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Advanced CNN Model for Helmet Detection in High-Risk Environments

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Abstract— The impact of a dangerous workplace on employee health and productivity has caused many firms to place a high priority on workplace safety. Employees are constantly exposed to a variety of risks at all times and places when working in today's vast construction/manufacturing complexes and other dangerous industrial locations. The incidence of accidents is therefore higher than in other industries due to the greater number of risk variables, and it is mandatory that workers wear personal protective equipment (PPE) to shield their bodies from hazardous causes. Accidents resulting from failure to wear personal protection equipment, such as safety helmets, are among the most frequent safety incidents at industrial sites. In actuality, the majority of current safety inspection procedures depend on the manual monitoring and reporting of inspectors. Observing construction sites by hand can be labour-intensive, prone to mistakes, expensive, and unsuitable for larger projects with multiple ongoing operations. Many studies on automatic helmet wearing detection and human identity identification have been published, with the goal of assisting safety inspectors on construction sites in their duties of monitoring worker safety. Another study claims that helmet wear can be integrated with person identification using computer vision. Stated differently, during helmet testing, we typically lack the ability to identify specific individuals, and vice versa. We suggest a computer vision-based approach to automatically detect workers' identity and helmet wear in order to address the aforementioned issues. Firstly, our approach combines two uses: identification and helmet wearing detection. Second, we evaluated the algorithm's accuracy and recall rate in various visual settings to determine its applicability in the actual construction site environment. This was done in accordance with the varying visual conditions on the construction site.

Index Terms- Computer vision base approach, Helmet detection, Features extraction, Object detection, Worker safety

Introduction

To lessen the hazards that come with working in such situations, it is essential to ensure worker safety on construction sites. It is recommended that all workers participate in comprehensive safety training programs that cover critical standards and are frequently reinforced through refresher sessions. Protecting workers from a variety of risks requires the regular use of Personal Protective Equipment (PPE), such as hard hats, safety glasses, gloves, and suitable footwear. Fall safety devices, such as guardrails and personal fall arrest systems, require extra consideration, particularly when performing work at heights. To guarantee the safe operation of machinery and equipment, routine maintenance and inspections are essential. Training programs that instruct employees on correct usage are also necessary. Good hazard communication helps to improve awareness and guarantees that workers are aware of potential risks. It can be achieved through labelling, signage, and regular safety meetings. Furthermore, implementing a methodical approach to documenting and resolving safety issues promotes a proactive safety culture on building sites. Stakeholders in the construction sector may greatly improve worker safety and reduce the likelihood of accidents and injuries by addressing these important factors.

In many industries, especially construction where there is a high danger of head injuries, helmets are an essential component of worker safety. The main purpose of helmets is to reduce the risk of serious head injuries by acting as a barrier of protection against potential hazards including falling objects, debris, or impacts. Furthermore, the use of helmets is compliant with occupational safety and health laws in numerous areas, highlighting their significance as a required safety precaution. Helmets are made of a hard outer shell, usually made of fiberglass or high-density polyethylene. This hard outer shell is designed to disperse impact force over a larger surface, increasing the helmet's effectiveness. A suspension system, comprising straps and a headband, is usually incorporated into the interior to provide a secure and comfortable fit on the wearer's head. There are many different kinds of helmets that are made for particular types of work situations. For example, there are industrial helmets that are made to resist electrical conductivity and construction helmets with brims to guard against sunlight and rain. By protecting workers from head-related risks, the various features and designs of helmets collectively contribute to a safer work environment. Fig 1 shows the multiple colors of helmets in construction site with code.

Fig 1: Helmet with color codes (refer: https://www.moglix.com/blog/safety-helmets-color-code-guide/)

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I. RELATED WORKS

Desu Fu, et.al,…[1] the helmet detection algorithm based on improved YOLOv5 (You only look once) is put forward in this paper. Firstly, the YOLOv5 network structure is improved. By increasing the size of the feature map, one scale is added to the original three scales, and the added 160*160 feature map can be used for the detection of small targets; Secondly, the K-means is used for re-clustering the helmet data set to get more suitable priori anchor boxes. The experimental results illustrate that the average accuracy of the improved YOLOv5 algorithm is increased by 2.9% and reaching 95% compared with the initial model, and the accuracy of helmet recognition is increased by 2.4% and reaching 94.6%. This algorithm reduces the rates of missing detection and misdetection of small target detection in original network, and has strong practicability and advanced nature. It can satisfy the requirements of real-time detection and has a certain role in promoting the safety of power industry. In the working process of power workers, our first impression of them is that they are wearing safety helmets, whether it is in sunny, rainy or snowy. If the power workers do not wear safety helmets during operation, they may be hit by objects falling from above, hurt their head due to falling from a height, or their heads may suffer from electric shock. Therefore, safety helmet is the safety guarantee for workers in power industry. Power workers must wear safety helmets to enter the operation area, but manual supervision is time consuming and laborious, and there are risks in close range supervision in some work scenarios. So, the intelligent real-time safety helmet detection system of power workers is particularly important. It can not only realize the automation and digitization of safety supervision and monitoring, but also improve the safety of power workers, which has practical development significance.

