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Enhancing Laboratory Safety with AI: PPE Detection and Non-Compliant Activity Monitoring Using Object Detection and Pose Estimation

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Abstract: Ensuring workplace safety and adhering to regulatory standards in pharmaceutical manufacturing is vital. However, traditional manual monitoring methods are inefficient, prone to errors, and labor-intensive, resulting in potential safety risks and non-compliance penalties. This research introduces an automated deep learning framework that employs video analytics for real-time compliance monitoring, providing a scalable alternative to manual inspection processes.

The system integrates YOLOv11n for detecting Personal Protective Equipment (PPE), such as gloves, masks, and goggles, identifying violations where PPE is either missing or improperly worn. Additionally, YOLOv8n-Pose is utilized to assess non-compliant postures, including actions like bending, hand-raising, and face-touching. A logging system tracks violations with precise timestamps, enabling efficient documentation for audits and regulatory purposes.

A curated video dataset was developed and annotated using Roboflow, featuring both compliant and non-compliant actions. To enhance the model's robustness, preprocessing techniques such as resizing, contrast enhancement, and data augmentation were applied. The system's performance, evaluated using metrics like mean Average Precision (mAP), F1-score, and precision, demonstrated an impressive 90% accuracy, with a mAP@50 of 92.1% and a processing speed of 25 frames per second (FPS), fulfilling the real-time monitoring criteria.

This solution offers a scalable, real-time alternative to manual inspections, reducing human intervention, improving workplace safety, ensuring compliance with regulations, and automating the documentation process. Future developments aim to integrate IoT devices, employ edge computing, and incorporate cloud-based analytics to further enhance safety monitoring and compliance.

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I. INTRODUCTION

Ensuring workplace safety and regulatory compliance is crucial in pharmaceutical manufacturing, where strict guidelines protect both product quality and worker well-being[1].

However, manual safety monitoring and reporting remain time-consuming, error-prone, and inefficient, often leading to delayed incident detection. Such delays increase the risk of safety violations, regulatory penalties, and operational setbacks, highlighting the need for an automated, real-time compliance monitoring solution[2].

Recent advancements in computer vision and deep learning have enabled video-based safety monitoring. This research presents an automated framework that integrates object detection and pose estimation to improve compliance tracking. The system employs YOLOv11n to detect Personal Protective Equipment (PPE) violations such as missing or improperly worn gloves, masks, and goggles while YOLOv8n-Pose is used to recognize unsafe postures and movements, including bending, hand-raising, and face-touching[3]. Unlike conventional PPE detection systems that focus only on equipment compliance, this approach also monitors worker behaviour, capturing actions that might lead to safety risks[4].

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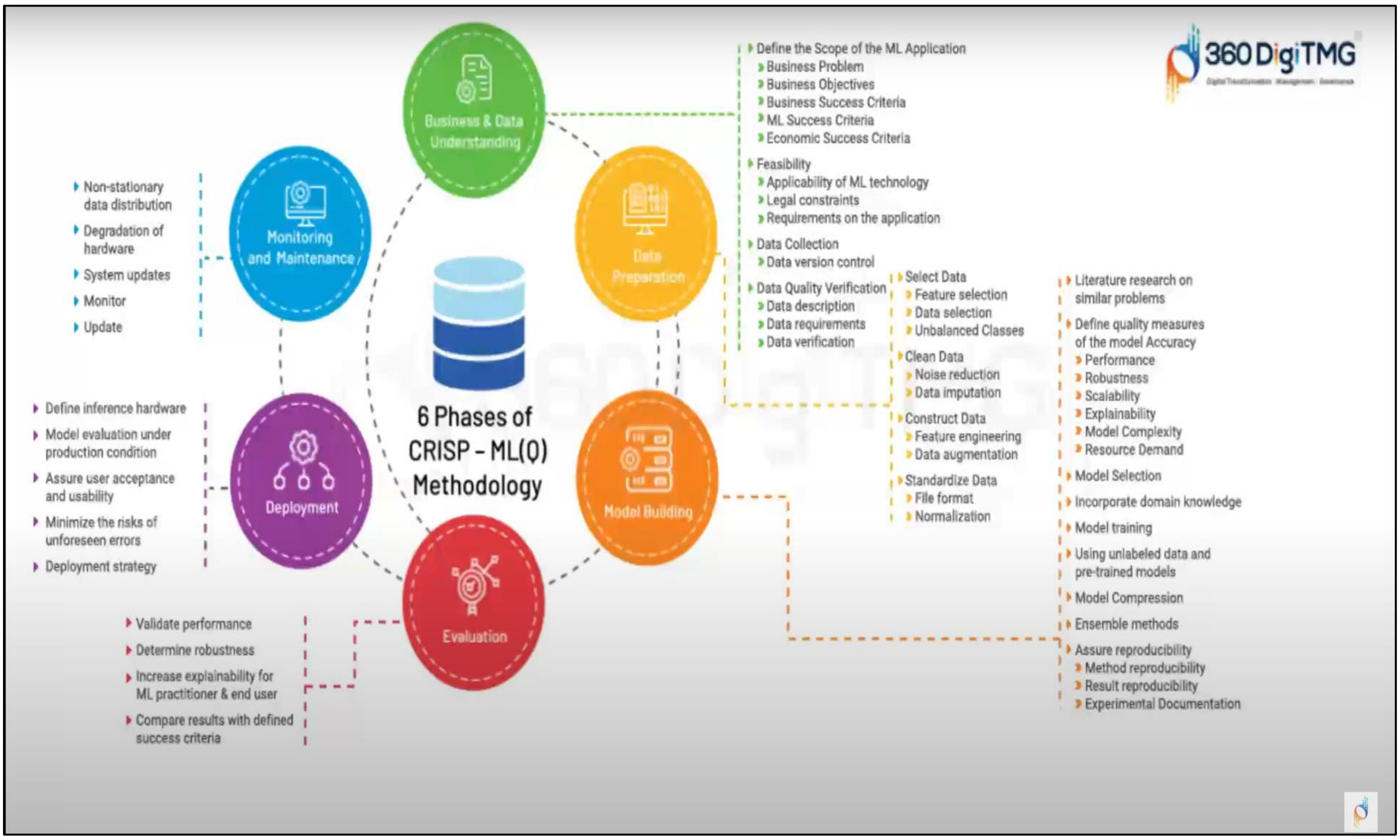

