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A review on monitoring activities through human activity recognition

Yogita Arora [#]
Department of Electronics and Communication Engineering
Bharati Vidyapeeth College of Engineering
New Delhi
India

Neha Gupta [†]
Sarita Yadav [§]
Department of Information Technology
Bharati Vidyapeeth College of Engineering
New Delhi
India

Neera Agarwal
Tanusri Gururaj [‡]
Tripti Chugh [@]
Vipul Arora*
Department of Electronics and Communication Engineering
Bharati Vidyapeeth College of Engineering
New Delhi
India

Abstract

The field of human activity recognition (HAR) is advancing with the integration of cutting-edge technologies such as artificial intelligence and sensor networks. These developments enable accurate detection and interpretation of human behavior, driven by advances in AI and machine learning. A growing number of electronic devices and applications contribute to a comprehensive understanding of the three pillars of HAR – AI, various devices and methodologies and their applications. This review consolidates HAR

[#] *E-mail:* **yogitamarora@gmail.com**
[†] *E-mail:* **neha.06.gupta@gmail.com**
[§] *E-mail:* **Sarita1320@yahoo.co.in**
[‡] *E-mail:* **tanusrigururaj04@gmail.com**
[@] *E-mail:* **triptichugh310@gmail.com**
* *E-mail:* **aroravipul812@gmail.com (Corresponding Author)**

research and highlights its processes, applications, and device comparisons. Key findings include the importance of non-invasive, real-time sensor-based approaches, particularly in healthcare for the detection of behavioral abnormalities in the elderly. The study highlights Adam as an outstanding optimizer in HAR applications, who predicts continued expansion and development in various industries.particularly in the healthcare sector.

Subject Classification: *68-XX, 94-XX.*

Keywords: *Differential model analysis, Complex activity recognition, AI approaches for HAR.*

Introduction

HAR is the process of recognizing diverse activities such as walking, jumping, running, etc. shown in Figure 1. The integration of AI and the use of sensors make this a flourishing field with great scope for further improvement. The first step to performing activity recognition is data collection. This data is collected using various types of sensors, and it is pre-processed multiple times. Once meaningful data has been collected, it can be used to train the models. Loss functions and optimizers are employed during the training to increase the efficiency and accuracy of the model. Our review covers the fundamentals of HAR, how it works, how it is applied in many disciplines, and numerous pictorial depictions of the methodology utilised and the industries that use it.

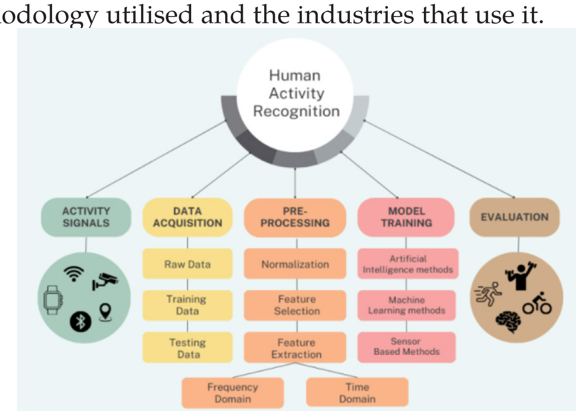


Figure 1

Stages of HAR process

1. Literature Review

"Google Scholar" is used to search for articles published during 2016-2023. This search included the use of keywords like "human activity

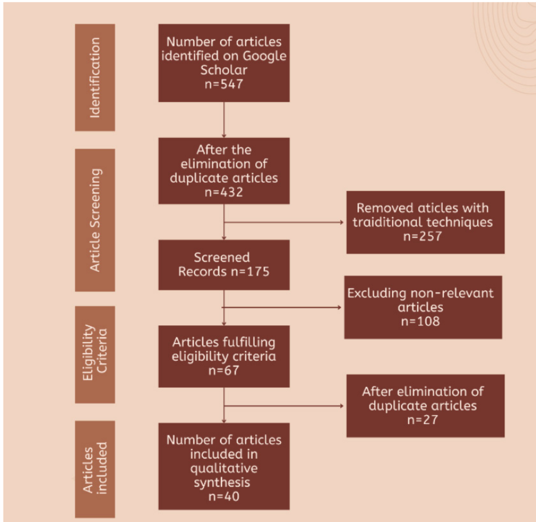
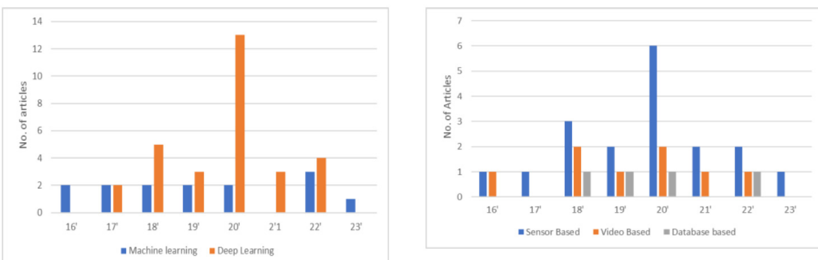