Shuai Wang, et.al,…[2] studied an intelligent vision-based method for worker identification is proposed. This method is implemented through three parts: motion extraction based on the GMM model, personnel identification based on MHOG and SVM, and helmet identification based on the OpenPose and transfer learning CNN. The proposed method can be successfully used to identify the worker types in a variety of industrial scenarios, such as construction site, factory workshop, power construction site, and interior decoration. In addition, the method can be applied to small-scale datasets, and the identification accuracy cannot be affected by helmet occlusion, worker size, and different lighting conditions. The testing results on our self-collected dataset show that the accuracy values vary little under different types of identification situations, and the mean value of the accuracy reaches 99.43%. It is worth considering that the visual features of the self-collected dataset in this study are relatively ideal, so the identification results are relatively excellent. Our next work will capture some worker videos in actual industrial environments and conduct in-depth research on the worker images to promote the application of vision-based worker identification.

Yi-Jia Zhang, et.al,….[3] design a practical helmet-wearing detection algorithm based on contour and color features for workers on construction sites. In order to reduce image noise, the image preprocessing including image smoothing and image enhancement is adopted. Based on the result of image preprocessing, the two-stage ROI for the helmet is extracted by face detection, skin color detection and helmet contour detection. According to the result of the region of interest extraction, the safety helmet wearing detection is implemented by color space conversion and color feature recognition to detect whether a helmet is worn or not for workers. In many scenarios, helmet-wearing plays a vital role, thus the detection of helmet wearing has certain practical significance for assisting construction safety. The algorithm in this paper mainly realizes the detection of wearing helmets in batches of images, which can meet some detection requirements, but for some real-time detection, this paper has not covered. The idea of future research is to realize the real-time detection of helmet wearing and set the non-wearing alarm prompt, to complete a safety helmet wearing assistance system which can be practically applied.

Ahatsham Hayat, et.al,…[4] developed machine and deep learning-based helmet detection systems, but few have focused on helmet detection at construction sites. This paper presents a You Only Look Once (YOLO)-based real-time computer vision-based automatic safety helmet detection system at a construction site. YOLO architecture is high-speed and can process 45 frames per second, making YOLO-based architectures feasible to use in real-time safety helmet detection. A benchmark dataset containing 5000 images of hard hats was used in this study, which was further divided in a ratio of 60:20:20 (%) for training, testing, and validation, respectively. The experimental results showed that the YOLOv5x architecture achieved the best mean average precision (mAP) of 92.44%, thereby showing excellent results in detecting safety helmets even in low-light conditions. It is critical to monitor construction workers' safety. Protection equipment use monitoring is part of construction site safety management. In most falling accidents, workers fall from heights and smash their heads on hard floors. Safety helmets can absorb and diffuse the impact of falling, reducing the risk of injury to workers who fall from heights. Hard helmets are made to withstand shock, object penetration, and contact with electrical hazards. Half of all fatalities from accidental falls and a considerable number of fatalities from slips, trips, and being struck by falling items may be reduced if employees wore hard helmets properly

Han Liang, et.al,…[5] proposed object detection network for helmet-wearing utilizes GhostNet, a lightweight network, as the backbone feature extraction network. It uses its cheap operation to make the model lighter overall while ensuring efficient automatic feature extraction. In the feature processing stage, we designed multiscale segmentation and feature fusion network (MSFFN) to improve the algorithm's robustness in detecting objects at different scales. In contrast, the design of the feature fusion network can enrich the diversity of helmet features, which is beneficial to the accuracy of helmet detection when the distance changes, viewpoint changes, and occlusion phenomena occur. The proposed lightweight residual convolutional attention network version 2 (LRCA-Netv2) is an improvement of the spatial attention module LRCA-Net proposed in our previous work. The main idea of the improvement is that by fusing the combined features along with the horizontal and vertical directions and then weighting the attention separately, such an operation can establish dependencies between the more distant features using precise location information. It has a good performance improvement over the previous module. The mAP and FPS of the proposed lightweight helmet-wearing detection network evaluated on the combined dataset reach 93.5% and 42, respectively, improving our model in execution speed and accuracy compared to other methods.

