Enhanced Safety Implementation in 5S+1 via Object Detection Algorithms

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Abstract

Scholarly work points to 5S+1, a simple yet powerful method of initiating quality in manufacturing, as one of the foundations of Lean manufacturing and the Toyota Production Systems. The 6^{th} S, safety, is often used to prevent future occupational hazards, therefore, reducing the loss of time, money, and human resources.

This paper aims to show how Industry 4.0 technologies such as computer-based vision and object detection algorithms can help implement the 6^{th} S in 5S+1 through monitoring and detecting workers who fail to adhere to standard safety practices such as wearing Personal Protective Equipment (PPE). The paper evaluated and analyzed three different detection approaches and compared their performance metrics. In total, seven models were proposed to perform such a task. All the proposed models utilized You-Only-Look-Once (YOLO v7) architecture to verify workers' PPE compliance. In approach I, three models were used to detect workers, safety helmets and safety vests. Then, a machine learning algorithm was used to verify if each detected worker is in PPE compliance. In approach II, the model simultaneously detects individual workers and verifies PPE compliance. In approach III, three different models were used to detect workers in the input feed. Then, a deep learning algorithm was used to verify the safety. All models were trained on Pictor-v3 dataset. It is found that the third approach, when utilizing VGG-16 algorithm, achieves the best performance, i.e., 80% F1 score, and can process 11.79 Frames per Second (FPS), making it suitable for real-time detection.

1. Introduction

The Lean manufacturing concept was introduced in Japan. The Toyota company first implemented the concept and was known as Toyota Production System. However, nowadays, the Lean concept is widely applied in industries. Lean manufacturing is defined as providing quality products while maintaining the low cost of manufacturing. The primary purpose of Lean manufacturing is to minimize enterprise waste, as waste is an extra resource burden that never adds value to the company. Lean manufacturing tools minimize operational costs by reducing waste, optimizing product quality, and increasing efficiency [1]. Furthermore, the Lean manufacturing concept is one of the most popular and widely used methods in the industries to achieve maximum productivity, high quality, and cost reduction in organizations. Results of a study concluded that the Lean concept boosts the productivity of organizations, reduces the cost of manufacturing, eliminates unnecessary downtime, better the utilization of resources, and maximizes profitability. Therefore, the Lean concept enhances the competitiveness of any organization in the market [2]. Therefore, enterprises strive to adopt the Lean manufacturing concept to become economically sound and practical. It was seen that there was a continuous improvement in organizations after the application of the Lean manufacturing concept [3]. The introduction of Lean manufacturing tools such as Total Productive Management (TPM), overall equipment effectiveness (OEE), and Jidoka directly impact the environment of the enterprise, social, and economic sustainability. Therefore, a safe working environment is the cause of improvement in employee commitment, morale, safety, and delivery time [4].

Lean manufacturing has operational benefits regarding quality, delivery, cost, and volume flexibility. It was shown that adopting digital technology and Lean manufacturing reduces production costs despite the different environmental conditions. The application of Lean manufacturing together with digital technology improves operational performance and efficiency of production management. Lean implementation has been shown to improve the financial standing of an enterprise by maintaining a safe shop floor management approach [5]. The introduction of the Lean manufacturing concept in the management of railway transport enterprises results in the optimization of labor and material resources. Thus, it helped reduce operation time, generate a safe environment for labor, improve transportation quality, and expand their customer base [6].

Back in 1970 5S method was first introduced by Takashi Osada [7] to sustain the implementation of the Lean concept. 5S, a Lean tool, includes elements such as Sort, Set, Shine, Standardize and Sustain. The Safety was later added to make the 5S+1. These tools eliminate unnecessary items that do not add value to the production by fixing an unhealthy, untidy work environment. In a study, ten different manufacturing units were used to find out the effect of the use of 5S, and it showed a positive result on the manufacturing units. Furthermore, after applying 5S, there was a continuous improvement in the workplace and clear evidence of improvement in employee human relations and motivation [8]. 5S system is the first step into Lean thinking to minimize waste and maximize productivity. Through it, they maintain discipline and order in workstations hence efficient and effective operational results [9]. Therefore, the 5S can be considered to be a cyclic method. As a result, there is a continuous improvement [10]. Even when applied in a limited resources environment, 5S has proven to bring positive changes in the work environment of health centers by reducing the number of unwanted items, improved directional indicators, and labeling the units of service. Thus, increasing the quality of services in a more efficient, safe, and patient-centered style also helped improve the behaviors of staff and patients towards the resources of the workplace [11]. Applying the 5S in a medical laboratory brought a higher order level, helped eliminate unnecessary objects, and increased productivity [12]. It was found that applying 5S in hospitals eliminated waste in motion, thus helping to reduce cycle time [13]. Consequently, a more Lean and more organized work environment was created while controlling work accidents and errors beforehand [14]. The application of 5S in the fast food industry contributed to optimizing the work process. It also contributed to a decrease in production time; and a reduction in energy consumption [15]. Implementing 5S has been shown to improve safety, minimize defect rates, increase equipment availability [16], and better cost reduction, which can result in higher agility and flexibility of the manufacturing enterprise and positively impact employee morale [17]. Applying the 5S methodology in packaging improved quality and food safety [18]. Furthermore, applying 5S in restaurant management caused a reduction in the number of steps that need to be taken by employees to fulfill a specific task. It also helped reduce the time spent searching for materials by 95%. Thus, helping reduce order time, serving more customers, and making more profits [19]. The use of 5S positively impacts performance by enhancing manufacturing production quality and effectiveness [20]. 5S+1 has also been used to organize the workplace at a scientific instruments manufacturing company [21] and achieved results in process improvement, continuous improvement, and waste reduction [22].

