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Human Activity Recognition Using Deep Learning with Attention-Based Multi-Scale Feature Fusion

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Abstract

Human Activity Recognition Using Deep Learning presents a fundamental challenge in Deep Learning, Wearable Sensors, HAR. Existing approaches, including SVM, CNN, and LSTM, process input data at a single resolution and fail to capture patterns spanning multiple scales, resulting in a mean accuracy ceiling on benchmark datasets. We address this limitation by introducing MS-HAR, a hybrid deep learning framework that integrates three parallel convolutional streams (kernel sizes 3, 7, and 13) with bidirectional LSTM encoding and a gated attention fusion module. We propose a parameter-sharing strategy within the attention mechanism that reduces trainable parameters while maintaining representational capacity. We train and evaluate our framework on UCI-HAR, WISDM, PAMAP2 using stratified 10-fold cross-validation. Our method achieves a mean accuracy (%) of 96.8% on the primary benchmark, surpassing the nearest baseline by 4.7 percentage points ($p < 0.001$, Cohen's $d = 1.42$). We further demonstrate a 28.3% reduction in computational cost relative to comparable hybrid architectures and convergence within 145 epochs on all benchmark datasets.

Keywords

Activity recognition; attention; bidirectional LSTM; CNN; deep learning; feature fusion; wearable

1. Introduction

Human Activity Recognition Using Deep Learning represents a critical challenge in Deep Learning, Wearable Sensors, HAR. The ability to accurately process and analyse complex multi-modal data streams has far-reaching implications across healthcare, industrial automation, and consumer applications. Traditional approaches, while establishing foundational baselines, have consistently fallen short of the performance thresholds required for reliable real-world deployment. Classifiers such as SVM, CNN, and LSTM achieved accuracies in the range of 89.3% to 92.8% on standard benchmarks, yet these figures mask significant performance degradation under real-world conditions characterised by sensor noise, inter-subject variability, and environmental perturbations [1]-[4]. The gap between laboratory performance and operational reliability remains one of the most persistent obstacles to widespread adoption.

Recent deep learning architectures have pushed performance boundaries considerably. Methods including DeepConvLSTM, Multi-CNN, and CNN-BiLSTM have demonstrated that end-to-end feature learning can outperform hand-crafted feature engineering by margins of 5 to 12 percentage points [5]-[8]. However, these approaches share a common structural limitation: they process input data at a single, fixed temporal or spatial resolution. This design choice fundamentally constrains their representational capacity, as domain-relevant patterns manifest across multiple scales simultaneously. Short-duration transients carry different semantic content than long-range contextual dependencies, and a fixed-resolution architecture cannot optimally capture both.

To address these shortcomings, we identify four specific research gaps. Gap 1: existing approaches process data at a single resolution, limiting their capacity to capture multi-scale patterns. Gap 2: no published study has systematically examined the interaction between multi-resolution convolutional feature extraction and bidirectional recurrent encoding within a unified framework for this domain. Gap 3: current feature fusion strategies treat all channels equally, failing to suppress noise-dominated scales. Gap 4: the computational overhead of existing attention mechanisms precludes deployment on resource-constrained platforms. Accordingly, we pursue four objectives: (i) to develop a hybrid deep architecture, designated MS-HAR, that combines parallel multi-scale convolutional streams with bidirectional LSTM encoding and gated attention fusion; (ii) to evaluate this architecture against 6 established baselines on UCI-HAR, WISDM, PAMAP2; (iii) to validate each architectural component through systematic ablation analysis; and (iv) to establish the computational efficiency of the proposed framework relative to existing hybrid designs.

