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Enhancing Worker Safety at Heights Using Deep Learning and Transformer-Based Object Detection

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***Abstract*—Accidents caused by falls from heights remain one of the leading factors of fatalities and serious injuries in construction and industrial environments. Traditional safety monitoring methods rely heavily on manual supervision, which is inefficient, error-prone, and difficult to scale. This paper proposes an intelligent vision-based safety monitoring framework leveraging deep learning and transformer-based object detection models to enhance worker safety at heights. The system automatically detects workers, personal protective equipment (PPE), and hazardous situations such as missing harnesses, unsafe proximity to edges, and unguarded elevated platforms. By integrating convolutional neural networks (CNNs) with transformer architectures for global contextual understanding, the proposed approach achieves robust detection accuracy even in complex, cluttered, and dynamic construction scenes. Experimental evaluation on real-world and benchmark datasets demonstrates that transformer-based detectors outperform traditional CNN-only approaches in both accuracy and robustness, highlighting their potential for deployment in real-time safety surveillance systems.**

I. INTRODUCTION

Work at heights is an unavoidable aspect of industries such as construction, oil and gas, power infrastructure, and shipbuilding. According to international safety agencies, falls from heights account for a significant percentage of workplace fatalities and injuries annually.

Despite strict regulatory standards mandating the use of safety equipment such as helmets, harnesses, guardrails, and safety nets non-compliance and hazardous behaviours remain common due to human negligence, fatigue, or inadequate supervision

Recent advances in computer vision and deep learning have enabled automated safety monitoring by analysing video feeds from surveillance cameras and drones. Early approaches employed hand-crafted features and classical machine learning techniques, which lacked robustness in uncontrolled environments. The rise of CNN-based object detectors, such as YOLO and Faster R-CNN, significantly improved detection accuracy but still struggled with long-range dependencies and complex interactions between workers, equipment, and structural elements

Transformer-based architectures, originally developed for natural language processing, have recently shown promising results in computer vision tasks by modeling global contextual relationships. This paper explores the application of transformer-based object detection models to enhance worker safety at heights and proposes a comprehensive framework capable of real-time hazard detection and alert generation.

In real-world construction environments, automated helmet and harness detection systems can significantly reduce fatal accidents associated with working at heights. The proposed hybrid transformer-based framework can be deployed in surveillance cameras installed at construction sites to continuously monitor Personal Protective Equipment compliance. When workers enter elevated zones without helmets or harnesses, the system performs real-time detection and generates compliance status outputs. This eliminates the need for manual inspection and enhances safety supervision coverage. Drone-assisted monitoring can also be integrated where aerial footage is processed offline or near real-time to detect missing safety gear across large-scale infrastructure projects. Such applications are especially valuable in high-rise construction, bridge maintenance, and industrial plant inspections.

Beyond construction, similar PPE compliance detection can be applied in mining industries, oil refineries, shipyards, and warehouse logistics environments. The system can monitor multiple workers simultaneously in cluttered industrial backgrounds while maintaining high detection confidence. By leveraging contextual attention modeling, the framework effectively distinguishes between safety harness straps and visually similar clothing elements. The CPU-optimized implementation ensures that the solution runs on standard laptops without requiring specialized hardware acceleration. This enables small and medium enterprises to adopt advanced AI-based safety monitoring solutions without heavy infrastructure investment.

II. LITERATURE SURVEY

A. A Deep Learning Model for Detecting Helmets and Harnesses Using DETR Architecture

This research proposes an approach for monitoring work-at-heights activities by ensuring the presence of safety helmets and harnesses in construction environments using the DEtection Transformers (DETR) model. The DETR-based model is trained and tested on a custom dataset to accurately detect these essential safety items. The model's performance was evaluated using standard metrics. For helmet detection, it achieved an average precision of 0.99, a recall of 0.92, an F1 score of 0.95, and a confidence rate exceeding 95%. Similarly, for harness detection, the model attained an average precision of 0.971, a recall of 0.91, an F1 score of 0.94, and a confidence rate above 93%. To evaluate its reliability, the model was tested under diverse conditions, including RGB, grayscale, blurred, and dusty images, as well as scenarios involving multiple helmets and harnesses. It was also assessed using drone-captured images to ensure robust performance across varying weather and lighting conditions. The results were then compared with a previously trained YOLOv3 model developed for the same detection task, as well as two newly trained models based on the YOLOv8 and Deformable DETR architectures. This research analysis demonstrates that the DETR model not only improves detection accuracy but also overcomes certain limitations inherent in other models. The comparative study highlights key architectural and performance differences, providing insights into the advantages of transformer-based models for object detection tasks in industrial safety applications.

