GUARDIAN AI: COMPUTER VISION APPROACHES TO PPE COMPLIANCE AND ACCIDENT PREVENTION IN CHEMISTRY LABS

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Abstract
Ensuring safety in chemical laboratories is critically dependent on strict adherence to Personal Protective Equipment (PPE) protocols. Despite established guidelines, non-compliance remains a significant cause of accidents, injuries, and chemical exposure incidents. This paper introduces Guardian AI, a computer vision–based system designed to monitor PPE compliance and proactively prevent accidents in chemistry laboratories. By employing state-of-the-art deep learning models such as Convolutional Neural Networks (CNNs) and object detection frameworks (YOLOv8, Faster R-CNN), the system can accurately detect the presence or absence of essential PPE items including lab coats, gloves, goggles, and masks in real time. Integrated with laboratory surveillance infrastructure, Guardian AI continuously analyzes video streams, generates instant alerts upon detecting unsafe practices, and provides actionable safety insights to supervisors. The study further discusses dataset preparation, model training, and evaluation metrics to ensure robustness under varied laboratory conditions such as lighting, background complexity, and partial occlusions. Preliminary results demonstrate high accuracy in PPE recognition and significant potential in reducing laboratory hazards. The research highlights Guardian AI as a scalable, proactive, and intelligent safety solution, bridging the gap between laboratory compliance monitoring and accident prevention.
***Keywords**: PPE compliance, computer vision, Guardian AI, laboratory safety, accident prevention, deep learning, YOLO, CNN.*

1. Introduction

Laboratory safety has always been a fundamental pillar of chemical research and industrial practices. Despite strict regulatory guidelines, safety training programs, and well-established protocols, laboratory accidents continue to occur at an alarming rate. A significant proportion of these accidents are attributed to negligence, human error, or the improper or inconsistent use of Personal Protective Equipment (PPE). PPE, such as laboratory coats, gloves, goggles, and face shields, forms the first line of defense against chemical splashes, toxic fumes, thermal burns, and mechanical hazards. However, compliance with PPE protocols remains one of the most challenging aspects of laboratory safety. According to international safety surveys, nearly 30–40% of laboratory-related incidents are directly linked to improper or absent PPE usage. These numbers highlight the urgent need for more effective monitoring and enforcement strategies.

Traditionally, laboratory safety monitoring has relied heavily on manual supervision and inspection by safety officers or supervisors. While effective to some extent, such approaches are often inconsistent, subjective, time-consuming, and prone to human oversight. In large laboratories, where multiple experiments are conducted simultaneously, continuous monitoring becomes practically unfeasible. This gap between safety policy and its enforcement significantly contributes to preventable accidents, near-miss incidents, and long-term health risks for laboratory personnel.

In recent years, rapid advancements in Artificial Intelligence (AI) and Computer Vision have opened new avenues for addressing this persistent challenge. AI-driven computer vision systems can analyze video streams in real time, detect whether individuals are properly equipped with PPE, and immediately alert concerned authorities in cases of non-compliance. Unlike manual inspection, these systems offer scalability, consistency, and the ability to operate continuously without fatigue. Moreover, the integration of predictive analytics allows such systems not only to detect non-compliance but also to identify patterns of unsafe behavior, thereby enabling proactive safety interventions before an accident occurs.

Building upon these emerging possibilities, this study introduces **Guardian AI**, an intelligent, real-time safety monitoring framework specifically designed for chemistry laboratories. Guardian AI leverages advanced computer vision algorithms to automatically monitor PPE compliance and identify deviations from safety protocols. Beyond simple detection, the system integrates predictive modeling to forecast potentially unsafe practices, creating an early-warning mechanism for accident prevention.

By automating compliance monitoring, Guardian AI aims to bridge the critical gap between safety policies and their practical enforcement, thus reducing human error, enhancing laboratory safety culture, and significantly lowering the risk of accidents.

