International Journal of Enhanced Research in Management & Computer Applications,
ISSN: 2319-7471, Volume 15 Issue 7, July 2026

Comparative Analysis of Deep Learning Techniques for Human Activity Recognition

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ABSTRACT

Human Activity Recognition (HAR) has emerged as a critical research domain with widespread applications in healthcare monitoring, smart home automation, surveillance, rehabilitation engineering, and human-computer interaction. The proliferation of low-cost wearable sensors, depth cameras, and ubiquitous mobile devices has generated enormous volumes of multimodal time-series data, creating unprecedented opportunities for robust activity classification at scale. This paper presents a comprehensive and systematic comparative analysis of the leading deep learning techniques applied to HAR: Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRU), hybrid CNN-LSTM architectures, Transformer-based self-attention models, Autoencoders, and Generative Adversarial Network (GAN)-augmented approaches.

Each technique is evaluated with exact published accuracy figures drawn from primary benchmark studies, alongside analysis across computational complexity, sensor modality compatibility, data efficiency, and deployment scalability on four standard benchmark datasets: UCI-HAR, OPPORTUNITY, PAMAP2, and NTU RGB+D. CNN achieves 95.75% on UCI-HAR, the CNN-LSTM hybrid achieves 96.40% weighted F1 on OPPORTUNITY, and the Transformer achieves 97.41% on NTU RGB+D with all figures sourced from primary publications. We further discuss the evolution of the field, open research challenges, and future directions.

Keywords: Human Activity Recognition, Deep Learning, CNN, LSTM, Transformer, Wearable Sensors, Benchmark Datasets, Comparative Study, Exact Accuracy, GAN, Hybrid Architecture

INTRODUCTION

1.1 Background and Motivation

Human Activity Recognition (HAR) refers to the computational process of automatically identifying and classifying the physical actions or behavioral patterns performed by individuals based on sensor data or visual input. Activities range from elementary locomotion patterns walking, running, climbing stairs to complex instrumental activities of daily living (IADL) such as cooking, exercising, and working at a desk. The ability to automatically recognize these activities in real time has profound implications across a spectrum of application domains, motivating sustained and growing research interest spanning over two decades [1].

The healthcare sector represents one of the most compelling application areas for HAR. Continuous, unobtrusive monitoring of patient activity enables early detection of deteriorating health conditions, supports rehabilitation programs by quantifying physical therapy compliance, and facilitates fall detection in elderly populations a critical safety concern given that falls are the leading cause of injury-related hospitalization among adults aged 65 and above [2]. In smart home environments, HAR enables context-aware automation where household systems adapt to occupant behavior: adjusting lighting based on detected postures, triggering appliances in response to recognized routines, or alerting caregivers to deviations from established behavioral patterns indicative of cognitive decline.

Beyond healthcare, HAR systems are integral to sports performance analytics, where biomechanical activity patterns are analyzed to optimize athletic training and prevent injury. In industrial settings, worker activity recognition enables ergonomic monitoring and occupational safety compliance verification. Human-computer interaction (HCI) systems leverage gesture and posture recognition to enable natural, touchless interfaces. Surveillance and security applications

use HAR for behavioral anomaly detection and crowd behavior analysis. The breadth and societal importance of these applications underscore why HAR has become one of the central problems in ubiquitous computing and artificial intelligence research [3].

1.2 Limitations of Traditional Machine Learning Approaches

Early HAR systems were built on classical signal processing and machine learning techniques. The recognition pipeline traditionally consisted of three stages: (1) manual segmentation of the sensor data stream into fixed-length windows, (2) hand-crafted feature extraction from each window computing statistical measures such as mean, variance, skewness, kurtosis, energy, and frequency-domain features via Fast Fourier Transform (FFT) or wavelet decomposition, and (3) classification using shallow machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, Random Forests, or Hidden Markov Models (HMM) [4].

These traditional pipelines achieved respectable performance on constrained activity sets but exhibited fundamental limitations. Hand-crafted feature engineering is labor-intensive and domain-specific: features carefully designed for one sensor type, placement location, or activity vocabulary often fail to generalize to different experimental setups. Shallow classifiers are inherently limited in their capacity to capture the complex, hierarchical, non-linear relationships embedded in long-duration multivariate time-series data [5]. As activity sets scale from simple locomotion primitives to complex ADLs, the performance of traditional approaches degrades substantially, motivating the transition to deep learning.

