International Journal of Sciences and Innovation Engineering

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

website: www.ijsci.com
Vol.03 No.01

E-ISSN : 3049-0251
DOI: https://doi.org/10.70849/ijsci0301260547539

ENERGY-EFFICIENT MACHINE LEARNING ALGORITHMS FOR CONTINUOUS HUMAN ACTIVITY RECOGNITION IN WEARABLE DEVICES

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Article Info

Article History:

Published:20 Jan 2026

Publication Issue:
Volume 3, Issue 01
January-2026

Page Number:
463-477

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Abstract:

Wearable sensing HAR systems have become central to a host of uses for individualized healthcare, fitness tracking, elderly care and contextual-aware intelligence. Machine learning to improve recognition accuracy has increased due to the increasing demand for continuous and real time activity monitoring. But, wearable devices are mechanically and inherently limited in battery power, processing power and memory resources, making conventional machine learning and deep learning models undesirable for sustained continuous use when not carefully optimized. Also, the design of smart wearable HAR systems is still concerned with energy efficiency. In this paper, I present a detailed analysis of energy efficient machine learning algorithms for recognition of continuous human activity through wearable devices. This paper evaluates classic machine learning models and light deep learning architectures using multimodal sensor data from standard benchmark datasets. In order to overcome energy constraints the proposed research incorporates energy-aware approaches such as optimized feature extraction, adaptive sensor sampling, model pruning, parameter quantization, and reduced-precision inference. These techniques are systematically tested to determine their influence on classification accuracy, computational complexity, inference latency and overall energy consumption. The experimental results support the claims that energy based models could provide recognition performance comparable to the current models, but also significantly reduce power consumption and extend device battery life. Specifically, light architectures and classical models carefully chosen for their features have favorable trade-offs between accuracy and energy consumption, and are thus suitable for continuous on-device inference. This data provides valuable insight into the relationship between model complexity and energy efficiency and highlights the design considerations of sustainable, scaleable HAR solutions for resource-sensitive wearables.

Keywords: Human Activity Recognition; Wearable Devices; Energy-Efficient Machine Learning; Sensor-Based Activity Monitoring; Lightweight Models; Power-Aware Computing; Embedded Systems; Continuous Monitoring.

1. INTRODUCTION

Wearable sensors and lenses have created a new wave of human-centered computing that allows for constant monitoring of physical activity in real-world settings. Human Activity Recognition (HAR), which seeks to recognize and categorize human actions from sensors, is increasingly being used in health monitoring, fitness tracking, rehabilitation support, older care, and smart environments. The latest wearable technology, including smartwatches, fitness bands, and medical sensors, now contains dozens of sensors with multiple inertial and physiological sensors - that can capture meaningful data stream to allow for accurate inferences about exercise.

Along with the advancements in hardware, machine learning has been instrumental in the improvement of HAR systems. The robustness and interpretability of classical machine learning models such as Support Vector Machines, k-Nearest Neighbors, and Random Forests have long been used for sensing activity recognition. More recently, deep learning algorithms such as CNNs and NRNs have been widely used to automatically learn hierarchical representations from raw sensor data. But, the use of such models on wearable devices poses significant challenges as these platforms represent limited resources.

