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A Review : Human Activity Recognition

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ABSTRACT

A discipline called Human Activity Recognition (HAR) uses embedded sensors in cellphones and wearable technology to collect raw time-series information and infer human actions from them. It has become quite popular in a variety of smart home situations, particularly for continually tracking people's actions in ambient assisted living to offer geriatric care and rehabilitation. The system uses a variety of operating modules, including data collecting, noise and distortion removal during pre-processing, feature extraction, feature selection, and classification. Modern feature extraction and selection methods have recently been suggested, and they are categorized using conventional machine learning classifiers. However, the majority of the solutions make use of antiquated feature extraction methods that cannot distinguish between complicated activities. Deep Learning algorithms are widely employed in several HAR systems to efficiently recover features and classify data as high computational resources have emerged and advanced. As a result, the review paper's main objective is to provide a thorough summary of the deep learning approaches utilized in sensor-based identification systems for smartphones and wearable devices. The suggested methods are divided into traditional and hybrid deep learning models, each of which is presented along with its special qualities, benefits, and drawbacks. The study also goes through numerous benchmark datasets that are employed in current methods. The report concludes by listing a few difficulties and problems that need more study and development.

Keywords : Human activity recognition, ML, DL, wearable sensors, smartphon

I. INTRODUCTION

The industry for wearable technology has rapidly expanded, and for good cause given the leading edge of the Internet of Things (IoT). This change alters the healthcare sector, from prevention to treatment. That is a variety of gadgets, including cellphones and smart wristbands are being used in business and research. These sensors' data are gathered, saved, and processed.

Analysis of it, including important judgments based on it. a major This device's objective is to categorize a person's activities at a certain moment in order to help and direct them. human activity recognition individual (HAR). The HAR's goal is to track basic, complicated, and postural changes. actions taken by people in the field of ambient assisted Sports injury prevention, wellbeing, and living (AAL) administration, medical diagnostics, and in particular senior care[1]. The main purpose of these recognition exercises is to identify activities of daily living (ADLs) and fall in senior citizens, preserve their long-term care, wellbeing, and independent lifestyle for someone living alone.

This HAR Machine learning or deep learning models are used by systems to by utilizing the signals acquired from the activities, vision systems, wearable sensors, and environmental sensors [2].

Installation of environmental sensors is necessary in the house, quite expensive, A camera is used by vision systems for recognition. Which are considered to be invasive gadgets [5]. The alternate remedy wearable technology draws researchers primarily because their widespread use. The wearable technology, particularly fitness Trackers and smart watches are primarily utilized for It has a number of built-in or integrated sensors, including Sensors for orientation, gyroscope, and acceleration [2] accessible for a favorable price. Moreover, contemporary cellphones are used as a substitute for wearable technology for exercise acclaim due to its affordability, discretion, and excellent having embedded sensors, similar to wearable technology, and Real-time applications mostly enable [3]. HAR recognition tasks have been successfully accomplished by machine learning-based solutions over the past ten years, but in some situations, like [4], they run into difficulties.

- Multiclass activity recognition training data are scarce.
- Using manually created features, recognizing arbitrary and complicated features
- Recognizing perplexing behaviors like walking with climbing stairs and looking under the bed with falls.
- A subject's dynamic mode of movement or activity in various simulations

Additionally, machine learning-based solutions rely entirely on pre-processed data from raw signals, which contains valuable and noteworthy features that can enhance the performance of classification algorithms. Deep learning models make it simple to solve or get around these problems. Recently, the deep learning models have demonstrated improvement and promise. performance of machine learning-based solutions on multiple benchmark datasets. It can lessen the workload during the phase of feature extraction and data pre-processing [5]. Additionally, it can enhance the deep learning model's resilience and generalization performance. Further benefits of deep learning over machine learning methods include:

- Less reliance on expert knowledge for feature engineering
- Shortened testing time for image-based recognition
- Accurate recognition on Temporal Dynamics of Features
- High performance even for data with poor labeling

Deep learning algorithms outperform HAR-based solutions thanks to all of these distinctive characteristics. Electronic databases like PubMed, PsycINFO, Web of Science, Scopus, and Google Scholar were used to search for and retrieve the published papers on HAR using deep learning techniques in order to provide an overview of the various deep learning models proposed for HAR in real-time and benchmark datasets. Although there are several research reviews accessible for HAR, such as in [6-7], the following highlights some of the work's main contributions in comparison to these reviews:

- Benchmark dataset exploration using sensors and other data collecting tools to identify the actions being conducted by the participants and their surroundings.
- Classified HAR techniques according to the peculiarities of architectural design.
- Contrasted the advantages and disadvantages, experimental architecture, and viability of the suggested HAR techniques.

