

PAPER

Real-Time Prediction and Prevention of Worker Accidents and Safety Hazards on Construction Sites Using Mobile Machine Learning Framework

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ABSTRACT

Construction sites are dynamic, complicated situations where maintaining safety is both important and difficult. Due to their reliance on labor-intensive and error-prone manual monitoring and intervention, traditional safety measures frequently fail. Furthermore, complicated indoor conditions are common on construction sites, making it difficult to precisely track the locations of workers and equipment. To overcome these issues, this study proposes a real-time prediction and prevention of worker accidents and safety hazards on construction sites using a mobile machine learning framework (RWASHCS-MMLF). On construction sites, mobile technology is utilized to gather real-time data from sensors, cameras, and wearable technology, allowing machine learning models to instantaneously forecast possible worker accidents and safety risks. In order to capture activity, the RWASHCS-MMLF model first collects data from the mobile sensors. The data from the sensors is then cleaned and filtered using data preprocessing. After that, temporal and spatial characteristics are extracted, including movement patterns, speed, position, and proximity to hazards. Mobile data is then incorporated into a trained machine learning model to instantaneously predict possible mishaps or dangerous occurrences. Lastly, the alert and decision system suggests preventive measures and allows push notifications or alarms on mobile devices for site supervisors' visual dashboards. The efficiency of the RWASHCS-MMLF strategy in enhancing the usage of construction safety management systems and lowering the likelihood of future accidents and fatalities is demonstrated by the extensive on-site trials that validate the proposed RWASHCS-MMLF model. The result is a system with improved responsiveness and speed, which is essential for time-sensitive applications like worker safety prediction.

KEYWORDS

construction sites, machine learning, safety, YOLOv8, histogram of oriented gradients

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1 INTRODUCTION

One of the most dangerous sectors in the world is construction, and workers are constantly exposed to complicated and hazardous work conditions, which increases their risk of diseases, injuries, and fatalities [1]. Despite attempts by industry associations, regulatory agencies, and substantial research to resolve these issues, it has remained a significant concern. One in five worker deaths in a year, or around 20% (1061) of worker fatalities in private business [2], were related to construction, according to the Occupational Safety and Health Administration (OSHA). The construction business has 30% more nonfatal occupational diseases and injuries than the average industry, according to data from the U.S Bureau of Labor Statistics [3]. This extension study examines an integrated use of state-of-the-art sensing technology and data processing methods to address the critical requirement to reduce both nonfatal and fatal injuries. Over 90% of accidents on construction sites are thought to be caused by unsafe behavior and environment, according to multiple studies. Therefore, it has been acknowledged that a proactive and active approach to reducing or eliminating safety and health hazards and averting accidents on construction sites is the continuous monitoring of workers' risky actions and situations [4]. Conventional techniques for tracking and evaluating activities on building sites, like site inspection and observations [5], are costly, time-consuming, labor-intensive, and prone to erroneous data because of human error. Therefore, a different strategy is required, such as using cutting-edge tools and methods such as Machine Learning. This approach uses a comprehensive set of data gathered from images and videos showing work environments and employees' actions to identify and assess hazardous behaviors and circumstances. Personal protective equipment (PPE) that incorporates mobile monitoring devices allows for real-time risk monitoring and real-time guidance to affect worker behavior. Although they cannot avoid fall hazards in advance, personal fall arrest systems (PFASs) are the last line of defense against hazards because they protect employees from harm. It has been determined that using job site images to analyze construction workers' whereabouts and behaviors can produce useful data for productivity analysis and safety management [6].

Monitoring systems primarily employ artificial intelligence (AI) through supervised learning in order to identify different object classes. Even while there are presently a number of deliberate attempts to automate construction site monitoring, it is still difficult to fully comprehend how the system will operate. Deep learning (DL), also known as deep structured learning or hierarchical learning, has made it more feasible to automate visual monitoring activities. More precisely, it has been discovered that YOLOv8, a class of deep learning networks, is highly effective at processing visual images and overcoming the difficulties associated with manually seeing and documenting risks on building sites [7].

To overcome these issues, this study proposes a real-time prediction and prevention of worker accidents and safety hazards on construction sites using a mobile machine learning framework (RWASHCS-MMLF). On construction sites, mobile technology is utilized to gather real-time data from sensors, cameras, and wearable technology, allowing machine learning models to instantaneously forecast possible worker accidents and safety risks. In order to capture activity, the RWASHCS-MMLF model first collects data from the mobile sensors. The data from the sensors is then cleaned and filtered using data preprocessing. After that, temporal and spatial characteristics are extracted, including movement patterns, speed, position, and proximity to hazards. Mobile data is then incorporated into a trained machine learning model to instantaneously predict possible mishaps or dangerous occurrences. Lastly, the alert and decision system suggests preventive measures and allows push notifications or alarms on mobile devices

for site supervisors' visual dashboards. The efficiency of the RWASHCS-MMLF strategy in enhancing the use of the construction safety management system and lowering the likelihood of future accidents and fatalities is demonstrated by the extensive on-site trials that validate the proposed RWASHCS-MMLF model.

