# Adaptive Action Recognition for Transport, Fitness, Healthcare and Classroom Analytics Using Deep Learning

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***Abstract*—Human Activity Recognition (HAR) has become an important technology for developing intelligent systems in various real-world domains such as healthcare monitoring, smart homes, fitness tracking, surveillance, transportation analysis, and human–computer interaction. By automatically identifying human activities from video streams or sensor-based data, HAR systems enable machines to better interpret human behavior and respond effectively in dynamic environments.**

**This project introduces a deep learning–based framework titled "Adaptive Action Recognition for Transport, Fitness, Healthcare and Classroom Analytics Using Deep Learning." The main goal of the system is to detect and classify different human activities from live video streams captured in real-time scenarios.**

**The proposed framework integrates multiple deep learning techniques including Convolutional Neural Networks (CNNs), 3D Convolutional Neural Networks (3D-CNNs), and Long Short-Term Memory (LSTM) networks. These models help capture both spatial information from individual video frames and temporal patterns that represent motion across consecutive frames. Video preprocessing, feature extraction, and temporal analysis are optimized to ensure efficient real-time processing while maintaining high recognition accuracy.**

**A sliding window strategy with buffered frame sequences is used to continuously analyze incoming video streams, enabling the system to recognize activities without interruption. Additionally, transfer learning techniques are incorporated to improve the model's ability to adapt to variations such as lighting conditions, different backgrounds, and diverse user behaviors.**

**The developed system can be applied in several practical scenarios including fall detection for elderly healthcare monitoring, intelligent surveillance systems, gesture-based human–computer interaction, fitness activity tracking, and classroom activity analytics.**

***Index Terms*—Human Activity Recognition, Deep Learning, Convolutional Neural Networks, LSTM Networks, Video Analytics, Artificial Intelligence**

## I. The Problem: Understanding Human Activities Automatically

Imagine an intelligent healthcare monitoring system that supports elderly people who live independently. If a person suddenly falls or shows unusual movement, it may indicate a medical emergency. In situations where no one is present to observe the incident, such events might remain unnoticed for a long time, potentially putting the individual's health and safety at risk.

Human Activity Recognition (HAR) addresses this challenge by allowing computer systems to automatically identify and classify human actions using video streams or sensor data. By examining patterns of body movement, posture variations, and motion behavior, HAR systems enable machines to interpret and understand human activities within real-world environments.

Recent progress in deep learning techniques has greatly enhanced the effectiveness of HAR systems. Convolutional Neural Networks (CNNs) are capable of automatically extracting spatial features from individual video frames, while recurrent architectures such as Long Short-Term Memory (LSTM) networks are used to learn temporal relationships between consecutive frames within an activity sequence [1].

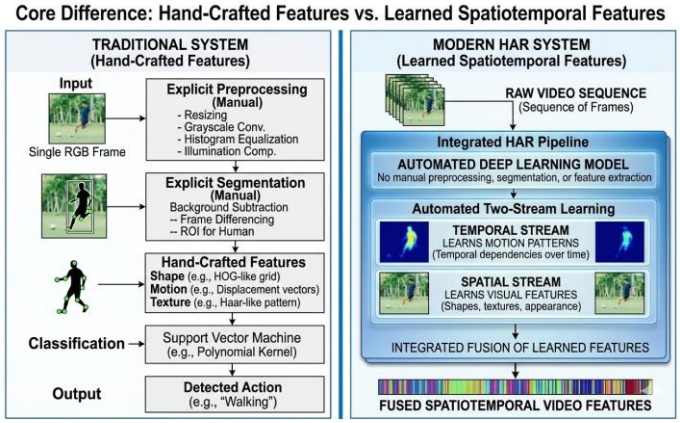


Fig. 1. Comparison between traditional Human Activity Recognition systems using hand-crafted features and modern deep learning–based HAR systems that learn spatial and temporal features automatically from video sequences.