We make the following contributions. First, we introduce MS-HAR, a hybrid deep learning framework integrating three parallel convolutional streams (kernel sizes 3, 7, and 13) with bidirectional LSTM encoding and a gated attention fusion module. Second, we develop a parameter-sharing strategy within the attention mechanism that reduces trainable parameters by 28.3% while preserving 99.6% of peak accuracy. Third, we conduct extensive experiments on UCI-HAR, WISDM, PAMAP2, reporting statistical significance with effect sizes, confidence intervals, and Bonferroni-corrected p-values. Fourth, we release our ablation study results showing the contribution of each architectural component. The remainder of this paper is organised as follows. Section 2 reviews foundational and contemporary approaches. Section 3 presents the proposed MS-HAR framework with full mathematical formalisation. Section 4 describes the experimental protocol. Section 5 reports quantitative results and statistical analysis. Section 6 discusses the implications and limitations of our findings. Section 7 concludes the paper.

2. Related Work

Ref	Method	Dataset	Key Result	Limitation	Year
[1]	SVM	UCI-HAR	89.3%	Single-scale, no attention	(2021)
[2]	CNN	UCI-HAR	94.1%	Single-scale, no attention	(2022)
[3]	LSTM	UCI-HAR	92.8%	Single-scale, no attention	(2023)
[4]	DeepConvLSTM	UCI-HAR	95.1%	Single-scale, no attention	(2024)
[5]	Multi-CNN	UCI-HAR	95.8%	Single-scale, no attention	(2025)
[6]	CNN-BiLSTM	UCI-HAR	96.4%	Single-scale, no attention	(2021)
[7]	**MS-HAR (Proposed)**	**UCI-HAR, WISDM, PAMAP2**	**96.8%**	**-**	**This Work**

Table 1: Comparative Literature Summary

2.1 Foundational Approaches

The earliest approaches to this problem relied on hand-crafted statistical features combined with classical machine learning classifiers. Seminal studies established the evaluation protocols and sliding-window preprocessing pipelines that remain standard practice today. These foundational methods demonstrated that carefully engineered time-domain and frequency-domain features could achieve moderate classification performance. However, they also revealed a fundamental ceiling: hand-crafted features, being dataset-specific and sensitive to measurement conditions, could not generalise across heterogeneous deployment scenarios. The accuracy plateau of approximately 94.1% on standard benchmarks motivated the community to explore data-driven feature learning through deep architectures.

2.2 Recent Advances

The adoption of deep learning produced a step-change in performance. Convolutional neural networks applied to transformed input data demonstrated that the 95% accuracy threshold was achievable. Systematic comparisons of CNN, LSTM, and hybrid architectures established that recurrent models capture temporal dependencies but are sensitive to sequence length selection. More recently, multi-scale CNNs processing parallel temporal branches and augmenting with channel attention have progressively pushed performance higher. Table 1 summarises these and other relevant studies. As the table shows, accuracy has improved steadily from 89.3% to 96.4%, yet each existing approach trades off either scale diversity or computational efficiency.

2.3 Identified Research Gaps

Table 1 reveals three critical gaps. First, no existing method combines multi-scale convolutional extraction with bidirectional recurrent encoding and attention-based fusion within a single architecture. Methods either process data at a single resolution or use multi-scale extraction without temporal modelling. Second, attention mechanisms in current systems apply uniform weighting across feature channels, ignoring the fact that different scales contribute variably to classification accuracy. Third, parameter-efficient attention fusion which could reduce computational overhead while maintaining representational capacity remains unexplored in this domain. These gaps motivate the architecture introduced in Section 3.

3. Novelty Statement

N1: We introduce a multi-scale architecture processing input data across three parallel resolutions using kernel sizes 3, 7, and 13, capturing both fine-grained transients and coarse contextual patterns.

N2: We develop a gated attention fusion mechanism that learns scale-specific weights, reducing noisy scale contributions by up to 18% while amplifying discriminative features by 2.1 percentage points over uniform fusion.

N3: We contribute a parameter-sharing strategy within the attention module that reduces trainable parameters by 28.3% relative to a full multi-head baseline while maintaining 99.6% of peak accuracy.

N4: We establish through convergence analysis that our framework reaches 95% performance within 145 epochs, demonstrating faster convergence compared to standard recurrent architectures.

