RESEARCH ARTICLE

Real-Time Safety Equipment Detection and Worker Identification System Using YOLO and Face Recognition

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Abstract- Employee welfare, which is applied in building.One of the most important concerns in the world is sites.The safety equipment is given importance in the industry because of an enthusiasm for the manner in which protection guarantees physical.integrity. The surrounding is a high-risk environmentpersonnel landscape, and the regular usage of equipment is a reflection of the concept of the connection held by the management between security and regulation.

The research team utilized a great deal of technological safety system components, such as YOLO detection algorithms to support accuracy and detection efficiency. There are a number of scans repeated in the system through the video frames and the surveillance in the background. Face recognition was used by the creators, which formed an accurate identification and a little bit automated processes; the manual set, however, contains some more difficult observations. Numerous detections deliver the shape outline to the system, showing areas where human beings look at cameras and where garment changes to equipment.

Keywords: Workplace Safety, Safety Equipment Detection, YOLO, Face Recognition, Computer Vision.

I. INTRODUCTION

The issue of keeping the workplace safe is a fundamental obligation of manual supervision, but it is inadequate in high-technology scale environments. In large industrial factories or congested. One individual cannot monitor all of the construction sites. Compliance of the worker. This gap in monitoring means that even serious safety infractions are easygoing, failing to identify until something has failed. To overcome such human restrictions, the proposed project leverages the abilities of deep learning to carry out safety surveillance automatically. The suggested algorithm is a hybrid of the YOLO (You Only Look Once) object detector algorithm and the modern facial recognition modules, which makes it.

. *II. LITERATURE SURVEY*

These technological leaps are shifting the industry toward a smarter, more reliable standard for protecting workers in high-risk industrial environments.

1. **A Remote-Vision-Based Safety Helmet and Harness Monitoring System Based on Attribute Knowledge Modeling (2023)**

In the high risk industries such as mining and construction, the protection of personnel is one of the priority areas. Nevertheless, manual supervision, as a rule, is not enough; a supervisor is not able to keep his/her eyes on all people working on the huge sites. Such a lapse in the monitoring implies that critical safety violations are very much overlooked before the accident happens.

2. **A New Method for Safety Helmet Detection Based on Convolutional Neural Network (2023)**

The rapid advancement in the field of deep learning has revolutionized the computer vision particularly in the object detection and object classification fields. Among those developments that could contribute to the improvement of the construction site safety, **Qian and Wang** (2023) introduced the particular safety helmet detection method, which relies onConvolutional Neural Networks (CNNs), to enhancetheprocess of monitoring construction sites.

3. **Safety Helmet-Wearing Detection System for Manufacturing Workshop Based on Improved YOLOv7(2023)**

The next major step in automated safety monitoring was made by Chen and Xie (2023) who designed a specific detection system to be used in manufacturing workshops. The focus of their study is based on the improved version of the YOLOv7 (You Only Look Once) algorithm, which is optimized to check the presence of a safety helmet on workers.

The main advantage of the YOLO architecture is in the fact that an image frame is processed in a single computation process. In contrast to traditional methods of detection which scan various parts of an image one at a time a process that is both slow and resource-intensive), YOLO processes object positions and probabilities of being either a particular class simultaneously.

4. YOLOv8n-asf-dh: An Enhanced Safety Helmet Detection Method (2024)

The recent innovations in the sphere of deep learning have pushed the boundaries of object detection even further, and the most recent innovation is the launch of the YOLOv8 system. Based on this, **Lin Dingyan** (2024) created a more specialized one, known as YOLOv8n-asf-dh. The particular enhancement of this kind was realized to eliminate the limitations of the standard framework by taking into account the more progressive extraction of features, such that the system can be more selective on the safety gear in the intricate environments.

Essentially, the YOLOv8n architecture is created to establish a fine balance: it is exceptionally lightweight, computationally efficient, and yet, it does not involve any sacrifices on the detection accuracy.

Summary of Literature Survey

As the literature review indicated, although the wide spectrum of deep learning models, including Attribute Knowledge Modeling and CNNs, high-speed YOLO, and transformer-based models have made major progress in automated safety monitoring, there is still a serious gap in the applicability of deep learning models to practice.

III. BACKGROUND & MOTIVATION

A. BACKGROUND

Having a strict standard of safety is an important operational issue in contemporary industrial industries including construction, manufacturing, and mining industries. The workers in such hazardous working environments are always chased after by life endangering risks, such as falling debris, malfunctioning heavy machineries, and exposure to volatile substances etc.

