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DETECTION OF PERSONAL PROTECTIVE EQUIPMENT IN EXTREME CONSTRUCTION CONDITIONS USING ANN

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ABSTRACT: The number of deaths in the construction industry is greater than in other industries through a number of countermeasures. Although workers may intentionally or unintentionally neglect to wear such safety measures, Personal protective equipment (PPE) was continuously being developed to prevent this types of accidents. Performing a safety check manually might be difficult since there can be a lot of coworkers at a site. It is essential to identify worker noncompliance with PPE in an automated and real-time manner. Detection of Personal Protective Equipment in Extreme Construction Conditions Using ANN is the topic of this paper. The web-based collection of 2,509 images from video recordings of many construction sites are utilized as the model's training data set. This Artificial Neural Networks (ANN) model is utilised in the study, which makes use of transfer learning and a basic variation of the YOLOv5 deep learning network. A dataset called CHVG to identify the workers PPE. Described model achieves the parameters as Accuracy as 97%, Recall 97% and Precision 96%. Overall, the analysis shows that computer vision-based techniques for automating safety-related compliance processes on construction sites are both feasible and useful.

KEYWORDS: Personal Protective Equipment, Artificial Neural Networks (ANN), construction safety.

I. INTRODUCTION

There are presently a lot of people working on construction sites throughout the world, to carry out major projects due to urbanization. There is usually an excessive amount of danger around construction sites. Many workers health and safety cannot be managed by a small number of inspectors [1].

Every year, approximately 2.3 million people die as a result of work-related accidents or diseases, according to the International labour organization (ILO) (Neale, 2013). Over the worldwide, every year, at least 60 million terrible accidents occur on construction premises (ILO, 2005) [2]. An accident is thought to happen every ten minutes, which is a clear warning about the risks associated with construction sites. Construction sites account for one out of every six fatal calamities.

With 15.8 accidents per 1,000 workers annually, according to (Patel and Jha (2014) India has one of the highest accident rates worldwide. Safety on construction sites is seen as an important problem, but it is made more difficult by the lack of efficient techniques for gathering information and keeping an monitoring on construction safety (Mahalingam and Levitt, 2007) [3]. In India as well as other countries, this industry has significant challenges with regard to security for workers [4].

Personal Protective Equipment (PPE) usage represents an indispensable practice that must be observed by all employees [5]. Nevertheless, monitoring and enforcing such practice manually can prove daunting as it requires significant attention to detail from supervisors or safety officers [6]. Examples of PPE include safety glasses, hardhats, gloves, goggles, vests, and so on. Hardhats are a useful tool for workers to prevent minor head injuries. When falling from a height, wearing a hardhat can reduce the possibility of getting a concussion, neck injury, or fractured skull (Hume, Mills & Gilchrist, 1995) [7]. Additionally, it reduces the chance of serious brain damage. Hardhats are a necessary component of PPE in construction sites. Especially on building sites, eye injuries are a very common problem at work [8].

Approximately 2,000 American workers have eye injuries connected to their work, according to the National institute for occupational safety and health (NIOSH). Approximately three out of every five workers are suffered eye injuries did not have a protective shield on the accident occurred, according to an analysis conducted by the Bureau of labour statistics (BLS). Another type of PPE that makes a worker more apparent to others in the workplace is a safety vest. According to (Wang 2021b), reflective strip lines on vests may be useful for determining workers location and reducing the risk of accidents during bad weather and low light. Colours of hardhats may be quite important for identifying workers in various countries.

