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1	Ryan C. Reyes	TUP	16.67%	
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3	Godofredo S. Zapanta Jr.	PLP	16.67%	
4	Jovencio V. Merin	TUP	16.67%	
5	Renato R. Maaliw III	SLSU	16.67%	
6	Al Ferrer Santiago	EARIST	16.67%	
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Prepared by:

RENATO R. MAALIW III, DIT
Faculty

Certified by:

NICANOR L. GUINTO, Ph.D
Research Director

Safety Gear Compliance Detection Using Data Augmentation-Assisted Transfer Learning in Construction Work Environment

Ryan C. Reyes
Department of Electrical Engineering
Technological University of the Philippines
Manila, Philippines
ryan_reyes@tup.edu.ph

Rovenson V. Sevilla
Department of Electrical Engineering
Technological University of the Philippines
Manila, Philippines
rovenson_sevilla@tup.edu.ph

Godofredo S. Zapanta Jr
College of Engineering
Pamantasan ng Lungsod ng Pasig
Pasig, Philippines
zapanta_godofredojr@plpasig.edu.ph

Jovencio V. Merin
Department of Electrical Engineering
Technological University of the Philippines
Manila, Philippines
jovencio_merin@tup.edu.ph

Renato R. Maaliw III
College of Engineering
Southern Luzon State, University
Lucban, Quezon, Philippines
rmaaliw@slsu.edu.ph

Al Ferrer Santiago
Computer Science
Eulogio "Amang" Rodriguez Insitute of Science
and Technology
Manila, Philippines
santiagomscs16@gmail.com

***Abstract*— The study provides a practical solution to the concern of detecting safety gear compliance in construction. This is imperative given that safety in the construction work environment is one of the greatest global concerns, and advancements in deep learning algorithms, especially in the area of machine learning and database management, enable the possibility to address this challenge in construction. This study developed a framework to recognize construction personnel's safety compliance with PPE, which is designed to be implemented into an organization's operational procedure. The Convolutional Neural Network model was constructed by employing machine learning to a basic version of the YOLOv3 deep learning model for the study. On the testing data, the detection method generated an F1 score of 0.9299, with a mean precision-recall rate of 92.99 %. The purpose of this study is to testify to the viability and applicability of machine vision-based methodologies for automated safety-related compliance processes on construction sites.**

Keywords*— *Personal protection equipment (PPE), worksite safety, machine learning, You Only Look Once (YOLO), image database, protective gear, and object recognition

I. INTRODUCTION

Construction is one of the riskiest labor sectors in the Philippines. According to the Philippine Statistics Authority, the most prevalent causes of accidents in the construction firm involve falls from lofty heights, accidents involving heavy machinery, and electricity, and also being hit by materials [1]. Supervising safety management practices is an important area of research because methods and algorithms fulfill the feedback mechanism to site supervisors, enabling them to evaluate the feasibility of the safety laws and guidelines used within a construction site [2]. Such methods can provide valuable information, which can eventually be examined to characterize employee conduct [3] and identify the construction site's safety environment and attitude [4]. However, implementing such detection methods that require human operators is not without risk, and there are multiple difficulties related to precision, responsiveness, and openness [5]. As a consequence, researchers are highly engaged in artificial intelligence methods of detecting and recognizing hazardous situations [6]. Reliable and actual automated systems that comply with safety requirements can be of significant assistance in this area. [7]. Deep learning and computer perception advanced technologies have renewed interest in research in automatic identification and early warning systems for safety practices. [8].

