Smart Industrial Safety using Computer Vision

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***Abstract*— More than 2.3 million people worldwide suffer from work-related injuries or illnesses each year, resulting in more than 6,000 deaths per day. Providing an unclear work environment and failing to wear appropriate personal protective equipment have been identified as significant contributors to workplace accidents, making it imperative that employers prioritize workplace safety as a priority. Providing proper personal protective equipment (PPE) and maintaining a well-organized, clearly marked (unsafe) work environment can help prevent inconvenient workplace incidents. Furthermore, it promotes a safe working environment, reduces the likelihood of life-threatening events, and enhances overall business and economic conditions. Therefore, this paper proposes safe, smart manufacturing by implementing computer vision technology to detect appropriate PPE worn by workers and ensure a safe workspace to reduce the risk of human injuries. By utilising computer vision technology, we can identify PPE, such as gloves, helmets, and working forklifts, used by workers in the manufacturing environment. A precision of 80.6% and 86% have been reached using YOLOv8 for all classes in both datasets. In general, an extensive review of both datasets, including five performance metrics, is considered.**

Keywords—Smart Manufacturing, Industrial warehouse, Computer vision, Manufacturing 4.0, Machine learning.

I. INTRODUCTION

According to estimates by the International Labour Organisation (ILO), over 2.3 million people worldwide are affected by work-related accidents or illnesses every year, which translates to more than 6,000 deaths every day [1]. Shockingly, there are approximately 340 million occupational accidents and 160 million victims of work-related illnesses annually, with updates suggesting an increase in these numbers. While the statistics may vary based on gender and nationality, it is evident that developed countries with stricter regulations and less hazardous work environments have lower fatality rates than underdeveloped countries that often fail to track workplace injuries or fatalities. In the United States, for instance, the Occupational Safety and Health Administration (OSHA) recorded a total of 5,333 occupational fatalities and an incidence rate of 2.8 per 100 full-time workers in 2019, highlighting the need for continued research and development of technologies that protect individuals at work [2]. The impact of safety laws, programs, and regulations cannot be overstated, as effective standards can significantly reduce accident and injury rates, thereby improving the overall business and economic environment [3]. Several studies underscore the importance of state and federal agencies adopting workplace safety regulations, as they have been shown to reduce the frequency of reported workplace injuries and improve workers' conditions. [4]

There are several reasons why workplace accidents may occur, and it is essential to identify and address them to prevent inconvenient and potentially life-threatening events. Among the most significant contributors to workplace accidents is the failure to wear appropriate personal protective equipment (PPE) [4]. Without PPE, workers are vulnerable to hazards such as falls, burns, and exposure to harmful substances. Another factor that can lead to accidents is an unclear work environment, where workers may not be able to navigate safely or identify hazards. These issues can result in accidents such as slips, trips, and falls, which can lead to serious injuries or even fatalities. It is therefore critical for employers to prioritize safety in the workplace by providing adequate PPE and ensuring that the work environment is well-maintained, organized, and marked to avoid accidents and promote a safe working environment.

Companies take considerable care to eliminate workplace accidents and injuries because they jeopardise workplace safety and can influence individual, team, and organisational achievements [5, 6]. The necessity for enterprises to proactively recognise dangerous behaviours and then undertake activities that avoid workplace incidents is of utmost priority to ensure a healthy work environment [7]. With this being said, the act of complying with established safety procedures and rules demonstrates safety compliance behaviour, whereas safety participation behaviour includes behaviours connected to contributing to a safer and better work environment [8]. Additional study on organisational safety concerns has taken two methods [9]. The first strategy of behaviour-based safety focuses on identifying and changing essential safety behaviours that contribute to workplace injuries and losses. As a result, tracking safety behaviour leads to appropriate actions, which can ultimately lead towards positively impacting work performances. The second method is the safety culture approach, which focuses on developing a safety culture inside the business. These consider creating a mechanism of moulding the approach of safety into every employee within the manufacturing site [9]. The two methods have recently been integrated since they both suggest the strategic role of promoting a safe working environment with a systematic approach towards managing safety [8, 9, 10].

In this paper, we aim to introduce safe smart manufacturing by introducing computer vision for detecting proper wear within manufacturing and ensuring a clear workspace to minimise human injuries. Using computer vision, we can detect PPE for workers, including gloves, helmets, and forklifts that are working in the workspace. This paper is organised as follows section II reviews the potential technology and reviews existing studies. Section III proposes safe smart manufacturing by identifying its requirements, proposing the architecture, and investigating the methodology and data utilised. Section IV presents and discusses the results of both scenarios. Section V concludes the work and identifies future work.