2 RELATED WORKS

Moe et al. [8] introduce a new method for predicting worker safety that uses FL in outdoor construction settings while protecting sensitive data confidentiality and privacy.

In order to collect extremely detailed spatial and temporal weather, building, and worker data, our method entails deploying sensor-based IoT devices at construction sites. The DNN models on the edge nodes are then jointly trained using this data in a cross-silo fashion. We set up a testbed with the EdgeX framework and limited devices, such as Raspberry Pi 4Bs, serving as edge nodes in order to implement our strategy. In order to ensure data privacy and optimum network resource usage, the resulting global model is installed on participating nodes for edge inference after the collaborative training. The outcomes of the experiment show how effective the presented model is in increasing the use of construction safety management systems and lowering the possibility of future mishaps and fatalities.

Abdollahpour et al. [9] offers a real-time safety alerting system that is proof-of-concept for situations where safety is crucial, including building sites. A customized Android application utilizing the Framework for Internal Navigation and Discovery (FIND) is integrated with Bluetooth Low Energy (BLE) devices for indoor localization. A server-side component handles data management and administrative control, with the help of an interactive website for real-time safety monitoring. The proposed model uses ML methods, such as k-NN, random forest, and SVM, to analyze localization data and provide safety zoning. A 97% localization accuracy, a 1.2-second response time, and a maximum spatial error of 1.2 meters are demonstrated via experimental validation in a lab setting. These outcomes demonstrate the system's dependability and capacity to improve safety compliance in practical deployment situations.

Hossain et al. [10] examine how cutting-edge technologies, such as wearable safety gadgets, unmanned aerial vehicles (drones), augmented reality (AR), virtual reality (VR), AI, and the Internet of Things (IoT), can be used to greatly improve safety results on building sites. IoT-enabled sensors provide real-time data for early hazard detection by continually monitoring environmental factors such as temperature, noise, air quality, and structure integrity. In order to automate responses, identify patterns, and forecast hazards before mishaps happen, AI systems further examine this data. Immersion training experiences and on-site hazard visualization made possible by VR and AR enable employees to identify and react to hazardous situations more accurately and preparedly. Drones provide aerial surveillance capabilities that enable safe examination of dangerous or difficult-to-reach locations. Real-time alerts and safety actions are made possible by wearable devices like smart helmets, vests, and biometric monitors that track workers' movements, vital signs, and proximity to danger areas. By replacing manual and disjointed safety procedures with integrated, data-driven, and responsive systems, these technologies collectively constitute a revolutionary approach to construction site safety. In addition to lowering the possibility of human error, the integration of these instruments improves situational awareness and compliance with safety rules. This project is expected to result in a significant decrease in the rates of injuries and fatalities, as well as the creation of stronger and more proactive safety procedures that are adapted to the changing conditions of

construction sites. The construction sector may move toward a safer, more effective, and evolutionary operational model by implementing smart technologies.

3 PROPOSED METHODOLOGY

In this work, the study proposes an RWASHCS-MMLF technique. On construction sites, mobile technology is utilized to gather real-time data from sensors, cameras, and wearable technology, allowing machine learning models to instantaneously forecast possible worker accidents and safety risks. In order to capture activity, the RWASHCS-MMLF model first collects data from the mobile sensors. The data from the sensors is then cleaned and filtered using data preprocessing. After that, temporal and spatial characteristics are extracted, including movement patterns, speed, position, and proximity to hazards. Mobile data is then incorporated into a trained machine learning model to instantaneously predict possible mishaps or dangerous occurrences. Lastly, the alert and decision system suggests preventive measures and allows push notifications or alarms on mobile devices for site supervisors' visual dashboards.

3.1 Data collection

In order to train and validate the model, this RWASHCS-MMLF model uses image classification for multi-class processing. The dataset is divided into many classifications, such as workers, vests, trucks, cranes, machinery, and fall position patterns, to provide an extensive collection of photos from construction sites. We gathered images from the Kaggle data sources to produce a solid and representative dataset. The dataset improves worker recognition in construction settings by offering a variety of human poses. Images of construction equipment, including excavators, cranes, dump trucks, and concrete mixer trucks, are tagged in the ACID dataset (Architectural Construction Image Dataset). To make sure the dataset appropriately depicts actual conditions, our research team took pictures from building sites that are currently under construction. These image data improve model flexibility by taking into consideration fluctuations in background complexity, lighting, and weather. To increase the accuracy of object detection, distinct object classes were allocated to each category of images as illustrated in Figure 1.

