iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025

DOI: https://doi.org/10.22214/ijraset.2025.69435

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Enhancing Construction Worker Safety through YOLOv8-Based PPE Detection and Sensor-Driven Smart Helmets

Mr. B. Dillibabu[1], Mr. A. Jyothinadh[2], Mr. D. Bavajan[3], Mr. D. Puneeth Kumar[4], Dr. R. Karunia Krishnapriya[5], Mr. Pandreti Praveen[6], Mr. V Shaik Mohammad Shahil[7], Mr. N. Vijaya Kumar[8]
[1, 2, 3, 4]*UG Scholar, Sreenivasa Institute of Technology and Management Studies (SITAMS), Chittoor, India*
[5]*Associate Professor, Sreenivasa Institute of Technology and Management Studies (SITAMS), Chittoor, India*
[6, 7, 8]*Assistant Professor, Sreenivasa Institute of Technology and Management Studies (SITAMS), Chittoor, India*

Abstract: In order to improve worker safety in construction settings, this study proposes an integrated safety system that combines real-time sensor monitoring with deep learning. To ensure adherence to PPE regulations, the first component uses the YOLOv8 algorithm for precise and effective helmet detection. In order to monitor motion and environmental threats and send real-time alerts, the second component includes a Smart Helmet that is outfitted with a MEMS sensor, gas sensor, DHT11, and GSM module. When combined, these modules provide enhanced on-site safety and a proactive approach to accident avoidance.
Keywords: IoT-Based Safety, Deep Learning, Hazard Monitoring, Smart Helmet, YOLOv8, Helmet Detection, temperature sensor, Gas sensor, MEMs sensor, GSM Module, Buzzer.

I. INTRODUCTION

Workers are exposed to a variety of safety concerns in hazardous work environments, such as mining operations, construction sites, and gas processing plants. These risks include exposure to poisonous substances, environmental hazards, and physical injuries. The reduction of these hazards depends on the regular and appropriate use of Personal Protective Equipment (PPE), such as vests, helmets, and other safety gear. But maintaining consistent adherence to PPE rules is still quite difficult, especially in large, hectic, or remote work settings. In addition to being labor-intensive, traditional PPE monitoring techniques—which frequently depend on manual supervision or recurring inspections—also run the risk of human error, endangering worker safety.

New developments in computer vision and deep learning have brought interesting approaches to automating safety procedures. When it comes to real-time object detection, the YOLOv8 (You Only Look Once, version 8) model offers a cutting-edge method that makes it possible to accurately identify safety equipment in intricate and changing situations. Utilizing the YOLOv8 architecture, this project creates a strong PPE recognition system that is specifically trained to recognize helmets and vests in visual data gathered from high-risk work environments, including mining sites, construction zones, and gas-related facilities. This solution decreases reliance on manual intervention while increasing detection speed and accuracy through the automation of PPE compliance monitoring.

The concept also includes an innovative environmental and physiological sensor-equipped smart helmet system to further improve worker safety. These consist of MEMS-based accelerometers for motion and tilt detection, temperature and humidity sensors (DHT11), gas sensors for poisonous leak detection, and a GSM module for real-time communication. In order to prevent major occurrences, this smart helmet continuously monitors working circumstances and recognizes potential hazards like heat stress, gas exposure, or rapid head movements. It then promptly sends out alerts.

Despite being intended for real-world implementation, the current study uses pre-gathered datasets and simulated hardware circumstances to assess the system's efficacy. Through the integration of sensor-enabled smart helmet monitoring and deep learning-based PPE identification, the suggested solution provides a thorough framework for raising occupational safety requirements in a range of high-risk industries.