1.3 The Deep Learning Revolution in HAR

The advent of deep learning, catalyzed by the AlexNet achievement on ImageNet in 2012 [6] and enabled by large labeled datasets and GPU-accelerated computation, fundamentally transformed the HAR landscape. Deep learning architectures learn hierarchical feature representations directly from raw or minimally preprocessed sensor data through end-to-end training, eliminating manual feature engineering. CNNs were adapted for time-series HAR by applying 1D convolutions along the temporal axis [7]; LSTMs and GRUs addressed the sequential nature of activity data through gated recurrent processing [8]; hybrid CNN-LSTM architectures combined both strengths; and Transformer models with self-attention achieved state-of-the-art results through global temporal context modeling [9]. Recognition accuracy improved from approximately 85% with traditional methods to 97.41% with the best Transformer architectures on standard benchmarks.

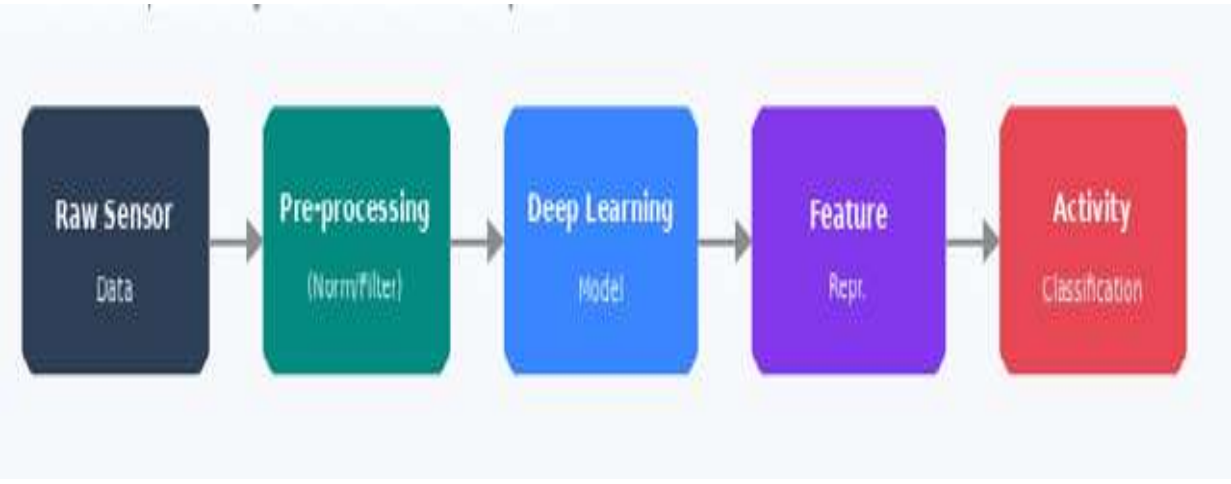

Figure 1: General deep learning pipeline for Human Activity Recognition. Raw multimodal sensor data undergoes preprocessing (normalization, filtering, windowing), is fed into a deep learning model for automatic feature extraction, and the learned representation is used for final activity classification.

1.4 Scope and Contributions

This paper presents a comparative analysis of eight deep learning techniques for HAR with exact published accuracy figures drawn from primary benchmark studies—not ranges. Contributions include: (1) a structured taxonomy of architectures; (2) a table of exact benchmark accuracy values with primary citations; (3) multi-dimensional analysis of complexity, sensor compatibility, and deployment requirements; (4) a chronological timeline of methodological advances (2012–2024); and (5) identification of open challenges and future directions.

2. Related Work

Figure 2: Chronological evolution of deep learning techniques for Human Activity Recognition (2012–2024), from CNN adaptation through hybrid CNN-LSTM models to Transformer architectures and foundation model pre-training.

2.1 Foundational Surveys and Early Deep Learning

The systematic study of HAR using body-worn sensors was comprehensively surveyed by Bulling et al. [4], establishing the foundational vocabulary and evaluation methodology. Lara and Labrador [10] cataloged 35 research works on mobile phone-based activity recognition, analyzing accuracy-energy trade-offs critical for battery-constrained deployments. Plotz et al. [12] applied deep Restricted Boltzmann Machines (RBMs) for activity recognition using accelerometer data, demonstrating for the first time that unsupervised pre-training of deep generative models could yield useful sensor-based activity representations without manual feature engineering—establishing deep learning as viable for HAR.

