Implementing Computer Vision Based Safety Protocols in Suspension Scaffolds through Drones

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Abstract. Suspended scaffolds are one of the main causes of fall related fatalities in the construction sector. Despite the presence of suspension scaffold inspectors and OSHA guidelines, fatalities resulting from OSHA violations are prevalent. This paper proposes a semi-autonomous drone system to detect guardrails and workers wearing safety harness on construction sites using YOLO algorithms. For onboard computations, this system utilizes the Nvidia Jetson nano development kit, supplemented by the Intel RealSense camera for detections and depth sensing. Algorithms were developed to adjust the camera view based on bounding box positions, improving real time detections, and to modify the drone's flight path for inspections.

Keywords: safety inspections, drone, computer vision, construction safety, automated inspections.

1 Introduction

Falls from height stand as the foremost cause of occupational fatalities within the construction sector, comprising roughly one-third of all accidents on site [1]. Despite advancements in construction techniques, construction safety protocols haven't improved much with time. Although fatalities have notably decreased after the adoption of personal protective equipment (PPE), the manual oversight of PPE compliance poses intricate challenges for site managers [2]. While there have been some research initiatives focused on the possible use of computer vision for construction safety inspections, its practical implementation has not yet fully developed [3].

As a solution, this study proposes a system that will assess the onsite construction safety protocols for three safety elements on suspension scaffold, namely guardrails and fall protection gear. This study leverages cutting-edge technology, integrating Nvidia Jetson Nano development kit for onboard processing and Intel RealSense camera for depth sensing. Combined with YOLO algorithms, custom neural networks, and advanced machine learning techniques, these technologies form the backbone of the semi-autonomous drone-based system. The integration of these automated identification processes, depth sensing capabilities, and semi-autonomous drone technology not

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only promises to enhance safety protocols [4] but also stands to revolutionize the construction industry's approach to mitigating specific fall-related accidents and fatalities. This system is designed not only to identify critical safety elements like guardrails, and fall protection systems in two-point suspension scaffold but also to conduct depth sensing and detections in areas beyond human accessibility.

This study will address the issue of worker safety on suspension scaffolds which is a critical concern in the modern construction industry while also focusing on the automation of construction industry for safety inspections in inaccessible areas. Therefore, this research focuses on the use of an AI powered semi-autonomous drone to enhance safety of workers by reducing scaffold related accidents. The main goal of this research is to find out how to harness the potential of artificial intelligence to effectively address the issue of scaffold related accidents.

The following objectives were selected based on OSHA guidelines for two point suspension scaffolds [5] and fatality cases in the past few years. A semi-autonomous drone was used to inspect these potential safety hazards and data from these inspections was collected and annotated to be displayed by the output unit.

1.1 Literary Review

Many studies have been focused on the possible use of computer vision technology in the construction industry but few have discussed the implementation of this system in a real environment.

For example, in [6] three object recognition scenarios have been studied in which mainly focus on the risk of falling, which they prevent by the detection of safety helmets and vests. This research model was verified using a virtual model. In [7] a computer vision based hazard identification system was studied relating computer vision to ontology. In a sense, a computer vision algorithm predicts the interaction between objects in images, and these interactions are converted to computer accessible format. This study is however limited to the creation of rules and does not discuss the implementation of this system on a construction site.

In [8] an assessment system has been devised based on computer vision algorithms for worker inspection and training and focuses mainly on corner points for measurements. Though it is planned to be used in the construction industry, the main focus of this study is to measure accuracy in workmanship of a trainees work and does not discuss a possible solution to the onsite safety problems.

1.2 Research Objectives

Fall front Height Inspections: This inspection has been proposed to identify potential fall hazards in the work area, such as unguarded openings and insufficient fall protection gear. The outcome of this inspection will be to ensure that proper fall protection equipment is in place and that workers are adequately protected from falling from heights following regulation 1926.451(g)(1)(ii) [9].