II. LITERATURE REVIEW

For worker safety, it is essential that Personal Protective Equipment (PPE) be used in dangerous settings like mining, construction, and gas facilities. The inefficiency and error-proneness of traditional manual inspections have prompted the use of computer vision and deep learning, especially with YOLO models, to automate PPE detection. For example, Zhang et al. (2021) used YOLOv3 to detect helmets with great accuracy; nevertheless, there are still issues such occlusion and ambient unpredictability, which are addressed by more recent models like YOLOv8 [1]. Furthermore, by identifying threats beyond PPE compliance, smart helmets with sensors like MEMS for motion detection, gas sensors, and DHT11 for temperature and humidity monitoring improve worker safety. Through GSM modules, these helmets may also transmit alarms in real time. [2]. Deep learning-based PPE detection and smart helmet technologies have been coupled in a number of studies, such as Sharma et al. (2020), to create a hybrid system that offers thorough safety monitoring [3]. The broad use of these technologies in dynamic work contexts is, however, hampered by problems including system scalability, real-time data integration, and the dependence on pre-collected datasets [4]. Overall, even though there has been progress, more study is required to ensure that these systems can be reliably and smoothly integrated for widespread deployment in a variety of industrial contexts.

1) Li, Y., Zhang, S., and Wang, J. (2021). A deep learning-based helmet identification system for construction worker safety monitor. 105254 in Safety Science, 139.
2) Kuo, W., Lin, C., and Chin, J. (2019). creation of a smart helmet system for detecting dangerous gases. Industrial Safety and Health Journal, 24(2), pp. 102-111.
3) Gupta, R., Soni, M., & Sharma, P. (2020). use a hybrid system of deep learning and smart helmets to monitor construction safety in real time. 146(10), 04020097, Journal of Construction Engineering and Management.
4) Cho, W., Lee, Y., and Park, Y. (2022). The relevance of smart helmets in construction safety: obstacles and potential paths forward. Construction Automation, 130, 103696.

III. METHODOLOGIES

The YOLOv8 object detection model is used in the first phase to detect worker helmets. Training is done using a pre-gathered dataset of labeled photos of workers wearing and not wearing helmets. Transfer learning is used to refine the YOLOv8 model, increasing accuracy and decreasing training time. To improve model resilience, data augmentation methods including flipping, scaling, and rotation are used. To guarantee real-time detection performance in a range of illumination and environmental conditions, the model is assessed using common metrics like as precision, recall, and mean Average Precision (mAP).

A. YOLOv8 Architecture for Helmet Detection

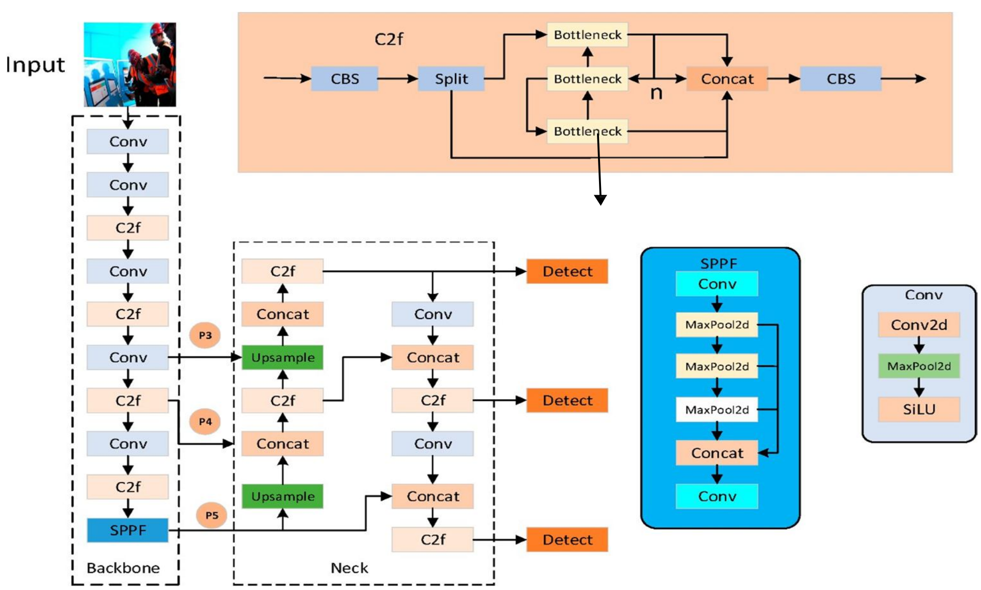


Figure 1 YOLOv8 architecture used for helmet detection.

