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CV-Based Mobile Application to Enhance Real-time Safety Monitoring of Ladder Activities

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Abstract: The construction industry has witnessed a concerning rise in ladder-related accidents, necessitating the implementation of stricter safety measures. Recent statistics highlight a substantial number of accidents occurring while using ladders, emphasizing the mandatory need for preventative measures. While prior research has explored computer vision-based automatic monitoring for specific aspects such as ladder stability with and without outriggers, worker height, and helmet usage, this study extends existing frameworks by introducing a rule set for co-workers. The research methodology involves training a YOLOv5 model on a comprehensive dataset to detect both the worker on the ladder and the presence of co-workers in real time. The aim is to enable smooth integration of the detector into a mobile application, serving as a portable real-time monitoring tool for safety managers. This mobile application functions as a general safety tool, considering not only conventional risk factors but also ensuring the presence of a co-worker when a worker reaches a specific height. The application offers users an intuitive interface, utilizing the device's camera to identify and verify the presence of co-workers during ladder activities. By combining computer vision technology with mobile applications, this study presents an innovative approach to ladder safety that prioritizes real-time, on-site co-worker verification, thereby significantly reducing the risk of accidents in construction environments. With an overall mean average precision (mAP) of 97.5 percent, the trained model demonstrates its effectiveness in detecting unsafe worker behavior within a construction environment.

Keywords: Ladder safety, Computer vision, Automatic monitoring, Co-worker presence, Safety measures

1. INTRODUCTION

Construction sites have a significantly higher incidence of accidents than other industries, largely attributed to their dynamic nature and complex environment. Approximately one out of every ten construction site workers sustain injuries annually. Each year, the U.S. Bureau of Labor Statistics reports approximately 150,000 construction accidents [1]. Additionally, OSHA identifies fall hazards as the primary cause of injury on construction sites [1,2]. Ladders are frequently utilized both indoors and outdoors at construction sites and ladders can be the reason for falls from height. Fall from height is a common reason due to defective ladders or climbing on the ladder at an unsafe height. According to the Health and Safety Executive (HSE) of Great Britain, falls from height accounted for the highest percentage of worker deaths in work-related incidents from 2022 to 2023, with 40 fatalities. Falls from height emerged as the leading cause of worker fatalities during this time frame [3]. Additionally, in 2021, KOSHA reported 1,427 accidents involving falls from height, which led to 33 fatalities and 1,394 injuries. The primary cause of these falls was attributed to working at heights without adequate fall protection measures, such as guardrails or safety harnesses [4]. KOSHA and OSHA have established standardized regulations to reduce fatalities and injuries [4,5]. Employing proactive strategies is crucial for minimizing accidents on construction sites. Two primary measures in this regard include providing proactive training for workers and real-time monitoring, Proactive training is essential for minimizing construction accidents, as miscommunication is a leading cause of incidents in this sector [6], and implementing real-time monitoring systems that can alert supervisors to potential hazards, facilitating swift action to prevent accidents by providing immediate work environment updates. Traditionally, the monitoring process is currently manual, requiring safety managers to be physically present at construction sites to identify potential hazards or violations of safety protocols. This approach is both time-consuming and reliant on the personal experience and expertise of safety managers [7–9]. CCTV-based solutions have been employed to monitor worker behavior on construction sites. However, these still necessitate the involvement of safety managers, introducing the possibility of human error. Additionally, obtaining a range of safety information, identifying relevant rules from a safety database, and manually enforcing them remain time-consuming tasks [7,10]. Recent advancements in computer vision (CV) technology have garnered significant attention as a solution to these challenges in different application [11,12]. Utilizing (CV)-based technology to gather data for risk analysis from on-site installed cameras emerges as an ideal solution on construction sites. It is particularly favored by workers who prefer not to attach sensors to their bodies [13]. Moreover, CV has received substantial focus due to its progress in key areas, including improvements in high-definition cameras, access to high-speed Internet, and advancements in augmented storage. Consequently, CV-based systems are widely employed for monitoring project progress [14]. Anjum et. al., 2020 has estimate worker height on ladder using Height computing model (HCM) by finding co-relation between worker and A-type ladder [15]. Although this type of relation can classify scenes as safe or unsafe, there is still a need for further implementation of safety rules to detect when a worker is at an unsafe height. According to KOSHA regulations, when a worker is operating at a height exceeding 1.2 meters, the presence of a co-worker is mandatory, and ascending to the top of a ladder is strictly prohibited [16].