Guardrail Inspection: This inspection focuses specifically on the guardrails installed on a suspension scaffold to prevent falls from height. The outcome of this inspection is to confirm that guardrails are in good condition and that they provide adequate fall protection for workers on scaffolding or elevated platforms following regulation 1926.451(g)(4)(i)[9].

2 Methodology

This section provides details for the overall development approach for this study which includes collecting raw data from online sources, refining this data for the creation of a dataset and the development of Artificial Intelligence (AI) model along with the software integration. Training an AI model for image detection requires image data. The AI model then extracts specific characteristics from these images based on the classified target objects provided by the user. This gives us a model which can be transferred and used on any platform with the required computational power. Training a detailed AI model requires high computation resources and running such a model at reasonable frames per second (FPS) requires a dedicated GPU with CUDA cores.

This study centers on the integration of the Nvidia Jetson Nano development kit, Intel RealSense camera D435, YOLO v5 based custom neural networks, and advanced machine learning techniques within a semi-autonomous drone-based system having a video transmission system for onsite detections. By enabling the identification of critical safety elements and depth sensing to inaccessible areas, this system holds the potential to not only improve the safety measures but also to revolutionize how the construction industry addresses fall related accidents and fatalities.

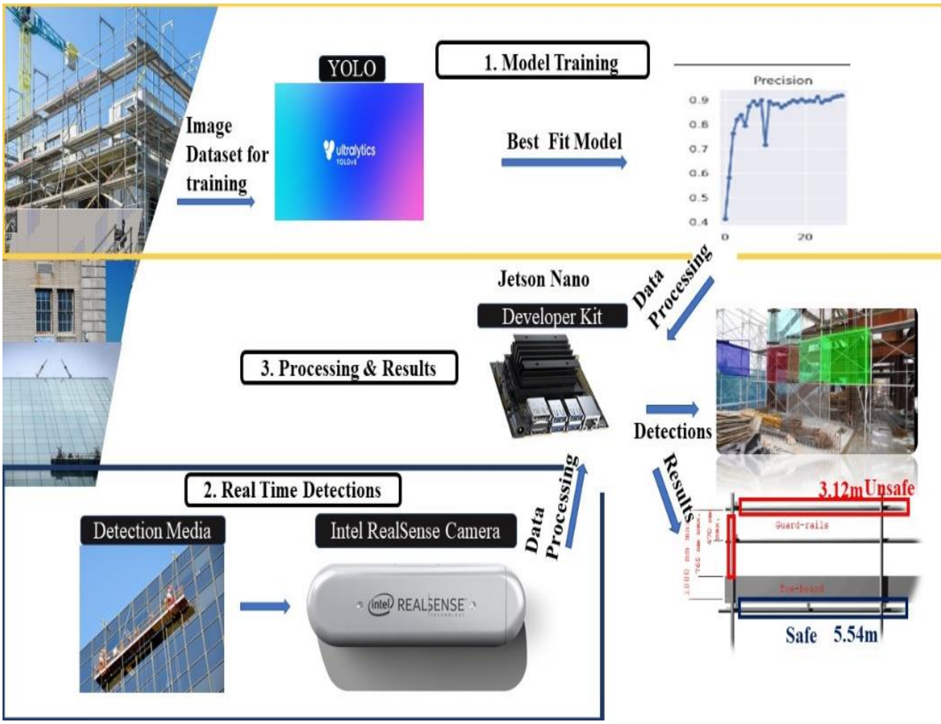

Fig. 1. System architecture diagram.

2.1 Data Collection & Preparation

Collecting Data: Construction site image data for suspension scaffolds was collected from online sources. These images and videos were categorized to fit the three main objectives: guardrails, fall protection gear. Videos were divided into frames for processing and images were filtered based on size of target object, detailing around the object and condition of the target object.

Synthetic Images: This study also involved synthetic images collected from a virtual environment using Blender and Fusion 360. This software allowed us to create realistic construction site environments and capture comprehensive data. This was done to ensure an increase in the quality of the dataset by providing detailed target imagery which is often blurred by the surrounding environment of the target object in real construction site images which is explained in detail in [10].

