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Real- Time Worker's Safety Monitoring On Scaffolding Using Vision Based System

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Abstract
The construction industry presents its problems regarding safety maintenance, particularly in matters of worker falls. In this case, falls are projected to grow from 33-38%. This project intends to reduce these dangers by developing a vision-based real-time worker's safety monitoring system that ensures proper use of Personal Fall Arrest Systems (PFAS) on scaffolding. PFAS patients must wear helmets, harnesses, and lanyards because their proper placement is critical in avoiding injury due to falls. The methodology starts with collecting an image dataset. Every image is painstakingly labelled to show all instances of the specific PFAS components and their relevant states. Normalization is performed to match the standards of image inputs with the selected object detection algorithm, YOLOv11. The dataset is divided into training, validation, and testing units, which is representative of the actual situation. This guarantees effective training and testing of the YOLOv11 model for reliable and accurate real-time detection. The verification tests are conducted using the F1 score metric, which evaluates the model in a holistic way. After configuration, the trained YOLOv11 model is deployed on Open CV in the Visual Studio Code (VS Code) environment to enable real-time detection. The ultimate objective is to deliver a system that significantly reduces fall accidents, enhances worker safety, and facilitates compliance with stringent construction site safety standards.

Keywords: *Worker Safety, Real-Time Monitoring, personal fall arrest systems(PFAS), scaffolding, YOLO, and F1 score.*

1. Introduction
Worker safety is the top priority in construction. Safe practices prevent accidents, injuries, and keep projects on track. Construction sites are dangerous, especially when working on scaffolding. Recent data shows a rise in scaffold-related falls, making better safety systems crucial. Manual inspections often miss hazards and have errors. We need automated systems for constant, accurate safety checks. These systems reduce human mistakes and ensure safety rules are always followed. This leads to safer sites and fewer injuries. Equipment like helmets, harnesses, and lanyards are vital. Helmets protect against head injuries from falling objects. Harnesses and lanyards prevent severe injuries during falls. They spread the force of a fall, protecting the body. Automated systems can use cameras and sensors to monitor safety. They can detect if workers are wearing safety gear and if safety rules are being followed. This real-time monitoring helps prevent accidents before they happen. Using technology improves site safety. It reduces risks for workers and ensures everyone goes home safe. It also helps companies avoid legal issues and shows they value their workers.

2. Improving Construction Safety Through Advanced Monitoring
Recent advancements in construction safety monitoring leverage deep learning and computer vision to enhance real-time hazard detection. Several studies highlight the effectiveness of YOLO-based models for PPE detection. For instance, [6] compared YOLO versions, finding YOLOv5 achieved a 94% mAP, demonstrating superior performance in real-

time PPE detection. Similarly, [9] utilized YOLOv5 and v8 to identify safety risks, including PPE non-compliance and unsafe actions, achieving mAP50 accuracies of 94.1% and 95.1%, respectively. These models effectively detect helmets, vests, and other safety equipment, significantly improving safety risk assessment. Beyond PPE detection, research explores broader safety monitoring. [8] developed a mobile scaffold safety system using Mask R-CNN and Object Correlation Detection (OCD) to analyse worker-scaffold interactions, achieving 86% system accuracy. This system detected harnesses and hard hats, alongside unsafe actions, demonstrating the potential for comprehensive scaffold safety monitoring. Furthermore, [10] utilized CNNs to analyse acceleration data from scaffolding sensors, accurately identifying fall motions with high F1 scores, enabling real-time fall detection and response. Studies also focus on the broader impact of deep learning on construction safety. [1] established sustainable methods for PPE detection using CNNs, achieving 90% accuracy, highlighting the influence of image quality and environmental factors. [2] developed vision-based systems to detect hazards, including unsafe worker conduct and faulty equipment, achieving 88% accuracy. This illustrates the effectiveness of proactive hazard detection [3]. They integrated IoT with computer vision for equipment, worker, and environmental monitoring with an accuracy of 92% for real-time interventions. Certain Use Cases, such as Edge-YOLO powered PPE non-compliance monitoring at power construction sites, aid in violation detection with inexpensive devices and enhance occupational safety. Furthermore, [5] applied visual PPE check systems for the Fukushima Daiichi decommissioning and achieved 85% accuracy with image processing and machine learning. Together these studies illustrate the breathtaking applications of deep learning and computer vision to enhance construction site safety. Advanced models such as YOLO and CNNs are employed by researchers for the reliable real-time detection of PPE, hazard detection, and unsafe action surveillance, which facilitates automation. This fosters compliance, lowers accidents, and makes construction environments safer.