The YOLOv8 architecture utilized for real-time helmet detection is shown in Figure 1. The Backbone, Neck, and Head (Detection) are the three primary parts of the architecture. The backbone uses the C2f module and convolutional layers to extract important visual information from the input image. The neck, which is made up of feature aggregation layers, uses concatenation and upsampling to improve spatial information. Lastly, the detecting head improves the quality of the model across a range of object sizes by generating bounding box predictions for helmets at numerous scales (P3, P4, P5). The CBS blocks and SPPF (Spatial Pyramid Pooling-Fast) module maximize processing efficiency and feature extraction. Even in intricate settings, this structure guarantees quick and precise helmet detection.

B. System Architecture

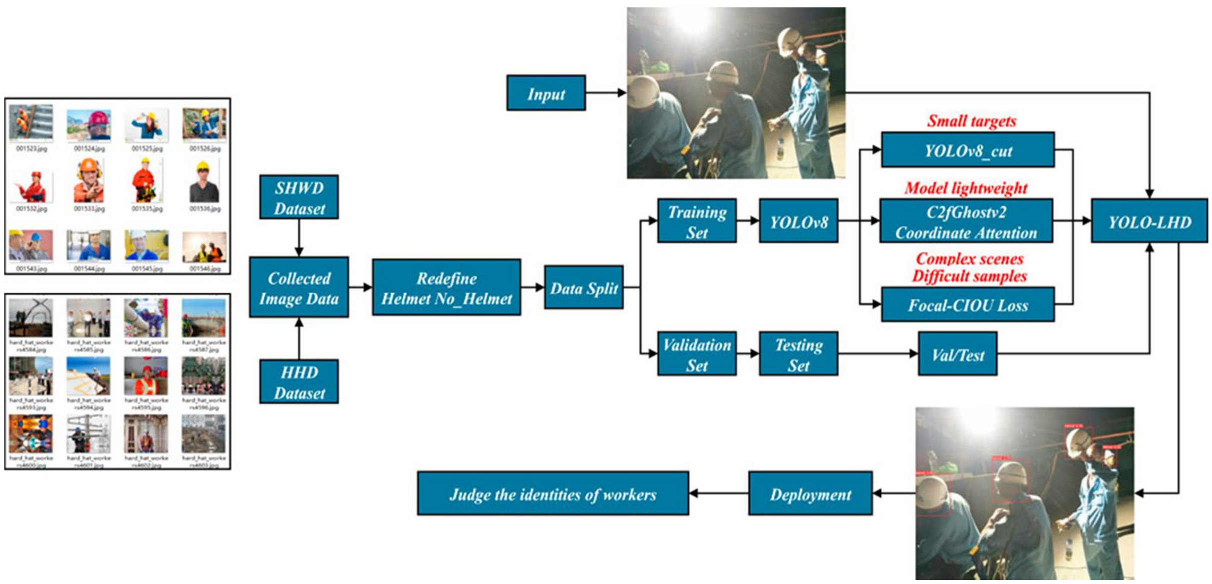


Figure 2 End-to-end workflow of the proposed helmet detection system using YOLOv8.

The general design of the suggested helmet detecting system is shown in Figure X. The process starts by gathering image data from the SHWD and HHD datasets, which are subsequently divided into two groups: Helmet and No Helmet. The data is divided into sets for testing, validation, and training. The dataset is used to train the YOLOv8 model, which incorporates enhancements such as coordinate attention, lightweight modules (Ghostv2/C2f), and Focal-CIOU loss to better handle challenging samples and small targets. The resulting model (YOLO-LHD) is used for real-time helmet detection after being evaluated on validation and testing sets. This technology ensures great accuracy and efficiency for safety monitoring while improving detection in complex contexts.