II.EXISTING METHODOLOGIES

Conventional video monitoring techniques are frequently used to manually oversee the donning of safety helmets on construction sites. These techniques mostly rely on human judgment for making final decisions. These conventional methods might not be as effective at accurately tracking safety helmet compliance as fully automated systems are. For this reason, conventional object detection methods are used a lot. These algorithms frequently use sliding window-based region selection techniques, which include the algorithm going through the image in a methodical manner. However, it can be challenging to choose the right aspect ratio and scale for the sliding window, which makes it challenging to precisely record helmets with different sizes and orientations. Furthermore, it can take some time to navigate through the entire image using sliding windows. Because of this, manual management methods could have issues with accuracy and efficiency. There is a rising interest in investigating increasingly sophisticated technologies, like automated computer vision systems and machine learning techniques, to overcome these difficulties. These technologies could provide precise, real-time detection of safety helmet use, minimizing the need for human intervention and offering a more efficient method of guaranteeing safety compliance on building sites. Making the switch to these automated systems might greatly improve the efficiency of safety monitoring procedures in the building sector. Adoption of front-line technical solutions is becoming more popular as a means of overcoming these obstacles. Promising substitutes include automated computer vision systems that are driven by machine learning algorithms. In real time, these algorithms may be trained to identify safety helmets with accuracy, eliminating the need for human monitoring. Deep learning techniques, which acquire complex patterns from a variety of datasets, offer a more flexible method for helmet detection.

III.PROPOSED METHODOLOGIES

Enhancing workplace safety through a comprehensive and cutting-edge approach is what the suggested helmet detection with facial recognition system embodies. Using state-of-the-art technology together attempts to offer a reliable way to keep an eye on and enforce safety procedures simultaneously.

By applying the Grassmann algorithm—a facial features extraction technique—the system places cameras in strategic locations throughout critical sections of the workplace. A solid foundation for further identification is provided by this algorithm, which makes it possible to extract distinguishing facial traits. Afterwards, instantaneous and precise identification is ensured by comparing the derived face features in streaming data with a database of authorized personnel. Using the YOLO (You Only Look Once) algorithm, the system incorporates helmet detection to enhance safety measures even more. This algorithm targets the identification of people without helmets in particular, allowing for quick and precise object detection. The solution creates a holistic method to guaranteeing that workers wear helmets and have allowed access in addition to following safety procedures by integrating facial recognition and helmet detection. The technology is intended to sound alarms as soon as it detects non-helmet use or unauthorized access. By guaranteeing that any departure from safety standards is promptly addressed, this proactive alarm mechanism enables prompt remedial action. The suggested method offers an advanced approach for improving workplace safety through real-time monitoring and prompt intervention by combining both face recognition and helmet detection algorithms. The proposed framework is shown in fig 2.

