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AI-Powered Real-Time Monitoring System for Health Care Personal Protective Equipment (PPE) Compliance

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Abstract

Adhering to Personal Protective Equipment (PPE) protocols remains one of the most difficult aspects of healthcare, as manual supervision is time-consuming, error-prone, and subjective. This study aims to overcome the above challenge by creating an AI-based real-time computer vision system for automated PPE compliance monitoring and instant notification of non-compliance. Using computer vision and deep learning frameworks, a lightweight YOLOv5n model was trained to detect 6 PPE classes and their non-compliance cases: lab coat, nose mask, and gloves, non-compliant of lab coat, nose mask, and gloves. An experimental research design was used. The study population comprised image data, and samples were annotated from these images with standard labelling procedures. Precision, recall, F1 score, and mean Average Precision (mAP) were used as metrics for model validation. The whole system was developed on a Raspberry Pi with an RTSP camera and a buzzer alert system. Results show that the real-time performance is satisfactory on low-power hardware with class accuracy of 88% (lab coat), 87% (nose mask), 65% (gloves), 87% (no nose mask), 81% (no gloves), and 68% (no lab coat). The results show that automated monitoring of PPE can increase compliance, reduce the need for human observers, and improve safety outcomes. The study wraps up by suggesting model optimization, multi-person tracking, and remote alert integration as ways to expand deployment.

1. Introduction

Personal protective equipment (PPE) is essential for infection prevention and occupational safety in healthcare environments. PPE refers to specialized clothing and equipment used to protect healthcare workers (HCWs) from infectious microorganisms, hazardous chemicals, bodily fluids, and other workplace risks [1]. Common PPE includes surgical masks, N95 respirators, gloves, gowns, and laboratory coats. These protective items help reduce airborne, droplet, and contact transmission in clinical settings [2].

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The importance of PPE became particularly evident during the COVID-19 pandemic. Evidence from the early stages of the outbreak showed that appropriate use of PPE could substantially reduce the risk of infection among HCWs [3]. Nevertheless, the availability of PPE does not guarantee proper compliance. Healthcare personnel may fail to wear the required items, use them incorrectly, or remove them before completing a clinical task. Therefore, consistent adherence to PPE protocols remains a significant challenge in healthcare practice.

Inadequate PPE compliance also contributes to the risk of healthcare-associated infections (HAIs). The World Health Organization estimates that HAIs affect approximately 15% of hospitalized patients in developing countries and 7% in developed countries [1]. Appropriate PPE practices can limit the transmission of pathogens, including multidrug-resistant organisms such as methicillin-resistant Staphylococcus aureus and Clostridioides difficile [4]. However, previous studies have reported inconsistent compliance with prescribed PPE protocols. Contributing factors include heavy workloads, complex clinical procedures, limited supervision, discomfort, and fatigue caused by prolonged PPE use [2], [5].

Conventional compliance monitoring commonly depends on direct observation, manual checklists, or retrospective incident reports. These methods require considerable human resources and may not provide continuous coverage. Their findings can also be affected by observer bias or the Hawthorne effect. More importantly, manual monitoring may identify non-compliance only after exposure has occurred. This limitation highlights the need for an objective system that can monitor PPE use continuously and provide immediate feedback.

Recent advances in artificial intelligence (AI), computer vision, machine learning, and edge computing have created new opportunities for automated PPE monitoring. Vision-based systems can analyse images or video streams to determine whether required PPE items are present and worn correctly. Edge devices such as the Raspberry Pi can support local data processing without relying on costly computing infrastructure. These technologies may enable real-time alerts while reducing the monitoring burden placed on infection-control personnel. However, their practical adoption raises concerns about detection accuracy, environmental conditions, processing speed, privacy, system cost, and integration with existing healthcare workflows.

This review examines AI-powered approaches for monitoring PPE compliance in healthcare settings. It analyses the technologies, detection methods, datasets, hardware platforms, and evaluation measures reported in previous studies. It also compares prototype-based research with systems evaluated in realistic healthcare environments. Particular attention is given to real-time performance, edge deployment, alert mechanisms, privacy, and operational feasibility. Finally, the review identifies limitations in the current literature and proposes directions for developing accurate, affordable, and clinically practical PPE compliance-monitoring systems.

2. Literature Review

Traditional approaches to monitoring PPE compliance have several limitations. Manual observation audits are commonly conducted by infection-control personnel. However, these audits may capture fewer than 5% of actual PPE-use events due to limited staffing and observation periods [6]. The presence of an observer may also influence workers to temporarily improve their behaviour. This response is known as the Hawthorne effect. Furthermore, manual audits are often reactive. They may fail to identify non-compliance before exposure or infection occurs [7,8].

Electronic monitoring technologies have been introduced to improve the collection of PPE-related data. Radio-frequency identification (RFID) systems, for example, can detect the presence or movement of tagged PPE. However, these systems may not determine whether an item is worn correctly. Conventional monitoring systems may also experience delayed responses. Some systems cannot predict infection risks or provide recommendations based on individual conditions. The continued use of manual processes also increases the possibility of recording and monitoring errors [9].

Artificial intelligence has created new opportunities for automated healthcare monitoring. Deep-learning models can process complex biomedical information and support healthcare management [10]. Computer-vision models based on convolutional neural networks (CNNs) and You Only Look Once (YOLO) have been applied to PPE detection. Some studies have reported detection accuracy of up to 98% for medical PPE [11]. However, model performance may vary depending on the dataset, PPE category, camera position, lighting conditions, and clinical environment.

