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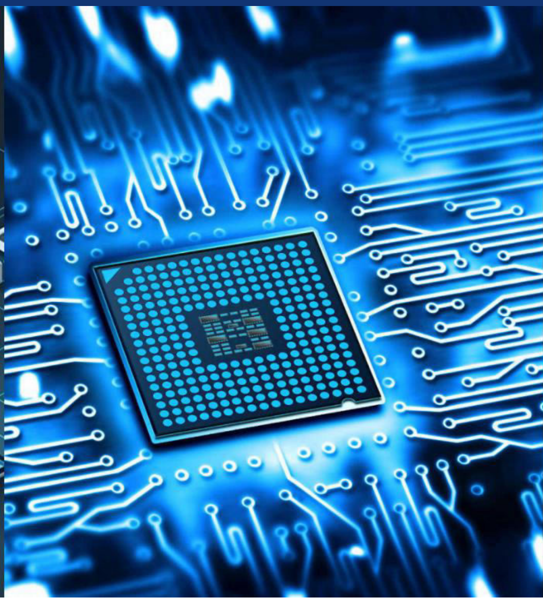

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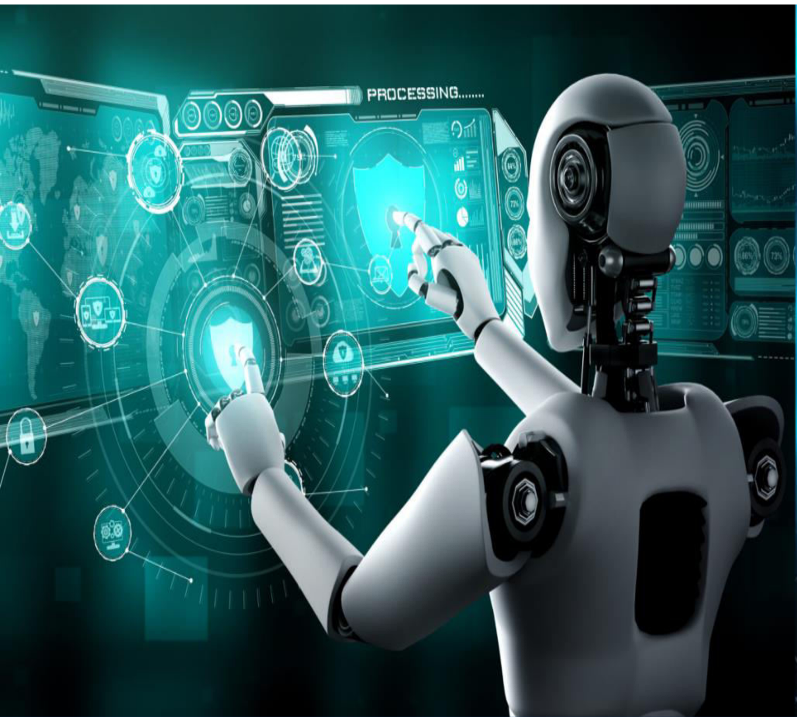

