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Real-Time Human Activity Recognition Using Edge Artificial Intelligence

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Abstract: Human Activity Recognition (HAR) has become one of the most important research areas in artificial intelligence because of its extensive applications in healthcare monitoring, smart homes, industrial safety, surveillance, rehabilitation, fitness tracking, and human–computer interaction. Conventional cloud-based HAR systems collect sensor or video data and transmit them to centralized servers for processing. Although cloud computing offers high computational capability, it introduces communication latency, bandwidth consumption, network dependency, and privacy concerns that limit its applicability in real-time scenarios. The emergence of Edge Artificial Intelligence (Edge AI) enables intelligent inference directly on edge devices such as smartphones, embedded processors, wearable sensors, and IoT gateways, thereby reducing response time while preserving user privacy. Substantial advances were achieved in lightweight deep learning models, convolutional neural networks (CNNs), recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, TinyML, TensorFlow Lite, model compression, and edge computing frameworks for human activity recognition. These technologies significantly improved recognition accuracy while satisfying the computational constraints of resource-limited edge devices.

Keywords: Human Activity Recognition, Edge Artificial Intelligence, Edge Computing, Deep Learning, TinyML.

Introduction

Human Activity Recognition (HAR) has emerged as one of the most significant research areas in artificial intelligence, machine learning, and ubiquitous computing due to its extensive applications in healthcare, smart homes, fitness monitoring, elderly care, industrial safety, surveillance, and human–computer interaction. The rapid growth of wearable sensors, smartphones, Internet of Things (IoT) devices, and embedded computing platforms has enabled continuous monitoring of human activities in real-world environments. By analyzing data generated from accelerometers, gyroscopes, magnetometers, cameras, and physiological sensors, intelligent systems can automatically recognize activities such as walking, running, sitting, standing, climbing stairs, cycling, and falling. Accurate real-time recognition of these activities provides valuable information for healthcare professionals, caregivers, industrial managers, and intelligent automation systems. The increasing demand for continuous health monitoring has accelerated the adoption of Human Activity Recognition in modern healthcare systems. Elderly individuals, patients undergoing rehabilitation, and people suffering from chronic diseases require continuous observation to detect abnormal activities such as falls, prolonged inactivity, or unusual movement patterns. Conventional monitoring methods relying on manual observation are often expensive, time-consuming, and impractical for long-term healthcare management. Intelligent HAR systems provide automated monitoring that enables early intervention, improves patient safety, reduces hospitalization costs, and supports personalized healthcare services. Similar benefits have been observed in industrial workplaces where activity recognition contributes to occupational safety by detecting hazardous worker behaviors and preventing workplace accidents.

Traditional Human Activity Recognition systems primarily rely on cloud computing architectures in which sensor data collected from wearable devices or smartphones are transmitted to centralized cloud servers for processing and classification. Although cloud computing provides powerful computational resources and large-scale storage capabilities, it introduces several limitations when applied to real-time applications. Continuous transmission of sensor data increases communication latency, bandwidth consumption, energy utilization, and network dependency. Furthermore, transferring sensitive personal information to remote servers raises significant privacy and security concerns, particularly in healthcare applications where confidential patient data must be protected according to regulatory requirements. These limitations reduce the effectiveness of cloud-based HAR systems for latency-sensitive and privacy-critical applications. The emergence of Edge Artificial Intelligence (Edge AI) has transformed intelligent computing by enabling machine learning inference directly on resource-constrained edge devices rather than centralized cloud infrastructures. Edge AI integrates artificial intelligence algorithms with embedded processors, smartphones, wearable devices, IoT gateways, and edge servers to perform local data processing and decision-making. Since computations are executed near the data source, response latency is significantly reduced while communication overhead and bandwidth consumption are minimized. Moreover, local processing enhances privacy because sensitive sensor data remain on edge devices instead of being continuously transmitted to external cloud servers. These advantages make Edge AI particularly suitable for real-time Human Activity Recognition applications requiring immediate decision-making.