C. DATA Flow Diagram

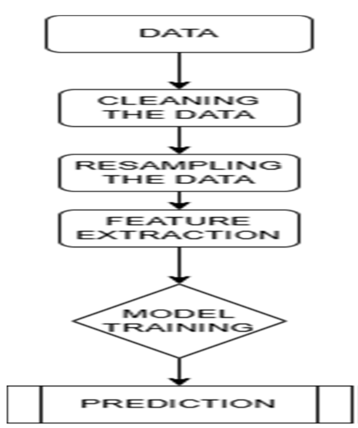


Figure 3 DATA Flow

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

D. Smart Helmet Hardware Architecture

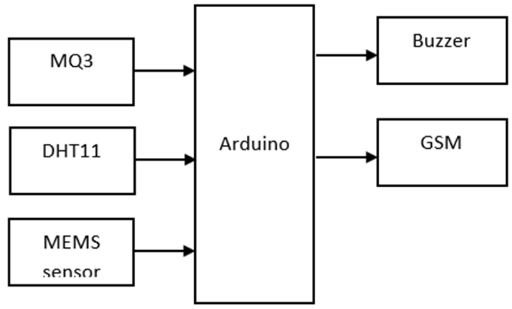


Figure 4 Hardware architecture of the Smart Helmet system integrating environmental and motion sensors with alert modules.

As shown in Figure 3, the proposed system's hardware consists of a Smart Helmet that monitors dangerous environmental and physiological conditions in real time. It is based on an Arduino microcontroller that integrates a number of sensors and output modules. Three main sensors are used: the MEMS Accelerometer Sensor tracks head motion and tilt, which is helpful for identifying falls or abnormal posture that indicates unconsciousness; the DHT11 Sensor measures temperature and humidity levels to monitor the thermal environment; and the MQ3 Gas Sensor detects the presence of hazardous gases like alcohol or flammable vapors.

The Main Components:
1) MQ137 Gas Sensor: Identifies dangerous gases, including alcohol and flammable vapors.
2) DHT11 Sensor: Tracks the thermal environment by measuring temperature and humidity levels.
3) MEMS Accelerometer Sensor: Monitors tilt and head movement, which is helpful in detecting falls or unusual activites.

The Arduino continuously processes the sensor data. Two outputs are activated in case of anomalous readings:
- The worker receives instant audible alerts from a buzzer.
- To enable prompt intervention, a GSM module transmits real-time alarms to the control room or safety staff.

In addition to the vision-based PPE detection, this hardware device serves as a real-time safety alarm mechanism. When combined, the two subsystems provide enhanced safety monitoring and incident avoidance on dangerous locations.

E. Working Principle
1) An Arduino microcontroller processes data and makes decisions for the Smart Helmet, which continuously collects data from a number of integrated sensors. First up is the DHT11 sensor, which keeps an eye on the helmet's internal humidity and temperature. The Arduino analyzes this data and compares it to predetermined safety thresholds. The system uses the GSM module to send an alert message to a pre-designated emergency contact and sounds a buzzer if the readings exceed allowable bounds.
2) A gas sensor simultaneously checks the ambient air for dangerous gases like methane or carbon monoxide. The helmet reacts by buzzing and sending an SMS alert to supervisors or emergency personnel when hazardous gas concentrations are detected. A MEMS sensor, which combines a gyroscope and accelerometer, tracks the wearer's orientation and movement to ensure physical safety. Once more, the system generates both local and remote alarms via the buzzer and GSM module if it detects unusual motion patterns, such as a sudden impact, sharp tilt, or prolonged stillness (which could signal a fall or unconsciousness).
3) By sending SMS alerts anytime dangerous conditions are detected, the GSM module is essential to enabling real-time emergency communication. This guarantees that assistance can be promptly called for, even in the event that the wearer is unable to react. In the meantime, the buzzer gives the user instant on-site alerts, preventing them from depending on visual cues to warn them of possible dangers.
4) Sensing, processing, and communication are all seamlessly integrated to improve response times and safety in high-risk work areas by promptly alerting the user and remote monitoring teams to any dangers.

