Recent Advances in Popular Deep Learning Techniques in HAR for Smart Homes

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Abstract

The recent developments in the field of technologies like IoT and the decrease in prices of different sensors have led to the promotion of intelligent environments, like smart homes system. Smart homes should provide automated home-based support services to enhance inhabitants' quality of life, independence, and fitness, particularly for the elderly, disabled, and other vulnerable groups. To automate such services at home, the smart home should recognize the everyday routine activities of inhabitants. Methods that detect human activity recognition in smart homes are still evolving, but many issues arise daily. In the present review article, we have reviewed the present status regarding current algorithms, datasets, research, and challenges of HAR in smart homes using sensors.

Keywords: Smart Home, HAR, activity Recognition, deep learning techniques, neural network, LSTM, CNN

1. Introduction

HAR is a domain concerned with recognizing Human Activities of Daily Living using sensor or video data, aiming towards helping human beings in easing their independent lifestyle, especially for disabled, ill, and elderly people, as well as many other applications [1]. The HAR gaining popularity among many sectors right from healthcare, sports smart homes etc. as smart devices and sensors being affordable to general public with the advancement of IoT. Owing to the ever growing demand of this domain primary objective of this review article is to provide introductory overview to the readers new to the field of HAR which includes the generalize HAR workflow, different datasets and their features for study of HAR, sensors and deep learning techniques used in HAR. Further we have compared different datasets and deep learning techniques in terms of different parameters i.e. accuracy, recall, precision, F1 score etc. This review also discuss about privacy and data quality challenges, which are important for smart home applications of HAR. Uniqueness of this review is the inclusion of latest literature regarding application of deep learning techniques and newer datasets up to year 2025. This article is a review of studies conducted btw 2011-2025. The articles reviewed were selected based on inclusion of performance matrices lie accuracies, precise, recall and F1 score in the articles for performance evaluation.

Human activity recognition offers various applications in different areas as:

Healthcare sector : HAR is now widely used to monitor impaired or ill persons remotely and in real-time so as to offer consultancy remotely [2], [3].

Sports : The primary goal of Human Activity Recognition in sports is to monitor players' performance through detection of the players, tracking their activities, identification of actions performed, relating various actions, evaluating various types and ability levels of performance, and facilitating automated statistical analysis [4].

Surveillance: In recent years, the increasing demand for security applications has led to a surge of interest in video surveillance systems within the field of computer vision. These systems enable effective observation and analysis of human motion, making the prediction and interpretation of human behaviour increasingly feasible [5].

Smart Homes: The smart home is actually a home furnished with different sensors as well as actuators, which are able to detect activities like light intensity in the room, door opening, humidity, and temperature, etc., and regulate various household system including lighting, heating, shutters, and other home appliances [6]. In modern times, smart homes are a better choice, in order to provide automated services to people like the elderly, the physically disabled, and Ill people to live independently with a healthy lifestyle in their own homes. Human activity recognition is a multidisciplinary field which primarily focus on detecting, analysing, and classifying human activities [6]. In order to develop real-time smart homes and provide automated services, smart homes essential to understand, recognize, and predict the actions of their

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inhabitants. In order to enable smart homes to recognize resident activities, it is a need of the hour to advance techniques of HAR with high efficiency and cheaper systems [7].

Human activity recognition is being utilized in smart homes at an enormous pace because of the rapidly growing aging population, which needs continuous monitoring and assistance in daily life due to its susceptibility to chronic diseases [8]. Present need of HAR in smart homes is complemented by rampant technological advancement in IoT, as well as exponential growth in number of smartphone and smart device users, and availability of sensors at cheaper prices. [9], [10].

In modern times, the IoT techniques have been significantly developed through assistance aimed at edge computing, mobile computing, and cloud computing. Among all typical applications that use IoT, the smart home is a very representative one and has a bright future [7].

