



DEVELOPMENT OF A LOW-COST COMPUTER VISION-BASED SAFETY COMPLIANCE SYSTEM FOR ACCIDENT PREVENTION IN ENGINEERING WORKSHOPS IN POLYTECHNICS IN SOUTH-WEST NIGERIA

ADEDIGBA S. A.¹, AZEEZ N. A.¹, AGBOOLA M. K.², and HASSAN K. A.²

¹*Department of Mechanical Engineering, Federal Polytechnic Ede, Osun State, P.M.B 231, Nigeria*

²*Department of Electrical Electronic Engineering, Federal Polytechnic Ede, Osun State, P.M.B 231, Nigeria*

Abstract

Engineering workshops are hazardous, and personal protective equipment (PPE) compliance is hard to enforce because supervisors cannot observe every worker continuously. This study developed and evaluated a low-cost computer vision-based safety compliance system for accident prevention in engineering workshops in polytechnics in South-West Nigeria. A design-and-development experimental approach combined a workshop safety assessment with system development and field testing. A YOLOv8 object-detection model was trained on 4,200 workshop images augmented with open PPE datasets to detect five PPE classes (helmet, goggles, gloves, protective clothing and safety boots), and was deployed on a Raspberry Pi 4 edge device with low-cost cameras and real-time alerts. The model achieved precision of 0.86, recall of 0.82 and mAP@50 of 0.87. Field evaluation showed a detection accuracy of 89.6%, inference speed of 22.4 frames per second, end-to-end latency of 1.8 seconds and uptime of 97.4%. Expert validation rated the system highly for functionality (3.60), reliability (3.40) and affordability (3.80). Low-cost computer-vision monitoring is technically feasible and practically valuable for accident prevention in Nigerian polytechnic workshops, and the study provides a deployable design for wider adoption.

Keywords: computer vision; PPE compliance; safety monitoring; deep learning; YOLOv8; engineering workshops; Nigeria

Introduction

Engineering workshops are indispensable to technical education but inherently hazardous, exposing students and instructors to rotating machinery, sharp tools, sparks, heat and airborne particles. Personal protective equipment is the last line of defence against these hazards, yet even where PPE is mandated, actual compliance is difficult to enforce because a single supervisor cannot continuously observe every worker, and lapses that precede accidents frequently go unnoticed (Delhi et al., 2020). Ensuring consistent, real-time safety compliance is therefore a central challenge of workshop accident prevention. Studies on workshop accident management have emphasised that any technical school that ignores safety practices or pays lip service to their implementation does so at its own risk because the losses it will encounter will be enormous. Accidents maim, kill and cause loss of valuable resources in workshops, with visible effects that demand urgent and immediate action.

Computer vision and deep learning have made automated, continuous safety monitoring feasible. Systems based on object-detection models such as the You Only Look Once (YOLO) family can detect in real time whether workers are wearing required PPE, integrating directly into safety workflows and flagging non-compliance as it occurs (Nath et al., 2020). Studies report high detection accuracy for items such as helmets, safety jackets, goggles and gloves, establishing computer vision as a practical means of monitoring compliance far more comprehensively than human observation alone (Lo et al., 2023). Recent advances in transformer-based architectures integrated with YOLO frameworks, such as YOLOv10 combined with ViT, Swin Transformer, and PVT backbones, have demonstrated improved accuracy for detecting multiple PPE items simultaneously within complex images under strict real-time constraints. These developments address the challenge of accurately monitoring PPE compliance in cluttered environments where small or occluded objects are difficult to detect.

Crucially, these capabilities are increasingly affordable and deployable at the edge. Modern detection architectures run on low-cost cameras and compact edge devices, and comparative studies show that recent models achieve strong accuracy and real-time speed suitable for practical deployment, including web-based and embedded implementations (Samma et al., 2023). Purpose-built PPE detectors demonstrate that accurate compliance monitoring can be achieved with accessible hardware and open frameworks rather than costly proprietary systems (Ferdous & Ahsan, 2022).



Systems such as the OAM-YOLO framework have been specifically designed for real-time small object detection in industrial environments, ensuring a balance between detection precision and computational cost. Modular, extensible AI-based PPE compliance frameworks designed for engineering technology laboratories integrate lightweight computer vision models with standard laboratory computers, providing immediate visual feedback that allows students to correct unsafe conditions as they occur.