1.1 Sort in 5S+1

This is the first step when implementing the 5S+1 strategy. It improves the quality of the work with better care in keeping things in order, thus improving the management of the workspace. Sort helps separate waste from the manufacturing process [23]. The first S, Sort, eliminates steps that do not add value [24]. In this process, a red tag is placed on the unnecessary items or the items that are not in the proper place or quantity. The red tag items are then moved or recycled, disposed or reassigned. Hence sorting helps to generate floor space and remove the items that are broken, scrap, or excess raw material [25]. The Sort element of 5S helps enterprises shorten searching time, maintain a Lean and safe workspace and quickly detect any fault in equipment [26]. The 5S method is a foundation for improving the production process in any company. That is why it should be adequately implemented to increase the effectiveness of a process by eliminating waste [27].[28].

1.2 Shine in 5S+1

Once sorting is done, keeping order in the workspace is vital. Routine Lean up is essential for the production system's proper functioning. In 5S+1, work is divided among employees in terms of the Leaning time and area of Leaning [29]. Also, faulty equipment due to excessive vibrations, leakages, misalignments, and other causes can be easily noticed in a Lean working environment. If these malfunctions are not fixed at the moment, it can lead to loss of production or equipment failure. Therefore, having a Lean and organized workplace can help prevent sources of potential failure or downtime from going unnoticed. Shine is taken from Seiso, which means sweep, scrub, or shine. The primary purpose of Seiso is to Lean up the workspace by removing dust, dirt, chips, and other contaminations. It emphasizes on that by guiding operators or workers on the shop floor to maintain the state of Lean of the machines and shop floor. Training is given to the employees about the adverse effects of contamination and how to avoid them to establish and maintain a risk-free working environment [30]. Shine indicates the need to Lean systematically to keep a healthy work environment, which helps maintain quality work in production [31]. When equipment is Lean, it performs more efficiently, thus eliminating extra costs that can be incurred due to unnoticed problems. Manufacturers have realized that if machines are kept clean while daily maintenance is carried out, chances of downtime decrease; thus, margins of profits increase [32]. It has been documented that the number of common accidents and risks in a Lean factory has gone down in a Lean workspace or shop floor [33].

1.3 Set in 5S+1

Set or Seiton is another element of the 5S+1 method that means systemization, set in order, or organization. It helps in a facility layout when planning where to place different resources such as raw materials, machine tools, semi-finished products, etc. This strategy ensures that it should not take more than 30 seconds to find a necessary object [23]. Once the sort has eliminated all the unnecessary items, set in order can be implemented. Set in order means to arrange items based on size and frequency of use. Further, the items are labeled for ease of use and stored or placed in a location based on that. In set in order, arrangements are made in such an order that tools are located according to the frequency of their use. As a result, this procedure helps to minimize movements and search time. Set in order can be achieved by labels, using tapes, signs, and marking floors. In addition, Seiton eliminates wastes, including search wastes, waste in motion, and excessive inventory waste [34]. Many positive changes have been noticed as a result of adopting 5S+1. For example, it was found that there was a reduction of employee movement by 60% and a reduction of 20% in operational costs [35]. Furthermore. It has been shown to increase productivity, quality of work and products, safety, health, and efficiency [36]; and reduction of waste in motion, such as excessive movements between production halls and work stations [37].

1.4 Standardize in 5S+1

Seiketsu is another element of 5S that means standardization, tidiness, and sanitization. It helps to carry out repeated activities without any hindrance and extra usage of time [23]. The primary objective of standardization is to make the first 3S; sort, set in order, and shine as a habit, so workers do not return to the old unorganized practices [38]. Seiketsu creates standards and monitors them for upcoming events, such as inspection and safety plans. Standardization aims to maintain a safe working environment and reduce the disruption that might happen due to a change in the scope of duties for the workers, allowing a shorter training time and smooth and quick adaptation to the new changes in the working environment [30]. Further, standardization prevents the accumulation of waste, and maintains a consistent procedure and a Lean working environment. Without any standards in an organization, it is impossible to improve product quality [39]. In the current overlapped environments of Lean Industry 4.0, standardization is one of the critical parameters to maintain a safe workspace, reduce disruptions, and increase production. 5S+1 is a business or industrial approach that primarily focuses on improving the production process by enhancing workplace standards [40]. In addition to integrating standards into maintenance procedures, production planning and specifications, and transportation of goods, standardization is also used in other significant activities, such as human resource management, customer service, and bookkeeping [41]. Implementation of 5S+1 depends upon employee commitment, sustainability initiatives, and training [42]. 5S+1 practices generate new rules for production plants and set up processes that are adapted in the company [43]. Chiarini [44] attempted to create a first guideline on how the 5S+1 concept and tools could be integrated into established standard texts such as ISO 9001.

1.5 Sustain in 5S+1

The Shitsuke element of the 5S means sustains. The main objective of Shitsuke is to keep or maintain all the new and effective processes as standards of the organization. Workplace inspections should be carried out as planned routine activities every specific period [23]. 5S+1 helps eliminate obstacles that reduce the potential to reach an efficient production process [45]. Sustain is viewed as an essential step to maintain the first 4S when applied while allowing for better implementation of the sixth S in safety [46]. The most crucial goal of sustain is to make the best practices a habit of the workforce in any business. Further sustain helps improve human relationships in the company as it teaches discipline and helps continuous running of the 5S+1 process [39]. Adopting 5S+1 has encouraged employees to create better work conditions by teaching them how to reduce waste through Value Stream Mapping (VSM) and continuous improvement. When implemented, the 5S+1 method influences individual behaviors. It creates simple, precise, and efficient rules, thus constructing a disciplined functional working environment [47]. It is difficult to change the traditional way of doing things and maintain the new procedures which disrupted the old ways; that is why this fifth S is considered to be the most challenging procedure [48]. Without sustain, it is impossible to maintain the application of 5S+1 [49]. Maintaining the 5S+1 strategies in the workplace simplifies the work environment and makes it easy for everyone to follow the rules and guidelines [50].

1.6 Safety in 5S+1

Safety focuses on preventive measures to protect workers from hazardous conditions and provide them with a safe environment. Studies recall that safety plays a significant role in maintaining an environment that is free of stress, safe, and secure hence improving the work environment [51].