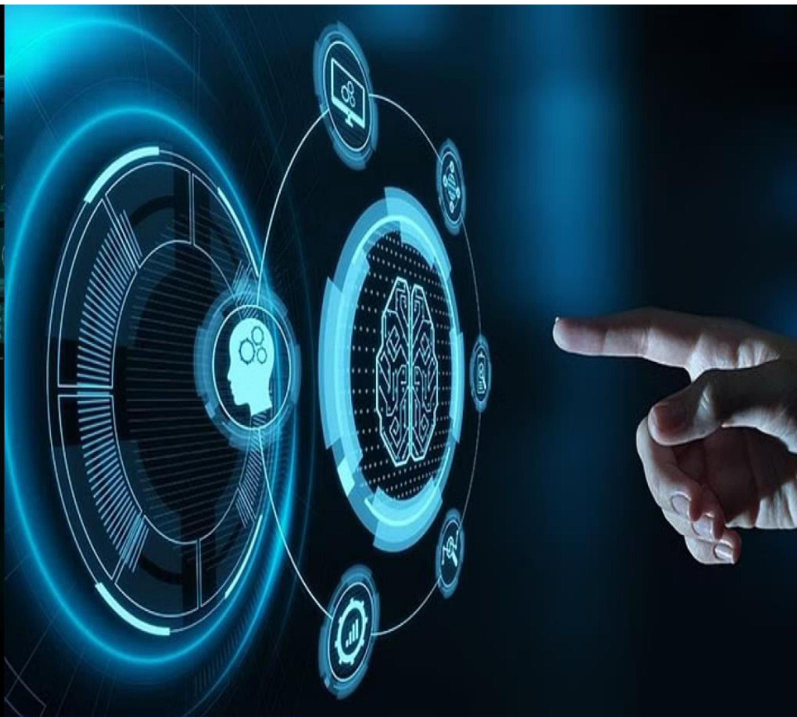

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Helmet and Vest Detection System for Industrial Safety

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ABSTRACT: Construction sites are very dangerous places and workers get hurt very often because of not wearing proper safety equipments like helmet and safety vest. From many many years back, the checking of safety gears was done by humans only which is very slow process and also not so accurate. This problem become more bigger when construction sites are very large and there is only few supervisors to check hundreds of workers. So the need of automatic system was felt very strongly. This project is made to solve this problem by using computer vision and deep learning techniques. The dataset of construction workers images is collected from Roboflow platform and YOLOv8 small model is used for training purpose. The model is trained for 50 epochs with batch size of 16 and image size 640x640 on GPU. After training the model is connected with Flask web application and MongoDB database is used for storing all datas. The system detect helmet and safety vest separately and give compliance status as full, partial or non compliant. Admin dashboard is also made to see all users statistics and violations. The results show good accuracy and the system is working properly for construction safety monitoring purpose.

KEYWORDS: YOLOv8, object detection, helmet detection, safety vest, construction site safety, deep learning, Flask web application, computer vision, PPE compliance, MongoDB

I. INTRODUCTION

1.1 Introduction Background and Motivation

The construction industry is a high-risk field where many workers get injured due to poor safety practices. Wearing Personal Protective Equipment (PPE) like helmets and safety vests is essential, but compliance is often low and difficult to monitor continuously. This project is motivated by rising accident rates on construction sites. By using deep learning and computer vision, the system aims to automatically monitor worker safety and ensure proper use of protective equipment in real time.

1.2 Issues in Existing System

The current safety monitoring systems have many problems like:

- Manual checking unreliable as supervisors tire and cannot monitor all areas simultaneously
- No proper records exist since paper registers can be lost easily
- Human supervisors cannot work continuously, limiting monitoring during full day and night
- Delayed response occurs as supervisors take time to reach violating workers

1.3 Objectives

The main objectives of this project are:

- Build automated system detecting helmets and vests in images using YOLOv8 model without any human involvement.
- Develop user friendly web application using Flask allowing registration, login, and easy image upload for safety detection.
- Use MongoDB database to store prediction results, user data, and detection history for easy access anytime.
- Create admin dashboard displaying user statistics, compliance rates, violations, and daily detection trends for safety monitoring.