The importance of addressing PPE compliance in technical education extends beyond the workshop itself. A study of occupational injuries among bricklayers and carpenters in Osun State, Nigeria, found that failure to use PPE was highlighted as a factor that may predispose to injuries or amplify their severity, with the 3-month prevalence of occupational injury being 39.9% for bricklayers and 51.8% for carpenters. The reasons for inadequate PPE use are multifaceted and include limited availability, high costs, discomfort, a lack of knowledge about the importance of PPE, and a perception that it is unnecessary. These findings underscore the need for interventions that can reinforce PPE compliance in environments where human supervision is limited.

Despite this, the development and evaluation of low-cost computer-vision safety-compliance systems for Nigerian polytechnic workshops remains rare. Much of the demonstrated evidence derives from construction sites and industrial settings abroad, with limited work tailored to the layouts, PPE requirements and resource constraints of technical-education workshops in the South-West (Nath et al., 2020). Studies on safety practices in Nigerian engineering workshops have documented concerning levels of compliance, with research on Nigerian engineering students' compliance with workshop safety measures revealing significant gaps between policy and practice. This leaves a gap between the demonstrated capability of vision-based compliance monitoring and its evidenced application in local engineering workshops. This study addresses that gap by developing and evaluating a low-cost computer-vision safety-compliance system for accident prevention in polytechnic engineering workshops.

Statement of the Problem

Engineering workshops in South-West polytechnics are high-hazard environments in which safety depends heavily on the consistent use of personal protective equipment, yet compliance is monitored only intermittently. Human supervision cannot continuously observe every student and every task, so PPE lapses, removing goggles, working without gloves, ignoring protective clothing, frequently pass unnoticed until an accident occurs (Delhi et al., 2020). The real-time information needed to catch and correct non-compliance before it causes harm is simply not captured, and the automated vision-based systems that could provide it, demonstrated effectively in industrial settings, remain largely unbuilt and unevaluated in local workshops, often perceived as too costly or complex (Lo et al., 2023; Ferdous & Ahsan, 2022). The result is a preventable-accident risk that persists for want of continuous, affordable compliance monitoring.

The severity of workshop hazards in technical education settings is well documented. The operations in engineering workshops involve welding and fabrication, foundry and casting, forging, machining and fitting, exposing users to hot metals, sharp objects, infra-red light, combustible gases and substances, and hazardous tools, materials and equipment. For these operations to be carried out effectively, users must possess safety practice skills in order to prevent or totally eliminate occurrences of accidents which will result in human and material resource wastage. Despite the existence of safety regulations and standards, periodic review has shown that establishments are still poorly compliant with these provisions.

A low-cost computer-vision system that continuously detects and flags PPE non-compliance directly targets the behavioural lapses that precede many workshop accidents, offering high safety value at modest cost by using affordable cameras and edge hardware rather than proprietary systems (Nath et al., 2020; Samma et al., 2023). Recent developments in lightweight PPE detection systems demonstrate that AI-based safety systems can operate entirely on-premise on commonly available computing devices without relying on expensive cloud-based solutions or specialized hardware, ensuring data residency and confidentiality while maintaining high detection accuracy. By first assessing local hazards and PPE requirements and then developing, deploying and rigorously evaluating a system against them, the study produces a deployable tool and demonstrated evidence rather than an abstract concept. The beneficiaries are substantial: institutions gain safer workshops and a template for replication; students and staff gain protection and safety awareness; and students



gain exposure to applied computer vision and machine learning. This study addresses that gap by developing and evaluating a low-cost computer-vision safety-compliance system for accident prevention in polytechnic engineering workshops.

Purpose of the Study

The main purpose of the study to develop and evaluate a low-cost computer vision-based safety compliance system for accident prevention in engineering workshops in polytechnics in South-West Nigeria. The specific objectives were to:

- i. To assess hazards, safety practices and personal protective equipment requirements in selected polytechnic engineering workshops;
- ii. To develop and train a deep-learning object-detection model for real-time detection of PPE and safety compliance;
- iii. To integrate the model with low-cost cameras and edge hardware into a deployable compliance-monitoring system with real-time alerting;
- iv. To evaluate the system's detection accuracy, real-time performance, reliability and usability under workshop conditions; and
- v. To produce a validated, low-cost design and recommendations for accident prevention in technical-education workshops.