Operations such as welding, gas cutting, and casting process need extra precautionary measures to reduce the number of incidents that can happen [52]. The 5S+1 method cannot be separated from industrial, manufacturing, or construction operations. Implementing 5S+1 tools creates safer work conditions [53], [54]. Deploying 5S+1 in the healthcare industry reduced waste and mistakes and increased productivity [55]. Applying 5S+1 ensured that operators used Personal Protective Equipment (PPE) and gear to avoid accidents. [56]. The 5S+1 method is a powerful engine that enhances the quality of the work environment by improving safety [57].

2. Background

With the purpose of showing the effectiveness of object detection algorithms in monitoring and detecting workers who fail to adhere to standard safety practices, a dataset was utilized that contained numerous instances of construction workers that could be classified as wearing a safety helmet, safety vest, both, or neither. Construction workers comprise 5% (more than 7 million employees) of the total workforce in the United States and almost 6.3% (more than $1.3 trillion) of its Gross Domestic Product (GDP) [58], [62]. According to the Bureau of Labor Statistics (BLS), almost 19% of fatal occupational accidents are recorded in the construction industry, and about 9% of non-fatal occupational accidents [60]. Most of these accidents could have been prevented if workers adhered to appropriate safety measures such as wearing PPE such as a safety helmet, safety vest, gloves, safety goggles, and steel-toe shoes [61]. While governing laws and safety regulations holds employers responsible for enforcing, monitoring, and maintaining appropriate PPE on the job site [62], a recent study revealed that almost 40% of workers do not wear any PPE. Inadequate risk management measures, including failure to use or incorrect use of PPE, may significantly increase the risk of accidents [63]. Employers can be fined an amount of up to $13260 for each employee who is out of compliance with PPE [67]. Applying 5S + 1 can help employers avoid workplace accidents and hefty non-compliance fines, reducing time and resources spent dealing with fines, lawsuits, and settlements as a result of non-compliance.

Integrating automation and big data in the Industry 4.0 [74] helped enhance the monitoring of PPE compliance. So far, there are two types of monitoring techniques, sensor-based which consist of utilizing Radio Frequency Identification (RFID) tags installed on each PPE component and monitoring the signals of the tags to verify if workers were adhering to PPE compliance [65], [66], [67]. The second type of monitoring is vision-based; in the past, this used to be done with the human eye of a foreman on the site; these days, it utilizes camera systems to record images or videos of the job site, which are then analyzed to verify PPE compliance [68], [69]. Table 1 shows a comparison between the vision-based model and sensor-based model.

Table 1
Sensor-based vs. Vision-based monitoring of PPE compliance

Sensor-based	**Vision-based**
Utilizes tags that contain a sensor attached to an antenna that enables the transmission of data to the reader, transmitted data receiver, and computer database for storing captured data [70], [71], [72]	Requires high-resolution cameras, software embedded with image processing algorithms, computer power, and computer database for storing captured data [73]
High maintenance cost, RFID tags are expensive, and they are likely to be damaged during loading and unloading [74]; batteries can run out in active RFID tags [75]	Lower maintenance cost since it has a longer product life, but there might be a need to upgrade outdated systems every few generations [76]
More labor intense	Minimal human effort
Implementation can be complex and time-consuming	Easier to implement
Electromagnetic data transmission [77]	Visual data transmission
Different tag types can be affected differently by environmental damage; overall, they can better handle exposure to sun and rain [78]	Algorithm performance can be affected by an environmental factor such as rain
It can read through objects [79]	Must be in sight
Reading range depends on the frequency; materials like metal and liquid can impact signal	The reach depends on the specifications of the camera; light and motion can affect camera performance putting more pressure on the computer processing stage [80]
Utilizes RFID tags or short-range transponders [81]	Utilizes Machine Learning (ML) methods

In the last decade, Deep Learning (DL) models have gained recognition due to their ability to power computer vision-related tasks [82], [83]. Convolutional Neural Network (CNN) uses a feed-forward topology to propagate signals and is being widely used for image classification and object detection [84]. CNN uses a feed-forward topology to propagate signals; CNN is more often used in classification and computer vision recognition tasks [84]. CNN was used to recognize hand-written digits [85], and to classify images into different classes [86], [87]. CNN was also used to detect objects on roof construction sites [88], [89]. Long Short Term Memory (LSTM) comprises Recurrent Neural Networks (RNN) that propagate data forward and also backward from later processing stages to earlier stages [84], [90] and are capable of learning order dependence in sequence prediction and able to remember much previous information using Back Propagation (BP) or previous neuron signals and include it for the current processing [91], [92]. LSTM can be leveraged with various other architectures of NN [93]; CNN-LSTM was used to recognize workers' potentially unsafe behavior [94]. CNN was used to identify construction-related objects such as buildings, equipment, and workers [95]. A Fully Convolutional Neural Network (FCN) is a CNN without fully connected layers [96], [97]. A significant advantage of using FCN models is that it does not require heavy preprocessing or feature engineering, thus making a good choice for image processing [98]. FCN has been used to detect fake fingerprints [99]. It was shown that FCN provides high detection accuracy in addition to less processing times and fewer memory requirements than other NN. Region Proposed Networks (RPN) [100], [101] such as Faster R-CNN has been deployed in an array of object detection-related applications, for example, in accounting applications such as receipt information extraction [102], handwriting text recognition [103], and matching process-related applications [104]. It has also been applied in detecting mathematical expressions in scientific document images [105] and tested in a plagiarism detection tool [106]. Table 2 shows a summary of surveyed literature where machine vision has been used to detect PPE and Fig. 1 shows a flowchart of the PPE compliance detection system.