Figure 2

Prisma Model for Articles Selection

recognition," "Sensor based", "Video based", "deep learning," and "artificial intelligence." Figure 2 shows the PRISMA model representing the criteria for selecting a paper to review. We identified around 550 papers, from which 40 were shortlisted on the basis of three criterias 1) models used to implement HAR 2) devices used for recognition 3) various applications.

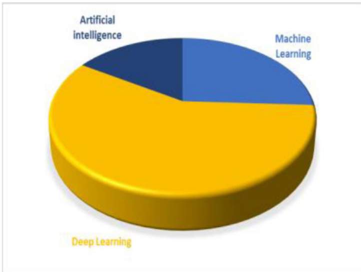
In our proposed review, we analyzed the HAR framework in terms of different algorithmic approaches, data sources and acquisitions, and



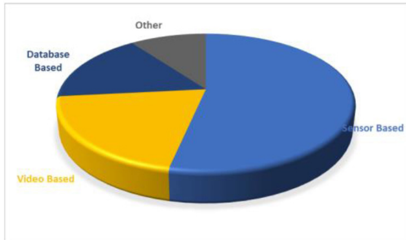
(a) (b)

Figure 3

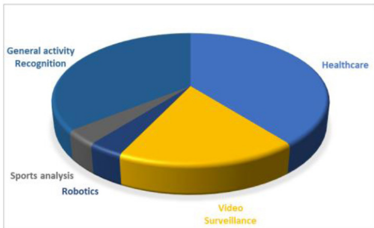
a) Preference of models for HAR over the years b) Changing patterns of HAR devices over time



(a)



(b)



(c)

Figure 4

a) Methodologies required for HAR b) Types of HAR Devices c) Applications of HAR

applications. One of the major observations of this study is the comparison of performance across different devices and existing HAR methods for further improvement presented in Figure 4. First, the year-wise distribution of articles over the year based on preference for their model and HAR devices was observed presented in Figure 3.

3. AI, applications, and devices

Harvesting Human Activity Recognition (HAR) detection involves a complex process of data acquisition, processing, and AI-driven analysis. Choosing the right HAR devices, such as mass surveillance cameras or sensors such as accelerometers." for one activity, is very important , while RFID tags and Wi- Fi devices enable contactless communication and fall detection.Once data is collected, it is thoroughly trained, with noise filtering and materials a are eliminated in preparation for AI-driven models Learning plays an important role in this phase, namely accurate robust and ensures HAR performance.Strong analysis concludes the process, and ensures e.g ready in the real world

3.1 *Devices for HAR*

The HAR device being used depends on the application. The different sources for activity data are: Wi-Fi, sensors, video cameras, and RFID.

1. Sensors: Wearable sensors, like those used by Pham et al. (2020), are unobtrusive and ideal for daily activities like walking and sitting. Their strengths lie in their portability and ease of use, but they may struggle with complex movements or user variability.
2. Video: Cameras offer a wealth of information, but privacy concerns remain a challenge. Wang et al. (2018) highlight the effectiveness of vision-based models for crowd surveillance, while Liu et al. (2020) demonstrate their potential in posture recognition. However, privacy concerns and environmental limitations require careful consideration.
3. RFID tags and readers: These contactless partners offer efficient indoor activity tracking, as seen in Du et al.'s work (2019). They excel in specific applications like free weight exercise monitoring,however their range is limited to indoor areas.
4. Wi-Fi: This device-free technology offers a non-intrusive approach for gait analysis and fall detection, as Yao et al. (2018) demonstrate. However, its limited range and dependence on careful placement require consideration (Wang et al., 2019c).