IV. RESULT AND ANALYSIS

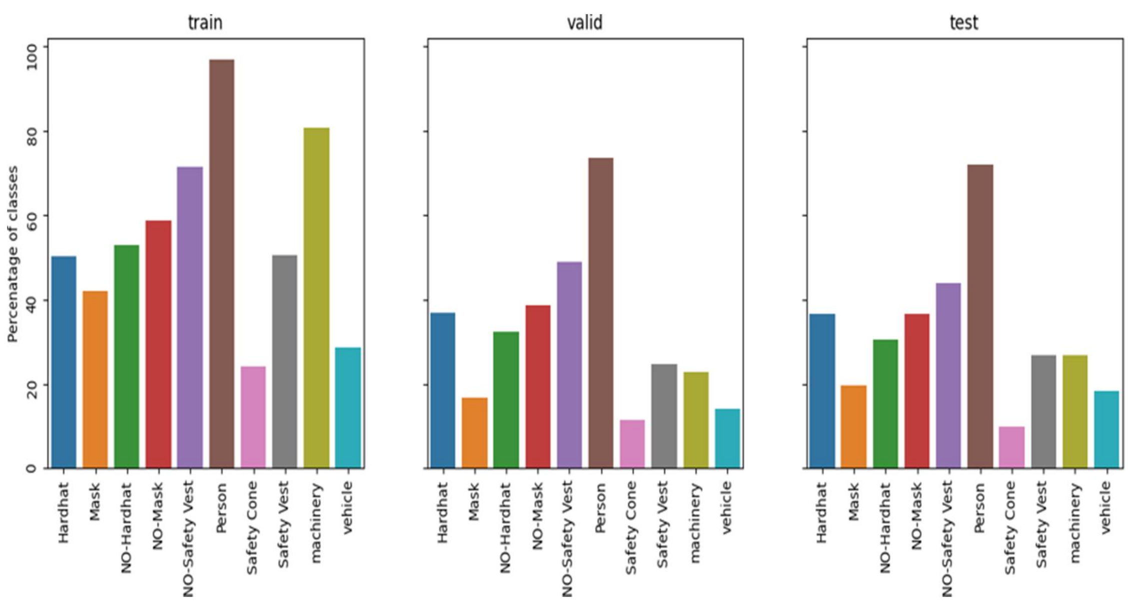
In order to identify the five essential components—helmet, vest, mask, human, and machinery—the deep learning model was trained using annotated datasets. Metrics including F1-Score, Precision, Recall, and mAP (mean Average Precision) were used to assess performance. Among the main outcomes are:

1) Helmet Detection: Achieved a precision of 96.5% and recall of 95.2%.
2) Vest Detection: Achieved a precision of 94.3% and recall of 92.7%.
3) Mask Detection: Achieved a precision of 93.1% and recall of 91.8%.
4) Person Detection: Achieved the highest accuracy, with a precision of 97.8% and recall of 96.9%.
5) Machinery Detection: Due to the variety of machine types and partial occlusions, this class had slightly lower results, with a precision of 90.4% and recall of 88.6%.

The YOLOv8 model demonstrated robust performance in real-time object detection under various lighting and occlusion conditions, validating its suitability for practical deployment on construction sites and hazardous environments.