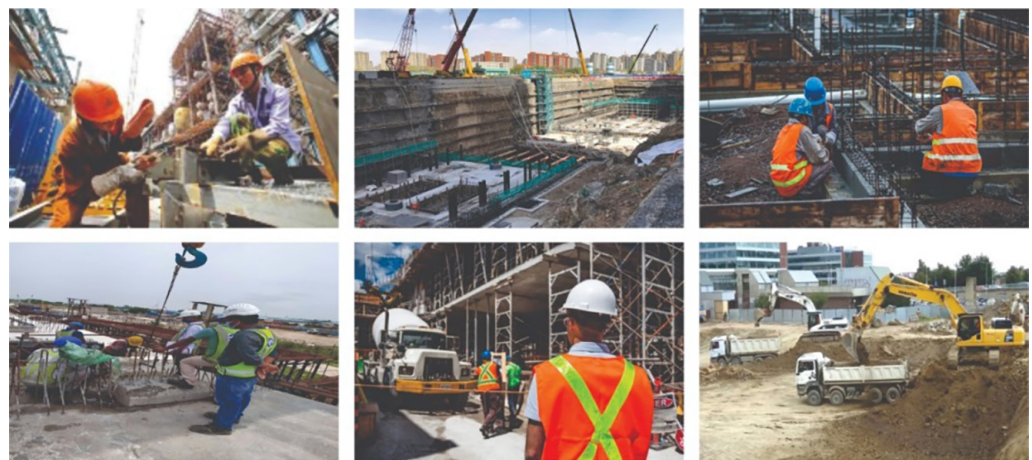


Fig. 1. Sample image dataset of construction sites

3.2 Data pre-processing

In real-world settings like construction sites, where picture data may be missing, noisy, or impacted by changing weather and lighting conditions, Min-Max Normalization is an essential step in data analysis and machine learning [11]. In order to enhance model performance and guarantee successful integration into object recognition and classification tasks, this procedure focuses on cleaning and modifying raw data. Min-Max Normalization is applied to the recorded frames to minimize illumination and scale fluctuation while maintaining computation efficiency for mobile devices. To maintain the relative relationships between feature values, the data is scaled to a particular range (such as [0,1]).

$$\chi^f = \frac{x - \min(\max_n - \min_n)}{\max - \min} + \min_n \tag{1}$$

In this case, x and x' represents the initial and the normalized value, and min and max represent the feature's minimum and maximum values, correspondingly. In ML and data analysis, $min - max$ data normalization is a technique used to equalize the weight of various attributes and make them have the same impact on the decision-making process. Figure 2 shows the overall working strategy of the RWASHCS-MMLF technique.