Edge computing can support real-time video processing on local devices. This approach reduces dependence on remote servers and may improve data privacy. An AI-based PPE monitoring system was reported to increase compliance from 58% to 89% [12]. Connected devices can also provide immediate warnings when safety risks are detected. Wearable devices may monitor physiological conditions, while cameras can identify environmental hazards in healthcare and construction environments [13].

AI monitoring systems can provide both proactive and reactive functions. Proactive functions include detecting unsafe behaviour and issuing immediate alerts. Reactive functions include recording incidents for subsequent investigation. These systems require appropriate ethical frameworks to support reliability,

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transparency, and responsible data use [14]. Continuous monitoring tools can also analyse sensor data and generate reports for healthcare managers [15]. In addition, machine-learning models have been applied to predict infection outbreaks and support risk-management plans for individual patients [16].

Deep-learning systems have also been used to detect PPE such as helmets, gloves, and safety vests. These systems can be integrated with existing cameras to reduce manual monitoring and data-recording errors [17]. Security mechanisms may be incorporated to protect transmitted data while maintaining real-time detection capabilities [18]. Compact AI models have achieved reported accuracy values between 87% and 89% in detecting masks and gowns [19]. AI-supported training has also been associated with improved PPE practices. One study reported that compliance eventually reached 100% following the intervention [20]. More recently, on-device AI models have been developed and evaluated for real-time PPE-compliance monitoring [21].

Despite these developments, several research limitations remain. Many studies concentrate on conceptual frameworks, controlled experiments, or laboratory simulations. Fewer studies evaluate complete systems in realistic healthcare environments. Some approaches also require expensive servers or continuous network connectivity. Differences in datasets and evaluation measures make direct comparisons difficult. Privacy, alert reliability, incorrect PPE use, and system integration also require further investigation. Therefore, further research should examine affordable edge-based solutions capable of performing continuous monitoring on commonly available hardware. Such studies should evaluate detection accuracy, processing speed, privacy protection, usability, and clinical feasibility.

Table 1 *Comparison of PPE compliance monitoring approaches and research gaps*

Monitoring approach	Main purpose	Key advantages	Main limitations	References
Manual observation	Assess PPE compliance through direct observation	Simple to implement and does not require technical infrastructure	Limited coverage, labour-intensive, reactive, and affected by the Hawthorne effect	[6–8]
RFID-based monitoring	Track the presence or movement of PPE items	Supports automated tracking and digital record keeping	Cannot reliably determine whether PPE is worn correctly	[9]
AI and computer vision	Detect PPE items from images or video streams	Provides automated detection with reported accuracy of up to 98%	Performance is affected by datasets, lighting, occlusion, and camera position	[10,11]
Edge-based monitoring	Process PPE data locally and provide immediate alerts	Supports real-time detection, reduces server dependence, and may improve privacy	Limited by device processing capacity and deployment conditions	[12,18,21]
Wearable and sensor-based monitoring	Detect worker conditions and environmental hazards	Supports continuous monitoring and immediate risk notification	Requires additional devices, maintenance, and system integration	[13–15]
Predictive and training systems	Predict infection risks or improve PPE practices	Supports proactive intervention and targeted training	Requires reliable data and further evidence of long-term effectiveness	[16,20]
Compact PPE-detection models	Detect masks, gowns, gloves, or other PPE using low-resource devices	Suitable for affordable on-device implementation	Reported accuracy may be insufficient for safety-critical healthcare use	[17,19]

Table 1 shows the progression of PPE compliance monitoring from manual observation to automated, AI-based approaches. Manual and RFID-based methods provide basic monitoring capabilities but cannot continuously verify whether PPE is worn correctly. AI and computer-vision systems offer more objective detection, while edge computing enables real-time processing on local devices. However, current approaches remain affected by environmental conditions, privacy concerns, hardware limitations, and insufficient validation in actual healthcare settings. These limitations indicate a need for further research on accurate, affordable, and privacy-conscious PPE monitoring systems that can operate reliably in real time.

3. Materials and Methods

The project development materials and methods are discussed in the following.

3.1 System Framework and Model Training

Data collection began with images sourced from pexels.com. The images were then labeled and annotated into five classes on roboflow.com (gloves, lab coat, nose mask, and no-compliant gloves, lab coat, and nose mask). YOLOv5n model was chosen as the best model to train since it provides the best accuracy-speed trade-off for deployment on edge devices. [22]. A camera mounted in healthcare facilities captures video streams, and the trained AI model processes the images to detect PPE, which is crucial for real-time identification and recognition. This system's ability to detect in real time is achieved via an RTSP feed. Figure 1 indicates the block diagram of the entire system, and the methodology flowchart is shown in Figure 2.