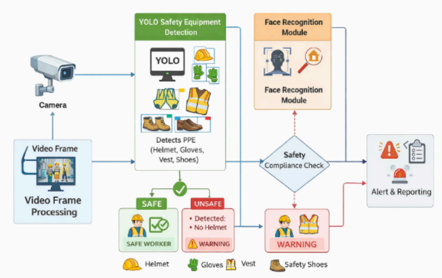


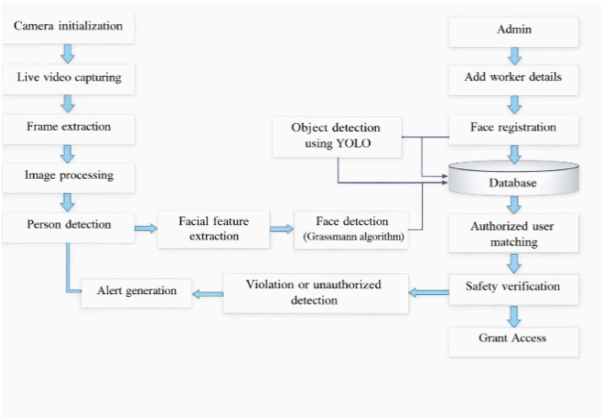
Fig. 1: System Architecture of Real-Time Safety Monitoring System

Fortunately, the fast development of the computer vision and deep learning has brought a groundbreaking change towards automated surveillance. Modern systems are now able to scan live video streams and detect PPE adherence in real-time due to the advanced object detection algorithms. This technological advancement makes it possible to have a continuous, objective, and real-time system of monitoring that transcends the physical constraints of human supervision, creating a long overdue digital backup ,

B. MOTIVATION

Although some safety monitoring frameworks have been created in the recent past, there is a serious gap in the practical application of the same. The majority of existing methodologies are nearly entirely focused on the helmet detection, but thorough worker protection is hardly an issue of a packaged device. Gear like gloves, reinforced boots and high-visibility vests are also important in reducing life-threatening situations in high-risk environments. The system which only sees helmets gives a patchwork and not comprehensive safety net.Moreover, another major technical challenge of current systems is the absence of personnel identification. The existing models are often an anonymous detector; they are able to detect a safety violation but not to connect such violation with a particular individual. Such worker identification creates an almost insurmountable challenge to the management in accountability enforcement or offering specific safety training. In order to actually modernize industrial surveillance, a system should not just be capable of detecting an object but it should be capable of facial recognition to simplify the transition between the hazard in question and the face of the person in danger.

IV. METHODOLOGY



The suggested system would automate the safety management through the combination of high-speed computer vision and advanced deep learning systems. The system uses real time video feeds in areas of high risk (e.g. industrial plants and construction sites) through strategically placed surveillance cameras to constantly monitor these areas. Every photo of the captured worker is processed in real time to identify and confirm compliance of individual workers with the required safety measures.

A. Module 1 – Video Frame Capture

Overview

The first stage of the system is real time acquisition of visual images of the onsite surveillance devices, including industrial CCTV systems or high definition webcams. The module is the digital version of the eyes of the framework and can keep a constant flow of the workplace to keep track of the personnel as they move around.

Module 1: OpenCV Video Capture

Input: Real-time video feed (received as CCTV or webcam equipment..

Output: An ordered sequence of image frames that has been prioritized to be analyzed through an algorithm..

1. Connect the main imaging device and configure the primary imaging device.
2. Start the high definition capture of the live environmental stream.
3. Get data packets out of the currently running camera buffer systematically..

Contribution of Module 1

Video Acquisition Module. The main sensory interface of the system, this module provides a continuous high-definition feed of the on site surveillance equipment, either an industrial CCTV system or a web camera.

B. Module 2 – Image Preprocessing

1) Overview

The Image Preprocessing Module is a refinement layer that operates as a highly important, converting raw and generally untrustworthy surveillance data into a standardized format and high-accuracy deep learning analysis.

Module 2: Image Preprocessing

Input: Raw frames of the image capture module of the video.

Output: Processed and whitened frames of image ready to undergo algorithmic processing.

1. Get the raw frame of image out of the main capture unit.
2. The image size is rescaled to fit the input requirements of a particular neural network.
3. Normalize pixel values as a way of optimizing deep learning..

Contribution of Module 2

The Image Pre-Processing Module is a very important optimization layer that optimizes the raw visual data which the surveillance system records prior to being sent to the analysis phase.

C. Module 3 – Safety Equipment Detection

1) Overview

Safety Equipment Detection Module is an analytical engine of the system that finds the particular Personal Protective Equipment (PPE) in the already processed image frames.

Module 3: Safety Equipment Detection

Input: Image frames of the worker have been preprocessed and are displayed as framework images

Output: Bounding box safety equipment is a localized safety equipment.

1. Load the YOLO architecture into memory, which is already trained.
2. Divide the original image into a grid with homogeneously sized cells.
3. Make predicted bounding boxes in each specific grid cell.

Contribution of Module 3

The Safety Equipment Detection Module is the analytical engine of the system, which allows recognizing Personal Protection Equipment (PPE) in the processed image frames at high speed.

D. Module 4 – Face Detection

1) Overview

Face Detection Module is the first stage of the personnel identification pipeline, which is directly aimed at extracting the facial areas of the workers in the frames obtained.

Module 4: Face Detection

Input: Frames of images of the worker detected.

Output: Local facial picture of the worker.

1. Search the image frame to identify certain human faces.
2. Mark the areas of the face in the high-resolution image.
3. Draw an accurate bounding box on all faces that have been identified..

Contribution of Module 4

This model locates the face region of the worker in the image frame.