Whether willingly or unwillingly, workers on construction sites forget to wear any PPE that might endanger themselves or the entire workplace [9]. Proper action might reduce the possibility of impending danger. Every worker should wear PPE when working on a construction site, according to the site authorities [10]. But it would take too much time and money to check by manually. When combined with BIM (Building Information Modeling) recent developments in interacting technologies like Augmented reality (AR) and virtual reality (VR) provides the potential to accurately visualize and virtualize construction management procedures [11]. When combined with BIM, these machine learning advancements might open up potential avenues for efficient information analysis and fast providing business knowledge to managers [12]. For these techniques are to provide any type of useful intelligence, substantial and accurate data sets are often required. This requirement translates into the utilization of different data-gathering devices (such as RFID technology or Radio Frequency IDs). While several types of field data must be gathered, rich visual records of activities are provided by images as well as videos, and computer vision-based techniques enhance the understanding on visual data. Essentially, understanding the information from visual data points is an issue that Computer vision (CV) aims to solve, such as an image or video sequence evaluated through a human eye's perspective [13].The development of vision-based construction management approaches and their application has closely tracked developments in deep learning and computer vision.

This analysis main goal is to accurately recognize personal protection gear in an average amount of time. Furthermore, false or incorrect detection would be harmful to the authority of the building site as well as the personnel. Because, it can identify objects in an image quickly and accurately, the YOLO architecture is performed. Megvii provides an architecture that is anchor-free, and this design is the one used for the purpose of the analysis. The YOLO satisfactory performance outperforms the results of the prior study on worker safety on construction sites.

II. LITERATURE SURVEY

Joshua, Hendryli J. and Herwindiati D. E., et. al. [14] YOLOv2 is used in the identification of vehicle license plates. Following detection, the license plate is first cropped before being transmitted to an image segmentation procedure, which separates and clips off each digit. The digits are classified by the CNN model ResNet. 500 images of bikes and cars with license plates have been gathered by the authors can use as a training, testing, and validation collection. The model's validation accuracy in the license plate recognition system is eighty percent. Though, sometimes the ResNet model is unable to accurately categorize the digits, mostly the system performs effectively. The noise in the image is the cause of this problem.

Lu H. -Y. and Sun K. -T., et. al. [15] offers COVID-19 Intelligent Epidemic Prevention Classroom System. The system authors have made use of face recognition, a deep learning library developed on top of Dlib, and computer vision libraries like Dlib and OpenCV. The goal of these libraries is to detect faces on students. Algorithms to extract face characteristics are available in these libraries. The face images of every student in a class are used to train the system, which then compares those images with newly registered students. A firebase database is used by the system to store GPS data, body temperature measurements, and recent six-month personal medical records, among other information. The machine learning method is utilized by the system to predict COVID-19 cases based on the data provided.

Horry M. J. et al., [16] COVID-19 has been identified using the VGG19 (Visual Geometry Group) image classification model. One national institutes of health X-Ray dataset and three openly gathered Coronavirus disease 2019 (COVID-19) datasets were used. Three types of images were present in all the datasets are combined: CT scan, X-ray images, and ultrasound. COVID-19 patients, pneumonia patients, and normal lung images were included in the datasets. A single COVID-19 image and a few non-COVID-19 images were eliminated from the combined dataset for cleaning. Because there were limited datasets available, complex models performed poorer on CT scan and X-ray images than simpler models. On ultrasound images, all of the models performed rather well, although the simpler VGG19 model had the greatest classification score. As a result, they described a deep learning model called VGG19 to diagnose COVID-19.

Kanimozhi S., Gayathri G. and Mala T., et. al. [17] used MobileNet and Single Shot MultiBox Detector (SSD) networks are to simultaneously identify a number of objects. In order to make the object detector more accurate and lightweight, they integrated two models. In basic terms, the benefits of SSD design and MobileNet feature extraction are combined in SSD with MobileNet model. The authors of the research reported that they constructed the dataset using around 500 images for each object. The dataset contains images of many objects, like cellphones and water bottles. The laptop webcam was utilized for object detection, and it worked effectively. Misclassification was observed in a few cases. The probability that an object will be detected decreases if it is farther away from the webcam than thirty meters. The authors propose that the 1.3 megapixel poor quality camera is the source of this decrease.

