ISAFE WELDING SYSTEM: COMPUTER VISION-BASED MONITORING SYSTEM FOR SAFE WELDING WORK

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ABSTRACT: *The construction industry faces significant challenges, including a high prevalence of occupational incidents, often involving fires, explosions, and burn-related accidents due to worker non-compliance with safety protocols. Adherence to safety guidelines and proper utilization of safety equipment are critical to preventing such incidents and safeguarding workers in hazardous work environments. Consequently, a monitoring system tailored for construction safety during welding operations becomes imperative to mitigate the risk of fire accidents. This paper conducts a brief analysis of OSHA rules pertaining to welding work and introduces the iSafe Welding system, an advanced real-time safety monitoring and compliance enforcement solution designed specifically for construction site welding operations. Harnessing the real-time object detection algorithm YOLOv7 in conjunction with rule-based scene classification, the system excels in identifying potential safety violations. Rigorous evaluation, encompassing precision, recall, mean Average Precision (mAP), accuracy, and the F1-Score, sheds light on its strengths and areas for improvement. The system showcases robust performance in rule-based scene classification, achieving high accuracy, precision, and recall rates. Notably, the iSafe Welding system demonstrates a formidable potential for enhancing construction site safety and regulatory compliance. Ongoing enhancements, including dataset expansion and model refinement, underscore its commitment to real-world deployment and its strength in ensuring worker safety.*

KEYWORDS: *Safety monitoring, scene classification, welding work, fire prevention, construction safety, OSHA rules compliance*

1. INTRODUCTION

The construction industry exhibits a pronounced prevalence of both fatal and non-fatal occupational incidents on a global scale (Hussain et al., 2022; Khan et al., 2023). Among the significant contributors to these casualties and injuries are fires, explosions, and burn-related incidents, often stemming from workers' non-adherence to precautionary safety protocols during hot work. The primary causes of fires at construction sites encompass highly flammable substances, including foam insulation, gas cylinders, chemical storage facilities, and oil-based paints. The proximity of these materials to welding and cutting activities can serve as a precipitating factor for fires at construction sites (Xu et al., 2022). According to the Occupational Safety and Health Administration (OSHA) accident database, a total of 80 accidents occurred between July 2019 and July 2023 related to burning incidents at construction sites attributed to welding and cutting work. Among these recorded incidents, 22 were categorized as fatalities. These accidents occur when workers fail to utilize safety gear properly or neglect its use altogether, leading to exposure to various hazards such as chemical splashes, flying debris, intense light, harmful fumes, and more (Nill, 2019). For instance, during welding or cutting operations, the absence of proper eye protection can result in severe eye injuries, potentially leading to temporary or permanent vision loss. Additionally, if a worker does not take necessary precautions while performing welding or cutting tasks, and flammable materials or chemicals are stored nearby, there is a significant risk of explosions or fires at the workspace, posing serious harm to the worker. It is essential for workers to adhere to safety guidelines and utilize the appropriate safety equipment to prevent such incidents and safeguard their well-being in hazardous work environments.

Nowadays, computer vision (CV) techniques have found applications in monitoring construction sites across various construction scenarios (Jeong et al., 2017). However, with regard to welding processes, researchers have focused on areas such as identifying welding defects (Ramadan et al., 2023; Wu et al., 2023), welding bead detection (JOHN, 2023), detecting welding quality (Yang et al., 2018), and classifying welding types (S. Chen et al., 2023; H. Liu et al., 2023). Chen et al. proposed YOLOv5 based welding helmet use detection during the welding work (W. Chen et al., 2023). However, it is worth noting that there have been relatively limited efforts directed towards ensuring compliance with safety regulations or implementing monitoring mechanisms specifically during welding operations. Hence, the need for a comprehensive monitoring system in construction safety during welding operations is evident, primarily to mitigate the risk of fire accidents. To enhance safety at the construction site, this paper briefly analyzes OSHA rules related to welding work. Further, a computer vision-based monitoring system, "iSafe Welding System," is proposed to ensure compliance with safety protocols during

Referee List (DOI: 10.36253/fup_referee_list)
FUP Best Practice in Scholarly Publishing (DOI 10.36253/fup_best_practice)
Syed Farhan Alam Zaidi, Rahat Hussain, Muhammad Sibtain Abbas, Jaehun Yang, Doyeop Lee, Chansik Park, *iSafe Welding System: Computer Vision-Based Monitoring System for Safe Welding Work,* pp. 669-675, © 2023 Author(s), CC BY NC 4.0, DOI 10.36253/979-12-215-0289-3.66

welding work. The Convolution Neural Network (CNN)-based You Only Look Once (YOLO) version 7 model is trained for the object detection module, and a rule-based algorithm is developed to assess safety rules compliance that classify the scene as "safe" or "unsafe". Moreover, a new dataset is collected from construction jobsite, web image scrapping, and generated synthetic data from OpenAI's DALL.E.2.