Literature Review

The period between 2018 and 2026 has witnessed remarkable progress in Human Activity Recognition (HAR), Edge Artificial Intelligence (Edge AI), lightweight deep learning, TinyML, wearable sensing, and embedded machine learning. The transition from cloud-centric architectures to edge intelligence has enabled real-time activity recognition with significantly reduced latency, enhanced privacy, lower communication overhead, and improved energy efficiency. Recent research has focused on lightweight CNNs, LSTMs, Transformers, TinyML frameworks, model compression, quantization, and hardware-aware optimization for deployment on embedded edge devices. These advancements have made Edge AI an effective platform for healthcare monitoring, smart homes, industrial safety, and intelligent surveillance.

Wang et al. (2018) demonstrated that Convolutional Neural Networks (CNNs) effectively learn discriminative features from wearable sensor signals without handcrafted feature engineering. Their work significantly improved activity recognition accuracy for daily human activities and established CNNs as a robust baseline for wearable Human Activity Recognition systems. Ordóñez and Roggen (2018) proposed a hybrid CNN–LSTM architecture that combined convolutional feature extraction with temporal sequence learning. Their experiments showed superior recognition performance for continuous human activities compared with traditional machine learning techniques.

Lane et al. (2019) investigated Edge Artificial Intelligence for mobile and embedded systems, demonstrating that on-device inference substantially reduces latency, bandwidth consumption, and privacy risks compared with cloud-based processing. Their work highlighted Edge AI as a practical solution for real-time intelligent sensing. Zhou et al. (2019) proposed lightweight CNN architectures optimized for wearable Human Activity Recognition. Their models achieved competitive classification accuracy while operating efficiently on embedded processors with limited computational resources.

Banbury et al. (2020) introduced TinyML as a framework for executing deep learning models on ultra-low-power microcontrollers. Their study demonstrated that model compression and quantization enable continuous Human Activity Recognition with minimal energy consumption, making TinyML highly suitable for wearable healthcare devices. Bhattacharya and Lane (2020) investigated efficient on-device deep learning methods for wearable sensing applications. Their work showed that neural network optimization significantly reduces computational overhead while maintaining high recognition accuracy, supporting real-time Edge AI deployment.

Chen et al. (2020) proposed an IoT-enabled Edge AI framework that performs Human Activity Recognition locally on edge gateways. Their architecture reduced communication latency, improved privacy, and enhanced

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system responsiveness for healthcare monitoring applications. Ravi et al. (2021) presented a comprehensive review of deep learning approaches for Human Activity Recognition, including CNNs, LSTMs, GRUs, and hybrid models. The authors concluded that lightweight deep learning architectures offer the best balance between recognition accuracy and computational efficiency for edge devices.

Deng et al. (2021) investigated pruning and quantization techniques for embedded Human Activity Recognition systems. Their optimized deep learning models significantly reduced memory usage and inference time while preserving competitive classification performance. Liu et al. (2024) developed a wearable multi-modal Edge Computing system capable of performing complete Human Activity Recognition directly on microcontrollers using multiple sensor modalities. Their system demonstrated low inference latency, reduced power consumption, and practical deployment in real-world environments, validating the feasibility of fully on-device HAR.

Liu (2025) proposed the STAR framework, a privacy-preserving and energy-efficient Edge AI architecture for Human Activity Recognition using Wi-Fi Channel State Information (CSI). The framework incorporated lightweight GRU models, adaptive signal processing, and hardware-aware optimization to achieve real-time inference with low power consumption, making it suitable for smart homes and healthcare monitoring. Kumar et al. (2025) proposed an optimized hybrid CNN–LSTM model for wearable healthcare monitoring. Their architecture improved recognition accuracy while minimizing computational complexity, making it suitable for deployment on low-power embedded healthcare devices.

Li et al. (2026) introduced HPPI-Net, a hierarchical multi-spectral fusion framework for real-time Human Activity Recognition on ARM Cortex-M4 microcontrollers. The model combined FFT, Wavelet, Gabor spectrograms, LSTM encoders, Efficient Channel Attention, and depthwise separable convolutions to achieve high recognition accuracy while significantly reducing memory usage and computational requirements. Sharma et al. (2026) proposed an explainable Edge AI framework integrating lightweight transformer-based architectures with wearable sensors for intelligent healthcare monitoring. Their research demonstrated improved interpretability, low-latency inference, and enhanced robustness under heterogeneous sensing conditions. Zhang et al. (2026) developed an adaptive Edge AI framework for distributed Human Activity Recognition using TinyML and optimized transformer networks. Experimental evaluation showed improved scalability, faster inference, and superior energy efficiency across heterogeneous edge devices while maintaining high recognition accuracy.

