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Safety Measure Detection Using Deep Learning

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ABSTRACT

This implementation is for a computer vision application that detects individuals and verifies their compliance with safety gear regulations, such as safety jackets and hard-hats. The system counts the number of individuals violating safety standards and keeps track of the total number of individuals detected. The system uses advanced image processing techniques, including object detection and classification, to accurately identify the presence or absence of safety gear. The user interface provides real-time analysis of the data, with the option to alert the user of any violations. This implementation is a valuable tool for organizations looking to ensure the safety of their employees and customers, providing a comprehensive solution for monitoring compliance with safety regulations. It can also be used to analyze trends and identify areas for improvement, making it an essential tool for safety professionals and facilities managers.

Keywords: Deep Learning, Convolutional Neural Network (CNN), Safety Measures , Object Detection, Image Classification

I. INTRODUCTION

The industry has a high accident rate and can be an extremely dangerous place to work. The high accident rate is a result of the industries use of hazardous machinery and heavy weights. In the sector, safety concerns are treated seriously and have always been a top focus. Nonetheless, given the frequency of incidents, there is always a necessity for development. New techniques are utilized to improve safety in manufacturing sectors as technology advances. One of the main goals of industry is to automate and simplify repetitive tasks by utilizing artificial intelligence and machine-to-machine communication. In addition, research is being done on how to employ contemporary technologies to boost safety. One example of how technology may be applied to properly train personnel and lower hazards is the use of Virtual Reality (VR) for training and education.

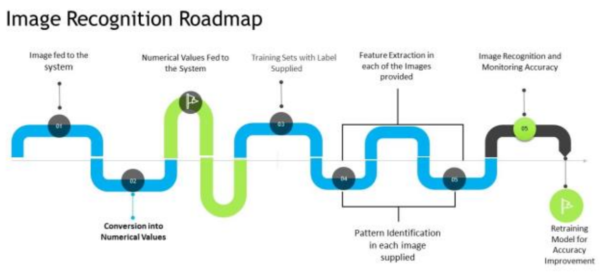

Figure 1. Image Recognition

It has been demonstrated that proactive measures are very important for accident mitigation and accident prevention. Examples of preventative measures include safety training for employees to learn and practice the workplace's safety principles and standard emergency procedure. The use of personal protective equipment (PPE), such as gloves, hard hats, safety glasses, and vests, is another form of proactive action. Researchers have investigated automated methods of observing and picking up harmful conditions, like the absence of personal protective equipment (PPE) in manufacturing and on building sites. Due to significant developments in the computer science and machine learning. workers' perceptions of such technology might change because of their awareness of it. The level of privacy in monitoring has also been suggested to be increased in many ways, for as by blurring areas like faces that can identify a person.

To investigate the potential for increasing the use of safety devices through picture recognition to improve worker safety. This is accomplished by offering a platform for the development of a system that employs image recognition to find safety gear.

II. LITERATURE SURVEY

In [1] introduced deep residual learning techniques for image recognition tasks, significantly advancing the field of computer vision and pattern recognition. This work has had a substantial impact on improving the accuracy and efficiency of image classification models, especially in complex recognition tasks.

In [2] discussed the integration of Realtime Locating Systems (RTLS) in enhancing safety measures at construction sites, offering valuable insights into RTLS technology's impact on safety protocols. The review emphasized the importance of real-time location data in improving worker safety and accident prevention on construction sites.

In [3] proposed a real-time monitoring system designed to control interference in large-scale construction projects, contributing to improved operational efficiency and safety. The system addresses critical challenges in construction site management, such as real-time interference control, leading to smoother project execution and reduced safety risks.

In [4] investigated the effectiveness of data augmentation techniques in deep learning for image classification tasks, evaluating various augmentation methods' impact on model performance. The study provided valuable guidance on selecting appropriate data augmentation strategies to enhance the robustness and generalization of deep learning models.

In [5] explored innovative data augmentation methods to improve the accuracy of image classification using convolutional neural networks (CNNs), contributing to advancements in image recognition technologies. The research focused on enhancing CNN performance through effective data augmentation, resulting in more reliable and accurate image classification results.