The development of construction site accident prevention has progressively gotten a lot of publicity from researchers and professionals [9]. The possible solutions are split into two categories: machine vision and non-machine vision technologies [10]. The study of [7] comes within the first type. The researchers developed an RFID-based interface to assess if the personnel's safety gear or PPE fulfilled the following criteria [11]. Location systems in real-time and fully interactive technologies are designed for workforce area services to evaluate whether the personnel should wear helmets as well as provide an alert, whereas the latex single-point detector is intended to indicate whether the equipment is used correctly for further behavioral analysis. [12]. Nevertheless, these solutions are constrained in their ways. For instance, the employee's ID card only reveals if the location between both the person and the PPE is close enough; sensor failure may be a factor when deploying. [9]. Several efforts have been conducted for hardhat recognition in computer vision-based algorithms, taking into consideration the vital function of a safety helmet [13]. A Histogram of Oriented Gradient (HOG) is used with the Circle Hough Transform (CHT) to obtain the characteristics of workers and protective hats. Related to visual information, it integrates face detection with hardhat identification [14]. Transfer Learning has progressed at a rapid pace in recent years, due to massive amounts of information and improved computer processing capabilities. [15]. The solutions for the challenge of object classification or identification are being gradually developed [9]: YOLO, Faster R-CNN, and Single Shot Multibox

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Detector [16], You Only Look Once (YOLO) [13], and Single Shot Multibox Detector (SSD) [17] are the most recent innovative algorithms in the field of object classification. Faster R-CNN has been used to recognize the unavailability of hardhats and identify prohibited operations [9].

The recommended process has been verified in various scenarios and proved its effectiveness. However, the majority of the current study involves recognizing the use of hard hats on work sites. Other gear, in contrast to the safety helmet, must be recognized.

The primary goal of protective gear identification is to evaluate safety and health adherence in terms of improving construction safety. When dealing with an accident, wearing a hard hat would reduce the risk of injury and even death [18]. In the meantime, another essential part of protective gear, high-visibility garments, must always be worn on construction sites to make it more visible. The vests with bright outlines would aid others to recognize construction employees and reduce accidents, particularly in rainy and foggy weather [19].

In this study, a high-quality dataset that incorporates various movements, orientations, and more are developed based on the gaps mentioned above. Additionally, we include a high-efficiency safety equipment sensor that surpasses the conventional one in terms of speed and precision.

YOLO v3 is recommended in this work, and it has features of outstanding precision and low computational difficulty. In the following sections, we will go through the framework of this technology, the procedure for protective gear, training of the model, and validation with a customized set of data. Section 3 describes the results of the research and discussions, while Section 4 provides the conclusions.

II. Methodology

The system's framework is represented in Fig. 1. The concept or development of the system undergoes various stages or steps, incorporating preparation of dataset preparation, splitting of data, training and model assessment, and lastly, the inferencing of the model.

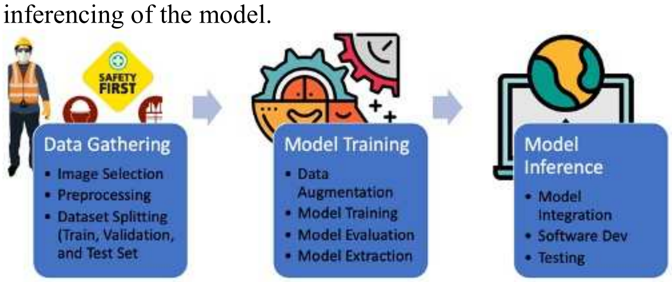

Fig. 1. System framework diagram

A. *Data Gathering and Preparation*

As illustrated in Fig. 2, the dataset applied in this work was gathered manually from a range of digital sources. Photos of people in different clothing and dimensions were obtained for the work, as seen in Fig. (a) 2 and (b). For the study, 300 images were collected: 150 of complying employees and 150 of non-compliant personnel. Datasets of images were used to generate training and testing data. The verification dataset had just 20% of each set of clothing, while the training data comprises 80%.