II. LITERATURE REVIEW

A. Potential Technology

The manufacturing industry has come a long way in recent years, with technology playing a major role in improving worker safety. Safety sensors are one type of technology that can be incredibly effective in preventing workplace accidents [11]. These sensors can be installed in strategic locations throughout the manufacturing site to detect unsafe conditions, such as a worker standing too close to a machine or a piece of equipment malfunctioning [12]. Another type of technology that can help ensure staff safety in manufacturing sites is wearable technology [13]. Wearable devices such as smart helmets, vests, or wristbands can monitor workers' vital signs and movement patterns. By tracking workers' physical condition, these devices can detect signs of fatigue, dehydration, and other health issues that can compromise workers' safety [14]. They can also alert supervisors or medical staff if an employee needs assistance. This can be particularly useful in high-risk manufacturing environments where workers are exposed to extreme temperatures, noise levels, and other hazards. Automated machinery is another type of technology that can help ensure staff safety by performing tasks that are too dangerous or difficult for humans. They can also reduce the need for manual labour, which can help minimise the risk of workplace injuries and keep workers safe [15].

Overall, the use of technology in manufacturing can help improve worker safety by reducing the risk of accidents and injuries, improving workplace conditions, and providing workers with the tools and resources they need to stay safe on the job. While no single technology can completely eliminate all risks associated with manufacturing work, a combination of technologies can be incredibly effective in preventing accidents and keeping workers safe. As the manufacturing industry continues to evolve, new technologies will likely emerge to further improve worker safety and prevent accidents.

B. Existing Studies

Computer vision has been adopted in smart manufacturing for ensuring the safety of workers including falling prevention, struck-by accidents, movement of equipment and workers and PPE recognition. Falling prevention for steeplejacks has been proposed using R-CNN, SSD, and YOLO has been proposed using the name of the dataset [16]. Struck-by accidents between the excavators and other heavy machinery are another case studies that are conducted using DNN, YOLOv3 [17]. Classification of risky sites using KNN, SVM and Random Forest [18]. Similarly, a system is discussed that detects human behaviour in dangerous situations and enables them to be avoided based on pre-trained data of collisions of humans and thermally dangerous areas [19, 20]. Detection of the movement of equipment and workers is also considered using SVM [21]. Also, an analysis of the potential of computer vision to automatically identify and capture unsafe behaviours and hazards in real-time from two-dimensional (2D) digital images/videos is presented [22]. Within the review, PPE and clear workspace have been investigated. In addition, PPE recognition has been explored in a few studies [23, 24]. Image segmentation of the workers is conducted for detecting whether the workers are wearing gloves and helmets or not [23]. None of these studies has considered gloves, goggles, helmet, shoes, mask and suit which we considered in our work. Another research direction is to use computer vision for social distancing and masking while manufacturing to reduce the risk of transmission [25]. object detection in medical manufacturing using computer vision has been examined for quality checks [26]. Moreover, several works have been checking for any defects in the used materials [27, 28].

III. SAFE SMART MANUFACTURING

This section highlights the safety requirements, the proposed architecture, and the methodology employed as well as the datasets that are utilized.

A. Safety Requirements

A smart manufacturing process integrates advanced technologies, such as robots, artificial intelligence (AI), and the Internet of Things (IoT), to improve efficiency and productivity. The implementation of smart manufacturing has the potential to provide many benefits, however, human safety must be prioritised. Several human safety requirements apply to smart manufacturing, including the following:

Personal Protective Equipment (PPE): Workers may require PPE such as safety glasses, gloves, respirators, or hard hats according to the nature of the manufacturing process.

Clear Workspace: It is essential to maintain a clear and organized working environment to prevent accidents and injuries. When equipment and tools are not in use, they should be properly stored, and all work areas should be free of debris and clutter.

Emergency Response Plan: An emergency response plan should be in place for manufacturing facilities in the event of an accident, fire, or other emergencies. A safety plan should include instructions regarding evacuation procedures, emergency contact information, and how to use safety equipment like fire extinguishers.

Regular Maintenance: Regular maintenance and inspections are essential for ensuring the safety of employees and equipment. Performing routine maintenance tasks, such as cleaning and oil changes, involves checking equipment for wear and tear.

