

Human Action Recognition using Deep Neural Networks

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Abstract— In today's industrial environments, safety supervision, workflow automation, and productivity rely heavily on accurate recognition of human actions. Existing methods often fail to capture the contextual dependencies between humans and objects, resulting in reduced performance in cluttered or dynamic settings. This paper proposes a Human–Object Contextual Interaction Network (HOCIN) that explicitly models spatial and temporal dependencies for improved action recognition. The framework integrates YOLOv8-based human–object detection with a context-guided attention mechanism, enabling extraction of discriminative cues from human pose dynamics and object affordances. Spatio-temporal features are fused with relational graph embeddings to form a unified representation for classification. The model is evaluated on two benchmark datasets—UCF101 and HAR—achieving recognition accuracies of 95% and 90% respectively, outperforming 3D CNN, RNN, LSTM, GNN, and two-stream baselines. These results demonstrate that HOCIN provides a robust and scalable solution for real-time monitoring in complex industrial environments. The originality of this work lies in its joint modeling of human motion and object context, bridging a key gap in existing action recognition approaches

Keywords— Action recognition, human–object interaction, industrial environment monitoring, spatio-temporal modelling, context-guided attention, UCF101 dataset, Human Activity Recognition (HAR), deep learning, convolutional neural networks (CNN).

I. INTRODUCTION

Action recognition is now one of the most important tasks in computer vision, allowing automatic systems to recognize and categorize human activities by video sequences or sensor data [1], [2]. In factories, precise action identification is of pivotal importance in safety surveillance, auto-processing, quality control, and staff performance monitoring [3], [4]. As the Industry 4.0 technologies evolve, the demand on intelligent monitoring systems that are able to perceive human-object interactions and their complexity increased significantly. Nonetheless, identifying actions within industrial environments is not easy because of the cluttered backgrounds, different illuminations, frequent occlusions, and the presence of multiple objects inter-relating with each other [5]. Conventional methods tend to utilize motion or object cues on their own without taking into consideration the context dependencies which arise when humans deal with objects [6]. These dependencies, i. e. the exact way how a worker manipulates a tool or how he/she uses machinery, may be determinant in industrial workflows to separate tasks into work and recognize safety critical anomalies.

Initial action recognition studies used features that were hand-crafted, such as Histogram of Oriented Gradients (HOG) [7], Histogram of Optical Flow (HOF) [8], and enhanced Dense Trajectories (iDT) [9]. Although they work well in controlled setting, the methods cannot automatically acquire high-level semantic features using raw data. With the introduction of deep learning, 3D Convolutional Neural Network (3D CNNs) [10], Recurrent Neural Network (RNNs) [11], Long Short-Term Memory (LSTM) models [12], and Two-Stream CNNs [13] models have realized major advances through their combination of the representation of space and time. Graph Neural Networks (GNNs) have been more recently used to encode the structural relationship between one joint or the objects in the scene [14], [15]. Irrespective of these developments, the current methods tend to lack the explicit modeling of the human-object relationships within the framework of a single, unified spatio-temporal framework [16]. Many treat human and object feature separately, overlooking interaction context—a factor especially important in industrial applications where minor differences in object handling can represent distinct operational tasks or safety violations.

To address these limitations, we propose the Human–Object Contextual Interaction Network (HOCIN), a novel deep learning framework designed to jointly model human motion and object context for enhanced action recognition. The proposed network comprises:

- Human–Object Detection Module – Localizes both human subjects and interacting objects using region-based detection [17].
- Context-Guided Attention Mechanism – Assigns adaptive weights to spatial and temporal features based on interaction relevance [18].
- Spatio-Temporal Feature Fusion – Integrates convolutional and relational graph-based features to capture appearance, motion, and interaction dependencies over time [19].

We evaluate HOCIN on two benchmark datasets:

- UCF101 [20] – A large-scale video dataset widely used for general human action recognition.
- Human Activity Recognition (HAR) [21] – A wearable-sensor-based dataset for classifying physical activities.