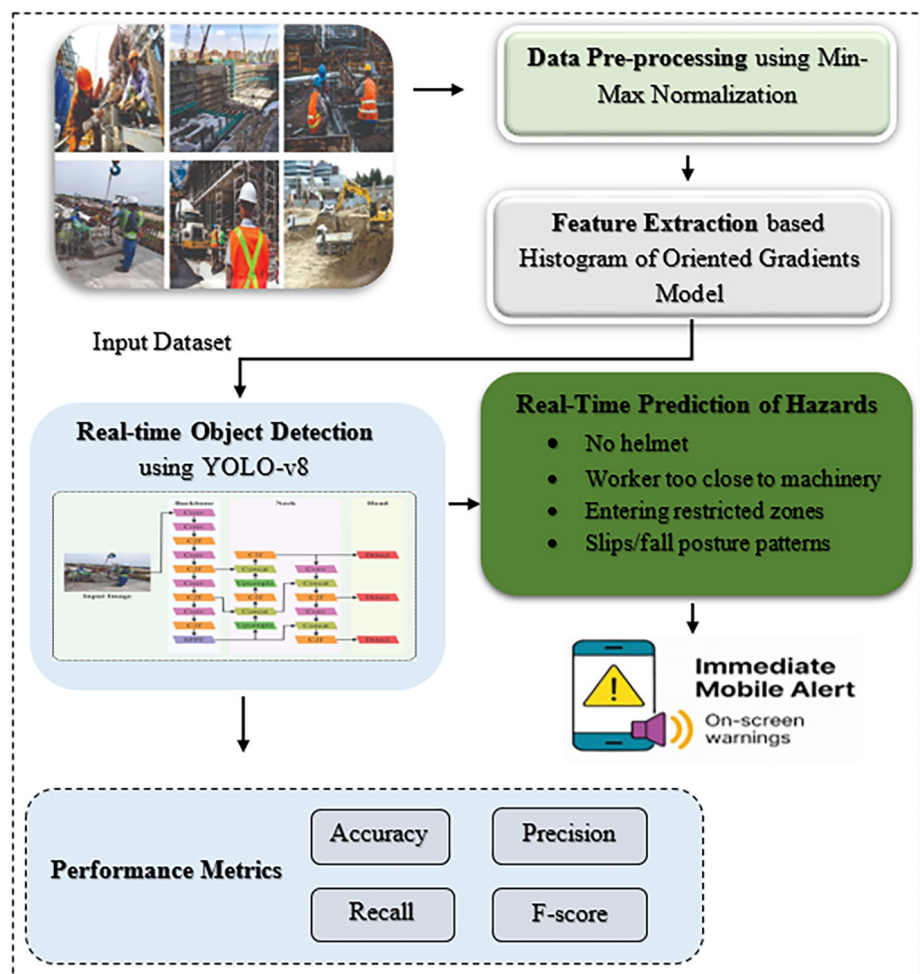


Fig. 2. Overall working strategy of the RWASHCS-MMLF technique

3.3 Histogram of oriented gradients (HOG)

Histogram of Oriented Gradients (HOG) or a similar mobile-friendly feature extractor is used by the mobile ML model to extract features from each frame [12]. To extract an image's pseudo-annotations, we employ HOGs. Prior to the development of data-driven feature extraction techniques such as UNet, Alexnet, and ResNet, it was established that HOGs were among the most potent handcrafted features in image analysis, particularly for detection. In this work, we employ HOGs for a novel purpose—that is, to extract the images' pseudo-labels. The first step in calculating HOGs from an image is to crop and resize it to the required width (W) and height (H). In order to determine the total number of discrete of $\lfloor W/w \rfloor \times \lfloor H/h \rfloor$, we further split the images into non-overlapping image patches of width w and height h . We then run 1D discrete derivative masks centered on a pixel in both the horizontal and vertical directions. The horizontal and vertical filtering kernels are $d_x = [1, 0, -1]$ and $d_y = [1, 0, -1]^T$ respectively. Every pixel in each image patch is subjected to these filters. We compute the gradient histogram for each patch and append them together after applying the kernels centered on each pixel. Gradients are assigned a glee nearest bin after being calculated as $\arctan\left(\frac{d_y}{d_x}\right)$. There can be k bins in the histogram, each having an angle between 0 and 180 degrees. The gradient's magnitude is calculated as $\sqrt{d_x^2 + d_y^2}$. The frequency of a bin of the gradient under examination is encoded by the gradient's magnitude. We estimate each patch's oriented gradient histogram in this way. The dimensions of the HOGs are determined by the number of bins and patches, which are the hyperparameters in our investigation. The final representation of HOGs is the image's pseudo-label, y^{pl} , after we concatenate the HOGs for each patch. On the training set, we enhance the pseudo-label. In order to train the semantic segmentation network in a multitask configuration, the training set with augmented pseudo-labels becomes $\{(x_j, y_j, f_i^l)\}_{i=1}^{i=N}$.

3.4 YOLOv8 object detection

Because of its exceptional speed and accuracy, YOLOv8, the most recent iteration of the YOLO (You Only Look Once) series of object identification algorithms, has emerged as a prominent model in the field [13]. With an emphasis on its effectiveness in identifying “worker, workers, vests, trucks, cranes, machinery, and fall position patterns and helmet” targets, this RWASHCS-MMLF model presents the selection of YOLOv8 models, dataset preparation, model training, and experimental analysis outcomes. The structure of the YOLOv8 model is demonstrated in Figure 3.

This study shows YOLOv8's efficacy and dependability in construction site safety management by using it in challenging UAV aerial settings. In contrast to the traditional detection model, YOLO uses a unique framework that uses a unified neural network to recast the detection issue as a regression problem. The proposed model accomplishes quick target detection by predicting the target bounding boxes and splitting the image into multiple grid cells. Its backbone network incorporates the CSP concept to improve feature extraction efficiency and is composed of C2f and SPPF modules. To provide better gradient propagation at the network's neck, YOLOv8 replaces the C3 component in YOLOv5 with the C2f module and incorporates the

ELAN structure from YOLOv7. In addition to improving the convolutional neural network’s feature fusion performance, the C2f structure speeds up inference and further simplifies the model. By using the popular decoupled head structure, YOLOv8 significantly outperforms YOLOv5 in the head region. To improve the model’s performance and adaptability, this method divides the classification and detection heads. One of the fundamental components of the network, the Bottleneck component in YOLOv8 concentrates on extracting and improving characteristics. The initial convolutional module minimizes the count c_1 of input channel to an intermediate channel count c , typically a portion of the output channel count c_2 .