2. SAFETY RULE ANALYSIS

The OSHA rule 1910.252 pertains to hot work, encompassing welding, cutting, and brazing activities. This regulatory framework is forked into distinct sections: section (a) addresses fire prevention and protection, while section (b) is devoted to personnel protection, encompassing guidelines pertaining to personal protective equipment (PPE) usage and the safe positioning of welding cables and equipment. A careful examination of these regulations reveals that, during the execution of welding operations, workers are mandated to use welding-specific PPE. Furthermore, provisions necessitate the presence of a fire extinguisher in close proximity, the employment of fire prevention measures such as the utilization of fire prevention nets, a prohibition on the presence of insulation or foam in the safe area, and the maintenance of a safe distance from chemicals and gas cylinders during welding activities. For a comprehensive exposition of OSHA rule 1910.252 relevant to welding, along with an outlining of requisite detection objects, readers are directed to Table 1 for further interpretation.

Table 1. The details of OSHA rule 1910.252 related to welding and objects require for detection

Sr. No.	Rule Code	Description	Objects
	a) Fire prevention and protection		
1	(a)(1)(ii)	Use guards to confine heat, sparks, and slag	Fire prevention Net
2	(a)(2)(i)	Combustible Material - Prevent exposure to sparks through floor openings, cracks, walls, doorways, and windows	
3	(a)(2)(ii)	Fire Extinguishers - Maintain ready-to-use fire extinguishing equipment	Fire Extinguisher
4	(a)(2)(iii)(A)(1)	Combustible material in building construction or contents closer than 35 feet (10.7 m) to the point of operation.	Flammable Material
5	(a)(2)(iii)(A)(2)	Appreciable combustibles are more than 35 feet (10.7 m) away but are easily ignited by sparks.	
6	(a)(2)(iii)(A)(3)	Wall or floor openings within a 35-foot (10.7 m) radius expose combustible material in adjacent areas including concealed spaces.	
7	(a)(2)(iii)(A)(4)	Combustible materials are adjacent to the opposite side of metal partitions, walls, ceilings, or roofs and are likely to ignite.	
	b) Protection of personnel		
8	(b)(1)(ii)	Protection of Personnel - Clear placement of welding cable and equipment	Welding machine
9	(b)(2)(i)(A-D)	Eye Protection - Helmets or hand shields for arc welding and cutting	Worker and Helmet with eye shield (PPE)
10	(b)(2)(i)(B)	Eye Protection - Goggles or suitable eye protection for gas welding or oxygen cutting	
11	(b)(2)(i)(C)	Eye Protection - Transparent face shields or goggles for resistance welding or resistance brazing	
12	(b)(2)(i)(D)	Eye Protection - Suitable goggles as needed for brazing operations	

3. METHODOLOGY

This section describes the comprehensive methodology employed in the development and implementation of the "iSafe Welding system", which comprises three main steps: dataset collection and preparation, training object detection model, and safety rules compliance. The details of these steps are as follows:

