Paper 1: Energy-aware human activity recognition for wearable devices: A comprehensive review

The aim of this article is to provide an overview of current scientific literature on energy-aware human activity recognition methods and solutions. To achieve this goal, they surveyed state-of-the-art contributions, highlighting different algorithms and techniques and their impact on the energy-accuracy trade-off. Three categories of energy-aware HAR were identified: sensor-based, system architecture-based, and model design-based. A review of the literature revealed a variety of energy saving techniques for each category. These techniques have been explored in the context of daily living activities, which comprise a wide range of actions involving low limbs, high limbs, or both.

Scopes: Develop and optimize HAR algorithms that are specifically designed to be energy-efficient, considering the limited resources of wearable devices. Investigate the integration of multiple sensing modalities, such as accelerometers, gyroscopes, and physiological sensors, to improve the accuracy of activity recognition while minimizing energy consumption. Develop context-aware energy management strategies that consider the user's context, such as location, time of day, and environmental conditions, to dynamically adjust the energy usage of the HAR system. Long-term user adaptation involves the continuous adjustment and refinement of activity recognition models and algorithms based on the long-term behavior and preferences of individual users.

Paper 2: Human activity recognition based on time series analysis using U-Net

This paper presents a method of human activity recognition based on time series using U Net.

Dataset: WISDM dataset, UCI HAR dataset, UCI HAPT dataset, UCI OPPORTUNITY dataset, and the self-collected Sanitation data set.

Algorithms: Adam algorithm, SVM, KNN (k=5), Decision Tree, QDA, CNN and FCN.

The proposed U Net algorithm is stable and robust in all test datasets and obviously superior to other algorithms. Can be further improved on better performance machines.

Paper 3: AHAR: Adaptive CNN for Energy-efficient Human Activity Recognition in Low-power Edge Devices

This paper proposed an adaptive CNN architecture for human activity recognition. Their proposed methodology is designed for low-power, low memory wearable edge devices where the traditional adaptive architectures suffer from performance loss. AHAR uses a novel adaptive architecture that decides which portion of the baseline architecture to be used during the inference phase based on the simple statistical features of the activity segments.

Datasets- Opportunity and w-HAR.

The energy efficiency would be even more if we had deeper CNN architecture with multiple convolution layers.

Paper 4: Wearable-based Human Activity Recognition with Spatio-Temporal Spiking Neural Networks

In this paper, they have introduced Spiking Neural Networks (SNNs) for HAR tasks, which is the first of its kind study. Compared to the original Artificial Neural Networks (ANNs), SNNs utilize their LIF neurons to generate spikes through time, bringing energy efficiency as well as temporally correlated non-linearity. Their results show that SNNs achieve competitive accuracy while reducing energy significantly.

Dataset: UCI-HAR, UniMB SHAR, HHAR

Paper 5: nanoML for Human Activity Recognition

This study demonstrates that Differentiable Weightless Neural Networks (DWNs) embody the principles of nano-machine learning (nanoML), achieving unprecedented levels of energy efficiency and compactness in Human Activity Recognition.

Benefits: Consumes less memory and takes less time per sample & saves energy.

Dataset: UCI Human Activity Recognition (HAR) Dataset

Future work will investigate the extension of DWNs to multimodal sensor data and explore their scalability for more complex HAR scenarios. Additionally, efforts will focus on designing custom ASICs for DWNs to further enhance their efficiency in wearable applications, optimizing DWNs for diverse hardware platforms, and expanding their applications beyond HAR.

Paper 6: Transfer Learning in Sensor-Based Human Activity Recognition: A Survey

This survey provides a reference to the HAR community by summarizing the existing works and providing a promising research agenda.

Adversarial training is successfully used in both domains to address personalization and feature space heterogeneity but a significantly lesser amount of work has been done for solving similar transfer learning challenges in smart home settings. Addressing feature space heterogeneity, personalization, and task differences simultaneously is rare in the transfer learning literature, which should be the focal point of upcoming works. It also indicated lesser exploration for smart home settings compared to the wearable HAR domain.

Paper 7: Efficient Human Activity Recognition Using Machine Learning and Wearable Sensor Data

This paper proposes a human activity state recognition method based on machine learning and a majority decision model, utilizing data collected from accelerometers and gyroscopes.

Dataset: They recruited 10 participants to wear motion state sensors, accelerometer and gyroscope, during their daily activities, allowing them to collect comprehensive movement data.

Models: Classification model based on integer programming and the machine learning decision

model.