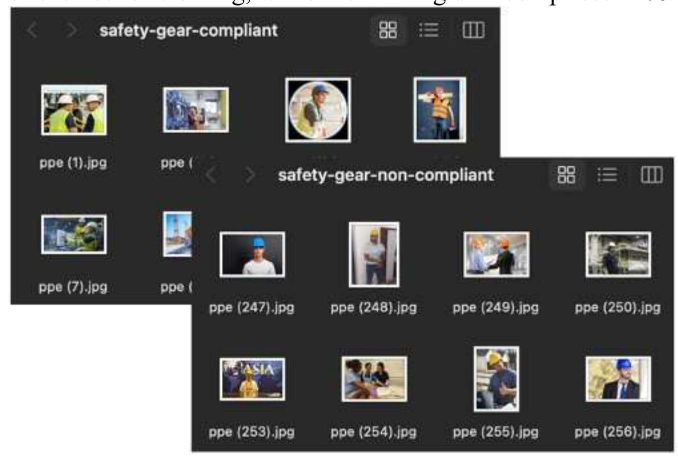

Fig. 2. Compliant and Non-Compliant sample data

B. *Interpretation of Datasets*

As illustrated in Fig. 3, LabelImg has been used in the study to analyze and label the information. For the identification of the information that will be used for training and then verification, a rectangular bounding box encompassing the top portion of a person was constructed. The output is an XML file that contains the parameters of the annotated images in PascalVOC format.

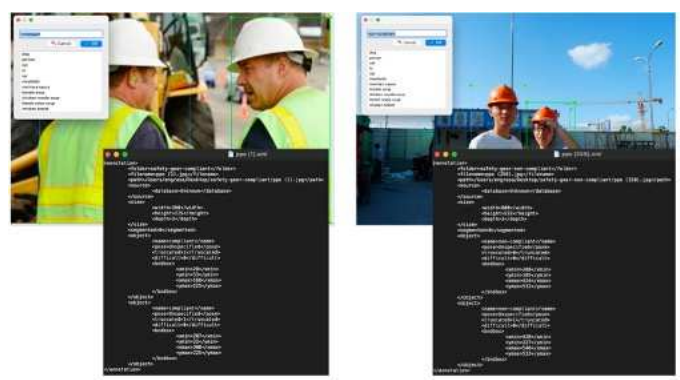

Fig. 3. Falling and standing images interpretation

C. *Algorithm for Transfer Learning*

One of the fastest object-recognition systems is YOLO v3 [20]. It anticipates border squares by implementing a specific CNN to the whole frame and then separating it into several parts. It becomes more effective as a result of its capacity to produce numerous forecasts at once. YOLO v3 [20] refers to "You Only Look Once," and this is one of the fastest object-detection processes. It splits the photo into unique portions by calculating border boxes with CNN [21] – [30]. This method is faster than the conventional feature extraction approach, which analyzes the entire frame pixel by pixel for objects. During the object identification process, some settings may be overly loud, congested, or confusing, enabling the object to be misinterpreted. To address this difficulty, YOLO v3 implements a localized procedure, delivering the image features with the highest optimal solutions that are closest to the recognized object [31].

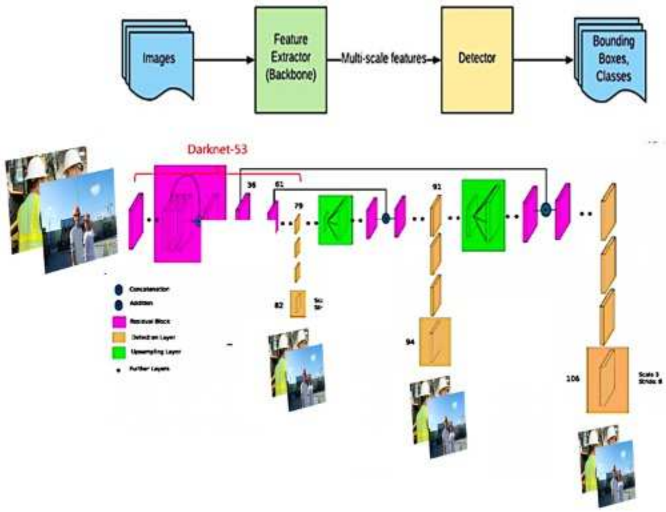

Fig. 4. YOLOv3 architecture

Since the technology mentioned (Fig. 4) is the most commonly used network in the industry, the study chose it as the backbone for many lightweight systems. The purpose of selecting YOLOv3 is because of its substantial configuration and simplicity.

Before training, the researchers recommended image enhancement for compliant / non-compliant identification, as shown in Fig. 1. The enhancement process requires the generation of stronger information. This augmented data includes the full information as well as a new batch generated using filtration techniques. Sizing, clipping, HSV deformation, and four sorting techniques for image flipping are included in the available data that assist the model to function better. Each image in this report only goes through the network once to verify whether the personnel is compliant or non-compliant. It also separates the photo into elements and performs a convolution operation on each before aggregating the discrete components to achieve detection. The training starts with a batch size of 4 and a set of experiments of twenty-five.