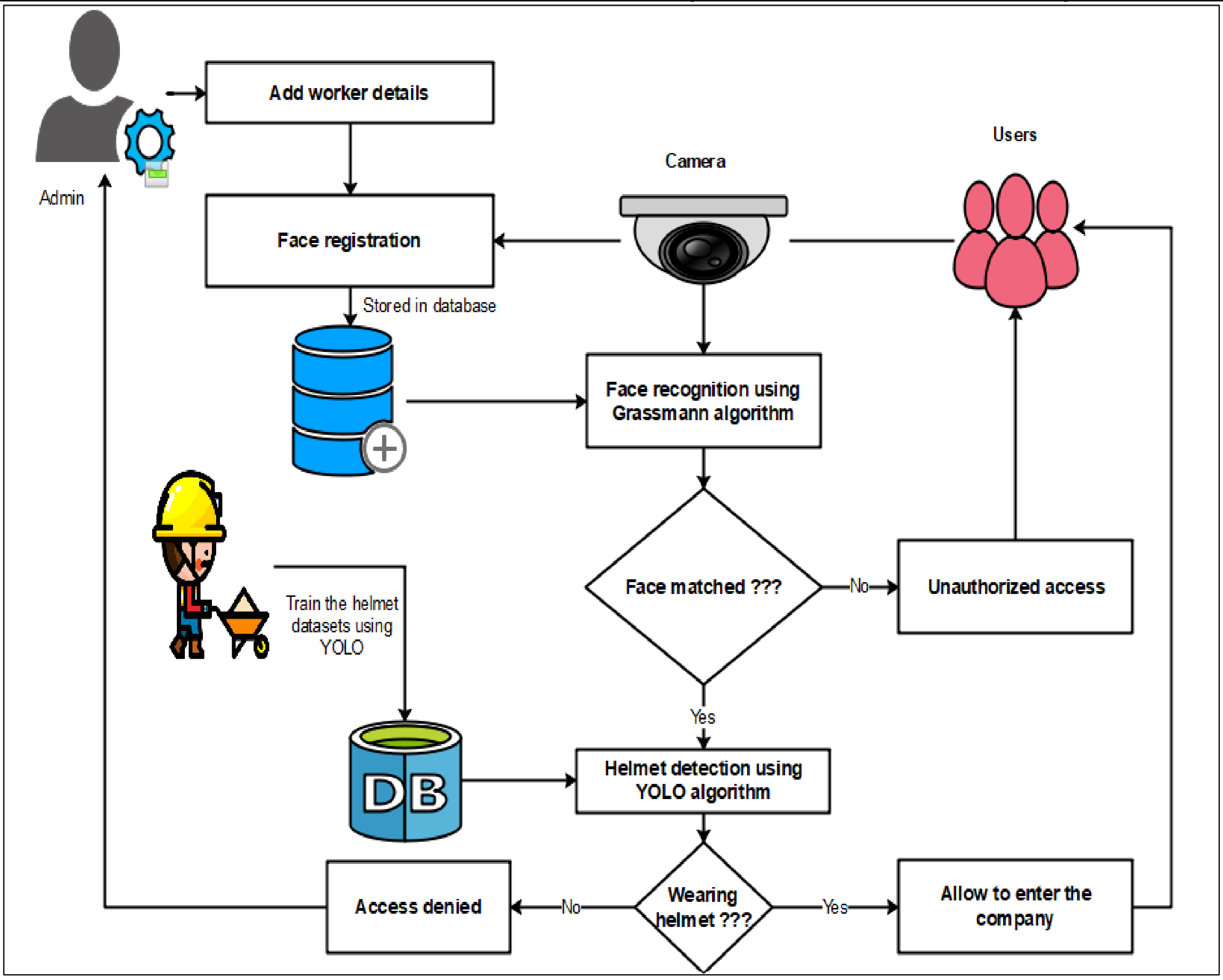

Fig .2 Architecture for Proposed Work

4.1 Proposed Algorithm

YOLO ALGORITHM

The You Only Look Once (YOLO) algorithm is a neural network-based real-time object detection system that runs in a single forward pass. The following are the main steps in the YOLO algorithm:

Division of the Input Image: The input image is separated into a grid of cells. The YOLO model's architecture dictates the size of this grid (YOLOv3 utilizes a 13x13 or 19x19 grid, for example).

Bounding Box Prediction: Multiple bounding boxes (typically two or three) are predicted for each grid cell. These bounding boxes provide dimensions like width, height, and the x and y coordinates of the box's centre, together with a confidence score that indicates the likelihood that an object is inside the box.

Class Prediction: The model forecasts the class probabilities for every bounding box. Softmax activation is used for this, and each class score indicates the likelihood that an object falls into a specific class (e.g., human, car, etc.).

Confidence Score Calculation: The highest-class probability multiplied by the objectness score (which indicates the likelihood of an object being present) yields the confidence score for each bounding box.

Non-Maximum Suppression (NMS): This technique is used to remove redundant or less certain bounding boxes for the same object. In order to do this, the bounding boxes are sorted according to their confidence scores, and boxes that exhibit significant overlap with a box with a higher confidence are suppressed.

Thresholding: To remove low-confidence detections, bounding boxes with confidence scores below a particular threshold are removed.

Output: The maintained bounding boxes, together with the confidence ratings and class labels that correspond with them, make up the final output. The objects found in the input image are represented by this data.

GRASSMANN ALGORITHM

A Grassmann manifold $G_{n,p}$ is a set of p-dimensional linear subspaces of R^n (p-planes in R^n) for $0 < p \leq n$. This Grassmann manifold has a natural quotient representation $G_{n,p} = V_{n,p} / O_p$, where Vn,p is a Stiefel manifold (a set of n×p orthonormal matrices) and O_p is the orthogonal group. This representation states that two matrices belong to the same equivalence class if their columns span the same p dimensional subspace. Hence, the entire equivalence class can be represented as the subspace spanned by the columns of a given matrix Y.

$$[Y] = \{YQ_p : Q_p \in O_p\}$$

In other words, a point on the Grassmann manifold is a linear subspace which may be specified by any arbitrary orthogonal basis.