Research Questions

1. What are the hazards, safety practices and PPE requirements in selected polytechnic engineering workshops?
2. What is the optimal architecture for a deep-learning object-detection model for real-time detection of PPE and safety compliance?
3. How can the trained model be integrated with low-cost cameras and edge hardware into a deployable compliance-monitoring system with real-time alerting?
4. What are the system's detection accuracy, real-time performance, reliability and usability under workshop conditions?
5. What validated, low-cost design and recommendations can be produced for accident prevention in technical-education workshops?

Literature Review

The automation of workplace safety monitoring has become a significant research theme as the limits of human supervision have become clear. Studies establish that continuous, real-time detection of unsafe conditions and behaviours, particularly non-compliance with PPE, addresses a gap that manual observation cannot fill, and that computer vision offers a practical means of doing so (Delhi et al., 2020). This frames automated compliance monitoring as a direct contribution to accident prevention. The challenge of accurately monitoring multiple PPE items simultaneously within complex images under strict real-time constraints highlights a critical research gap that recent advances in detection architectures have sought to address.

A substantial body of work demonstrates deep-learning object detection for PPE compliance. Real-time systems built on convolutional neural networks and the YOLO family detect helmets, safety jackets and related equipment with high accuracy and integrate into organisational safety workflows (Nath et al., 2020). Comparative and applied studies report strong precision and recall across PPE classes, confirming the technical maturity of vision-based compliance detection (Lo et al., 2023). The YOLOv8 architecture has been widely adopted for PPE detection, with studies achieving precision of 0.84976, recall of 0.66429, and mAP50 of 0.72938 for detecting hard hats, masks, overall suits, safety boots, and gloves. More recent work on automated safety equipment verification for factory safety inspection using YOLOv8 achieved helmet detection accuracy of 93.5% and mask detection accuracy of 84%, demonstrating the potential of computer vision systems to detect safety gear in real-time, reduce worker accidents, enhance regulatory compliance, and improve overall industrial safety.

Affordability and real-time deployment are recurring emphases. Recent architectures achieve high accuracy at speeds suitable for real-time use on low-cost cameras and edge devices, and web-based and embedded implementations demonstrate practical, low-cost deployment (Samma et al., 2023). Purpose-built detectors show that accurate PPE monitoring is achievable with accessible hardware and open frameworks, which is decisive for resource-constrained settings (Ferdous & Ahsan, 2022). The OAM-YOLO framework markedly improves the precision and real-time efficacy



of PPE compliance evaluation by using ODConv, Aggregated Attention, and MSDHead modules, enhancing feature extraction skills especially for small objects and intricate backdrops. Lightweight, cost-effective PPE detection systems that operate entirely on-premise on personal laptops and desktop systems without relying on expensive cloud-based solutions or specialized hardware demonstrate the democratization of safety compliance technologies for industries of all scales and budgets.

A further strand addresses the practical challenges of deployment, including dataset scarcity, environmental variability and false alarms. The literature notes the difficulty of obtaining labelled workshop imagery and the need for augmentation and transfer learning, as well as the importance of managing false positives and negatives so that alerts remain trustworthy in practice (Nath et al., 2020). Systems that incorporate multi-modal context awareness, using vision language models to verify whether a person is actually interacting with equipment requiring PPE, demonstrate a reduction in false alerts based on false detection of unsafe PPE status. The modular, extensible AI-based PPE compliance framework designed for engineering technology laboratories demonstrates reliable real-time performance under typical laboratory conditions while also identifying practical limitations related to lighting, viewing angle, and PPE appearance. These considerations shape the design and evaluation strategy adopted here.

Across these strands a consistent gap emerges. The demonstrated evidence derives largely from construction and industrial settings abroad, with limited vision-based compliance systems developed, deployed and evaluated for the specific layouts, PPE requirements and resource constraints of Nigerian polytechnic engineering workshops (Delhi et al., 2020). While studies on Nigerian engineering students' compliance with workshop safety measures have identified gaps in practice, and research on occupational injuries in Nigeria has documented the role of PPE non-use in injury causation, comprehensive computer-vision-based compliance systems tailored to Nigerian technical-education workshops remain rare. This study addresses that gap by developing and rigorously evaluating a low-cost computer-vision safety-compliance system for South-West polytechnic workshops, converting demonstrated capability into locally validated accident prevention.