Predictive Maintenance: Intelligent manufacturing relies heavily on predictive maintenance, which is a process that identifies and resolves potential equipment failures prior to their occurrence. Machine learning algorithms and data analytics can be used to optimize maintenance schedules, reduce downtime, and improve the overall efficiency of operations.

Employee Training: A comprehensive training program should be provided to all employees on safe equipment operation, handling of hazardous materials, and emergency response procedures. Whenever there are any changes in safety protocols or changes in training, it is imperative that this training is regularly updated and reinforced.

This paper focuses on PPE and clear workspace using computer vision. If any of these two cases have been recognised, then an emergency response plan can be triggered based on the report. This paper did not focus on the emergency response plan but rather on the recognition of unsafe events within manufacturing.

B. Architecture

The architecture utilises the CCTV cameras in the manufacturing plant for human safety and well-being through two subcategories in which one video streaming of the CCTV cameras are transmitted to multiple processing as shown in Fig. 3. Both categories are implemented using computer vision for ensuring human safety through their day-to-day shifts. According to the literature, the new technologies emerging within the manufacturing industry creates further risks to humans in the workplace. Hence, the first approach of this research will focus on detecting Forklifts as a preliminary study due to them potentially posing risks to human safety. As for the second approach, employees tend to forget to wear the correct PPE especially when there is a procedural dress code for each area within the manufacturing site.

To accomplish these objectives, Cameras that are generally used for surveillance purposes can be utilised to monitor such behaviours, during which the organisational leads can become aware of their exposure to safety and how this can be potentially improved. As for this research, the detection of hazards is considered through computer vision techniques is explored in two use cases which are as follows:

- Personal protective equipment (PPE)
  PPE is essential in manufacturing environments to protect workers from various hazards, including physical, chemical, and ergonomic risks. The use of PPE such as gloves, eye protection, respiratory protection, and protective clothing helps to reduce the risk of workplace injuries and illnesses, which can result in increased productivity, reduced absenteeism, and improved employee morale. With this being said, the use of PPE is required by law in many countries, and failure to comply with these regulations can result in penalties and legal action against the manufacturing company.
- *On-going Forklift Detection*
  Forklifts are essential tools for material handling in manufacturing environments, but they can also pose significant safety hazards if not used properly. Generally, proper forklift safety measures, including regular maintenance, proper training for operators, clear communication protocols, and safety barriers are always considered in the workplace. However, the use of forklifts around humans can always pose a risk and accidents can always occur. Hence, the implementation of visionary sensing as shown in Fig. 3 can help assess the position of the forklift and determine if any close encounters have arisen.

Taking inspiration from Conway Packing Services, the business system architecture can be extended with Smart Industrial Process Planning Development to evaluate the health and safety record of workers. By extracting these health and safety records, they can be applied to workers. Many industries do not rely on video streaming from CCTV to record their functions or employees' performance.

C. Methodology

Based on two datasets as previously mentioned, this paper uses YOLOv8 and Faster R-CNN to detect objects. The YOLOv8 algorithm is a fast object detection algorithm based on a single neural network that proposes bounding boxes and classifies objects within those boxes, resulting in very fast inference times. Another popular algorithm for detecting objects is the Faster R-CNN algorithm, which utilises a region proposal network to generate potential locations for objects before classifying them. This results in higher accuracy, but slower inference time than other algorithms.

In this experiment, NVIDIA V100 Tensor Core GPUs is used, which are designed for deep learning workloads using the collab platform.

D. Datasets

1) Personal protective equipment (PPE)

This dataset has 11,978 images in which each image might have multiple classes or objects [29]. There are 12 classes within the dataset which are: no gloves, glove, googles, no goggles, helmet, no helmet, shoes, no mask, no shoes, mask no-suit and suit. This dataset suffers from unbalanced of the dataset which can be seen in Fig. 1. The gloves, no_gloves, and googles labels are over-labelled, while the helmet, no_helmet, shoes, no_shoes, mask, no_suit, and suit labels are under-labelled. This dataset has been cross-validated into 78% training (with 19000 images), 14% validation (with 3600 images) and 8% testing (with 1900 images). Additionally, real-life images obtained from the Conway Company are mixed with the trained model for testing, as illustrated in Figs. 2 and 4.

