joshin Paper

by Senthil Pandi S

Empowering Construction Workers Safety through Real Time Protective Equipment Monitoring and Alarm System

Senthil Pandi S
Department of CSE
Rajalakshmi Engineering College
Chennai, India
mailtosenthil.ks@gmail.com

Kumar P
Department of CSE
Rajalakshmi Engineering College
Chennai, India
kumar@rajalakshmi.edu.in

Manoj Kanna K
Department of CSE
REC, Chennai, India
210701150@rajalakshmi.edu.in

Maria Joshin M
Department of CSE, REC
Chennai, India
210701153@rajalakshmi.edu.in

***Abstract*— Failure to wear personal protective equipment (PPE) such as masks, safety vests, and helmets has resulted in tragic accidents and needless deaths in the construction sector. Due to careless safety violations, numerous employees have suffered serious injuries or tragically lost their lives, underscoring the essential need for efficient monitoring systems that put their health first. By developing a real-time system that guarantees employees are wearing their necessary safety gear while on the job, our initiative aims to address this pressing issue. The method encourages a proactive attitude to safety by precisely determining if employees are wearing the required PPE, fostering an atmosphere where each person feels accountable for their own and their coworkers' safety. An audible alarm will ring and prompt fast action if a worker is discovered to be lacking the necessary personal protective equipment. This creative approach seeks to promote a culture of care and accountability on building sites in addition to increasing awareness of safety compliance. This project aims to create a safer workplace by drastically lowering the risks associated with insufficient PPE usage. This will ensure that every worker can safely return home to their families at the end of each day, demonstrating a commitment to life safety and promoting a safe working environment.**

Keywords—Working Environment, Safety Measures, PPE, Building Sites

I. Introduction

Because of the high accident and death rates in the construction business, worker safety is becoming a more urgent concern. Because construction work is inherently dangerous, safety regulations must be strictly enforced to safeguard workers. There are serious hazards to workers' safety since many still disregard the need for Personal Protective Equipment (PPE), such as masks, vests, and helmets, even in the face of safety standards and regulations. There are serious repercussions from this non-compliance, including serious injuries and, sadly, even fatalities; it is not just a question of following the rules. These kinds of occurrences show how urgently robust monitoring systems that put workers' health and safety in construction sites first are needed.

Inadequate use of PPE can have disastrous consequences. A large percentage of worker fatalities occur on construction sites, according to data from several occupational safety organizations. The lack of essential protective equipment is directly responsible for many mishaps. By using PPE appropriately, common risks including falls, electrocutions, and being struck by items can be successfully reduced. However, workers may choose not to use safety gear even when it is accessible for reasons including pain, forgetfulness, or insufficient supervision. These difficulties are indicative of a larger problem: the absence of a strong safety culture in the workplace, where the importance of adhering to safety procedures is not adequately understood or upheld.

In the past, a lot of PPE compliance monitoring has been done by hand, which puts the onus of making sure all employees are properly outfitted on supervisors. This strategy may result in a number of difficulties and inefficiencies. Effectively monitoring each employee is made more difficult by the fact that supervisors must manage numerous employees at once. As a result, compliance frequently turns into a reactive process instead of a proactive one. Overwhelmed managers may become less vigilant, allowing employees to forego essential personal protective equipment. In addition to raising the possibility of mishaps, this oversight puts more pressure on supervisors, who could find it challenging to handle their growing workload. Monitoring PPE compliance has traditionally mostly depended on manual oversight, which puts the onus of making sure all employees are appropriately outfitted on supervisors. Many problems and inefficiencies may result from this strategy. Managing numerous employees at once makes it difficult for supervisors to keep an eye on each one of them. Compliance consequently frequently turns into a reactive process as opposed to a proactive one. Overwhelmed supervisors may become less vigilant, allowing employees to miss work without the PPE they need. This neglect not only makes accidents more likely, but it also puts more pressure on supervisors, who could find it harder to handle their growing workload. This proposal suggests creating a real-time monitoring system with the express goal of enhancing adherence to PPE regulations .