Fig 1 This Figure Depicts the CRISP-ML(Q) Architecture that we have followed for this Research Study.
(Source: Mind Map - 360DigiTMG)

A key feature of this system is its automated logging mechanism, which records violations with timestamps, providing a structured method for compliance tracking and audits. The combination of PPE detection and behavioural analysis enhances workplace safety by identifying risk-prone actions that may go unnoticed in manual inspections.

To evaluate the system, a diverse dataset was compiled using video footage from pharmaceutical laboratories, covering both compliant and non-compliant scenarios. The dataset underwent rigorous preprocessing, including resizing, contrast enhancement, and data augmentation, to optimize model accuracy.

This research introduces a scalable, real-time compliance monitoring solution that minimizes human intervention, reduces workplace hazards, and streamlines regulatory processes. Future developments will explore integration with IoT and edge computing to enhance deployment flexibility and further improve workplace safety and operational efficiency.

To ensure a structured and rigorous development process, we followed the CRISP-ML(Q) methodology, which emphasizes data understanding, preprocessing, model development, evaluation, and deployment with quality assurance. The CRISP-ML(Q) process adopted in this study is illustrated in [Fig.1], demonstrating the systematic approach taken for data collection, annotation, model training, and validation [5].

II. ARCHITECTURE

Architecture plays a crucial role in the design and development of any intelligent system, providing a structured framework that defines how different components interact and function together. A well-defined architecture ensures scalability, efficiency, and seamless integration of various modules, ultimately improving the system's reliability and performance.

The PPE Detection and Compliance Monitoring System is designed to ensure laboratory safety through an automated deep learning-based approach that integrates object detection and human pose estimation. The architecture follows a structured pipeline that includes data collection, preprocessing, model training, integration, and deployment, ensuring accurate and efficient real-time monitoring [6].