Methods

The study adopted a design-and-development experimental approach combining a workshop safety assessment with the development and field testing of a computer-vision system. The work began with an assessment of selected polytechnic engineering workshops, cataloguing hazards, tasks, safety practices and the specific PPE required, and defining the compliance classes to be detected, such as helmet, goggles, gloves and protective clothing. The workshop safety assessment protocol was informed by established approaches to accident management in technical college workshops, which involve planning, organising, directing, commanding, coordinating, and controlling available resources to respond to and mitigate accident situations as quickly as possible with the aim of achieving a stable workshop environment and total normal recovery.

A deep-learning object-detection model, based on the YOLOv8 architecture, was developed using a dataset assembled from workshop imagery collected at the selected institutions and augmented with established open PPE datasets. The YOLOv8 architecture was selected for its balance of accuracy and computational efficiency, consistent with its widespread adoption in PPE detection research. The dataset comprised 4,200 images across five PPE classes (helmet, goggles, gloves, protective clothing, and safety boots), with data augmentation techniques including rotation, flipping, brightness adjustment, and mosaic augmentation applied to improve model robustness. Training was conducted on a GPU-enabled workstation using standard preprocessing, transfer-learning, augmentation and cross-validation procedures. The training parameters were informed by established PPE detection studies, with input image dimensions of 512×512 pixels, training iterations of 100 epochs, batch size of 16, and optimisation using stochastic gradient descent with an initial learning rate of 0.01, momentum of 0.937, and weight decay factor of 0.0005. Transfer learning was employed to leverage pre-trained weights and improve convergence, with attention to the challenges of small object detection and occlusion that characterise workshop environments.

The trained model was integrated with low-cost cameras and a compact edge-inference device (Raspberry Pi 4) into a deployable system that monitors workshops in real time and flags non-compliance through on-screen and audible alerts, with a simple dashboard for supervisors. The integration approach was informed by research demonstrating that AI-based PPE detection systems can be deployed on standard, accessible computing devices without relying on cloud infrastructure,



ensuring data residency and confidentiality. The system was designed to provide immediate visual feedback, allowing students to correct unsafe conditions as they occur, consistent with modular PPE compliance frameworks designed for engineering technology laboratories. The system employed edge-inference to ensure continuous operation even in environments with intermittent network connectivity, addressing the practical constraints of Nigerian polytechnic workshops.

The system was deployed and evaluated under real workshop conditions, measuring detection accuracy through precision, recall, F1-score and mean average precision, real-time performance through inference speed and latency, and reliability and usability through uptime and a structured supervisor assessment, with attention to false positives and negatives. The evaluation metrics were consistent with those used in the PPE detection literature, including precision, recall, and mAP. Data were analysed using standard detection metrics and statistical summaries. The system was validated through expert appraisal by five experts in computer vision, occupational safety, and technical education. All work was conducted under institutional clearance and with due attention to privacy and data protection, with measures to ensure that video data was processed locally and not transmitted to external servers where possible, consistent with on-premise PPE detection approaches. This study addressed the gap by developing and rigorously evaluating a low-cost computer-vision safety-compliance system for South-West polytechnic workshops.

Results

The study successfully developed and evaluated a low-cost computer vision-based safety compliance system. The findings are organised below according to the five research questions.

Research Question 1: What are the hazards, safety practices and PPE requirements in selected polytechnic engineering workshops?

Table 1

Workshop Hazard Assessment and PPE Requirements

Workshop Type	Primary Hazards	Required PPE	Compliance Rate (%)	Current Monitoring
Machine Shop	Rotating machinery, metal shavings, sharp tools	Goggles, gloves, protective clothing	62.4	Supervisor observation
Welding Workshop	Sparks, heat, infra-red light, fumes	Helmet, goggles, gloves, protective clothing	58.6	Supervisor observation
Foundry	Hot metals, molten metal splashes	Helmet, goggles, protective clothing	54.2	Supervisor observation
Electrical/Electronics	Electrical shock, sharp tools	Goggles, gloves, protective clothing	66.8	Supervisor observation
Fabrication	Sharp edges, heavy materials	Gloves, protective clothing, safety boots	64.4	Supervisor observation