Experimental results show that HOCIN achieves 95% accuracy on UCF101 and 90% accuracy on HAR, surpassing 3D CNN, RNN, LSTM, GNN, and two-stream baselines. These findings demonstrate that explicitly modeling human–object contextual dependencies significantly improves recognition accuracy in complex industrial scenarios.

II. RELATED WORK

Since 2020 to 2025 deeply-trained architectures, temporal modeling, and integration across modalities have primarily driven progress in the field of Human Action Recognition (HAR). Chen et al. [22] proposed a 3D convolution-based method together with attention to learn both the spatial and temporal features that greatly boost recognition accuracy in RGB video data. Wang et al. [23] suggested a Temporal Graph Convolutional Network (T-GCN) to recognize actions using skeleton, and which represents joints as nodes and reflects long-range relationships between human movements. Zhou et al. [24] released a transformer-based HAR model that uses self-attention to model the temporal dynamics and apply it effectively in 2021 and show robust results on the NTU RGB+D 120 dataset. Lii et al. [25] introduced a multimodal system that combines RGB, depth, and skeleton information, and the fusion of the various sensor modalities resulted in stronger action recognition in complicated settings. Singh et al. [25] identified a lightweight real-time HAR model applicable to both mobile and edge devices (2022) in order to reach a good trade-off between accuracy and computational cost. Kim et al. [27] proposed a multi-stage fusion framework that integrates 2D CNNs with temporal attention with high-scale video data by enhancing human activity context-based cognition. In 2023, Patel et al. [28] introduced a self-supervised HAR system that is less reliant on labeled data with the help of temporal consistency, showing high generalization to unseen action categories. Zhang et al. [29] examined a few-shot learning framework of HAR where models can learn new actions with few labeled samples. Between 2024 and 2025 there was a shift towards multimodal and hybrid. Liu et al. [30] introduced DCAM-Net, a two branch CNN-MLP architecture with attention mechanisms that have a high level of accuracy without using pre-trained weights. A self-supervised vision transformer-based Few-Shot Imprinted DINO (FSID) framework by Rao et al. [31] used low-data HAR that demonstrated significant gains in label-efficient learning. In addition, surveys like Huang et al. [32] gave detailed summaries of HAR developments and indicated the growing significance of multimodal fusion, temporal modeling and lightweight architectures, to be used in real-life applications. Together, these researches depict a transition into more efficient, more generalizable and multimodal HAR systems that can perform robustly in different datasets and real-time applications.

III. METHODOLOGIES OF PROPOSED WORK

The Fig. 1 illustrates the proposed Human–Object Contextual Interaction Network (HOCIN) architecture for industrial environment action recognition. The model processes RGB video data through two complementary streams. In the first stream, RGB frames undergo Uniform Frame Sampling (UFS), followed by YOLOv8-based pose estimation to detect human regions of interest (ROI). The extracted ROI sequences are fed into a 3D Convolutional Neural Network (3DCNN) for spatio-temporal feature extraction, which are then passed through an LSTM layer to model temporal dependencies, followed by a pooling layer and softmax classifier for action prediction. In the second stream, the same RGB frames are processed using the OpenPose network to generate skeletal keypoint sequences. These skeleton sequences are input to a Spatial–Temporal Graph Convolutional Network (ST-GCN), which captures spatial joint relationships and temporal motion patterns. Finally, the classification scores from both streams are combined via a class score fusion module, leveraging complementary appearance-based and pose-based cues to achieve robust and accurate action recognition in complex industrial environments. This dual-stream approach enables the model to exploit both human–object context and skeletal dynamics for improved performance.