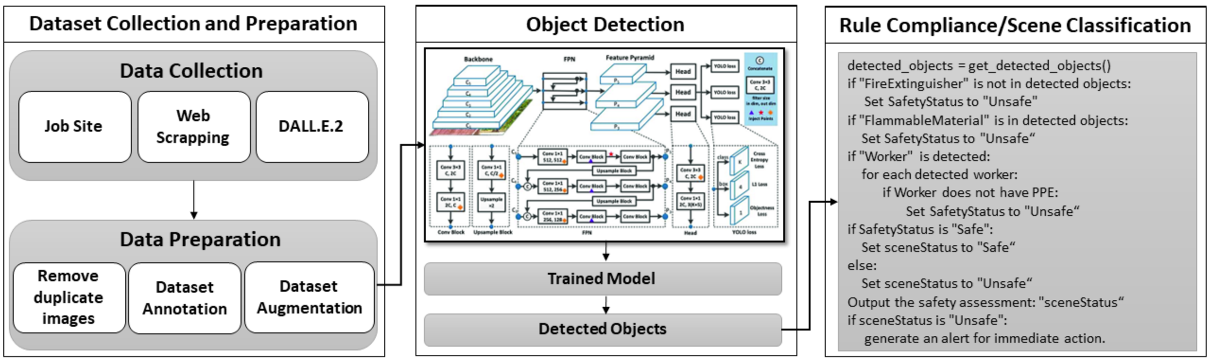

Fig. 1. Methodology for training iSafe Welding System

3.1 Dataset Collection and Preparation

The dataset employed in this research comprises 633 meticulously curated images collected from construction jobsite, web image scrapping, and generated synthetic data from OpenAI's DALL.E.2. The dataset was divided into training (511), validation (61), and testing (61) sets for the iSafe Welding system. This dataset includes 1,935 annotated instances, categorized into five classes: "Welding Equipment" (621 instances), "Worker with PPE" (607 instances), "Welding Machine" (348 instances), "Fire Extinguisher" (197 instances), and "Flammable Material" (162 instances). These categories represent essential elements and scenarios within welding environments, emphasizing equipment, worker safety, welding machinery, fire prevention measures, and flammable material management. The roboflow platform is used for annotating dataset by drawing bounding boxes. For data augmentation, a series of transformative techniques are employed exclusively on the training dataset using roboflow. These augmentation methods included horizontal flip, shear, hue adjustment, brightness variation, exposure modification, cutout, and the mosaic technique. The training set was increased 3 times of original training set after augmentation.

3.2 Training Object Detection Model

In pursuit of real-time object detection capabilities, iSafe Welding has strategically adopted single-stage detection algorithms. These algorithms are renowned for their efficiency and speed, offering high frame-per-second (fps) rates for rapid and real-time object detection (Diwan et al., 2023). The decision to favor single-stage detectors over two-stage detectors aligns with the project's primary objective of ensuring swift and accurate detection of objects during welding operations within the construction industry. In the realm of real-time object detection algorithms, two prominent options, Single Shot Multibox Detector (SSD) (W. Liu et al., 2016) and the YOLO series detectors, were considered for this research work. After careful evaluation, the YOLO series detectors were selected as the preferred choice due to their notable strengths in achieving a commendable balance between accuracy, as measured by mean Average Precision (mAP), and fps rates. Specifically, YOLOv7 (Wang et al., 2023) was chosen as the model of preference for training, enhancing its capabilities to excel in the task of object detection, a critical component of the iSafe Welding system aimed at enhancing safety and compliance during welding operations in the construction industry.

YOLOv7 is a single-stage anchor-based object detector that uses a custom backbone network and a new head network. The basic YOLO model architecture (Long et al., 2020) is shown in the object detection module of Fig. 1. The backbone is a convolutional neural network (CNN) that extracts features from the input image. YOLOv7 uses a modified ELAN architecture for the backbone, which is more efficient and has better learning ability than the original ELAN architecture. The head is responsible for predicting bounding boxes and object classes. YOLOv7 uses a single-stage head, which means that it predicts bounding boxes and object classes directly from the features extracted by the backbone and neck. YOLOv7 uses a new anchor box selection algorithm that is more efficient and effective than the algorithm used in previous YOLO models. This helps to improve the accuracy of the model, especially for small objects. YOLOv7 has a reduced parameter count and computation compared to previous YOLO models. This makes it faster and more efficient to run on devices with limited resources (Wang et al., 2023).

The training process of the model was conducted using hardware resources consisting of an Intel Core i9-10900 CPU, operating at 2.80GHz, complemented by 32 GB of RAM, and further accelerated by the inclusion of an RTX 3090 graphics processing unit, boasting 24 GB of dedicated memory. The model was trained on 300 epochs, with a batch size parameter set to 16, and an input image size established at 640x640 pixels. In pursuit of model optimization, the YOLOv7 framework uses the default Stochastic Gradient Descent (SGD) optimizer, initialized with a learning rate of 0.01, culminating in a final learning rate of 0.1. Additional optimization parameters encompassed a weight decay factor of 0.0005 and a momentum coefficient of 0.9, collectively contributing to the refinement of the model's performance.