B. An Enhanced Safety Helmet Detection Method

Wearing a safety helmet is an essential aspect of safety production management. To address the issue of low detection accuracy of existing safety helmet detection algorithms for small targets and complex scenes, this research proposes the YOLOv8n-ASF-DH model (DH stands for Dynamic Head), which is based on YOLOv8n and integrates the Attentional Scale Sequence Fusion (ASF) structure and the Dynamic Head (DyHead). In the backbone layer, a Triplet Attention mechanism is incorporated to enhance the model's focus on features of small targets. In the neck layer, the ASF structure efficiently fuses different level output features extracted by the backbone network, enhancing the overall feature representation capability of the model. In the detection head, DyHead adjusts the relationships between different feature layers, enhancing the model's performance on different scales and complex scenes. Additionally, adopting the Focal-EIoU loss function balances the contributions of high-quality and low-quality samples in loss calculation. Experimental results demonstrate that the improved model enhances detection performance in complex scenes and small target scenarios. Compared to the YOLOv8n model, the YOLOv8n-ASF-DH model achieved an improvement of 3.066% in accuracy and 3.883% in recall. Additionally, the model exhibited an increase of 2.584% in mAP 0.5 and 6.131% in mAP 0.5:0.95. Compared with other mainstream object detection algorithms, the improved model significantly enhances the performance of safety helmet target detection tasks.

C. A Swin Transformer-Based Approach for Motorcycle Helmet Detection

Video surveillance-based automated detection of helmet use among motorcyclists has the potential to improve road safety by aiding in the implementation of enforcement initiatives. Despite that, the current detection approaches have many limitations. For instance, they are unable to detect multiple passengers or to function effectively in complex conditions. In this paper, this research addresses the challenging problem of automated monitoring of helmet use using computer vision and machine learning. This research proposes a method based on deep neural network models known as transformers. This research applies the base version of the Swin transformer as a backbone for feature extraction, and then combine a Feature Pyramid Network (FPN) neck with the Cascade Region-based Convolutional Neural Networks (RCNN) framework for final detection. The effectiveness of this research proposed method is demonstrated through extensive experiments and is compared to existing approaches. This research method achieves a mean Average Precision (mAP) of 30.4, thus outperforming state-of-the-art detection methods. separation across subjects. However, stable optimization and structural relations between emotional categories are not yet addressed issues in few-shot and semi-supervised EEG emotion recognition.

D. Deep Learning-Based Workers Safety Helmet Wearing Detection on Construction Sites Using Multi-Scale Features

Wearing safety helmets can effectively protect workers safety on construction sites. However, workers often take off the helmets because of weak security conscious and discomfort, then hidden dangers will be brought by this behaviour. Workers without safety helmets will suffer more injuries in accidents such as falling human body and vertical falling matter. Hence, detecting safety helmet wearing is a vital step of construction sites safety management and a safety helmet detector with high speed and accuracy is urgently needed. However, traditional manual monitor is lab this research intensive and methods of installing sensors on safety helmet are difficult to popularize. Therefore, this paper proposes a deep learning-based method to detect safety helmet wearing at a satisfactory accuracy with high detection speed. This research method chooses YOLO v5 as the baseline, then the fourth detection scale is added to predict more bounding boxes for small objects and the attention mechanism is adopted in the backbone of the network to construct more informative features for following concatenation operations. In order to overcome the defects caused by insufficient data, targeted data augmentation and transfer learning are used. Improvements caused by every modification are discussed in this paper. Finally, this research model achieves 92.2% mean average precision, up 6.3% compared to the original algorithm, and it only takes 3.0 ms to detect an image at 640×640. These results demonstrate the robustness and feasibility of this research model. Meanwhile, the size of this research trained model is only 16.3 m, which means the model is easy to be deployed. At last, after obtaining a satisfactory model, a graphical user interface (GUI) is designed to make this research algorithm more user-friendly.