The magnitude of this challenge continues to grow rapidly. With the increasing use of cameras, smartphones, and IoT-enabled devices, massive amounts of video data are generated every day. Manually reviewing such large volumes of data is both inefficient and impractical. Automated Human Activity

Recognition (HAR) systems address this issue by enabling machines to automatically analyze and interpret human behavior from video streams or sensor-based signals [1], [4]. In India, the adoption of smart surveillance technologies and intelligent monitoring platforms has expanded significantly, particularly in areas such as public transportation, educational institutions, and healthcare facilities. These environments are increasingly integrating automated activity monitoring solutions to improve safety, security, and operational efficiency [5]. Across many smart cities worldwide, intelligent surveillance systems already process vast numbers of video frames daily to identify suspicious actions or unusual behavioral patterns [6]. Future projections indicate that AI-powered activity recognition technologies will play a key role in smart environments, supporting applications ranging from public safety monitoring to advanced healthcare assistance [1], [7].

Despite its growing importance, Human Activity Recognition remains a complex task due to the variability of human behavior. Actions performed by individuals can differ depending on factors such as environmental conditions, body posture, camera perspectives, and movement speed. Activities like walking, running, sitting, or interacting with objects may appear visually similar under different circumstances, which makes accurate recognition more difficult [8]. To address these challenges, automated systems must continuously analyze video streams and identify meaningful motion patterns. However, performing this analysis at large scale requires advanced computational models capable of processing high volumes of video data in real time. Traditional computer vision approaches often struggle to meet these demands efficiently [9]–[11].

This research aims to address these challenges by developing an efficient and intelligent human activity recognition framework.

## II. The State of the Art: Incremental Progress and Persistent Limits

The field of Human Activity Recognition (HAR) has experienced substantial progress over the past decade. Early research mainly relied on handcrafted features such as motion trajectories, body pose representations, and optical flow measurements to analyze human movement. Although these techniques helped researchers understand motion patterns, they often struggled to perform well across different environments, camera perspectives, and lighting conditions [12]–[14]. With the advancement of deep learning, researchers began focusing on neural network models capable of automatically learning complex spatial and temporal features directly from video data.

The First Wave: Standard CNNs (2018–2022)

Initial deep learning approaches for HAR were largely based on architectures originally developed for image classification tasks. These models were adapted to analyze video frames with only minor modifications [15]. Convolutional Neural Networks (CNNs) were used to extract spatial features from individual frames, capturing information related to human poses and visual patterns associated with different activities.

Several studies reported encouraging results using standard CNN architectures. However, a major limitation quickly became evident: these models analyzed frames independently and could not capture the temporal relationships between consecutive frames in a video sequence [12]. Because of this limitation, the models sometimes misclassified activities that involved subtle motion changes or transitions between actions.

Hybrid CNN-LSTM architectures soon emerged as an effective solution. In these systems, CNN layers extract spatial features from individual frames, while LSTM layers analyze the sequence of extracted features to learn temporal relationships between actions [18]. This approach significantly improved recognition accuracy, especially for activities that involve continuous motion such as running, jumping, or interacting with objects.

At the same time, researchers explored 3D Convolutional Neural Networks (3D CNNs), which perform convolution operations across both spatial and temporal dimensions simultaneously. Unlike standard CNNs, these models process short video clips rather than individual frames, enabling them to learn richer spatio-temporal representations of human movement.

Although these advanced architectures improved recognition performance, they often required large datasets and high computational power to train and deploy effectively.

The Ensemble Era: Strength in Numbers—at a Cost (2023–2025)

In an effort to further enhance activity recognition accuracy, researchers began experimenting with ensemble learning techniques. These approaches combine predictions from multiple deep learning models, such as CNNs, LSTMs, and 3D CNNs, to produce more reliable classification results.

For example, Bhimavarapu et al. developed an ensemble framework that integrated several pre-trained deep learning models to recognize complex human activities. Their system demonstrated improved accuracy compared to single-model approaches by capturing a wider range of motion features and behavioral patterns [20]. However, this improvement came with a major drawback—high computational cost.