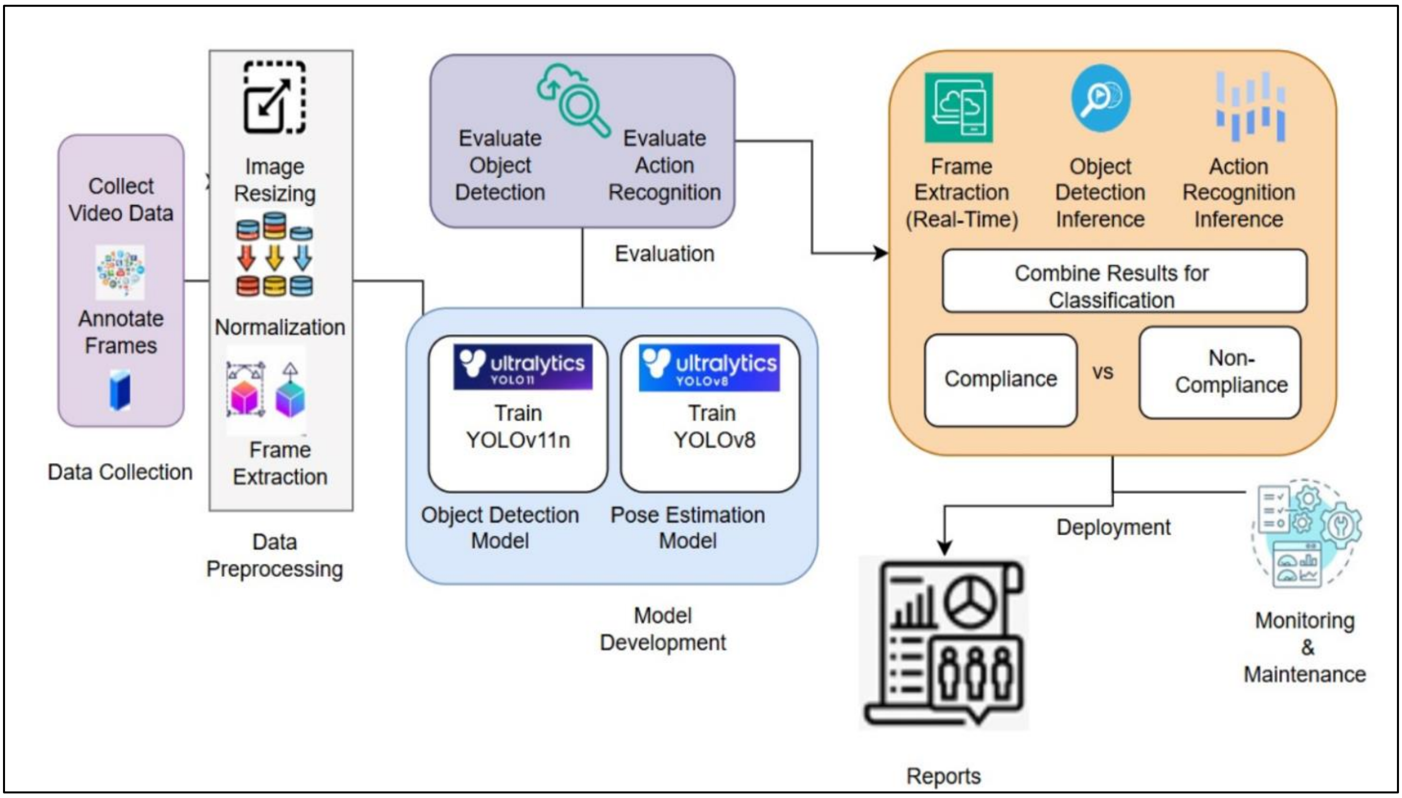

Fig 2 High Level Architecture Diagram Representing PPE Detection and Compliance Monitoring System Incorporating Object Detection and Pose Estimation Models

➢ *System Workflow:*

As depicted in [Fig.2], the system begins with video data collection from the Opensource platform, capturing real-world scenarios where compliance needs to be monitored. Frames are extracted and annotated using Roboflow, where Personal Protective Equipment (PPE) components such as hair cover, no hair cover, goggles, no goggle, face masks, gloves, shoes, and lab coats etc are labelled. To enhance model performance, preprocessing techniques such as image augmentation and resizing are applied, ensuring robustness across varied environments.

For PPE detection, a YOLOv11n model is trained to identify missing protective equipment in real-time. Parallelly, pose estimation using YOLOv8 extracts key-points corresponding to human body joints, which are further analysed through a rule-based approach to identify non-compliant activities, such as bending, raising hands, or touching the face. The integration of these two models enables a comprehensive compliance assessment, capturing both equipment violations and unsafe human actions within the laboratory environment [7].

In the model integration phase, the outputs from the object detection and pose estimation models are merged into a unified framework. Fine-tuning is conducted to optimize detection accuracy and reduce false positives, ensuring high precision in compliance monitoring.

The deployment phase involves use of streamlit framework and it can run on both local machine and cloud, enabling real-time video processing for compliance verification. The system generates log files that record detected violations, facilitating auditability and further analysis. The deployed system operates in a continuous monitoring mode, with regular performance evaluations to ensure accuracy and adaptability to dynamic laboratory environments.

By leveraging deep learning-based object detection, pose estimation, and rule-based compliance verification, this system provides an automated, scalable, and efficient solution for laboratory safety enforcement. The architecture minimizes human intervention, enhances compliance monitoring, and enables real-time enforcement of safety protocols, ensuring a safer working environment in laboratory settings [8].

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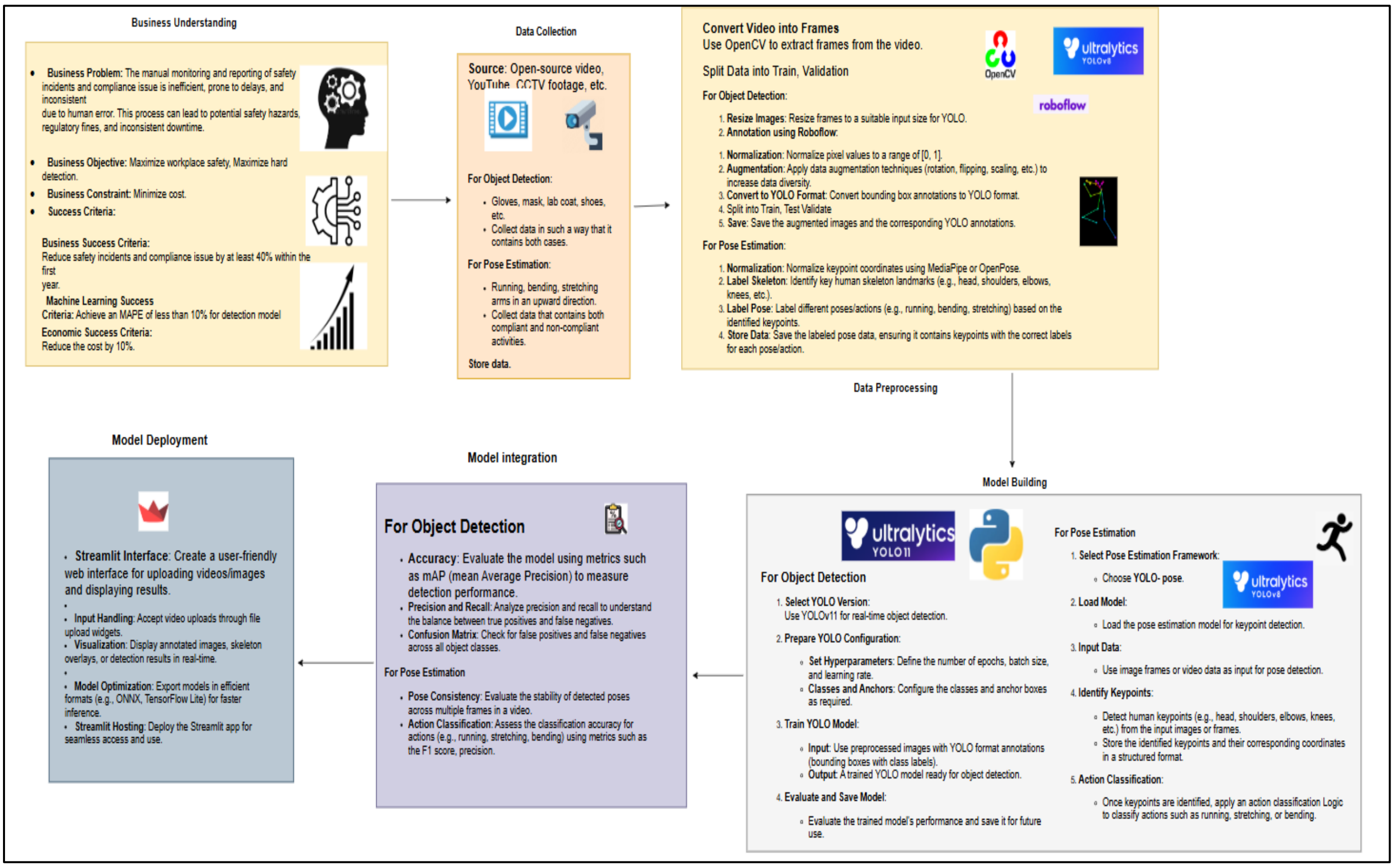