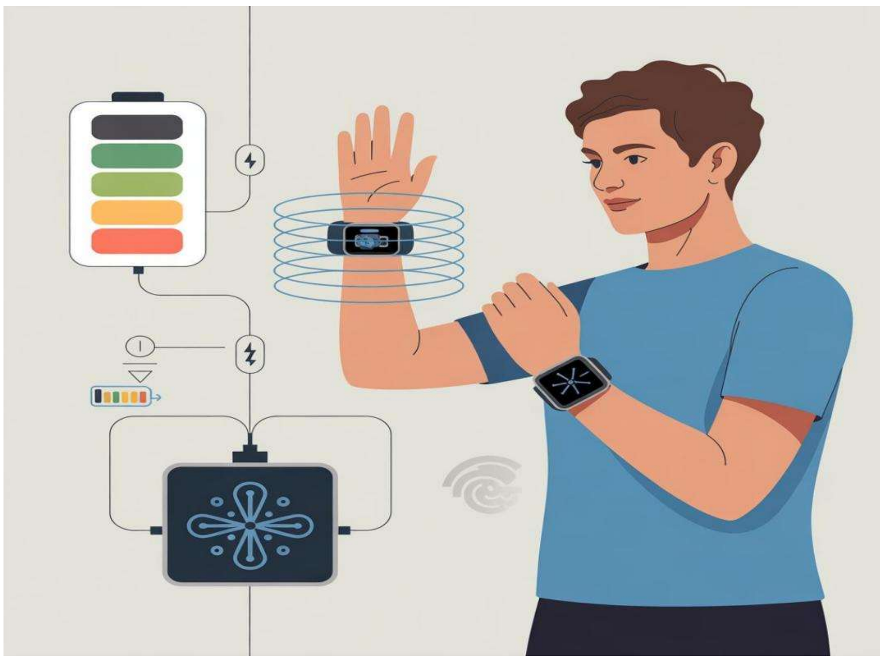

Fig 1. *Energy-efficient human activity recognition using wearable devices.*

The limitations of wearable devices lie in their batteries, processor power, memory and thermal limitations. Without properly optimized batteries, continuous activity recognition requires continuous sampling from sensors, processing data and modeling inference. High-level machine learning models, such as deep neural networks, require a large number of computational operations and memory access, thus increasing energy consumption and decreasing device life. In other words, there is a critical balance between accuracy of recognition and energy efficiency that needs to be found for continuous HAR systems to work with wearables.

So energy efficiency has become a topic of major interest for wearable HAR. In addition to model accuracy, studies must also consider system design that takes advantage of power, algorithm selection that is light weight, and intelligent processing that efficiently consumes less power while maintaining good performance. Several strategies to reduce computational overhead and power consumption have been proposed, including feature optimization, dimensionality reduction, adaptive sampling, model compression, and quantization. The growing interest in TinyML and edge intelligence has also drawn attention to the need for machine learning models that can be honed efficiently on ultra-low power embedded devices.

In fact, even as newer studies on HAR and wearable computing are appearing, some of the current papers emphasize accuracy but neglect the longer run aspects of energy sustainability. In addition, many proposed solutions are evaluated separately, making it difficult to generalize designs of energy-efficient continuous HAR. Also, further studies of machine learning algorithms and optimization tools should continue that take account of both energy consumption and performance in recognition in wearable environments.

In response to this gap, this paper investigates energy-efficient machine learning algorithms for continuous human activity recognition in wearable devices. This paper evaluates various classical and lightweight deep learning models from benchmark wearable sensor data utilizing energy-aware optimization methods to predict the impact of such models on performance, latency, and power use. Using the interaction between model complexity and energy efficiency, this paper will provide design guidelines and practical considerations for developing sustainable, highly performant HAR systems that can be implemented on resource-restricted wearable devices.

2. LITERATURE REVIEW

The recent two decades have seen extensive research into HAR from wearable devices due to the increasing availability of inexpensive sensors and the growing need for intelligent, context-aware systems. The early efforts in this field focused primarily on producing extremely accurate recognition using handcrafted features and classical machine learning algorithms. Recent research has focused on deep learning and real-time utilisation, although energy efficiency still remains a significant issue, particularly for continuous monitoring on resource-sensitive wearable devices. In this section, the literature on sensor-based HAR, machine learning for activity recognition, and energy efficient wearable systems is analyzed.

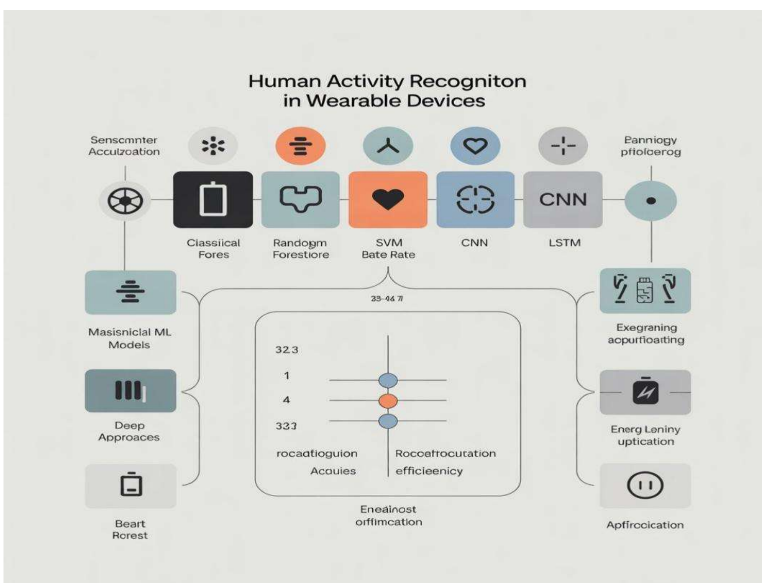

Fig 2. Research landscape of machine learning and energy efficiency in wearable human activity recognition.