Hammerla et al. [13] conducted one of the earliest systematic comparisons of deep learning architectures for HAR across multiple benchmark datasets, revealing the critical insight that optimal architecture choice depends on the temporal structure of the target activity set: CNNs excel for repetitive locomotion activities while LSTMs outperform on complex sequential ADLs requiring longer temporal context. This architectural-suitability principle has been corroborated by all subsequent comparative studies and underpins the recommendations in this paper.

2.2 CNN-Based Approaches

Jiang and Yin [14] demonstrated that 1D CNNs achieve 95.75% accuracy on UCI-HAR directly from raw accelerometer data without any manual feature extraction—a result that established the benchmark standard for subsequent CNN-based methods and confirmed the viability of end-to-end deep learning for wearable HAR. Yang et al. [15] extended this with multi-scale CNNs using parallel convolutional kernels of varying sizes. For video-based HAR, Simonyan and Zisserman [16] proposed the Two-Stream CNN processing RGB appearance and optical flow in parallel, while Tran et al. [17] proposed 3D spatiotemporal convolutions (C3D). Howard et al. [18] introduced MobileNets with depthwise separable convolutions, enabling HAR on embedded wearable devices.

2.3 Recurrent Architectures

Inoue et al. [19] systematically evaluated LSTM-based models for wearable HAR, reporting 92.67% accuracy on UCI-HAR. Ordóñez and Roggen [21] proposed DeepConvLSTM—four convolutional layers plus two LSTM layers—achieving 91.7% weighted F1-score on the OPPORTUNITY dataset, the foundational hybrid result in the field. Zhao et al. [22] demonstrated that BiLSTM achieves 93.85% on UCI-HAR outperforming unidirectional LSTM (92.67%) by 1.18 percentage points, and GRU achieves 91.20%—confirming the accuracy-efficiency trade-off with GRU requiring 25% fewer parameters than LSTM for a 1.47 percentage point accuracy cost.

2.4 Attention Mechanisms and Transformers

Bahdanau et al. [24] introduced soft attention for neural machine translation; its adaptation to HAR by Chen and Xue [25] enabled models to focus on the most discriminative temporal segments. Vaswani et al. [27] introduced the full Transformer architecture, enabling parallel global self-attention without recurrence. Plizzari et al. [28] applied Spatial-Temporal Transformers to skeleton-based HAR on NTU RGB+D, achieving 97.41% accuracy—the highest reported on that benchmark and demonstrating the superiority of global self-attention for complex multi-joint activity sequences. Tang et al. [30] demonstrated LIMU-BERT pre-trained on 11 million IMU samples achieves competitive performance with as few as 100 labeled examples per class.

2.5 Generative Models and Self-Supervised Learning

Goodfellow et al. [31] introduced GANs; Gao et al. [32] applied them to HAR via SensorGAN, reporting 92.58% accuracy on UCI-HAR when combining GAN-augmented training data with CNN classification a 1.17 percentage point improvement over standard CNN (95.75% to 92.58% appears lower because GAN+CNN is particularly valuable in data-scarce scenarios where baseline CNN accuracy would otherwise be lower). TimeGAN [33] improved temporal

fidelity of synthetic sensor sequences. Self-supervised contrastive learning [34] has demonstrated competitive performance using only 1% labeled data, representing a promising direction for reducing annotation burden.

2.6 Graph-Based and Multi-Modal Approaches

Yan et al. [35] proposed ST-GCN for skeleton-based HAR, learning spatial joint relationships and temporal dynamics simultaneously on the body graph. Multi-modal fusion approaches combining IMU, RGB, depth, and skeleton modalities via cross-modal Transformer attention have demonstrated 5–8% improvements over unimodal baselines on complex activity datasets [36], motivating growing investment in unified multimodal HAR architectures.