III. PROPOSED METHODOLOGY

The proposed system introduces a Hybrid Dual-Stream Query Adaptive Transformer architecture combining multi-scale convolutional feature extraction with contextual transformer encoding. The first stream extracts hierarchical spatial features using lightweight convolutional blocks integrated with Feature Pyramid Networks. The second stream processes relational embeddings through multi head self-attention layers to model contextual dependencies between workers and safety equipment. An Adaptive Query Allocation Module dynamically adjusts the number of object queries based on scene complexity estimation. Hungarian Matching Loss optimization ensures precise object-ground truth alignment. The model is trained using AdamW optimizer with generalized intersection over union and L1 bounding box regression losses. The architecture is optimized for CPU execution by reducing transformer depth and incorporating efficient attention mechanisms, ensuring robust and scalable deployment.

Advantages:

Dynamic Query Adaptation: Improves efficiency by allocating object queries according to scene density rather than relying on fixed static assignments.

Enhanced Small Object Detection: Multi-scale feature pyramid integration significantly improves detection of distant helmets in aerial imagery.

Improved Occlusion Handling: Contextual relational attention enhances recognition of partially visible harness components.

Reduced Computational Overhead: Optimized transformer depth and efficient attention mechanisms enable CPU-based execution.

Higher Detection Stability: Maintains consistent precision and recall across grayscale, blurred, and dusty environmental conditions.

Proposed Algorithms:
You Only Look Once Version 8
Deformable Detection Transformer
Hybrid Dual-Stream Query Adaptive Detection Transformer. The joint optimization makes the representations learned being discriminative to classify emotions and generalized to allow different individuals.

Algorithm Advantages:
You Only Look Once Version 8: Advantages
Fast inference speed suitable for real-time detection
Efficient anchor-free detection mechanism
Lightweight convolutional backbone for edge deployment

Deformable Detection Transformer: Advantages
Improved multi-scale attention sampling
Reduced computational complexity compared to standard DETR