Fig 3 Low Level Architecture Diagram Representing PPE Detection and Compliance Monitoring System Incorporating Object Detection and Pose Estimation Models

For a more detailed breakdown of system components, data flow, and processing stages, a Low-Level Architecture (LLA) is provided [Fig.3]. The LLA delves deeper into module-specific interactions, highlighting key functionalities such as data preprocessing, model inference, decision-making logic, and deployment structure. This detailed architectural view further enhances understanding of the system's real-time processing pipeline [9].

III. DATA COLLECTION AND PREPROCESSING

The success of an AI-driven PPE Detection and Compliance Monitoring System heavily depends on the quality, diversity, and balance of the dataset used for training. A well-structured dataset ensures that the model can generalize effectively, reducing false positives and negatives in real-world laboratory environments.

➢ *Data Collection:*

To build a realistic and diverse dataset, video footage was sourced from open platforms such as YouTube, replicating real-world laboratory environments where PPE compliance is crucial. These videos provided varied lighting conditions, camera angles, and subject movements, ensuring that the model learns to adapt to dynamic lab settings.

Using OpenCV, frames were extracted from these videos, forming the foundation of the object detection dataset. However, a raw dataset alone is insufficient—it requires meticulous annotation to make it meaningful. For this, Roboflow was used to manually label 12 PPE-related classes.

This manual annotation step was critical in ensuring accuracy, as precise bounding boxes allow the detection model to differentiate between compliant and non-compliant scenarios effectively [10].

During initial analysis, an imbalance was observed—certain PPE classes had significantly fewer samples. This posed a risk of biased detection, where underrepresented classes might be overlooked by the model. To address this, additional frames were extracted, and targeted. augmentation techniques were applied, ensuring each class had sufficient representation.

Preprocessing for Object Detection: Making Data Model-Ready.

To improve model accuracy and simulate real-world variations, the following preprocessing and Augmentation steps were applied:

➢ *Preprocessing*

- Auto-Orient.
- Resizing
- Auto-Adjust Contrast Data

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➢ *Augmentation:*

- Horizontal Flip.
- Random Cropping.
- Saturation Adjustment.
- Blur Simulation.
- Noise Addition.

The collected dataset includes both compliant and non-compliant activities, ensuring a comprehensive understanding of laboratory safety violations. By leveraging pose estimation, the system can identify unsafe actions alongside missing PPE, enhancing overall compliance monitoring.

A robust data collection and preprocessing pipeline is the foundation of any AI-powered monitoring system. By curating a balanced dataset, applying intelligent augmentations, and leveraging pose-based action recognition, this system moves beyond traditional PPE detection—it enforces compliance through a multi-dimensional approach, ensuring a safer laboratory environment.

IV. MODEL BUILDING

➢ *Object Detection*

Object detection serves as the foundation of our automated workplace safety framework, enabling the identification and localization of Personal Protective Equipment (PPE) in video frames. This ensures real-time compliance monitoring by flagging safety violations as they occur.

➢ *Overview*

The primary objective of object detection in this system is to accurately identify and classify PPE items such as gloves, masks, goggles, and helmets, enabling the distinction between compliant and non-compliant scenarios. This serves as the foundation for further analysis and compliance monitoring. The detection technique is based on bounding boxes, which are used to determine the precise locations of objects within images, ensuring an effective and structured approach to safety enforcement.

➢ *YOLOv11n – The Backbone of Detection*

The architecture of YOLOv11n follows a structured workflow where images are divided into grids, and the model predicts bounding boxes along with class probabilities in a single forward pass. It leverages anchor boxes and convolutional layers to enhance object localization, ensuring precise detection.

For training, the model was pre-trained on large-scale datasets and then fine-tuned using a domain-specific dataset containing over 700 manually annotated images spanning 12 PPE classes. Various preprocessing techniques, including resizing, contrast adjustment, and data augmentation, were applied to enhance performance across different lighting and environmental conditions.

During inference, the model generates bounding boxes with confidence scores to indicate detected objects. To further refine detections, it applies thresholding and Non-Max Suppression (NMS) to eliminate low-confidence predictions and redundant detections, ensuring accurate and efficient PPE identification.