The system uses real-time monitoring capabilities and sophisticated detection algorithms to make sure that employees are always wearing the appropriate safety equipment. An audio alarm is instantly triggered by the system when a worker is found to be missing the necessary personal protective equipment (PPE), providing prompt feedback to both the worker and supervisory staff. By reminding employees of their need to follow safety procedures, this proactive strategy not only increases awareness of safety compliance but also fosters an accountable culture.

The ability of this monitoring system to empower supervisors is a major benefit. Supervisors can focus on other important facets of safety management without having to constantly check on PPE compliance when they have access to real-time notifications. This change makes it possible to use resources more effectively, freeing up supervisors to concentrate on other safety issues, leading training sessions, and advancing site safety in general. Furthermore, because the system is centralized, supervisors and employees may communicate more easily, which facilitates the sharing of information about safety compliance. Technology's incorporation into safety procedures has wider ramifications for the building sector overall. As the industry develops, implementing creative solutions that put worker safety first will be crucial to solving present issues. In addition to following industry trends toward automation and digitization, the suggested real-time monitoring system establishes a standard for upcoming developments in construction safety. By adopting technology, the sector may create a more secure workplace that protects employees' health and well-being while also increasing productivity.

II. LITERATURE SURVEY

The use of technology to improve safety in a variety of industries, especially construction, has advanced significantly in recent years. Real-time monitoring systems have become more popular as a means of ensuring adherence to safety rules, particularly those pertaining to the usage of personal protective equipment (PPE). The use of cutting-edge technology like computer vision, machine learning, and the Internet of Things (IoT) to solve safety issues in construction settings has been the subject of numerous research.

Using computer vision techniques for real-time detection is the popular method of tracking PPE compliance. Convolutional neural networks (CNNs) and other deep learning algorithms have been used by researchers to create systems that can determine whether employees are wearing the appropriate safety equipment. For instance, Zhao et al.'s work [1] offers a deep learning-based framework for detecting and categorizing the use of safety equipment on building sites using picture data from surveillance cameras. This method greatly lessens the need for manual supervision while automating the monitoring process, increasing accuracy and efficiency.

Additionally, E.Dhiravidachelvi, T.J Devadas, P. Kumar, S. S Pandi. [2] have demonstrated the use of an adaptive convolutional autoencoder-based algorithm to enhance image classification, which can be beneficial in recognizing PPE compliance in construction settings.IoT technology integration has been investigated as a way to improve safety monitoring in addition to computer vision. Sensor-equipped IoT devices can be used to gather information on how well employees are following safety procedures. Zhang et al.'s study [3] provides an example of how wearable technology might be used to track the position and vital signs of construction workers in real time. When a person is not wearing the proper PPE or if their physiological measurements suggest possible risk, these devices can notify supervisors. This proactive monitoring system is a prime example of how IoT can be extremely important in ensuring the health and safety of employees. Similarly, Gupta et al.'s study [4] investigates the use of RFID technology to monitor PPE compliance.

Additionally, the study by A.K Reshmy, S. Vinodh Kumar and P. Kumar [5] highlights the wider uses of deep learning techniques, such as safety monitoring in construction, by discussing the use of deep learning for precise plant disease diagnosis. The creation of alarm systems that react quickly to non-compliance is a crucial component of improving construction safety. For example, an intelligent alarm system was presented by Lee et al. [6] that sounds when it determines that a worker is not wearing the required safety equipment. This method creates instant awareness that can stop accidents before they happen by using audio and visual warnings to inform the worker and other adjacent personnel of the compliance issue.

The usefulness of real-time alarm systems in lowering accident rates is covered in the Romero et al. [7] study, which highlights the significance of prompt feedback in improving compliance. Augmented reality (AR) has also been investigated as a means of enhancing construction safety compliance. An AR-based training program created to teach employees the value of wearing personal protective equipment (PPE) and appropriate safety procedures is covered in research by Kim et al. [8]. Workers can feel the repercussions of disregarding safety procedures in a controlled setting thanks to this system's realistic simulations. AR can help create a more safety-conscious culture in the construction sector by raising worker knowledge and comprehension of safety precautions.