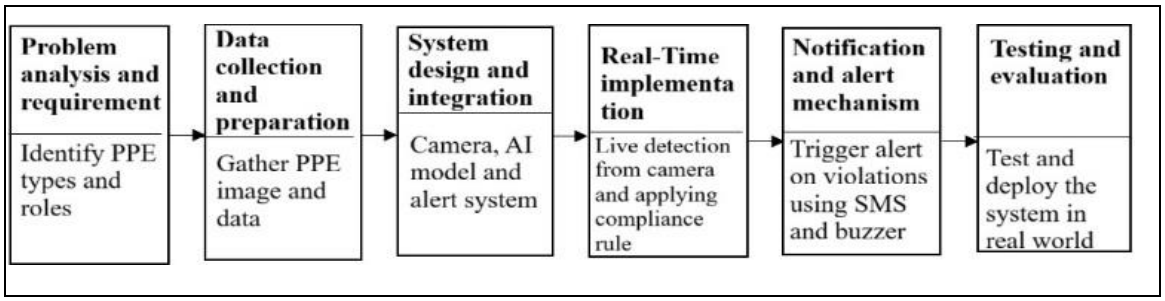


Fig. 1 *Block diagram of complete project framework*

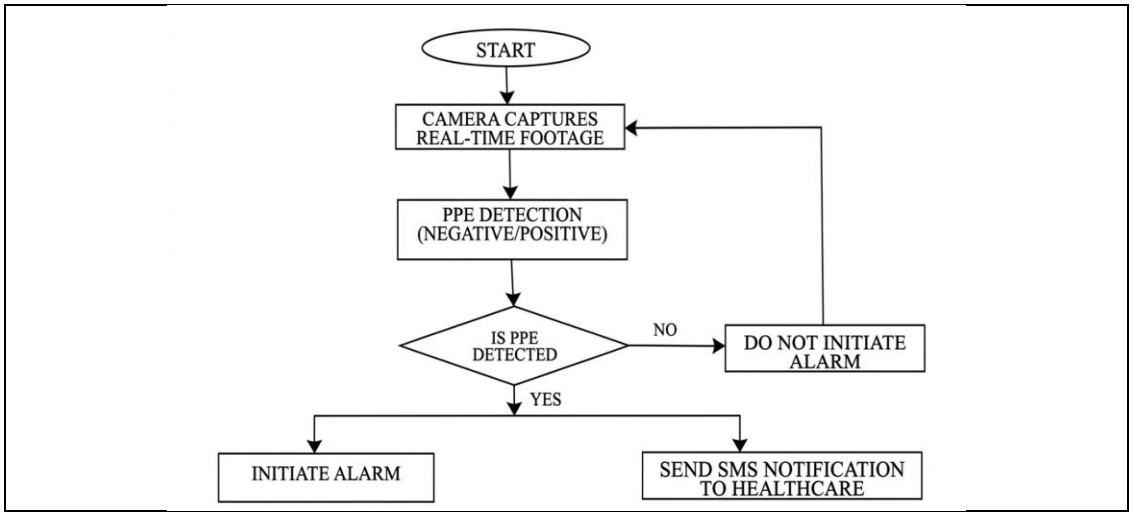


Fig. 2 *Project flowchart*

3.2 System Components and Integration

The main components of the system are the camera, the Raspberry Pi main controller, the GSM module, and the buzzer.

(i) Raspberry Pi (Main Controller): The Main Controller is a Raspberry Pi 4. It has enough CPU capability (Quad-core Cortex-A72 processor, up to 8GB of RAM) to process video and perform AI inference with the YOLOv5n model in real time. It runs all the components, supplies power to them, and communicates with them via GPIO pins. The functions involve processing video feeds, executing the trained model, and triggering alerts.

(ii) Camera: This continuously monitors video feeds from healthcare settings, which are used for real-time PPE detection. For testing purposes, a 25-FPS-RTSP camera was used to emulate live monitoring.

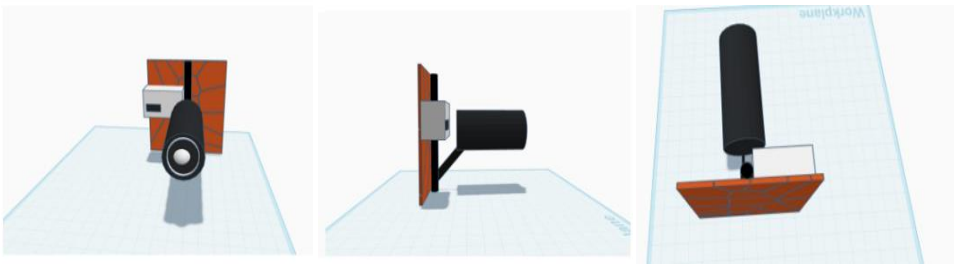
(iii) Alert Mechanisms: If the AI model determines that non-compliance has occurred (such as not wearing a lab coat), the alert mechanism will be triggered. The buzzer is connected to GPIO 15. The buzzer will provide an immediate, loud warning to healthcare personnel in the vicinity.

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(iv) GSM Module (SIM900A): This module can communicate using cellular networks. It's used to alert health care workers in real time via Short Message Service (SMS). The GSM module was chosen as it is reliable, and messages will be sent even when there is no Wi-Fi signal available.

3.3 Device System Design

The casing for the Raspberry Pi and GSM module is designed in 3D and was created using Tinkercad. The circuit design, created using Cirkit software, also verifies that the Raspberry Pi will provide power and ground to both the camera module and the GSM module, and control data communication via specific GPIO pins. The side view, front view, and top view of the device are shown in Figure 3 (a), (b), and (c), respectively.