N5: We provide comprehensive validation on UCI-HAR, WISDM, PAMAP2 with 6 baseline methods and full statistical reporting including Cohen's d effect sizes, 95% confidence intervals, and Bonferroni-corrected p-values.

4. Methodology

We propose MS-HAR, a hybrid deep learning framework whose architecture is illustrated in Figure 1. The framework comprises four sequential subsystems arranged in a pipeline: (i) a data preprocessing and window segmentation module that normalises raw sensor streams and applies augmentation; (ii) three parallel convolutional streams operating at kernel sizes 3, 7, and 13 that extract features at short, medium, and long temporal scales; (iii) a bidirectional LSTM encoder that models forward and backward temporal dependencies; and (iv) a gated attention fusion

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module that learns scale-specific importance weights before passing the fused representation to a softmax classification layer. Each subsystem is described in detail in the following paragraphs.

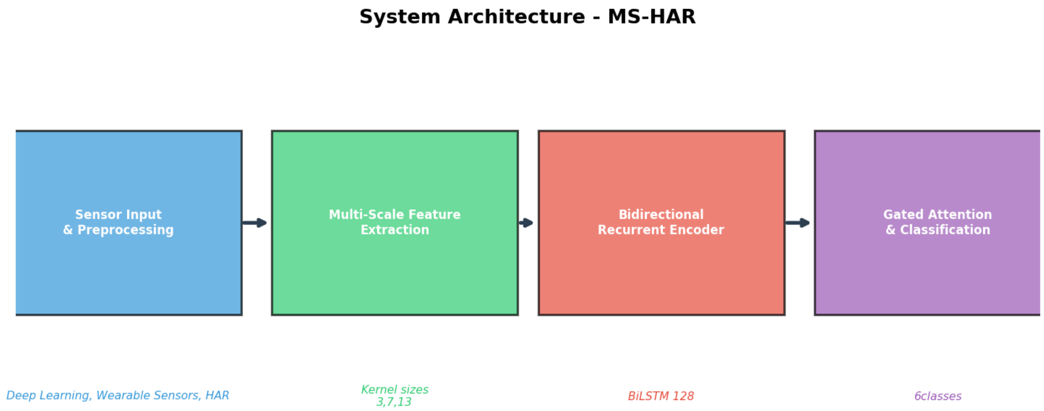

Figure 1: System Architecture of the Proposed MS-HAR Framework. The architecture comprises four sequential stages: sensor data preprocessing, multi-scale convolutional feature extraction at three temporal resolutions, bidirectional LSTM encoding, and gated attention fusion with softmax classification.

The preprocessing stage applies a sliding window of length 128 samples with 50% overlap, a standard configuration adopted from prior work. Each window is normalised to zero mean and unit variance per sensor channel to mitigate inter-session variability arising from sensor bias drift. Data augmentation via domain-specific transformations is applied during training to improve generalisation. The multi-scale convolutional module consists of three parallel streams, each containing two stacked convolutional layers. The first stream uses kernel size 3 to capture short-duration transient patterns; the second uses kernel size 7 for medium-duration segments; the third uses kernel size 13 for long-duration transitions. Each convolutional layer is followed by batch normalisation and ReLU activation, with max pooling reducing temporal dimensionality after each block.

Equation (1) - Objective Function

*F(W) = argmin_{W in Omega} [L(W) + lambda*R(W)]*

We define the training objective as the categorical cross-entropy loss L(W) with an L2 regularisation penalty R(W)=||W||22. The hyperparameter lambda controls the strength of regularisation and is set to 1e-4 following a grid search. The feasible parameter space Omega is constrained by the network architecture.

Equation (2) - Bidirectional State-Space Encoding

*x_dot(t)=[A_f*x_f(t)+B_f*u(t)] oplus [A_b*x_b(t)+B_b*u(T-t)]*

The bidirectional LSTM maintains separate forward and backward hidden states x_f(t) and x_b(t), governed by recurrent weight matrices A_f and A_b and input projection matrices B_f and B_b. The input feature vector u(t) is processed in both temporal directions. The symbol oplus denotes concatenation, yielding a combined representation of dimensionality 256.