To address this challenge, the paper introduces an algorithm designed to ascertain the presence of a co-worker when a worker operates at a height exceeding 1.2 meters, specifically when positioned at top of a ladder, while also accounting for previously established safety protocols. Furthermore, dataset is curated for each scenario to facilitate the training of the computer vision model. Object detection is facilitated through the utilization of the YOLOv5 model, which is trained on the aforementioned dataset. Following this, a mobile application is developed for real-time object detection using Android Studio, with the model weights subsequently converted to the tflite format for seamless integration with the Android application.

2. METHODOLOGY

This study focuses on the implementation of research methodology pertaining to A-type Ladders. Its aim is to expand the existing HCM module to detect the presence of co-workers. Specific regulations outlined by KOSHA govern worker behavior when using ladders at various heights. According to KOSHA regulations, when a worker is using a ladder at a height of 1.2 meters, it is mandatory for a co-worker to hold the ladder [16]. Additionally, it is strictly prohibited for the worker to work atop the ladder [16]. In **Figure 1**, of this study, various scenarios of workers using ladders are depicted as follows:

Case 1: Safe - Worker operating the ladder at a height deemed safe.
Case 2: Safe - Worker utilizing the ladder at a height exceeding 1.2 meters with the presence of a co-worker.
Case 3: Unsafe - Worker operating the ladder at a height surpassing 1.2 meters without the presence of

a co-worker.
Case 4: Unsafe - Worker positioned at the top of the ladder, violating safety regulations.