II. Benchmark Datasets

To independently assess HAR activity to deep learning and machine learning-based solutions, researchers have developed a number of benchmark datasets [5-6]. The dataset includes of motion signals obtained from the head, shin, forearm, chest, upper arm, thigh, waist, and legs of the participants using embedded sensors of gadgets. Smartphones are tucked into pockets of clothing or pants, while smart watches are fastened to dominant hands. The wearable gadgets are secured firmly to the aforementioned places. These include an accelerometer (A), gyroscope (G), orient meter (O), magnetometer (M), object sensor (Obj), temperature sensor (T), and ambient sensor (A) (AM). Each dataset's signals from the data collection include a distinct description of the participants in terms of their age, height, weight, and other physical characteristics. The individuals are given instructions for both easy and difficult tasks to complete during the sensory data collection. Cycling is easy, as are walking, leaping, lying down, running, and jogging. Complex activities include cleaning the kitchen, washing clothing, and cooking. Postural transitions, such as from sitting to standing or from sitting to lying down, are those that occur between two activities. Table I displays the characterization of the benchmark datasets together with their extensive descriptions [8-9].

Table. 1: List of open benchmark datasets to the publicly

S.N.	Datasets	Activities	Device(s) used
1	HHAR [13]	6	4 Smart watches & 8 Smartphone
2	MHEALTH [14-15]	12	Shimmer2 wearable sensors
3	OPPORTUNITY [16]	6	Body-worn, Object and Ambient Sensors
4	PAMAP2[12]	12	3 IMU units 1 Heart rate monitor
5	UCI-HAR [16]	6	Smartphone
6	WISDM [15]	16	Smartphone Smart watch

Deep learning models

Because of the benefits of machine learning algorithms, the researcher is interested in using deep learning models for human activity recognition (HAR). As a classification of the proposed models, Figure 1 illustrates how some strategies used the gathered raw sensory data (time series signals) while others adjusted the signals to imaging of signals like frequency or virtual pictures for activity detection [10].

Convolutional Neural Network

CNN is a powerful tool for categorizing large-scale images and extracting useful information [29]. Researchers have also employed the representation of time series signals as visual cues to the classification of time series signals using CNN. It works quite well. This prompts different HAR systems, as illustrated in Figure 1, to encode the raw time-series data into visual cues like virtual pictures and frequency images for CNN classification.

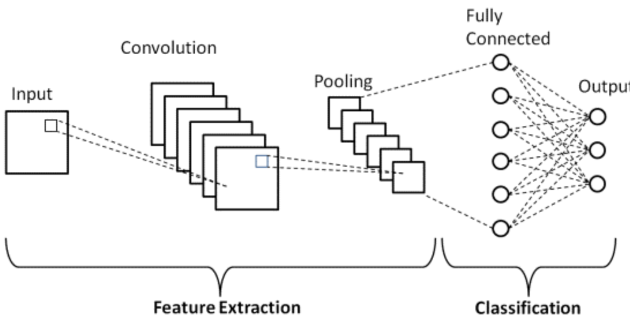

Figure.1 : The design of CNN's virtual image classification system

The Convolutional Neural Network (CNN) models are capable of both image classification and signal prediction for unprocessed time series. As a result, several researchers have combined CNN models to categorize unprocessed inertial sensor information for the identification of human activities. In the field of HAR, feature extraction using CNN offers certain benefits over standard shallow learning techniques, including local dependence, scale invariance, and the ability to capture all potential complicated non-linear interactions between the features [11].

A CNN model has been put out by Chen and Xue [12] to identify basic activities from smartphone tri-axial accelerometer information. Convolution kernels are adjusted in accordance with the CNN model that has been built in order to handle triaxial accelerometer inputs. A unique CNN design by Ronao and Cho [34] has been presented to extract complicated features utilizing an exploited (1x9–1x14) Convolutional layer with a small pooling size of (1x2-1x3). The suggested method has tested with CNNs built with raw data and Fast Fourier Transformed signals' temporal properties [13].

III.LSTM

Instead of categorizing a picture like the CNN model, the LSTM models are very good at predicting the unprocessed sequences of time series data. CNN models use "spatial correlations" to categorize the picture, whereas the LSTM model uses feedback connections to analyze whole data sequences to categorize time series data. The researchers have suggested certain strategies on LSTM-based HAR models, which have an advantage over CNN models [34]. The proposed LSTM-based HAR system is summarized in Table III, along with the obstacles it faces and potential future improvements [11, 12,13]

With 15 participants, Chung et al[46] .'s pilot research concerning the on-body sensor positioning system. This study uses eight body-worn Inertial Measurement Units (IMU) sensors to establish a testbed for a variety of easy activities. The performance of the LSTM model was then assessed in controlled testbed and real-world environments. To further illustrate the class probability of multi-sensor modalities, an ensemble model has been combined with the LSTM model. The suggested system has several difficulties because it was designed to test simple activity recognition with a small number of users, making it unsuitable for widespread applications [13].

IV.Portions of Future Amendment

Recognizing human activity is essential for Ambient Assisted Living, smart homes, sports, and workplace injury detection. Recently, a number of cutting-edge methods have proposed more conventional, generative, and discriminative deep learning models.