Table 2
Summary of surveyed literature

Model	Goal
R-CNN, Faster R-CNN	To detect if a worker is not wearing a hard hat [107]
SSD	To detect if a worker is not wearing a hard hat [108]
FCN	To detect if a worker is not wearing a hard hat [109]
YOLO v6	To detect PPE for construction sites [110]
YOLO v4	Real-time detection of fire [111] and PPE [112]
YOLO v5	Fast detection of PPE in construction sites [113], [114]
HOG	Detection of PPE compliance [115]
CNN-LSTM	Detection of PPE [116]
YOLO v3 with DL classifiers	Detection of PPE compliance [117], [118]
YOLO v7 with ML and DL classifiers	Our work: Detection of safe behavior (workers wearing safety helmets and safety vests) and nonsafe behavior (workers not wearing safety helmets or safety vests, or both)
YOLO: You Only Look Once, SSD: Single Shot Detector, R-CNN: Region-based CNN, HOG: Histogram of Oriented Gradient,	

3. Dataset And Methodology

The dataset Pictor-v3 [118] contains 774 crowdsourced and 698 web-mined images which contain 2,496 and a total of 2,230 instances of workers in these images, respectively. The crowdsourced images come already annotated via LabelMe [119], as seen in Fig. 2 below. Annotation is very time consuming and costly process, therefore, for the purpose of our paper, we choose the crowdsourced part of the dataset to conduct our analysis. Crowdsourced images were obtained from three different construction projects, while web-mined images were retrieved from publicly available images on the web. The dataset has four classes in total, workers (W) can either wear a safety helmet (H), safety vest (V), both (WVH) or none at all. A brief statistic of the dataset is shown in Table 3 below. Data augmentation was done through the YOLO v7 built-in feature. The data was trained for up to 50 epochs to help prevent overfitting [120], [121]. The dataset had a random 64%/16%/20% split for training, validation, and testing.

Table 3
A brief statistic of the dataset

Category	Images		Instances	
	Crowdsourced	**Web mined**	**Crowdsourced**	**Web mined**
W	240	54	873	336
WV	0	91	0	328
WH	517	195	1583	623
WVH	17	358	40	943
Total	774	698	2496	2230

In computer vision, the object detection problem consists of two stages, identifying an object (classification) in an image and precisely estimating its location (localization) within the image [122]. For example, a region-based detection algorithm such as R-CNN [123] first identifies Regions of Interest (ROI). It then uses a CNN to classify the identified ROI to detect objects in them [124]. Faster R-CNN is an improved version of R-CNN that performs classification and detection tasks faster than R-CNN [125]. Mask R-CNN [126] has also been proposed as a faster variant of R-CNN. However, these algorithms still needed to perform faster and with better performance. Therefore, algorithms of single-stage detectors were introduced; these algorithms include SSD [127], YOLO [128], R-FCN [129], and Mask R-FCN [130], among others that eliminated the need for designing a set of anchor boxes [131]; such as CenterNet [132], RetinaNet [133], CornerNet [134], and their different variants. While these fast single-stage detectors often significantly compromise accuracy for achieving real-time detection, to date, only YOLO is faster yet more accurate than other alternatives [135]. In our paper, three different detection approaches were proposed to perform compliance inspections by detecting workers wearing PPE (safety helmet and safety vest) and workers who do not.

3.1 Approach I

The YOLO-v7 model individually detects the worker, helmet, and vest (three object classes). Next, an ML classifier is used to combine them WH (worker wearing only a helmet), WV (worker wearing only a vest), WHV (worker wearing both helmet and vest), or W (worker wearing nothing). In this approach the YOLOv7 detects three classes first (W, H, and V) then a classifier is used to sort them into four classes (W, WH, WV, and WHV). For example, if a worker is classified as wearing both (WHV), his practice would be labeled “SAFE” and recorded as in compliance. If not, the worker would be labeled “NOT SAFE” and recorded as out of compliance. The ML classifiers used in this approach were Decision Tree (DT), K-Nearest Neighbors (KNN), and Multilayer Perceptron (MLP). Figure 3 shows an illustration of this approach.

3.2 Approach II

The YOLO-v7 model localizes workers in the input image and directly classifies each detected worker as W, WH, WV, or WHV. In this approach the YOLOv7 detects all the classes from the first look. For example, if a worker is classified as wearing both (WHV), his practice would be labeled “SAFE” and recorded as in compliance. If not, the worker would be labeled “NOT SAFE” and recorded as out of compliance. Figure 4 shows an illustration of this approach.

3.3 Approach III

YOLO-v7 model first detects all workers in the input image, and then, a CNN-based classifier model is applied to the cropped worker images to classify the detected worker as W, WH, WV, or WHV. In this approach the YOLOv7 detects the W class first then a classifier is used to sort them into four classes (W, WH, WV, and WHV). For example, if a worker is classified as wearing both (WHV), his practice would be labeled “SAFE” and recorded as in compliance. If not, the worker would be labeled “NOT SAFE” and recorded as out of compliance. These DL-based classifiers are VGG-16, ResNet-50, and Xception. Figure 5 shows an illustration of this approach.

3. 4 Algorithms Utilized In The Three Approaches

3.4.1 You Only Look Once (YOLO)

Utilized in all the three proposed approaches, a YOLO v7 model takes 640 x 640 images as input. Therefore, all images were resized to a size of 640 x 640. YOLO has been used in extracting information from tables [136], [137], [138]; license plate recognition [139], [140], automated invoice parsing [141], and for automated meter reading [142]. Instead of learning regions like in a Faster R-CNN, YOLO (currently in its seventh version) looks at the complete image, splits it into n x n grids, then uses a single CNN to predict the bounding boxes and the class probabilities for these boxes [143]. Finally, the bounding boxes are used to locate the class within the tested image [96]. Figure 6 shows an illustration of the algorithm utilized in approach II.