3.3 Safety Rules Compliance/Rule-based Scene Classification

After conducting an in-depth examination of the OSHA regulation regarding welding work, as detailed in Section 2, significant and crucial findings were obtained. It was determined that the presence of specific safety parameters significantly impacts the safety status of a welding scenario. Specifically, if a welding task is being executed and no fire extinguisher is positioned in proximity, or if flammable materials are detected in the surrounding area, the scene is deemed unsafe as per OSHA guidelines. Furthermore, any detection results indicating the absence of PPE on a worker subsequently flag the scene as unsafe. Upon completion of the object detection module, the results are seamlessly transitioned to the safety rules compliance module. Herein, a algorithm is developed to examine the adherence to safety rules, discerning whether the detected scenario should be categorized as safe or unsafe, effectively enhancing safety and compliance during welding operations within the construction industry. The algorithm is described in Algorithm 1.

Algorithm 1: Safety Rules Compliance Module

Input: Results from the object detection module, including detected objects and their attributes.

Output: Safety assessment for the detected welding scenario, categorized as "Safe" or "Unsafe."

```
1. Initialize a variable SafetyStatus to "Safe"
2. if "FireExtinguisher" is not in detected objects:      // Check for the presence of a fire extinguisher
       Set SafetyStatus to "Unsafe"
3. if "FlammableMaterial" is detected:                    // Check for the presence of flammable materials
       Set SafetyStatus to "Unsafe"
4. if "Worker" is detected:                               // Check for worker PPE
       for each detected worker:
           if Worker does not have PPE:
               Set SafetyStatus to "Unsafe"
5. if SafetyStatus is "Safe":                             // Perform a final safety assessment
       Set sceneStatus to "Safe"
   else:
       Set sceneStatus to "Unsafe"
6. Output the safety assessment: "Safety Assessment: sceneStatus"
7. if sceneStatus is "Unsafe":
       Log safety assessment results and generate an alert for immediate action.
```

4. EVALUATION AND DISCUSSION

The evaluation of the iSafe Welding system encompassed two key aspects: object detection performance and rule-based scene classification. These assessments aimed to validate the system's efficacy in real-time safety monitoring and compliance enforcement within construction site welding operations.

4.1 Object Detection Performance

In the context of object detection, essential metrics such as precision, recall, and mean Average Precision (mAP) were rigorously calculated to gauge the system's ability to accurately identify and localize objects of interest. Concurrently, accuracy and the F1-Score were employed for scene classification as "safe" or "unsafe." The results are presented in Fig. 2 and Table 2. A significant observation is the disparity in mAP scores between the validation and test sets. The validation set exhibited a notably higher mAP, suggesting a degree of overfitting to the training and validation datasets. This phenomenon highlights the need for model refinement to enhance generalization capabilities and ensure reliable performance in real-world scenarios. The class-specific analysis reveals that the "flammable materials" class achieved a perfect recall of 100%. This remarkable recall rate can be attributed to the dataset's inherent limitation, featuring only a single type of flammable material. Conversely, the "welding equipment" class exhibited a 67.4% mAP on the test set, primarily due to the small and slender nature of these objects, rendering them challenging to detect accurately.

Table 2. Result of object detection model on validation and testing set with confidence threshold 0.5

Dataset	**Precision %**	**Recall %**	**mAP@0.5 %**
Validation set	97.9	97.9	99.2
Test Set	80.5	92.6	88.5