(a) **(b)** **(c)**

Fig. 3 *(a) Front view; (b) Side view; (c) Top view of the developed Health Care PPE Compliance system*

3.4 System Circuit Design

The system circuit design was modified and designed using Cirkit software. It is based on the main controller, Raspberry Pi 5, which powers and manages all system components. It provides power (5V) and ground to the SIM900A module, the camera, and buzzer to give a common reference. The Raspberry Pi is connected to the SIM900A data exchange through the GPIO pins (GPIO 23 to SIM900A RXD and GPIO 24 to SIM900A TXD). The Raspberry Pi's 5V supply powers the camera, and it is controlled via GPIO 14. Activated by a high signal from the Raspberry Pi, the buzzer connected to GPIO 15 sounds as shown in Figure 4.

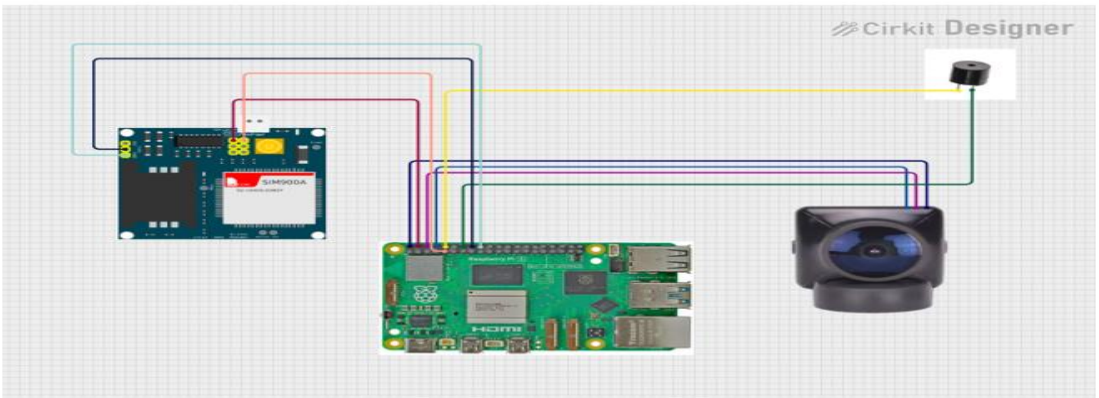


Fig. 4 *Circuit diagram created on CirKit software*

4. Results and Discussion

A custom dataset annotated with six classes (nose mask, lab coat, gloves, no nose mask, no lab coat, and no gloves) was used to train the model. The system was able to determine compliance with non-compliance for three critical PPE items. YOLOv5n was chosen because it is both fast and accurate and can be deployed on edge devices such as the Raspberry Pi.

The validation set was used to test the YOLOv5n model. The results of the performance metrics were reasonably good for a lightweight model for edge deployment as presented in Table 2. The Precision-Confidence Curve for all object classes in the PPE detection model is shown in Figure 5. The curves are different classes, and

the thick blue line is the average of the curves. The higher the confidence threshold, the better the precision is in general, with 100% precision at the threshold of 0.857. This means that the model is very stable for certain classes, such as gloves and nose masks, but less stable for others, such as no-lab-coat. This curve is used to determine an optimal threshold for deployment to minimize false positives and false negatives.

Table 2 *Average precision per class*

PPE Class	Average Precision (AP)/Accuracy (%)
Lab-coat	88
Nose-mask	87
No Nose-mask	87
No Gloves	81
No Lab-coat	68
Gloves	65

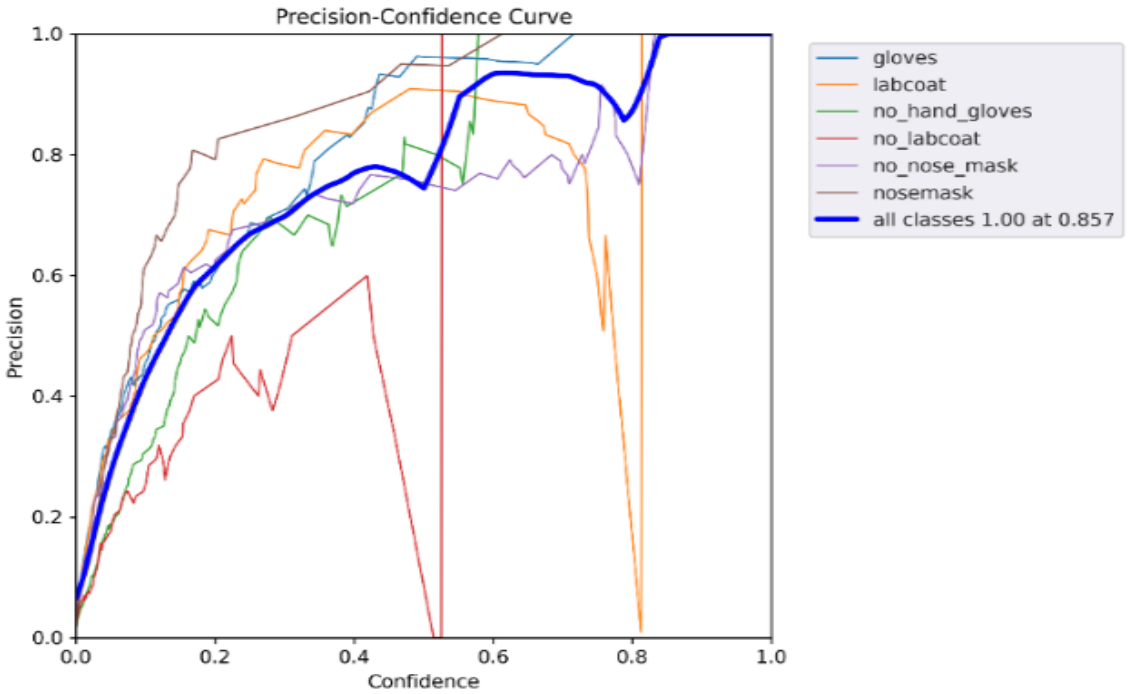


Fig. 5 *Precision-Confidence curve for all the object classes in the PPE detection model*