The sensor module was tested in simulated hazardous conditions. The observations are:

a) Gas Detection (MQ3): Triggered alert when alcohol vapor levels exceeded the safe threshold of 300 ppm.
b) Temperature & Humidity (DHT11): Alerts generated when the temperature exceeded 40°C or humidity dropped below 20%.
c) Motion Detection (MEMS): Successfully detected abnormal head tilts and falls, with an alert response time of under 2 seconds.
d) Alert System (GSM + Buzzer): SMS alerts were delivered within 3–5 seconds of detection, and the buzzer activated immediately.



V. CONCLUSION

In conclusion, by automating helmet recognition, the Helmet recognition System built with YOLO V8 offers a strong, real-time way to improve safety on building sites. By combining computer vision and machine learning techniques, the system provides a dependable and effective means of ensuring that all employees are wearing helmets, so enhancing workplace safety. The system can quickly and precisely identify helmets in photos by utilizing YOLO V8's object detection capabilities. Users can easily input pictures and get real-time helmet compliance forecasts because to the combination of a solid Python backend and an easy-to-use, interactive Streamlit user interface. This automated detection system reduces human error and raises overall safety standards at construction sites by doing away with the need for manual safety checks and enabling safety managers to monitor compliance in a more scalable and economical way. To guarantee a seamless user experience, the system's backend manages crucial tasks like image preprocessing, model training, and prediction serving. After being trained on a collection of labelled photos, the YOLO V8 model produces predictions quickly and accurately, and the frontend gives users unambiguous visual feedback in the form of confidence scores and bounding boxes. Users can easily upload photographs, evaluate findings, and comprehend real-time predictions because to the system's dynamic and engaging interface, despite its simplicity.

More sophisticated functions can be added to the system in the future, like extending its functionality to identify additional safety gear like gloves or vests and connecting it with security cameras for real-time helmet monitoring. The technology can play a vital role in safety enforcement and accident prevention across a variety of domains, with potential applications in industries other than construction. There are a number of ways to expand and improve the Helmet Detection System's capabilities as it develops. First, by integrating live video feeds, building sites might identify helmets in real time, instantly alerting safety inspectors when a worker is discovered not wearing one. To further guarantee worker safety, the system should be expanded to detect additional personal protective equipment (PPE), such as boots, gloves, and safety vests. A cloud-based storage function for pictures and forecasts might be added to the system, allowing safety managers to examine past data and monitor changes in helmet compliance over time. Furthermore, incorporating more sophisticated machine learning models and methods—like multi-task learning or transfer learning—could increase the speed and accuracy of detection.

VI. ACKNOWLEDGMENT

We express our sincere gratitude to all those who contributed to this study.For giving the resources and support needed for this study, we would like to thank Sreenivasa Institute of Technology and Management Studies-SITAMS. We are particularly grateful to Dr. D. Bright Anand, Dr. R. Karunia Krishnapriya, Mr. Pandreti Praveen, Mr. Manikandan, and Mr. Vijay Kumar for their invaluable guidance and expertise in the fields of embedded systems and deep learning. Their insights significantly raised the standard of our work.

REFERENCES

[1] M. S. Arshad, M. A. Khan, and S. U. Jan, “Smart Helmet for Hazard Detection and Worker Safety Monitoring using IoT,” International Journal of Computer Applications, vol. 182, no. 17, pp. 25–29, 2018.

[2] Sharma and R. K. Gupta, “Automatic Safety Helmet Wearing Detection,” International Journal of Computer Vision and Image Processing (IJCVIP), vol. 9, no. 1, pp. 60–76, 2019.

[3] J. Patel, R. Patel, and H. Shah, “PPE Compliance Monitoring Using YOLO Object Detection Algorithm,” International Journal of Innovative Research in Science, Engineering and Technology (IJIRSET), vol. 9, no. 6, pp. 5568–5574, 2020.

[4] N. Jain, M. K. Patel, and K. Shah, “Real-time Personal Protective Equipment (PPE) Detection using Deep Learning,” Proceedings of the International Conference on Intelligent Computing and Control Systems (ICICCS), 2021.