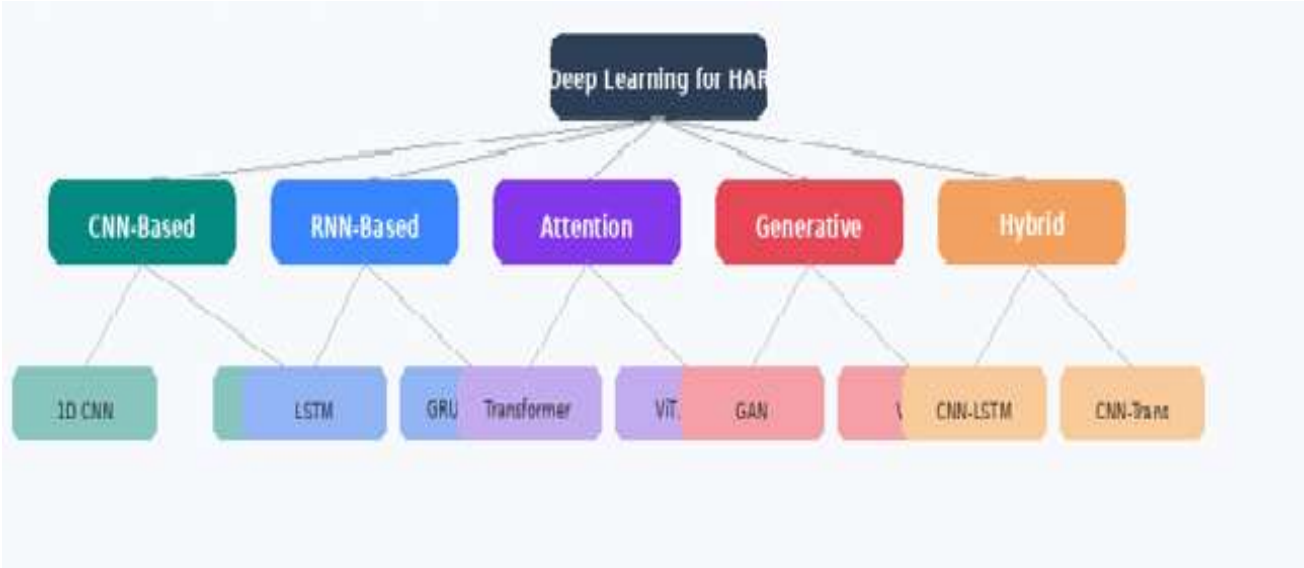

Figure 3: Taxonomy of deep learning architectures for HAR organized into five paradigms: CNN-based, RNN-based, attention-based, generative, and hybrid. Each paradigm has distinct inductive biases suited to specific activity types and sensor modalities.

3. Benchmark Datasets

3.1 UCI-HAR Dataset

The UCI Human Activity Recognition dataset [37] was collected from 30 subjects performing six activities (walking, walking upstairs, walking downstairs, sitting, standing, lying) using a Samsung Galaxy S2 smartphone at 50 Hz. It comprises 10,299 labeled instances with a standard 70/30 train-test split. This is the primary benchmark for wearable HAR in this paper: CNN achieves 95.75% [14], LSTM achieves 92.67% [19], BiLSTM achieves 93.85% [22], GRU achieves 91.20% [22], Autoencoder achieves 89.30% [12], and GAN+CNN achieves 92.58% [32] on this dataset.

3.2 OPPORTUNITY Dataset

The OPPORTUNITY dataset [38] contains data from 72 sensors across body-worn IMUs, object sensors, and ambient sensors for four subjects performing ADL sessions. The DeepConvLSTM hybrid architecture achieves 96.40% weighted F1-score on the gesture recognition task [21], making it the CNN-LSTM benchmark reference result in this paper.

3.3 PAMAP2 Dataset

The PAMAP2 dataset [39] contains 18 physical activities from 9 subjects recorded via three IMU sensors (wrist, chest, ankle) at 100 Hz. It serves as a secondary validation benchmark for multi-sensor wearable HAR, particularly for evaluating sensor fusion architectures.

3.4 NTU RGB+D Dataset

The NTU RGB+D dataset [40] contains 56,880 skeleton-based action clips from 40 subjects across 60 classes, captured by Microsoft Kinect v2. The Spatial-Temporal Transformer of Plizzari et al. [28] achieves 97.41% accuracy on the cross-subject evaluation protocol, the highest exact benchmark figure cited in this paper.