HAR is based on the data generated either through cameras or sensors. The input data from sensors used in HAR can be gathered from different sensors, like ambient sensors, wearable sensors, cameras, and other suitable sensors [11]. There are different techniques employed in HAR for input data processing, including machine learning techniques, computer vision, and signal processing [12]. One of the issue to be considered in HAR is privacy issue while generating data because home monitoring of people's activities through cameras can cause serious privacy issues as people are typically reluctant to install cameras and surveillance systems and activate them when at home. In such case, sensor-based systems became the first choice for recognition of daily routine activities in smart homes. Further, cyber secure systems are required for trustworthy data storage [6]. Though the field of HAR is evolving daily, there are still some inherent lacunas and improvement demands over time. So, it is essential to address those inherent problems in order to make smart homes a real-time application. The present review is an attempt to review inherent issues in current HAR systems, possible directions, research possibilities, and solutions to the rampant development of HAR systems.

The general workflow of HAR involves five different steps, which are explained below and depicted in the Figure.1

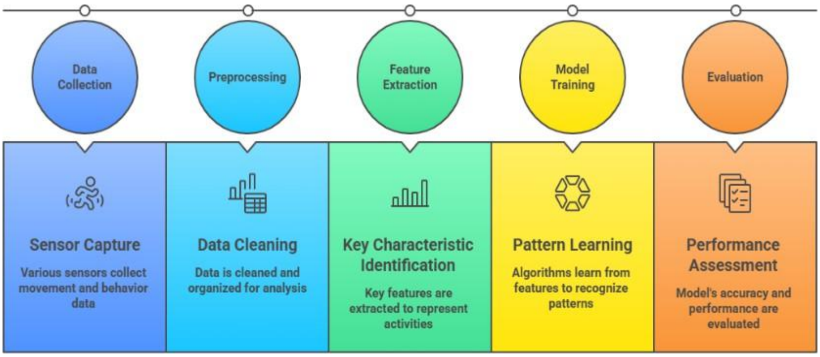

Fig 1. General workflow of HAR

Data Collection Activity: Raw data is the primary source from which subsequent processes will take place in order to recognize human activity. The raw data required can be collected from different sources, like cameras or sensors, of which the later is widely used.

Sensors : Data can be gathered from sensors that are positioned within the environment (ambient sensors) or that are worn by humans (wearable sensors), which are accelerometers, gyroscopes, magnetometers, GPS sensors, and movement detectors [13].

Data Pre-processing : Data Preprocessing comprises of cleaning, filtering, and transformation of raw data to make it fit for further analysis. This may involve the removal of noise, handling of missing values, and normalization of data

Segmentation of Data: This step divides the raw data stream into different segments corresponding to specific activities. It identifies changes in the data that indicate a transition between different activities.

Feature Extraction: The Pre-processed data is further used to extract relevant and discriminative features that are used to detect patterns with the help of PCA, such as (Time- domain: mean, variance, RMS & frequency domain FFT, Wavelets), transition (Standing to walking), and Auto encoders for (de-noising or embedding)

Classification: The classification step uses different algorithms to classify the extracted features into different activity classes. Common classification approaches comprise decision trees, support vector machines, random forests, as well as deep learning models.

2. Different Datasets and Sensors Used In The HAR

There are widely recognized and utilized datasets by the research community for studies in HAR, which are Opportunity, PAMAP2, UniMiB, WISDOM, Extra Sensory, USC-HAD, Skoda, Marble, UCI-HAR, UCI-SBHAR, and various CASAS datasets such as Aruba, Cairo, Kyoto Multi- resident, Milan, Tokyo, and Tulum [14]. Details of the widely used datasets, along with their characteristics and sensors used by them, are described in Table 1.