Data Annotation: Critical safety elements, such as guardrails, fall protection systems and suspension scaffolds were annotated. Annotation involved placing a bounding box over the target object for the machine learning model to identify while training. For annotation, Roboflow annotation tool was used which was selected for its accuracy and availability of tools. To make the annotations more precise, polygons were used instead of the standard bounding box tool. As shown in Figure 2, the polygon shape covers the shape of the suspension scaffold. The dataset for suspensions scaffold and guardrails was annotated by the authors while different publicly available and annotated datasets on Roboflow for safety harness were collected and combined to make the required models[11], [12], [13], [14].

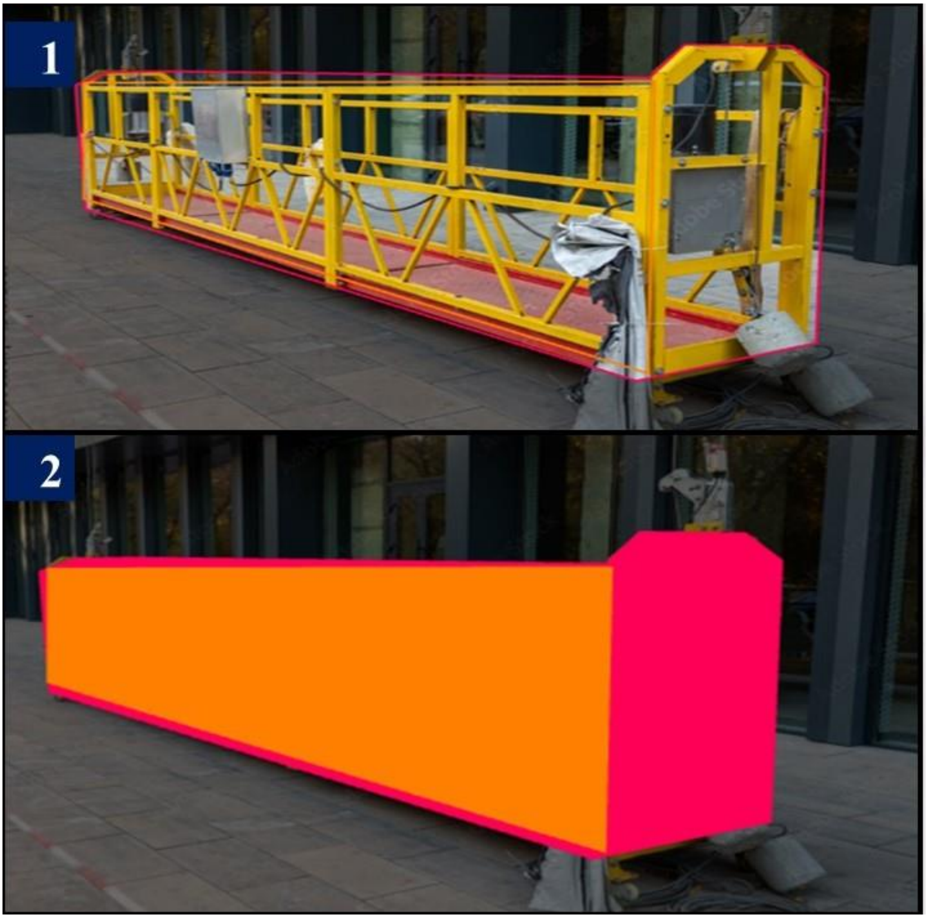

Fig. 2. Shows a suspension scaffold with annotations (1) and with highlighted area (2).

Data Augmentation: To improve the quality of this data augmentation techniques were applied, particularly with Roboflow. By applying augmentation techniques, images were generated that varied by different angles, lighting conditions, and environmental factors. This was done to ensure the adaptability of the machine learning model to a wide range of real-world situations, ultimately strengthening the accuracy of the safety analysis and hazard detection system. Augmentations used in these datasets such as brightness exposure and rotation were used to simulate the video frames from the drone.