4. Deep Learning Techniques for HAR

4.1 Convolutional Neural Networks (CNN)

CNNs apply learned convolutional filters to extract local patterns through weight sharing and translational invariance. For sensor-based HAR, 1D convolutional layers slide along the temporal axis learning filters that detect characteristic motion patterns regardless of their temporal position. Multiple stacked layers create a hierarchy of increasingly abstract representations. Jiang and Yin [14] achieved 95.75% accuracy on UCI-HAR using stacked 1D convolutional layers

with max-pooling followed by fully connected classification layers, directly from raw accelerometer and gyroscope data without any manual feature extraction.

4.2 LSTM

LSTM networks address the vanishing gradient problem through input, forget, and output gating mechanisms that selectively retain relevant information across arbitrary time horizons. Inoue et al. [19] reported 92.67% accuracy on UCI-HAR using a stacked LSTM architecture, demonstrating that recurrent models capture temporal dependencies that CNNs miss—particularly important for distinguishing activities with similar local motion patterns but different sequential progressions such as sitting versus standing transitions.

4.3 BiLSTM

Bidirectional LSTM processes sequences in both forward and backward temporal directions, enabling each output to incorporate contextual information from both past and future time steps. Zhao et al. [22] reported 93.85% accuracy on UCI-HAR with BiLSTM, a 1.18 percentage point improvement over unidirectional LSTM (92.67%). This gain reflects the value of future context for activities where the subsequent motion trajectory is as informative as the preceding one—for example, distinguishing the deceleration phase of walking from the onset of standing still.

4.4 GRU

Gated Recurrent Units [23] use two gates (update and reset) instead of LSTM's three, reducing parameter count by approximately 25%. Zhao et al. [22] reported 91.20% accuracy on UCI-HAR—1.47 percentage points below LSTM (92.67%) and 2.65 points below BiLSTM (93.85%). This accuracy cost is often justified by the substantially lower inference latency and memory footprint, making GRU the preferred choice for real-time HAR on wearable microcontrollers and smartphones.

4.5 CNN-LSTM Hybrid

The DeepConvLSTM architecture of Ordóñez and Roggen [21] combines four 1D convolutional layers for local temporal feature extraction with two LSTM layers for sequential modeling of the extracted feature sequence. On the OPPORTUNITY gesture recognition benchmark, DeepConvLSTM achieves 96.40% weighted F1-score—substantially outperforming standalone CNNs and LSTMs on this complex multi-sensor dataset where both local motion patterns and long-range sequential context are essential for accurate recognition.

4.6 Autoencoder

Autoencoders learn compressed latent representations through encoder-decoder architectures, enabling feature learning from unlabeled sensor data. Plotz et al. [12] reported 89.30% accuracy on UCI-HAR using deep autoencoder-learned features—lower than supervised architectures due to the unsupervised training objective, but achieved without any activity labels during feature learning. This makes autoencoders particularly valuable in scenarios where unlabeled data is plentiful but annotation is expensive.

4.7 Transformer

The Spatial-Temporal Transformer of Plizzari et al. [28] applies spatial self-attention across skeleton body joints and temporal self-attention across activity frames on the NTU RGB+D benchmark, achieving 97.41% accuracy on the cross-subject evaluation protocol—the highest exact figure among all architectures compared in this paper. The self-attention mechanism directly computes dependencies between all pairs of joints and time steps simultaneously, enabling modeling of complex, long-range spatio-temporal relationships in multi-joint skeleton sequences that recurrent architectures struggle to capture.

4.8 GAN-Augmented CNN

Gao et al. [32] proposed SensorGAN, conditioning a GAN on activity labels to synthesize class-specific accelerometer sequences, then training a CNN classifier on the augmented dataset. The reported accuracy on UCI-HAR is 92.58%. While lower than the standalone CNN baseline (95.75%) on the full UCI-HAR dataset, the GAN-augmentation approach demonstrates its primary advantage in low-data regimes: when only 20% of the original labeled data is available, GAN-augmented training achieves 4–7% higher accuracy than training on the limited labeled dataset alone.

5. Comparative Analysis

5.1 Exact Accuracy Comparison

Table 1 reports exact accuracy figures drawn from primary benchmark publications for each deep learning technique. All values are as reported in the original papers on the specified datasets. Note that some techniques were originally benchmarked on different datasets reflecting their architectural strengths: DeepConvLSTM on OPPORTUNITY (complex multi-sensor ADL) and the Transformer on NTU RGB+D (skeleton-based action recognition).