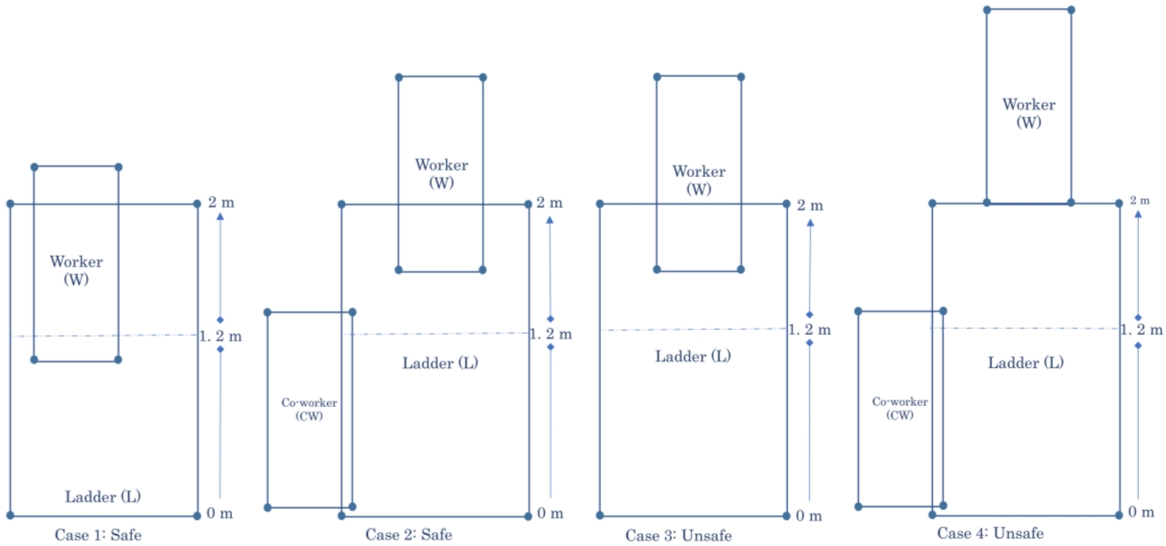


Figure 1: Safety Scenarios for Ladder Use According to KOSHA Regulations

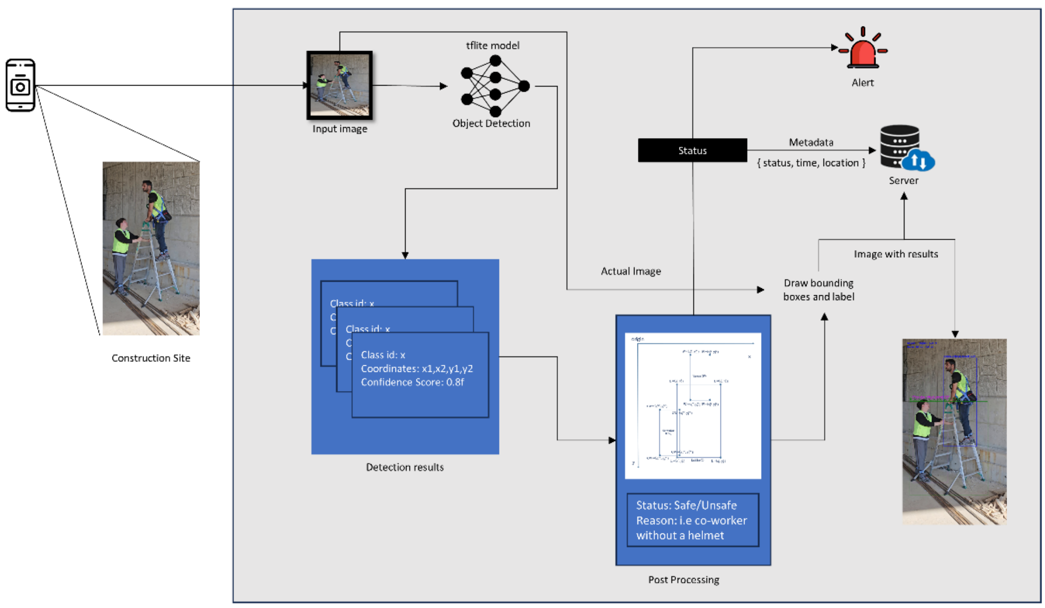


Figure 2: Real-Time Co-Worker Presence Verification By Utilizing CV-Based Mobile Application