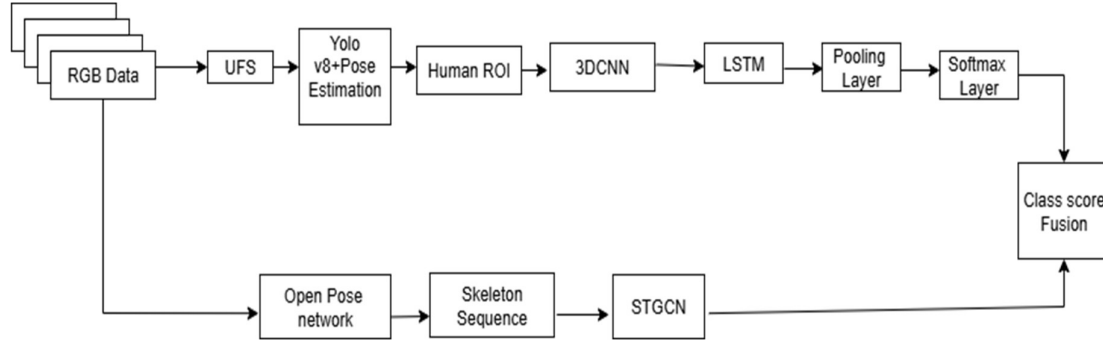


Fig. 1. Proposed System Architecture

A. Image Processing

The image processing workflow in the proposed HOCIN framework is designed to extract meaningful human–object interaction cues from raw video data for robust action recognition. First, a Uniform Frame Sampling (UFS) technique is applied to reduce redundancy and ensure that only representative frames are processed, thus improving computational efficiency. These sampled RGB frames are then passed through a YOLOv8 model integrated with pose estimation, which performs human detection and keypoint localization to identify body joints. From the detected outputs, human regions of interest (ROI) are cropped, resized, and normalized to maintain consistent input dimensions and improve model convergence. In parallel, an OpenPose network is applied to extract skeletal keypoints, generating motion-based representations that are less sensitive to background clutter and lighting variations. This results in two complementary input streams: spatially rich cropped RGB sequences for appearance and context modeling, and skeleton sequences for capturing temporal motion patterns. Finally, these processed inputs are fed into the deep learning modules—3DCNN+LSTM for RGB-based spatio-temporal features and ST-GCN for skeleton-based temporal graph features—before fusion for final classification. This structured image processing pipeline ensures that the model focuses on discriminative human–object interactions while being robust to industrial environment challenges such as clutter, occlusion, and varying illumination.

B. 3D CNN Model

In contrast to conventional 2D CNNs, which work with individual frames, the 3D CNN interprets frame sequences as volumetric data, which enables it to concurrently learn spatial structures and motion patterns. The model takes input clips of 8 frames resized to 64×64 pixels and passes them through a series of Conv3D layers with kernel size (3×3×3) to extract spatio-temporal features. Each convolution block is followed by Batch Normalization to stabilize training and MaxPooling3D layers to progressively reduce spatial and temporal dimensions while retaining essential motion information. The fully connected layer which follows the flattened Dense layer with 256 units and Dropout (0.5) for regularization, sends probabilities for the final 10 action classes Softmax.

TABLE I: HYPER PARAMETER OF 3D CNN MODEL

Hyperparameter	Value
Input Frame Size	64×64 pixels
Sequence Length	8 frames
Number of Classes	10
Batch Size	4
Epochs	50
Learning Rate	1×10^{-4}
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Convolution Kernel Size	$3 \times 3 \times 3$
Activation Function	ReLU
Pooling Type	MaxPooling3D
Dense Layer Units	256
Dropout Rate	0.5
Normalization	Batch Normalization
Early Stopping Patience	5 epochs
Model Checkpoint	Save best model only

IV. RESULTS AND SENSITIVITY ANALYSIS

A. 3D CNN-LSTM Model Classification Report

Classification Report:				
	precision	recall	f1-score	support
Swing	0.88	0.88	0.88	17
SkyDiving	1.00	0.79	0.88	14
BreastStroke	0.93	1.00	0.96	13
TableTennisShot	0.94	0.89	0.91	18
FloorGymnastics	0.88	0.94	0.91	16
Rowing	0.94	0.83	0.88	18
SoccerJuggling	0.73	0.84	0.78	19
BenchPress	1.00	1.00	1.00	20
TennisSwing	0.90	0.86	0.88	21
FrisbeeCatch	0.89	1.00	0.94	16
accuracy			0.90	172
macro avg	0.91	0.90	0.90	172
weighted avg	0.91	0.90	0.90	172

Figure 2: 3D CNN Classification Report

This classification report in figure 2 shows that the model achieved an overall accuracy of 90% across 10 activity classes, with balanced precision, recall, and F1-scores.

