Automated PPE Adherence Monitoring in Biosafety Level 2 Laboratories

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Abstract

We have designed an automated system for monitoring adherence to personal protective equipment (PPE) guidelines in Biosafety Level 2 (BSL-2) laboratory environments using real-time object detection. The primary objective is to enhance safety compliance by identifying instances of missing PPE. Our system integrates the YOLOv8 object detection framework, utilizing a pre-trained model on the COCO dataset for person detection and a custom-trained model—based on a subset of the SH17 dataset—for detecting gloves, masks, and safety glasses. The custom model was trained over five epochs and achieved a precision of approximately 78%, recall of 70%, F1 score of 74%, and mean average precision (mAP) of 68% on a held-out test set. A user-friendly Streamlit web interface enables the uploading of images or video streams and displays detection outcomes. The backend algorithm quantifies the number of individuals and their corresponding PPE items; it triggers an alert if any essential PPE component is missing. Our results demonstrate the system's effectiveness in identifying PPE non-compliance in real time, offering a practical and scalable solution for improving biosafety standards in laboratory settings.

Keywords

Biosafety Level 2 (BSL-2) laboratories, Personal protective equipment (PPE) compliance, Real-time object detection, YOLOv8, Custom-trained deep learning model, Streamlit web interface, PPE monitoring system, Glove, mask, and safety glasses detection, Computer vision in biosafety, Safety compliance

1 Introduction

The proper use of personal protective equipment (PPE) is essential for safety in biosafety laboratories. In BSL-2 laboratories, guidelines mandate that personnel wear protective gloves, safety glasses, face shields, lab coats, and face masks in many cases. For example, Addgene's lab protocol specifies close-toed shoes, gloves, and eye protection for BSL-2 work, and SEPS Services notes that face protection (goggles or masks) is *"first and foremost"* required in BSL-2 settings. Ensuring adherence to these PPE rules is critical, but traditionally requires manual supervision or checklists. Automated visual monitoring promises to improve compliance by continuously ensuring that all people in the lab are properly equipped.

Recent advances in deep learning have made real-time object detection practical for safety monitoring applications. In this study, we developed a system based on the YOLOv8 (You Only Look Once) architecture to detect persons and PPE items (gloves, masks, safety glasses) in real-time. We trained a custom YOLOv8 model on relevant PPE classes from the SH17 dataset of industrial safety images and used a separate YOLOv8 model pretrained on the COCO dataset for person detection. The system raises alerts whenever a detected person is missing a mandated PPE item. To make the system accessible to lab personnel, we implemented a user interface using Streamlit.

The contributions of this study are as follows:

- **PPE detection system:** A YOLOv8-based pipeline for real-time detection of gloves, masks, and safety glasses in laboratory images.
- **Custom training on the SH17 subset:** A fine-tuned YOLOv8 model trained for five epochs on a BSL-2-relevant subset of the SH17 PPE dataset.
- **Interactive frontend:** A Streamlit web app that allows users to upload images/videos and view detection results with alerts for missing PPE.
- **Performance evaluation:** The experimental validation showed 78% precision, 70% recall, and 68% mAP for the PPE detection model, demonstrating the viability of automated PPE monitoring.

2 Methodology

Our automated PPE monitoring system consisted of data preparation, model training, and a real-time detection pipeline. The main components are outlined below.

2.1 Nomenclature

- **BSL-2:** Biosafety Level 2 – A safety level for laboratory work involving moderate-risk biological agents.
- **PPE:** Personal Protective Equipment – Includes gloves, masks, safety glasses, lab coats, etc., required for laboratory safety.
- **YOLOv8:** You Only Look Once version 8 – A real-time object detection architecture used for detecting people and PPE items.
- **COCO dataset:** Common Objects in Context – A large-scale object detection dataset used for pretraining object detectors.
- **SH17 dataset:** A dataset for human safety and PPE detection, particularly in industrial and manufacturing settings.
- **mAP:** Mean Average Precision – A metric for evaluating the accuracy of object detectors across all classes.

- **Precision:** The proportion of correctly identified instances among all detected instances.
- **Recall:** The proportion of correctly detected instances among all actual instances.
- **F1-score:** Harmonic mean of precision and recall, representing the overall accuracy.
- **Streamlit:** A Python-based open-source web framework used to create interactive machine learning applications.
- **Object Detection:** A computer vision technique to identify and locate objects within an image or video.
- **Custom-trained model:** A neural network trained on a specific dataset (subset of SH17) to detect PPE relevant to BSL-2 labs.
- **Real-time inference:** The ability of a system to process and produce detection results instantly or with minimal delay.
- **Best.pt:** The saved weights file of the YOLOv8 model that performed best on validation data during training.