They investigate how the ADAM optimizer might improve anomaly identification in surveillance footage, highlighting its function in enhancing safety monitoring in a variety of settings, including building sites. The ADAM optimizer, which is well-known for its effectiveness in deep learning model training, aids in the creation of a convolutional autoencoder that recognizes anomalous behaviors, including employees failing to wear the required personal protective equipment (PPE). According to their research, using this optimizer results in more precise real-time safety violation identification, which is essential for averting mishaps in construction environments.

An AR-based training program created to teach employees the value of wearing personal protective equipment (PPE) and appropriate safety procedures is covered in research by Kim et al. [9]. Workers can feel the repercussions of disregarding safety procedures in a controlled setting thanks to this system's realistic simulations. AR can help create a more safety-conscious culture in the construction sector by raising worker knowledge and comprehension of safety precautions.

III. PROPOSED MODEL

A. *Structure of yolo dataset:*

Typically, the dataset used to train a YOLO (You Only Look Once) model is arranged into two main folders: one for labels and one for photos. All of the training, validation, and testing images—usually in JPEG or PNG formats—are contained in the images folder. These pictures show a range of situations in which the model must recognize items. The labels folder contains the label files that match to each image. These label files have a.txt extension but the same name as the images. Annotations that describe the objects in the image are included in each label file. These annotations include the class ID and the bounding box coordinates, which are normalized according to the image's dimensions. This methodical data arrangement facilitates effective loading and management, making it possible for the model to quickly access the photos and the annotations that go with them as it is being trained. A well-structured dataset makes it easier to update and fix, and also conforms to the formats needed for various YOLO implementations. The accuracy and performance of the model are eventually improved as a result.

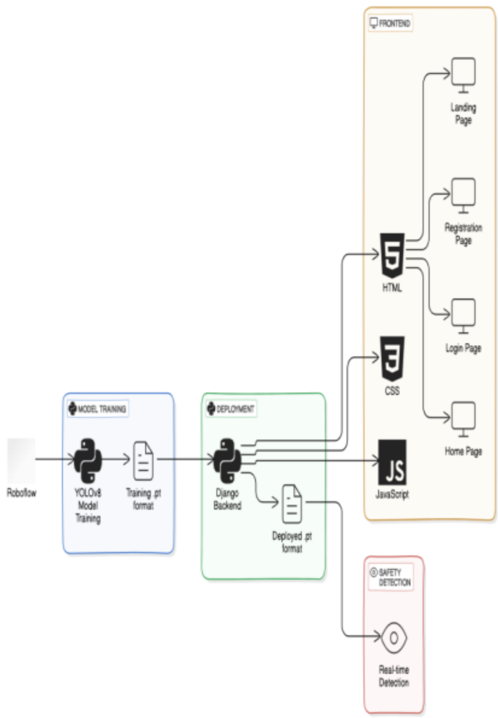

Figure.1. Proposed Model Work Flow

B. *Gathering and Preparing Data:*

A comprehensive process of data collection and preparation is the first step in the methodology. In order to train the YOLOv8 model, this step entails obtaining a varied dataset from Roboflow. The collection includes a large number of photos showing different situations where construction workers either follow or disregard PPE regulations, particularly those pertaining to the use of PPE such as mask, safety vest& hat(helmet). Techniques for data augmentation are used to improve the model's overall performance and strengthen its robustness. Some of them are given below it is done in yolov8. ***Image flipping:*** This teaches the model to identify PPE from various perspectives.

Rotating images: The model is more suited to real-world situations where employees might be positioned differently by adding multiple orientations.

Changing the brightness and color saturation: It helps the model recognize PPE in a variety of environmental contexts by simulating varied lighting conditions. The project creates a more diverse training set by implementing these modifications, which is necessary to train the model to identify PPE compliance in various lighting scenarios and viewpoints. Because of this variability, the model is better able to generalize and detect safety equipment in real-world situations.