➢ *Performance Metrics:*

- Accuracy: Achieves a mean Average Precision (mAP@50) of over 92%. [Fig.4,5] include training, validation results]
- Speed: Processes video streams at 25 frames per second (FPS), meeting real-time requirements.
- Robustness: Extensive data augmentation and fine-tuning enable reliable performance across different scenarios.

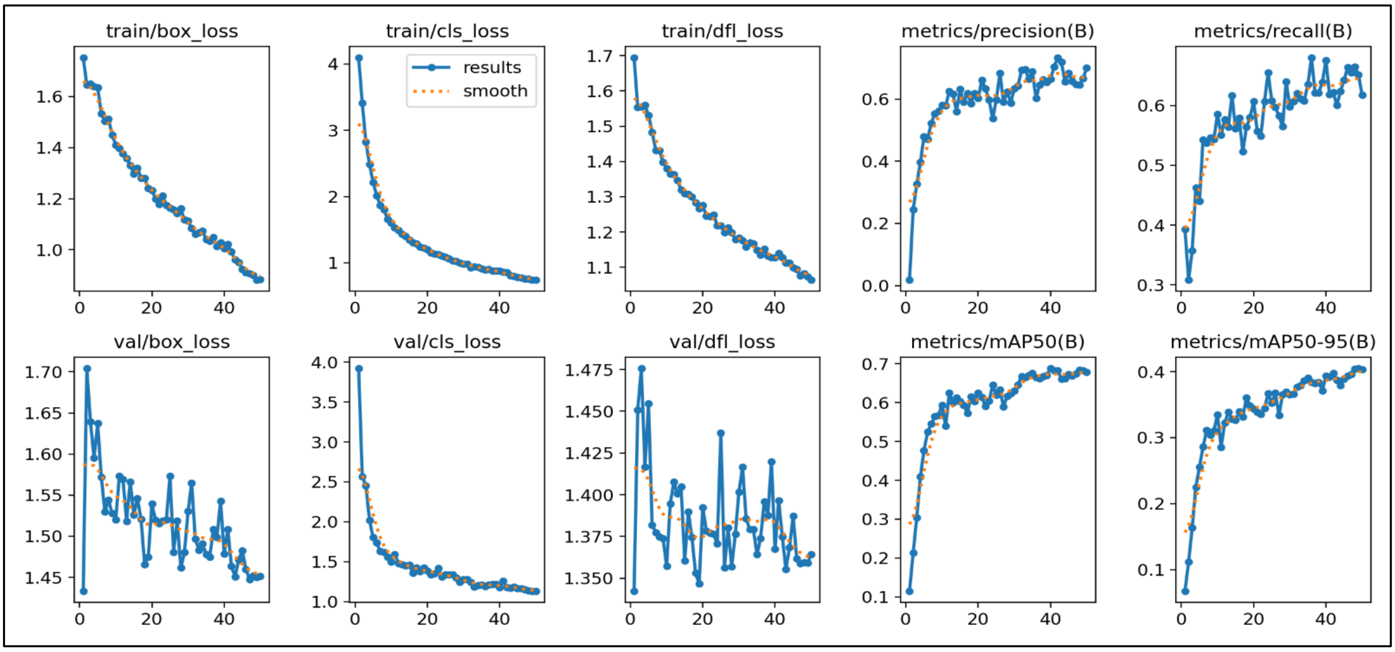

Fig 4 Training Graphs for the YOLO Model, Presenting its Learning Progress and Performance.

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Fig 5 Output of Validation Batch

➢ *Integration:*

The PPE detection module serves as the first stage in the safety monitoring pipeline. Detected PPE data is seamlessly passed to the pose estimation module (YOLOv8n-Pose), which further analyzes worker behavior. This integration creates a comprehensive real-time compliance system by combining object detection and pose-based activity monitoring.

➢ *Pose Estimation and Non-Compliance Detection (YOLOv8n-Pose)*

Non-Compliant Behavior Identification: Successfully recognized unsafe postures and activities such as bending, hand-raising, and face-touching.

➢ *System-Level Outcomes*

- Real-Time Logging: The system generated detailed log files that include timestamps and compliance statuses for each detected violation. This automated documentation enhances traceability for audits.

➢ *Compliance and Non-Compliance Activity:*

- *Compliance Activities in the Pharmaceutical Industry*

✓ Regulatory Compliance – Adhering to government and industry regulations to ensure drug safety and efficacy.
✓ Good Manufacturing Practices (GMP) Compliance – Following strict guidelines for drug production to maintain quality and hygiene.
✓ Good Clinical Practices (GCP) Compliance – Conducting ethical and well-monitored clinical trials with proper patient consent.
✓ Pharmacovigilance Compliance – Monitoring and reporting adverse drug reactions to protect public health.
✓ Data Integrity and Documentation – Ensuring accurate, secure, and tamper-proof records throughout drug development.

- *Non-Compliance Activities in the Pharmaceutical Industry*

✓ Manufacturing Violations – Ignoring GMP standards, leading to contamination or substandard drug production.
✓ Clinical Trial Misconduct – Conducting trials unethically, such as falsifying data or bypassing approval protocols.
✓ Marketing and Advertising Violations – Misleading promotions, false claims, or promoting off-label drug use
✓ Product Quality Issues – Selling drugs with incorrect labeling, contamination, or potency problems.
✓ Bribery and Corruption – Engaging in unethical practices like bribing officials for faster approvals or regulatory favors.