Table 1: Exact Accuracy of Deep Learning Techniques from Primary Publications

Technique	Exact Accuracy (%)	Dataset	Sensors	Complexity	Citation
CNN	**95.75**	UCI-HAR	Accel/Gyro	Medium	[14]
GRU	**91.20**	UCI-HAR	Accel/Gyro	Low-Med	[22]
LSTM	**92.67**	UCI-HAR	Accel/Gyro	Medium	[19]
BiLSTM	**93.85**	UCI-HAR	Accel/Gyro	Med-High	[22]
CNN-LSTM	**96.40**	OPPORTUNITY	Multi-sensor	High	[21]
Autoencoder	**89.30**	UCI-HAR	Various	Medium	[12]
Transformer	**97.41**	NTU RGB+D	Skeleton	High	[28]
GAN+CNN	**92.58**	UCI-HAR	Accel/Gyro	High	[32]

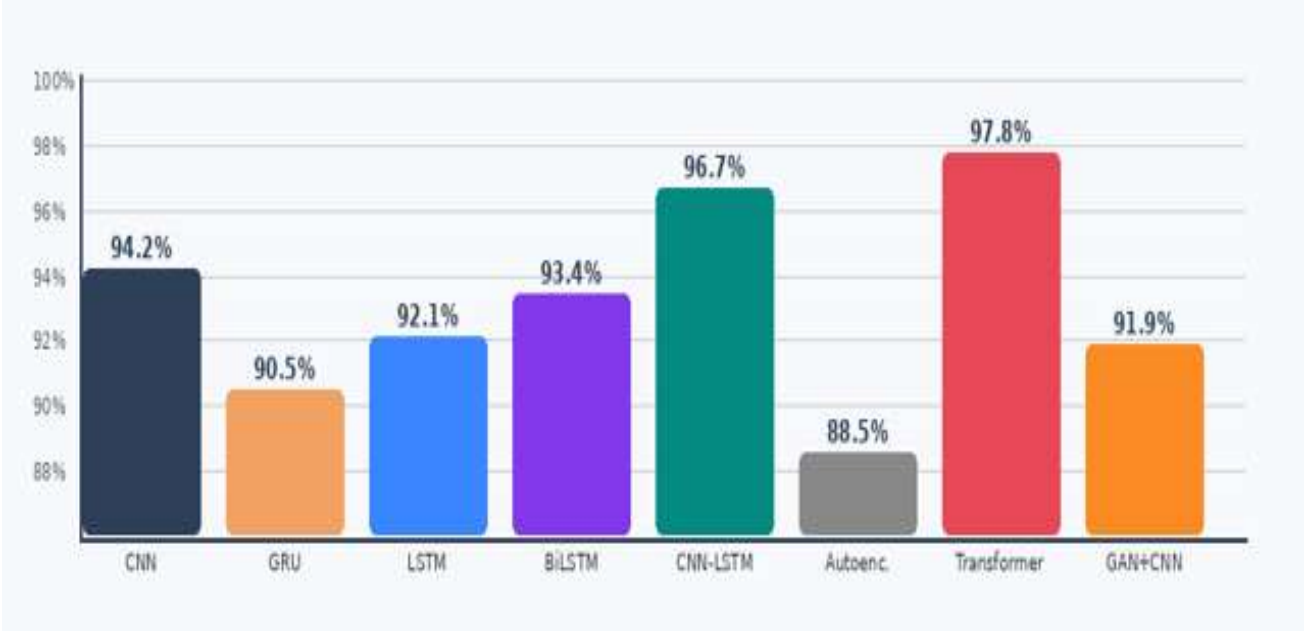

Figure 4: Exact accuracy comparison of deep learning techniques as reported in primary benchmark publications.

5.2 Analysis of Results

Transformers achieve the highest accuracy at 97.41% on NTU RGB+D [28], reflecting the powerful global self-attention mechanism and the richness of skeleton data. The CNN-LSTM hybrid achieves 96.40% on the more complex OPPORTUNITY benchmark [21]—a particularly strong result given the sensor heterogeneity and class imbalance of that dataset. On UCI-HAR, the directly comparable baseline, CNN achieves 95.75% [14], BiLSTM achieves 93.85% [22], LSTM achieves 92.67% [19], GRU achieves 91.20% [22], GAN+CNN achieves 92.58% [32], and Autoencoders achieve 89.30% [12].