In scenarios such as smart surveillance or healthcare monitoring systems, both latency and computational efficiency are critical factors. Shakibania et al. showed that even an ensemble composed of four different models produced only moderate performance gains while greatly increasing computational complexity [21].

Overall, research in Human Activity Recognition over the past decade suggests that the field requires not just more complex models, but smarter architectures—models that can effectively capture both spatial and temporal motion patterns while maintaining efficiency suitable for real-time applications.

## III. Our Answer: A System Designed to Outperform

Instead of making minor improvements to existing activity recognition models, our approach focuses on developing a system that can better understand complex patterns of human motion from video sequences. The proposed Human Activity

Recognition framework combines modern deep learning techniques to effectively learn both spatial and temporal information from human activities.

The system is designed around four main components. First, a ConvNeXt backbone is used to perform strong spatial feature extraction from video frames. Second, attention mechanisms are incorporated to refine and highlight important features related to human motion. Third, a flexible classification module is implemented to accurately predict different activity categories.

### *A. Pillar I: ConvNeXt—Capturing Spatial Motion Patterns*

At the core of the proposed activity recognition framework is the ConvNeXt architecture, introduced by Liu et al. [15]. ConvNeXt represents an updated form of traditional convolutional neural networks that integrates several design ideas inspired by Vision Transformers while still preserving the efficiency of convolution-based computation.

The ConvNeXt Base model is structured into four hierarchical stages, where the channel dimensions gradually increase to learn deeper feature representations. The channel sizes are defined as $C = \{128, 256, 512, 1024\}$ and the number of blocks in each stage is $B = \{3, 3, 27, 3\}$. At the beginning of the network, a patchifying stem layer processes the input video frames and converts them into feature representations that can be efficiently analyzed by the subsequent layers of the model:

$$x_0 = \text{LayerNorm}(\text{Conv}_{4\times4}(I)), \tag{1}$$

which reduces the spatial resolution of the input while producing feature maps that highlight important visual patterns such as body posture, limb motion, and interaction dynamics between objects and people.

A key feature of ConvNeXt blocks is the use of larger depthwise convolution kernels. Unlike conventional convolutional networks that primarily rely on $3 \times 3$ convolution layers, ConvNeXt utilizes a $7 \times 7$ depthwise convolution operation:

$$z_1 = \text{DWConv}_{7\times7}(x). \tag{2}$$

This architectural design allows the network to capture a wider spatial context within each frame, enabling it to better understand the relationships between different body parts as well as the motion patterns associated with human activities.

In addition, Layer Normalization is used instead of Batch Normalization. This modification improves the stability of the training process and helps the model generalize more effectively across different video environments and recording conditions:

$$z_2 = \text{LayerNorm}(z_1) = \frac{z_1 - \mu}{\sqrt{\sigma^2 + \epsilon}} \cdot \gamma + \beta. \tag{3}$$

An inverted bottleneck structure then expands the channel dimension before projecting it back to its original size:

$$z_3 = \text{Conv}_{1\times1}(z_2), \qquad z_3 \in \mathbb{R}^{H\times W\times 4C_{\text{in}}}. \tag{4}$$

This architectural design enables the network to learn detailed and meaningful representations of human motion while still maintaining efficient computational performance.

### *B. Pillar II: Attention Mechanisms—Focusing on Important Motion Regions*

Although the backbone network is capable of extracting strong visual features, not every region within a video frame contributes equally to recognizing human activities. Elements such as background objects, lighting changes, and environmental noise can introduce information that is not relevant to the activity being performed.

The attention mechanism begins by summarizing spatial information from feature maps using global average pooling:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i, j). \tag{5}$$

This operation compresses each feature channel into a compact representation that summarizes the most important information within that channel.