3. Methodology

This outlines a methodology for real-time detection of PFAS components to improve scaffolding safety. The methodology consists of four main steps: dataset collection, image annotation, model training, and evaluation. Figure 1 is the representation of the methodology.

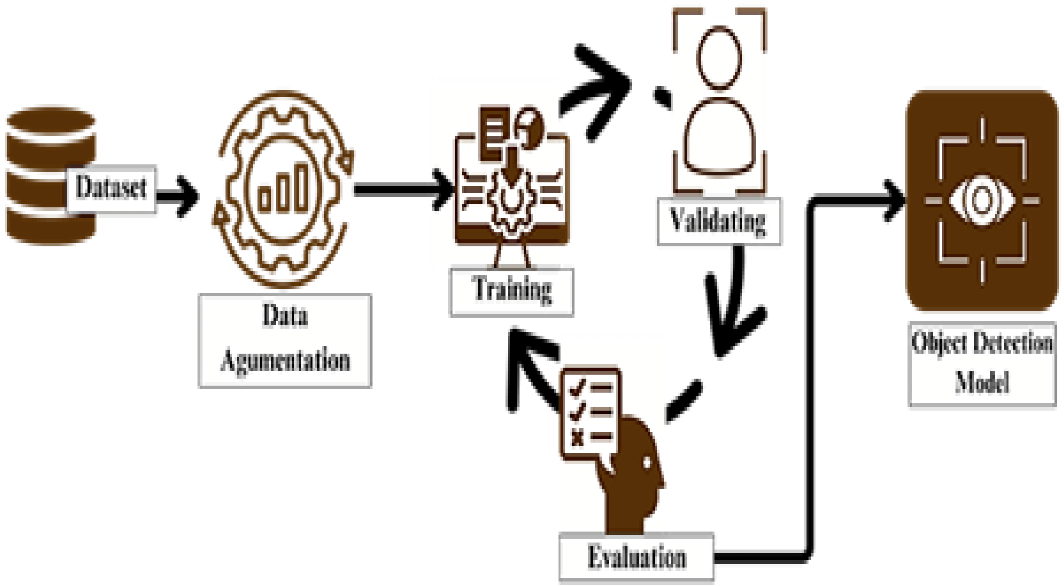

Figure 1 Methodology Flow Chart

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4. Image Collection and Labelling

The foundation of an effective detection model lies in a robust dataset. In this study, datasets were sourced from Roboflow culminating in a collection of 2240 images. To ensure model compatibility and efficiency, images were annotated in the YOLO format, utilizing normalized coordinates relative to a 640x640 pixel resolution. Normalization mitigates the impact of varying image sizes, enhancing model generalization [5]. Data augmentation techniques, including random cropping, horizontal flipping, rotation, and brightness adjustments, were employed to diversify the dataset, improving the model's robustness. These operations were performed using Python scripting. The dataset was then partitioned into training, validation, and testing sets in a 70:15:15 ratio, respectively. provides examples of images from the prepared dataset. Roboflow was utilized for image annotation, a critical step in preparing data for machine learning models. This tool facilitates the creation of bounding boxes around objects of interest and assigns corresponding labels. (Figure 2)

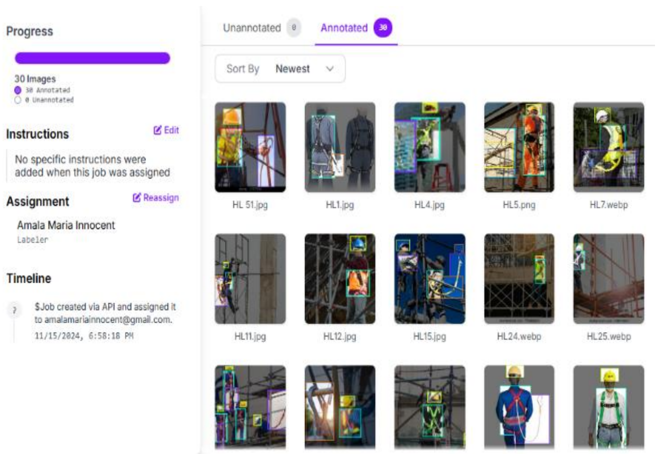

Figure 2 Labelling of PFAS Components

5. Model Training

The labelled dataset was then used to train a YOLO (You Only Look Once) model. YOLO's real-time object detection capabilities, achieved through single-pass image processing, make it ideal for applications requiring rapid object identification, such as autonomous driving and surveillance. Specifically, YOLOv11s and YOLOv11n models were selected for their optimal balance of speed and accuracy. Transfer learning, leveraging pre-trained weights, was employed to reduce training time and enhance initial performance [8][9]. The training process was accelerated using a GPU-enabled environment, enabling efficient hyper parameter tuning. Key hyper parameters, including learning rate, batch size, and epochs, were meticulously adjusted to optimize model performance. Finally, the YOLO model's performance was evaluated using F1 score which were directly generated by the model. This comprehensive methodology aims to develop a reliable system for real-time PFAS component detection, contributing to improved scaffolding safety. (Figure 3)