- Use eye coordinates to determine the initial affine registration parameters for each image.
- Sample the affine registration manifold by perturbing the affine parameters
- Compute the k nearest neighbours from the registration manifold
- Apply color equalization and filter features values
- Construct the tangent space
- Embed the approximated tangent space and compute canonical angles
- Compute the subspace distance

5. RESULTS AND DISCUSSION

Obviously, in order to test the system some faces are required. There are so many standard face databases for testing and rating a face detection algorithm. A standard database of face imagery is essential to supply standard imagery to the algorithm developers and to supply a sufficient number of images to allow testing of these algorithms. Without such databases and standards, there will be no way to accurately evaluate or compare facial recognition algorithms. All the experiments described here have been executed mainly on the faces provided by the real time face database.

Accuracy

Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0.

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \text{ x } 100$$

True positive (TP): number of true positives - perfect positive prediction
False positive (FP): number of false positives - imperfect positive prediction
True negative (TN): number of true negatives - perfect negative prediction
False negative (FN): number of true negatives - imperfect negative prediction

ALGORITHM	ACCURACY
PRINCIPAL COMPONENT ANALYSIS	65%
LINEAR DISCRIMINATIVE ANALYSIS	85%
GRASSMANN ALGORITHM	98%

From the above graph, proposed system provides improved accuracy rate than the existing PCA and LDA algorithm

IV. CONCLUSION

In conclusion, technology has changed the landscape of worker safety on construction sites by improving compliance and monitoring. Using the Grassmann and YOLO algorithms, the suggested system combines helmet detection and facial recognition, offering a sophisticated outcome. With the help of real-time data processing and well-placed cameras, this system not only enforces safety regulations by looking for safety helmets but also guarantees allowed entry through facial recognition. The YOLO algorithm efficiently streamlines helmet detection, while the Grassmann method makes exact facial feature extraction possible, offering a dependable foundation for identification. By combining these cutting-edge technologies, a comprehensive approach to workplace safety is provided, enabling prompt reactions to instances of unauthorized entry and non-compliance with helmet regulations via proactive alarm systems. With its strong and flexible approach to risk mitigation, the suggested system is at the cutting edge of innovation in the construction industry, which is still very focused on safety. The integration of automated technology with conventional safety protocols enhances precision and efficacy while promoting a more secure work atmosphere. Accepting these innovations is a show of a dedication to raising workplace safety standards, protecting employees, and reducing risks on building sites.

. References

[1] Fu, Desu, et al. "Research on safety helmet detection algorithm of power workers based on improved yolov5." Journal of Physics: Conference Series. Vol. 2171. No. 1. IOP Publishing, 2022.
[2] Wang, Shuai, et al. "An intelligent vision-based method of worker identification for industrial internet of things (IoT)." Wireless Communications and Mobile Computing 2022 (2022).
[3] Zhang, Yi-Jia, Fu-Su Xiao, and Zhe-Ming Lu. "Safety Helmet Wearing Detection Based on Contour and Color Features." Journal of Network Intelligence: Taiwan, China 7 (2022): 516-525.
[4] Hayat, Ahatsham, and Fernando Morgado-Dias. "Deep learning-based automatic safety helmet detection system for construction safety." Applied Sciences 12.16 (2022): 8268.
[5] Liang, Han, and Suyoung Seo. "Automatic detection of construction workers' helmet wear based on lightweight deep learning." Applied Sciences 12.20 (2022): 10369.
[6] Li, Yange, et al. "Deep learning-based safety helmet detection in engineering management based on convolutional neural networks." Advances in Civil Engineering 2020 (2020): 1-10.
[7] Cheng, Rao, et al. "Multi-scale safety helmet detection based on SAS-YOLOv3-tiny." Applied Sciences 11.8 (2021): 3652.
[8] Hayat, Ahatsham, and Fernando Morgado-Dias. "Deep learning-based automatic safety helmet detection system for construction safety." Applied Sciences 12.16 (2022): 8268.
[9] Deng, Lixia, et al. "A lightweight YOLOv3 algorithm used for safety helmet detection." Scientific reports 12.1 (2022): 10981.
[10] Huang, Li, et al. "Detection algorithm of safety helmet wearing based on deep learning." Concurrency and Computation: Practice and Experience 33.13 (2021): e6234.