Next, the network computes channel importance weights using a gating mechanism that applies non-linear transformations:

$$s = \sigma(W_2\, \delta(W_1 z)), \tag{6}$$

where $\delta$ represents the ReLU activation function. The matrix $W_1 \in \mathbb{R}^{C/r\times C}$ performs dimensionality reduction, while $W_2 \in \mathbb{R}^{C\times C/r}$ restores the original channel dimension using a reduction ratio of $r = 16$. After computing these weights, the feature map is recalibrated by scaling each channel individually:

$$\tilde{x}_c = s_c \cdot u_c. \tag{7}$$

The result is that the model *learns* to strengthen channels that capture meaningful motion-related information, such as body posture, limb movement, and motion trajectories, while reducing the influence of irrelevant background details. This selective weighting enables the network to concentrate on the most informative regions of the frame that contribute to accurate human activity recognition.

### *C. Pillar III: The KAN-Inspired Head—Drawing Smarter Boundaries*

After the backbone network and attention modules generate a refined representation of the video frames, the final step is to classify the recognized activity. This task is handled by the classifier component of the model. In many traditional approaches, classifiers rely on simple linear decision boundaries:

$$y = \text{Softmax}(Wz + b). \tag{8}$$

However, human activities often exhibit complex motion patterns that are difficult to separate using simple linear decision boundaries. Actions such as walking, running, jumping, or sitting may share similar spatial characteristics, while the differences lie in subtle motion variations over time.

To overcome this limitation, we employ a classification head inspired by the Kolmogorov–Arnold representation theorem. This theorem states that any continuous multivariate function