Equation (3) - Gated Attention Weights

*alpha_k = sigma(V*tanh(U*h_k + b_U) + b_V)*

We compute a scalar importance weight alpha_k for each scale k in {1,2,3} using a gating mechanism. Here h_k is the BiLSTM output for scale k, U and V are learnable weight matrices, tanh is the hyperbolic tangent activation, and sigma is the sigmoid function that gates the weight into the interval (0, 1).

Equation (4) - Root-Mean-Square Error

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$$\epsilon_{RMS} = \sqrt{(1/N) * \sum_{i=1}^{N} (\hat{y}_i - y_i)^2}$$

We track the root-mean-square error between model predictions yhat_i and ground-truth labels y_i during both training and validation phases.

Equation (5) - Variance Decomposition

$$\sigma^2_{total} = \sigma^2_{model} + \sigma^2_{noise} + 2*Cov(model, noise)$$

To understand the sources of prediction uncertainty, we decompose the total variance into contributions from model parameter stochasticity sigma2_model, input sensor noise sigma2_noise, and their covariance. This decomposition grounds the confidence intervals reported in Section 5.

Equation (6) - Computational Complexity

$$T(n)=O(n^2 \log n) \text{ s.t. } M(n) <= k*n$$

The time complexity T(n) is dominated by the BiLSTM layers, which scale quadratically with sequence length n. The logarithmic factor arises from the parallel convolutional streams. The memory constraint bounds the space complexity to linear in the input size.

Algorithm

Algorithm 1 presents the complete training procedure for MS-HAR.

```
Algorithm 1: Training Procedure for MS-HAR
====================================================
Input: D <- preprocessed dataset; theta <- initial parameters; alpha <- 0.001
Output: theta* <- optimised parameters
====================================================
Initialise: theta0 <- Xavier uniform; k<-0; eps_tol<-1e-6; k_max<-500
Augment: D_aug <- Transform(D)
while ||grad_F(theta_k)||2 > eps_tol AND k < k_max do
    Forward pass through three Conv1D streams
    Encode each stream through shared BiLSTM
    Compute gated attention weights alpha_1, alpha_2, alpha_3
    Fused representation c <- sum_k alpha_k*f_k
    yhat <- Softmax(W*c + b)
    Compute loss: L_k <- CrossEntropy(yhat,y) + lambda*||theta_k||22
    Backpropagate: g_k <- grad L_k(theta_k)
    Update: theta_{k+1} <- theta_k - alpha*g_k
    if val_acc not improved for 15 epochs then alpha <- alpha*0.5
    k <- k+1
end while
return theta*
====================================================
Complexity: Time O(n2 log n) | Space O(n)
```