D. *Assessment of the Model*

To assure that the best-trained model was selected for model interpretation recognition, the trained algorithms were validated using the mAP (mean Average Precision). It will process data that will be needed during the assessment process. The model's detection rate increases as the mAP rise.

Average Precision (AP): To decrease the impact of the curve wobbles, reconstruct the correctness at consecutive recollection stages until the AP (1) is defined. The region under the approximated curve is referred to as AP, and it may be determined using the process described below. The adjusted accuracy (2) specifies a given rate of recall 'r' as the highest possible precision met at any phase of recall $r' \geqslant r$:

Mean Average Precision (mAP): The mean precision (AP) throughout all experiments is known as mean average precision (mAP) (3), where O represents the overall number of entries in the set and APi indicates the average precision (AP) for a direct question, o.

$$AP = \sum_{i=1}^{n-1}(r_{i+1} - r_i)p_{interp}(r_{i+1}) \quad (1)$$

$$p_{interp}(r_{i+1}) = \max_{r' \geq r_{i+1}} p(r') \quad (2)$$

$$mAP = \frac{\sum_{i=1}^{o} AP_i}{O} \quad (3)$$

E. *Interpretation, Testing, and Modeling*

The study employed different approaches to developing a graphical user interface (GUI). The primary functions of the GUI are image identification, video recognition, and live stream surveillance. The selected machine learning model h5 file and its supplementary JSON software framework were employed for model interpretation.

The study introduced a novel series of images and video data in a mimicked construction work setup for the testing phase. Because they were not among the 300 images used for verification and training, these images were implemented to avoid distortions in the assessment precision (4) outcomes.

$$Accuracy = \frac{\#\ of\ Detected\ Object}{Total\ \#\ of\ Objects} x\ 100 \quad (4)$$

III. Data and Results

This section discusses the training, verification, and assessment results.

A. *Results of Training and Verification*

Fig. 5 illustrates the training and verification results of the dataset. As shown in the graph, the level of training through experimentation is set to 29 as 4 pieces of training do not have models.

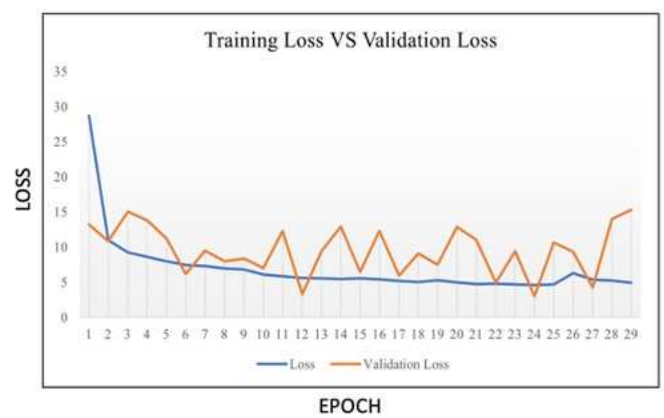

Fig. 5. Training Result of the model

The values of the training loss (indicated by the blue region) and the verification loss are also given in Fig. 5 (indicated by the orange region).

When the training started, it had a training and verification score of 28.61 % and 13.17 %, accordingly. It yielded on the 29th epoch with training and verification losses of 4.89 % and 15.27 %, accordingly. As seen in Fig. 5, the training and verification loss rate for the 24th epoch was the lowest, but the training loss at the first epoch was the highest, and the highest validation loss value was at the 29th epoch.