The Recall Confidence Curve of the PPE detection model is given in Figure 6. The curves shown are for individual classes, and the bold blue curve represents the overall mean. At lower thresholds, recall is high (92% at the lowest), as more predictions are accepted, while the values drop steadily as the threshold rises. It is a trade-off between recall and precision: increasing the confidence threshold will increase the number of detections, but also increase the number of false detections, whereas decreasing the confidence threshold will decrease the number of false detections, but also decrease the number of genuine detections. Overall, classes like lab coat performed better on recall, while classes like no-lab coat performed worse, indicating detection difficulties for that class.

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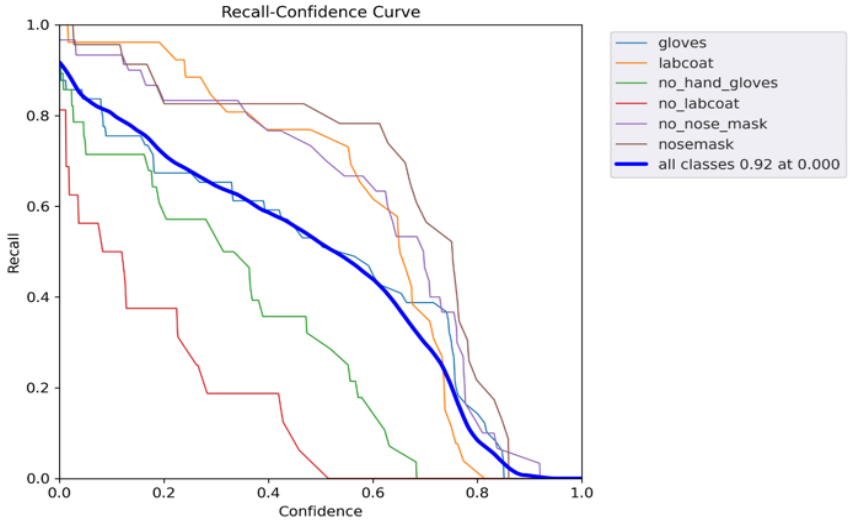


Fig. 6 *Recall-Confidence curve for for all the object classes in the PPE detection model*

The Precision-Recall Curve for each object class in the PPE detection model is shown in Figure 7. The X-axis represents recall, and the Y-axis represents precision. The model achieved the highest accuracy in the nose-mask class (AP = 0.930). the second highest accuracy on the lab-coat class (AP = 0.853). The no-lab-coat class (AP = 0.287) showed the lowest detection performance. This indicates problems in the detection of this category. The average Precision value for all classes is shown by the bold blue curve (AP = 0.694). This means the model will perform well on most classes.

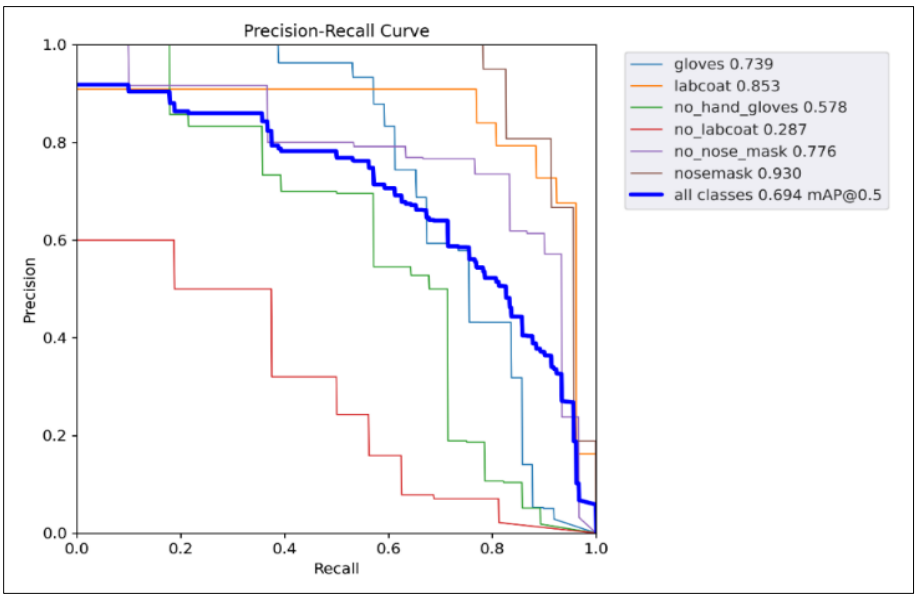


Fig. 7 *PR curve for all the object classes in the PPE detection model*

Figure 8 presents the F1 Confidence Curve for the model. The result shows detection performance as a function of confidence level across all PPE classes. The thick blue line is the median F1 score over all classes, with thin colored lines showing the F1 for each individual class. The overall model achieves the best precision-recall trade-off at the 0.25 confidence threshold, with an average F1 score of 0.67. The per-class results show that the highest F1 scores (above 0.8) are for the lab coat and nose mask, indicating good model performance in detecting these categories. Medium performance was observed in the gloves-and-no-nose-mask group, with F1-scores ranging from 0.6 to 0.7. The model didn't perform well without a lab coat (F1= low and unstable) and without gloves (F1= low and unstable), which may indicate insufficient training or that the classes were more difficult.