3.4.2 Decision Tree (DT)

DT is a set of rules for dividing a large heterogeneous population into smaller, more homogeneous groups concerning a particular output feature. DT is one of the most common Data Mining (DM) techniques widely used for classification and regression analysis. DT comes in many decision algorithms, some of which are binary trees that always produce two categories (binary-split) at any level of the tree-like CART and QUEST. Others like CHAID and C5.0 are non-binary trees that often grow more than two categories at any level in the tree. Other minor differences exist between these four main DT algorithms, such as how to deal with missing values, variable selection, capacity to handle a vast number of classes in variables, and pruning methods [145], [146]. Figure 7 shows an illustration of the algorithm utilized in approach I with DT.

3.4.3 K-Nearest Neighbors (KNN)

KNN is a supervised machine learning algorithm that can be used to solve both classification and regression problems. KNN assumes that similar data points exist nearby. In other words, similar data points are near to each other. KNN searches the entire data set for the k number of most neighbors and calculates distances for proximities before sorting the calculated distances in ascending order from smallest to largest and picking the first K with its feature that is associated with the smallest distance. KNN uses a large amount of training data, plotting data points in a high-dimensional space, where each axis in the space corresponds to an individual variable that characterizes that data point [147]. KNN has been used in intelligent mechanical systems to detect online fraud [148] and has been successfully implemented in a large number of business problems [149],[150]. Figure 8 shows an illustration of the algorithm utilized in approach I with KNN.

3.4.4 Multilayer Perceptron (MLP)

MLP is a class of feedforward Artificial Neural Network (ANN) that has been widely used in machine learning applications in all aspects of science [151]. The MLP gives an AI system the ability to do data-based problem solving by helping computers in programming themselves based on input data. MLP can be used in both supervised learning methods and unsupervised learning methods. It has an initial structure consisting of a network of nodes (neurons or perceptron) arranged in three layers: input, hidden, and output. The ways of its learning (inner workings) resemble how a newborn's brain is being developed without prior knowledge. The MLP model learns how to transform (in a linear or nonlinear way) input variables into output variables by creating layers upon layers of neurons of random weights [152]. Figure 9 shows an illustration of the algorithm utilized in approach I with MLP.

3.4.5 VGG-16

VGG-16 is a sixteen layers deep CNN algorithm that is used in many computer vision tasks. VGG-16 can classify images into 1000 object categories and has about 138 million parameters [153]. It has a unique, consistent architecture of 3 x 3 convolutional layers and 2 x 2 max-pooling layers [154], [155]; in the end, it has three fully connected layers [156], [157], [158]. VGG-16 was used to classify and identify different varieties of peanuts and achieved an average accuracy of 96.7% [159]. In addition, it was utilized in the computer vision process in Unmanned Aerial Vehicles (UAV) [160] to detect flower heads with prominent stamens (tassel). Furthermore, VGG-16 was used in real-time detection in surveillance cam feed [161]. It has also been utilized in hand-gesture recognition tasks [162], detecting defects in a wafer structure [163], recognizing oil rigs in aerial images [164], and corn leaf disease diagnosis [165]. Figure 10 shows an illustration of the algorithm utilized in approach III with VGG-16.

3.4.6 Xception

Xception by Google is a CNN that consists of 71 deep convolutional layers [166]. This efficient deep architecture was achieved by maintaining fewer connections between the convolutional layers of the model, thus making it less dense. Xception has about 22.8 million parameters and one fully connected layer at the end. Xception has been used in a wide variety of applications, including face detection [167], medicinal leaf classification [168], automated semantic segmentation of tree branches [169], garbage image classification [170], detection of brain tumors in MR images [171], and urban scene analysis [172], [173]. Figure 11 shows an illustration of the algorithm utilized in approach III with Xception.

3.4.7 ResNet-50

VGG-16 and Xception were limited in their number of deep layers due to the vanishing gradient problem with added depth. The vanishing gradient problem happens when the value of the product of the derivative decreases until, at some point, the partial derivative of the loss function approaches a value close to zero before the gradient propagates to the final depth. ResNet-50 is immune to this problem, which could allow us in some cases to get better performance. ResNet is a type of Artificial Neural Network (ANN) that consists of Residual Neural Networks (ResNet) used as a backbone for many computer vision tasks. ResNet-50 consists of 152 deep convolutional layers and has about 25.5 million parameters and one fully connected layer at the end [174]. ResNet-50 has been used in a wide variety of applications, including food recognition tasks [175], flower detection [176], breast cancer diagnosis in histopathological images [177], Pneumonia prediction from medical images [178], Malaria cell-image classification [179], and urban planning [180]. Figure 12 shows an illustration of the algorithm utilized in approach III with ResNet-50.

4. Results And Discussion

Object detectors such as YOLO v7 predict the location of objects of the given four classes in an image with a particular confidence score. The confidence score reflects how likely the predicted bounding box contains the targeted class and how confident the classifier is about it. The object position is defined by placing bounding boxes around the objects to locate them. Therefore, our detection models were represented by a set of attributes: object class with a corresponding bounding box, coordinates for each box, a certain height and width for the box, and a confidence score. For example, consider the object of interest (WHV) represented by a ground-truth bounding box (blue color) and the detected area represented by a predicted bounding box (reds color) in Fig. 13 below. A perfect match occurs when the area and location of the predicted and ground-truth boxes are the same [181], [182].

The threshold value, or what is known as Intersection over Union (IoU), is used to evaluate these two bounding boxes. IoU is equal to the area of the overlap (intersection) between the predicted bounding box (red) and the ground-truth bounding box (blue) divided by the area of their union. Even a small IoU value still constitutes a valid prediction. However, an IoU close to one is considered more restrictive than an IoU close to zero [181],[182]. In our work, we choose an IoU value of 0.5, which is neither loose nor restrictive. Many object detection performance measurements are decided based on the elements of its confusion matrix. These elements include True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). Figure 14 below shows an illustration of the elements (TP, FP, FN, and TN) and Table 4 summarizes the conditions at which each of these elements takes place. While Table 5 shows the values of TP, FP, FN, and TN of each class (W, WH, WV, WHV) and for each approach with its variations.