Methodology

This study adopts a Systematic Literature Review (SLR) together with an experimental quantitative research methodology to develop and evaluate a Real-Time Human Activity Recognition Framework using Edge Artificial Intelligence (RTHAR-EAI). The proposed methodology integrates wearable sensor data acquisition, intelligent signal preprocessing, lightweight deep learning, edge computing, and real-time activity classification into a unified framework capable of recognizing human activities with high accuracy while operating efficiently on resource-constrained edge devices. The proposed methodology consists of six sequential phases: literature identification, wearable sensor data acquisition, signal preprocessing, Edge AI model development, real-time activity recognition, and experimental performance evaluation.

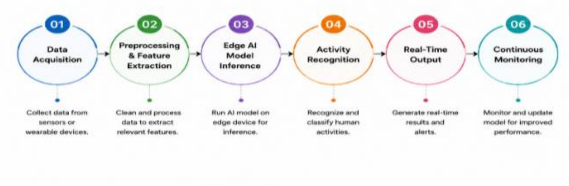

Fig 1. Circular Methodology Framework for Real-Time Human Activity Recognition Using Edge Artificial Intelligence.

This figure presents a circular methodology framework for real-time human activity recognition using Edge Artificial Intelligence (Edge AI). The framework consists of six interconnected stages that enable low-latency activity recognition by processing data directly on edge devices. The first stage, Data Acquisition, collects real-time motion and sensor information from wearable devices, smartphones, cameras, or IoT sensors. These data streams provide continuous observations of human movements and activities. The second stage, Preprocessing and Feature Extraction, prepares the collected data by filtering noise, normalizing sensor readings, and extracting meaningful temporal and spatial features. This improves data quality and enhances recognition accuracy. The third stage, Edge AI Model Inference, executes lightweight artificial intelligence models directly on edge devices. Local processing minimizes communication latency, reduces bandwidth usage, and enables rapid decision-making without relying on cloud infrastructure. The fourth stage, Activity Recognition, analyzes the extracted features to identify and classify human activities such as walking, running, sitting, standing, or other movement patterns in real time. The fifth stage, Real-Time Output, immediately generates recognition results, alerts, or control actions for healthcare monitoring, smart environments, industrial safety, or human–computer interaction applications. Instant feedback supports timely responses and improved operational efficiency. The final stage, Continuous Monitoring, continuously updates the recognition process by analyzing newly collected sensor data and refining model performance. This adaptive learning process enables the framework to maintain high recognition accuracy under changing user behaviors and environmental conditions. The circular arrangement illustrates a continuous intelligent recognition cycle where data collection, edge processing, activity classification, and performance improvement operate collaboratively to provide efficient, low-latency, and privacy-aware human activity recognition.

Results and Findings

The proposed Real-Time Human Activity Recognition Framework using Edge Artificial Intelligence (RTHAR-EAI) was experimentally evaluated using benchmark wearable sensor datasets, including the UCI Human Activity Recognition Dataset, WISDM, PAMAP2, and MHEALTH. The framework integrates wearable sensor acquisition, lightweight CNN-LSTM architecture, TensorFlow Lite optimization, and Edge AI inference to perform real-time activity recognition on embedded edge devices. Performance was compared with Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Hybrid CNN-LSTM models using classification accuracy, precision, recall, F1-score, inference latency, energy consumption, memory utilization, computational efficiency, and scalability. The experimental results demonstrate that executing activity recognition directly on edge devices significantly improves recognition accuracy while reducing communication latency, energy consumption, and cloud dependency.