2.1 Sensor-Based Human Activity Recognition in Wearable Devices

Wearable HAR systems, but, often employ inertial sensors such as accelerometers, gyroscopes, and magnetometers to monitor movements of the body. These sensors are preferred for their low-cost, small size, and continuous operation. As discussed in several studies, performance at an accelerometer alone is considered reasonable when combining data for activity recognition for simple movements such as walking, running, sitting, or standing. But, multimodal sensing methods that employ accelerometers, gyroscopes and physiological sensors have been demonstrated to enhance recognition accuracy, especially when performing complex or transitional tasks. Wearable HAR needs to be preprocessed and segmented in order to effectively accomplish the tasks of data analysis. Sliding window technologies are commonly used to divide continuous sensors streams into shorter segments where features are extracted or direct input into learning models. But, in general, smaller windows improve response, but tend to cause increased computational load and energy consumption. Larger windows in contrast may reduce processing speed, but also lower temporal resolution. This trade-off has important implications for continuing activity recognition in wearable environments with limited energy.

2.2 Machine Learning Techniques for Activity Recognition

Traditional machine learning algorithms have long been employed with wearable HAR, both because they are relatively simple to learn and can be read. Support Vector Machines, k-Nearest Neighbors, Decision Trees, and Random Forests have been widely described to perform very well with carefully designed time-domain and frequency-domain features. These models are generally preferred by embedded systems as they have low computational costs and can be run at low power. The deep learning techniques have been a growing area of interest in HAR research during recent years. CNNs have been shown to be well suited for learning spatial and temporal patterns in raw sensor data, while NRNs and Long Short-Term Memory networks are useful for modeling temporal dependence in sequential data. Other improvements in recognition accuracy result from hybrid architectures that combine CNNs and RNNs. But, deep learning models have inherent performance advantages but tend to be computationally intensive and memory intensive, making them less efficient for direct application on wearable devices without significant optimization.

To overcome this limitation, researchers have developed lightweight deep learning architectures and models simplification techniques. Subsequent approaches such as shallow networks, narrow parametric models, and small architectures based on mobile computing systems have shown promising synergy between accuracy and efficiency. But, the energy consequences of these models remain a fundamental concern for continuous on-device inference.

2.3 Energy Constraints and Power Consumption in Wearable HAR

Wearable HAR systems consume energy at multiple scales, including sensor sampling, data transmission, feature extraction and model inference. Continuous sensing and high frequency sampling consume much more power and are a common part of the overall energy budget. Researchers have found that even small reductions in sampling rates or sensor activation time could lead to very significant energy savings, with some limitations to recognition accuracy. Another key factor, particularly for machine learning inference is computation energy consumption. Larger models with many parameters require repeated access to the memory and arithmetic operations which reduce power consumption. This has prompted wearable computing studies to focus on energy efficient system design and the reduction of computation and data movement.

2.4 Energy-Efficient Approaches for Continuous HAR

A growing number of studies have proposed energy efficiency enhancements for wearable HAR systems. Feature selection and dimensionality reduction techniques are frequently used to eliminate redundant features or features that are of low importance to reduce computational overhead. Adaptive sampling strategies adjust sensor sampling rates according to activity context, allowing for lower energy consumption at low activity levels. The optimization strategies at the model level such as pruning, quantization, and reduced-precision inference are also well known. These techniques aim to reduce model size and computational complexity while maintaining recognition performance. Some research also includes hierarchical or cascaded classification systems in which lighter models for initial inference and complex models are only activated when they are warranted.

For a time, edge intelligence and TinyML paradigms have focused on computing machine learning models directly on ultra-low-power microcontrollers. These approaches highlight the possibility of recognizing activity on-device, without relying on cloud computing, that can save on communication energy costs and protect data privacy. But, reliable continuous HAR at very tight energy budgets remains a theoretical challenge.