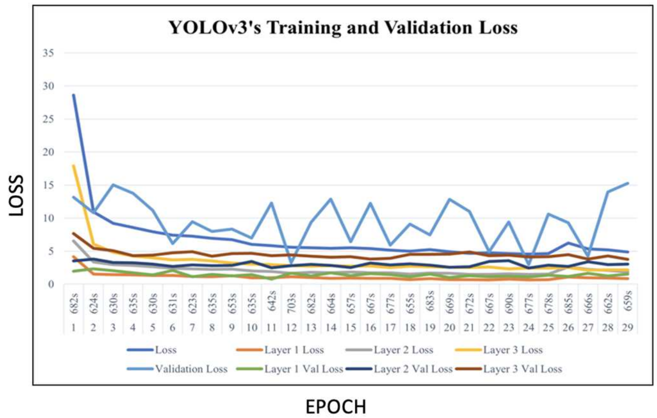

Fig. 6. Training result of the layer

As illustrated in Fig. 6, as the training time lengthens, the loss minimizes as it learns from the information supplied as it continues the training phase. The val loss, meanwhile, differs, however, it lowers over time. A verification data analysis was performed to analyze a particular model, but it might also be used to test different types of models as well.

B. Model Assessment

The mAP score represents the reliability of the dataset assessment. Because the mAP is equivalent to one, the reliability score is near its maximum attainable value (100%). The mAP achieved during the model assessment is represented in Fig. 7. Model 5 has the lowest efficiency in this graph, with an mAP of 0.2888. Presented in Fig. 2, Model 2 provided the best outcomes, with an mAP value of 0.9299 (92.99 %) and a training loss equivalent to 10.90. 7. Model 2, which had the highest mAP, was used for testing and interpretation.

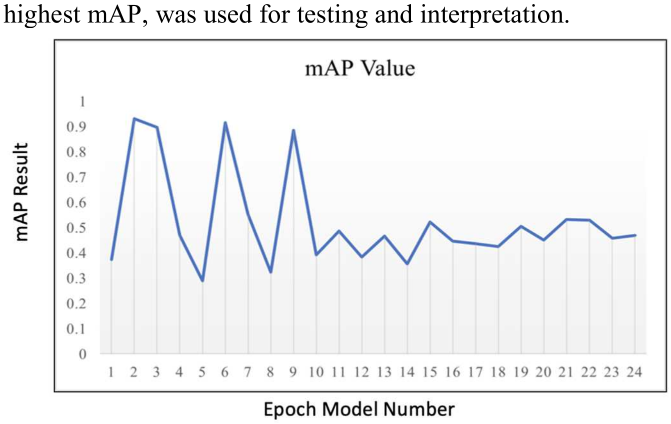

Fig. 7. Model Assessment

C. Model Interpretation and Validation

The second developed framework was employed for each boundary recorded by the device. Fig. 8 shows how a primitive GUI was developed to analyze the functionality of the technology and 2nd model interpretation. As seen in Fig 8, for implementation, three methods were used: import your image, import your clip, and open your webcam. The detection system generated the compliant/non-compliant clothing as a CSV file.

Fig. 8. The interface of the Model

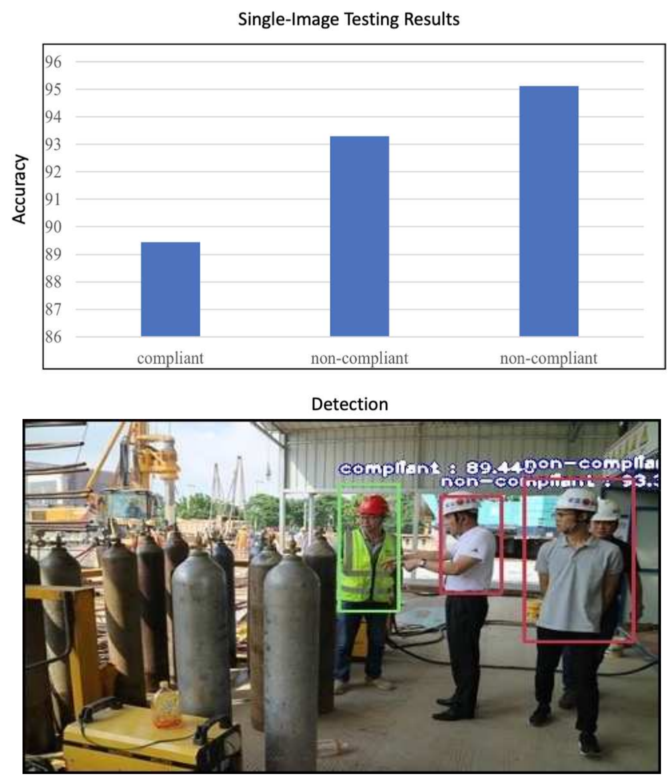

Fig. 9. Single-Image testing results.

