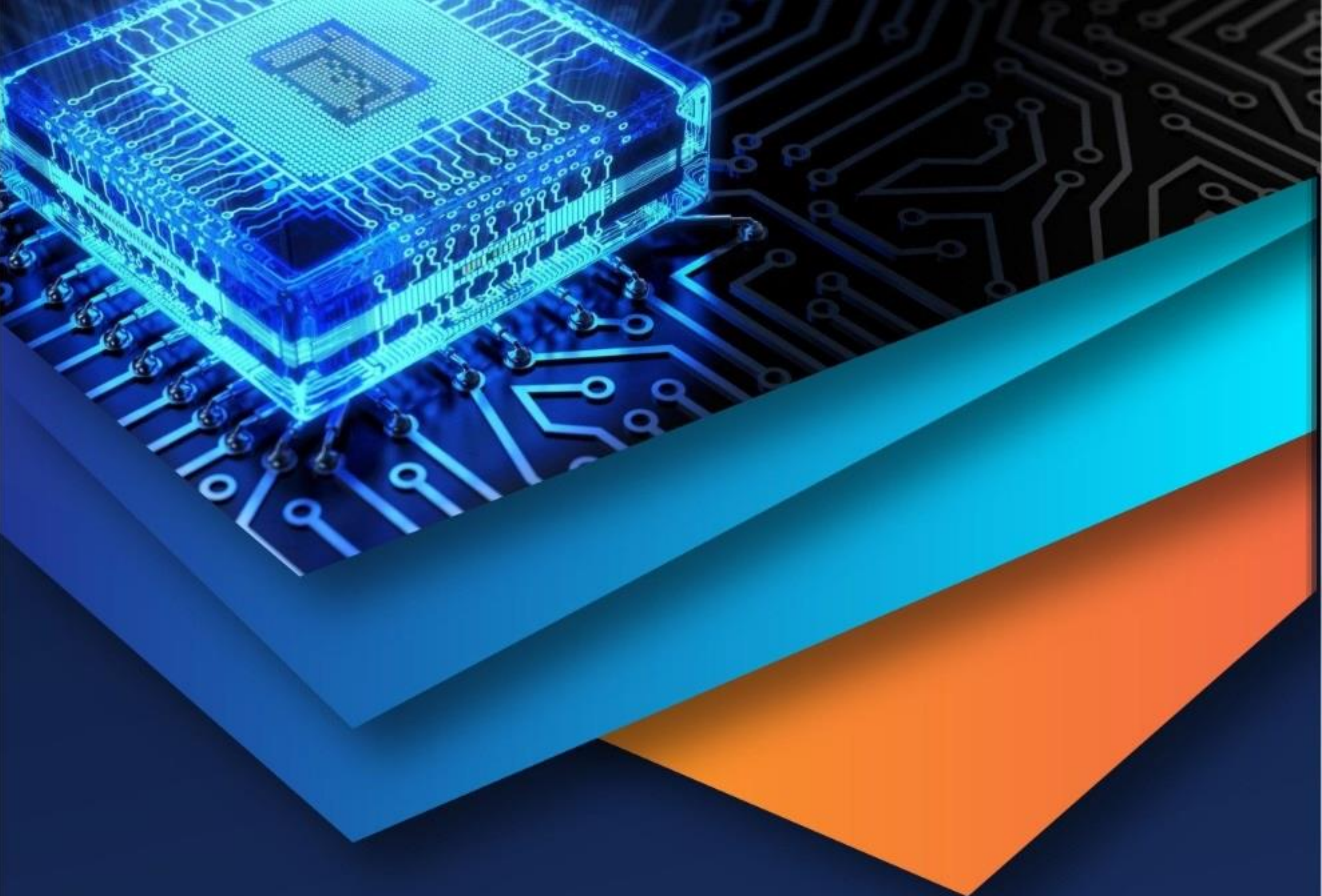

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