S. Dong, Q. He, H. Li, and Q. Yin, et al. [18] In order to determine if a worker should wear a helmet and give a warning, Real-time location systems (RTLS) and virtual construction are used to follow their location. A silicone single-point sensor is intended to indicate whether PPE is being utilized correctly in order to do additional behaviour analysis. Though, all of these approaches have limitations. For example, the worker's identity card, simply states that the worker and PPE are close in distance and that the loss of sensors could be taken into consideration when applying.

S. Du, M. Shehata, and W. Badawy, et al. [19] uses colour information to combine hardhat and facial detection. The volume of training data available in recent years has allowed deep learning to progress quite quickly and enhanced computer processing capabilities. The challenge of object identification or categorization has produced a results. A. Sieber, P. Enoksson and A. Krozer, et. al. [20] offers on-board data storage for manufacturing and calibration, digital temperature correction, and digital readout. In order to test the Pb (Plumbum or Lead) anode for exhaustion, voltammetry cycles may be performed using the special low read-out electronic circuit for galvanic O_2 sensors that is included. Data from the ultimate electrochemical sensor characterization technique, a Solartron SI 1287 impedance analyzer, are compared with the initial measurements and reported.

Y. Fukuda, M. Q. Feng, J. Zheng and V. Halls, et. al. [21] offered the developing of a combined sensor system and a light emission pattern-based blast detection algorithm; the sensor system was connected with a personal airbag that was already in existence; field explosion testing for the experimental validation of the head protection system and sensor system; and the field measurement of explosions are describe their patterns of light emission in the ultraviolet to infrared range. The head impact force is reduced by 60% when the airbag is successfully activated before to the test dummy hitting the ground. Within 100 μs of the improvised explosive device (IED) detonating, the sensor system accurately detects the explosions.
Ö. Hatipoğlu and A. K. Hocaoğlu, et. al. [22] developed a special detection algorithm to determine whether personal protective equipment, which is required to be worn by occupational safety personnel on construction sites is used by employees. In this study, they concentrated on the places where people move their personal protection equipment. The originality of this work is the creation of a new data set that is not included in the literature, designing a classification of the data is obtained from the moving areas within the scope of the study, and the development of the Gaussian Auto Labeling algorithm. The operator's indicated helmet points on the images are utilized to train interest regions that are automatically extracted from moving areas. The results of this research allowed for the classification of the helmets used by construction workers.

III. DETECTION OF PERSONAL PROTECTIVE EQUIPMENT

Figure 1 represents the block diagram of Detection of Personal Protective Equipment in Extreme Construction Conditions Using ANN.

The gathering and processing of data is to support the model's validation is a crucial step in training the machine learning algorithm. The most time-consuming and important step was preparing the dataset since it allowed for effective algorithm training and accurate identification. A CV-based system is selected in this analysis over a sensor-based system because to its lower cost, simpler design, and ease of use in the field. A dataset called CHVG short for Colour Hardhat, Vest, and Glass was used to identify the workers personal protection gear. Eight classes are included in the CHV dataset: vest, person head, safety, person body, and the four different coloured hardhats (blue, white, yellow, and red). There are 1,699 images and annotations are five important conditions are low light, intense light, sand dust, fog, and rain are included in the CHVG collection.