In [6] introduced a real-time monitoring system for personal protective equipment (PPE), ensuring worker safety by continuously monitoring PPE usage and compliance. This system plays a crucial role in preventing workplace accidents and ensuring regulatory compliance in hazardous work environments.

In [7] discussed the application of deep learning techniques for real-time detection of PPE at construction sites, contributing to the development of automated safety systems. The research improved hazard detection and risk prevention on construction sites, enhancing overall safety protocols.

In [8] delved into the application of machine learning in predictive maintenance for smart manufacturing, highlighting machine learning algorithms' role in optimizing maintenance processes. The study emphasized the importance of predictive maintenance in ensuring equipment reliability and reducing downtime in smart manufacturing environments.

In [9] proposed a comprehensive safety management system for construction sites based on computer vision and deep learning technologies, automating hazard detection and monitoring to enhance safety protocols. The system integrated advanced technologies to improve safety measures and reduce the likelihood of workplace accidents.

In [10] demonstrated the effectiveness of the Haarcascade algorithm in detecting safety equipment across diverse work environments, contributing to improved safety management systems. The research enhanced safety protocols by accurately identifying safety equipment usage and compliance in various working environments.

In [11] presented a method for detecting safety gear using advanced deep learning techniques, promoting safer working conditions. Their approach leveraged deep learning algorithms to improve safety gear detection accuracy, ensuring workers' adherence to safety protocols and regulations.

In [12] presented enhancements for detecting industrial safety gear using a re-ID conditioned detector, contributing to the development of more accurate safety gear detection systems. The research focused on improving the efficiency and reliability of safety gear detection, enhancing overall workplace safety.

In [13] introduced deep residual learning techniques for image recognition tasks, significantly advancing the field of computer vision and pattern recognition. This work has had a substantial impact on improving the accuracy and efficiency of image classification models, especially in complex recognition tasks.

In [14] discussed the integration of Realtime Locating Systems (RTLS) in enhancing safety measures at construction sites, offering valuable insights into RTLS technology's impact on safety protocols. The review emphasized the importance of real-time location data in improving worker safety and accident prevention on construction sites.

In [15] proposed a real-time monitoring system designed to control interference in large-scale construction projects, contributing to improved operational efficiency and safety. The system addresses critical challenges in construction site management, such as real-time interference control, leading to smoother project execution and reduced safety risks.
These papers collectively contribute to advancements in safety management, deep learning, computer vision, and predictive maintenance, addressing critical challenges and improving safety measures in various industrial and construction environments.

III.PROJECT FLOW AND METHODOLOGY

A. Image Enhancement

Image enhancement involves adjusting digital images to make them more suitable for display or further analysis. This can include tasks such as noise reduction, sharpening, or brightening an image to improve the visibility of important features.

B. Feature Extraction

Feature extraction methods identify distinct features in images, such as edges and corners, which can then be used to distinguish or match images with similar features. An algorithm was developed in this study to extract color features from samples. Typically, color, shape, and texture features are extracted from images to aid in image recognition.

C. Image acquisition

Images were acquired through two methods: the first system utilized a scanner (hp 1370) and a Pentium IV Computer unit, while the second system used a digital video camera. Key point descriptors were generated for both training and test images. These key points serve as reference points to identify objects in the training image, which may also exist in the test image alongside other objects. The matches were evaluated based on the Euclidean distance between matched points in the training and test images.