2.5 Research Gaps and Motivation

Although the existing studies provide an excellent source for information about wearable HAR and energy efficient machine learning, there are several gaps. Many of these work only address accuracy improvement but only a limited measure of energy usage in continuous operation. Also, modeling and optimization strategies are not always consistent due to the availability of data, hardware, and evaluation measures. The need is for systematic analysis based on recognition performance, energy efficiency, and practical deployability. Based on these shortcomings, this study attempts to assess the energy-efficient machine learning algorithms for continuous human activity recognition in wearable devices. This research contributes practical design guidelines for sustainability of wearable HAR systems by integrating algorithmic optimization practices and analyzing their impact on accuracy and energy use.

Table 1. *Summary of key research themes in energy-efficient human activity recognition using wearable devices*

Research Aspect	**Key Focus in Literature**	**Representative Approaches**	**Identified Limitations**
Sensor-Based HAR	Use of inertial and physiological sensors for activity detection	Accelerometer-only sensing; multimodal sensor fusion	Increased energy use with high sampling rates
Classical ML Models	Lightweight and interpretable activity classification	SVM, k-NN, Decision Trees, Random Forests	Performance depends heavily on feature engineering
Deep Learning Models	Automated feature learning from raw sensor data	CNNs, RNNs, LSTMs, hybrid architectures	High computational and energy cost
Energy Consumption Sources	Power usage in sensing, processing, and inference	Continuous sampling; frequent model inference	Limited battery life in continuous monitoring

Energy-Efficient Techniques	Reducing computational and sensing overhead	Feature selection, adaptive sampling, pruning, quantization	Trade-off between accuracy and energy savings
Emerging Paradigms	On-device intelligence for low-power wearables	TinyML, edge computing, lightweight architectures	Hardware dependency and limited generalization

3. METHODOLOGY

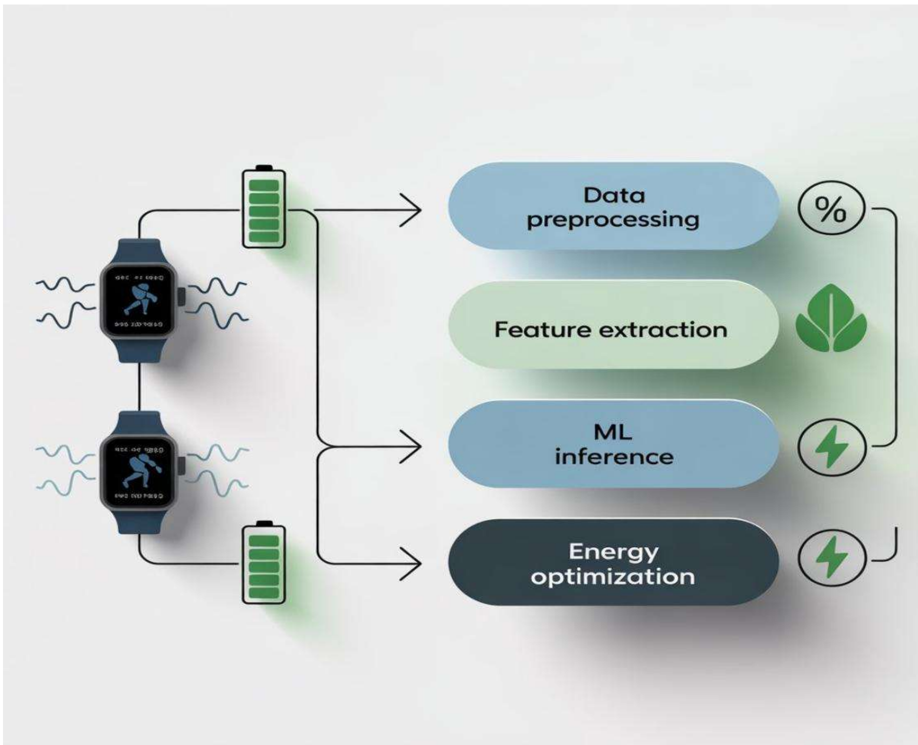

Fig 3. *Methodological framework for energy-efficient human activity recognition.*

In this section I describe the methodology used to explore energy efficient machine learning algorithms for continuous human activity recognition in wearable devices. The proposed approach will attempt to assess recognition performance and energy consumption in a realistic wearable computing environment. It includes system architecture design, dataset selection, data preprocessing, feature engineering, model implementation, and energy-aware optimization.