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- *Pose Estimation:*

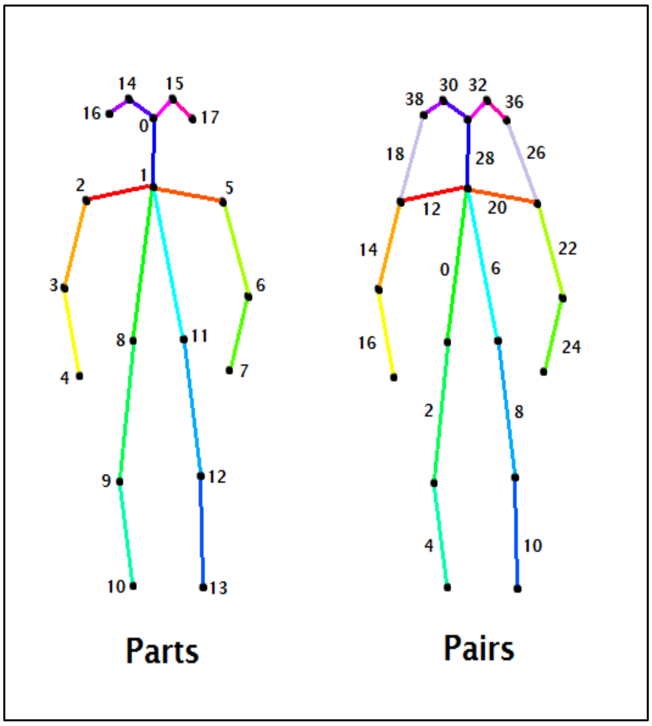

Fig 6 YOLO Key Point

Table 1 Key Points

Number	Key Point
0	Nose
1	Neck
2	Left Shoulder
3	Left Elbow
4	Left wrist
5	Right Shoulder
6	Right Elbow
7	Right Wrist
8	Left Hip
9	Left Knee
10	Left Ankle
11	Right Hip
12	Right Knee
13	Right Ankle
14	Left Eye
15	Right Eye
16	Left Ear
17	Right Ear

YOLOv8-Pose extends object detection by predicting key points along with bounding boxes. Each detected human is represented by a bounding box (x, y, width, height, confidence score) and key points {(x_kp, y_kp, conf_kp)} for each joint, where x_kp, y_kp are the pixel coordinates and conf_kp represents the confidence score of the key point prediction. The model follows a single-stage detection approach, directly predicting key points from an input image without requiring a separate detection step. It detects 18 key [Fig.6] points for each person, covering crucial anatomical landmarks:

- Nose: Central reference point on the face, commonly used for orientation detection.
- Neck: Central point connecting the head to the torso, crucial for tracking body posture.
- Left Shoulder: Marks the left shoulder joint, useful in movement tracking and posture correction.
- Left Elbow: Indicates the left elbow joint, essential for tracking arm movement .
- Left Wrist: Tracks the left wrist position, useful in hand gesture recognition.
- Right Shoulder: Represents the right shoulder joint, similar to the left shoulder.
- Right Elbow: Represents the right elbow joint, mirroring the left elbow.
- Right Wrist: Tracks the right wrist position, aiding in hand tracking applications.
- Left Hip: Represents the left hip joint, crucial in gait analysis and activity tracking.
- Left Knee: Tracks the left knee joint, which is important for walking and running motion analysis.
- Left Ankle: Indicates the left ankle joint, useful in foot placement and balance tracking.
- Right Hip: Marks the right hip joint, providing symmetry to the body structure.
- Right Knee: Represents the right knee joint, similar to the left knee in tracking movement.
- Right Ankle: Represents the right ankle joint, aiding in motion analysis and balance assessment.
- Left Eye: Represents the left eye position, useful for facial recognition and gaze tracking.
- Right Eye: Represents the right eye position, similar to the left eye in functionality.
- Left Ear: Indicates the left ear’s location, which is important for head pose estimation.
- Right Ear: Indicates the right ear’s location, aiding in head angle calculations[Table.1].

Training YOLOv8-Pose for key point detection involves optimizing a multi-task loss function, including key point loss (measuring the difference between predicted and ground-truth positions), bounding box loss (ensuring accurate localization), and confidence loss (evaluating certainty in key point predictions). The model is trained on datasets like COCO, which provide human images annotated with key points. To improve robustness to variations in human poses, data augmentation techniques such as flipping, scaling, and rotation are applied during training.

➢ *Angle Calculations for Movement Analysis:*

- The function calculate angle (a, b, c) computes angles between three key points to analyze joint movements.
- Angles are calculated for hips, knees, and elbows, which are crucial for identifying postures like bending and arm movements.

➢ *Action Recognition:*

- **Jump Detection**: Uses ankle height relative to a baseline (calculate jump) to determine if a person is jumping.

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- **Bending Detection**: If knee angles are less than 105 degrees, it classifies the action as "BENDING."
- **Face Touching Detection**: Uses Euclidean distance to check if the wrist is close to the nose.
- **Running Detection**: Evaluates ankle speeds, step length, and vertical motion.
- **Lying on the Floor Detection**: Based on the height of the hips relative to the frame.

V. DEPLOYMENT

The PPE Detection and Compliance Monitoring System is deployed on a cloud-based infrastructure, ensuring efficient real-time processing and accessibility. The system is built using Streamlit, providing an interactive interface for seamless monitoring of compliance violations. The deployment allows video streams to be processed in real time, where the model detects PPE and identifies non-compliant actions.