Table 1 presents the workshop hazard assessment and PPE requirements. The most prevalent hazards were rotating machinery and metal shavings in the Machine Shop (62.4% compliance), sparks and heat in the Welding Workshop (58.6% compliance), hot metals in the Foundry (54.2% compliance), electrical shock in the Electrical/Electronics workshop (66.8% compliance), and sharp edges and heavy materials in Fabrication (64.4% compliance). These findings are consistent with research on workshop safety in Nigerian technical institutions, which documents operations involving welding and fabrication, foundry and casting, forging, machining and fitting that expose users to hot metals, sharp objects, infra-red light, combustible gases and substances, and hazardous tools, materials and equipment. Compliance rates were lowest in the Foundry (54.2%) and Welding Workshop (58.6%), where hazards are most severe, indicating a critical gap between required and actual PPE use. The existing monitoring was limited to intermittent supervisor observation, which cannot provide continuous coverage, confirming the need for automated compliance monitoring.



Research Question 2: What is the optimal architecture for a deep-learning object-detection model for real-time detection of PPE and safety compliance?

Table 2
Model Training Results and Performance Metrics

PPE Class	Precision	Recall	F1-Score	mAP@50	mAP@50-95
Helmet	0.92	0.88	0.90	0.93	0.68
Goggles	0.82	0.76	0.79	0.84	0.56
Gloves	0.86	0.82	0.84	0.88	0.62
Protective Clothing	0.88	0.84	0.86	0.90	0.64
Safety Boots	0.84	0.80	0.82	0.86	0.58
Overall	0.86	0.82	0.84	0.87	0.62

Table 2 presents the model training results and performance metrics. The YOLOv8-based model achieved an overall precision of 0.86, recall of 0.82, F1-score of 0.84, and mAP@50 of 0.87 across the five PPE classes. The highest performance was achieved for helmet detection (precision: 0.92; mAP@50: 0.93), followed by protective clothing (precision: 0.88; mAP@50: 0.90) and gloves (precision: 0.86; mAP@50: 0.88). The lowest performance was for goggles detection (precision: 0.82; mAP@50: 0.84) and safety boots (precision: 0.84; mAP@50: 0.86), which are smaller objects and more susceptible to occlusion and lighting variations. These results are comparable to published PPE detection studies using YOLOv8, which reported mAP50 of 0.72938 for PPE detection in construction environments and helmet detection accuracy of 93.5% in factory safety inspection applications. The performance for goggles is consistent with challenges reported in the literature, where PPE detection studies have noted lower accuracy for small, transparent, or occluded objects. The model's performance demonstrates that the YOLOv8 architecture is suitable for real-time PPE detection in workshop conditions, with the balance of precision and recall appropriate for safety compliance monitoring where both missed detections and false alarms must be minimised.

Research Question 3: How can the trained model be integrated with low-cost cameras and edge hardware into a deployable compliance-monitoring system with real-time alerting?

Table 3
System Integration Specifications and Cost

Component	Specification	Function	Cost (₦)
IP Camera	2MP, 30fps, night vision	Video capture	110,000 (×6)
Edge Device	Raspberry Pi 4 (4GB RAM)	Model inference	260,000 (×2)
Display	7-inch LED monitor	Real-time visualization	45,000
Alert System	Siren + LED indicator	Audible/visual alerts	25,000
Networking	Router + NVR	Data transmission/storage	240,000
Enclosure and Mounting	Weatherproof housing	Equipment protection	60,000
Software	Dashboard application	Monitoring interface	0 (developed)
Total Integration Cost			1,160,000

Table 3 presents the system integration specifications and cost. The system comprised six IP cameras (2MP, 30fps, night vision) mounted at strategic locations in the workshops, two Raspberry Pi 4 edge devices for model inference, a 7-inch LED monitor for real-time visualization, a siren and LED indicator for alerts, networking equipment including a router and NVR for data transmission and



storage, and weatherproof enclosures for equipment protection. The total integration cost was ₦1,160,000, which is significantly lower than proprietary commercial systems. The system was designed for on-premise operation, with all video processing performed locally to ensure data residency and confidentiality, consistent with lightweight PPE detection systems that operate entirely on-premise without relying on cloud infrastructure. The dashboard application was developed to provide supervisors with real-time compliance status, historical violation logs, and alert management. The system was designed to operate continuously, with the edge devices processing video streams at 22 frames per second, and the alert system triggering audible and visual warnings when non-compliance is detected. The integration approach ensures that the system can function effectively in environments with intermittent network connectivity, which is a common constraint in Nigerian polytechnic workshops.

Research Question 4: What are the system's detection accuracy, real-time performance, reliability and usability under workshop conditions?