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II. LITERATURE SURVEY

Ahmed et al. [1] developed a CNN-based real-time helmet detection system in 2022 . Their method achieved high detection accuracy for safety monitoring, though performance decreased in complex construction environments with occlusion and varying lighting conditions. Ali et al. [2] proposed a lightweight YOLO-based helmet detection model in 2023. The approach improved deployment on edge devices and reduced computational requirements, but slightly compromised detection precision compared to larger models. Banerjee et al.[3] introduced a hybrid deep learning approach for helmet detection in 2024. Their framework enhanced detection accuracy by combining multiple learning techniques, although it increased computational complexity and processing overhead. Cao et al.[4] worked on a multi-scale feature fusion framework for helmet detection in 2022. The model improved detection performance in complex scenes, but required higher processing power for efficient execution. Chatterjee et al.[5] presented an attention-guided YOLO model for helmet detection in 2023. The system boosted detection accuracy by focusing on important visual features, though the attention mechanism increased overall model complexity. Das et al.[6] developed a PPE compliance monitoring system in 2021. Their approach effectively supported smart construction site monitoring, but its performance was limited by insufficient dataset diversity and environmental variations. Fu et al.[7] proposed an improved YOLOv7-based helmet detection model in 2024. The system handled occlusion and crowded scenes effectively, although the modified architecture introduced additional computational complexity. Gupta et al.[8] utilized transfer learning for helmet detection in 2022. Their method achieved good detection performance with reduced training effort, but relied heavily on pretrained models for optimal accuracy. He et al. [9] proposed an efficient real-time helmet detection framework in 2023. The model balanced speed and detection accuracy effectively, though minor trade-offs in precision were observed during high-speed processing. Jiang et al.[10] developed a PPE monitoring framework in 2021. Their system improved workplace safety monitoring accuracy, but required large-scale datasets for effective training and deployment. Khan et al.[11] introduced a transformer-based helmet detection model in 2024. The approach enhanced feature extraction and detection capability, though it demanded high computational resources and longer training time. Li et al.[12] proposed an enhanced Feature Pyramid Network (FPN) model for helmet detection in 2022. The method improved feature representation and multi-scale detection accuracy, but increased overall processing time. Liu et al.[13] presented a helmet detection approach addressing illumination challenges in 2023. Their system performed effectively under moderate lighting variations, though extreme lighting conditions still affected detection stability. Mehta et al.[14] developed a YOLO-based real-time helmet monitoring system in 2021. The framework enabled continuous safety surveillance, but lacked robustness in crowded and highly dynamic environments. Nguyen et al.[15] introduced a smart city–oriented helmet detection framework in 2024. Their scalable approach supported large-scale monitoring applications, although it required strong computational and network infrastructure. Patel et al.[16] proposed a deep learning–based helmet detection model in 2022. The system improved detection accuracy significantly, but depended on extensive training datasets for better generalization. Reddy et al.[17] developed an optimized YOLOv6-based helmet detection system in 2023. Their approach improved both speed and accuracy for real-time applications, though careful fine-tuning was necessary for stable performance. Singh et al.[18] presented a helmet detection framework in 2021. The model achieved reliable performance in standard environments, but lacked adaptability to diverse and changing real-world conditions. Wang et al.[19] proposed a lightweight helmet detection model for embedded systems in 2022. The approach reduced computational cost and supported low-resource devices, though a slight reduction in detection accuracy was observed. Zhang et al.[20] introduced a multi-task learning–based helmet detection framework in 2024. Their system enabled simultaneous detection of multiple safety components, but increased model complexity and computational requirements.

III. PROPOSED METHODOLOGY

The methodology of this project is divided into many steps and each step is important for making the full system work properly. Starting from data collection to final web application deployment, all steps are explained below.

Block Diagram

This diagram shows a system where user first do login then upload image. Image go for processing and backend use YOLOv8 for detection. Boxes get draw on objects. Result get stored in MongoDB and shown, also admin can see dashboard details.