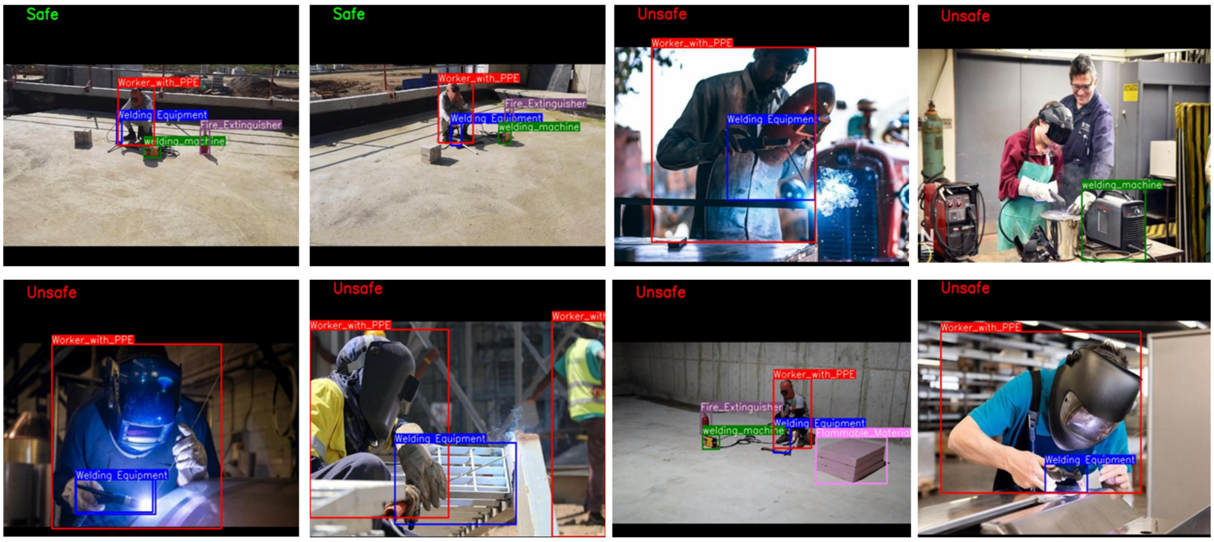

Fig. 2. Object detection and scene classification results of iSafe Welding System

4.2 Rule-Based Scene Classification

The rule-based scene classification component of the iSafe Welding system demonstrated its effectiveness in categorizing scenes as "safe" or "unsafe." The testing dataset was thoughtfully divided into these two categories, yielding 14 images classified as "safe" and 47 as "unsafe." Applying Algorithm 1 to these scenes led to notable results. The achieved accuracy, precision, recall, and F1-score of 96.72%, 97.87%, 97.87%, and 97.8%, respectively, underscore the algorithm's proficiency in accurately classifying scenes based on safety criteria. These outcomes affirm the algorithm's potential to enhance safety compliance and enforcement in the context of welding operations.

4.3 Future Directions

To address the observed issue of overfitting and to further enhance the system's capabilities, future efforts will primarily focus on expanding the dataset. Additionally, while the dataset used in this study inherently ensures that all depicted workers are equipped with PPE, future dataset extensions will include instances of workers without PPE. Furthermore, this expansion will involve the inclusion of various flammable materials and augmenting the dataset with a more diverse set of welding scenarios set in varied environmental contexts. Such measures are anticipated to significantly enhance the model's generalization and real-world applicability. As the OSHA rules require proximity between welding equipment and flammable materials as shown in Section 2, the future work will utilize real-sense camera to find distance between objects to calculate safe distance. Further, the updated algorithm will classify scene as safe or unsafe based on the safe distance.

5. CONCLUSION

Computer vision techniques have emerged as valuable tools for enhancing safety and efficiency on construction sites. While previous research has concentrated on aspects such as defect identification, welding bead detection, quality assessment, and type classification, there has been a noticeable gap in addressing safety compliance during welding operations. This gap underscores the need for a comprehensive monitoring system to mitigate the risk of fire accidents and ensure compliance with safety regulations. This paper has provided a brief analysis of OSHA rules related to welding work and introduced the iSafe Welding System, a computer vision-based monitoring solution designed to uphold safety protocols during welding operations. The integration of the YOLOv7 model for object detection, along with a rule-based algorithm for safety rule assessment, represents a robust approach to classifying scenes as safe or unsafe. Furthermore, the creation of a new dataset, comprising data from construction job sites, web image scraping, and synthetic data generated using OpenAI's DALL.E.2, enhances the system's adaptability and accuracy. The evaluation results demonstrate the system's effectiveness in real-time safety monitoring and compliance enforcement within construction site welding operations, with high precision and recall rates. The iSafe Welding System offers the potential to significantly improve workplace safety in the construction industry. By addressing the critical need for safety monitoring during welding, this system contributes to a safer construction environment, reducing the potential for accidents and improving overall workplace safety. Its applications extend to various industries requiring safety compliance and object detection, making it a valuable asset for enhancing safety and efficiency in dynamic work environments.

ACKNOWLEDGEMENT

This research was conducted with the support of the "National R&D Project for Smart Construction Technology (No.23SMIP-A158708-04)" funded by the Korea Agency for Infrastructure Technology Advancement under the Ministry of Land, Infrastructure and Transport, and managed by the Korea Expressway Corporation.

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