2.2 Procedure

- **Data preparation:** We used a subset of the SH17 safety dataset that included images of gloves, masks, and safety glasses. The SH17 dataset has 8,099 annotated images with 17 PPE classes; we filtered it to obtain annotations for the three classes of interest (gloves, masks, and safety glasses) that are relevant for BSL-2 laboratories. This yielded a training set of several thousand annotated instances. All annotations were converted to YOLOv8 format.
- **Model Training:** We trained two YOLOv8 models using an ultralytics implementation. The first model is the COCO-pretrained YOLOv8 (medium size) for person detection. The second was a custom YOLOv8 model fine-tuned on our PPE dataset subset. Both the models were trained for five epochs on an NVIDIA GPU. The training hyperparameters (learning rate, batch size, etc.) follow the ultralics-recommended defaults for small datasets. After each epoch, we evaluated a validation split and recorded precision, recall, and mean average precision (mAP). We achieved the final evaluation metrics of approximately 78% precision, 70% recall, and 68% mAP for PPE detection. These metrics are computed in the standard way (intersection-over-union 0.5) and yield an F1-score of approximately 74%.
- **Detection and logic:** During inference, each input image or video frame is processed using both models. The person detector identifies all the people in the scene. Simultaneously, the PPE detector finds gloves, masks, and safety glasses. We then associate PPE with persons by spatial proximity, and for each person bounding box, we check which PPE boxes overlap that person. Each person is required to have at least one glove, mask, and pair of safety glasses. If the count of any PPE type is less than the person count (e.g., three people but only two gloves are detected), we flag the missing PPE. This logic can be summarized as follows:

  1. Count persons ($N\_persons$) and each PPE type (N_gloves, N_masks, $N\_glasses$).

2. If N_gloves ¡ N_persons, raise the ”missing gloves” alert similarly for masks and glasses.
3. Otherwise, report compliance.

- **Streamlit front-end:** We implement a user interface using Streamlit. The web app allows users to upload static images or provide video streams. Upon submission, the app displays the image with detected bounding boxes for people and each PPE type. It also shows a textual alert if any PPE is missing (for example ”Alert: 1 person missing safety glasses”). The Streamlit app is built with a few lines of Python using st.file_uploader for images/videos and st.image/st.video to display the results. In this way, lab supervisors can interactively test images or webcam feeds and immediately see the detection and alert output.

2.3 Related Work

Object detection models have been widely applied for PPE compliance and worker safety. The seminal You Only Look Once (YOLO) architecture introduced a unified, real-time detection approach that can run at 45 frames per second while maintaining high accuracy. Subsequent YOLO versions (including v8) continue this lineage of fast detectors, suitable for safety applications. For example, Ahmad et al. introduced the SH17 dataset for PPE detection in industrial settings and demonstrated that advanced YOLO variants can achieve over 70% accuracy in multiple PPE classes. Our work builds on this idea by focusing on a subset of SH17 relevant to BSL-2 lab PPE and integrating person-PPE association logic.

Other deep-learning detectors have been used for PPE and safety monitoring in workplaces. Studies have applied YOLOv4 and YOLOv5 to detect hard hats, vests, and gloves in construction and manufacturing scenes, often reporting mAP values in the 60–80% range. Compared to these, our BSL-2 laboratory scenario is somewhat different because it emphasizes masks and safety glasses rather than hard hats or vests. Nonetheless, fundamental techniques (real-time CNN-based object detection) are similar.

In addition to the detection accuracy, system integration is important for practical deployment. StreamLit provides a Python framework for quickly building interactive ML applications. Several recent works have used Streamlit to host computer vision models in web apps, making our choice of Streamlit for the front end a common practice in the ML community.

2.4 Illustrations

To provide a clear understanding of the practical application and real-time performance of the proposed system, this section presents a step-by-step visual depiction using annotated images. These figures illustrate the transformation of input data through the system's inference pipeline and its corresponding output via a graphical user interface.

2.4.1 Pre-Processing: Input Image

Figure 1 displays the raw input image as captured or uploaded by the user. At this stage, the image has not undergone any processing. It represents the data point that will be subjected to real-time analysis by the trained detection model. This unprocessed visual input serves as the foundation for further computational inference.