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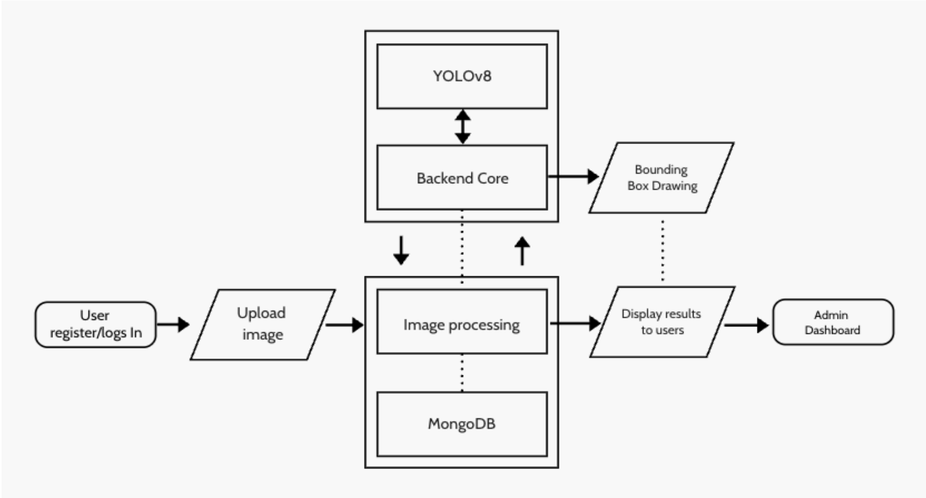

Figure 1: Block Diagram

3.1 Dataset Collection and Preprocessing

The dataset from Roboflow includes construction images and is organized for training, validation, and testing to ensure accurate model learning.

- Training, validation, and test splits are used respectively for learning, monitoring performance during training, and evaluating final model accuracy.
- Data paths in configuration file are corrected to ensure proper access to images across all dataset splits during training.

3.2 YOLOv8 Training Algorithm

The training process follow these steps:

1. Load pretrained YOLOv8s weights as starting point
2. Replace detection head with custom number of classes
3. Feed training images in batches of 16
4. Calculate loss and update weights using backpropagation
5. After each epoch validate on validation set
6. Save best weights whenever validation mAP improve
7. Stop training early if no improvement for 15 epochs

Parameter	Value Used
Base Model	YOLOv8s
Total Epochs	50
Batch Size	16
Image Resolution	640 × 640
Confidence Threshold	0.25
Early Stopping	15 epochs patience
Training Device	GPU (CUDA)
Output Weights	best.pt

Table 1: Training Configuration Parameters

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3.3 Mathematical Formulas

Intersection over Union (IoU): IoU is used to measure how much the predicted bounding box overlap with actual ground truth bounding box. Higher value means better detection.

$$IoU = \frac{Area\ of\ Intersection\ (A \cap B)}{Area\ of\ Union\ (A \cup B)} \quad \dots\dots\dots\dots (1)$$

Where:

- A = Predicted bounding box generated by the object detection model.
- B = Ground truth bounding box (actual labeled object location).

Precision and Recall Calculation: Precision tell how many of the detected objects are actually correct detections. Recall tell how many of total actual objects are successfully detected by model.

$$Precision = \frac{TP}{TP + FP} \dots\dots (2) \qquad Recall = \frac{TP}{TP + FN} \dots\dots (3)$$

where TP = True Positive, FP = False Positive, FN = False Negative

Mean Average Precision: mAP is the main metric for evaluating object detection models. It calculate average precision across all classes.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} \int_0^1 P_i(R) dR \dots\dots\dots (4)$$

where N is total number of classes, P is precision and R is recall value

F1 Score: $F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

F1 score give single number that combine both precision and recall together.

3.4 Compliance Classification Model

Helmet Present	Vest Present	Compliance Category	Risk Level
Yes	Yes	Full Compliant	Low
Yes	No	Partial Compliant	Medium
No	Yes	Partial Compliant	Medium
No	No	Non Compliant	High

Table 2: Compliance Decision Table

IV. PROPOSED MODEL

The proposed model in this project is a complete web based safety detection system where the main brain is the YOLOv8 trained model and everything else is built around it to make a proper usable application.