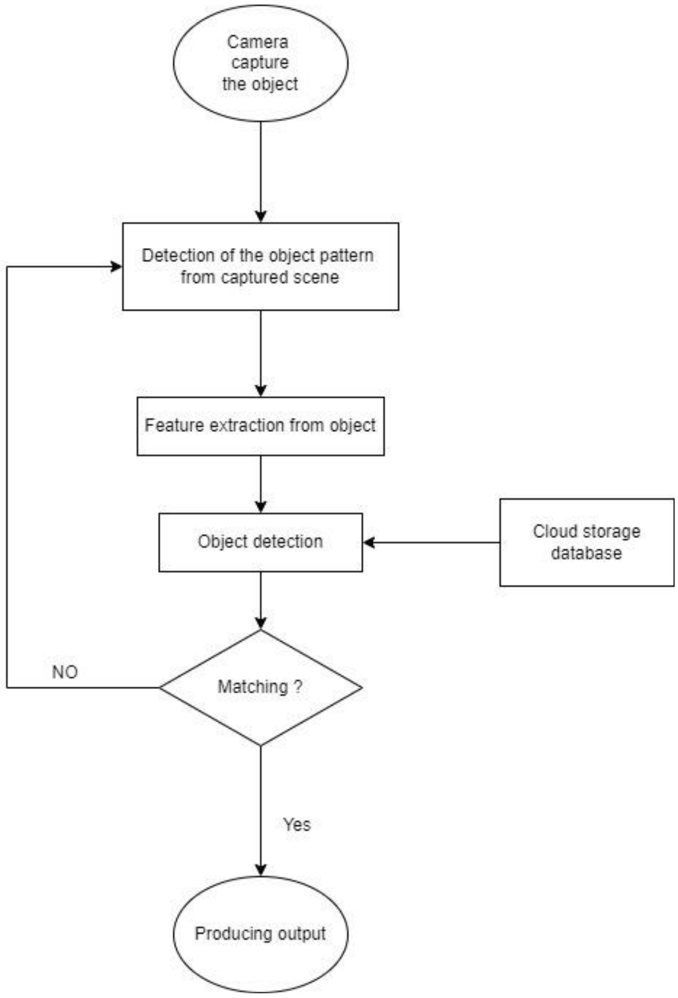

Figure 2. Workflow

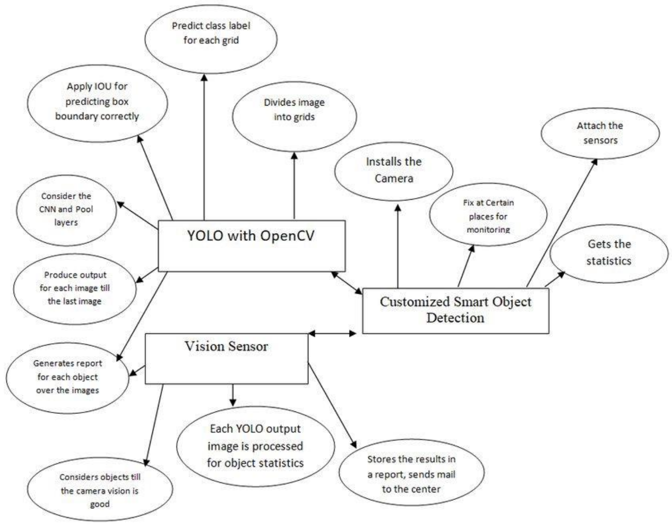

Figure 3. ER Diagram

D. Training application

The training application begins by receiving a video stream from a connected camera. Frames are extracted from this stream to capture images at an adjustable rate. The application continues this process until it reaches a default target of 30 images, uploading these images to the designated Custom Vision resource. During this image capture phase, the camera can be exposed to the specific

objects you want the model to recognize. Once the images are uploaded, they are available within the Custom Vision resource. Alternatively, images can be directly uploaded to Custom Vision from a local folder via the Custom Vision web portal.

E. Training the model in Custom Vision

In Custom Vision, models are constructed using training images. When creating a model, specific objects you want the model to detect are determined. This is accomplished by defining class labels. For instance, when building a model to detect a person with and without a reflective vest, class labels like "PersonWithVest" and "PersonWithoutVest" are defined. The most effective approach involves simultaneously detecting both the person and the vest, as it has been demonstrated to yield the best performance.

IV.MATERIAL METHODOLOGY

A safety gear detection system using deep learning methodology typically follows the following steps:

A. Data Collection:

The first step is to collect a large dataset of images that contain workers wearing safety gear, such as hard hats and safety vests. The dataset should include images captured in different lighting conditions, angles, and orientations.