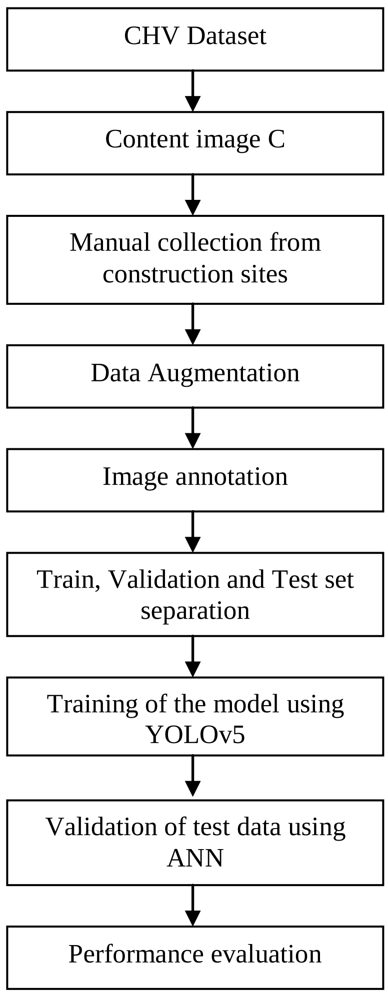

Fig. 1: BLOCK DIAGRAM OF DETECTION OF PERSONAL PROTECTIVE EQUIPMENT

The Neural style transfer (NST) is a superior technology for extreme conditions simulation because it makes very few changes to the content and only transfers the extreme style from the style image to the content image. The arbitrary NST model with modular structure was adopted in this analysis, which divides the task into style extraction, style transfer and assigns them to two different networks for execution. Real-time data augmentation is done throughout the fine-tuning and re-training stages. Specifically, to obtain a greater range of data and minimize overfitting, training images and annotations are randomly distorted at the start of each epoch. 1,699 images that were gathered using common augmentation techniques like flipping and rotating 30 degrees to the left and right were put through to data augmentation.

Using the graphical image annotation application labelImg-master, the dataset was labelled once it was gathered. With bounding boxes, the images were labelled NoHardhat, NoJacket, NOTSAFE, and SAFE in accordance with the four possible cases. XML (eXtensible Markup Language) files were used to store annotations. For training and validation reasons, finally, a code-readable text file was created by combining the XML files..

The train, test, and validation sets are the three subcategories that made up the CHVG dataset. In addition, the validation set and test dataset are provided during model training to ensure that the training is proceeding appropriately. For training, a 90:8:2 random split train-validation-test set was used.

A real-time object identification system is the goal of the You Only Look Once (YOLO) algorithm. YOLO creates a S × S grid out of the provided image. One object and a certain number of border boxes are predicted for each grid cell. Each grid cell has one box confidence score, and it predicts B boundary boxes for each box. Regardless of the number of boxes B, it then detects a single object. It concludes by predicting C conditional class probabilities, one for each class related to the object class's probabilities. Five elements x, y, w, and h as well as a box confidence score are present in every boundary box.

The YOLOv5 has several improvements over the previous version YOLOv4. First, YOLOv5 add a new Focus module to reduce parameters increase forward and backward calculation speed. Second, the Cross Stage Partial (CSP) technique is utilized in YOLOv5’s Neck structure, improving the feature extraction ability 114 in the Neck stage compared with the ordinary stacking of convolution modules in YOLOv4. In finally, YOLOv5 uses genetic and K-means learning algorithms to automatically determine bounding box anchors for various datasets, which is quite helpful in making sure the most appropriate anchor boxes are used for the specific dataset to have better detection results.

In this paper, Artificial Neural Networks (ANN) are used to achieve the validation procedure. An artificial neural network is a network of linked nodes that was created by simplifying the structure of neurons in the brain. In this example, an arrow shows the connection between the input and output of each artificial neuron, which is represented by a circular node. Similar to the neurons in a human brain, the neurons in artificial neural networks are linked to one another at various levels of the network. They refer to these neurons as nodes. Finally, a calculation of the model's performance is performed. The amount of correct predictions to total predictions are used to determine the model's accuracy. To test and validate the dataset, a confusion matrix was developed.

IV. RESULT ANALYSIS

The PPE of the workers was identified using a dataset called CHVG (CH for Colour Hardhat, V for Vest, and G for Glass). 1,699 images and the corresponding annotations are five extreme conditions low light, intense light, sand dust, fog, and rain are included in the CHVG collection. For training, a 90:8:2 random split train-validation-test set was used. The trained model's performance was assessed using a confusion matrix that collected both human interpretations and model predictions. The model's performance was evaluated using three parameters: accuracy, recall, and precision. The values of each class's True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) were to achieve.