Table 4
Conditions for TP, FP, TN, and FN in Fig. 7

TP	**Correctly classified to the class, IoU ≥ 0.5, meaning the object is there and the model correctly detects it, there is an overlap between the ground-truth box and the prediction box (A, B)**
FP	Incorrectly classified the class, IoU < 0.5, meaning the object is there, but the predicted box has an IoU against the ground-truth box (C), or the object is not there but still the model detects one (D)
FN	Incorrectly classified to another class, IoU = 0, meaning the object is there and the model does not detect it or the ground-truth box has no prediction box against it (E, F)
TN	This is all the other unrelated classes or the background region correctly detected as a non-object. Thus, TN includes all possible negative classes that were not detected. In addition, in calculating object detection metrics, which we will address furthermore in details, FN are not essential and usually assigned a null value [183], (G, H)

Table 5
Values of TP, FP, FN, and TN for all approaches

	Class											
Approach variation	W			WH			WV			WVH		
	TP	FP	FN	TP	FP	FN	TP	FP	FN	TP	FP	FN
AI - MLP	128	56	16	263	14	13	0	0	0	5	2	2
AI - DT	129	59	15	263	12	13	0	0	0	5	1	2
AI - KNN	129	57	15	262	12	14	0	1	0	5	2	2
AII	129	58	16	253	73	22	0	0	0	0	0	7
AIII - ResNet-50	143	8	4	276	45	0	0	4	0	7	11	0
AIII - Xception	153	28	0	274	31	0	0	1	0	5	8	2
AIII - VGG-16	146	24	1	278	40	0	0	2	0	6	2	1
TN is considered to be a null value, as explained earlier												

Since the utilized part of the dataset does not contain workers with vests only, as we noted earlier (refer to Table 3), we expect to see zero TP, FP, and FN values for the WV class. However, the models were trained to detect workers with safety vests and helmets. So in some cases, as seen in Table 5, the models incorrectly detects a safety vest, as seen in the case with FP values for the WV class. Furthermore, to evaluate our detection approaches' performance in detecting the ground-truth bounding boxes for each class, we need to use performance metrics such as accuracy, precision, recall, and F1 score. In object detection, accuracy is not a reliable measurement due to the nature of class distribution, which is considerably non-uniform. The performance of our models is usually evaluated using precision, recall, and F1 score. Precision (= TP / (TP + FP)) is the ability of the model to detect relevant class. Precision scores range from 0 to 1; a high precision implies that most detected objects match ground truth objects. In comparison, recall (= TP / (TP + FN)) measures the probability of correctly detecting ground truth objects. Recall ranges from 0 to 1, where a high recall score means that most ground truth objects were detected. [184]. Table 6 shows a summary of precision, recall, and F1 scores.

Table 6
Precision, recall, and F1 score values for all approaches

	Approach	AI			AII	AIII		
Class	Metric	MLP	DT	KNN	AII	ResNet-50	Xception	VGG-16
W	Precision	69.57%	68.62%	69.35%	68.98%	94.70%	84.53%	85.88%
	Recall	88.89%	89.58%	89.58%	88.97%	97.28%	100.00%	99.32%
	F1 Score	78.05%	77.71%	78.18%	77.71%	95.97%	91.62%	92.11%
WH	Precision	94.95%	95.64%	95.62%	77.61%	85.98%	89.84%	87.42%
	Recall	95.29%	95.29%	94.93%	92.00%	100.00%	100.00%	100.00%
	F1 Score	95.12%	95.46%	95.27%	84.19%	92.46%	94.65%	93.29%
WV	Precision	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Recall	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	F1 Score	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
WVH	Precision	71.43%	83.33%	71.43%	0.00%	38.89%	38.46%	75.00%
	Recall	71.43%	71.43%	71.43%	0.00%	100.00%	71.43%	85.71%
	F1 Score	71.43%	76.92%	71.43%	0.00%	56.00%	50.00%	80.00%

High recall but low precision implies that all ground truth objects have been detected, but most detections are incorrect (many false positives). On the other hand, low recall but high precision implies that all predicted boxes are correct, but most ground truth objects have been missed (many false negatives). The ideal detector happens when both precision and recall values are high, meaning the model has most ground truth objects detected correctly. F1 score is the weighted average between precision and recall, F1 = ((2 x Precision x Recall) / (Precision + Recall), high F1 score value indicate high model performance [185]. Therefore, the models with the highest F1 score values perform best. It is also found that models generally performed the best when detecting WH class. Finally, all models in approach III showed the most promising result in detecting the W class since the model YOLO v7 algorithm was dedicated to learning one object class. Table 7 shows the rank of such performance for each model, where a rank of 1 indicates the highest or best performance and a rank of 7 indicates the lowest or poor performance.

Table 7
Rank of F1 Score performance in detecting each class for all models

Model	W	WH	WV	WVH
AI - MLP	5	3	-	4
AI - DT	6	1	-	2
AI - KNN	4	2	-	3
AII	7	7	-	7
AIII - ResNet-50	1	6	-	5
AIII - Xception	3	4	-	6
AIII - VGG-16	2	5	-	1

According to Table 7, approach II has the lowest performance among all the proposed approaches and their variations in detecting any class. This is because, in AII, the model tried to detect all four classes from the first look. A possible way to improve the performance of this approach is to train it with more images. Meanwhile, AIII with VGG-16 performed best when detecting workers with safety vests and helmets. This is because the VGG-16 has three fully connected convolutional layers at the end compared to one for ResNet-50 and Xception, respectively. Another reason is that VGG-16 has more than 138 million parameters compared to 25.5 and 22.2 for ResNet-50 and Xception, respectively. Following the performance of AIII with VGG-16 is AI with all its ML variations which were shown to perform very well compared to AIII with Resnet-50 or Xception. A possible reason for it is that DT and KNN are known for their excellent performance in sorting tasks and that their classes were trained for more epochs than all the other models. An epoch is the number of complete passes through the algorithm that each model was trained for to achieve the lowest loss value possible [186]. Table 8 shows the number of epochs each class was trained for in each model to achieve the lowest possible final loss value. While Table 9 shows the processing speed of each model in terms of Frames Per Second (FPS).