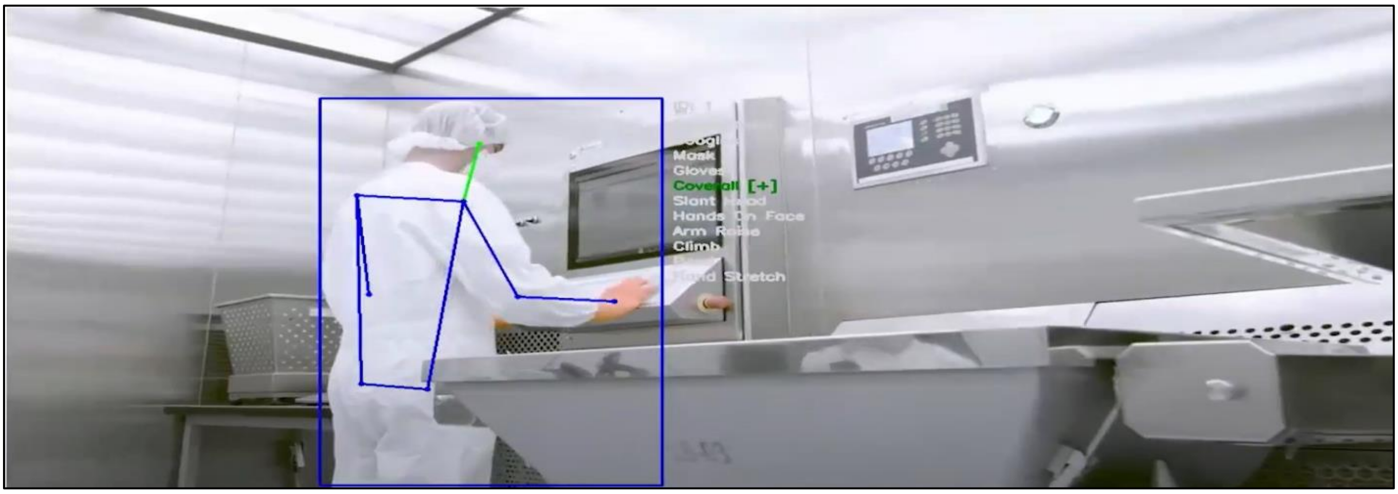

Fig 7 Illustrates the Deployed System's Output

Each detected individual is enclosed in a bounding box, with PPE components labeled near the corresponding body parts. Additionally, pose estimation highlights non-compliant actions such as bending or touching the face. The processed video output is displayed through the interface, allowing users to monitor violations and maintain safety standards effectively. [Fig.7 Illustrate output].

VI. RESULT

➢ *Object Detection Performance (YOLOv11n)*

Mean Average Precision (mAP@50): Achieved 92.1%, indicating that the model reliably detects Personal Protective Equipment (PPE) items.

Overall Detection Accuracy: Registered at 90%, demonstrating robust performance across varied laboratory environments.

➢ *Precision and Recall:*

- Precision: ~99%[Fig.8], confirming that the vast majority of identified objects were indeed PPE.
- Recall: ~88%[Fig.9], illustrating the model’s ability to capture most instances of PPE.
- Inference Speed: The model processes video streams at 25 frames per second (FPS), ensuring real-time detection, which is critical for dynamic environments.

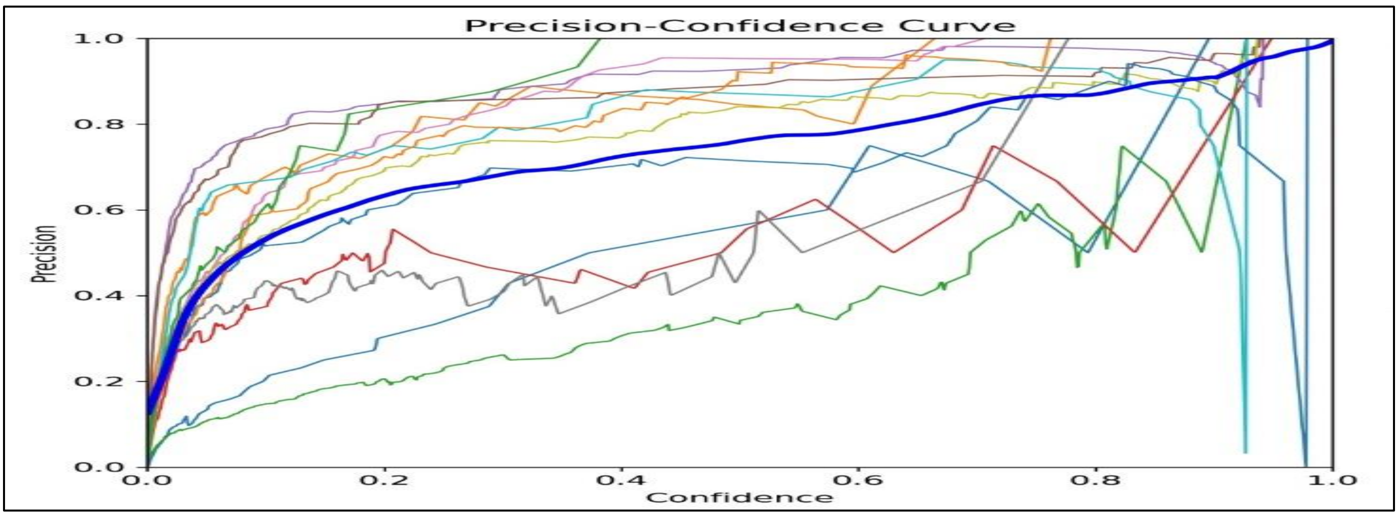

Fig 8 Precision- Confidence Curve

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This research has developed and evaluated object detection and pose estimation models based on YOLO architectures. With high accuracy and computational efficiency, our models are going to find applications in work safety monitoring and action recognition. With wise preprocessing techniques and augmentation, the model's ability to generalize across various situations has been enhanced, and therefore its reliability in real-world scenarios is bolstered. The main contribution of this paper lies in combining object detection and pose estimation that brings gains in action recognition and benefits sectors like healthcare, security, and industrial automation.