Table.1 Different Datasets and sensors used in HAR

Sr. No	Dataset	Sensors used	No. of Activities	Participants involved	Device used	Sensor Placement	Sampling rate
1	**PAMAP 2 Dataset** [15]	➢ Inertial Measurement Units ➢ yroscope ➢ Accelerometer ➢ Magnetometer ➢ heart rate monitor	18	10 individual participants	IMUs	Chest, arm, Ankle	100 Hz
2	**WISDM Dataset** [16]	➢ Accelerometer	6	36 participants are involved	Smartphone and Smart watch	Front pocket	20 Hz
3	**UCI HAR** [17]	➢ Accelerometer ➢ Gyroscope	6	A total of 30 subjects with aged 19–48	Smartphone	Waist	50 Hz
4	**ARAS** [18])	➢ PIR motion Sensors ➢ Door sensors, ➢ Temperature sensors ➢ Electricity usage sensors	27	4 participants at two residences.	Ambient sensors (motion, contact, temperature)	Installed in different rooms	Event driven (not fixed)
5	**OPPORTUNITY** [19]	➢ Wearable ➢ Object sensor ➢ ambient sensors	Fine – Grained gestures	4 participants are involved	Wearable	Body, object	30 Hz
6	**USC-HAD**[20]	➢ 3-axis Magnetometer	12	14 participants	Wearable IMU sensors	waist	100 Hz
7	**SHOAIB**[21]	➢ Accelerometer ➢ Gyroscope ➢ Magnetometer	10	7 participants	Smartphone	Wrist, upper arm, belt, left pocket, right pocket.	50 Hz

3. Deep Learning Techniques Used For HAR

Depending on the model type (CNN, RNN, LSTM, GRU, DNN, etc.), deep learning techniques for Human Activity Recognition use a variety of mathematical formulations. A summary of popular deep learning architectures for HAR is provided below, along with mathematical formulas defining their fundamental functions:

Deep neural networks, sometimes referred to as Multilayer Perceptrons (MLPs), these are feed-forward neural networks is characterized by each neuron in one layer being linked to every neuron in the previous layer [22].

$$^{(l}=(\boldsymbol{w}^{(l)}\boldsymbol{a}^{(l-1)}+\boldsymbol{b}^{(l)}) \quad (1)$$

Where:

- *a(l): The Output (activation) of the network generated by the lth layer.*
- *a(l−1): Output of the previous (l−1) (the input vector to current layer)*
- *W(l): Learnable Weight matrix*
- *b(l): Bias values*
- *f(·): The Activation function used in this model is (e.g., tanh, ReLU or sigmoid)*

CNNs are utilized to capture spatial dependencies in sensor inputs like accelerometer data, improving the extraction of meaningful features.

$$\boldsymbol{yj} = (\textstyle\sum^{k-1} \boldsymbol{wi} \cdot \boldsymbol{x}_{j+i} + \boldsymbol{b}) \quad (2)$$

Where:

- *x = input signal*
- *w = filter weights*
- *k = filter size*
- *b = bias*
- *j index for the output position*
- *i=index within the filter window*
- *f = activation (ReLU, tanh, etc.)*

Long Short-Term Memory its type of system capable of selectively memorizing or forgetting data. A simplified LSTM with fewer gates.

$$\boldsymbol{f}_t = (\boldsymbol{w}_{xf} \times \boldsymbol{x}_t + \boldsymbol{w}_{hf} \times \boldsymbol{h}_t - \mathbf{1}, \boldsymbol{x}_t + \boldsymbol{b}_f) \quad \text{(forget gate)} \; (3)$$

Where,

- *σ = Sigmoid Activation function.*
- *w_{xf} = input Weight matrix*
- *w_{hf} = Weight matrix for hidden state*
- *[h_t - 1, x_t] = Merging the present input with the prior hidden representation.*
- *X_t =Present input at time t*
- *b_f = bias*

$$\boldsymbol{i}_t = (\boldsymbol{w}_i\boldsymbol{x}_t\,[\boldsymbol{h}_t - \mathbf{1}, \boldsymbol{x}_t] + \boldsymbol{b}_i) \quad \text{(input gate)} \; (4)$$

$$\acute{\boldsymbol{c}}_t = \tan \boldsymbol{h}\,(\boldsymbol{w}_c[\boldsymbol{h}_t - \mathbf{1}, \boldsymbol{x}_t] + \boldsymbol{b}_c)$$

Where,

- *w_i = Weight matrix.*
- *h_t-1 = concatenation of the past memory and new input.*
- *Bias Vector for the input gate.*
- *wc Weight matrix for candidate memory.*
- *tanh = hyperbolic tangent function.*