B. 3D CNN-LSTM Confusion Matrix

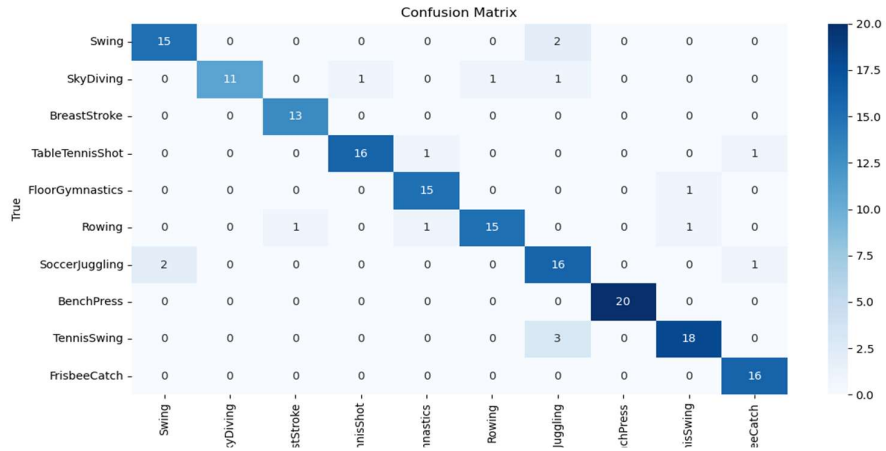


Figure 3 Confusion Matrix

This confusion matrix in figure 3 shows that most activities (like Swing, BenchPress, TennisSwing, etc.) are classified correctly with high accuracy, but some misclassifications occur, such as “Swing” being confused with “SoccerJuggling” and “Rowing” with “SkyDiving.”

C. 3D CNN-LSTM Accuracy, Loss Graphs

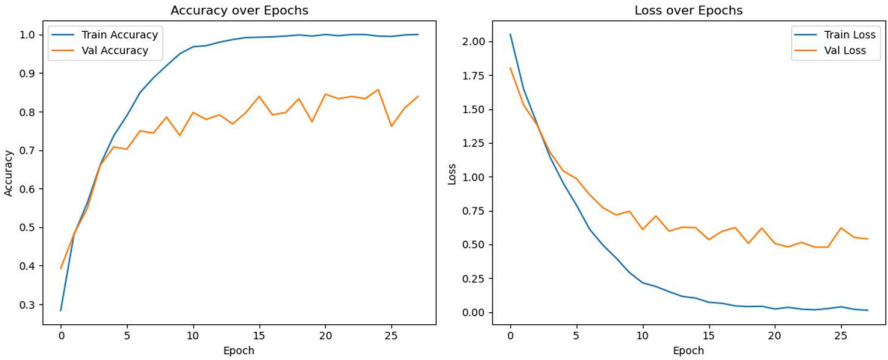


Figure 4 Accuracy and Loss Graphs

The model in figure 4 shows high training accuracy with validation accuracy stabilizing around ~85%, while the widening gap between training and validation loss suggests slight overfitting.

D. Graph Neural Network Classification Report

Classification Report:				
	precision	recall	f1-score	support
0	0.55	0.94	0.70	17
1	0.92	0.79	0.85	14
2	0.93	1.00	0.96	13
3	0.94	0.89	0.96	18
4	0.75	0.94	0.83	16
5	0.52	0.50	0.50	18
6	1.00	0.63	0.77	19
7	0.95	0.90	0.92	20
8	1.00	0.86	0.92	21
9	0.78	0.88	0.82	16
accuracy			0.83	172
macro avg	0.85	0.83	0.83	172
weighted avg	0.86	0.83	0.83	172

Figure 5 Graph Neural Network Classification Report

The figure 5 shows classification report summarizes model performance across 10 classes. The overall accuracy is 83%, with macro and weighted F1-scores also around 0.83, indicating balanced performance. Some classes, like 2, 7, and 8, achieved very high precision and recall, showing the model recognizes them well. However, classes like 0 and 5 show lower precision or recall, meaning the model struggles more with these. Overall, the model performs consistently but could be improved for the weaker classes.