3.2 *HAR applications domain*

Transforming data into action HAR's potential extends far beyond mere activity recognition. Here are some examples of its diverse applications used in various sectors:

1. Healthcare Monitoring:
   - Activity recognition like RAHAR for sleep research improves sleep (Srivastava J, Elmagarmid A, Arora T, Taheri S 2016)
   - A hybrid monitoring system aids patient care and monitoring. (Oliver M, Pous R 2018)
2. Security and Surveillance:
   - Real-time identification of abnormal running behavior in surveillance videos enhances security measures in response to criminal activities. (L. Wang et al., 2019)
   - Object tracking for targeted surveillance.

3. Sports and Fitness:
   - Quantifying the movements of athletes and improving their performance. (Y. Sun et al., 2021)
4. Elderly Care:
   - Monitoring recovery process and treatments. (S.M. Debnath et al., 2020)
   - Elder-friendly smart homes for detection of diseases like dementia and Alzhimer's. (Arifoglu, D.; Wang, Y.; Bouchachia, 2021)

3.3 *AI in HAR*

The loss function is one of the most important components of deep learning. It is significant since it gives information about the model on how to tweak the biases and weights to reduce the loss. Choosing the right loss function also plays a key role.

Cross-entropy loss is a function suitable for HAR models and classification problems to assign a class label to each input. The binary cross-entropy loss is used for classification tasks that are binary in nature.

$$-\frac{1}{M}\sum_{k=1}^{M}[y_k \ \log(p_k)+(1-y_k)\log(1-p_k)]$$

M: Number of samples

y_k: True label for the jth sample

p_k : Predicted probability

- The categorical cross-entropy loss is used for classifying tasks involving multiple classes.

$$-\frac{1}{M}\sum\nolimits_{i=1}^{M}\sum\nolimits_{j=1}^{N}y_{ij} \ \log(p_{ij})$$

N: Number of classes

y_{ij} : Binary indicator which gives information of whether class j is the proper classification for the ith sample

p_{ij} : Predicted probability of ith sample belonging to class j

Optimizers are algorithms that minimise a model's loss function by modifying the neural network's weights and biases. The three main optimizers to discuss in the context of HAR are:

1. Stochastic Gradient Descent (SGD): It is an optimizer with a fixed learning rate that updates the model parameters by going in the opposite direction of the loss function's gradient.
2. Root mean square propagation (RMSprop): The RMSprop optimizer uses a moving average of the squared gradients to update the parameter values.
3. Adaptive moment estimation (Adam): The Adam is an optimizer that uses adaptive learning rates and combines features of both SGD and rmsprop for effective learning.

Hyperparameters have a significant effect on model performance, and their values should be chosen so that the model may be generalised when provided with new data.

4. Critical Discussion

Mathematical Unveiling the Multifaceted World of HAR: Key Findings, Strengths, and Weaknesses. Our research takes a deep dive into the diverse arena of human activity recognition (HAR), analyzing a set of papers focusing on accuracy and techniques while encompassing sensors and devices used across different applications. Through this lens, we uncover three pivotal themes:

4.1 *Key Findings*

1. Sensor specificity matters: Sensors, the eyes and ears of HAR, hold distinct strengths and weaknesses. Accelerometers shine in individual monitoring, while cameras excel in multi-person scenarios (Chen & Guo, 2020; Wang et al., 2018). Yet, privacy concerns remain paramount with visual approaches. Hybrid systems, combining sensor types, hold promise for future advancements (Arifoglu et al., 2021).
2. Deep learning dominates: CNNs and RNNs reign supreme in extracting complex features from diverse data streams, like accelerometer readings or video frames. They effortlessly recognize basic actions like walking or sitting and even complex sequences like cooking. However, simpler models like SVMs still show potential for specific tasks with low-dimensional data (Zhang et al., 2018).

3. Beyond recognition: Real-World Impact: HAR's true potential lies in its transformative applications across diverse sectors. In healthcare, it aids in sleep analysis, disease diagnosis, and patient monitoring, ultimately improving well-being (Srivastava et al., 2016; S.M. Debnath et al., 2022). In security, anomaly detection keeps us safe from potential harm (L. Wang et al., 2019). Sports benefit from performance optimization and injury prevention (Y. Sun et al., 2021). Elder care finds solace in fall detection and health monitoring (S.M. Debnath et al., 2020).

