Detection of Unsafe Behavior in conveying Vehicle Parts using Computer Vision

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ABSTRACT

Deep Learning (DL) has experienced notable growth in various applications, which highlights its use in vision systems for object detection. The present work proposes a proof of concept for detecting unsafe acts in a vehicle assembly plant. The employment of Convolutional Neural Networks (CNNs) for either object or event detection was studied, and a vision system specifically trained for real-time detection of unsafe acts carried out by personnel while conveying car body parts was implemented. The intention of this research is to prevent workplace accidents and promote safety in the production environment by creating a personalized dataset composed of images that capture some incorrect ways of loading the car body doors, labeled as unsafe acts. For this purpose, a YOLOv8 DL model was trained to recognize unsafe behaviors, and after the test execution, the system efficiently identified safe and unsafe acts. Therefore, the proposal is feasible to be deployed to improve surveillance in daily operations, deliver automated reports for decision-making, and establish countermeasure actions.

Keywords-deep learning; object detection; unsafe acts; safety; YOLOv8

I. INTRODUCTION

Despite the development of technology and the benefits of industrialization in modern society, work accidents are one of the most important challenges in the health, social and economic sectors of the industrial and developing communities and constitute the third mortality cause in the world [1]. Occupational accident prevention is typically analyzed using ex-post-accident analysis. Zero accident vision focuses on identifying, reporting, and analyzing accident precursors, such as near-miss events, unsafe acts performed by personnel, and unsafe conditions at the workplace to prevent their occurrences [2].

Car component transportation by workers is an essential but dangerous activity in the automotive industry as it often involves handling heavy pieces with sharp edges. Therefore, ensuring employees' safety in the work environment is of utmost importance. Identifying and preventing unsafe actions are crucial elements for accident prevention. On the other hand, companies rely on effective and efficient implementation of manufacturing strategies such as lean manufacturing and agility management to improve competitiveness, particularly in the automotive supply chain [3]. For instance, the guidelines of the control directions at the workplace or factory shop emphasize the importance of establishing a safe and comfortable work environment that fosters motivation and worker performance [4, 5]. Monitoring workers' unsafe behaviors and work conditions can be considered a proactive way of removing safety and health risks and preventing accidents [6]. Such a task can rely on computer vision technology to improve supervision and define strategies to analyze safety management and worker risk assessment [7, 8].

The present work examines the safety management system implemented in an automotive company dedicated to vehicle assembly. The objective is to evaluate the performance of employees by analyzing surveillance video to detect unsafe actions and deliver a proactive technological solution applying DL techniques for the occupational safety field in the automotive industry. This article proposes a proof of concept for designing and implementing an artificial vision system that detects unsafe behavior of workers while transporting car body doors. The solution allows the generation of detailed reports with the date, time, and frequency of such acts. The paradigm switching from reactive to preventive increases the capacity to monitor unsafe conditions and acts. The aim is to contribute and achieve a significant improvement in monitoring unsafe conditions and acts while providing advantages such as greater control over unsafe acts and incident records. The inconsistent human behaviors and unstable working environments in the construction industry often affect negatively the manufacturing chain. Thus, organizations must reduce human errors and develop mitigation strategies to hamper possible accidents and incidents [9].

Computer vision focuses on interpreting and understanding digital images or videos to automate tasks. The former also concentrates on how computational models can gain a high-level comprehension of events or activities, including human activity recognition [10]. Moreover, the wide range application of DL and CNNs help overcome issues related to manual observation and the recording of unsafe acts [11]. Authors in [12] stress that the array of viewpoints required to identify a hazardous action, poses a significant challenge. Thus, they propose a hybrid DL model that integrates a CNN and Long Short-Term Memory (LSTM) that automatically recognizes workers' unsafe actions. Another type of unsafe behavior involves workers who do not wear Personal Protective Equipment (PPE) in construction, and industrial settings. For example, in [13], construction workers, PPE and heavy equipment utilization are identified through surveillance videos deploying the You Only Look Once (YOLO) model. Authors in [14] present an approach for safety helmet recognition in real-time recordings to reduce the number of violations and ensure safety. They propose a Deformable Perspective Perception Network (DPPNet) by integrating a Fixed Perspective Perception (FPP) module with YOLOv5. On the contrary, in [15] a framework combining computer vision, ontology, and natural language processing is developed to improve safety management, while in [16], the OpenPose network is implemented for the detection of anthropometric points of workers.