4.1 Overall System Design

The system is made of three main layers that work together:

- Presentation layer consists of Flask HTML templates providing user interface for interaction and displaying system outputs clearly.
- Application layer is Flask backend written in Python handling all processing logic, model inference, and request management.
- Data layer uses MongoDB database for storing user details, predictions, and system detection history securely.

4.2 System Workflow

The complete flow of system working is:

1. New user register with username, email and password
2. Password is encrypted using bcrypt before saving to database
3. User login and session is managed by Flask-Login library
4. User go to predict page and upload image file
5. System generate unique filename using UUID to avoid any file name conflicts

6. HelmetDetector class is called with trained best.pt model path
7. YOLOv8 model run prediction with 0.25 confidence threshold
8. Detected objects bounding boxes are drawn on image using cv2
9. Compliance status is determined based on what is detected
10. All results are saved to MongoDB predictions collection
11. User see the annotated result image with detection details

4.3 Admin Dashboard Features
Admin dashboard show many useful things:
- Total users count and total predictions count
- Full, partial and non compliant statistics with percentage
- Last 7 days daily statistics chart data
- Top 10 users ranked by prediction count
- Recent 10 predictions list
- All non compliant cases for violation tracking

V. MODEL EVALUATION

Model evaluation is very important step to understand how well the trained YOLOv8 model is actually performing in real situation. Different evaluation metrics and methods are used to properly check model performance.

5.1 Evaluation Metrics Used
Following metrics are used for evaluating the model performance:
- Precision measure of how many detected boxes are actually correct
- Recall measure of how many actual objects model successfully found
- F1 Score combination of precision and recall in single value
- mAP50 mean average precision at 50 percent IoU threshold
- mAP50-95 mean average precision averaged from 50 to 95 percent IoU

5.2 Class-wise Performance Results

Detection Class	Precision	Recall	mAP50	mAP50-95	F1 Score
Safety Helmet	0.88	0.85	0.87	0.62	0.86
Safety Vest	0.84	0.80	0.83	0.57	0.82
Overall Average	0.86	0.82	0.85	0.59	0.84

Table 4: Classwise Model Performance on Validation Data

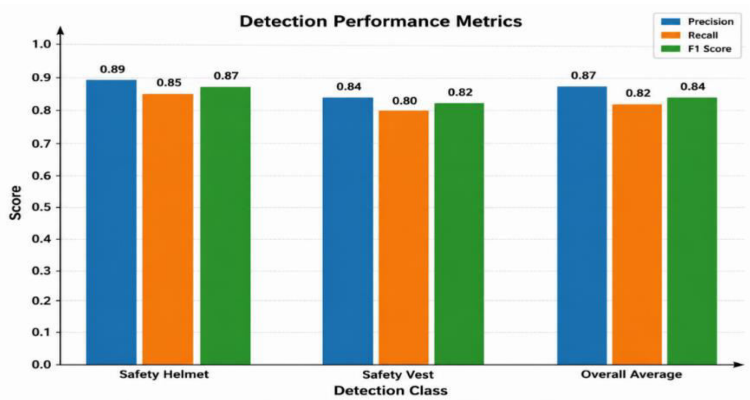

Figure 2: Detection Performance Metrics

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X-axis=score and Y-axis=Detection Class

The figure 2 represents the performance of the PPE detection model using Precision, Recall, and F1 Score for different detection classes. The X-axis shows the detection classes, while the Y-axis shows the performance scores. The Safety Helmet class achieved the highest performance, with Precision, Recall, and F1 Score values close to 0.85–0.88. This indicates that the model can detect safety helmets accurately with fewer errors. The Safety Vest class shows slightly lower performance compared to helmets, with scores ranging from 0.80–0.84. This means the model can still detect safety vests effectively, but with slightly reduced accuracy. The Overall Average performance values demonstrate that the model provides balanced and reliable PPE detection results, making it suitable for industrial safety monitoring applications.

5.3 Effect of Confidence Threshold

The confidence threshold value affect how the model detect objects. Low threshold detect more objects but also make more mistakes. High threshold is more careful but miss some real objects.