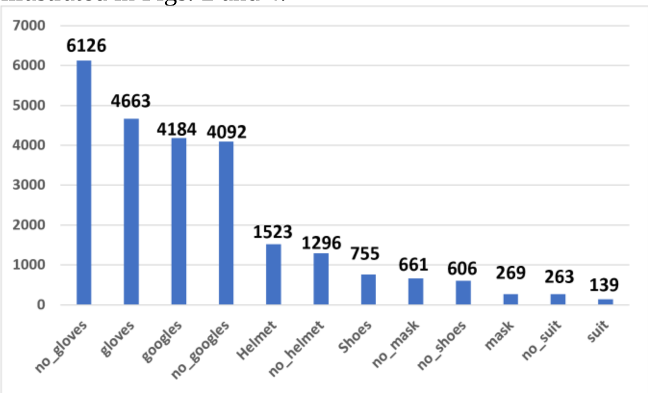

Fig. 1. PPE Dataset representation

Fig. 2. Examples of the images used for testing from Conway.

2) On-going Forklift Detection

This dataset has 421 images in which two classes are only recognised [30]. Forklift and person are the two considered

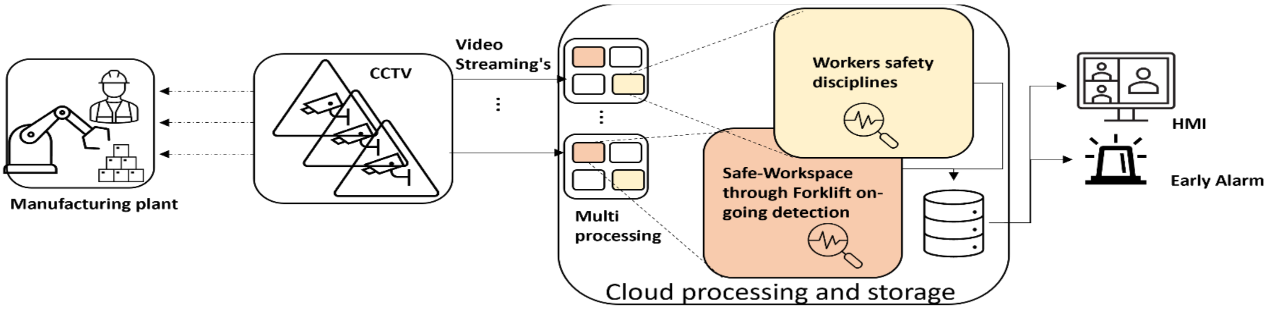

Fig. 3. System Architecture.

classes within this dataset in which forklift has been classified 458 times and persons have been labelled 415 times. This dataset has been cross-validated into 88% training (with 885 images), 8% validation (with 84 images) and 4% testing (with 42 images).

Fig. 4. Examples of the images used for testing from Conway.

E. Evaluation

The recognition of PPE has been evaluated based on five performance metrics which are precision (P), Recall (R), F1score (F1), mAP50 and mAP 50-95. The precision of the model is assessed by its ability to identify PPE items accurately, while the recall is measured by its ability to detect all instances of PPE items present in the image. An F1 score measures the overall accuracy of a model by combining precision and recall. The mAP50 and mAP50-95 are calculated using Intersection over union (IoU) thresholds and assess the model's accuracy in identifying PPE items overlapping the ground truth.

IV. Results and Discussion

1) Personal protective equipment (PPE)

The results and discussion about the presented PPE show that precision, Recall, F1 score, mAP50 and mAP50-95 have reached 80%, 56.7%, 44.4%, 40.7%, 57.2%, 47.4%, 30.5%, 27%, 16.2% and 15.3% for all classes using YOLOv8 and Faster R-CNN, respectively as shown in Table I. Moreover, the mapping for the class names is shown in Fig. 1. In addition, it varies from class to class. It can be demonstrated that the performance of the under-labelled classes is less than that of the high-labelled classes in general. Furthermore, the detection of the images can be observed in the example in Fig. 5.

2) On-going Forklift Detection

The results and discussion about the presented forklift show that precision, Recall, F1 score, mAP50 and mAP50-95 have reached 86%, 57.8%, 62%, 19.3%, 72%, 28.9%, 73.5%, 8.54%, 41.5% and 2.8% for all classes using YOLOv8 and Faster R-CNN, respectively as shown in Table III. In addition, it varies from class to class. It can be demonstrated that the performance of the under-labelled classes is less than that of the high-labelled classes in general. Furthermore, the detection of the images can be observed in the example in Fig. 6.