Creating Dataset: After the data passed all filters, a dataset was created for model training. For this a configuration file for custom training was required. This was done using roboflow, which streamlined the process of augmenting and preparing data. Figure 3 shows the number of images dataset splitting.

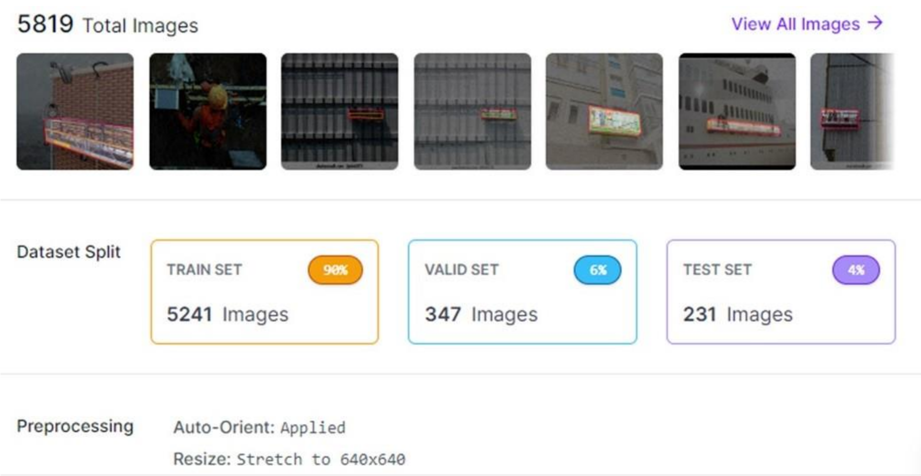

Fig. 3. Image division for the suspension scaffold dataset

2.2 Software Development

YOLO v5s is chosen for its real-time object detection capabilities and accuracy compared to other available algorithms. Custom training of the YOLO v5s models were performed to recognize specific safety elements which include guardrails and fall safety equipment. Most models were trained on a Nvidia GeForce RTX 3060 GPU with intel core i7 processor while some were trained on Google Collab.

The Nvidia Jetson Nano and Intel RealSense camera will be integrated into the semi-autonomous drone system. This will be done on an Ubuntu based Linux based operating system (OS) using the available software development kit (SDK) and the Real sense Camera Manager. A python program will be used to access the camera from the Jetson Nano which will run the algorithms on its available Graphical Processing Unit. Figure 4 shows the results for the yolov8 model testing on an image.

Fig. 4. Suspension scaffold and Guardrail detections after model training

2.3 Drone Deployment

The study utilizes the Nvidia Jetson Nano development kit for onboard processing. The Jetson Nano is equipped with a powerful GPU, making it suitable for real-time computer vision tasks involving CUDA cores. This integration was done to ensure efficient data processing and analysis on the drone.

This study will incorporate Intel RealSense camera, D435, for real time depth sensing which is required for calculating requirement for a fall protection safety gear on the construction site. Using its peripheral vision and stereo camera system, the camera will allow the drone to navigate across the construction site avoiding collisions and locating the suspension scaffold as it enables accurate depth perception, essential for identifying safety elements and obstacles in 3D space.

The drone uses Mission Planner software to simulate and complete an autonomous flight along specified waypoints using GPS coordinates. This software allows the drone to have safety features such as return to Launch (RTL), advanced failsafe configurations and easy access to scripting. Using Software in the Loop (SITL) simulator, scripts can be used to program the drone.

During flight, drones are susceptible to extreme vibrations and drifts usually caused by strong winds. To solve this, an algorithm was devised to compare the bounding box coordinates of the detections to the coordinates of the boundary of each video frame. After the detection of the target object, the mission plan followed by the drone is interrupted by the jetson nano through the addition of an exception in the mission planner SITL. The algorithm communicates with the Pixhawk flight controller to adjust the drone movements based on the bounding box positions. This helps the drone detect the targets with improved accuracy. Moreover, the drone surveys one side of the construction site at a time from a 2D perspective and climbs at a low speed to improve battery efficiency.