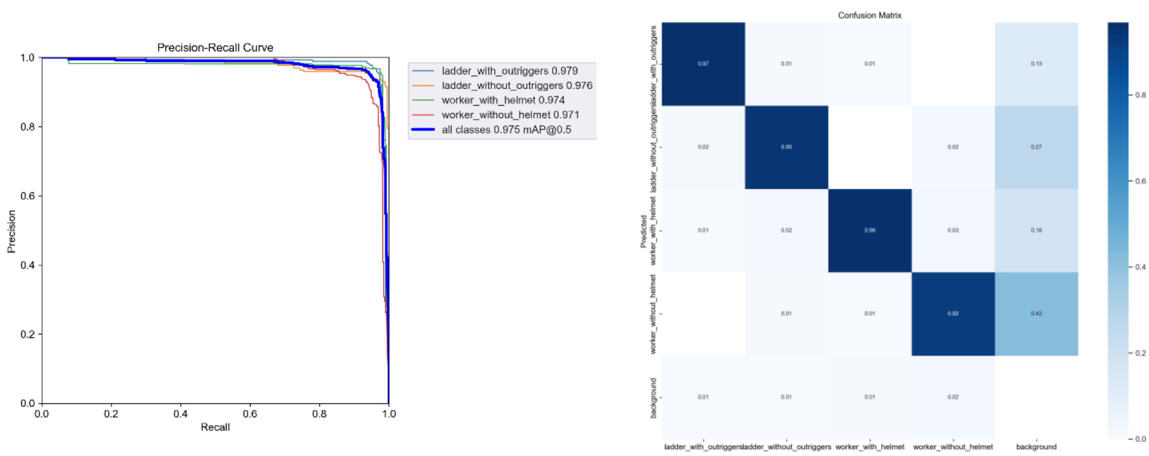
The method presented in this study is illustrated in **Figure 2**. Initially, an image frame is captured from a video stream through an Android camera using the ConTI Lab's "iSafe Ladder" application. This image frame is then processed by an object detection model, following object detection, the YOLOv5 model is converted to a tflite format with int 8 quantization to optimize deployment on mobile devices. This tflite model is then integrated into the Android application using Android Studio, enabling real-time object detection capabilities on the mobile platform. This integration enhances the application's functionality, allowing users to utilize the YOLOv5 model directly on their Android devices for enhanced safety monitoring during ladder-related activities. which outputs the detection results, including the class ID, coordinates, and confidence score of the detected object. In the subsequent post-processing stage, the coordinates and class ID are utilized to determine whether workers are equipped with helmets and whether a ladder, if present, is accompanied by outriggers. Additionally, the height of a worker on the ladder is calculated using pixel values. This information is then used to ascertain if a worker is situated at a height exceeding 1.2 meters on the ladder. Concurrently, the presence of any co-workers is assessed by examining the height of other individuals and the intersection of their bounding box with that of the ladder. A worker is classified as a co-worker if found within the proximity of the ladder. The safety status is established based on these analyses: if a co-worker is present, the situation is deemed safe. However, in scenarios where a worker is alone at the top of the ladder or even if a co-worker is present, but the worker is still at the top, the post-processing module designates the status as 'unsafe'. Subsequently, metadata encompassing the safety status, time, and location information are recorded in an online database for future reference. In cases of unsafe behavior, an alert is generated. Finally, the processed image, complete with bounding boxes and the designated safety status, is relayed back to the live monitoring module of the application.

An experiment was conducted wherein a dataset was gathered from various job site locations and through web scraping. Initially, 4523 images were collected, and subsequent augmentation expanded this to 11093 images. Of these, 9984 images were allocated to the training set, 666 to the validation set, and 443 to the test set. The images were meticulously labeled and augmented using Roboflow online software.

The dataset comprised four classes:

1. Ladder with outrigger.
2. Ladder without outrigger.
3. Worker with helmet
4. Worker without helmet

The dataset was then exported into the YOLOv5 PyTorch format for further processing YOLOv5 is recognized for its real-time object detection capabilities owing to its accuracy and efficient inference time [17]. The input image size was standardized to 300 × 300 × 3, while the number of classes was set to 4. The model trained for 300 epochs. The training process was executed on a machine equipped with Windows 11 Pro, powered by an Intel Core i9 10th generation processor clocked at 3.30 GHz, supported by 32 GB of RAM, and utilizing an NVIDIA GeForce RTX 3090 GPU for accelerated computation.



(a) (b)

Figure 3: (a) Precision and Recall Curve of the best-fit model trained on the Ladder Dataset, **(b)** Confusion matrix for selected classes

The mean average precision achieved by the trained model is 97.5%. Notably, it detects instances of "Ladder with outrigger" with an accuracy of 97%, "Ladder without outrigger" with 97%, workers with helmets with 97.4% accuracy, and workers without helmets with 97.1% accuracy. These accuracies are measured at a confidence score of 50%, as illustrated in Figure 3 (a). Additionally, Figure 3 (b) presents the confusion matrix for each class in the dataset.

Table 1 outlines the algorithm for the proposed method aimed at identifying unsafe worker behavior on a ladder. The model requires a frame from a video stream as an input parameter. Steps 1 to 6 involve obtaining an image and retrieving the detection results. Steps 7 and 8 involve defining lists and loading workers into the list, along with loading variables with their respective classes. In Step 9, the algorithm calculates the height of each worker if they are on a ladder. Step 10 involves sorting the workers by height to identify the worker on the ladder with the maximum height, while Step 11 focuses on finding co-workers. Finally, Steps 11 and 12 are dedicated to finalizing the status if any unsafe conditions are identified.