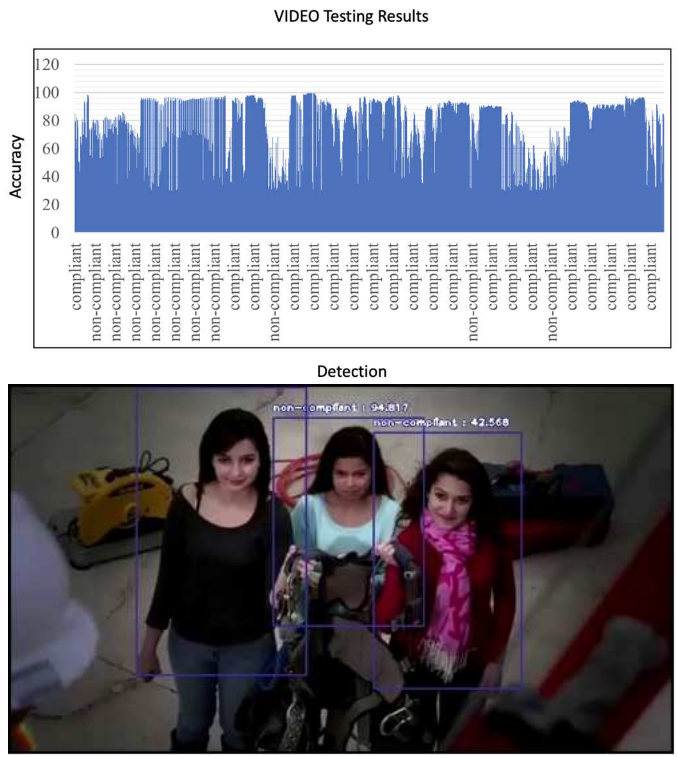

Fig. 10. Video testing result

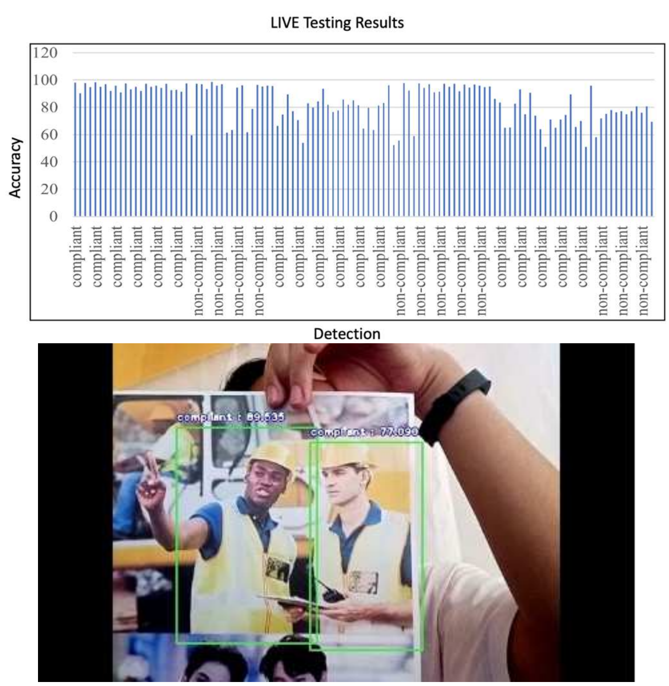

Fig. 11. Live testing result

The study tested a single-image, video clip, and live capture using the 2nd model inference. The image used is not included in the trained validated datasets and it shows an unbiased high accuracy result (Fig. 9). For the video testing, the study used a 78-second video with 20 frames per second producing 1,560 frames, as shown in Fig. 10 the accuracy is fluctuating, yet higher ones dominate. Furthermore, the live capture test performs as well as the video test, it is a time-lapsed capture due to the adjustment on the code producing a 2-second video with 20 frames per second as well, totaling 40 frames. As the various testing method shows, the performance in identifying the compliant and non-compliant person is notable. The accuracy can be seen from the snaps (Fig. 11) showing that high accuracy is significant.