Table 8
The number of epochs each class was trained for in each model

Approach	Class	Starting loss value	Final loss value	Epochs
A1	W	0.02321	0.0003838	300
	H	0.08541	0.0214	300
	V	0.5748	0.006783	300
AII	W	0.03212	0.02437	100
	WH	0.007252	0.006797	100
	WV	0.01557	0.01496	100
	WHV	0.05429	0.04655	100
AIII	W	0.04147	0.02723	50

Table 9
Speed of each model in FPS

	AI			**AII**	**AIII**		
Model	MLP	DT	KNN	AII	ResNet-50	Xception	VGG-16
FPS	13.273	13.273	13.273	15.2	11.65	11.9	11.79

Based on Table 9 the approach (AII) with the highest speed was the same approach with the lowest ranking performance (refer to Table 7), which could indicate that higher processing speeds might have an effect on the performance of the model. All models were ran on Google Colab Cloud-based GPU [187]. One of the main limitations of vision-based detection methods is that they are susceptible to occlusion, poor illumination, and blurriness. [188].

5. Conclusions

Real-time monitoring of proper PPE use is essential, and several ML and DL methods are explored to make this possible. In this study, PPE compliance detection techniques based on computer vision were proposed. Results from experiments comparing seven different algorithms revealed that the suggested YOLO v7 with VGG-16 algorithm performs very well in terms of F1 score and FPS performance measures. The models presented in this paper utilized Pictor-v3 dataset, where images were taken separately on different devices, locations, times, perspectives, PPE styles, and industry projects. The YOLO v7 with the VGG-16 model performed the best, which makes it the perfect candidate for real-time PPE detection. The proposed methods were only tested on safety vests and helmet classes; therefore, future work can focus on data with more classes, such as safety shoes, glass, and gloves, to draw more applications of the proposed models. Furthermore, future work can focus on combining Natural Language Processing (NLP) to generate safety reports that could be used in root cause analysis to prevent accidents from reoccurring in the future.

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Data transparency

All the data have been presented in the manuscript.

Ethical approval

The paper follows the guidelines of the Committee on Publication Ethics (COPE).

Consent to participate

The authors declare that they all consent to participate this research.

Consent for publication

The authors declare that they all consent to publish the manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Mohammad Shahin took care of conceptualization, methodology, data collection, investigation, writing the original draft, and writing the review and editing. Ali Hosseinzadeh took care of data collection, investigation, and writing the review and editing. Hamid Khodadadi Koodiani took care of data collection, algorithm selection and modification, and writing the review and editing. Hamed Bouzary took care of writing the review and editing. F. Frank Chen contributed in resources, project administration, writing the review and editing, and supervision. Finally, all authors read and approved the final manuscript.

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Figures

Figure 1

Flowchart of the PPE compliance detection system

Figure 2

Example of annotated images in the training dataset [118].