Table 1 : Algorithm for co-worker module

Algorithm

Args:

image: The image to be analyzed.
model: The YOLO model to be used for detection.

Returns:

The modified image and status.

Steps:

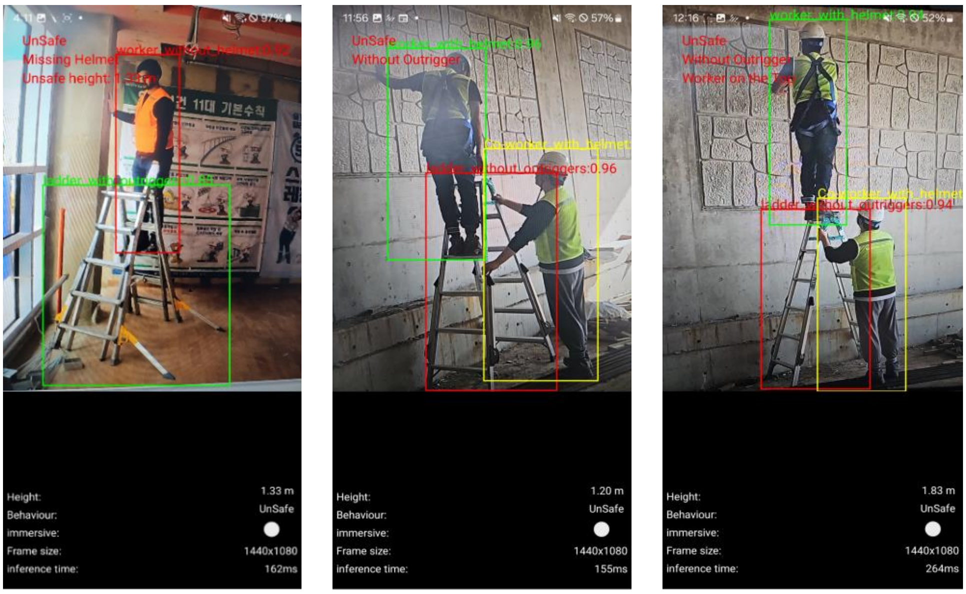
1. Load the trained object detection model.
2. Set up the real-time video stream or access the video file.
3. Iterate through every frame in the video.
4. Get frames from the video
5. Pass the frame to the object detection trained model for inference.
6. Retrieve the detection results, which include bounding box coordinates (x_l, y_t, x_r, y_b), class id , and scores
7. Initialize lists and variables
   Worker = [ ] *// definition of a list*
   Ladder = Null *// definition of a variable*
   Status = "Safe" *// set default status to safe*
8. Check classes, change status to unsafe if any unsafe class detected and append results in the list.
   if class id = = 0 : *// Process Ladder with outriggers*
     Ladder = results[0]
   else if class id = = 1: *// Process Ladder without outriggers*
     Ladder = results[0]
     status = Unsafe
   else if class id == 2: *// Process Worker with helmet*
     Worker ->add(results[0])
   else if class id == 3: *// Process Worker without helmet*
     status = Unsafe
     Worker ->add(results[0])
9. Check the height of workers on Ladder
   For each W in worker:
     $x_l^l, y_t^l, x_r^l, y_b^l$ = Ladder
     $x_l^w, y_t^w, x_r^w, y_b^w$ = W *// For one instance of worker*
     if $\left((x_l^w > x_l^l) \; or \; (x_r^w > x_l^l)\right) \; and \; ((x_l^w < x_r^l) \; or \; (x_r^w < x_r^l))$:
       if $\left((y_t^w > y_t^l) \; or \; (y_b^w > y_t^l)\right) \; and \; ((y_t^w < y_b^l) \; or \; (y_b^w < y_b^l))$:
         ladderHeightInPx = $y_b^l - y_t^l$
         workerHeightInPx = $y_b^w - y_t^w$
         ladderHeightInPercentage = ladderHeightInPx * 2 / 100
         workerHeightInPercentage = (workerHeightInPx/ladderHeightInPx)*100f
         workerHeight = (workerHeightInPercentage / 100f) * 2f
         WorkersWithHeightOnLadder - > add(worker, workerHeight
10. Sort WorkersWithHeightOnLadder list w.r.t workers height
11. Check worker height and co-worker presence
    workerOnLadder = WorkersWithHeightOnLadder.get(0)
    for each worker in WorkersWithHeightOnLadder starting from the second worker:
      co-worker = co-worker + 1
12. if co-worker = = 0 and workerOnLadder.getHeight()>1.2:
    status = Unsafe
13. if workerOnLadder.getHeight() == max height
    status = Unsafe