IV. Conclusion and Recommendation

Safety in the construction work environment is one of the greatest global concerns. Still, after risk evaluations have been performed and satisfactory controls have been executed, workers are subject to safety hazards in construction work environments. The need for protective gear (PPE) is essential in this environment. To provide an appropriate response, safety gear adherence detection must be reliable and fast. To execute a deep learning method, the system employs the YOLOv3 method, which employs CNN. The study yielded an mAP of 0.9299 in the second iteration. This implies that it is an efficient method for detecting safety equipment conformity, even with a limited number of data, and especially in individuals who may not be equipped for construction. When examined, the system received a high overall testing average precision.

The study recommends detecting other essential safety gear in the construction workplace to further improve safety. Future researchers may use higher versions of YOLO in their future studies. Adding more datasets and training models is also suggested.

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Reyes, Ryan C.[a] ; Sevilla, Rovenson V.[a] ; Zapanta, Godofredo S.[b] ; Merin, Jovencio V.[a] ; Maaliw, Renato R.[c] ; Ferrer Santiago, Al[d]

Save all to author list

[a] Technological University of the Philippines, Department of Electrical Engineering, Manila, Philippines
[b] Pamantasan Ng Lungsod Ng Pasig, College of Engineering, Pasig, Philippines
[c] University Lucban, College of Engineering Southern Luzon State, Quezon, Philippines
[d] Eulogio "Amang" Rodriguez Insitute of Science and Technology, Computer Science, Manila, Philippines

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Abstract

The study provides a practical solution to the concern of detecting safety gear compliance in construction. This is imperative given that safety in the construction work environment is one of the greatest global concerns, and advancements in deep learning algorithms, especially in the area of machine learning and database management, enable the possibility to address this challenge in construction. This study developed a framework to recognize construction personnel's safety compliance with PPE, which is designed to be implemented into an organization's operational procedure. The Convolutional Neural Network model was constructed by employing machine learning to a basic version of the YOLOv3 deep learning model for the study. On the testing data, the detection method generated an F1 score of 0.9299, with a mean precision-recall rate of 92.99 %. The purpose of this study is to testify to the viability and applicability of machine vision-based methodologies for automated safety-related compliance processes on construction sites. © 2022 IEEE.

Author keywords

and object recognition; image database; machine learning; Personal protection equipment (PPE); protective gear; worksite safety; You Only Look Once (YOLO)

Indexed keywords

SciVal Topics

Metrics

References (31)

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1 Hossain, M., Fakhruddin, A., Chowdhury, M., Gan, S.
(2022) *Impact of ship-Breaking activities on the coastal environment of Bangladesh and a management system for its sustainability*

Safety Gear Compliance Detection Using Data Augmentation-Assisted Transfer Learning in Construction Work Environment

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Ryan C. Reyes ; Rovenson V. Sevilla ; Godofredo S. Zapanta ; Jovencio V. Merin ; Renato R. Maaliw ; Al Ferrer Santiago **All Authors**

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I. Introduction

Construction is one of the riskiest labor sectors in the Philippines. According to the Philippine Statistics Authority, the most prevalent causes of accidents in the construction firm involve falls from lofty heights, accidents involving heavy machinery, and electricity, and also being hit by materials [1]. Supervising safety management practices is an important area of research because methods and algorithms fulfill the feedback mechanism to site supervisors, enabling them to evaluate the feasibility of the safety laws and guidelines used within a construction site [2]. Such methods can provide valuable information, which can eventually be examined to characterize emp[...] Sign in to Continue Reading construction site's safety environment and attitude [4]. However, implementing such detect[...]perators is not without risk, and there are multiple difficulties related to precision, responsiveness, and openness [5]. As a consequence, researchers are highly engaged in artificial intelligence methods of detecting and recognizing hazardous situations [6]. Reliable and actual automated systems that comply with safety requirements can be of significant assistance in this area. [7]. Deep learning and

Authors

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