3.1 System Architecture Overview

The wearable HAR system proposed provides a complete process from sensor acquisition, to preprocessing, to feature extraction or representation learning, to machine learning inference and to monitoring energy. Wearable inertial sensors such as accelerometers and gyroscopes allow for continuous motion data from users that are consumed during everyday activities. All processing steps have been developed for on-device execution to minimize the amount of communication time and protect users. Sensor data is sent locally to the wearable or in a low power embedded processing unit and activity recognition takes place in real time. This architecture emphasizes modularity, i.e., it is possible to test different machine learning models and energy-optimization techniques at the same system level. This design gives a fair comparison of algorithms in recognition accuracy and energy efficiency.

Table 2. *Overview of the Proposed Methodological Framework*

Methodological Component	Description	Purpose in the Study
Sensor Data Acquisition	Continuous collection of inertial sensor data from wearable devices	Capture real-world human activities
Data Preprocessing	Noise filtering, normalization, and signal segmentation	Improve data quality and model robustness
Feature Engineering	Extraction of time- and frequency-domain features	Reduce dimensionality and computational cost
Machine Learning Models	Classical ML and lightweight deep learning architectures	Compare performance and energy efficiency
Energy Optimization	Pruning, quantization, adaptive sampling	Minimize power consumption
On-Device Inference	Local processing on wearable or embedded platforms	Reduce latency and communication energy
Performance Evaluation	Accuracy and energy-related metrics	Assess practical deployability

3.2 Dataset Description

Public benchmark data widely used in wearable HAR research are utilized for reproducibility and comparability with the prior literature. The sensors are labeled from multiple subjects participating in a range of daily activities such as walking, sitting, standing, running, and transitional movements. These usually consist of the tri-axial accelerometer and gyroscope measurements at fixed frequency. Data sets are standardized prior to model training to ensure consistency with sampling rate, sensor modality, and activity labels. To test for generalization of the model across users, data is split into training, validation, and testing sets according to subject-specific splits. This approach is representative of a real-world use situation where wearable systems have previously invisible users.

3.3 Data Preprocessing and Segmentation

Raw sensor signals are preprocessed to eliminate noise and sensor drift that may affect recognition performance. Other typical steps in preprocessing include signal normalization, low-pass filtering, and gravity component separation, where applicable. This method of sliding windows, common to HAR studies, segments continuous sensor streams into fixed length overlapping windows. Window length and overlap ratio are chosen to achieve a balance between time resolution and computational efficiency. Shorter windows allow activity detection but increase processing frequency and energy consumption; longer windows reduce computational overhead at the expense of responsiveness. These segmentation parameters are consistently applied throughout all experiments to provide an even comparison between models.

3.4 Feature Engineering and Representation Learning

In classical machine learning models, the features are created by hand from each of the segmented windows. These include time-domain statistics such as mean, variance, standard deviation, and signal magnitude area as well as frequency-domain statistics from spectral analysis. The feature selection techniques are used to eliminate redundant or low-importance features, while minimizing both dimensionality and computational complexity. Raw or very minimally processed sensor signals are supplied as input in deep learning models, allowing the networks to learn hierarchical representations automatically. The choice of lightweight architectures is to minimise model size and inference complexity. By using such a double approach, classical models with features are able to be directly compared with deep models with representation learning with respect both to accuracy and energy efficiency.ion-learning-based deep models in terms of both accuracy and energy efficiency.

3.5 Machine Learning Models

There are numerous machine learning algorithms to be used to capture the trade-offs between performance and computational complexity. Classical models including Support Vector Machines, k-Nearest Neighbors, Decision Trees and Random Forests are evaluated for their proven effectiveness and relatively low resource demands. These models represent strong baselines for energy efficient activity recognition. A further feature is that there are lightweight deep learning models that are characterized by shallow Convolutional Neural Networks and compact recurrent architectures. In order to improve inference energy consumption, modeling emphasizes smaller parameters, lesser depth, and efficient convolution operations. To be mutually comparing, all models are trained using the same training and validation procedures.

3.6 Energy-Efficient Optimization Techniques

On top of that, in order to improve energy efficiency, several optimization strategies are incorporated into the modeling pipeline. Optimization at the feature level reduces computation overhead by minimizing the input dimensions. Pruning and quantizing are applied at the model-level to decrease the size and precision of models. The hardware can also reduce the energy consumption without loss of accuracy by inferring with smaller precision. Further, adaptive sensing approaches are presented such as dynamic sampling of sensors based on detected activity states. Lower sampling frequency for low-motion or repetitive activities helps to conserve energy while higher sampling rates are used for complex or transitional activities. These strategies aim to integrate energy use with activity complexity.