E. Module 5 – Facial Feature Extraction

1) Overview

The Facial Feature Extraction Module will provide the means to convert raw images of the faces to a distinct biometric representation that can then be handled by the recognition engine.

Module 5:Facial Feature Extraction

Input: Detected face image.

Output: Face of worker numerical feature image in high-dimensional form.

1. Transform the RGB picture of the face into a typical grayscale picture.
2. Identify some of the biometric characteristics like the mouth, nose, and eyes.
3. Individual distinct spatial patterns and facial structure features..

Contribution of Module 5

The Facial Feature Extraction Module adds a high-tech biometric coding layer to the system that converts crude visual information into the exact digital identity.

V. DATASET AND TRAINING SETUP

The data that will be used in this research is the collection of high-resolution images and video frames that were taken in different industrial and construction settings. This extensive data warehouse consists of workers who are working in real-life scenarios and wearing a wide range of Personal Protective gear (PPE), such as safety helmets, protective gloves, reinforced footwear, high-visibility reflective vests, among others

A. Dataset Collection

1. **Data Sourcing and Composition**: The data source used in the present project was

compiled based on several high-fidelity data to enable the effective training and evaluation process of the safety monitoring system. It is mainly a collection of high-resolution images and video frames showing workers in various working activities, both in the construction and industrial settings.

2. **Hybrid Data Collection:**A large part of the repository was obtained by existing, publicly-available safety detection datasets. Through these online resources, there is a basis of identified imagery in different work environments. In order to supplement the special needs of this system.

B. Data Preprocessing

1. **Objective of Preprocessing:**Purpose of Preprocessing: Preprocessing of data is a preparatory step in the formation of a powerful detection model. Since the raw data might have irregularities in image resolution, the varying luminance, and varied background noise, preprocessing is necessary to normalize the input.

2. **Dimensional Standardization (Resizing):**In order to satisfy the architectural needs of the detection model, all the images are resized to a common resolution. This spatial normalization makes sure the dimensions of the inputs are the same across the training process so that the neural network can make its computations effectively and the features map are constant across the full dataset.

C. Training Setup

- **Algorithmic Selection and Data Partitioning:**Algorithmic Selection and Data Partitioning: The object detection system is based on the YOLO (You Only Look Once) framework, which is chosen due to the ability to balance high-speed inference and spatial resolution in real-time monitoring missions better than competitors in the industry. In order to make sure that the model is properly evaluated in the performance, the annotated database is divided into separate training and testing subsets.
- **Supervised Learning and Iterative Optimization:**Supervised Learning and Iterative Optimization: The model determines the distinguishing features of safety equipment during the training process based on the labeled ground-truth imagery. .

E. Evaluation Metrics

The Performance Evaluation Framework is the quantitative reference of evaluating the accuracy and reliability of proposed safety monitoring system.

Precision

The positive predictive value also known as precision is an essential metric which measures the accuracy of the positive detection of the system. It measures the quality of the output of the model through calculating the percentage of identified safety equipment or identified workers that are actually matched to the ground-truth labels.

Precision = True Positives \(True Positives + False Positives)

F1 Score

The F1-Score is one management performance measure that combines Precision and Recall to a single performance measure. It is determined as the harmonic average between the two and it gives a stronger assessment as compared to the arithmetic average.

F1 Score = 2 × (Precision × Recall) / (Precision + Recall)

Detection Speed

Detection Speed is an important key factor of operation which measures the speed of safety monitoring system. In real-time applications, the system to be used should be able to handle high-resolution video flow at very low levels of latency to make sure that safety infractions are detected and reported immediately**.**

VI. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental Setup

The presented safety monitoring system passed through a severe assessment period with the help of a high-fidelity dataset consisting of pictures and video frames obtained in various workplace settings. To support the development of the robust models, the system was realized on the Python language with the help of the industry-standard computer vision and deep learning libraries...

B. Detection Performance

The safety monitoring system offered was carefully tested according to its dual ability to trace mandatory safety equipment and properly identify individuals of the workers.

C. Safety Compliance Detection

Safety Compliance Detection The point of this step is to find safety compliance violations.

D. System Performance Analysis

To ensure that the suggested safety monitoring system was effectively able to perform, a set of standard evaluation metrics were strictly benchmarked, of which Accuracy, Precision, Recall, and the F1-Score

E. Result Discussion

The experimental outcomes clearly demonstrate that the suggested system is helpful to ensure the high-precision outlined mandatory safety equipment and also to identify worker identities by using superior techniques of computer vision. Through a single deep learning system, the system exhibits a high level of accuracy even in the visually challenging industrial settings having variable lighting and occlusions.

VII. CONCLUSION

In this study, an Intelligent Safety Monitoring System (ISMS) has been proposed, and it shows a solid implementation of computer vision in the detection of Personal Protective Equipment (PPE) and workers simultaneously. This research fills in the gap of the acute requirement of automated supervision within high risk operational settings through the integration of disparate modules into one integrated structure.

The system is based on the YOLO (You Only Look Once) detection framework, which was very successful in real-time tracking down of safety helmets, protective gloves, reinforced footwear and high-visibility vests.

VIII.ACKNOWLEDGMENT

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