[5] M. T. Hasan, S. R. U. Ahmed, and M. S. Hossain, “A Smart Safety Helmet Using IoT and Sensor Technology for Worker Protection in Hazardous Areas,” IEEE International Conference on Robotics, Automation, Artificial Intelligence and Internet-of-Things (RAAIIoT), 2022.

[6] Ultralytics, “YOLOv8 - Real-Time Object Detection and Fine Tuning,” GitHub Repository, 2023. [Online]. Available: https://github.com/ultralytics/ultralytics

[7] Roboflow, “Roboflow Dataset and Annotation Tool,” 2023. [Online]. Available: https://roboflow.com

[8] H. S. Lee, Y. H. Park, and J. W. Jung, “Development of a Construction Worker Safety Monitoring System Using Wearable Smart Helmet and Sensors,” Automation in Construction, vol. 122, pp. 103–113, 2021.

[9] "Smart helmet with real-time accident detection and tracking," article by S. K. Sharma and R. Jindal, International Journal of Advanced Research in Computer Science and Software Engineering, vol. 5, no. 4, 2015, pp. 234–238.

[10] G. Z. A. Rajkumar and R. P. S. Nair, "Smart helmet system with fall detection and safety alerts using machine learning," Procedia Computer Science, vol. 132, pp. 243-248, 2018.

[11] P. G. Avasarala, R. S. R. Choudary, and D. S. Rajesh, "IoT-based smart helmet system for monitoring health and safety of workers," Procedia Computer Science, vol. 132, pp. 57-63, 2018.

[12] H. Patel, A. A. Patel, and R. S. Bhalala, "Design and implementation of smart helmet with health monitoring system," International Journal of Advanced Research in Electronics and Communication Engineering, vol. 5, no. 4, pp. 54-59, 2016.

[13] Z. Ye, C. Feng, and S. Jiang, “CIB-SE-YOLOv8: An Optimized YOLOv8 Model for Real-Time Safety Equipment Detection on Construction Sites,” arXiv preprint arXiv:2410.20699, 2024. [Online]. Available: https://arxiv.org/abs/2410.20699

[14] T. Wang, X. Liu, and J. Zhang, “Detection Method for Safety Helmet Wearing on Construction Sites Based on UAV Images and YOLOv8,” Buildings, vol. 15, no. 3, p. 354, 2024. [Online]. Available: https://www.mdpi.com/2075-5309/15/3/354

[15] P. R. Gokhale, P. Khandagale, and M. B. Potdar, “Real-Time Personal Protective Equipment Non-Compliance Recognition on AI Edge Cameras,” Electronics, vol. 13, no. 15, p. 2990, 2024. [Online]. Available: https://www.mdpi.com/2079-9292/13/15/2990