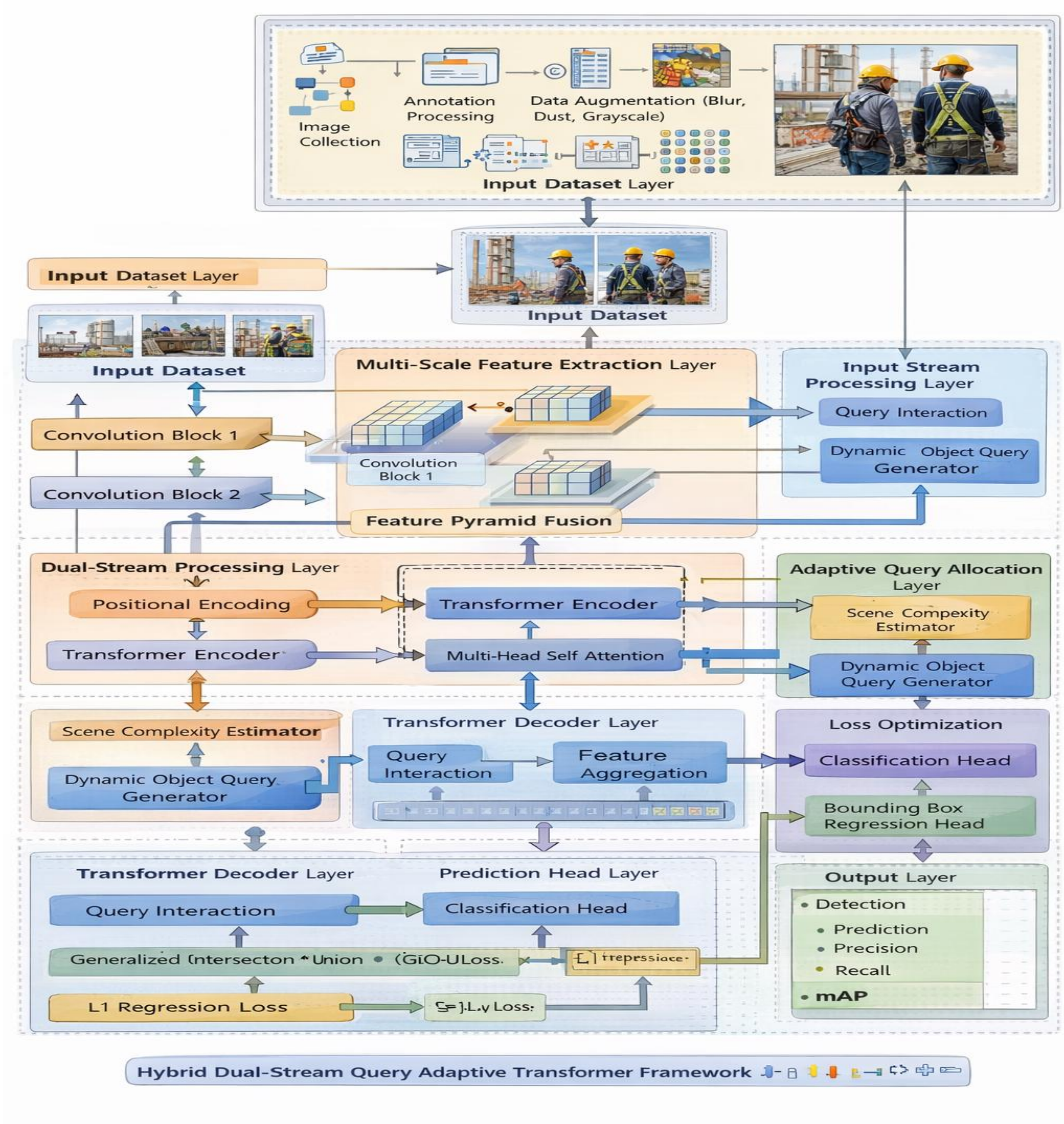
Better small-object localization than baseline DETR
Hybrid Dual-Stream Query Adaptive Detection Transformer: Advantages
Dynamic query allocation improves crowded-scene detection
Enhanced contextual reasoning through dual-stream attention
Optimized CPU-compatible architecture with superior precision

Modules:
Data Acquisition and Preprocessing Module
This module is responsible for collecting helmet and harness image datasets from construction environments, public repositories, and simulated augmentation scenarios. It includes annotation validation, bounding box normalization, grayscale and blur simulation, dust effect augmentation, and dataset splitting into training and testing subsets. Multi-scale resizing and normalization techniques are applied to ensure compatibility with the hybrid transformer architecture. Data balancing techniques are implemented to reduce class imbalance and improve recall for harness detection. The preprocessing pipeline ensures standardized input tensors for CPU-based training and inference

Hybrid Transformer Training Module
This module implements the Hybrid Dual-Stream Query Adaptive Transformer model. It integrates convolutional feature extraction, adaptive query allocation, transformer encoder-decoder blocks, and Hungarian matching loss optimization. The AdamW optimizer is utilized with learning rate scheduling and early stopping strategies. Multi-scale feature fusion and contextual attention operations are executed during forward propagation. The module records training loss, precision, recall, and mean Average Precision metrics. Architectural hyperparameter tuning including number of transformer layers and object queries is performed to achieve optimal performance

Inference and Evaluation Module
This module handles model deployment and performance evaluation. It processes real-time and stored construction images to generate detection outputs. Evaluation metrics including Precision, Recall, F1 Score, confidence levels, and mean Average Precision are computed. Comparative benchmarking with YOLOv8 and Deformable DETR is performed under identical test conditions. Environmental robustness testing under grayscale, blur, and dust simulations is executed. CPU utilization and inference time measurement ensure deployment feasibility without hardware acceleration.