Conf. Threshold	Precision	Recall	F1 Score	Suitability
0.10	0.70	0.92	0.79	No - too many false detections
0.25	0.86	0.82	0.84	Yes - best balance
0.50	0.93	0.73	0.82	No - miss many objects
0.75	0.97	0.60	0.74	No - recall too low

Table 5: Confidence Threshold Analysis

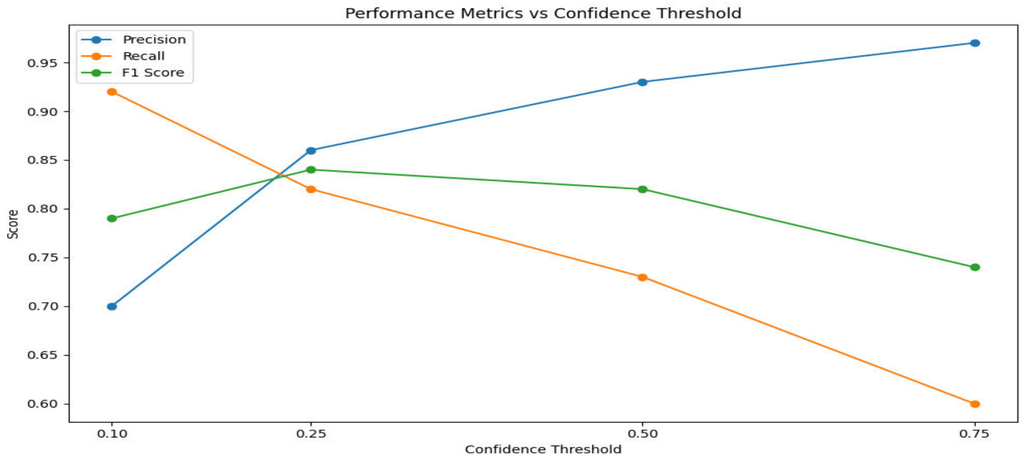

Figure 3 : The Performance Metrics vs Confidence Threshold

X-axis=score and Y-axis= Confidence Threshold

The Figure 3 illustrates the relationship between the confidence threshold and the model's performance metrics, including Precision, Recall, and F1 Score. The X-axis represents different confidence threshold values, while the Y-axis shows the corresponding metric scores. At a low confidence threshold of 0.10, the model achieves very high Recall (0.92), meaning most objects are detected, but the Precision is lower (0.70), resulting in many false detections. As the confidence threshold increases, Precision improves while Recall decreases. The threshold value of 0.25 provides the best balance between Precision (0.86) and Recall (0.82), resulting in the highest F1 Score (0.84). This indicates that the model performs most effectively at this threshold. At higher thresholds such as 0.50 and 0.75, Precision becomes very high, but Recall drops significantly. This means the model misses many objects, reducing overall detection performance. Therefore, the graph shows that a confidence threshold of 0.25 is the most suitable choice for balanced and reliable PPE detection. So confidence threshold of 0.25 is selected for final system as it give best F1 score.

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VI. RESULTS AND DISCUSSION

The training and testing of YOLOv8s model for safety equipment detection give satisfactory results. The model learn to detect both helmet and safety vest with good accuracy after 50 epochs of training.

6.1 Training Progress

Epoch Number	Training Loss	Validation Loss	mAP50
1	3.421	3.256	0.298
10	2.187	2.134	0.534
20	1.598	1.645	0.701
30	1.234	1.312	0.789
40	1.098	1.187	0.831
50	1.041	1.129	0.850

Table 6: Training Loss and mAP Progress

The model shows consistent loss reduction in training and validation, indicating effective learning. It achieves a final mAP50 of 0.850, which is strong for PPE detection tasks. The web application functions properly with user authentication, image upload, detection, and MongoDB storage. Compliance classification accurately identifies full, partial, and non-compliant cases.