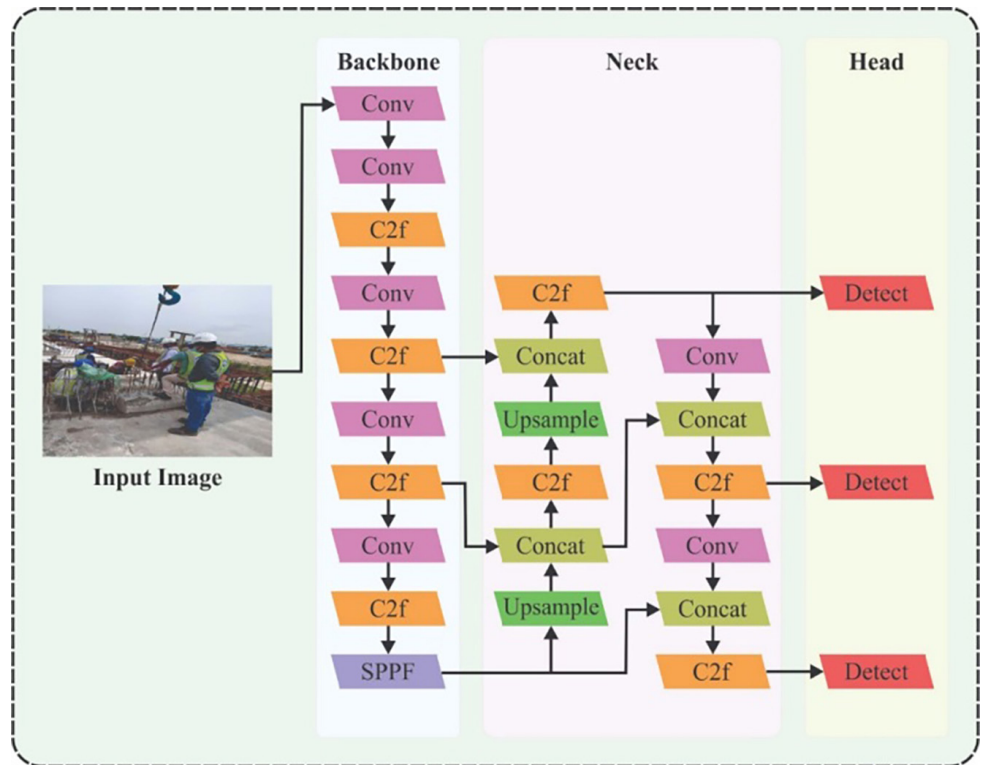


Fig. 3. Structure of YOLOv8 model

The subsequent convolutional module, which may use group convolution techniques to improve efficiency, then expands the intermediate channel count c to the output channel count c_2 . The module will enable residual concatenation when the configuration parameter shortcut is set to true and the input channel count (c_1) equals the output channel count (c_2). In order to improve the network’s information flow and learning capacity, the input features will be directly superimposed on top of the output characteristics, forming a jump connection. The Bottleneck module is primarily used to reduce the number of parameters in the network. This improves the efficiency of feature extraction while accelerating both training and inference. In this manner, the Bottleneck module maintains network performance while achieving a lightweight model. A mobile-optimized detection model, such as YOLOv8-Nano or YOLOv8-Mobile, receives the processed frame and uses it to identify workers, machinery, safety gear (helmets, vests), and hazard zones [14]. The algorithm forecasts hazardous situations such as not wearing a helmet, workers being too close to machinery, entering restricted areas, and slips and falls, and an instant mobile warning to the smartphone app provides audio, vibration, and on-screen alerts. The detected outcome of YOLOv8 is shown in Figure 4.