The total number of data points divided by the sum of TP is represented the model's accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \ldots .(1)$$

Precision, or the probability of being accurate, was determined by taking the product of TP and FP for each class prediction made by the classifier model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \ldots .(2)$$

Recall was classified as TP over the total of TP and FN, and determined the classifier model would detect

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \ldots .(3)$$

Table 1 compares the various models of Neural Style Transfer (NST) and Single-Shot Detector (SSD) with the identification of Personal Protective Equipment in Extreme Construction Conditions Using Artificial Neural Networks (PPE-ANN).

Table 1: COMPARATIVE PERFORMANCE ANALYSIS

Models	Accuracy	Precision	Recall
SSD	91	90	91
NST	92	92	91
PPE-ANN	97	96	97

The comparative graphical representation of the accuracy parameter for the three models appears in Fig. 2. The comparative graphic representation of the Precision and Recall parameters for the three models is displayed in Fig. 3.

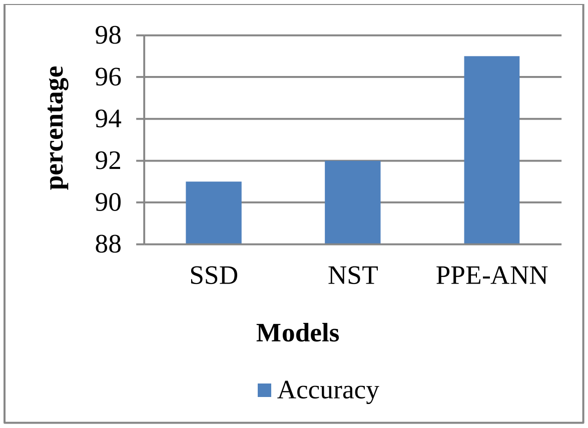

Fig. 2: COMPARATIVE ANALYSIS OF ACCURACY PARAMETER

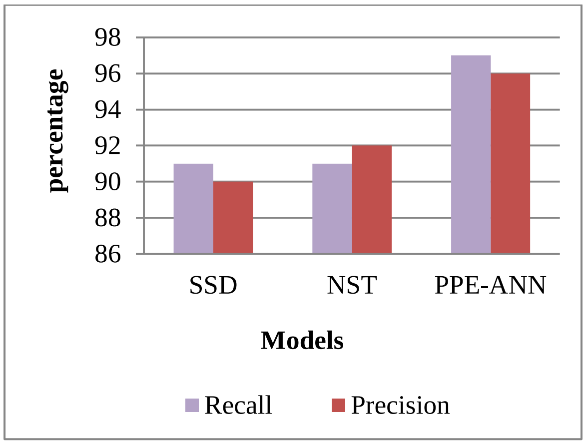

Fig. 3: COMPARATIVE ANALYSIS OF PRECISION AND RECALL PARAMETERS

Described model achieves the parameters as Accuracy as 97%, Recall 97% and Precision 96%. Regarding the identification of PPE is worn by construction workers, the results make it clear that, the YOLOv5 network structure is used as the basis for the development and training of an Artificial neural network (ANN) model, which demonstrated strong accuracy, precision, and recall.

V. CONCLUSION

The detection of personal protective equipment in extreme construction conditions using ANN is explained in this analysis. The Artificial Neural Networks (ANN) model used in this analysis, it was developed by combining transfer learning with the YOLOv5 deep learning network's basic version. Construction work is highly risky and dangerous. Despite concerns, construction work safety management always results in a high number of occupational accidents. In order to replace manual inspection, monitoring and enable data management and retrieval, they have designed a PPE detection, identification system based on the practical demands, urgent requirements established at construction sites. Through the use of a trained algorithm is to evaluate data from locations using YOLOv5, this analysis shows a state-of-the-art object identification approach can be used to automatically detect safety compliance. A dataset called CHVG is for Colour Hardhat, Vest, and Glass was used to identify the workers PPE. For training, a 90:8:2 random split train-validation-test set was used. The parameters of accuracy (97%), recall (97%), and precision (96%), are reached by the model that is described. The developed and trained Artificial neural network (ANN) model, when it came to recognizing PPE worn by construction workers, the YOLOv5 network structure-based system performed well in terms of precision, recall, and accuracy.

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