B. Data Pre-processing:

The collected data is pre-processed by resizing the images, removing irrelevant features, and normalizing the pixel values. The pre-processed data is then divided into training, validation, and test sets.

C. Model Development:

The next step is to develop a deep learning model using a suitable framework, such as TensorFlow or PyTorch. The model can be a convolutional neural network (CNN) or a hybrid model that combines CNN with other deep learning architectures. The model is trained on the training set using backpropagation and gradient descent algorithms.

D. Model Evaluation:

Once the model is trained, it is evaluated on the validation set to assess its performance. The evaluation metrics used can include accuracy, precision, recall, and F1 score.

E. Model Optimization:

The model is optimized by fine-tuning the hyperparameters, such as learning rate, number of layers,
and batch size. The optimized model is then tested on the test set to evaluate its generalization performance.

F. Deployment:

Once the model is trained and optimized, it can be deployed in the field using suitable hardware and software components. The input images captured by the camera are pre-processed and fed into the model for safety gear detection. The output of the model can be displayed on a monitor or integrated with other safety equipment for real-time alerts.

V. RESULTS

The toolkit for Intel® Distribution of OpenVINOTM contains an inference engine that is used by the application. First, a trained neural network finds persons in the frame and shows a bounding box over them in a green colour. The programme checks everyone it finds to see if they are donning a hard helmet and safety gear. If they are not, the system registers an alarm.

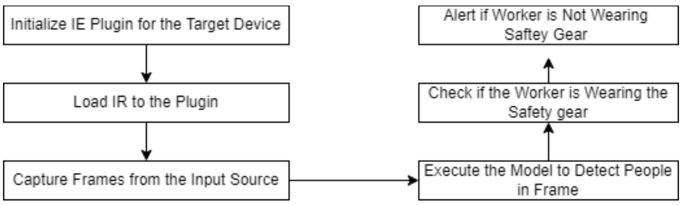

Figure 4. Working System

To prepare the environment for utilizing the Intel® Distribution of OpenVINO™ toolkit, configureit by exporting the necessary environment variables:
command: source /opt/intel/openvino/bin/setupvars.sh

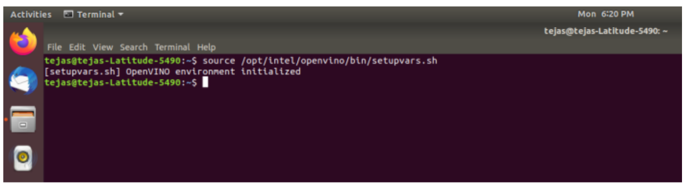

Figure 5. Environment Setup

This command is essential for setting up the required environment variables. The system can access crucial OpenVINOTM libraries, tools, and dependencies by sourcing this script. In order to enable for easy interaction with OpenVINOTM components, it makes sure that the system environment is configured correctly.
Begin by changing the current directory to the specific location of the code on your system.

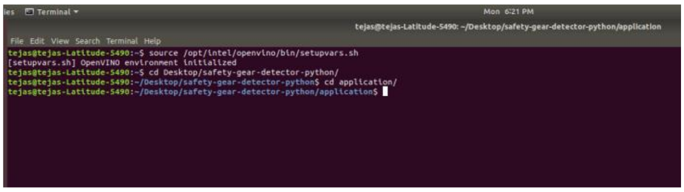

Figure 6. Run Code

Our application's interoperability with a variety of input sources contributes to its versatility. The system adjusts fluidly to various input sources, whether using pre-recorded video footage or providing real-time monitoring through a linked camera. Users' freedom to switch between several video sources improves the application's capacity to adapt to various surroundings. Additionally, the device has the ability to dynamically activate the camera, enabling real-time runtime analysis. Real-time monitoring is ensured by this feature, enabling prompt answers to safety compliance problems. Our programme is able to respond to a variety of settings thanks to its versatility, making it a reliable option for safety gear identification in dynamic contexts.