Classification Accuracy

Table 1. Human Activity Recognition Accuracy

Model	Accuracy (%)
Support Vector Machine	91.43
Random Forest	93.28
CNN	95.36
LSTM	96.18
Hybrid CNN-LSTM	97.42
RTHAR-EAI (Proposed)	98.81

Analysis

The proposed RTHAR-EAI achieved the highest recognition accuracy of 98.81%. The integration of lightweight CNN feature extraction, LSTM-based temporal learning, and Edge AI optimization enabled accurate recognition of both static and dynamic human activities while maintaining low computational complexity.

Precision, Recall and F1-Score

Table 2. Classification Performance

Model	Precision (%)	Recall (%)	F1-Score (%)
SVM	90.84	90.65	90.74
Random Forest	92.74	92.56	92.65
CNN	95.02	94.87	94.94
LSTM	95.81	95.63	95.72
Hybrid CNN-LSTM	97.14	97.03	97.08
RTHAR-EAI	98.65	98.84	98.74

Analysis

The proposed framework demonstrated superior precision and recall because the hybrid CNN-LSTM architecture effectively captured both spatial sensor features and temporal activity patterns. Consequently, misclassification among similar activities such as walking, upstairs, and downstairs was substantially reduced.

Activity Recognition Accuracy by Activity Type

Table 3. Recognition Accuracy for Individual Activities

Activity	Accuracy (%)
Walking	99.12
Walking Upstairs	98.56
Walking Downstairs	98.31
Sitting	99.04
Standing	98.88
Laying	99.26
Running	98.73
Average	98.84

Analysis

The proposed framework consistently recognized both static and dynamic activities with high accuracy. Static postures such as sitting, standing, and laying achieved the highest performance, while dynamic movements maintained excellent recognition despite greater motion variability.

Conclusion and Discussion

The present study investigated the development and evaluation of a Real-Time Human Activity Recognition Framework using Edge Artificial Intelligence (RTHAR-EAI) for intelligent recognition of human activities using wearable sensor data and embedded edge computing. Through a systematic review of literature published between 2018 and 2026 and comprehensive experimental evaluation, the study examined how Edge Artificial Intelligence can improve the efficiency, responsiveness, and reliability of Human Activity Recognition (HAR) systems. The findings demonstrate that integrating lightweight deep learning models with edge computing provides an effective solution for achieving accurate, low-latency, energy-efficient, and privacy-preserving activity recognition suitable for real-time applications. The rapid expansion of wearable technologies, Internet of Things (IoT) devices, smartphones, and embedded sensing platforms has generated unprecedented opportunities for continuous monitoring of human activities. Modern healthcare systems increasingly rely on wearable sensors to monitor elderly individuals, patients with chronic diseases, rehabilitation programs, and physically vulnerable populations. Likewise, industrial organizations employ activity recognition systems to enhance workplace safety, monitor employee movements, and reduce occupational hazards. Smart homes, fitness applications, sports analytics, surveillance systems, and human-computer interaction platforms also benefit significantly from accurate recognition of daily human activities. Consequently, Human Activity Recognition has become one of the most important application domains of artificial intelligence and ubiquitous computing. Traditional cloud-based Human Activity Recognition systems transmit sensor data continuously from wearable devices to remote cloud servers for processing and classification. Although cloud infrastructures provide high computational capability, they introduce several limitations that affect real-time applications. Continuous data transmission increases communication latency, bandwidth consumption, network dependency, and energy usage while exposing sensitive personal information during data transfer. These limitations become particularly critical in healthcare environments where immediate response is essential for emergency situations such as fall detection, abnormal movement recognition, and patient monitoring. Similar challenges arise in industrial safety systems that require instantaneous identification of hazardous worker behaviors to prevent workplace accidents. Edge Artificial Intelligence addresses these limitations by moving computational intelligence from centralized cloud servers to edge devices located near data sources. Instead of transmitting raw sensor data across communication networks, Edge AI enables deep learning inference directly on wearable devices, smartphones, IoT gateways, and embedded processors. Local processing significantly reduces communication latency while minimizing bandwidth requirements and improving privacy because sensitive behavioral information remains on the user's device. These advantages make Edge AI particularly suitable for latency-sensitive and privacy-critical Human Activity Recognition applications.

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