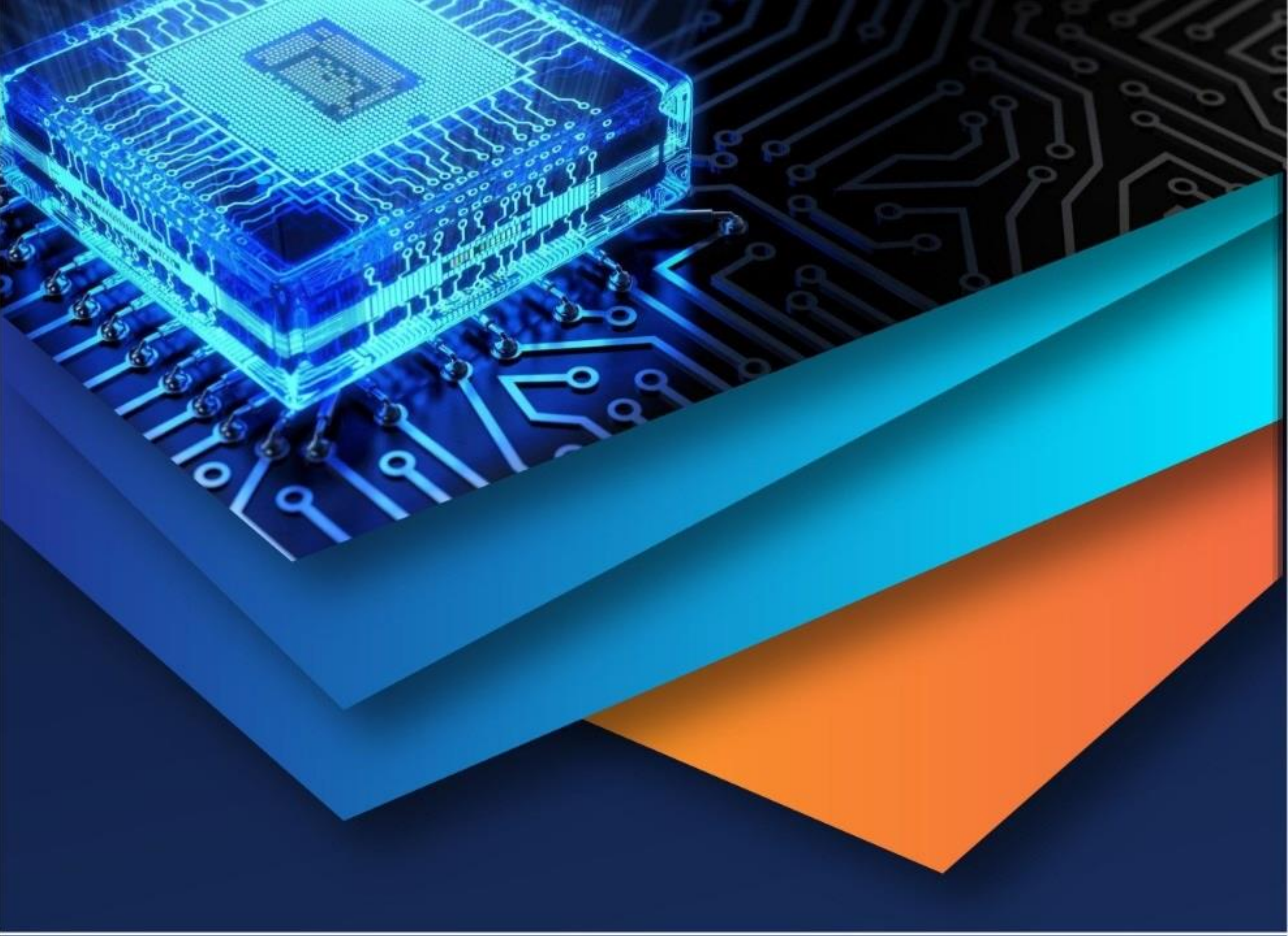
[16] B. Patel and M. Joshi, “Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach,” Sustainability, vol. 15, no. 18, p. 13990, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/18/13990

[17] X. Liu et al**.**, “CIB-SE-YOLOv8: An Optimized YOLOv8 Model for Real-Time Safety Equipment Detection on Construction Sites,” arXiv preprint arXiv:2410.20699, Oct. 2024. [Online]. Available: https://arxiv.org/abs/2410.20699

[18] T. Wang et al**.**, “Detection Method for Safety Helmet Wearing on Construction Sites Based on UAV Images and YOLOv8,” Buildings, vol. 15, no. 3, p. 354, 2024. [Online]. Available: https://www.mdpi.com/2075-5309/15/3/354

[19] P. R. Gokhale et al., “Real-Time Personal Protective Equipment Non-Compliance Recognition on AI Edge Cameras,” Electronics, vol. 13, no. 15, p. 2990, 2024. [Online]. Available: https://www.mdpi.com/2079-9292/13/15/2990

[20] B. Patel and M. Joshi, “Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach,” Sustainability, vol. 15, no. 18, p. 13990, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/18/13990



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY