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CONSTRUCTION PLOT LABOUR'S SAFETY AND ACTIVITY MANAGEMENT SYSTEM

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Abstract — The construction industry is highly labor-intensive and often fraught with risks due to hazardous conditions. Ensuring worker safety and efficient monitoring is essential to prevent accidents, improve productivity, and meet regulations. This paper proposes a smart safety and activity monitoring system using IoT sensors, wearable devices, and real-time analytics to track workers' vital signs, movements, and locations, promoting a safer and more efficient work environment[1].

KEYWORDS — IOT (INTERNET OF THINGS), DNN (DEEP NEURAL NETWORK), IOU (INTERSECTION OVER UNION)

I. INTRODUCTION

Construction sites are hazardous, making safety protocols essential. This project uses AI-driven image processing with the YOLO V8 algorithm to monitor helmet usage on-site. If a worker is detected without a helmet, the system instantly notifies the administrator and triggers a buzzer to alert supervisors for immediate action[2][6].

This project goes beyond helmet detection by integrating RFID technology for effortless attendance tracking. Workers simply tap their RFID cards at the entrance, enabling the system to log their attendance and automatically open gates for authenticated personnel. This ensures that only authorized, safety-compliant individuals are allowed on-site. Additionally, workers can access a dedicated website to view their attendance, profile, and basic details, fostering transparency and accountability[5].

By combining AI-driven helmet detection with RFID-based identity authentication, this project highlights how machine learning can transform construction site safety. This innovative approach enhances worker protection, prevents accidents, reinforces safety protocols, and streamlines daily operations, showcasing the potential of AI in the construction industry[2][5].

II. RELATED WORK

The system incorporates RFID-based attendance logging, with insights from [5] focusing on chipless RFID solutions for IoT applications. This study highlights the use of low-cost, secure RFID tags, suggesting exploration into durable RFID tags for worker authentication.

Although Federated Learning (FL) is not explicitly mentioned, [1] provides valuable ideas on integrating real- time edge intelligence into worker safety monitoring by combining FL with edge-based deep neural networks (DNNs) for collaborative safety prediction. This suggests the potential to extend the YOLOv8 model to interact with distributed edge nodes for scalable safety monitoring.

For systems that need to cover large sites with multiple cameras or workers, [7] offers strategies for improving recognition and tracking through multi-camera localization using YOLO. This approach can guide cross- camera detection for worker movement monitoring, ensuring comprehensive site coverage.

To enhance the system, attention mechanisms (e.g., CBAM) and advanced loss functions (e.g., EIOU) can be added. Training on diverse datasets can help manage occlusions and object size variability, improving overall detection accuracy and performance.

Experimentation with chipless RFID can make attendance tracking more cost-efficient and scalable. Integrating RFID data with detection results can create a comprehensive safety dashboard that provides real-time insights for better decision-making.

Additionally, incorporating edge-based computing can enable faster, real-time inference, improving the system's responsiveness on-site. GUI improvements using Tkinter can enhance data visualization, such as displaying attendance logs and detection summaries, for a more user- friendly experience.

Finally, applying multi-camera solutions can support monitoring across extensive zones, allowing for better scalability and extended coverage of large construction sites. This approach ensures that worker movements and safety conditions are monitored effectively across the site.

III. LITERATURE REVIEW

Safety in construction sites is a critical concern, particularly in ensuring that workers comply with safety regulations such as wearing helmets and other protective equipment. Recent advancements in deep learning, edge intelligence, and IoT technologies have contributed to enhanced safety monitoring systems. This literature review explores various methods and frameworks proposed in related studies to address safety compliance, object detection, and efficient attendance tracking in construction environments.

A. Object Detection for Safety Gear Compliance

Object detection models have shown promising results in identifying safety gear compliance among workers. An improved YOLOv5-based model, YOLO- ESCA [2], enhances safety helmet detection by introducing attention mechanisms like the Convolutional Block Attention Module (CBAM) and loss functions such as the Efficient Intersection over Union (EIOU). These modifications achieve high accuracy and real-time performance, making it highly suitable for dynamic environments. Similarly, [3] employed YOLOv3 to enforce PFAS compliance, focusing on detecting helmets and safety harnesses, achieving high precision in detection tasks. Addressing occlusion-heavy scenarios, [4] utilized Online Hard Example Mining (OHEM) and multi-part combination techniques to improve helmet detection, making the system robust against challenges like partial visibility. Furthermore, [6] combined deformable convolutions with YOLOv5 to handle dense and cluttered environments effectively, ensuring reliable detection in complex construction sites.

B. RFID for Attendance Tracking and Worker Identification

Worker authentication and attendance tracking systems have leveraged RFID technologies for seamless integration into IoT environments. A low-cost and secure solution is presented in [5], which proposes chipless RFID tags that are easily deployable and resistant to cloning attacks. This method provides a scalable approach to worker identification while maintaining affordability and security.

C. Federated Learning and Edge Intelligence

Federated Learning (FL) has emerged as a viable solution for real-time hazard prediction and safety monitoring. In [1], FL is integrated with edge-based deep neural networks (DNNs) to enable collaborative safety prediction mechanisms. By distributing data processing across edge nodes, this framework enhances scalability and privacy while ensuring efficient site monitoring.

D. Multi-Camera and Multi-Worker Scenarios

Monitoring large-scale construction sites requires solutions capable of handling multiple cameras and workers. In [7], a multi-camera localization approach based on YOLO improves tracking and recognition in overlapping camera zones. This framework ensures accurate worker movement tracking, providing comprehensive surveillance across extensive construction zones.

Integration and Scalability

Combining insights from these studies offers potential enhancements for safety monitoring systems. For instance, integrating attention mechanisms like CBAM and advanced loss functions such as EIOU into YOLO models can improve detection accuracy. Chipless RFID technologies can be adopted for cost-efficient attendance tracking, while edge computing facilitates faster inference and scalability. Multi-camera systems ensure robust monitoring of large sites, addressing challenges of overlapping zones and worker tracking.

Conclusion

The reviewed studies demonstrate the feasibility of integrating deep learning, RFID, and edge computing technologies to improve construction site safety. By leveraging these advancements, systems can be developed to ensure real-time safety compliance monitoring, efficient worker identification, and scalable solutions for large construction projects.

IV. METHODOLOGY

A. Data Acquisition and Preparation

Data acquisition is a critical step in building a robust worker detection system, where diverse and realistic datasets are gathered to train the model effectively. This project utilizes images and videos from construction sites, ensuring representation of various scenarios, such as workers with and without safety gear. The inclusion of real- time webcam and video feed integration enables dynamic data collection, enhancing the model's capability to adapt to real-world conditions. The acquired data is organized into structured datasets with labeled annotations indicating helmet compliance, facilitating supervised learning.

B. Image Preprocessing

Before feeding the data into the model, image preprocessing is applied to ensure consistency and improve model performance. Techniques like resizing, normalization, and augmentations such as rotations and flips are employed to simulate varied conditions. Preprocessing ensures that the images conform to the input requirements of the YOLOv8 model, while enhancing the model's robustness to diverse lighting, angles, and occlusions. These steps also reduce overfitting by enriching the training dataset with variations that mimic real-world challenges.

C. Model Development

The YOLOv8 algorithm is central to the system, selected for its high accuracy and real-time detection capabilities. The model's architecture incorporates enhancements like anchor-free detection and lightweight design, suitable for deployment in edge devices. Pre-trained weights from general object detection tasks provide a strong initialization, which is fine-tuned using the collected construction-site-specific data. The integration of confidence thresholds ensures that predictions prioritize accuracy while reducing false positives.

D. Model Training

Model training involves iterative learning on the prepared dataset, leveraging techniques such as transfer learning to expedite convergence and optimize detection performance. The system is trained to identify workers and assess their helmet-wearing compliance, using a loss function tailored to object detection tasks. Continuous validation ensures that the model generalizes well across unseen data, with metrics like precision, recall, and mAP

guiding performance optimization. By integrating hardware- accelerated training setups, the system achieves efficient and scalable learning.

E. Evaluation

Figure 1 illustrates a YOLO-based worker safety monitoring system designed to ensure compliance with safety protocols at a construction site. The system integrates multiple components, including RFID authentication, a YOLO machine-learning model, a database, and a notification system.

As shown in *Fig. 1*, the process begins with workers logging in using RFID tags, which are authenticated by the system and linked to their profiles stored in a database. Once authenticated, the workers enter the construction site, where the YOLO model is employed to detect whether they are adhering to safety compliance requirements, such as wearing proper safety gear. If a worker is identified as not following safety guidelines, the system triggers a safety buzzer to alert the worker and others on-site.

Simultaneously, safety compliance violations are recorded in the database and shared with a monitoring system that generates daily reports for review by the site owner or supervisor. By logging all safety data, the system enhances accountability, monitoring, and safety practice improvements. This automated approach, as shown in Fig. 1, ensures consistent enforcement of safety standards, reducing risks and improving workplace safety.

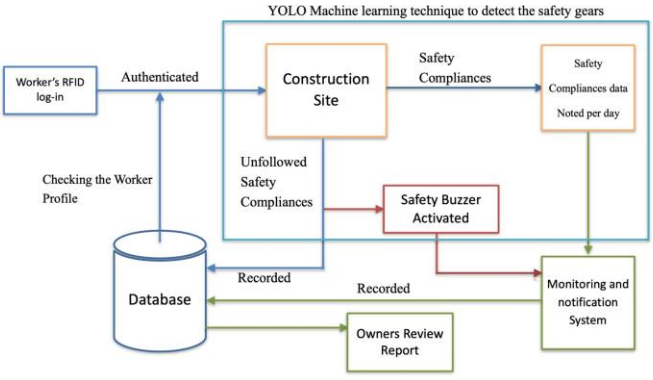

Fig 1 : Architecture Diagram

F. Sequence Flow

Fig. 2 represents a Worker Detection System using a YOLO model for object detection and classification. It highlights the interaction between the user, GUI, YOLO model, webcam, and file system. The system supports three functionalities: uploading an image, starting a webcam, and uploading a video. For image processing, the user uploads an image via the GUI, which opens a file dialog, retrieves the file path, loads the YOLO model, processes the image, and displays the classification results. For webcam processing, the system initializes the webcam, captures frames in a loop, processes and analyzes each frame, annotates it, and displays the output. Similarly, for video processing, the user uploads a video, and the system processes each frame iteratively, analyzes it, and displays annotated results. The application concludes with resource cleanup upon exit. This setup, as shown in Fig. 2, ensures seamless detection and analysis across various input sources.

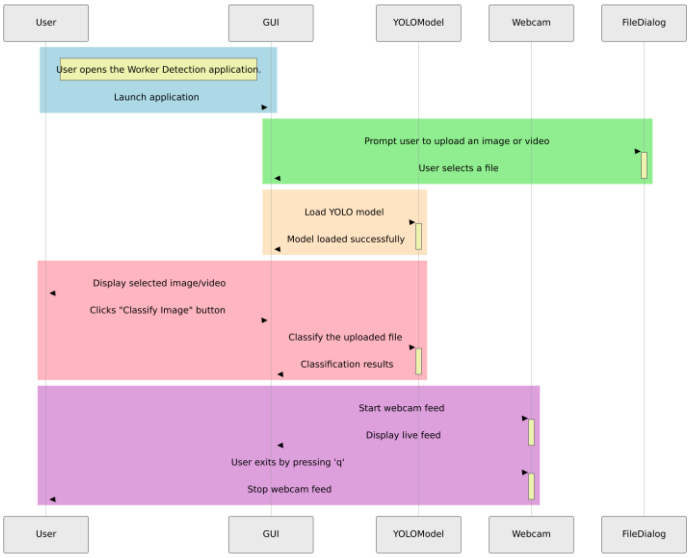

Fig2: Sequence flow Diagram

G. Image and Classification Flowchart :

The below flow chart outlines a system for image and video classification using a YOLO model, a machine- learning framework designed for object detection. The process begins with initializing the graphical user interface (GUI), providing users with three options: uploading an image, uploading a video, or using a webcam. Each pathway includes steps to load the respective input, whether it be an image, video, or webcam feed. For image classification, the system displays the uploaded image and performs a one- time classification, generating results. In the case of videos or webcam feeds, the system processes individual frames in real-time, classifies each frame, and iteratively displays the predictions. At the core of this workflow is the YOLO model, which is loaded to perform accurate object detection. Once the process is complete, resources are released, and the program terminates. This flow is structured to handle various input types while maintaining efficient classification, resource management, and scalability, as demonstrated in the below flow chart.demonstrated in the below flow chart.

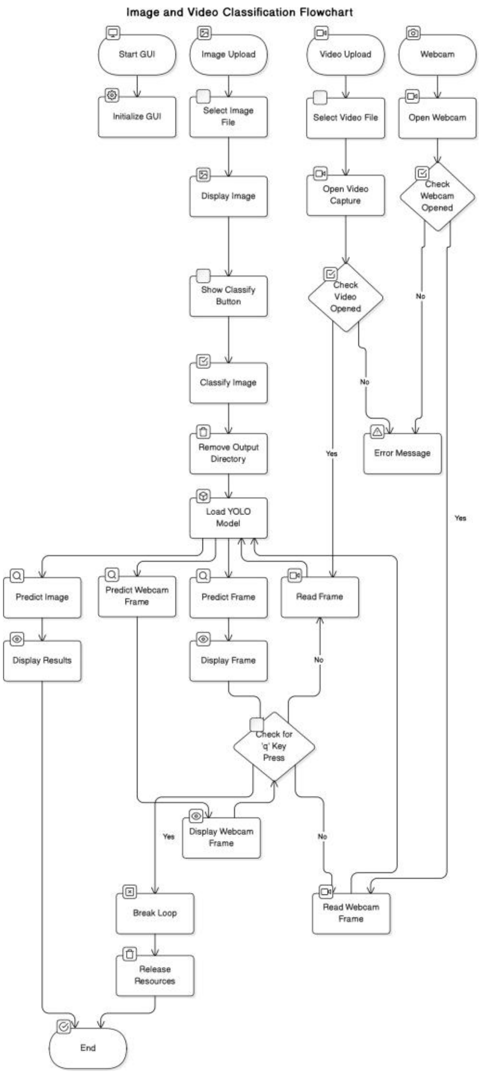

Fig3:Sequence flow Diagram

H. Class Diagram :

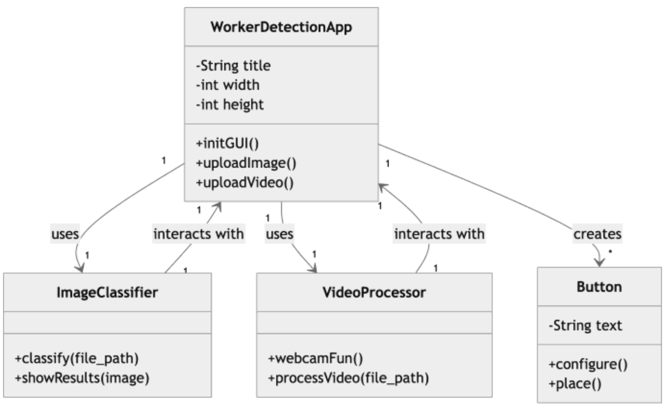

Fig 4 : Class Diagram

Fig 4 represents a class diagram depicting the architecture of the WorkerDetectionApp and its interactions with supporting classes. The WorkerDetectionApp class serves as the central component, with attributes title, width, and height defining the application's properties. It includes methods such as initGUI() for initializing the graphical user interface, uploadImage() for uploading images, and uploadVideo() for uploading videos.

The WorkerDetectionAppuses the ImageClassifier class, which provides methods classify(file_path) for image classification and showResults(image) for displaying results, and the VideoProcessor class, which offers webcamFun() for enabling webcam functionality and processVideo(file_path) for processing video files. Additionally, the application creates multiple instances of the Button class, which has a text attribute and methods like configure() for setting properties and place() for positioning the buttons in the interface. The relationships in the diagram include one-to-one associations between the WorkerDetectionApp and both the ImageClassifier and VideoProcessor classes, as well as a one-to-many relationship with the Button class, ensuring modular functionality for image and video processing alongside user interactivity.

V. RESULT ANALYSIS AND VALIDATION

The validation process and overall results highlighted the robustness and accuracy of the YOLO model in detecting safety gear in real-world scenarios. A labeled validation dataset with ground truth annotations was used to systematically evaluate the model's performance. Metrics such as precision, recall, F1-score, and mean average precision (mAP) were employed to measure the effectiveness of the model in accurately identifying safety gear while minimizing false positives and negatives. The results underscored the model’s reliability for real-time detection, demonstrating its potential to enhance worker safety in dynamic and challenging environments.

The validation process was conducted using a labeled dataset containing ground truth annotations to comprehensively evaluate the model's performance. Precision was used to measure the percentage of correctly identified instances among all predictions, providing an indication of the model's ability to minimize false positives. Recall assessed the percentage of ground truth instances correctly detected, reflecting the model's capability to identify true positives. The F1-Score, a harmonic mean of precision and recall, offered a balanced evaluation of accuracy and completeness. Additionally, the Mean Average Precision (mAP) metric was employed to evaluate the model's prediction accuracy across multiple Intersection over Union (IoU) thresholds, providing insights into its localization precision. The validation involved generating predictions on the dataset using the YOLO model, which were then compared with the ground truth annotations to compute the relevant performance metrics, ensuring a thorough and reliable assessment of the model's detection capabilities.

ability to achieve high performance in detecting safety-related features with precision and recall metrics, making it suitable for real-world applications where accurate detection is crucial.

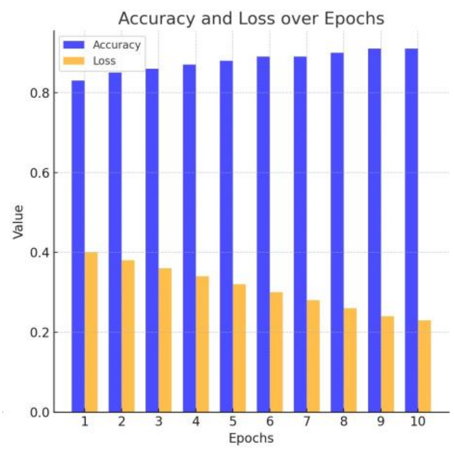

Fig 6:Accuracy and Loss Over Epochs

Fig 7 :Result Output Based on Validation

Figure 7 illustrates the output of a worker detection model applied in a construction site scenario. The image showcases individuals categorized as "Worker," "Engineer," or "Unsafe," with confidence scores displayed alongside bounding boxes. The model effectively identifies individuals wearing safety gear, such as helmets and reflective vests, labeling them as "Worker" or "Engineer" with high confidence (e.g., 0.91 and 0.98). Simultaneously, individuals without appropriate safety gear are marked as "Unsafe," with confidence scores ranging from 0.78 to 0.87. This dual categorization highlights the model's capability to differentiate between compliance with safety protocols and potential violations.

The results suggest a robust performance in detecting workers in diverse postures and contexts, even in a crowded environment. High-confidence annotations indicate a well-trained model capable of distinguishing essential visual features associated with safety compliance. However, there are areas for potential improvement, such as refining predictions in overlapping bounding boxes or detecting partially visible individuals. This system offers significant potential for real-time occupational safety monitoring by providing actionable insights into unsafe conditions. When integrated into video surveillance systems, it could proactively enhance safety protocols by notifying supervisors of potential risks, thereby minimizing workplace accidents.

VI. CONCLUSION

This research successfully demonstrated the effectiveness of an advanced YOLO-based worker detection system integrated with RFID technology for enhancing safety in construction environments. The system achieved significant precision and recall metrics, as validated through rigorous testing using a labeled dataset. The precision and recall rates, along with the F1-score and mAP metrics, consistently improved over the training epochs, indicating robust detection capabilities and effective localization of safety violations. The use of Fig. 5 and other evaluations highlighted the system's ability to adapt to complex scenarios with minimal errors, making it reliable for real- time applications.

Additionally, the RFID-based attendance tracking system further enhances worker monitoring by ensuring efficient and cost-effective authentication. The combination of YOLOv8's real-time object detection and RFID's scalability provides a comprehensive solution to enforce safety compliance and streamline worker management. The validation results underline the system's potential for deployment in large-scale construction sites, demonstrating its capability to ensure safety, improve productivity, and adapt to dynamic environmental conditions. This study sets a strong foundation for future advancements in AI-driven construction safety systems.

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