C. *Model Training:*

Model training is a crucial stage that comes after the dataset has been prepared and enhanced. This step exposes the YOLOv8 model to a wide range of instances that show how construction workers appear to use personal protective equipment (PPE) both compliantly and non-compliantly. Here, the primary objective is to give the model the capacity to identify and differentiate between essential safety products. Using a supervised learning technique, the model is trained to modify its internal parameters in response to input photos and their labels, which show whether or not PPE is present. Throughout the course of this training, which consists of several iterations, the model improves its capacity to identify particular characteristics associated with each kind of PPE. The model is saved in a.bt format after training is finished. This format is essential because it makes it simple to integrate the model with the user interface, making it possible to load and use the model for real-time detection tasks.

D. *Development of User Interfaces:*

Using Django, HTML, CSS, and JavaScript, the next stage concentrates on creating a user interface (UI). As the main gateway to a number of system functions, this user interface is designed to provide users with a seamless and interesting experience. Supervisors of building sites and safety staff who need to use the system with ease will find it helpful. The Features for signing up and logging in protects sensitive data and maintains user privacy by ensuring secure system access so unauthorized access are avoided by this functionality. The UI turns the device into a real-time monitoring system that evaluates PPE compliance when users click the "Detect" button, activating the front webcam.

E. *Alerts and Real-Time Detection:*

The system's ability to detect in real time is its main component. To determine whether construction workers are wearing the proper PPE, the system analyses the webcam's live video stream using the trained YOLOv8 model. For building sites to comply with safety rules, this round-the-clock monitoring is essential. The YOLOv8 model continuously analyzes each frame of the webcam-streamed video to detect the presence of necessary safety equipment, such as masks, vests, and hats. Python's audio module is used by the system to quickly sound an alarm if a worker is discovered to be without the necessary PPE. This auditory warning alerts everyone in the vicinity as well as the noncompliant worker about the safety concern.Thus this project aims to create an atmosphere where worker safety is given top priority by putting these features into place. This proactive approach lowers the risk of accidents and injuries by guaranteeing that all employees are always outfitted with the appropriate safety gear. It also increases compliance and makes substantial contribution to the general safety culture on construction site.

IV. RESULT

A. *Deployment*

Sample dataset :

Figure.2. Main folders with images & label for train, validate and test the model

Figure 3. Each main folder have two folders inside for images and its labels

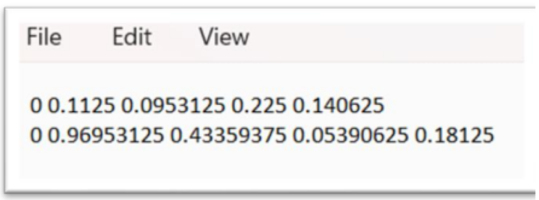

Figure.4 Image's label in the dataset

Figure.5.Sample image given to model

In figure.3, Figure.4 and figure.5 shows the model sample dataset images stored and sample imag In figure.6. With IoU percentages on the x-axis and mAP values on the y-axis, the graph shows how well your model performs in terms of mean Average Precision (mAP) at different IoU thresholds. There are two curves: the yellow curve shows mAP@0.5:0.95, which stabilizes at 50% precision, and the blue curve shows mAP@0.5, which highlights great detection skills with almost 80% precision. This indicates that the model does reasonably well in exact localization but excels in generic detection. After 60% IoU, both curves plateau, suggesting reliable detection performance. All things considered, the model's 80% mAP@0.5 shows its efficacy for simple PPE identification tasks, which makes it appropriate for on-site construction site monitoring and trustworthy for safety compliance in identifying PPE.