In academic contexts, unsafe behaviors can be related to the violation of health protocols, entailing crowd counting, social distancing, and mask detection, which leads to contagious diseases [17] as well as to suspicious activities happening in an exam [18]. Numerous research efforts have been made to pinpoint unsafe acts, mainly in construction sites or industrial settings, applying computer vision and DL techniques. Table I exhibits a summary of related works. This study addresses the development of a proof of concept to detect unsafe actions while the worker moves car body doors. The intention is to identify hazardous personnel behaviors, generate reports based on video evidence, and provide the safety supervisors with the means to apply sanctions or countermeasures to reinforce standard operation and injury prevention in a vehicle assembly plant.

II. MATERIALS AND METHODS

A. Problem Statement

Within a vehicle assembly plant, security experts carry out daily random patrols limited, though, in duration to monitor compliance with security measures. They verify that workers follow safety regulations, use PPE, and respect operating procedures. Any anomaly spotted is manually logged and reported to the management. The latter in turn takes action to prevent future occurrences. After a thorough analysis of the events reported in 2022, the predominant causes for such incidents are the hazardous conditions and the lack of compliance with the established safety protocols.

TABLE I. RELATED WORKS

Ref.	Behavior detected	Domain	Method used
[6]	Safety helmet usage	Construction	Faster R-CNN and YOLOv3
[14]	Safety helmet usage	Construction or industry	DPPNet integrating an FPP module and YOLOv5
[15]	Safety helmet usage	Construction	VtransE
[13]	Workers, PPE, and heavy equipment	Construction	YOLOv5
[16]	PPE usage	Cconstruction	OpenPose
[12]	Unsafe action	Construction	CNN and LSTM
[17]	Unsafe and unhygienic activities	Academic	Single Shot Detector and MobileNet architecture
[18]	Suspicious behaviors in classrooms	Academic	EfficientNet B2, SPNASNet 100, EfficientNet B3, and MobileNetv3 Large 100

The security personnel confirmed that some unsafe actions are prevalent in the behavior of the working personnel. For instance, workers do not correctly follow the established procedure for handling and transferring auto parts within the workshop. The former tend to carry body doors on their shoulders despite the procedure that should be followed which indicates that the components must be held from their ends, while both hands and carts must be used. Such a practice carries a latent risk of injury to elbows and shoulders due to the pressure exerted on the sharp edges of the piece. This type of injury requires medical attention while the affected workers will not be able to perform their regular duties until they have fully recovered.

B. Proof of Concept Description

The proposed strategy comprises implementing an artificial vision system. As depicted in Figure 1, such a system engages: (a) an IP camera that transmits video data to (b) an image analysis model capable of detecting unsafe acts and (c) stores relevant data, including the location, date, time, and type of anomaly detected. From this information, the system (d) automatically generates a report of hazardous acts aiming for management review and decision-making according to the observed actions.

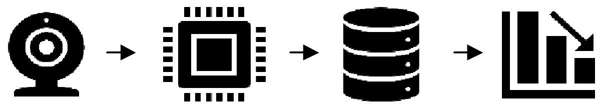

Fig. 1. Computer vision system for detecting unsafe actions.

C. Image Analysis Model for Unsafe Action Detection

The system was developed on an Apple MacBook Air computer with 16 GB of RAM and a core_i5 processor. The procedure followed for developing the image analysis model to pinpoint unsafe actions includes four stages:

1) Data Preparation

Images representing sequences of diverse sceneries of unsafe actions (i.e. mishandling carrying car body door) along with sceneries of safe actions during the operation were collected. For this collection a phone camera with a resolution of 12 megapixels was utilized and annotations were made with the addition of Roboflow [19] by tracing rectangles into the regions of interest identified in the image and adding the label "Safe Act" or "Unsafe Act" according to their class. Initially, a dataset comprising 55 labeled images was created and enhanced through preprocessing and image augmentation. The preprocessing operations applied included auto-orient and resize, while the augmentation parameters entailed flip, crop, rotation, shear, grayscale, hue, saturation, brightness, exposure, blur, and cutout. Figure 2 depicts one original image (top left) and instances derived from the image augmentation process. Applying such operations resulted in a detailed adaptation of each image's visual characteristics, improving its quality, diversity, and uniformity, which made the dataset more robust. This processing led to seven versions of the dataset, each with a standardized format. The 55 original images plus the 78 generated ones through the processing operations and augmentation sum up to 133 images.

Fig. 2. Original image and results of the image augmentation process.