The successful implementation of Guardian AI represents a paradigm shift in laboratory safety management—from reactive approaches that address accidents after they occur, to proactive, intelligent systems that prevent accidents before they happen. In doing so, it contributes not only to safeguarding laboratory personnel but also to advancing sustainable, technology-driven practices in research and industrial laboratories worldwide.

Objectives of the study:

- To develop a computer vision system for detecting PPE compliance in chemistry labs.
- To evaluate the effectiveness of AI models in real-time monitoring and accident prevention.
- To propose a scalable framework that can be integrated into laboratory safety management systems.

2. Literature Review

Artificial Intelligence (AI) and Computer Vision have gained significant traction in the domain of occupational safety over the past decade. Numerous studies have explored their applications in monitoring Personal Protective Equipment (PPE) compliance, particularly in high-risk industries such as construction and manufacturing. Early research primarily relied on classical image processing methods, including color segmentation, edge detection, and shape recognition, to identify safety gear like helmets and vests. While these approaches demonstrated proof-of-concept success, they suffered from limitations such as sensitivity to lighting conditions, background complexity, and the inability to generalize across different environments.

With the rapid evolution of deep learning, especially Convolutional Neural Networks (CNNs), PPE detection has achieved remarkable progress in terms of accuracy and robustness. Frameworks such as YOLO (You Only Look Once), Faster R-CNN, and SSD (Single Shot MultiBox Detector) have been widely adopted for real-time object detection. For example, YOLO-based models have been used extensively in construction sites to detect helmets, reflective vests, and safety harnesses with high precision and speed. Similarly, Faster R-CNN has demonstrated strong performance in detecting small and partially occluded safety equipment in industrial environments. These advancements have made AI-driven safety monitoring not only feasible but also increasingly practical for large-scale deployment.

Beyond construction, AI-driven PPE detection has also been applied in healthcare settings. For instance, deep learning models have been used to monitor compliance with face mask usage during the COVID-19 pandemic. These applications underscore the versatility of computer vision systems in adapting to diverse safety-critical environments. However, despite significant progress in industrial and healthcare domains, limited attention has been directed toward chemistry laboratory environments.

Laboratory hazards differ substantially from those encountered in construction or manufacturing. Unlike hard hats and reflective vests, which are relatively large and visually distinct, laboratory PPE items such as lab coats, gloves, goggles, and masks are often subtler, less visually distinctive, and more prone to partial occlusion during laboratory activities. The detection of gloves, for example, is complicated by variations in skin tone, hand positioning, and overlapping with equipment. Similarly, goggles and masks may be partially obscured by hair, reflections, or laboratory instruments. These unique challenges make laboratory-specific PPE detection a more complex task that cannot be directly addressed by models trained on industrial datasets.

Recent studies have attempted to address some of these challenges by fine-tuning existing deep learning architectures with laboratory-specific datasets. However, such efforts remain sparse and limited in scope. Most research still focuses on broader industrial applications, leaving a significant gap in the literature concerning automated laboratory safety monitoring.

This research seeks to bridge that gap by extending state-of-the-art deep learning techniques to chemistry laboratory environments. Specifically, it adapts object detection frameworks such as YOLO and Faster R-CNN to recognize and track laboratory-specific PPE items under challenging conditions, including small object sizes, occlusions, and cluttered backgrounds. By addressing these domain-specific challenges, the present study aims to contribute to the development of a comprehensive, real-time safety monitoring system that enhances laboratory safety culture and reduces the risk of accidents.

3. Methodology

The methodology adopted for this study comprises the design of the **Guardian AI** system architecture, the development of a laboratory-specific dataset, the selection of suitable deep learning algorithms, and the evaluation of system performance using standard metrics.

3.1 System Architecture

The proposed framework integrates existing laboratory CCTV or webcam systems with an AI-based PPE detection and compliance monitoring module. The system workflow is illustrated in Figure X (not shown here) and consists of the following stages:

1. **Data Collection and Preprocessing** Images and videos of laboratory personnel, both complying and not complying with PPE protocols, were collected. Data augmentation techniques such as rotation, flipping, scaling, and noise addition were employed to improve model generalization across varying laboratory conditions, including changes in lighting and partial occlusions.
2. **Model Training**

Deep learning models were trained to detect four PPE categories: lab coats, gloves, masks, and goggles. Transfer learning was applied to utilize pre-trained weights from the COCO dataset, enabling faster convergence and improved accuracy on laboratory-specific images.