- *Bc Bias Vector.*

$$o_t = (w_o \times x_t\,[h_t - 1, x_t] + b_o) \quad \text{(Output gate) (5)}$$
$$\acute{c}_t = \tan h\,(c_t)$$

Where,

- w_i =*Matrix of weight*
- $b_{o=}$ *Bias Vector for output gate.*
- $\acute{c}_t$= *Ready for filtering by output gate*
- c_t = *updated cell state at time*

There are different approaches that are being used in HAR, and the choice largely relies on the intended application, type of data available, and the expected outcome. The methodologies mostly used currently are explained below.
Numerous machine learning approaches, like k- Nearest Neighbors, Decision Trees, Random Forests, as well as Support Vector Machines, are widely utilized for activity recognition because they are computationally efficient and perform well with smaller datasets [12], [27]. In contrast, deep learning approaches such as CNNs, RNNs, LSTMs, and GANs are progressively utilized for their capability to acquire complex patterns as well as features directly from raw data. now replacing traditional machine learning models because of comparatively higher capability to learn features automatically from raw data collected from sensors and identify complex patterns with lower cost than traditional machine learning techniques [12], [23]. Neural networks, typically deep learning techniques, for example, Convolutional neural network, Deep Neural Network, and Auto-encoder, provide major advantages in terms of versatility and their ability to perform better over conventional machine learning approaches [24]. Recently, deep learning techniques or a hybrid framework combining different deep learning techniques or their slightly modifications are being tested for increasing accuracy in predicting activities in HAR while reducing computational demand. Here we have reviewed recent studies concerning the application of different deep learning techniques in predicting activities for real-time use of smart homes.

4. Recent Related Literature

A study proposed HAR models that leverage deep learning approaches like Convolution Neural Networks, Long short term Memory and Gated Recurrent Units Networks to detect and recognize actions with use of smartphone based sensors using UCI-HAR and WISDM datasets. Among all the methods evaluated, GRU Networks achieved the highest accuracy of 98.00% for WISDM dataset and 96.83 % with UCI-HAR datasets respectively. [25]

An innovative HAR architecture, 'HARMamba', was introduced [26], which could combine a selective bidirectional State Spaces Model and hardware-aware design in order to optimize real-time use of resources. Effectiveness of HARMamba was tested with four datasets, viz., WISDM, PAMAP2, UCI, and UNIMIB SHAR. HARMamba outperformed other frameworks, giving either better or comparable accuracy and significantly reducing computational and memory needs. The F1 scores of HARMamba with the above four datasets were found to be 99.20%, 99.74%, 97.01% and 88.23% respectively. The reason behind the effectiveness of HARMamba is its ability to use linear recursive mechanisms and parameter discretization, which makes it possible to focus selectively on relevant input sequences. In addition to this, HARMamba uses independent channels to process sensor data streams to divide each channel into patches and attach classification tokens at the end of the sequence, which is subsequently processed by the HARMamba Block in order to deliver the activity category as an output by the classification head.

A novel HAR system designed to apply data enhancement techniques prior to capturing robust and discriminative features from every activity.[27] Further, set of captured features is subjected to transformer model for activities recognition with UCI HAR, PAMAP2 and WISDM datasets. This HAR model could achieve 98.2%, 98.6% and 97.3% accuracy for PAMAP2, UCI HAR and WISDM respectively. The reason behind high accuracies from this model was its ability to capture low-level as well as high-level information derived from sensor data.

HAR-Res GCNN approach uses a multi-layer outstanding assembly comprising a graph convolutional neural network (Res GCNN) to perform sensor-based HAR [28]. This model was evaluated with two datasets, viz., PAMAP2 and health, in which it was found that Res GCNN delivered an accuracy of 98.18% and 99.07%, respectively. Res GCNN was then used to advance a deep transfer learning model and found it exhibits excellent transferability, as well as small sample with learning ability.

The BiLSTM model is being suggested for Human activity recognition utilizing the PAMAP2 dataset [29]. A BiLSTM-based model could deliver excellent performance with 98.75% training accuracy and 99.27% validation accuracy.