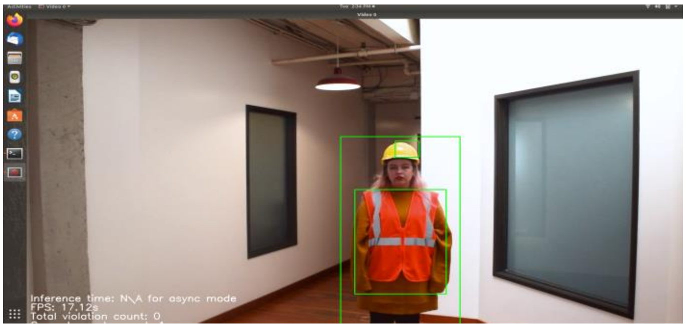

Figure 7. Video Detection

The bottom left corner of the screen in the visual depiction shown in Figure 3.6 prominently displays important metrics. These metrics include" Total Violation Count," which shows instances of safety equipment non-compliance," Current People Count," which shows the number of people currently visible in the frame, and" Total People Count," which shows the total number of people seen. These metrics offer insightful information briefly and act as real-time indicators of safety compliance and human presence.

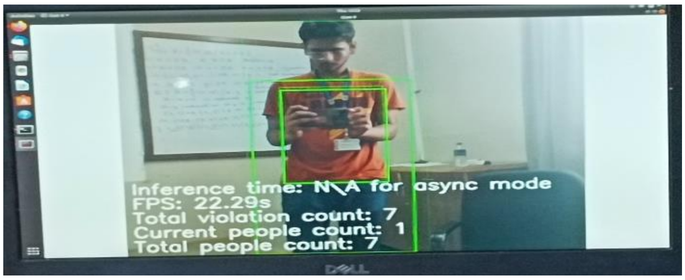

Figure 8. Input Stream

The system's versatility is further seen in Figures 3.6 and 3.7. Figure 3.6 shows how the programme analyses video material that has been uploaded, showcasing its capacity to analyse previously recorded information and provide precise violation counts and person tracking. The system's smooth transition to real-time monitoring is shown in Figure 3.7. Our programme utilises the potential of instant data capture by connecting to a live camera stream. The technology can identify safety infractions in real time thanks to this film, ensuring prompt reactions and improving overall safety procedures. The application's adaptability is demonstrated by these numbers, which make it a dependable option for both static and dynamic contexts.

VI.CONCLUSION & FUTURE SCOPE

The implementation of safety gear detection systems using deep learning technologies has paved the way for numerous advancements in various industries. As we move forward, there are several promising future scopes and potential applications for these systems, driven by ongoing advancements in artificial intelligence and machine learning. Here are some key areas where the future of safety gear detection systems using deep learning appears particularly promising Safety gear detection system using deep learning has great potential in various industries and can lead to numerous future scopes. Some of the possible future scopes are:

A. Industrial safety

The safety gear detection system using deep learning can be used in industries to detect the usage of safety gear such as helmets, gloves, safety shoes, goggles, etc. This can prevent accidents and ensure the safety of the workers.

B. Construction safety

Construction sites are considered high-risk areas, and the safety of the workers is of utmost importance. The safety gear detection system can be implemented in construction sites to detect the usage of safety gear such as helmets, safety harnesses, safety shoes, etc.

C. Healthcare safety

The safety gear detection system can be used in healthcare settings to detect the usage of personal protective equipment (PPE) such as masks, gloves, goggles, and gowns. This can prevent the spread of infectious diseases and ensure the safety of healthcare workers.

D. Sports safety

The safety gear detection system can be implemented in sports settings to detect the usage of safety gear such as helmets, pads, and mouthguards. This can prevent injuries and ensure the safety of athletes.

E. Transportation safety

The safety gear detection system can be used in transportation settings such as aviation, rail, and maritime industries to detect the usage of safety gear such as helmets, life jackets, and harnesses. This can prevent accidents and ensure the safety of the passengers and crew.