Table II lists the specifications and processing operations for each dataset version. The creation of data versions with different preprocessing techniques allows a comparison of the model's performance and enables the selection of the one that performed best. Dataset versions v1, v2, v3, v6, and v7 were split into 88 % (117 images) for training, 8% (11 images) for validation, and 4% (5 images) for testing. Whereas v4 and v5 used 89% (49 images) for training, 7% (4 images) for validation, and 4% (2 images) for testing. All dataset versions included ground truth data for training an image classification model to detect unsafe actions.

TABLE II. SPECIFICATIONS OF DATASET VERSIONS

Dataset version	v1	v2	v3	v4	v5	v6	v7
Number of images in dataset	133	133	133	55	55	133	133
Class "Unsafe Acts"	Y	Y	Y	Y	Y	Y	Y
Class "Safe Acts"	N	N	Y	Y	Y	Y	Y
Outputs per training example	3	3	3	N	N	3	3
Auto Orient	Y	Y	Y	N	Y	Y	N
Resize: 640×640	Y						
Resize: 416×416		Y	Y		Y	Y	
Flip: Horizontal	Y	Y	Y	N	N	Y	Y
Crop	Y	Y	Y	N	N	Y	Y
Rotation: (between -12° / and +12°)	Y	Y	Y	N	N	Y	Y
Shear: (Horizontal ±2° & Vertical ±2°)	Y	Y	Y	N	N	Y	Y
Grayscale: (to 10% of images)	Y	Y	Y	N	N	Y	Y
Hue: (between -20° and +20°)	Y	Y	Y	N	N	Y	Y
Saturation: (between -20° and +20)	Y	Y	Y	N	N	Y	Y
Brightness: (between -20° and +20°)	Y	Y	Y	N	N	Y	Y
Exposure: (between -20° and +20°)	Y	Y	Y	N	N	Y	Y
Blur: Up to 0.75px	Y	Y	Y	N	N	Y	Y
Cutout: (5 boxes with 3% size each)	Y	Y	Y	N	N	Y	Y

2) Architecture Selection

The YOLOv8 architecture was chosen to perform the detection of unsafe actions. It is an advanced version of YOLO designed to be fast, accurate, and easy to use for a wide range of object detection tasks [20]. This architecture encompasses two core components for object detection: the backbone and the head. The backbone serves as the foundation for feature extraction from input images. It employs a series of stacked convolutional layers to analyze images at various levels of abstraction, thereby detecting and extracting essential visual features. These features range from basic patterns in early layers to more complex abstract features in subsequent layers. If trained on extensive datasets, the backbone learns general visual representations, enabling it to comprehend the structural nuances of diverse objects within images [21]. On the other hand, the head is responsible for object detection in the final stages of the process. It is positioned after the backbone, and integrates connections between different convolutional and detection layers. These connections enable feature fusion at multiple scales, allowing the head to combine and enhance features from various levels of abstraction. Additionally, the head incorporates post-processing layers for refining predictions. This process is crucial for accurately predicting object locations by deploying bounding box coordinates, estimating object sizes, and classifying the detected objects. The seamless integration of the YOLOv8 backbone and head components results in a cohesive architecture that excels in real-time object detection tasks. Further details regarding the architecture can be found in [22, 23].

3) Model Development

The YOLOv8 series offers a suite of pre-trained models specialized for specific computer vision tasks. This work employs the yolov8s.pt model from the Ultralytics library [24] due to its versatility, efficiency, and accuracy in detection tasks [25]. The YOLOv8s model was seamlessly integrated with the created image datasets, dividing them into training, validation, and testing sets during the data preparation phase. Leveraging the capabilities of Python and the Ultralytics library, the used YOLOv8s model initiated the training process and was ready to detect unsafe acts. Next, the code snippet below showcases the training setup, the yolov8s.pt pre-trained model serves as a starting point for training.

```
#Train the model YOLOv8 from ultralytics
import YOLO
model = YOLO('yolov8s.pt')
model.train(data='/Users/user/BodyshopDete
ctorSunday/Unsafeacts-2/dataVer2.yaml',
epochs=10, project='Versionx',
name='MyVersionx')
#Export the model in ONNX Format
results = model.export(format='onnx')
```

Afterwards, the YOLOv8s.yaml configuration file was utilized to define the model architecture and transfer the pre-trained weights to the new model. The model was trained for 10 iterations (epochs), and hyperparameters such as learning rate, batch size, loss function, and optimizer were set to their default values [25]. This process was performed for all seven of the dataset versions in YAML format. After completing the training phase, we were able to achieve a finely tuned model with optimized weights. A top-performing model was chosen and exported to the ONNX format to encapsulate its capabilities, allowing a precise and efficient detection of unsafe acts. The ONNX format enables the deployment of the model on specific portable platforms, such as iOS and Android environments, showcasing its capability to detect unsafe acts in real time on mobile devices and tablets.