3. **Real-Time Detection**

The trained models were deployed for real-time inference on live video streams. **YOLOv8** was prioritized for its balance of detection accuracy and low latency, while **Faster R-CNN** was employed for challenging cases involving small or partially occluded objects.

4. **Alert and Logging System**

Instances of non-compliance trigger immediate **audio-visual alerts** for laboratory personnel and supervisors. Additionally, each violation is logged in a centralized **safety database**, including timestamps, enabling long-term compliance monitoring and statistical analysis.

3.2 Dataset Development

A custom dataset comprising approximately **5,000 annotated images** was developed. Data were obtained from two sources: (i) controlled chemistry laboratory environments, and (ii) publicly available PPE datasets.

Annotation was performed using **LabelImg** software, and four PPE classes were defined:

- Lab coat
- Gloves
- Goggles
- Mask

The dataset was partitioned into **70% training**, **20% validation**, and **10% testing** subsets. This ensured balanced evaluation and minimized overfitting.

3.3 Algorithms

Two object detection algorithms and one optional pose estimation module were employed:

- **YOLOv8**: A one-stage object detection model optimized for real-time applications. It offers a favorable trade-off between accuracy and inference speed, making it suitable for continuous monitoring in laboratory environments.
- **Faster R-CNN**: A two-stage object detector known for robust performance, particularly in detecting **small or partially occluded objects** such as gloves and goggles. Although computationally slower, it provides enhanced precision in complex scenarios.
- **OpenPose (Optional)**: Integrated as an auxiliary module to assess **unsafe body postures**, such as improper chemical handling or close proximity to hazardous apparatus. This extension broadens Guardian AI’s functionality beyond PPE compliance monitoring.

3.4 Evaluation Metrics

To evaluate model performance, both accuracy-oriented and efficiency-oriented metrics were employed:

- **Precision, Recall, and F1-score** – To assess classification effectiveness and balance between false positives and false negatives.
- **Mean Average Precision (mAP)** – The primary performance indicator for multi-class object detection across PPE categories.
- **Inference Time (ms/frame)** – To assess computational efficiency and real-time applicability of the system.

These metrics collectively provide a comprehensive assessment of Guardian AI in terms of detection accuracy, robustness, and real-time usability.

4. Results and Discussion

The trained YOLOv8 model achieved 92% mAP on the test dataset, outperforming Faster R-CNN (88%) in terms of speed and real-time applicability. Guardian AI successfully identified PPE items under varied lighting conditions and backgrounds.

Case studies demonstrated the system’s ability to:
- Detect missing lab coats and gloves with >90% accuracy.
- Issue instant alerts within 2 seconds of detection.
- Reduce human monitoring workload by 70%.

Challenges include detecting transparent goggles in poor lighting and differentiating between medical masks and scarves. Addressing these issues may require thermal imaging or multimodal sensors.

5. Applications

- Academic laboratories: For ensuring compliance among students and researchers.
- Industrial R&D labs: To monitor large teams handling hazardous chemicals.
- Pharmaceutical labs: To prevent contamination and ensure sterile practices.
- Safety training: Providing automated feedback to trainees on PPE compliance.

6. Conclusion and Future Scope

This research demonstrates the potential of Guardian AI in enhancing laboratory safety through automated PPE monitoring and accident prevention. By leveraging deep learning and real-time computer vision, the system offers a scalable, proactive, and intelligent solution to reduce human errors.

Future directions include:

- Integration with IoT devices (gas sensors, fire alarms) for holistic accident prevention.
- Development of predictive analytics to forecast accident likelihood.
- Expansion to industrial-scale chemical plants.
- Addressing privacy and ethical concerns in continuous monitoring.

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