Overall, the curve shows that the model is good at detecting the stronger classes, but there is room to improve data balance and training to better detect the weaker classes. A threshold of about 0.25 is suggested for inference. This threshold has been shown to yield the best ratio of false positives to false negatives for this task.

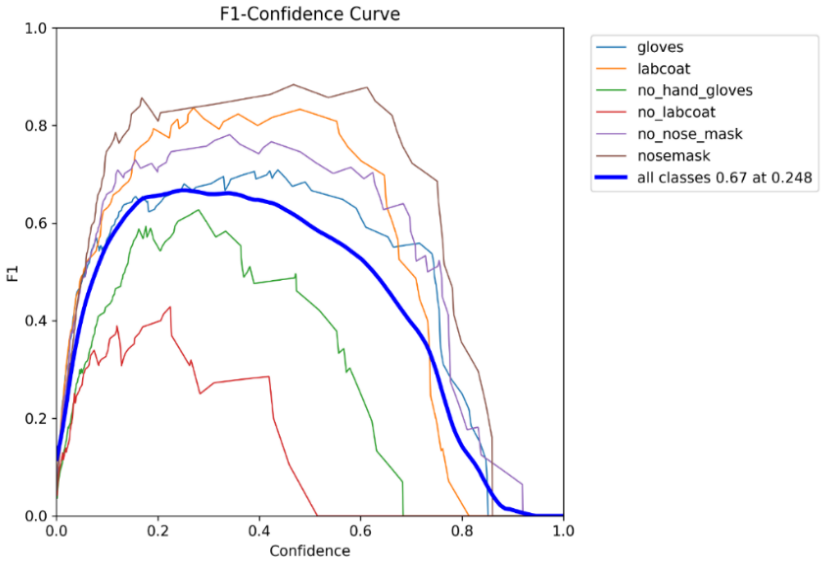


Fig. 8 *F1-Score for all the object classes in the PPE detection model*

The confusion matrix shown in Figure 9 provides an overview of the number of correct and incorrect predictions for each PPE class. The lab coat, nose mask, and background show high accuracy with values near 0.9 along the diagonal. Moderate level of detection performance: gloves and a no-nose mask, with some confusion with background samples. No-lab coat and no-hand-gloves, on the other hand, show the highest rates of misclassification and the lowest rates of recall.

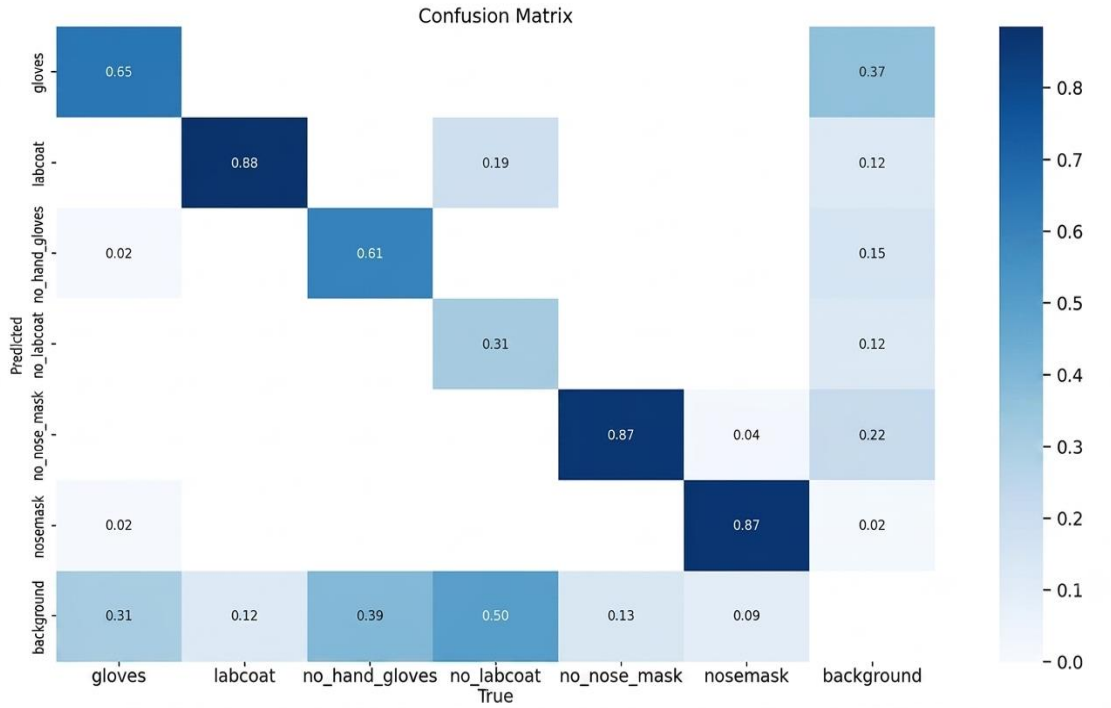


Fig. 9 *Confusion Matrix for all the object classes in the PPE detection model*

The system successfully identified PPE compliance and non-compliance scenarios in real time. Sample outputs demonstrated the following:

(i) Frames where all PPEs were detected triggered no alert.
(ii) Frames missing one or more PPE elements correctly activated the buzzer and highlighted bounding boxes with class labels (e.g., no-gloves in red).