III. RESULTS AND DISCUSSION

A. Dataset

Regarding the dataset, Table II presents the specifications and attributes considered for each dataset version used in the conducted experiments, which include preprocessing and augmentation parameters.

B. Evaluation Metrics

Figure 3 illustrates the standard metrics employed to evaluate object detection in images: precision, recall, and mean average precision (mAP), as achieved by models trained over 10 iterations with all dataset versions. The precision graph depicts the correctness of the model's detections. The recall graph shows the proportion of actual positives correctly predicted. Whereas mAP50 and mAP50-95 graphs manifest the overall accuracy of the models utilizing confidence levels of 50% and 50-95%, respectively, for the object localizations. As do precision and recall metrics, higher mAP values indicate better detection models. Table III presents the validation results during the YOLOv8 model's training deploying different dataset versions. It reports precision values for both the "Unsafe Act" and "Safe Act" classes, as well as the misclassification rate.

Furthermore, Table IV exhibits the testing stage results of the YOLOv8 models generated for all dataset versions. It reports accuracy and precision for the "Unsafe Act" and "Safe Act" classes, the false positive rate for the "Unsafe Act" class, the count of occurrences of multiple detections, and the number of images with multiple detections.

It is worth noting that, during the testing stage, a dataset composed of 22 representative images from simulated operational scenarios in a real-world environment was used. As observed in Tables III and IV during the validation and testing stages, version 5 demonstrates superior performance across all metrics. Such an outcome is attributed to the absence of erroneous detections. Despite its apparent excellence, version 5 was not chosen for the proof of concept and deployment due to its lack of image preprocessing and augmentation. Instead, version 3, which achieved the second place among the top-performing models and includes these techniques, is selected and converted to ONNX format for its deployment. In consequence, version 3 demonstrated adaptability in handling the variability inherent in real-world environments.

TABLE III. VALIDATION STAGE RESULTS OF YOLOV8 MODELS

Dataset version	v1	v2	v3	v4	v5	v6	v7
Precision for class unsafe act	0.36	0.71	1.00	0.55	1.00	0.75	0.60
Precision for class safe act	-	-	0.83	1.00	1.00	0.56	0.71
Misclassification rate	0.64	0.28	0.08	0.38	0.00	0.35	0.35

TABLE IV. TESTING STAGE RESULTS OF YOLOV8 MODEL

Dataset version	v1	v2	v3	v4	v5	v6	v7
Accuracy	0.27	0.41	0.95	0.55	1.00	0.77	0.45
Precision for class unsafe act	0.60	0.90	0.90	0.90	1.00	0.90	0.90
Precision for class safe act	-	-	1.00	0.33	1.00	0.83	0.08
False positive rate for class unsafe act	0	0	0	0	0	0	0
Count of occurrences of multiple detections	22	3	2	11	0	11	19
No. of images with multiple detections	6	1	1	2	0	5	5

C. Visual Results of Model Deployment

An example of the visual results presented in Figure 3 displays the system's detection findings of the simulated scenarios, demonstrating the load of the front and rear car doors carried on the worker's shoulder. Each image is labeled with a detection bounding box marked as "Unsafe Act" in addition to the date and time, located at the bottom left corner of each image. As depicted in Figure 4, each image detected as an unsafe act is saved, including its corresponding timestamp and class label. All records for the spotted unsafe acts are stored in a CSV file serving as a log and evidence. Afterwards, data can be accessed through a dashboard for the total number of incidents during a specific period to be viewed.