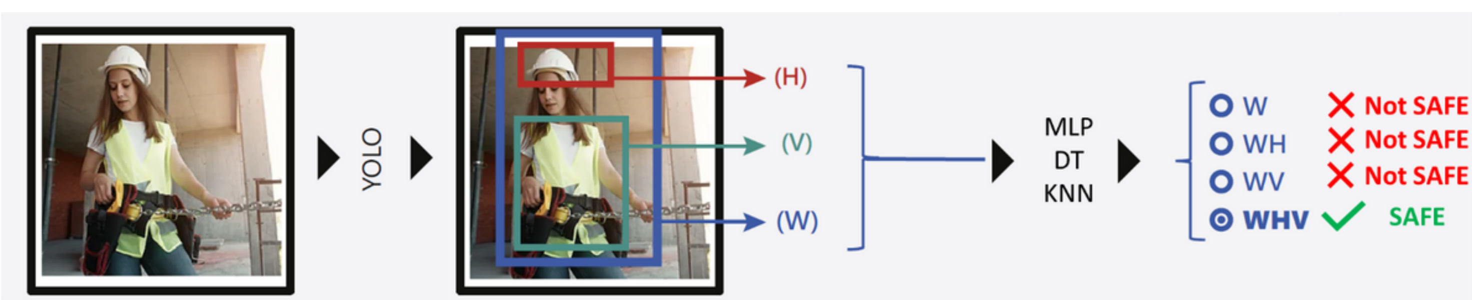


Figure 3

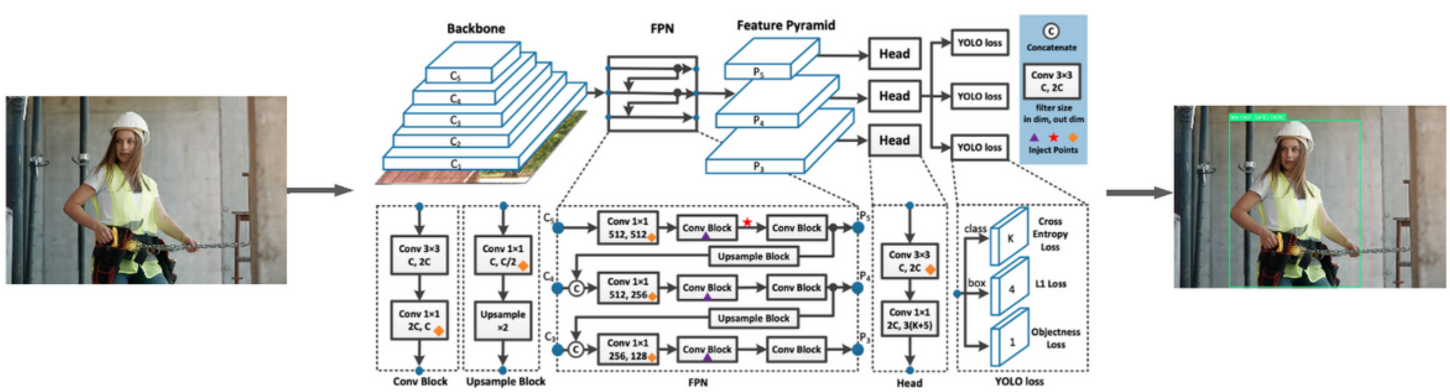
Illustration of Approach I

Figure 4

Illustration of Approach II

Figure 5

Illustration of Approach III



Yolov7

Figure 6

Illustration of approach II algorithm

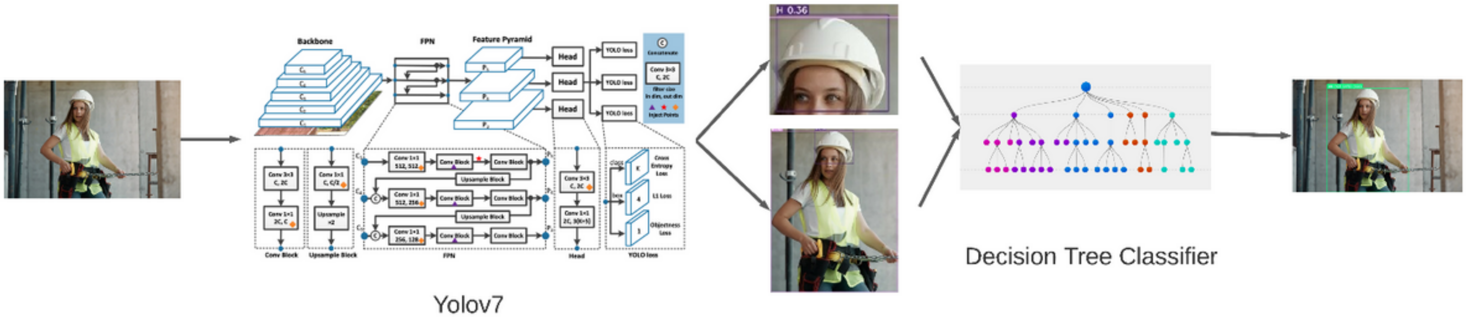


Figure 7

Illustration of approach I algorithm with DT

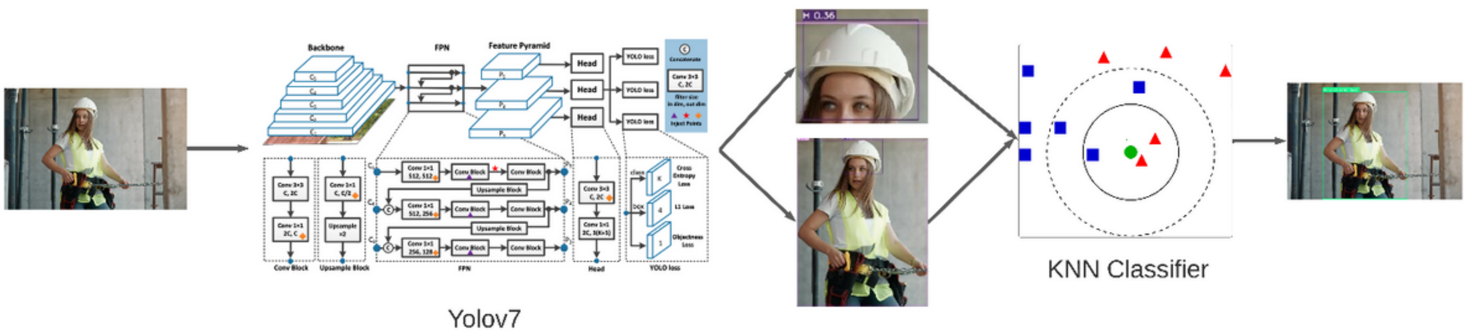


Figure 8

Illustration of approach I algorithm with KNN

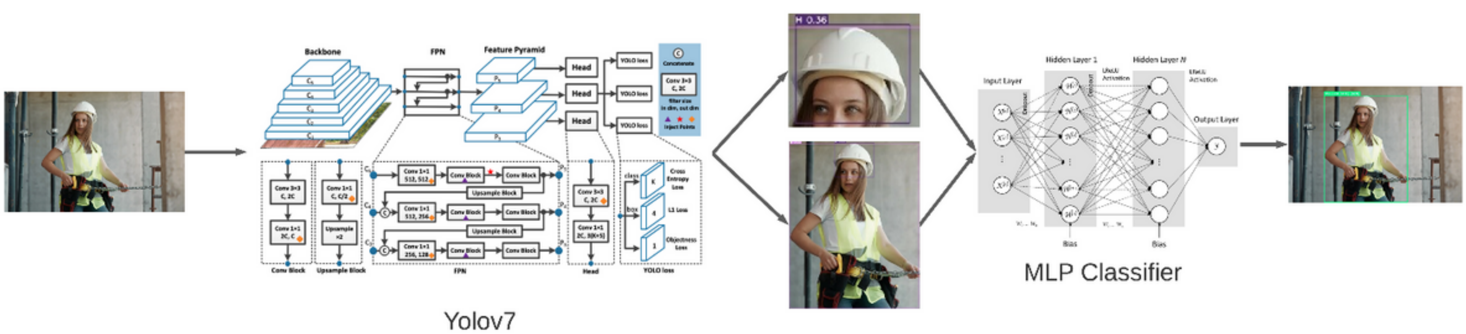


Figure 9

Illustration of approach I algorithm with MLP

Figure 10

Illustration of the algorithm utilized in approach III with VGG-16

Figure 11

Illustration of the algorithm utilized in approach III with Xception

Figure 12

Illustration of the algorithm utilized in approach III with ResNet-50

Figure 13

Prediction area in red vs. ground-truth area in blue

Figure 14

Illustration of TP, FP, FN, and TN