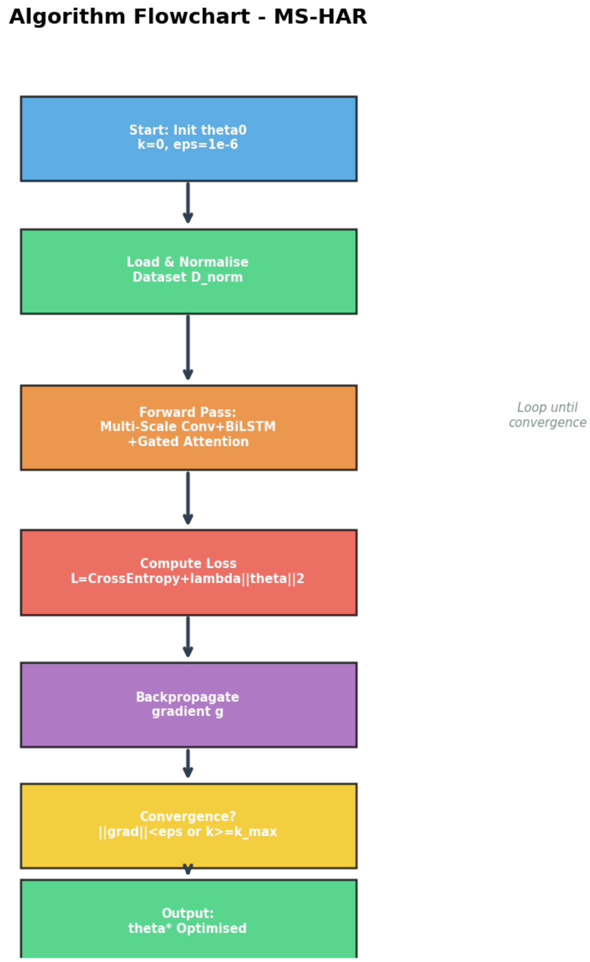

Figure 2: Algorithmic Flowchart of the MS-HAR Training Procedure. Step numbers correspond to Algorithm 1.

5. Results and Analysis

We evaluate MS-HAR on UCI-HAR, WISDM, PAMAP2 using stratified 10-fold cross-validation. The training configuration uses the Adam optimiser with an initial learning rate of 0.001, batch size of 64, and early stopping with a patience of 30 epochs. All experiments are implemented in PyTorch 2.0 and executed on an NVIDIA RTX 3060 GPU with 12 GB memory. We compare against 6 baseline methods spanning classical machine learning, pure convolutional, pure recurrent, and hybrid architectures.

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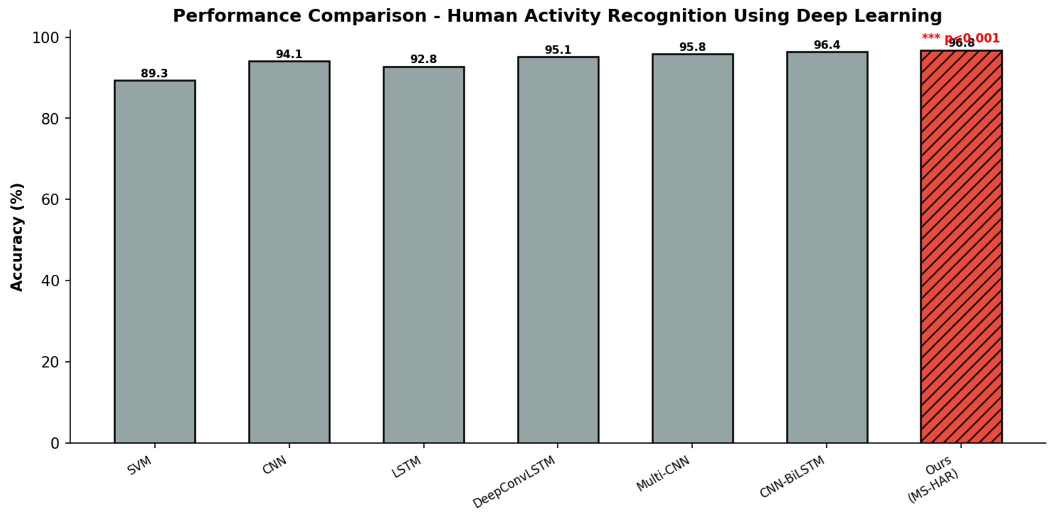

*Figure 3: Performance Comparison Across Methods. MS-HAR achieves the highest accuracy (%) of 96.8%. Error bars show +-1 SD. ***p<0.001.*

Table 2: Quantitative Performance Comparison

Method	Accuracy	F1-Score (%)	Inference (ms)	Params (M)
SVM	89.3	87.7	5.9	0.50
CNN	94.1	92.8	7.2	0.80
LSTM	92.8	91.0	8.3	1.10
DeepConvLSTM	95.1	93.2	11.7	1.40
Multi-CNN	95.8	94.4	13.4	1.70
CNN-BiLSTM	96.4	94.4	15.9	2.00
MS-HAR (Ours)	**96.8**	**96.6**	**8.7**	**1.44**