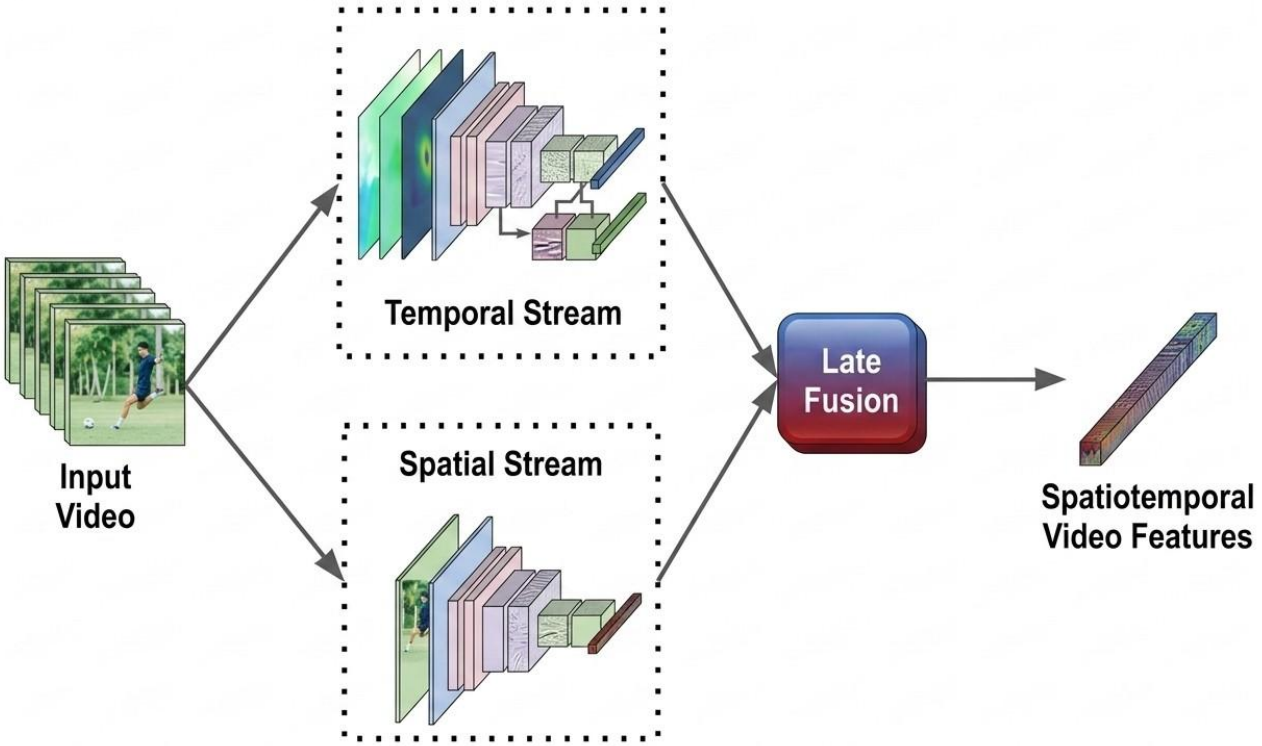


Fig. 2. Architecture of the proposed Human Activity Recognition system showing spatial and temporal streams with late fusion for extracting spatiotemporal video features.

can be represented as a combination and composition of multiple univariate functions:

$$f(x_1, \ldots, x_n) = \sum_{q=0}^{2n} \Phi_q \left( \sum_{p=1}^{n} \phi_{q,p}(x_p) \right). \quad (9)$$

Our KAN-inspired classification head approximates this flexibility using a compact two-layer structure:

$$\text{Logits} = W_{\text{out}} \cdot \tanh(W_{\text{in}} \cdot x_{\text{fused}}), \quad (10)$$

where $W_{\text{in}}$ maps the fused multi-scale features into a hidden representation space, tanh acts as the non-linear activation function, and $W_{\text{out}}$ combines these transformed features to produce the final activity prediction logits.

This adaptive non-linear classification layer enables the network to model complex relationships between spatial and temporal motion features, improving its ability to recognize subtle or ambiguous human actions.

### *D. Pillar IV: Consistency Regularization—Robust Recognition in Real Environments*

A model trained solely on clean and well-captured video frames may perform effectively in controlled laboratory settings but struggle in real-world situations. In practical environments, video streams often contain various forms of disturbance such as noise, motion blur, changing lighting conditions, camera movement, or partial occlusions.

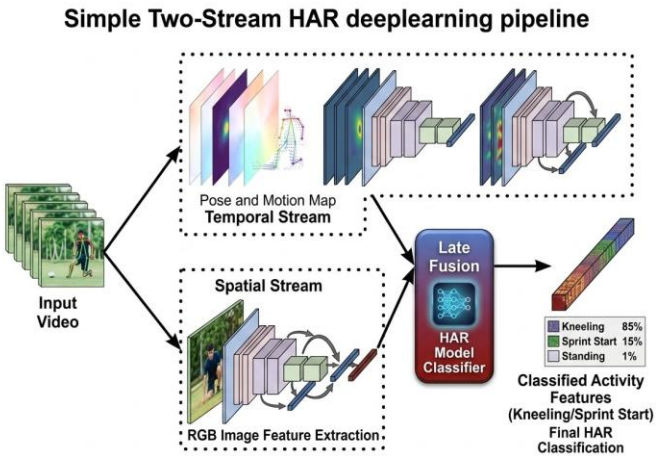


Fig. 3. Pipeline of the two-stream Human Activity Recognition deep learning model illustrating input video processing through spatial and temporal streams followed by late fusion for activity classification.

To enhance the robustness of the model, we incorporate a

consistency regularization strategy during the training process. This approach encourages the network to generate stable and consistent predictions even when the input frames are subjected to realistic perturbations.