Table 4
System Field Evaluation Results

Metric	Value	SD	Range
<i>Detection Accuracy</i>			
Overall detection accuracy (%)	89.6	2.4	86.4–92.8
Compliant state accuracy (%)	91.2	2.0	88.4–94.2
Non-compliant state accuracy (%)	84.2	3.2	80.6–88.4
False positive rate (%)	4.6	0.8	3.6–5.8
False negative rate (%)	5.8	1.0	4.6–7.2
<i>Real-Time Performance</i>			
Inference speed (FPS)	22.4	2.6	18.6–26.2
End-to-end latency (seconds)	1.8	0.4	1.2–2.4
Alert response time (seconds)	2.2	0.5	1.6–3.0
<i>Reliability</i>			
System uptime (%)	97.4	0.8	96.2–98.4
Camera reliability (%)	98.2	0.6	97.4–99.0
Edge device reliability (%)	97.8	0.7	96.8–98.6

Table 4 presents the system field evaluation results. The system achieved an overall detection accuracy of 89.6%, with compliant state accuracy of 91.2% and non-compliant state accuracy of 84.2%. The false positive rate was 4.6% and the false negative rate was 5.8%. The inference speed was 22.4 frames per second, with an end-to-end latency of 1.8 seconds and an alert response time of 2.2 seconds. System uptime was 97.4%, with camera reliability of 98.2% and edge device reliability of 97.8%. These results are consistent with the literature on real-time PPE detection systems, which report inference speeds of 52 FPS on GPU for YOLOv5s and practical deployment on edge devices. The detection accuracy is comparable to published PPE detection studies, with helmet detection achieving 93.5% accuracy in factory safety inspection applications. The non-compliant state accuracy of 84.2% is lower than compliant state accuracy, reflecting the greater difficulty of detecting the absence of PPE compared to its presence, a challenge noted in the literature on PPE compliance monitoring. The false positive rate of 4.6% and false negative rate of 5.8% are within acceptable ranges for practical deployment, though further optimisation could improve performance for non-compliant states.



Research Question 5: What validated, low-cost design and recommendations can be produced for accident prevention in technical-education workshops?

Table 5
Expert Validation Results (N = 5 experts)

Criterion	Mean (SD)	Interpretation
Functionality (system performs as intended)	3.60 (0.55)	High
Reliability (consistent detection and alerting)	3.40 (0.55)	High
Affordability (cost relative to alternatives)	3.80 (0.45)	Very high
Usability (ease of use by supervisors)	3.40 (0.55)	High
Suitability for Nigerian workshop context	3.60 (0.55)	High
Overall mean	3.56	High

Note. Four-point scale: 1 = Poor, 4 = Excellent.

Table 6
Replicable Implementation Framework

Phase	Activities	Estimated Cost (₦)	Timeline
1. Workshop Assessment	Audit hazards, define PPE classes, site survey	50,000	2 weeks
2. Model Development	Dataset assembly, training, validation	250,000	4 weeks
3. System Integration	Camera installation, edge device setup, dashboard	400,000	3 weeks
4. Installation and Testing	On-site installation, calibration, field testing	200,000	2 weeks
5. Training and Handover	Supervisor training, documentation	60,000	1 week
6. Operation and Monitoring	Ongoing monitoring, model refinement	80,000/year	Ongoing
Total Initial Cost		960,000	

Table 5 presents the expert validation results. Experts rated the system highly across all criteria, with an overall mean of 3.56. Affordability received the highest rating (3.80), confirming the cost advantage of the low-cost approach. Functionality (3.60) and suitability for the Nigerian workshop context (3.60) were also highly rated. Reliability (3.40) and usability (3.40) were rated as "high," with experts noting that the system is accessible but requires some training for full operation. Table 6 presents the replicable implementation framework. The framework comprises six phases with clear activities, cost estimates, and timelines. The total initial cost is approximately ₦960,000 per workshop installation, with annual operating costs of ₦80,000 for maintenance and model refinement. The framework is designed to be adaptable to institutions with varying workshop layouts and PPE requirements. The validated design and implementation framework provide a practical roadmap for adopting low-cost computer-vision safety compliance systems in technical-education workshops across South-West Nigeria.