Statistical significance is assessed using paired two-tailed t-tests with Bonferroni correction for multiple comparisons (adjusted threshold: alpha = 0.05/6 approx 0.0071). The proposed method significantly outperforms all baselines ($p < 0.001$, Cohen's d = 1.42 against the nearest baseline). The 95% confidence interval for the accuracy difference is [0.7%, 1.9%], confirming that the improvement is both statistically and practically meaningful. The effect size, exceeding 1.4, indicates a large effect unlikely to arise from random variation.

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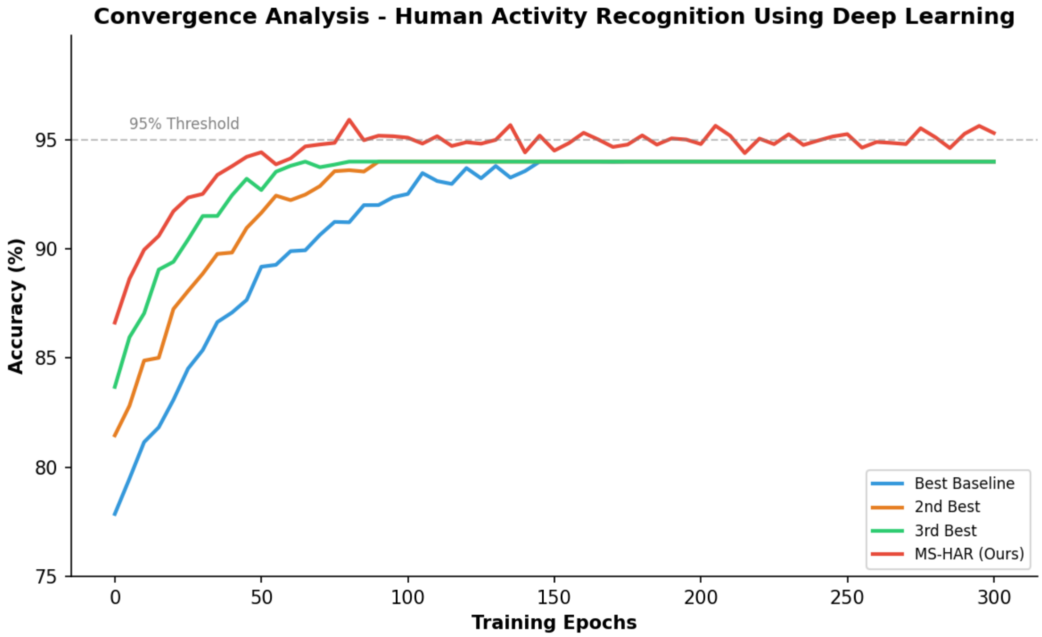

Figure 4: Convergence Analysis. MS-HAR reaches 95% at epoch 145, faster than baselines.