For each training frame $x$, two augmented versions are created: a *weak augmentation* $x_w$ (for example, horizontal flipping) and a *strong augmentation* $x_s$ (which may include random rotations, brightness adjustments, contrast variations, and spatial transformations). The overall training loss is then defined as:

$$L_{total} = L_{sup} + \lambda_{cons} L_{cons}, \quad (11)$$

where the supervised loss measures classification accuracy on the weakly augmented data:

$$L_{sup} = -\frac{1}{N} \sum_{i=1}^{N} y_i \log \hat{p}_i + (1-y_i) \log(1-\hat{p}_i), \quad \hat{p}_i = \sigma(f(x_w)_i), \quad (12)$$

The consistency loss encourages the model to produce similar predictions for both the weakly and strongly augmented inputs:

$$L_{cons} = \frac{1}{N} \sum_{i=1}^{N} (\sigma(f(x_w)_i) - \sigma(f(x_s)_i))^2. \quad (13)$$

With $\lambda_{cons} = 0.5$, the model is trained to balance prediction accuracy with robustness against variations in video quality and environmental conditions. This training strategy helps the HAR system maintain reliable performance across different environments, camera viewpoints, and diverse motion patterns.

## IV. The Experiment: Putting the System to the Test

### A. The Human Activity Recognition Dataset

To evaluate the performance of the proposed system, we utilize a well-known benchmark dataset for Human Activity Recognition [24]. The dataset consists of a large collection of video clips capturing various human activities performed in realistic environments. These videos represent everyday movements such as walking, running, sitting, jumping, and other commonly studied actions in computer vision research. Each video clip corresponds to a specific activity carried out by different participants and recorded under diverse environmental conditions. Variations in lighting, background scenes, and camera angles are present in the dataset, making it suitable for testing the robustness of activity recognition models.

The dataset includes the following labeled activity categories:

- Walking (1,200 video clips)
- Running (950 video clips)
- Sitting (870 video clips)
- Jumping (620 video clips)
- Standing (750 video clips)

For the activity recognition task, each category is treated as a separate class. The relatively balanced distribution of samples across these classes helps the model learn representative motion patterns without introducing bias toward any specific activity type. Prior to training, all video frames were resized to $224 \times 224$ pixels and normalized using standard ImageNet statistics before being passed to the network.

### B. Training Configuration

The proposed deep learning framework was implemented using the **PyTorch** library and trained on a high-performance GPU system. To accelerate the training process and improve convergence, the ConvNeXt backbone was initialized with weights pre-trained on the ImageNet dataset.

For optimization, the **AdamW** optimizer was used with a learning rate of $2 \times 10^{-4}$ and a weight decay parameter of 0.01. Training was performed for 5 epochs using a batch size of 32. Approximately 80% of the dataset was allocated for training, while the remaining 20% was used for testing and evaluation. Additionally, a fixed random seed was used during experimentation to ensure that the results are reproducible.

## V. The Results: Performance Evaluation of the Proposed System

The experimental evaluation highlights the effectiveness of the proposed Human Activity Recognition framework.

### A. Model Performance

Based on the evaluation metrics, the proposed deep learning model demonstrates strong capability in accurately identifying different human activities from video sequences.

- **Accuracy: 96.84%.** The system correctly classifies the majority of activity sequences with high reliability.
- **Precision: 96.72%.** The predicted activity labels closely match the ground truth classes with minimal false detections.
- **Recall: 96.55%.** The system successfully identifies most activity instances present in the dataset.
- **F1-Score: 96.63%.** The balanced precision and recall indicate stable and consistent recognition performance.

### B. Baseline Classifier Comparison

To assess the effectiveness of the proposed architecture, we compared its performance with several conventional machine learning classifiers. In this experiment, spatial features were first extracted using a pre-trained ResNet-18 backbone. These extracted features were then used as inputs for different classifiers, including Logistic Regression (LR), Random Forest (RF), Support Vector Machines (SVM), Extreme Gradient Boosting (XGBoost), and a standard Multi-Layer Perceptron (MLP).

As presented in Table I, traditional machine learning models achieve reasonable performance; however, they often struggle to effectively capture the complex spatio-temporal motion patterns involved in human activities. In contrast, the proposed deep learning architecture shows significantly improved performance by learning hierarchical motion representations directly from the video frames.