Figure 3 Training of PFAS Components

6. Integrating Yolo with OpenCV in Vs Code

Figure 4 Real Time checking Using Vs Code

Integrating YOLO with OpenCV in VS Code typically involves using Python. Install libraries like openCV-python and a YOLO implementation like ultralytics. Write Python code within VS Code to

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load the YOLO model, capture frames from a video source, perform object detection on each frame using the loaded model, and then draw bounding boxes and labels onto the frame using OpenCV drawing functions. Display the processed frames. VS Code's Python extension aids in debugging and execution. (Figure 4)

7. Result and Discussions

The F1-Confidence Curve for a YOLO object detection model, evaluating its performance across various object classes: Helmet, Helmet-On, No-Helmet, No-Vest, Person, Vest, Hook, Harness, and Lanyard. The x-axis represents the confidence threshold used to filter the model's predictions, ranging from 0.0 to 1.0. The y-axis shows the corresponding F1 score, a harmonic mean of precision and recall, which provides a balanced measure of the model's accuracy in identifying objects without being overly sensitive to false positives or false negatives. Each coloured line represents the F1 score for a specific object class at different confidence thresholds. The thicker blue line illustrates the average F1 score across all classes, reaching a peak of 0.72 at a confidence threshold of 0.450. The F1 score holds immense importance within the measures of model evaluation pertaining to object detection and classification, particularly for imbalanced datasets. It is computed with the following formula: (Figure 5)

$$\textbf{F1 Score} = \frac{\textbf{2 * (Precision * Recall)}}{\textbf{(Precision + Recall)}}$$

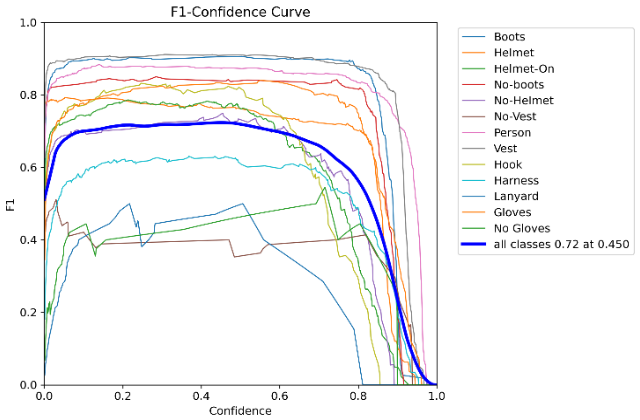

Figure 5 F1 Score Value Obtained from YOLO

Where:

A single unified evaluation metric is what the F1 score provides through its ability to merge recall with precision measurement into one unified value. An F1 score that stands high demonstrates that the model maintains proper performance at detecting positive cases while suppressing both positive and negative errors. The F1-Confidence Curve enables researchers to pick an appropriate confidence threshold that optimizes the F1 score performance for each model class or the total model output as observed in this system where the overall F1 score reaches its maximum at 0.450. The individual class curves display performance variations between different object types thus showing which objects the model detects best and which it detects least effectively.

Conclusion

In this particular work, a computer vision model was developed based on the YOLO architecture, and it was able to automatically identify some essential PFAS parts like helmets, harnesses, and lanyards with an F1 score of 0.72 and a confidence level of 0.45. This outcome accentuates the benefits that come along with applying computer vision for safety monitoring concerning real-time hazard detection and with regard to the processing of large volumes of data. Such capabilities enhance the possibilities of accident prevention, thus improving the efficiency and cost-effectiveness by reducing manual labor supervision. The system achieved its best performance with helmet detection while harness detection had moderate performance but lanyard detection showed the worst results. An insufficient number of training data samples for lanyards represents a fundamental drawback in this study. The incomplete data collection appears to have negatively affected the performance rate for detecting fundamental protection elements. The study needs an increased focus on gathering more training data particularly regarding underrepresented safety equipment like lanyards to achieve improved model integrity. The implementation of site imagery allows promise for better application and operational performance of the model during active real-world settings. Future work in object detection model development shows potential for significant improvement in safety monitoring detection capabilities and enhanced accuracy rates. An enhanced computer vision-based PPE detection system accuracy and reliability emerges possible by addressing limitations and developing specific future directions which provide contributions toward safer environments for work.

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