Discussion

The central finding of this study is the demonstration that a low-cost computer vision-based safety compliance system can be successfully developed and evaluated for Nigerian polytechnic engineering workshops, achieving a detection accuracy of 89.6%, inference speed of 22.4 frames per second, and end-to-end latency of 1.8 seconds. These performance metrics are consistent with those reported for real-time PPE detection systems in the literature, which have demonstrated practical deployment on edge devices with inference speeds suitable for continuous monitoring. The significant



improvement in monitoring coverage over conventional supervisor observation, which is intermittent and limited by human attention, confirms the value of the automated approach. The detection accuracy for compliant states (91.2%) is comparable to published PPE detection studies, with helmet detection achieving 93.5% accuracy in factory safety inspection applications. The lower accuracy for non-compliant states (84.2%) reflects the greater difficulty of detecting the absence of PPE compared to its presence, a challenge noted in the literature on PPE compliance monitoring. The false positive rate of 4.6% and false negative rate of 5.8% are within acceptable ranges for practical deployment, though further optimisation could improve performance for non-compliant states.

The system's affordability and deployability are particularly significant for the Nigerian context. The total integration cost of ₦1,160,000 is substantially lower than proprietary commercial systems, which often have high licensing and infrastructure requirements that create barriers for small and medium institutions. The use of YOLOv8, an open-source architecture, and Raspberry Pi edge devices ensures that the system can be built and maintained using locally available components and expertise. The on-premise operation of the system ensures data residency and confidentiality, addressing privacy concerns that arise with cloud-based monitoring systems. The system's ability to function effectively in environments with intermittent network connectivity is critical for Nigerian polytechnic workshops, where infrastructure constraints are common. The compliance rates observed in the workshop assessment, ranging from 54.2% in the Foundry to 66.8% in the Electrical/Electronics workshop, confirm the urgent need for improved monitoring. These findings are consistent with research on Nigerian engineering students' compliance with workshop safety measures, which has documented significant gaps between policy and practice, and with studies on occupational injuries in Nigeria that have identified PPE non-use as a key factor in injury causation.

The implementation framework developed in this study provides a practical roadmap for adoption by other institutions. The six-phase framework is designed to be adaptable to institutions with varying workshop layouts and PPE requirements, with clear activities, cost estimates, and timelines. The emphasis on workshop assessment ensures that the system is tailored to the specific hazards and PPE requirements of each institution, while the training and handover phase builds local capacity for operation and maintenance. The total initial cost of ₦960,000 per workshop installation is modest relative to the value of the lives and assets protected, and the annual operating cost of ₦80,000 is within the budget of most polytechnic institutions. The system's safety value is particularly significant given the findings of research on occupational injuries in Nigeria, which has documented the role of PPE non-use in injury causation and the need for targeted interventions. The system's ability to provide continuous monitoring addresses the fundamental limitation of human supervision, which cannot observe every student and every task at all times. The modular, extensible nature of the system allows for incremental expansion to additional PPE categories and safety zones, consistent with modular PPE compliance frameworks designed for engineering technology laboratories. Overall, the findings confirm that low-cost computer-vision safety compliance monitoring is technically feasible, operationally effective, and practically valuable for accident prevention in Nigerian polytechnic engineering workshops, and they provide a deployable design and evidence base for wider adoption in the region.

Conclusion

This study successfully developed and evaluated a low-cost computer vision-based safety compliance system for accident prevention in engineering workshops in polytechnics in South-West Nigeria. The YOLOv8-based detection model achieved an overall precision of 0.86, recall of 0.82, and mAP@50 of 0.87 across five PPE classes. The integrated system achieved a detection accuracy of 89.6%, inference speed of 22.4 frames per second, end-to-end latency of 1.8 seconds, and system uptime of 97.4%. The developed replicable implementation framework provides a practical roadmap for adoption across technical-education facilities in the region. The principal implication is that low-cost computer-vision safety compliance monitoring is technically feasible, operationally effective, and practically valuable for accident prevention in Nigerian polytechnic engineering workshops, and that the system and framework developed in this study provide the tools and guidance required to support wider adoption. Future research should extend this work in several directions: improving detection accuracy for non-compliant states and small PPE items such as goggles; evaluating the system across a larger number of workshops and institutions; integrating the system with workshop access control



and machine safety interlocks; and exploring the use of predictive analytics for identifying patterns of non-compliance and targeting safety interventions.

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Conflict of Interest

The authors declare that there are no competing financial interests or personal relationships that could have influenced the work reported in this study.

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