TABLE I. PPE DATASET RESULTS AND EVALUATION

	YOLOv8					**Faster R-CNN**				
	P	**R**	**F1**	**mAP50**	**mAP50-95**	**P**	**R**	**F1**	**mAP50**	**mAP50-95**
A	**80.6**	**44.4**	**57.2**	**30.5**	**16.2**	56.9	40.7	47.4	27	15.3
1	72	92.6	81	90.3	47.7	68.9	93.7	79.4	89.7	46.1
2	82.2	62.3	70.8	72.6	44.7	76.8	60.3	67.5	64.1	37.5
3	1	0	0	0	0	1	0	0	0	0
4	1	0	0	0	0	1	0	0	0	0
5	2	80	3.9	5.2	4.5	1.5	80	2.99	22.1	20
6	50.3	70.8	58.8	55.9	26.6	44.1	72.5	54.8	61	27.3
7	77.7	64.5	70.4	70.7	34.4	62.7	45	52.3	48.6	27
8	1	0	0	0	0	1	0	0	0	0
9	1	0	0	0	0	1	0	0	0	0
10	11	7.1	8.6	2.5	0.6	2.6	72.4	5.0	0.77	0.13
11	99.4	55	70.8	57.8	20.8	21.8	30.2	25.3	16.5	5.0
12	4.5	1	1.6	11	10.7	4.21	1	1.6	21.7	20.5

TABLE II. PPE DATASET RESULTS MAP

Notation	Class Name
A	all
1	no_gloves
2	gloves
3	googles
4	no_googles
5	helmet
6	no_helmet
7	shoes
8	no_shoes
9	mask
10	no_mask
11	suit
12	No_suit

Fig. 5. PPE Dataset detection example

TABLE III. FORKLIFT DATASET RESULTS AND EVALUATION

	YOLOv8					Faster R-CNN				
	P	R	F1	mAP50	mAP 50-95	P	R	F1	mAP50	mAP 50-95
A	86.4	62	72.1	73.5	41.5	57.8	19.3	28.9	8.54	2.8
0	90.7	70.8	79.5	85.2	52.9	15.7	38.5	22.3	17	5.58
1	82.1	53.3	64.6	61.7	30	1	0	0	0.024	0.006
A= All			**0=Forklift**			**1=Human**				

V. CONCLUSION AND FUTURE WORK

Using computer vision technology, this paper proposes a smart manufacturing process that is safe and helps reduce the risk of worker injury by detecting appropriate personal protective equipment (PPE) worn by workers. The use of computer vision technology can assist in identifying protective equipment used by workers in manufacturing environments, such as gloves, helmets, and forklifts. A precision of 80.6% and 86% have been reached using YOLOv8 for all classes in both datasets. The datasets were extensively reviewed, and five performance metrics were considered to evaluate the results. With adequate accuracy attained from our proposed detection system, the safety of the workplace can be immensely improved by tracking the position of the forklift and detecting any behaviours that may pose a risk to humans. This work can be extended to have a computer vision system that can monitor the work progress for the sake of enhancing the quality of service of the production line.

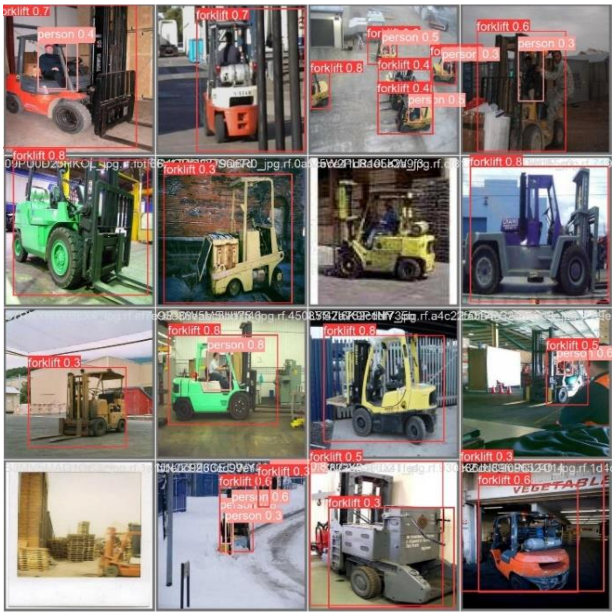

Fig. 6. Forklift Dataset detection example

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