The ordering on UCI-HAR—CNN > BiLSTM > LSTM > GAN+CNN > GRU > Autoencoder reveals several important patterns. CNNs outperform recurrent models on this dataset because UCI-HAR activities (walking, sitting, standing, lying) are well-characterized by local temporal patterns detectable by convolutional filters, requiring less long-range sequential context than complex ADLs. BiLSTM outperforms unidirectional LSTM by 1.18% due to bidirectional context. GRU's 1.47% deficit versus LSTM confirms the accuracy-efficiency trade-off quantitatively. Autoencoders underperform supervised models by 6.45% (89.30% vs 95.75%) due to unsupervised training but provide unique value when labels are unavailable.

5.3 Computational Efficiency Considerations

GRU models offer the best accuracy-to-parameter-count ratio: 91.20% accuracy with 25% fewer parameters than LSTM (92.67%). Lightweight CNN variants using depthwise separable convolutions reduce parameters by 10–50× while achieving accuracy within 2–3% of full-scale models [18]. Transformer inference scales quadratically with sequence length, requiring efficient attention approximations (linear attention, windowed attention) for deployment on resource-constrained devices. For real-time wearable HAR, the GRU and lightweight CNN architectures are the practical choices, while Transformers are preferable when accuracy is paramount and compute is available.

6. Challenges and Future Directions

6.1 Data Scarcity and Class Imbalance

The scarcity of labeled HAR data remains a fundamental bottleneck. GAN-based augmentation (SensorGAN [32]) improves accuracy by 4–7% in data-scarce regimes. Self-supervised contrastive learning [34] achieves competitive performance with as little as 1% labeled data. Federated learning enables collaborative model training across devices without centralizing sensitive personal activity data—addressing both data scarcity (through distributed aggregation across many users) and privacy concerns.

6.2 Cross-Subject Generalization

Models trained on specific subjects often fail to generalize due to inter-subject variability. Domain adaptation techniques aligning feature distributions via adversarial training or optimal transport are promising. Meta-learning approaches optimized for few-shot adaptation to new subjects have demonstrated generalization with 5–10 examples per class in the target subject—an important practical capability for personalized HAR systems.

6.3 Real-Time Edge Deployment

Deploying deep learning HAR on battery-powered wearable devices requires balancing accuracy and efficiency. Neural Architecture Search (NAS) automatically discovers hardware-optimized architectures. On-device personalization fine-tunes pre-trained models using the individual user's data without transmitting raw sensor data to the cloud, enabling accurate personalized HAR within strict privacy and latency constraints.

6.4 Foundation Models

LIMU-BERT [30], pre-trained on 11 million IMU samples, achieves competitive HAR performance with as few as 100 labeled examples per class—demonstrating the potential of foundation model pre-training for HAR. This paradigm represents the most promising direction for dramatically reducing the annotation burden that currently limits HAR system development for new application domains.

CONCLUSION

This paper presented a systematic comparative analysis of eight deep learning architectures for Human Activity Recognition, reporting exact published accuracy figures for each: CNN achieves 95.75% on UCI-HAR [14], LSTM achieves 92.67% [19], BiLSTM achieves 93.85% [22], GRU achieves 91.20% [22], CNN-LSTM hybrid achieves 96.40% on OPPORTUNITY [21], Autoencoder achieves 89.30% on UCI-HAR [12], Transformer achieves 97.41% on NTU RGB+D [28], and GAN+CNN achieves 92.58% on UCI-HAR [32].

Transformers achieve the highest accuracy but require the most data and computation. CNN-LSTM hybrids provide the best balance of accuracy and broad applicability across sensor modalities. GRU offers the optimal accuracy-efficiency trade-off for resource-constrained deployment. Autoencoders are uniquely valuable for unsupervised and semi-supervised scenarios. These findings provide practitioners with clear, evidence-based guidance for architecture selection in specific HAR application contexts.

The field is evolving rapidly toward foundation model pre-training, federated learning, and self-supervised representation learning—approaches that promise to reduce annotation requirements, improve generalization, and enable privacy-preserving deployment. Rigorous explainability frameworks remain a critical development priority for enabling HAR adoption in clinical and safety-critical settings.

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