2.4.2 Post-Processing: Annotated Output

Following inference, the input image is annotated by the system based on the detected features or objects of interest. As illustrated in Figure 2, bounding boxes and class labels are superimposed on the image to highlight identified regions. This annotated output enables users to visually verify the model's predictions. The annotation process is automated and integrated into the backend logic, ensuring consistent and accurate detection across multiple instances.

2.4.3 Streamlit Interface with Real-Time Feedback

To facilitate user interaction, a custom-built graphical interface is developed using Streamlit. This interface enables users to upload images, view the annotated results, and interact with the system in real time. As shown in Figure 3, the Streamlit app displays both the original and processed images simultaneously. In addition to visual output, an integrated auditory alert system emits a **beep sound** whenever a critical object or condition is detected. This multimodal feedback mechanism enhances the system's usability in real-world scenarios by providing both visual and auditory cues.

Figure 1: Raw input image before processing

Figure 2: Annotated output after processing

3 Results and Discussion

After training, the PPE detection model achieved a **precision** of approximately 78%, **recall** of 70%, and **mean Average Precision (mAP)** of 68% on the test set. The corresponding **F1-score** is approximately 74%. These values indicate that the model correctly identified PPE items in most cases, but there were some false negatives (undetected items) and false positives. A precision of 78% means that most detections are accurate, whereas a 70% recall suggests that some PPE instances are missed. The mAP of 68% reflects an overall moderate detection performance, comparable to that of other PPE-detection systems. The detected F1 (74%) exhibited balanced performance.

In practical laboratory images, the system correctly flagged the missing PPE in the test scenarios. For example, in a test image with three people where one person had no safety glasses, our system detected three persons and only two pairs of glasses, and thus raised an alert for missing glasses. Similar tests confirmed that missing gloves or masks could trigger alerts. Most cases of failure occurred when PPE objects were small, occluded, or partially visible. For instance, a partially slid-off glove at the edge of an image can be missed, thereby reducing recall. Conversely, rare false positives occur when background objects are misidentified as gloves (e.g., green wires mistaken for gloves). Overall, these error modes suggest that better coverage of challenging poses and backgrounds during training could improve future performance.

System responsiveness: The YOLOv8 detector runs in real time on a modern GPU, processing dozens of frames per second. This makes the system suitable for live monitoring through video streams. In our Streamlit demo, processing a single image takes under one second, making it interactive for users. The straightforward count-and-compare alert logic operates instantly after detection, so alerts appear with minimal delays. Thus, the combined system is capable of near-real-time PPE compliance monitoring.

Summary of findings:

- *Detection accuracy:* Precision 78%, recall 70%, and mAP 68% (F1 74%). PPE items are reliably detected in clear views, but small or occluded items sometimes fail to be detected.

- *Alert performance:* Alerts correctly identify missing PPE in the test images. In our informal testing, the system caught all deliberately missing gloves/masks/glasses in over 90% of the cases, demonstrating its utility.

- *Usability:* The StreamLit interface allows easy image/video upload and displays annotated outputs and alerts on-the-fly. This lowers the barrier for lab staff to use the system without writing the code.

In summary, the results suggest that a YOLOv8-based approach can effectively monitor PPE compliance in BSL-2 laboratory environments. Although there is room for improvement (e.g., collecting more training data for rare poses), even the current performance can assist safety officers by automating routine checks.

4 Conclusion

We developed and evaluated an automated PPE adherence monitoring system tailored for Biosafety Level 2 laboratories. Using the YOLOv8 object detection framework, we built a two-model pipeline: one model detects persons and another (custom-trained on SH17 data) detects gloves, face masks, and safety glasses. The trained models achieved approximately 78% precision and 68% mAP for PPE detection, thereby validating the feasibility of this approach. A stream-based front-end makes the system user-friendly, allowing lab personnel to upload images or video streams and immediately see whether anyone is missing the required PPE.

This automated monitoring can help improve safety compliance by providing continuous, objective checks against PPE guidelines. In future work, we plan to expand the system to include additional PPE (e.g., lab coats) and incorporate temporal smoothing for video feeds. We also explore the integration of alert logs with laboratory management systems. Overall, our results demonstrated that real-time computer vision can play a valuable role in enforcing laboratory safety protocols.

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