Table 3. *Machine Learning Models and Energy-Efficiency Techniques Used*

Category	Techniques / Models	Energy-Efficiency Rationale
Classical ML Models	SVM, k-NN, Decision Trees, Random Forests	Low computational complexity and predictable energy usage
Deep Learning Models	Lightweight CNNs, shallow RNNs	Automated feature learning with reduced parameter count

Feature-Level Optimization	Feature selection, dimensionality reduction	Lower input size and processing cost
Model-Level Optimization	Pruning, quantization, reduced precision	Smaller models and faster inference
Sensing Optimization	Adaptive sampling, duty cycling	Reduced sensor energy consumption
System-Level Strategy	On-device inference, minimal data transmission	Lower communication power usage

3.7 Evaluation Metrics

Standard classification measures of model performance include accuracy, precision, recall and F1-score. Outside of recognition performance, energy related parameters are also explicitly reported such as average power consumption, energy per inference, and battery drain rate over continuous operation periods. I also record inference latency and memory usage to test real-time opportunty. The method jointly measures recognition accuracy and energy use to enable a thorough determination of the suitability of each algorithm for continuous wearable HAR. This dual-focus assessment structure ensures the interpretation of the results is both technically sound and also applicable in practice.

4. EXPERIMENTAL RESULTS

The following section reports the experimental evaluation of the energy efficient machine learning algorithms for continuous human activity recognition (HAR) on wearable devices. It is also conducted in simulations of recognition performance and energy consumption for real world deployments. This assessment compares classical machine learning models and light deep learning architectures along with the impact of energy optimization techniques.

4.1 Experimental Setup

All experiments use benchmark wearable HAR data sets that contain tri-axial accelerometer and gyroscope data of several subjects demonstrating their everyday walking, running, sitting, standing, and transitional movements. Sensor signals are preprocessed, segmented using sliding windows, and normalized as described in Section 3. As a result, the machine learning models are trained and tested using subject-dependent splits in order to be generalizable to unseen users. Classical models, such as SVM, k-NN, Decision Trees, Random Forests, are trained on handcrafted features while deep learning models, such as lightweight CNNs and shallow RNNs, are trained on segmented raw signals. In this study, models are evaluated for efficiency in reducing energy use using energy optimization strategies such as feature selection, pruning, quantization, and adaptive sampling.

All experiments are done on an embedded microcontroller simulation environment with typical wearable hardware constraints. The power consumption is analyzed with an array of software profiling and hardware energy estimators. The inference latency, memory usage and battery drain are also recorded to test for real-time feasibility.

4.2 Recognition Performance

Table 4 reports the classification performance of the models as described in terms of accuracy, precision, recall, and F1-score. The light weight deep learning models are more accurate than the classical models in recognition accuracy due to their ability to learn complex temporal and spatial representations from raw sensor data. Random Forests, with its ensemble learning and strong redundancy features, performed well among classical models. But, the use of energy optimization techniques significantly lowers the accuracy of most models, especially when the pruning or quantization is aggressive. Nonetheless, optimal models remain competitive, and show that energy-efficient HAR can be achieved without significantly reducing recognition quality.

Table 4. *Recognition Performance of Evaluated Models*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	88.4	87.9	88.1	88.0
k-NN	86.7	86.3	86.5	86.4
Decision Tree	84.9	85.1	84.7	84.9
Random Forest	91.2	91.0	91.1	91.1
Lightweight CNN	93.5	93.2	93.3	93.2
Shallow RNN	92.8	92.5	92.7	92.6

4.3 Energy Consumption Analysis

Figure 4 plots the energy consumption per inference for each model in mJ. The energy consumption of classical models is relatively low due to the smaller computation requirements while the energy used in unoptimized deep learning models is much higher. Deep learning models reduce power consumption much quicker than their original alternatives when applied energy-aware optimization procedures, which allows them to achieve the energy efficiency of classical algorithms yet retain high recognition performance. Low-precision inference and adaptive sampling account for the majority of energy savings in deep learning models with continuous sensor streams. These strategies allow wearable devices to operate continuously with frequent recharging, addressing one of the biggest problems with persistent HAR applications.