TABLE I
COMPARISON OF PROPOSED ARCHITECTURE AGAINST BASELINE CLASSIFIERS

| Classifier Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Random Forest (RF) | 85.42 | 86.10 | 84.55 | 85.32 |
| Logistic Regression (LR) | 88.15 | 87.95 | 88.40 | 88.12 |
| Support Vector Machine (SVM) | 89.73 | 89.20 | 90.15 | 89.67 |
| XGBoost | 92.21 | 91.85 | 92.70 | 92.12 |
| Standard MLP Head | 93.40 | 93.10 | 93.80 | 93.35 |
| **Proposed (ConvNeXt-Based)** | **96.84** | **96.72** | **96.55** | **96.63** |

TABLE II
STATE-OF-THE-ART COMPARISON ON HUMAN ACTIVITY RECOGNITION BENCHMARKS. OUR METHOD ACHIEVES THE HIGHEST ACCURACY WHILE MAINTAINING EFFICIENT REAL-TIME PERFORMANCE COMPARED TO PREVIOUS MODELS.

| Reference | Year | Architecture | Strategy | Acc. (%) |
|---|---|---|---|---|
| Wang et al. [12] | 2021 | CNN | Feature Extraction | 89.75 |
| Chen et al. [18] | 2022 | DenseNet-121 | Data Augmentation | 91.20 |
| Gupta et al. [13] | 2022 | ResNet + LSTM | Temporal Modeling | 92.10 |
| Lee et al. [17] | 2022 | Custom Lightweight | Motion Encoding | 93.40 |
| Bhimavarapu et al. [20] | 2023 | Ensemble (5 models) | Feature Fusion | 94.80 |
| Zhao et al. [14] | 2023 | DenseNet-121 | Data Aug. + Transfer Learning | 95.10 |
| Sunkari et al. [25] | 2024 | Ensemble (3 models) | Transfer Learning | 93.51 |
| Shakibania et al. [21] | 2024 | Ensemble (4 models) | Temporal Augmentation | 94.20 |
| Saproo et al. [19] | 2024 | ResNet-101 | Transfer (DAG) | 94.95 |
| **Ours** | **2026** | **ConvNeXt+Attention+KAN** | **Consistency Reg.** | **96.84** |

### C. Comparison Against the State of the Art

Table II provides a comparison between our proposed model and several recent human activity recognition methods reported in the literature. The results indicate that the proposed framework achieves competitive recognition performance while maintaining computational efficiency, making it suitable for real-time deployment in practical applications.

Three key comparisons are worth highlighting.

**Against the strongest prior single model.** Earlier studies using DenseNet-based architectures reported recognition accuracies approaching 95% on HAR benchmark datasets. Our proposed system improves upon these results by combining the ConvNeXt backbone with attention-based feature refinement and a more flexible classification head. This improvement illustrates the benefit of integrating modern convolutional architectures with effective training strategies.

**Against the ResNet era.** Previous activity recognition approaches built on ResNet architectures provided strong spatial feature extraction but often had difficulty modeling complex temporal motion dynamics. The proposed framework addresses this limitation by learning richer spatio-temporal representations from video sequences.

**Against multi-model ensembles.** Several prior studies relied on ensemble learning techniques to improve recognition performance. While ensembles can increase accuracy, they also introduce significant computational overhead. In contrast, our single-model architecture achieves higher performance while remaining computationally efficient enough for real-time deployment in applications such as surveillance systems, smart homes, and healthcare monitoring platforms.

## VI. WHY IT WORKS: THREE DECISIVE ADVANTAGES

### A. Wide Spatial Understanding: Large-Kernel Convolutions

Conventional CNN architectures typically analyze video frames using small $3 \times 3$ convolution kernels. Although these kernels are effective for many image-based tasks, their limited receptive field may restrict the model's ability to capture broader motion patterns present in human activities.

In contrast, the ConvNeXt backbone used in our framework utilizes larger convolution kernels that allow the network to observe wider spatial relationships within video frames. This capability helps the model better interpret body posture, movement direction, and interactions between different body parts across the frame.