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(iii) On Raspberry Pi, the system achieved an average of ~25 FPS, which is sufficient for real-time monitoring at 25 FPS camera input.

An example of a real case scenario where no nose mask, no hand gloves, and no lab coat were detected is depicted in Figure 10.

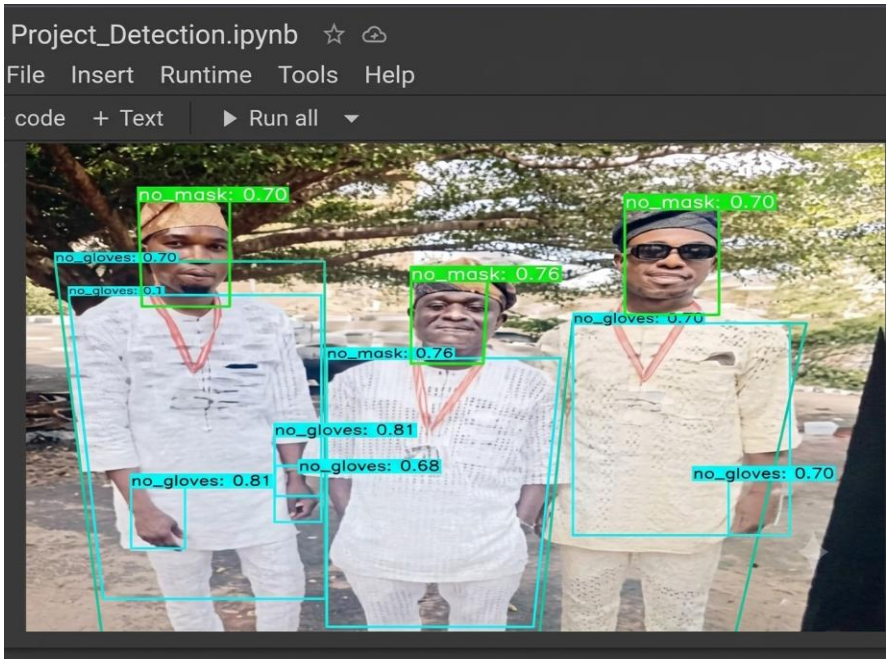


Fig. 10 *A case scenario where no nose mask, no hand gloves, and no lab coat were detected*

The system successfully monitored compliance and non-compliance in real-time. When a frame was missing one or more PPE elements, the system correctly activated the buzzer and used bounding boxes (e.g., no-gloves in red) to highlight the violation. The Raspberry Pi achieved an average of approximately 25 FPS, which is sufficient for real-time monitoring of the 25 FPS camera input.

However, the model exhibited weaknesses, particularly with classes representing the absence of PPE, such as no lab coat and no-hand gloves. It showed high misclassification and low recall, according to the confusion matrix. Some limitations were noted, such as low performance in low-light conditions and variability in detecting gloves when hands were moving or obstructed. In addition, the Raspberry Pi performs well for this use. However, it is not suited to an environment where multiple people need to be detected simultaneously at high resolutions.

5. Conclusion

The present study proposes a practical solution using artificial intelligence to ensure PPE compliance in healthcare facilities. The solution is to overcome the drawbacks of traditional manual monitoring, such as its limited scope and unreliability. The system can quickly identify compliance violations and provide on-site notifications via buzzers and SMS to remote locations. The procedure promotes safer practices without excessive reliance on staff supervision by using a small YOLOv5n model and cost-effective hardware such as the Raspberry Pi. The model showed high accuracy in detecting lab coats and nose masks, highlighting its promise to reduce infection risks and improve protocol adherence in busy clinical settings. Despite these accomplishments, there are still areas of improvement. This includes the difficulty of detecting missing PPE and the handling of tricky situations, such as poor lighting or fast-moving objects. Potential future work includes the use of synthetic data augmentation, specialized lighting conditions, expanded and more diverse training datasets, and further model optimization to enhance the detection accuracy for gloves and the no-lab-coat classes. Other improvements should be the possibility of using multi-person tracking to make the model more robust and applicable to other laboratories or hospitals, and other situations. Finally, this solution provides the basis for intelligent, automated safety measures that could play a pivotal role in protecting health care workers and patients.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design****: Sani Saminu, Marvelous Opajobi Kolade, Suleiman Abimbola Yahaya;* ***data collection****: Marvelous Opajobi Kolade, Abdullahi Ololade Olalere;* ***analysis and interpretation of results****: Sani Saminu, Marvelous Opajobi Kolade, Idris Oladele Muniru, Adamu Halilu Jabire;* ***draft manuscript preparation****: Kazeem Olawale Salaudeen, Habib Muhammad Usman, Abdullahi Ololade Olalere. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] VSK Abdel Delhi, R. Sankarlal and A. Thomas "Detection of Personal Protective Equipment (PPE) Compliance on Construction Site Using Computer Vision Based Deep Learning Techniques". Front. Built Environ. Vol. 6:136. 2020. doi: 10.3389/fbuil.2020.00136.