However, because most of the techniques classify simple activities rather than complex activities and have a higher number of false alarms, they are not appropriate to use in real-world scenarios. As a result, this section focuses on a few difficulties and issues that need further study and development [14-15].

Scarcity of annotations - Deep learning models need a lot of data to be trained and evaluated. The process of classifying, gathering, and annotating sensory activities is very expensive.

Outdoor Activities: The majority of the subjects' activities take place in supervised lab settings. Real-time implementation is thus a challenge because outdoor activities can differ from those in a controlled environment.

Class imbalance - Emergent and unforeseen activities like accidents and unattended falls are another major challenge because they are difficult to perform and may result in additional injuries if performed without safety precautions.

Complex activities and Postural Transitions - The majority of HAR tasks are straightforward, such as walking, sitting, sleeping, etc.

However, each subject also performs more difficult tasks as part of daily responsibilities like mopping the floor, bathing the pet, and washing clothes. Additionally, there may be a chance of falling when performing postural transitions, such as going from sitting to standing, standing to walking, etc. Postural transitions are only addressed by the UCI-HAPT dataset [15-16].

V. Conclusion

The automatic extraction of characteristics for effective human activity classification is growing significantly, and it has a broad application across many disciplines. This is due to the continual increase in processing resources like GPU devices as well as the ease with which sensory inputs from smartphones and wearable technology may be collected. This study examines a number of deep learning models that allow for the automatic extraction of features for the detection of human activities, highlighting each model's distinct implementation and design, benefits, and drawbacks.

The design and collecting of a number of benchmark datasets that are publicly available for performance evaluation have also been considered. Finally, unresolved issues that must be addressed in order to forward future research are also presented.

VI. REFERENCES

[1]. Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., &Amirat, Y. (2015). Physical human activity recognition using wearable sensors. Sensors, 15(12), 31314-31338.

[2]. Lockhart, J. W., & Weiss, G. M. (2014, September). Limitations with activity recognition methodology & data sets. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication (pp. 747-756).

[3]. Masoud, M., Jaradat, Y., Manasrah, A., &Jannoud, I. (2019). Sensors of Smart Devices in the Internet of Everything (IoE) Era: Big Opportunities and Massive Doubts. Journal of Sensors, 2019.

[4]. Nweke, H. F., Teh, Y. W., Al-Garadi, M. A., &Alo, U. R. (2018). Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges. Expert Systems with Applications, 105, 233-261.

[5]. Nweke, H. F., Teh, Y. W., Mujtaba, G., & Al-Garadi, M. A. (2019). Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. Information Fusion, 46, 147-170.

[6]. Ramasamy Ramamurthy, S., & Roy, N. (2018). Recent trends in machine learning for human

activity recognition—A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1254

[7]. Sathyanarayana, S., Satzoda, R. K., Sathyanarayana, S., &Thambipillai, S. (2018). Vision-based patient monitoring: a comprehensive review of algorithms and technologies. Journal of Ambient Intelligence and Humanized Computing, 9(2), 225-251.

[8]. Wang, J., Chen, Y., Hao, S., Peng, X., & Hu, L. (2019). Deep learning for sensor-based activity recognition: A survey. Pattern Recognition Letters, 119, 3-11.

[9]. Xu, T., Zhou, Y., & Zhu, J. (2018). New advances and challenges of fall detection systems: A survey. Applied Sciences, 8(3), 418. doi:10.3390/app8030418.

[10]. Chen, Y., &Xue, Y. (2015, October). A deep learning approach to human activity recognition based on a single accelerometer. In 2015 IEEE international conference on systems, man, and cybernetics (pp. 1488-1492). IEEE

[11]. Bhat, G., Tran, N., Shill, H., & Ogras, U. Y. (2020). w-HAR: An Activity Recognition Dataset and Framework Using Low-Power Wearable Devices. Sensors, 20(18), 5356.

[12]. Alemayoh, T. T., Lee, J. H., & Okamoto, S. (2019, June). Deep Learning-Based Real-time Daily Human Activity Recognition and Its Implementation in a Smartphone. In 2019 16th International Conference on Ubiquitous Robots (UR) (pp. 179-182). IEEE

[13]. Ronao, C. A., & Cho, S. B. (2016). Human activity recognition with smartphone sensors using deep learning neural networks. Expert systems with applications, 59, 235-244.

[14]. Ignatov, A. (2018). Real-time human activity recognition from accelerometer data using Convolutional Neural Networks. Applied Soft Computing, 62, 915-922.

[15]. Avilés-Cruz, C., Ferreyra-Ramírez, A., Zúñiga-López, A., & VillegasCortéz, J. (2019). Coarse-fine convolutional deep-learning strategy for human activity recognition. Sensors, 19(7), 1556.

[16]. Wan, S., Qi, L., Xu, X., Tong, C., &Gu, Z. (2020). Deep learning models for real-time human activity recognition with smartphones. Mobile Networks and Applications, 25(2), 743-755.

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