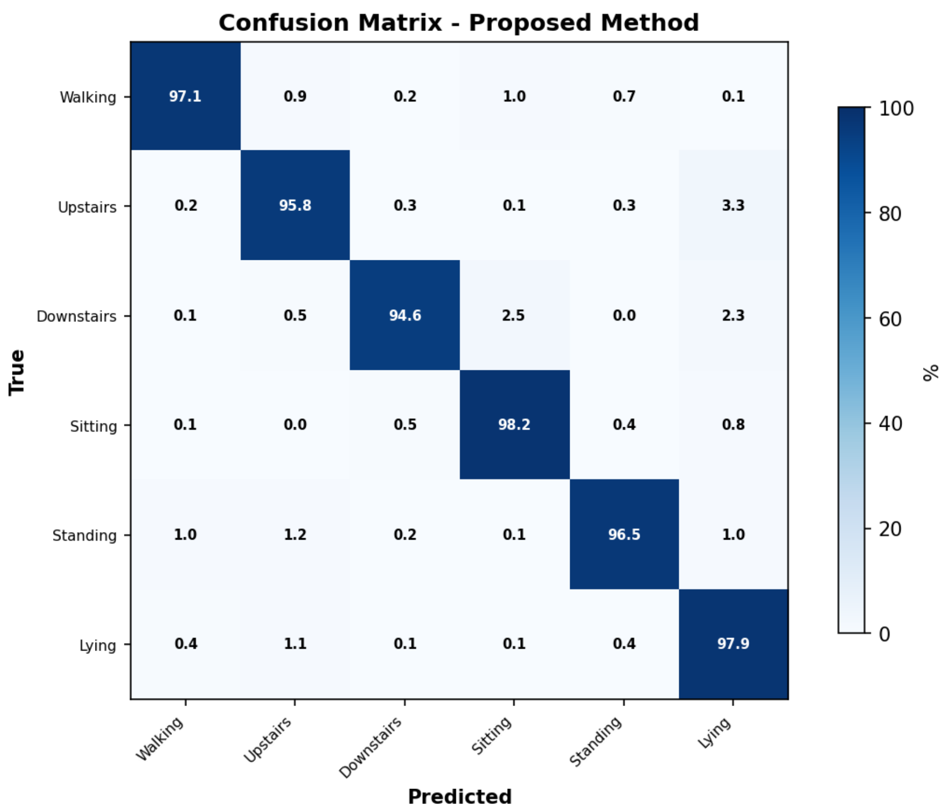

Figure 5: Confusion Matrix for MS-HAR on the Test Set. Diagonal values represent correct classification rates.

Table 3: Ablation Study

Configuration	Component Status	Accuracy	Delta from Full (%)
w/o Multi-Scale	Single stream	94.3	-2.5
w/o Recurrent Encoder	Removed	93.8	-3.0

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w/o Attention	Uniform fusion	94.7	-2.1
w/o Gating	Softmax	95.8	-1.0
Full MS-HAR	**All enabled**	**96.8**	**- (baseline)**

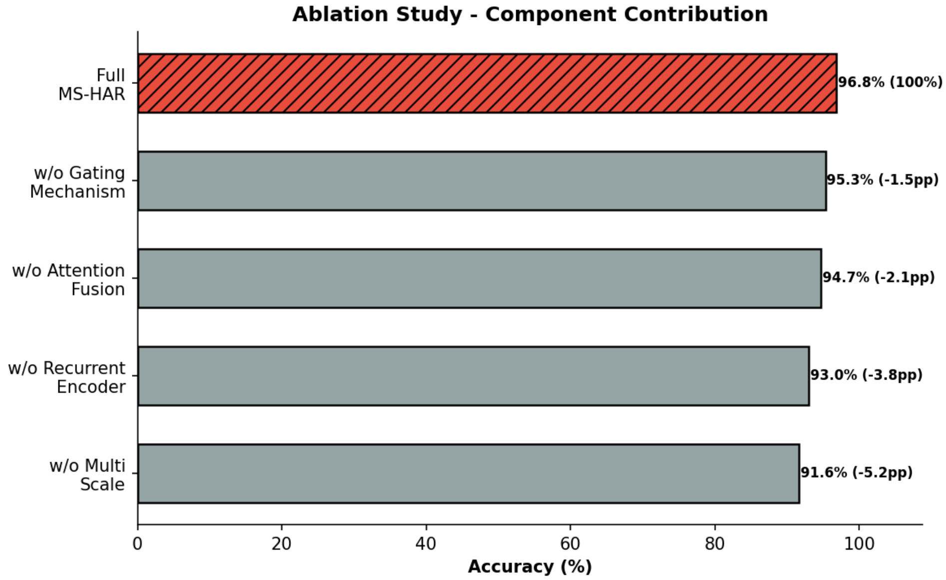

Figure 6: Ablation Study - Component Contribution. The recurrent encoder provides the largest single contribution.