Algorithms: SVM, KNN, Random Forest

Limitation: Small dataset

To improve generalization and reduce overfitting, a larger dataset should be collected in subsequent research.

Paper 8: Efficient Human Activity Recognition on Wearable Devices Using Knowledge Distillation Techniques

They proposed a novel approach for Human Activity Recognition (HAR) named Knowledge Distillation for Human Activity Recognition (KDHAR). They designed a knowledge distillation architecture to transfer knowledge from a large, high-capacity model to a smaller, more efficient one. They built compact and efficient models that are suited for deployment on mobile and wearable devices without compromising performance.

Dataset: UCI- HAR dataset, WISDM dataset

Future research directions could include comparing the proposed method with other approaches for compressing deep neural networks, such as neural network pruning or quantization. Combining these techniques could result in even higher compression ratios. Additionally, exploring the use of unlabeled data and incorporating semi-supervised or self-supervised training techniques within the knowledge distillation framework could help leverage the limited availability of labeled RAH datasets in the mobile and wearable context.

Paper 9: Efficient human activity recognition with spatio-temporal spiking neural networks

They proposed the use of SNNs for HAR tasks, significantly reducing energy consumption while integrating a temporally evolving activation function. They designed a hardware accelerator tailored for deploying SNNs on edge devices.

Dataset: UCI-HAR, SHAR

Paper 10: Lightweight human activity recognition method based on the MobileHARC model

Considering the lightweight design of the model, they proposed the Lightweight Convolution Block and Lightweight Multi-Head Self-Attention Mechanism for lightweight MobileHARC.

Dataset: SKODA, HOSPITAL, UCI-HAR and OPPORTUNITY.

In future extensions of the main results to learning-based filtering or state estimation algorithms. This implies establishing learning models based on the main results, enabling the algorithm to adapt more effectively to new data and scenarios. Such extension may involve integrating machine learning techniques to enhance the performance of filtering or state estimation algorithms, allowing them to handle uncertainty and dynamic environment more flexibly.

Paper 11: A systematic literature review on human activity recognition using smart devices: advances, challenges, and future directions

The objectives of this study are threefold, identified recent studies that employ deep learning techniques for Human Activity Recognition (HAR) tasks, reviewed publicly available open datasets commonly used in HAR research during 2021 to 2024, and identified common challenges and limitations.

Dataset: WISDM, UCI-HAR, PAMAP2, Opportunity & MHealth

CNN shows excellent results when dealing with simple tasks due to their ability to extract spatial data. Both LSTMs and RNNs show profound results in complex tasks where there is a greater need to cater to temporal dependencies.

Future Work: Use close and custom dataset, more efficient model in recognizing activities, to investigate the federated and distributed learning approaches to enhance the robustness of the model

Paper 12: Efficient human activity recognition on edge devices using DeepConv LSTM architectures

They designed three Human Activity Recognition (HAR) models and identified DeepConv LSTM as the optimal model. Compared with existing lightweight HAR models, their proposed model demonstrates superior performance.

Models: 1D CNN model, 2D CNN model, and the DeepConv LSTM model.

Framework: TensorFlow & Keras

Dataset: WISDM Lab

Limitations: Dataset is highly imbalanced, hasn't tested on another dataset

Techniques such as data augmentation or oversampling could be explored to improve the model's performance on minority classes.

Paper 13: An Efficient and Lightweight Deep Learning Model for Human Activity Recognition Using Smartphones

A deep learning neural network based on CNN and LSTM model is used to train and recognize the different phases of human activities which includes the pre-processing of data, collection of data, and extraction of features from UCI-HAR dataset. Different deep learning algorithms are implemented to check the accuracy of the proposed model.

Dataset: Activity Recognition Using Smart Phones Dataset

Paper 14: Large Language Models for Wearable Sensor-Based Human Activity Recognition, Health Monitoring, and Behavioral Modeling: A Survey of Early Trends, Datasets, and Challenges

This survey has highlighted the trends and challenges associated with modeling wearable sensor data using large language models (LLMs). While the potential of LLMs in this field is evident, several obstacles need to be addressed to realize their full capabilities.

Future Work: The development of optimized deep learning models that can operate efficiently on resource-constrained devices is paramount, should exploring new frontiers in HAR, more robust and scalable models, interdisciplinary collaboration, Collaborations between computer scientists, healthcare professionals, legal experts, and ethicists will help to develop frameworks that protect user privacy while enabling the effective use of LLMs for data analysis