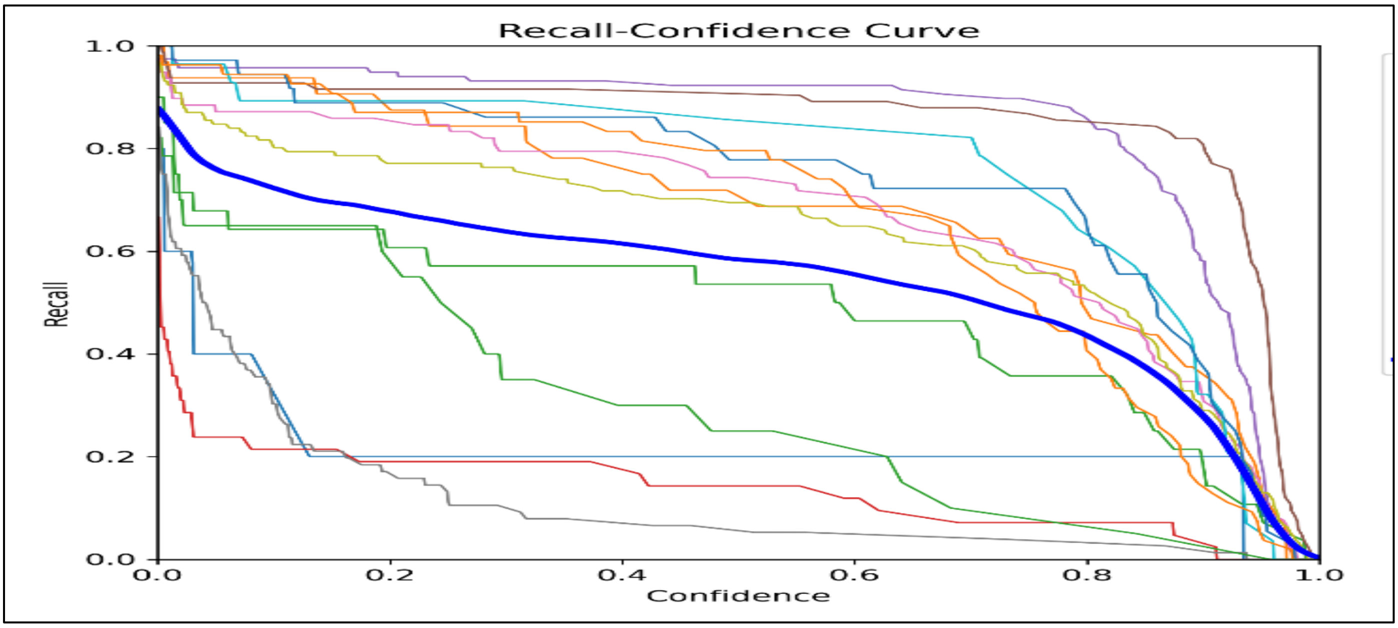

Fig 9 Recall- Confidence Curve for Object Detection

The results prove that it strikes a good balance between precision and computational efficiency for the real-time application. However, there are limitations to our research. Improving the model's performance would involve including a larger and more diverse dataset. One main challenge for future research is to enable efficient real-time inference suitable for low-power edge devices. For future work, transformer-based models and other advanced deep learning techniques will be explored for further detection accuracy improvement.

In addition, integration of the real-time deployment strategy and enhanced interpretability of the model will be the main tasks towards making this approach more universal and scalable for different real-world applications.

VII. CONCLUSION

This research has developed and evaluated object detection and pose estimation models based on YOLO architectures. With high accuracy and computational efficiency, our models are going to find applications in work safety monitoring and action recognition. With wise preprocessing techniques and augmentation, the model's ability to generalize across various situations has been enhanced, and therefore its reliability in real-world scenarios is bolstered. The main contribution of this paper lies in combining object detection and pose estimation that brings gains in action recognition and benefits sectors like healthcare, security, and industrial automation.

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- The authors confirm that they have no financial or non-financial conflicts of interest to disclose.

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➢ *Data Availability Statement:*

The datasets utilized, generated, and/or analyzed during the current study are not publicly accessible due to internal data privacy policies. However, they can be obtained from the corresponding author upon reasonable request.

FUTURE SCOPE

The future of this automated deep learning framework in pharmaceutical manufacturing safety monitoring is promising, with a significant opportunity to enhance data collection through the integration of IoT devices. By adding sensors like temperature and humidity monitors, the system can gather comprehensive environmental data, improving real-time insights into worker activities and workplace conditions. This multi-sensor approach would strengthen safety protocols and ensure better compliance with regulatory standards.

Additionally, adopting edge computing can improve the system's efficiency by processing data locally, reducing response times and enabling real-time monitoring without relying on cloud infrastructure. This decentralized model would allow the system to function independently at multiple manufacturing sites, improving scalability and resilience while providing faster, more effective insights for large-scale pharmaceutical operations.

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