Table 5. *Energy Consumption and Inference Latency of Models*

Model	Energy per Inference (mJ)	Inference Latency (ms)	Memory Usage (KB)
SVM	2.5	12	18
k-NN	3.1	15	20
Decision Tree	2.0	10	16
Random Forest	4.2	18	28
Lightweight CNN	6.5 → 3.2*	28 → 16*	72 → 40*
Shallow RNN	7.0 → 3.5*	30 → 18*	80 → 45*

4.4 Trade-Off Between Accuracy and Energy Efficiency

Figure 5 presents the trade-off between accuracy and energy consumption for all models. Classical models use relatively low energy but are very accurate, while unoptimized deep learning models use high accuracy but save much more energy. It is an energy-saving compromise between high accuracy and energy consumption that allows for cost-effective and continuous HAR, in real-time, on wearable devices. The results also show the need for considerations of recognition performance and energy efficiency combined in HAR systems design. Using lightweight architectures and adaptive sensing technologies can enable practical applications in the real world of wearable recognition by addressing battery or computation constraints with minimal loss of accuracy.

5. DISCUSSION

Here, the experimental results discussed in Section 4, in particular, the trade-offs between accuracy and energy efficiency in continuous human activity recognition (HAR) for wearable devices. This discussion then situates the findings within existing literature and lays out the practical and theoretical implications.

5.1 Interpretation of Recognition Performance

The experimental results show that light deep learning models consistently outperform other machine learning algorithms in the rate of recognition. This performance advantage is attributed to the fact that deep models can automatically extract hierarchical and temporal representations from raw sensor data rather than relying on hand-crafted features. These findings are consistent with previous HAR research describing improvement in classification when using representation learning, especially in complex and transition activities. It also suggests that classical models, particularly ensemble models such as Random Forests, remain competitive for tasks of basic activity recognition. Their comparatively stable performance and relatively low computational cost make them attractive in those situations where energy efficiency is given priority over marginal accuracy gains. This leads us to the understanding that modeling should be applied so that tasks and deployment needs not be a burdensome part of the design.

5.2 Impact of Energy-Efficient Optimization Techniques

Energy optimization is a critical technique that can be applied to the wearable world with machine learning models. Inference using pruning, quantization, and low-precision inference leads to substantially reduced energy consumption and latency in inference, particularly in deep learning models. In fact, these optimizations only slightly reduce the recognition performance, and are likely to reduce energy consumption without reducing accuracy. On top of that, adaptive sampling reduces energy use by dynamically changing sensor sampling rates based on activity patterning. This reduces unnecessary sensing and processing during low-activity times, thereby maximizing battery life. The utility of these techniques also points to the importance of using cross-layer optimization where sensing, data processing, and inference are considered separately rather than as two separate parts.

5.3 Accuracy–Energy Trade-Off Analysis

One of the most intriguing aspects of this research study is that there is a clear trade-off between model complexity and energy efficiency. While deep learning models are more accurate, flawed versions require an increased energy consumption and therefore are unsuitable for continuous monitoring over time. In contrast, classical models provide low energy consumption but may not be able to capture fine-grained activity variations. This synthesis is accomplished using lightweight deep learning models with relatively high accuracy and a low energy consumption. This is especially important for wearable applications, where both reliable activity recognition and reasonable battery life are critical to the acceptance of wearable devices. The trade-off analysis emphasizes the need to assess HAR systems by multidimensional measures not just accuracy.