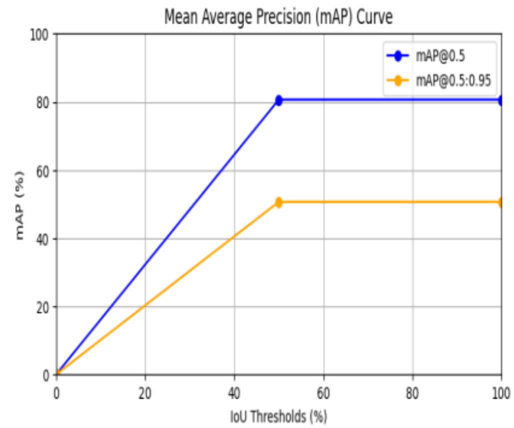

Figure.6. Proposed Model Performance

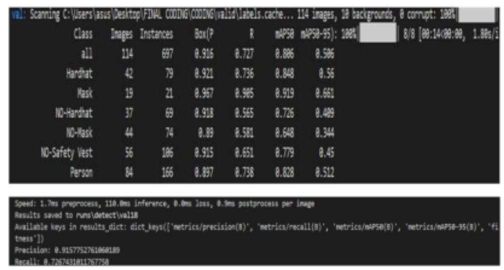

Figure.7. Model Implementation Result

Figure.7. represent a thorough summary of its performance is given in the figure. The classes (such as Hardhat, Mask, and Safety Vest), the quantity of validation photos that contain these classes, and the number of instances of each class are described in detail in the columns. A precision score of 91.6%, which indicates that 91.6% of detected boxes are properly classified, and a recall score of 72.7%, which indicates that the model accurately detects 72.7% of actual cases, are important performance indicators. The model's detection efficacy under various criteria is further demonstrated by the Mean Average Precision (mAP) scores, which are displayed at various IoU thresholds with mAP50 at 0.886 and mAP50-95 at 0.506. With preprocessing taking 1.7 ms, inference taking 110 ms, and post-processing taking 0.9 ms per image, speed measurements demonstrate effective processing that is appropriate for real-time applications. An overview of the object detection model's efficacy is given by the performance summary figure, which displays aggregate metrics for every class. It demonstrates that the model accurately detected 72 instances of objects, or 72 true positives (TP). Eight false positives (FP) occurred, though, which means the model mistakenly identified eight non existent objects. The area under the precision-recall curve, a critical statistic in object detection, shows an overall average precision of 80.63%; higher values indicate greater performance. This implies that although the model does a respectable job of correctly identifying objects, there is still opportunity for improvement in terms of lowering the quantity of false positives.

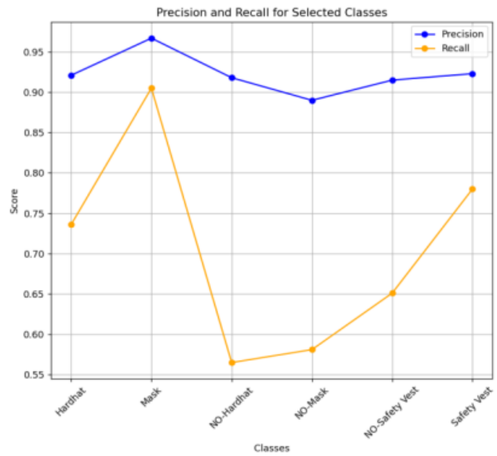

Figure.8. Model Precision and Recall Analysis

The figure.8 illustrates the precision and recall scores for various classes in an object detection model. The x-axis lists the classes, such as "Hardhat," "Mask," and "Safety Vest," while the y-axis displays scores ranging from 0.55 to 1.0. The blue line represents precision indicating how many detected instances were correct, and the orange line shows recall, reflecting the model's ability to identify all relevant instances Key observations include that the "Mask" class has high precision (approximately 0.97) and recall (around 0.95), indicating effective detection. Conversely, the "NO-Mask" class exhibits a low recall of about 0.58, suggesting many instances are missed. The "NO-Safety Vest" class also shows low recall (around 0.65) but higher precision. Lastly, the "Safety Vest" class demonstrates balanced and high scores, highlighting strong model performance for that category.