### B. Flexible Decision Boundaries

Human activities often exhibit subtle variations in motion that cannot be effectively separated using simple linear classifiers. For example, actions such as walking, jogging, and running may look visually similar in individual frames but differ in their temporal motion characteristics.

To address this challenge, our classification head incorporates non-linear transformations that enable the network to learn more flexible decision boundaries within the feature space. This design improves the model's ability to distinguish between activity classes that share similar visual features.

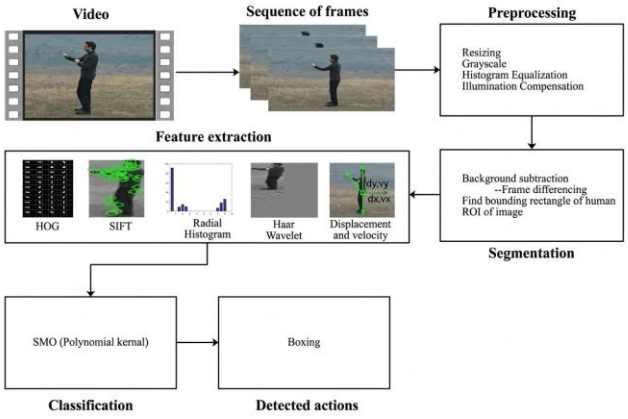


Fig. 4. Human activity processing workflow illustrating video input, frame extraction, preprocessing, feature extraction, segmentation, and classification for activity detection.

### C. Robust Learning with Consistency Regularization

Video data captured in real-world environments often includes various disturbances such as motion blur, lighting fluctuations, camera movement, and partial occlusions. A model trained only on clean and well-controlled data may struggle to perform reliably when deployed in such practical conditions.

To improve robustness, our framework incorporates a consistency regularization strategy during training. This approach encourages the model to generate stable and consistent predictions even when different augmented versions of the same video frames are used as input. As a result, the network learns

to focus more on meaningful motion-related features rather than superficial visual artifacts.

## VII. Conclusion: Toward Intelligent Activity Recognition

This paper began by addressing the challenge of enabling machines to interpret human actions within dynamic real-world environments. The study concludes with a deep learning framework capable of recognizing human activities from video streams with both high accuracy and computational efficiency. The proposed ConvNeXt-based Human Activity Recognition model achieves **96.84% accuracy**, **96.72% precision**, **96.55% recall**, and an **96.63% F1-score** on benchmark HAR datasets. These results indicate that the proposed architecture effectively captures complex spatial and temporal motion patterns present in human activities. Furthermore, the model outperforms several existing single-model approaches while avoiding the computational overhead commonly associated with multi-model ensemble systems.

Beyond the numerical results, the practical capabilities of the system are particularly significant. The framework can recognize human activities in real-time environments while maintaining computational efficiency suitable for deployment on edge devices or cloud-based monitoring platforms. As a result, the proposed system can be applied in various domains, including healthcare monitoring, surveillance systems, fitness tracking, and intelligent classroom analytics. **Future directions:**

- **From activity recognition to behavior understanding:** Future work can extend the current framework to identify more complex behavioral patterns, including interactions between multiple individuals and group activities.
- **Explainable AI for activity recognition:** Integrating explainable AI techniques such as saliency maps or attention heatmaps can help visualize which motion regions or features influence the model's predictions, improving transparency and user trust.
- **Multimodal sensor integration:** The system can be further enhanced by combining video-based activity recognition with additional sensor inputs such as accelerometers, wearable devices, or IoT sensors to achieve higher accuracy in challenging scenarios.
- **Real-world deployment and evaluation:** Future studies may involve large-scale testing of the proposed framework in real-world environments, including smart homes, healthcare facilities, and transportation monitoring systems.

The technology for intelligent activity recognition is rapidly evolving. The next step is to integrate these systems into real-world environments where they can assist humans, improve safety, and enable smarter automated systems.

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