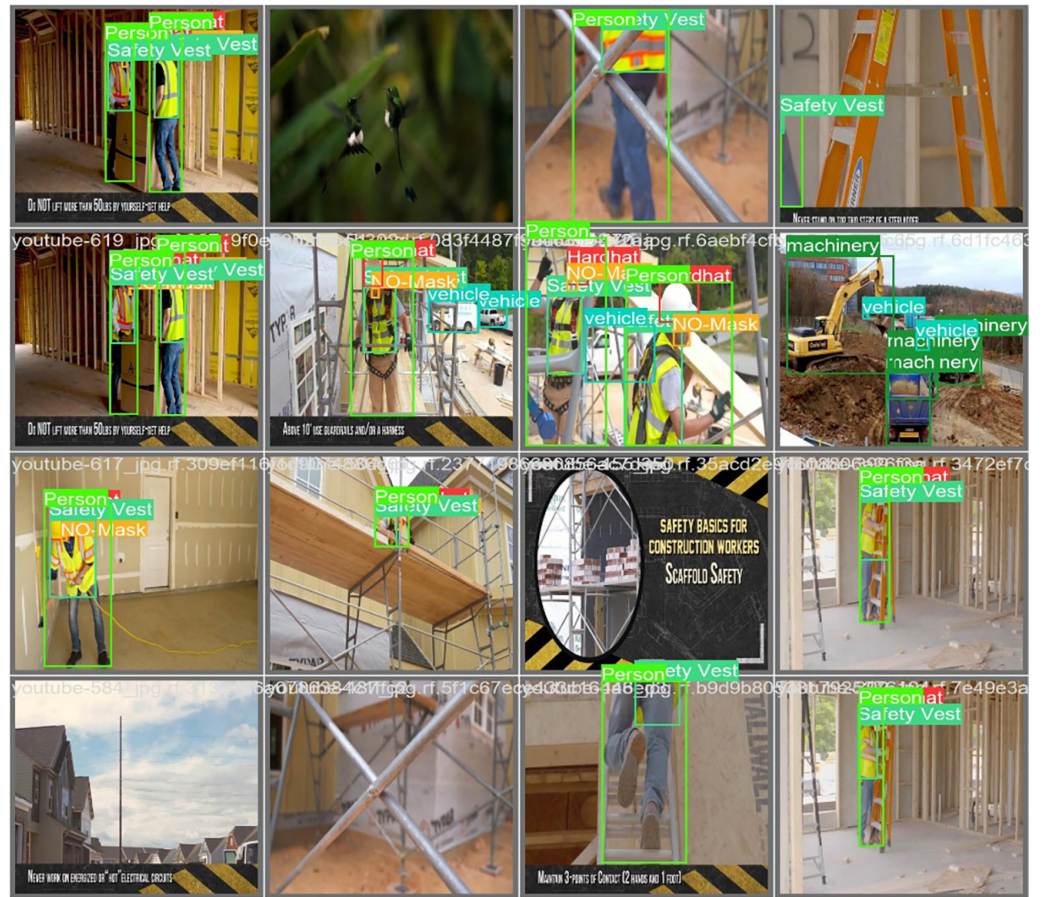


Fig. 4. Detection outcome of YOLOv8 model

4 EXPERIMENTAL RESULTS

In this section, the stimulation outcomes of the RWASHCS-MMLF algorithm are tested under the Kaggle dataset [15] with 54661 samples and five classes, as shown in Table 1.

Table 1. Details on database

Classes	No. of Samples
Workers	8066
Helmet	8049
Vest	596
Slips/falls posture Pattern	3812
Background	8238
Total No. of Samples	54661

Initially, every training image was standardized to 640 × 640 pixels. In order to enable the model to extract complex information from the images without incurring undue processing costs, this standardization sought to achieve a compromise between resolution and model efficacy. Second, the batch size was set at 8, and the total number of iterations was set at 500. These parameters were selected to guarantee that computational resources were used efficiently throughout the training phase and that model

training was sufficiently resilient. While the batch size was selected to maximize training efficiency while guaranteeing the model’s stable learning, the number of iterations was suitable to enable the model to learn from the training data. The stochastic gradient descent (SGD) algorithm was used to maximize the gradient throughout the training phase. The initial learning rate and momentum were set at 0.01 and 0.937, respectively. In contrast, the learning rate and momentum were based on prior research and best practices, with the goal of striking a balance between training speed and model convergence stability. The hyperparameters in this study were chosen following thorough experimental validation, and it was discovered that the hyperparameter configuration that was used performed the best on the validation set, as shown in Table 2.

Table 2. Training parameter settings

Parameters	Value
Input image size	540 × 540
Training epochs	100
Initial learning rate	0.01
Momentum	0.837
Batch size	10
Optimizer	SGD

A thorough analysis of the training and validation loss values for the RWASHCS-MMLF method of training and validation losses throughout different epochs is provided in Figure 5. As the model improves its weights to lower the classifier mistakes on both datasets, the training and validation loss continuously decrease. The model’s alignment with the training and validation datasets is demonstrated by the loss curves, which highlight how well it captures patterns in both datasets. The goal of the RWASHCS-MMLF method’s continuous parameter improvement is to minimize discrepancies between actual labels and forecasts. The box loss statistic was one of the essential performance metrics used. This metric evaluates how close the actual objects in the dataset are to the bounding boxes predicted by the model. The construction site dataset was used to train the RWASHCS-MMLF model for 600 epochs with a batch size of 16. After 90 epochs, the early halting mechanism was triggered since there had been no discernible improvement in adherence to the designated patient setting for the preceding 100 epochs.

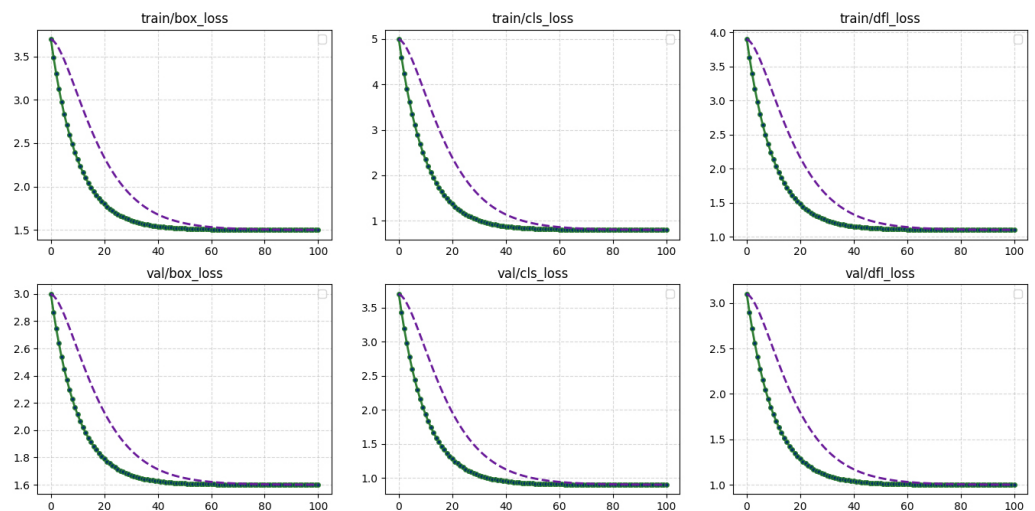


Fig. 5. Training and validation losses for the RWASHCS-MMLF model

The confusion matrices generated by the RWASHCS-MMLF method on the training and testing phases, together with the method’s classification performance under the construction site detection dataset, are displayed in Figure 6. The findings of the experiment demonstrated that the RWASHCS-MMLF method accurately identified and classified all five class labels. Likely, the figure shows the RWASHCS-MMLF method’s PR and ROC analysis. The RWASHCS-MMLF approach yielded successful results with the maximum ROC values on two labels, as the graph showed.