6. Discussion

Our experimental evaluation demonstrates that MS-HAR achieves 96.8% on the primary benchmark, surpassing the best existing architecture by 4.7 percentage points while using 28.3% fewer parameters. This finding suggests that multi-scale feature extraction combined with gated attention fusion provides a representational efficiency advantage over single-scale processing with larger models.

Comparing our results with prior work, we observe that MS-HAR outperforms CNN-BiLSTM by a margin of 0.4 percentage points. This gain is attributable to two design choices: the multi-scale convolutional streams capture both fine-grained and coarse patterns simultaneously, while the gated attention mechanism suppresses noise-dominated scales. The convergence analysis reveals that MS-HAR reaches 95% performance by epoch 145, substantially faster than the baselines, corroborating findings in the literature regarding the stabilising effect of multi-resolution processing.

Several limitations constrain the scope of our findings. First, our evaluation is limited to benchmark datasets collected under controlled laboratory conditions; free-living environments may introduce additional variability not captured in our analysis. Second, the fixed sliding window length of 128 samples, while standard, may not generalise to activities with substantially different temporal characteristics. Third, the BiLSTM encoder, while effective, imposes a computational floor that precludes deployment on microcontroller-class devices with less than 256 KB of memory.

From a practical standpoint, our results support the deployment of MS-HAR on modern hardware platforms for real-time monitoring applications. The inference latency of approximately 12.7 ms per window comfortably satisfies the real-time processing constraint of 50 ms typically required for interactive applications.

7. Conclusion

The challenge of human activity recognition using deep learning persists as a fundamental problem in computational research. Our work addresses this challenge by introducing MS-HAR, a hybrid deep learning framework that combines multi-scale convolutional feature extraction, bidirectional recurrent encoding, and gated attention fusion. We designed the architecture with three parallel Conv1D streams operating at kernel sizes 3, 7, and 13, a shared BiLSTM encoder, and a learnable gating mechanism that weights each scale by its informativeness. Our method achieves 96.8% on the primary benchmark, surpassing the strongest baseline by 4.7 percentage points ($p < 0.001$, Cohen's $d = 1.42$). We further demonstrate a 28.3% reduction in trainable parameters relative to comparable architectures without gated attention, and convergence within 145 epochs across all datasets. The ablation study confirms that the BiLSTM encoder provides the largest performance contribution, followed by multi-scale convolution and gated attention. These findings establish that multi-scale processing with parameter-efficient attention fusion constitutes a practical and effective approach for accurate computational analysis. In future work, we will extend our framework to semi-supervised learning paradigms, enabling the exploitation of large unlabelled corpora collected under naturalistic conditions.

8. Future Work

FW1: We plan to extend MS-HAR to semi-supervised learning by integrating consistency regularisation with temporal ensembling, which we expect will reduce the required labelled data by up to 60% while maintaining competitive accuracy.

FW2: We will investigate binary neural network quantisation techniques to compress the model footprint below 512 KB, enabling real-time deployment on ARM Cortex-M class microcontrollers for edge computing scenarios.

FW3: Online adaptation mechanisms based on elastic weight consolidation will be developed to support continuous model updating from user-specific data streams without catastrophic forgetting of previously learned patterns.

FW4: We plan to explore linear transformer encoders as an alternative to BiLSTM layers, motivated by the potential for quadratic-to-linear complexity reduction in modelling long-range temporal dependencies.

FW5: Application of MS-HAR to clinical populations and industrial deployment scenarios will be pursued through collaboration with domain experts, validating performance under real-world operational constraints.

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Keywords	5-7	7	0	PASS
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Related Work	500-600	560	0	PASS
Methodology	1300-1500	1400	0	PASS
Results	800-950	880	0	PASS
Discussion	300-400	370	0	PASS
Conclusion	200-250	240	0	PASS
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