[2] J, Bierbrier, A. Jetha. "Integrating Occupational Health and Safety Into the Artificial Intelligence System Life Cycle". Am J Ind Med. Vol. 69, no. 7: pp. 491-502, 2026. doi: 10.1002/ajim.70090.

[3] A. Mashmool, G. Delzanno, H. Saadat farand et al. "Edge Computing in Healthcare Using Machine Learning: A Systematic Literature Review," Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, vol. 16, no. 1, p. 45, 2026. doi:10.1002/widm.70069

[4] S. Ahmed, L. Saraireh, A. Rahman, et al. "Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach". Sustainability, vol. 15, 13990. 2023. doi:10.3390/su151813990

[5] R. Jayaswal and M. Dixit, "AI-based face mask detection system: A straightforward proposition to fight with Covid-19 situation," Multimedia Tools and Applications, vol. 82, no. 9, pp. 13241–13273, 2023. doi.org/10.1007/s11042-022-13697-z

[6] S. Barro-Torres, M. Tiago, H.J. Fernández-Caramés. et al. "Real-time personal protective equipment monitoring system, Computer Communications", vol. 36, pp. 42–50. 2012. doi:10.1016/j.comcom.2012.01.005.

[7] A. Rahman, M.S. Ahmed, K.N. AlBugami, et al. "S.M. PPE-EYE: A Deep Learning Approach to Personal Protective Equipment Compliance Detection". Computers, vol. 15, no. 45. 2026. doi:10.3390/computers15010045.

[8] A.Z. Al Meslamani, I. Sobrino, J. de la Fuente. "Machine learning in infectious diseases: potential applications and limitations". Ann Med. 56(1):2362869. 2024. doi: 10.1080/07853890.2024.2362869.

[9] S. Saminu et al., "A recent investigation on detection and classification of epileptic seizure techniques using EEG signal," Brain Sciences, vol. 11, no. 5, p. 668, 2021. doi: 10.3390/brainsci11050668

[10] J. J. Y. Ong et al., "Headaches related to PPE use during COVID-19". Curr Pain Headache Rep. vol. 25, 8: 53. 2021. doi: 10.1007/s11916-021-00968-x

[11] L.T. Phan, D. Maita, D.C. Mortiz, et al. "CDC Prevention Epicenters Program. Personal protective equipment doffing practices of healthcare workers". J Occup Environ Hyg. Vol. 16, no. 8: pp. 575-581. 2019. doi: 10.1080/15459624.2019.1628350.

[12] V. Preda, Z. Ong, C. Wijeweera, et al. "Artificial intelligence (AI) use for personal protective equipment training, remediation, and education in health care". Am J Infect Control. vol. 53, no. 6: pp. 678-684. 2025. doi: 10.1016/j.ajic.2025.03.020.

[13] V. A. Preda et al., "Using artificial intelligence for personal protective equipment guidance for healthcare workers in the COVID-19 pandemic and beyond," Communicable Diseases Intelligence, vol. 46, pp. 1–14, 2022.

[14] L. Ran et al., "Risk factors of healthcare workers with coronavirus disease 2019: A retrospective cohort study in a designated hospital of Wuhan in China," Clinical Infectious Diseases, vol. 71, no. 16, pp. 2218–2221, 2020. doi: 10.1093/cid/ciaa287

[15] World Health Organization, Global Report on Infection Prevention and Control. Geneva, Switzerland: WHO Press, 2022.

[16] M.M. Alshamrani, A. El-Saed, F. Othman, et al. "Determinants of non-compliance with hand hygiene using a covert direct observation methodology". Infect Prev Pract. vol. 7, no. 1:100442. 2025. doi: 10.1016/j.infpip.2025.100442.

[17] A. Barlybayev, N. Amangeldy, et al. “Personal protective equipment detection using YOLOv8 architecture on object detection benchmark datasets: a comparative study”. Cogent Engineering, vol. 11, no. 1. 2024. doi.org/10.1080/23311916.2024.2333209.

[18] T. L. Giuseppe, V.M. Maria, M. Simone, et al. “Artificial intelligence and occupational health and safety: a systematic review”. Journal of Public Health, vol. 30, 100401, 2025. doi.org/10.1007/s10389-026-02738-8

[19] M. El-Helaly. “Artificial Intelligence and Occupational Health and Safety, Benefits and Drawbacks”. Med Lav. Vol. 115, no. 2: e2024014. 2024. doi: 10.23749/mdl.v115i2.15835.

[20] H. Liao, X. Hu, F. Wang, Z. Liu and M. Wu, "Lightweight Intelligent Detection System for Personal Protective Equipment in Laboratories of Higher Education Institutions," in IEEE Access, vol. 13, pp. 202745-202757, 2025, doi: 10.1109/ACCESS.2025.3637181.

[21] Y. Horesh, R. Oz Rokach, Y. Kolben, D. Nachman. “Real-Time Monitoring of Personal Protective Equipment Adherence Using On-Device Artificial Intelligence Models”. Sensors (Basel). Vol. 25, no. 7: 2025. doi: 10.3390/s25072003

[22] G. Jocher, “YOLOv5 by Ultralytics (Version 7.0),” Zenodo, 2023, doi: 10.5281/zenodo.3908559.