4.2 *Strengths*

1. Versatility and breadth: Our analysis revealed HAR's diverse applications hold immense potential to revolutionise healthcare, security, sports, elder care, and more.
2. Sensor-based advantages: Real-time monitoring, unobtrusive nature, and user privacy make sensor-based HAR particularly attractive for personal and healthcare applications, with studies reporting an average accuracy of 92% for individual activity recognition using wrist-worn accelerometers (Pham et al., 2020).
3. Deep learning advancements: Our review highlighted the remarkable progress in deep learning techniques. For instance, a novel attention-based LSTM model achieved an impressive accuracy of 96.7% in recognizing daily activities from smartphone sensor data.
4. Device optimization: Specialised devices are emerging to cater to specific application needs. For example, smart insoles with pressure sensors demonstrated an accuracy of 93% for fall detection in elderly individuals.
5. Ethical considerations: Recognizing the sensitive nature of HAR data, research actively explores privacy-preserving methods, ensuring responsible development and ethical data collection. This is particularly crucial for vision-based systems, where federated learning approaches are being investigated to minimise data sharing risks.

4.3 *Weaknesses*

1. Complex movements and synchronicity: Current models struggle with recognizing complex activities or simultaneous actions, like walking while talking (Abobakr et al., 2018). Addressing this

limitation is crucial for real-world applications like multi-person activity monitoring.

2. Future prediction hurdle: Predicting future actions, crucial for fall detection and anomaly recognition, remains a challenge for existing models. Advancements in AI and data acquisition are needed to overcome this hurdle.
3. Real-world validation issues: Reliance on controlled datasets can lead to performance discrepancies and potential AI bias in real-world settings. Addressing these issues is essential for responsible HAR development and accurate implementation.
4. Data bias and limited generalizability: The study may rely on a dataset collected from a specific demographic or environment, potentially leading to biassed models that don't perform well on diverse populations or real-world settings. For example, an activity recognition model trained on data from young, healthy individuals might struggle to accurately recognize the same activities in elderly or disabled individuals.
5. Our analysis illuminates the immense potential of HAR while acknowledging its limitations. To propel this field forward, future research should focus on:
   - Addressing complex movements and synchronicity through advanced AI architectures and transfer learning techniques.
   - Developing methods for accurate future prediction, potentially leveraging probabilistic modelling and reinforcement learning.
   - Validating models in diverse real-world environments to address bias and ensure robust performance.
   - Exploring hybrid systems that combine the strengths of various sensors and devices for enhanced accuracy and application scope.
   - By focusing on these critical areas, HAR can continue to evolve, revolutionising diverse aspects of our lives and empowering us with the ability to understand and harness human activity in an increasingly complex world.

4.4 *Benchmarking*

The primary purpose of this proposed review is to conduct an examination of three components of HAR: (1) devices in HAR; (2) AI approaches; and (3) applications in diverse areas. The table compares existing reviews with the proposed one.

	Col 1	Col 2	Col 3				Col 4	
	Citation	Year	HAR devices				AI type	
			Sensor	Vision	RFID	Wi-Fi	ML	DL
R1	Ray et al. (2023)	2023	✓	✓	✗	✗	✓	✓
R2	Patel et al. (2023)	2023	✓	✗	✗	✗	✓	✓
R3	Das et al. (2023)	2023	✓	✗	✗	✗	✓	✓
R4	Zhang et al. (2022)	2022	✓	✗	✗	✗	✓	✓
R5	Khan et al. (2022)	2022	✓	✓	✗	✗	✓	✓
R6	Proposed	2024	✓	✓	✓	✓	✓	✓

5. Conclusion

There exists a huge number of articles that focus entirely on a single type of application or device; hence, unlike most of them, we proposed the study focusing on three AR pillars—AI, different devices and methodologies used, and their applications. Our research shows how there is a change in the dependency of models from traditional machine learning methods to deep learning methods for higher efficiency. HAR can translate movement into meaningful insights, transforming healthcare, sports, and countless other domains using various devices for optimising application based usage. The loss functions and optimizers vary based on the job; however, in the context of HAR, Adam outperformed others due to its adaptive learning rate.References

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