Edge AI devices are power dependent and may lose efficiency when low on power. Thus, the drone is equipped with a secondary 3-cell Lithium-ion battery in addition to the main Lithium Polymer (LiPo) battery to power the Jetson Nano device and the Intel Real sense camera.

3 Results & Discussions

The integration of these automated identification processes, depth sensing capabilities, and semi-autonomous drone technology promises to revolutionize safety protocols in the construction industry. This system aims to significantly reduce fall-related accidents and fatalities by providing real-time data for safety assessments on suspension scaffolds, improving the accuracy of safety inspections, and ensuring compliance with OSHA safety standards.

Annotated imagery collected from the suspension scaffold will be transmitted and stored for further validation. This will allow inspections to be quick and onsite. The dataset created in this study will be available publicly. This means it will be possible to improve and implement similar models for industrial use, thus improving safety in the construction industry.

The implementation of this system will improve the current standards for construction safety inspection for suspension scaffolds. The drone-based system will be able to navigate through the construction sites allowing inspections at more angles. The final output of this study is the semi-autonomous drone equipped with essential hardware for advanced machine learning processes.

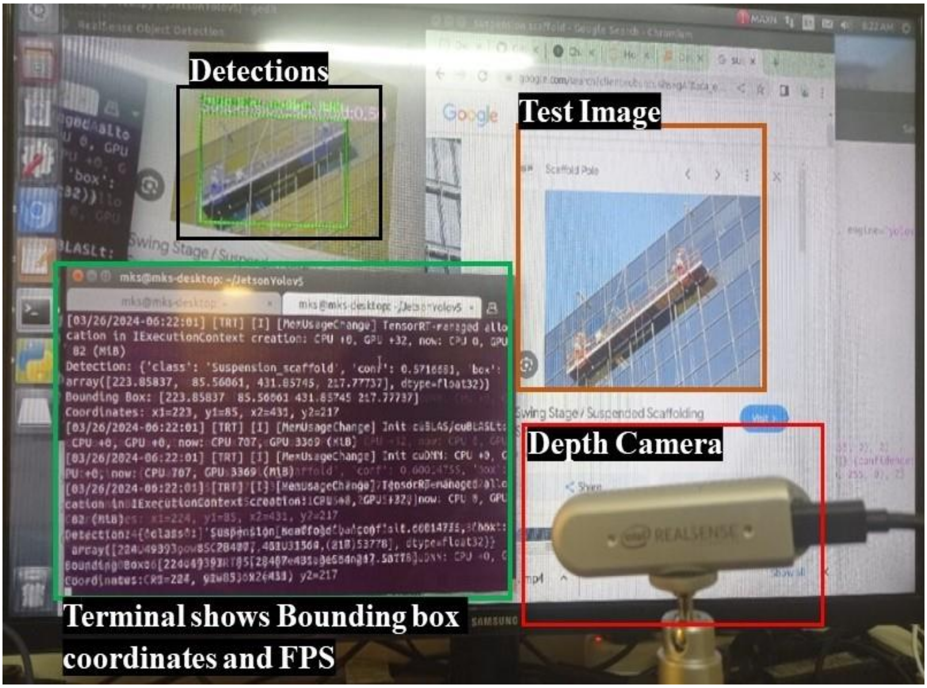

Fig. 5. Depth camera results using YOLO v5s with optimization

4 Conclusion

This study is focused on developing a research-based model that can inspect certain safety elements and eventually prevent some of the common safety related accidents in the construction industry by the implementation of an AI based algorithm on a drone-based system. The AI model will use hardware to detect certain safety elements in the suspension scaffolds. The target of this study is to make construction sites safer and mitigate specific fall-related accidents and fatalities. The potential use of advanced computer vision technology for construction safety is not limited to this study alone, it extends into a future where safety standards are continually elevated. We envision a landscape where automated safety inspections become the norm, fall related accidents are almost none and construction sites are monitored autonomously.

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