F. Military safety

The safety gear detection system can be used in military settings to detect the usage of protective gear such as helmets, body Armor, and gas masks. This can ensure the safety of the soldiers during combat.

G. Firefighter safety

The safety gear detection system can be implemented in firefighting settings to detect the usage of safety gear such as helmets, boots, gloves, and breathing apparatus. This can prevent injuries and ensure the safety of the firefighters.

VII. REFERENCES

[1] K. He, X. Zhang, S. Ren and J. Sun, ”Deep Residual Learning for Image Recognition,” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778, doi : 10.1109/CVPR.2016.90.

[2] Soltanmohammadlou, N., Sadeghi, S., Hon, C.K., Mokhtarpour-Khanghah, F. (2019). Realtime locating systems and safety in construction sites: A literature review. Safety Science.

[3] Naticchia , Berardo et al. “A monitoring system for real-time interference control on large construction sites.” Automation in Construction 29 (2013):148-160.

[4] Perez, L., Wang, J. (2017). The Effectiveness of Data Augmentation in Image Classification using Deep Learning. ArXiv, abs/1712.04621.

[5] Shijie, Jia Ping, Wang Peiyi, Jia Siping, Hu. (2017). Research on data augmentation for image classification based on convolution neural networks. 4165-4170. 10.1109/CAC.2017.8243510.

[6] Barro-Torres, Santiago Fern´andez-Caram´es, Tiago P´erez-Iglesias, H´ector Escudero, Carlos. (2012). Real-Time Personal Protective Equipment Monitoring System. Computer Communications. 36. 42-50. 10.1016/j.comcom.2012.01.005.

[7] Nath, Nipun Behzadan, Amir Paal, Stephanie. (2020). Deep learning for site safety: Realtime detection of personal protective equipment. Automation in Construction. 112. 103085. 10.1016/j.autcon.2020.103085.

[8] C¸ ınar, Z.M.; Abdussalam Nuhu, A.; Zeeshan, Q.; Korhan, O.; Asmael, M.; Safaei, B. Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0. Sustainability 2020, 12,8211. 32.

[9] Lee J, Lee S. Construction Site Safety Management: A Computer Vision and Deep Learning Approach. Sensors (Basel). 2023 Jan 13;23(2):944. doi: 10.3390/s23020944. PMID: 36679738; PMCID: PMC9863726.

[10] Le, Billy Phuc Jeon, HyeJun Truong, Nguyen Hak, Jung. (2019). Applying the Haarcascade Algorithm for Detecting Safety Equipment in Safety Management Systems for Multiple Working Environments. Electronics. 8. 1079. 10.3390/electronics8101079.

[11] Cinar, Zeki Nuhu, Abubakar Zeeshan, Qasim Korhan, Orhan Asmael, Mohammed Safaei, Babak. (2020). Machine Learning in Predictive Maintenance towards Sustainable SmartManufacturing in Industry 4.0. Sustainability. 12. 8211. 10.3390/su12198211.

[12] Lee J, Lee S. Construction Site Safety Management: A Computer Vision and Deep Learning Approach. Sensors (Basel). 2023 Jan 13;23(2):944. doi: 10.3390/s23020944. PMID: 36679738; PMCID:PMC9863726.

[13] X. Wang, D. Niu, P. Luo, C. Zhu, L. Ding and K. Huang, ”A Safety Helmet and Protective Clothing Detection Method based on Improved-Yolo V 3,” 2020 Chinese Automation Congress (CAC), Shanghai China, 2020, pp. 5437-5441, doi:10.1109/CAC51589.2020.9327187.

[14] Ravikiran, Manikandan. (2019). Improving Industrial Safety Gear Detection through Re-ID conditioned Detector.

[15] le, Billy Phuc Jeon, HyeJun Truong, Nguyen Hak, Jung. (2019). Applying the Haar-cascade Algorithm for Detecting Safety Equipment in Safety Management Systems for Multiple Working Environments. Electronics. 8. 1079. 10.3390/electronics8101079.