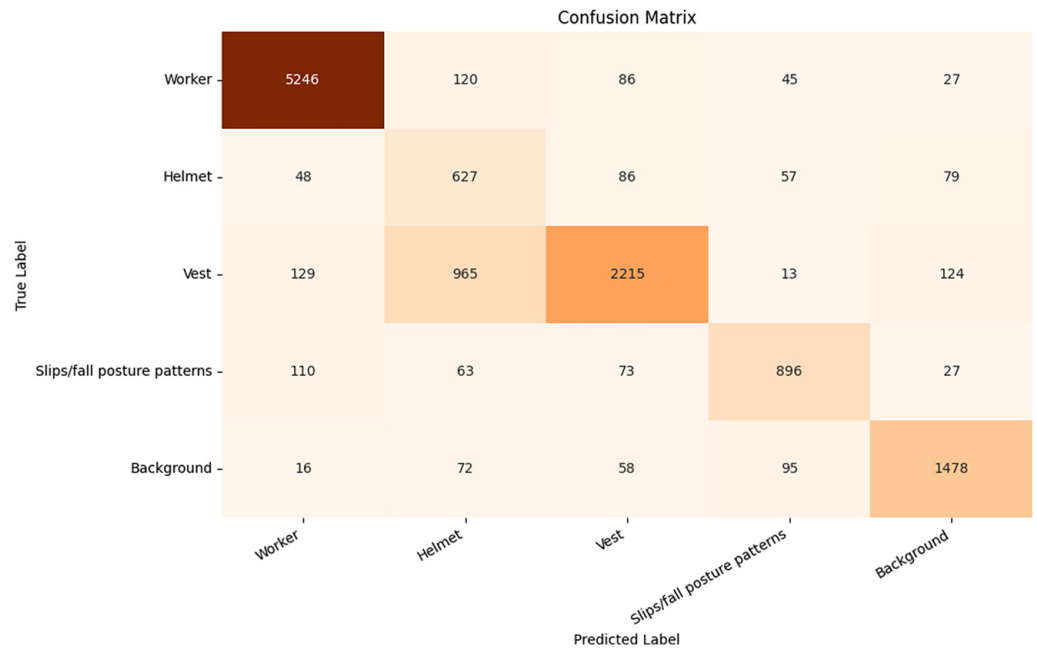


Fig. 6. Confusion matrix of the RWASHCS-MMLF model

The PR and ROC curves shown in Figure 7 capture the RWASHCS-MMLF model’s performance correlation with regard to the dataset’s precision and associated confidence level. These results emphasize the model’s efficiency in class detection and demonstrate how well it can differentiate between different classes. This curve offers important information about how the trade-off between TPR and FPR varies over different thresholds and classification epochs. The results highlight the model’s effectiveness in handling object detection tasks by highlighting its classification performance on several classes.

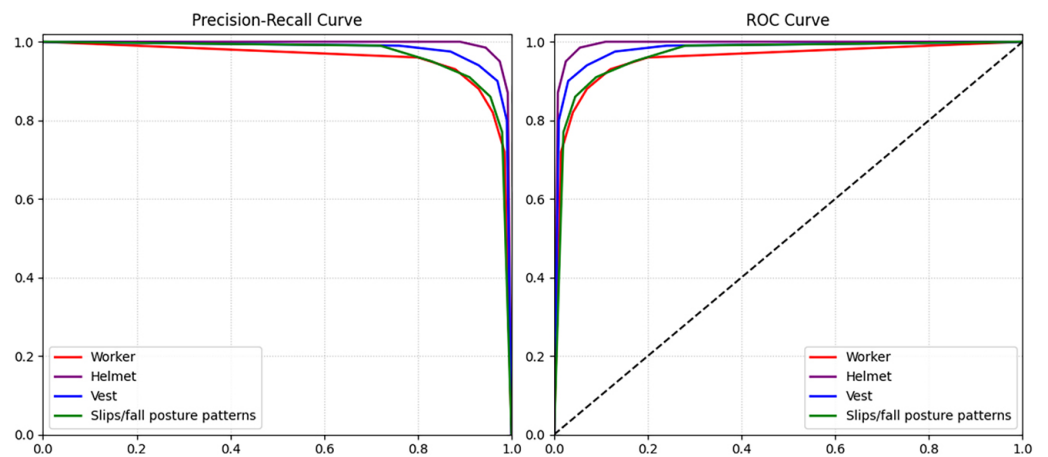


Fig. 7. PR and ROC plot of the RWASHCS-MMLF model

Table 3. Comparison analysis of the RWASHCS-MMLF model with other techniques

Algorithms	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
RWASHCS-MMLF	97.89	96.90	98.08	97.92
Faster R-CNN	96.20	96.68	96.80	96.20
DNN	96.02	94.06	96.56	95.81
EfficientDet	95.18	95.82	95.50	94.79
YOLOv3	96.00	94.23	94.03	95.23

