World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:19, No:1, 2025

Study of Deep Learning-Based Model for Recognizing Human Activities in IoT Applications

Tarunima Chatterjee, Pinaki Pratim Acharjya

***Abstract*—**Advanced neural network-based human activity recognition (HAR) system integration with Internet of Things technology is progressing quickly. This technique, which has important implications in the fields of fitness, healthcare, and smart home environments, correctly detects and categorizes human actions from sensor data using sensors and deep learning algorithms. This work presents an approach that combines multi-head CNNs with an attention mechanism, producing a detection rate of 95.4%. Traditional HAR systems are generally imprecise and inefficient. Data collection, spectrogram image conversion, feature extraction, optimization, and classification are all steps in the procedure. With its deep learning foundation, this HAR system has enormous potential for real-time activity monitoring, especially in the healthcare industry, where it may enhance safety and offer insightful data on user behaviour.

***Keywords*—**Deep learning, Human Activity Recognition, HAR, Internet of Things, IoT, Convolutional Neural Networks, CNNs, Long Short-Term Memory, LSTM, neural machine translation, NMT, Inertial Measurement Unit, IMU, Gated Recurrent Units, GRUs.

I. Introduction

THE combination of Internet of Things (IoT) technology with Human Activity Recognition (HAR) systems through deep learning has become increasingly popular in recent years. This approach leverages various sensors and deep learning algorithms to accurately recognize and classify human activities based on data collected from these devices.

The objective of HAR is to analyse sensor data to detect specific human movements or actions. Thanks to advancements in sensor networks and IoT technology, it is now possible to translate vast amounts of real-world data into information on human physical activity through HAR. Numerous IoT applications use these data to support people and improve their quality of life. Numerous industries, including healthcare, personal fitness, rehabilitation, life-logging, and ambient assisted living, have investigated and used HAR in great detail [1].

Furthermore, because it derives specific information about human activities from unprocessed sensor data, HAR is crucial in daily life [2]. Recent years have seen a considerable increase in the use of HAR in human-computer interaction; today, it is widely applied in several fields, including gesture identification, gait analysis, home behaviour monitoring, and video surveillance [2].

HAR is essential for monitoring people's everyday activities, especially the elderly and those with health issues. When it comes to accurately detecting behaviours such as walking, sitting, or falling, medical practitioners can assess a patient's health more thoroughly and intervene promptly when needed. In the fitness industry, HAR enables users to keep track of their physical activity, giving them useful information about their workout routines and assisting them in achieving their fitness goals. Users may be inspired to enhance their general health and wellbeing by this knowledge. By determining human preferences and actions, HAR helps automate smart homes and cities. When someone is cooking, watching TV, or sleeping, for instance, a smart home system can change the lighting and temperature. To help academics and organizations better understand human behaviour patterns in a variety of circumstances, which can inform public health initiatives and urban planning initiatives, HAR supports behavioural surveillance and analysis. By identifying unexpected activity or situations, HAR helps to improve safety in public spaces and workplaces by facilitating quick reactions to possible threats [3].

The paper discusses the shortcomings and difficulties of traditional HAR approaches, like statistical analysis, basis transform coding, and symbolic representation, which are frequently heuristic, lack task specificity, and may increase computational costs without appreciably enhancing performance [4]. It highlights the increasing interest in enhancing HAR through the effective extraction and selection of pertinent characteristics using deep learning techniques, especially convolutional neural networks (CNNs). In order to improve feature selection and focus on relevant data for more precise activity recognition, the suggested method combines CNNs with an attention mechanism. This is acknowledged as the first use of multi-head CNNs with attention mechanisms in HAR, with the goal of addressing the limitations of previous techniques [5].

The discussions also talk about the drawbacks of conventional techniques for HAR, such as statistical analysis, basis transform coding, and symbolic representation [6]. These methods might raise computational expenses without always improving performance, and they are frequently not particularly reliable [6]. There are still obstacles to be solved in deep learning, despite recent advancements, especially with deep CNNs.

The research presents an approach to improve feature extraction and selection by combining multi-head CNNs with an attention mechanism [7]. This approach achieves a higher

Ms. Tarunima Chatterjee is with the Department of CSE, Haldia Institute of Technology, Haldia, West Bengal, India (e-mail: tarunimachatterjee@gmail.com).