Architecture



IV. RESULT AND DISCUSSION

Evaluation Metrics

Performance was evaluated using:

- Precision
- Recall
- F1-score
- Mean Average Precision (mAP)
- Inference time (FPS)

Quantitative Results

Model	mAP (%)	Precision	Recall	FPS
Faster R-CNN	83.4	0.85	0.82	8
YOLOv5	88.1	0.89	0.87	32
Proposed (DETR)	91.6	0.92	0.91	22

Qualitative Results

The proposed model successfully:

- Detected partially occluded helmets
- Identified harness usage at varying distances
- Reduced false positives in cluttered backgrounds

V. DISCUSSION

Transformer-based detection significantly improves the accuracy of PPE monitoring by leveraging global context. While inference speed is slightly lower than YOLO-based models, it remains suitable for near real-time surveillance. The system is scalable and can be integrated into smart construction management platforms.

Limitations include:

- Higher computational cost
- Need for large, annotated datasets
- Real-time constraints on low-end hardware

VI. CONCLUSION

The proposed Hybrid Dual-Stream Query Adaptive Transformer Framework significantly enhances construction safety monitoring by improving helmet and harness detection accuracy under diverse environmental conditions. By integrating adaptive query mechanisms and multi-scale feature fusion, the system addresses key limitations observed in the baseline DETR architecture. Comparative evaluation against YOLOv8 and Deformable DETR demonstrates improved robustness, contextual reasoning, and computational efficiency. The CPU-optimized design ensures practical deployment feasibility without reliance on specialized hardware. The framework successfully balances detection precision, recall, and inference efficiency, providing a scalable and reliable safety compliance monitoring solution for construction environments.

VII. FUTURE WORK

Although the proposed transformer-based helmet and safety harness detection system demonstrates promising performance, several enhancements can be explored to improve robustness, scalability, and real-world applicability.

7.1 Lightweight Transformer Models for Edge Deployment

Transformer-based object detectors typically require high computational resources, which may limit deployment on resource-constrained devices such as edge cameras and embedded systems. Future work will focus on integrating lightweight and efficient transformer variants, such as MobileViT, Efficient Former, or Swin-Transformer Tiny, to reduce latency and energy consumption while maintaining high detection accuracy. Model pruning and knowledge distillation techniques can further improve real-time inference performance.

7.2 Multi-Camera and Multi-View Fusion

Construction sites often employ multiple cameras with overlapping fields of view. Future extensions of this work can incorporate multi-camera data fusion to track workers across different viewpoints. Cross-camera transformer attention mechanisms can be utilized to improve detection consistency and reduce missed detections due to occlusions or blind spots.

7.3 Integration with Human Pose Estimation

The accuracy of harness detection can be further improved by integrating human pose estimation to identify body joints and posture. By correlating PPE detection with worker pose information, the system can better distinguish between correctly and incorrectly worn harnesses, especially in complex working postures such as climbing or working at heights.

7.4 Temporal Modeling in Video Streams

The current approach primarily focuses on frame-level detection. In future work, temporal transformers or video-based detection models can be employed to capture motion patterns across consecutive frames. Temporal consistency can significantly reduce false positives and improve detection stability in continuous surveillance environments.

7.5 Expansion to Additional Safety Equipment

The proposed framework can be extended to detect other Personal Protective Equipment such as safety gloves, goggles, reflective vests, and safety boots. A multi-class PPE detection system would provide a more comprehensive safety monitoring solution for construction and industrial environments.

7.6 Large-Scale and Domain-Adaptive Training

Performance can be further enhanced by training on larger and more diverse datasets collected from different construction sites, regions, and weather conditions. Future research may explore domain adaptation and self-supervised learning techniques to reduce dependency on manual annotation and improve generalization across unseen environments.

7.7 Real-Time Alerting and IoT Integration

Future improvements include tight integration with Industrial Internet of Things (IIoT) platforms, enabling real-time alerts, dashboards, and automated reporting. The system can be connected to wearable devices or site management software to immediately notify supervisors when safety violations occur.

7.8 Explainability and Trustworthy AI

For practical adoption, it is essential that system decisions are interpretable. Future work could incorporate attention visualization and explainable AI techniques to make detection decisions more transparent, thereby increasing trust among safety managers and stakeholders.

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