An innovative 1D-CNN-based deep learning technique was proposed to perform HAR and evaluated using three datasets available on public platform like WISDM, UCI-HAPT, and PAMAP2 [15]. In order to enhance model performance, architectural refinement and hyper-parameter fine-tuning were conducted through parameter optimization methods. The model was estimated on the UCI-HAPT dataset using activity sets comprising 6,7and 12 classes, yielding classification accuracies of 98.0%, 96.9%, and 94.8%, respectively. Additionally, the model has achieved accuracies of 90.27% using PAMAP2 dataset and 97.8% using WISDM dataset.

5. Comparative Analysis

The performance of Human Activity Recognition techniques is quantitatively assessed through standard metrics like accuracy, precision, recall, and F1-score. These actions are being calculated on the basis of counts for true positives, false positives, false negatives, and true negatives. In few cases, all four metrics can be computed. Here, we have tried to compare the precision, recall, accuracy and F1 score of different deep learning techniques from previous reported studies,

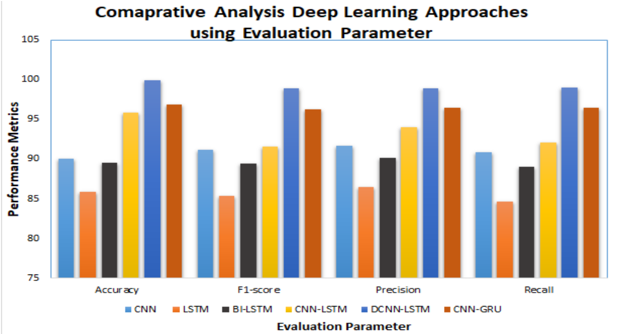

Fig.1 Comparative Analysis of Different Methods based upon Evaluation Results

According to the above graph, DCNN-LSTM method seems to be performing best across the four parameters, viz., Accuracy, Recall, F1 score, and precision. [30],[31] with the help of the Histogram depicted in Fig.1.

The accuracy percentage yielded with different deep learning methods using three datasets generated with wearable sensors is depicted in Fig. 2. [15], [27], [31], [32].

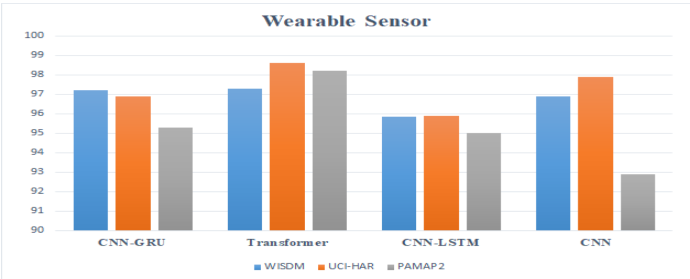

Fig.2 Comparative analysis of accuracies from three datasets based on wearable sensor data with different deep learning methods

The accuracy percentage generated with two deep learning methods i.e LSTM, Bi-LSTM using three datasets generated with ambient sensors is depicted in Fig. 3. [33]

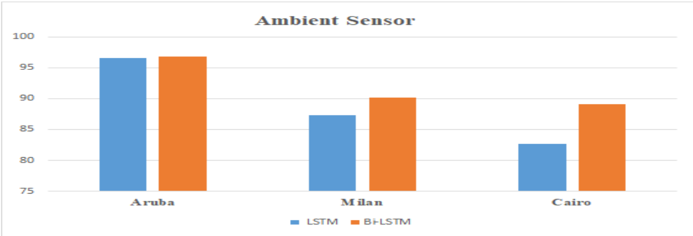

Fig.3. Comparative analysis of accuracies from three datasets based on ambient sensor data with two deep learning methods

6. Conclusion

In this review paper, we have reviewed recent developments in the utilization of different modified deep learning approaches in HAR, which have greatly improved the robustness and performance of HAR systems in smart homes. Moreover, a combination of different deep learning models and hybrid models has enhanced the accuracy and versatility of recognition. Though the HAR system in Smart homes is evolving daily, it has some inherent issues regarding feature extraction, data quality, and privacy issues which need to be addressed in order to adapt it as a real-time application.

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