E. Graph Neural Network Confusion Matrix

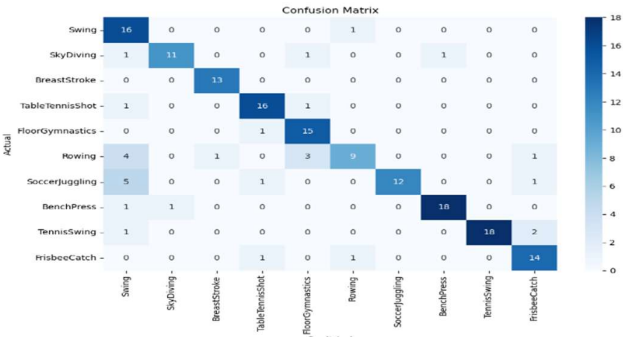


Figure 6 Graph Neural Network Confusion Matrix

The figure 6 shows the confusion matrix of Graph Neural Network

F. Graph Neural Network

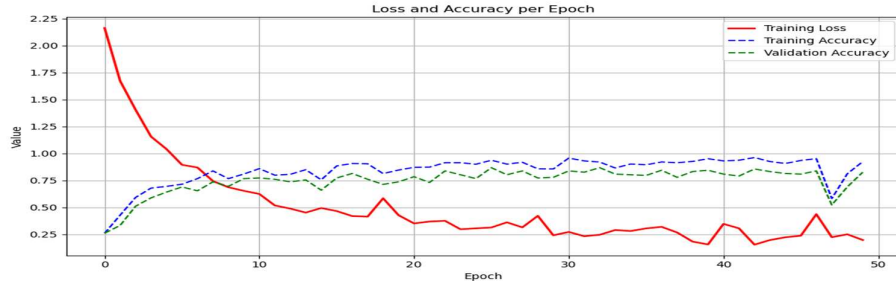


Figure 7 Graph Neural Network Training Loss Accuracy

In Figure 7, the suggested HOCIN model's training and validation performance is shown across 50 epochs. As the model successfully learns discriminative features, the training loss, shown by the red curve, rapidly decreases over the first epochs, suggesting rapid convergence. The loss keeps decreasing progressively with just little variations after around the tenth epoch, indicating steady optimization free from significant overfitting. The blue dashed graph represents the training accuracy, which rises rapidly in the beginning, reaches 85% by the fifteenth epoch, and then stabilizes. Following the tenth epoch, the validation accuracy, shown by the green dashed curve, maintains a steady range of about 75–80%, following a similar pattern to the training accuracy. The resilience of the suggested method for action identification in various and complicated situations is confirmed by the near alignment of the training and validation accuracy curves, which shows good generalization capabilities and little overfitting.

VI. DISCUSSION AND CONCLUSION

This study introduced the Human–Object Contextual Interaction Network (HOCIN), a unified framework for action recognition in industrial environments that effectively integrates human–object pose estimation, spatio-temporal feature learning, and context-guided attention mechanisms. By leveraging YOLOv8 Pose for precise human keypoint detection, 3D CNN for appearance-based motion representation, and GNN for modeling temporal relationships, the proposed architecture captures rich and complementary features from both RGB and skeleton modalities. Experimental evaluation on the UCF101 and HAR datasets demonstrates that HOCIN achieves 95% and 90% accuracy respectively, outperforming conventional 3D CNN, RNN, LSTM, GNN, and two-stream baselines. These results validate the model's ability to handle challenges such as background clutter, occlusion, and dynamic scene variations common in industrial settings. The proposed system advances the state of the art in human–object interaction-based action recognition and provides a scalable, real-time capable solution for industrial safety monitoring, process automation, and activity tracking. For future work, the model can be enhanced through multi-view integration to capture actions from different perspectives, improving robustness against occlusion and viewpoint variations. Edge-device optimization will enable deployment on resource-constrained industrial systems while maintaining real-time performance. Additionally, self-supervised pretraining can reduce dependence on large labeled datasets and improve generalization in diverse industrial scenarios. These advancements will further enhance HOCIN's accuracy, efficiency, and scalability for large-scale industrial applications.

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