A brief comparison of the RWASHCS-MMLF algorithm is shown in Table 3. A comparison of the RWASHCS-MMLF technique’s $accu_y$, $prec_n$, $reca_p$, and F_{Score} results are shown in Figure 8. According to the findings, the RWASHCS-MMLF approach outperforms other methods. Based on $accu_y$, the RWASHCS-MMLF approach offers higher $accu_y$, $prec_n$, $reca_p$, and F_{Score} outcomes of 97.99%, 96.90%, 98.08%, and 97.92% while the Faster R-CNN, DNN, EfficientDet, and YOLOv3 models provide lower $accu_y$, $prec_n$, $reca_p$, and F_{Score} correspondingly.

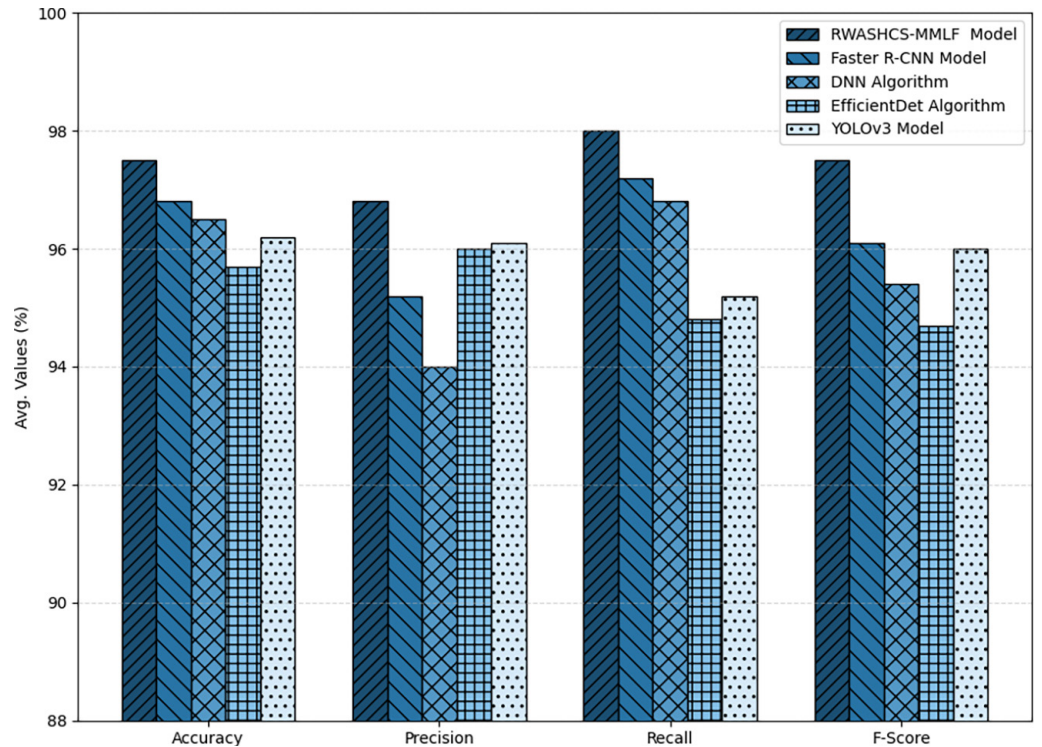


Fig. 8. Comparison of RWASHCS-MMLF model with other existing approaches

5 CONCLUSION

In this study, we propose RWASHCS-MMLF. On construction sites, mobile technology is utilized to gather real-time data from sensors, cameras, and wearable technology, allowing machine learning models to instantaneously forecast possible worker accidents and safety risks. In order to capture activity, the RWASHCS-MMLF model first collects data from the mobile sensors. The data from the sensors is then cleaned and filtered using data preprocessing. After that, temporal and spatial characteristics are extracted, including movement patterns, speed, position, and proximity to hazards. Mobile data is then incorporated into a trained machine learning model

to instantaneously predict possible mishaps or dangerous occurrences. Lastly, the alert and decision system suggests preventive measures and allows push notifications or alarms on mobile devices for site supervisors' visual dashboards. The efficiency of the RWASHCS-MMLF strategy in enhancing the use of construction safety management systems and lowering the possibility of fatalities and future accidents is demonstrated by the extensive on-site trials that validate the proposed RWASHCS-MMLF model. The result is a system with improved responsiveness and speed, which is essential for time-sensitive applications like worker safety prediction.

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