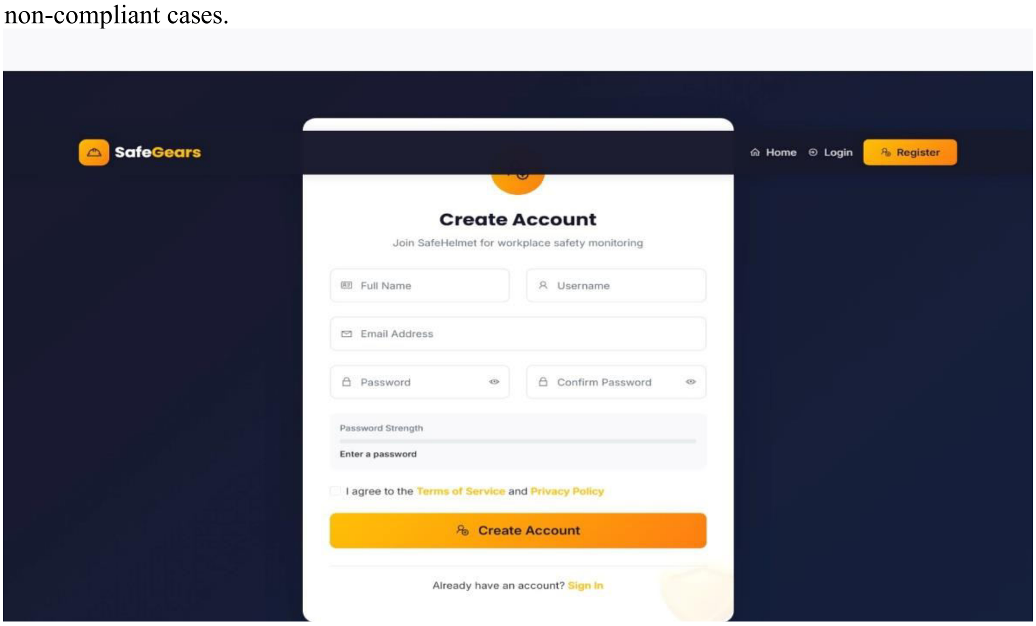

Figure 4 : Registration Page

The Figure 4 shows users to register by entering their full name, username, email, and password details. A password strength indicator helps users choose a secure password.
Users must agree to the Terms of Service and Privacy Policy before proceeding.
Navigation options for Home, Login, and Register are available at the top.