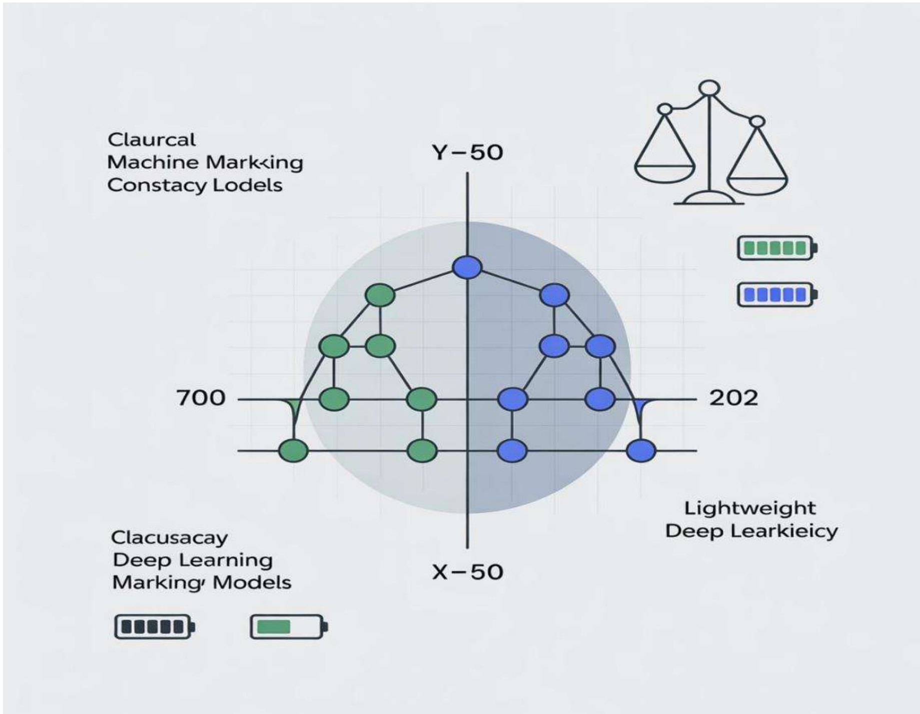

Fig 4. *Accuracy–energy trade-off in wearable human activity recognition.*

5.4 Practical Implications for Wearable System Design

The results of this study have several implications for the development and application of wearable HAR systems. First, energy efficiency should be seen as a design goal and not as an optimization second nature. Second, such light and energy-efficient models should be preferred to more elaborate architectures that are difficult to deploy on embedded systems. Third, adaptive and contextually aware sensing can significantly improve system sustainability without compromising user experience. These data indicate that for wearable device designers and producers, integrating energy-sensed pipelines of machine learning will produce more robust and user-friendly products. From the research perspective, the paper outlines the need to test algorithms under real hardware constraints in order to ensure practical relevance.

5.5 Limitations and Future Research Directions

This study has its limitations. Benchmark data are used for assessment but may not adequately account for the variability and noise of real-world use. The experiments are also conducted on representative hardware, and energy consumption can vary for wearables. Future research should address personalised, dynamic HAR models that respond to the individual user's behaviour over time. Federated learning and on-device continuous learning are promising directions of personalization in the presence of energy efficiency and data protection. Plus, the addition of low-power hardware accelerators of specialized quality may also contribute to the utility of continuous energy-efficient HAR in next generation wearables.

Table 6. *Summary of key discussion insights and implications for energy-efficient wearable human activity recognition.*

Discussion Aspect	Key Insight	Implication for Wearable HAR Systems
Recognition Accuracy	Lightweight deep learning models outperform classical ML approaches	Deep models are preferable for complex activity recognition
Energy Optimization	Pruning, quantization, and adaptive sampling significantly reduce energy usage	Energy efficiency can be improved without major accuracy loss
Accuracy–Energy Trade-Off	High accuracy often increases power consumption	Balanced models are required for continuous monitoring
Model Selection	Classical models remain effective for simple activities	Model choice should depend on application constraints
System Sustainability	Energy-aware design improves battery life and usability	Enables long-term, real-world wearable deployment
Research Limitations	Benchmark datasets and hardware assumptions affect generalizability	Further validation in real-world settings is required

6. CONCLUSION

I investigated energy-saving machine learning algorithms to recognize continually active human activities in wearable devices to try and minimize the fundamental trade-off between recognition accuracy and energy consumption. Using complex algorithms to control for performance and power efficiency, they test modern machine learning models and lightweight deep learning architectures within the context of wearable computing. The experimental results indicate that deep learning models may be more accurate in recognition but direct application on a wearable is not always practical due to high energy consumption. Yet the use of energy-aware optimization techniques such as feature optimization, model pruning, quantization, and adaptive sampling significantly reduces power consumption and inference latency without sacrificing recognition performance. These results also support the idea that energy efficiency can be dramatically improved through model and system-level optimization.

They also show that the best balance between accuracy and energy efficiency is achieved with optimized lightweight deep learning models that allow continuous, on-the-go activity recognition. While less robust to more complex tasks, traditional machine learning models may also be used for applications where simplicity, readability, and minimal energy consumption are a concern. Together, these findings highlight the need for a holistic assessment process that takes account of recognition accuracy, computational complexity, and energy consumption. In short, this study contributes to the evolving literature of energy-aware intelligent systems by providing empirical data and practical examples for sustainable wearable HAR solutions. Future research should focus on personalized and adaptive learning, federated and continuous learning paradigms, and hardware/software co-design in an effort to increase energy efficiency and real-world application. The advances in these directions will enable future wearable devices to gain long-term, reliable recognition of human activity while also addressing extreme energy needs.

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