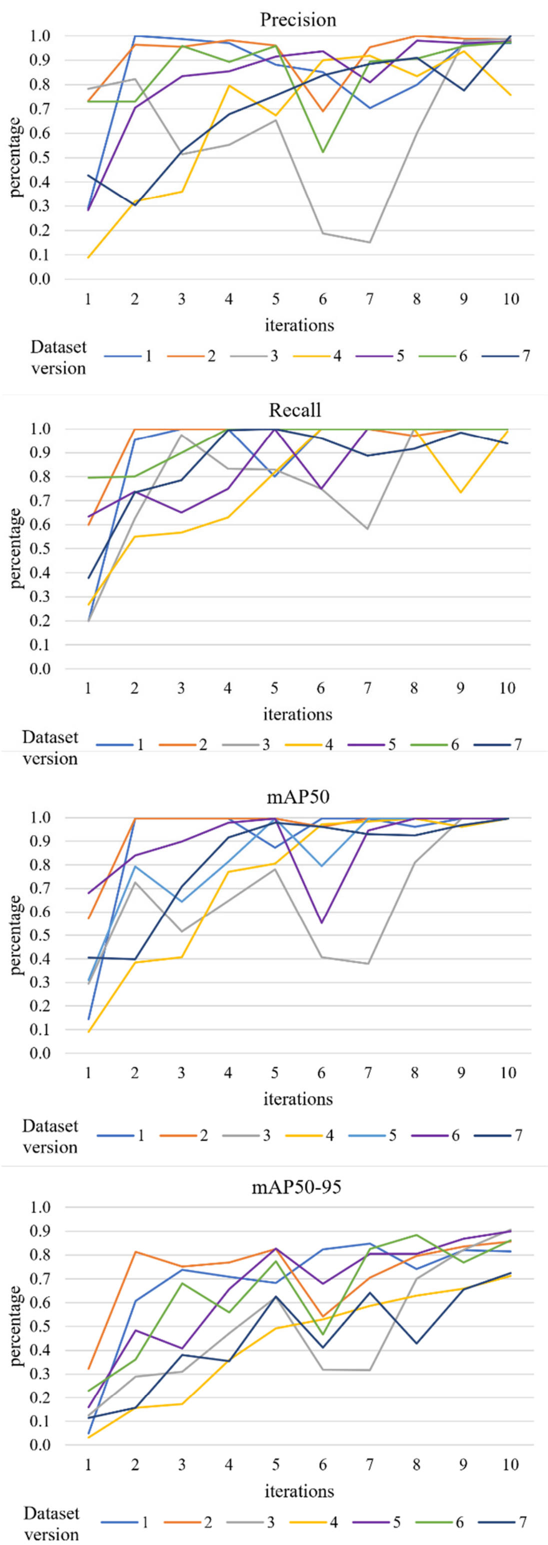

Fig. 3. Metrics evaluation at 10 iterations.

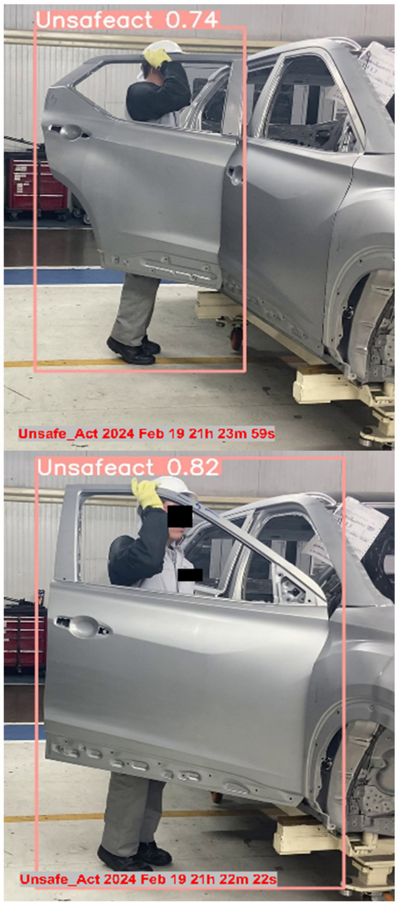

Fig. 4. Visual results of unsafe acts proof of concept of the proposed system.

IV. CONCLUSIONS

The present work addressed the detection of unsafe behaviors occurring while conveying car body doors through a vision system. The algorithm implemented in such a system can discern unsafe acts automatically, increasing the surveillance time without biasing the detection evaluations due to the differences in the criteria among security experts, which expands its scope and reliability. The identified unsafe acts can be delivered in a report, in addition to saving an image labeled with the date and time. These elements can be used for decision-making proactively, that is, before an injury occurs.

The results exhibit that vision systems with artificial intelligence, through the training of the YOLOv8 model can considerably contribute to detecting human behaviors and generating reports to make preventive decisions. Therefore, the developed proof of concept is feasible to be implemented in the future on a large-scale setting with more unsafe acts and more cameras to capture images. The gathered information enables the utilization of evidence that supports the necessary sanctions or countermeasures to be applied to the personnel, reinforces the respect for the standard operating rules, and prevents injuries.

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