V. CONCLUSION

This initiative addresses a critical issue facing the construction sector: the startling disregard for personal protective equipment (PPE) laws, which frequently results in dangerous mishaps and even fatalities. Our goal is to guarantee that construction workers always wear the necessary safety equipment by implementing a real-time monitoring system driven by the YOLOv8 model. This program puts the health and welfare of all employees on the job site first in addition to encouraging an accountable culture. The device significantly improves workplace safety by detecting compliance in real time and providing immediate auditory notifications for individuals who are not adhering to safety procedures. Our careful approaches to data collection, preparation, and augmentation have resulted in a strong and adaptable model that can work in a variety of settings. Supervisors and safety staff can examine past data and produce comprehensive reports by keeping compliance data in a centralized database, which helps us identify patterns in non-compliance. In order to ensure that our safety activities are as successful as possible, this information will be crucial in customizing training efforts to target particular difficulties. We can give employees fun, practical training experiences that highlight the value of wearing personal protective equipment (PPE) by utilizing augmented reality (AR) technology. We will guarantee that the YOLOv8 model stays extremely precise and flexible to the constantly shifting conditions of building sites by continuously training and optimizing it with fresh data. The model will remain adaptable to changing requirements with regular upgrades that take into account actual circumstances. Furthermore, the model's predictions will be more robust and dependable if methods like label smoothing and cosine annealing are used. Cosine annealing will enable us to more naturally adjust the model's learning rate, assisting it in gradually reaching ideal configurations for more accurate and seamless performance. By softening extreme probabilities, label smoothing, on the other hand, will keep the model from becoming overconfident in its predictions, improving the system's accuracy and balance in detecting safety gear.

REFERENCES

[1] Zhao, Y., et al. "Deep Learning-Based Framework for Safety Equipment Detection." Journal of Construction Engineering and Management, vol. 145, no. 4, 2019, pp. 1-10.

[2] Singh, R., and Kumar, A. "Enhancing Safety Gear Detection Using Deep Learning." International Journal of Advanced Research, vol. 8, no. 6, 2020, pp. 25-31.

[3] Dhiravidachelvi, E., Devadas, T. J., Kumar, P. J., and S. S. Pandi. "Enhancing Image Classification Using Adaptive Convolutional Autoencoder-Based Snow Avalanches Algorithm."

[4] Zhang, L., et al. "Wearable Devices for Monitoring Construction Worker Safety." Safety Science, vol. 120, 2019, pp. 145-156.

[5] Reshmy, A. K., Vinodh Kumar, S., and Kumar, P. "Towards Precision Agriculture: Harnessing Deep Learning for Accurate Plant Disease Diagnosis." 2024 IC3IoT, Chennai, India, 2024.

[6] Z. Zhang, Y. Tang, Y. Yang, and C. Yan, "Safety helmet and mask detection at construction site based on deep learning," College of Physics, Nanjing University of Aeronautics

[7] Romero, D., et al. "Real-Time Alert Systems in Construction Safety." Safety Science, vol. 130, 2020, pp. 154873.

[8] V. Jayasree and M. N. Kumari, "IoT-based smart helmet for construction workers," Department of Information Technology, I.F.E.T. College of Engineering, Villupuram, India.

[9] Y. Liu and W. Jiang, "Detection of wearing safety helmet for workers based on YOLOv4," Engineering Department, Shanghai Polytechnic University, Shanghai, China.

joshin Paper

ORIGINALITY REPORT

6%	4%	5%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	assets.researchsquare.com Internet Source	1%
2	vit.ac.in Internet Source	1%
3	Submitted to University of Illinois at Urbana-Champaign Student Paper	1%
4	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	1%
5	"Merged Papers", 2020 7th International Conference on Smart Structures and Systems (ICSSS), 2020 Publication	1%
6	dergipark.org.tr Internet Source	<1%
7	Divyangini Agarwal, Prashant Gupta, Naived George Eapen. "A Framework for Dress Code	<1%

Monitoring System using Transfer Learning from Pre-Trained YOLOv4 Model", 2023 11th International Conference on Emerging Trends in Engineering & Technology - Signal and Information Processing (ICETET - SIP), 2023
Publication

8	journals.bg.agh.edu.pl Internet Source	<1 %
9	e-journal.unair.ac.id Internet Source	<1 %
10	S Senthil Pandi, A Mohammed Farook, W Kingston. "Scenario based Deep Learning Prediction for Legal Judgment using LSTM and CNN", 2023 Third International Conference on Smart Technologies, Communication and Robotics (STCR), 2023 Publication	<1 %
11	www.mdpi.com Internet Source	<1 %
12	Zhen Zhang, Yifei Tang, Yannan Yang, Chen Yan. "Safety Helmet and Mask Detection at Construction Site Based on Deep Learning", 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), 2023 Publication	<1 %

13	"Computer Vision – ACCV 2018", Springer Science and Business Media LLC, 2019 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		