3. RESULTS

The Android mobile application is specifically designed for conducting on-site safety assessments, utilizing the device's camera for realtime monitoring and providing immediate safety analysis results directly through the application interface, as shown in **Figure 5**. The application's functionality is

Figure 5 : Realtime mobile application for detecting worker behavior on A-type Ladder

thoroughly evaluated through testing across three distinct unsafe scenarios as illustrated in **Figure 4**. For instance, In scenario (a), the application detects a worker who is operating at an unsafe height on a ladder. Notably, the worker is not wearing a helmet, and there is no co-worker present. This situation represents a significant safety concern as the worker is exposed to potential fall hazards without proper head protection and lacks the safety backup of a co-worker to assist or alert in case of emergencies. And scenario (b) involves a worker at a safe height on a ladder, attributed to the presence of a co-worker holding ladder. However, despite the presence of a co-worker, the scenario is deemed unsafe due to the absence of an outrigger on the ladder. Without the outrigger providing stability and balance, the worker is exposed to the risk of ladder instability and potential falls, despite being at a seemingly safe height. Lastly, scenario (c) depicts a worker situated at the top of a ladder without the necessary outrigger support. This scenario is inherently unsafe as the ladder lacks proper stability and support, increasing the risk of ladder slippage or tipping over. Without the outrigger in place, the worker's safety is compromised, especially considering the elevated position at the top of the ladder, amplifying the potential consequences of a fall. The "iSafe Ladder" application is capable of providing real-time results within an impressive timeframe, ranging from 100 milliseconds to 300 milliseconds.



(a) (b) (c)

Figure 4: a) Worker without a helmet operating at an unsafe height on a ladder without a co-worker; **b)** Worker is at a safe height due to the presence of a co-worker, but unsafe due to the absence of an outrigger; and **c)** Worker is at the top of a ladder without the

4. CONCLUSION AND FUTURE WORK

The proposed method leverages computer vision technology in a mobile application to actively monitor co-worker presence and identify unsafe behavior in real-time within a construction site. The flexibility offered by the developed cost-effective mobile application allows to deploy proposed solution at multiple locations, ensuring scenario base worker monitoring. The developed mobile application functions as a general safety tool, considering not only the CV based hazard identification but also incorporates requirements of additional resources at specific situations to successful implementation of safety regulations. For instance, ensuring the presence of a co-worker when a worker reaches an unsafe height. Additionally, this research contributed to the field by creating a comprehensive dataset from diverse real job site environments.

Notably, it is important to recognize the prevailing disparity in the accuracy of object detection algorithms, especially concerning height estimation. Although our algorithm successfully identifies workers at the top of the ladder, it can still be improved by integration of state-of-the-art algorithms such as transformer-based object detection models. However, the transformer-based models are not recommended due to their low frames per second (fps) rate. Future research may focus on alternative methodologies that balance accuracy with real-time processing constraints and researchers can focus on improving fps of transformer-based methods. Recognizing the limitations in height estimation accuracy due to factors such as worker behind the ladder and occlusions, further studies can integrate the depth information. Collecting depth data alongside width and height measurements, either through advanced technologies like LiDAR or stereo vision techniques, can enhance the accuracy of determining objects' actual positions in a three-dimensional (3D) plane. This path of exploration holds the potential to mitigate errors and further refine the precision of our monitoring system. Also collecting more data for dataset is needed to make it more accurate.

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