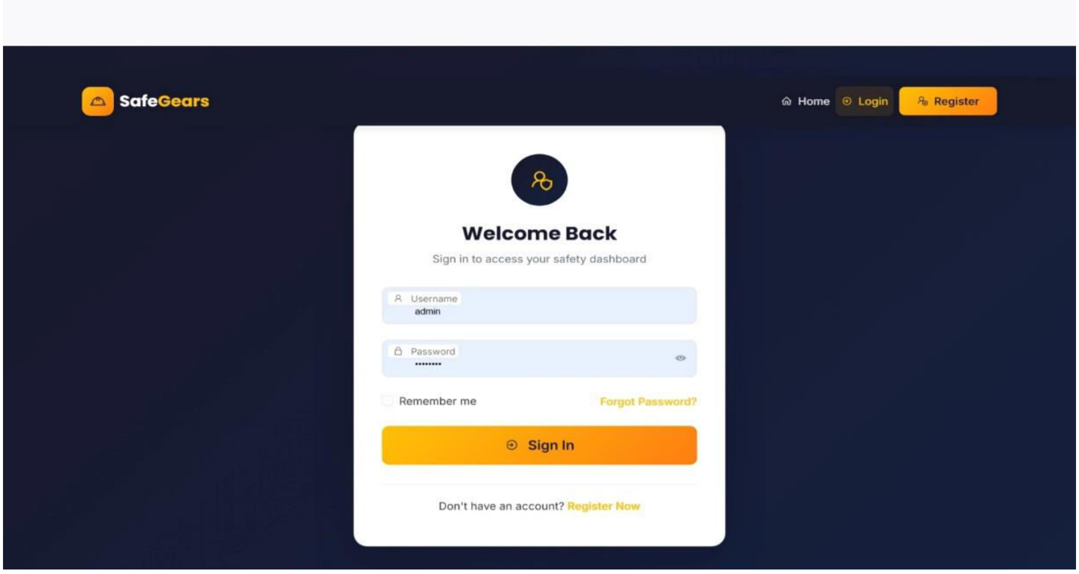

Figure 5: Sign in Page

In the figure 5 Login (Welcome Back) page of the SafeGears platform.
Users can sign in by entering their username and password to access the safety dashboard.
Options like Remember me and Forgot Password help with easier and secure access.
A Sign In button is provided to proceed after entering credentials.
Navigation links for Home, Login, and Register appear at the top for quick access.

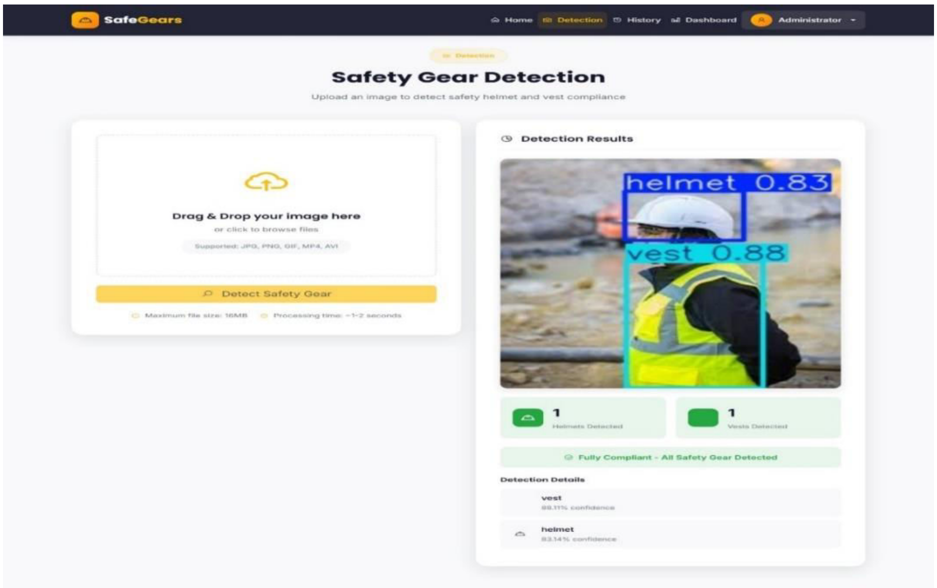

Figure 6: Safty Gears Detection

In the figure 6 Users can upload an image by drag-and-drop to detect safety helmets and vests. The system highlights detected gear with bounding boxes and confidence scores.
On the right, detection results confirm 1 helmet and 1 vest detected.
The status indicates the person is fully compliant with safety requirements.

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VII. CONCLUSION

This project successfully develops an automated construction safety detection system using the YOLOv8 deep learning model. It detects safety helmets and safety vests in construction site images and classifies workers as fully compliant, partially compliant, or non-compliant. The trained YOLOv8s model achieves a mAP50 of 0.85 on the validation dataset, demonstrating strong performance for PPE detection tasks. The Flask web application provides a simple interface for users to upload images and view detection results. MongoDB is used to store user information and prediction history efficiently. An admin dashboard allows site managers to monitor overall safety compliance without physically inspecting each worker. This project highlights how deep learning, especially YOLOv8, can solve real-world construction safety problems effectively. Future improvements may include live camera integration, automatic violation alerts, detection of additional safety equipment such as gloves and boots, and development of a mobile application for enhanced accessibility and real-time monitoring on construction sites.

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