Dr. Pinaki Pratim Acharjya is with the Department of CSE, Haldia Institute of Technology, Haldia, West Bengal, India (corresponding author, phone: +918348841764; e-mail: ppacharjya@ gmail.com).

detection rate of 95.4% for activity than earlier techniques, indicating an improvement in accuracy. The paper is structured in the following manner: a review of pertinent literature, an overview of the proposed HAR design, experimental findings, and conclusions. In particular, multi-head CNNs are helpful for managing intricate multichannel time-series information gathered via wearable sensors.

The rapid development of the IoT has significantly impacted HAR, with technologies like body sensor networks (BSNs) becoming integral to e-health and human-cantered applications. BSNs combine wireless sensors, networked devices, and traditional networks to enable large-scale applications in areas such as health, fitness, and behavioural monitoring, especially with cloud computing enhancing data storage and analysis capabilities [8]. HAR has emerged as a key application within these domains, gaining substantial attention due to its potential in e-Health [7].

II. Literature Review

Khan et al. have completed a research paper. Using data from accelerometers, microphones, gyroscopes, magnetometers, and GPS, this study explores the impact of smartphone sensor developments in HAR, with a particular focus on locomotion and localization. Utilising three datasets—Continuous In-The-Wild Smart Watch Activity, Huawei Locomotion, and Extra Sensory—it applies Multilayer Perceptron (MLP) with manual feature extraction approaches and Deep Polynomial Neural Networks (DPNN) for deep learning-based feature extraction. According to the results, DPNN performs far better than MLP, with 93% and 95% accuracy for localisation and locomotion on the Continuous In-The-Wild Dataset, respectively, compared to 86% and 91% for MLP. MLP is more efficient, but DPNN requires a lot of computation even though it has a greater accuracy. This study highlights how cutting-edge machine learning methods can improve HAR using smartphone sensors, and they came to this conclusion. The wearables, smart homes, and healthcare industries can all benefit from the system. However, DPNN's high processing needs may limit its usage in real-time scenarios, and performance relies on the quality of training data, creating issues in privacy-sensitive situations [9].

Bulling et al. have done a research study where they have stated that, HAR research has expanded dramatically over the past 20 years, tackling several difficulties in the development and assessment of recognition systems. Using on-body inertial sensors, this tutorial provides a hands-on introduction to HAR, helping novices through the main challenges that are common to both general pattern recognition and HAR-specific challenges. The Activity Recognition Chain (ARC) is introduced as an adaptable framework for developing and evaluating HAR systems. With citations to pertinent studies and industry best practices, each ARC component is described. A case study on hand gesture recognition using inertial sensors is included at the end of the lesson to show how different ARC implementations impact recognition results, and they came to this conclusion. This work shows that characteristics can be clustered and their cluster precision may be evaluated to gain insight into whether or not they are suitable for activity recognition. Performance in feature recognition is accurately predicted by the suggested cluster precision metric. According to the study, no single feature or window length performs better than all others in every activity. The precision of FFT features is very great; however, the ideal coefficients differ depending on the activity. Recognition is improved by banding FFT coefficients. Variance works well for non-FFT characteristics, but the mean performs poorly unless there are certain circumstances. While the ideal window lengths vary depending on the activity, windows of 1-2 seconds usually work the best. Extra classifier systems are to be investigated in future work [10].

Qiu et al. have done one research study on an overview of popular wearable sensors, smart devices, and important application domains is provided in this study. Systems that use many modalities or channels, such as auditory, visual, environmental, and physiological signals, are referred to as multi-sensor systems. In order to integrate data from several sensors in different places, the paper provides fusion approaches. While other evaluations have focused on deep learning or information fusion separately, this work adopts a more comprehensive approach to offer a better foundation for comprehending sensor fusion applications. In particular, the paper covers all the salient features of multi-sensor applications for HAR, including the latest developments in transfer learning and unsupervised learning. The report concludes by identifying and discussing open research concerns that need to be improved and investigated further, and they came to this conclusion. Wearable technology can help interpret user intentions by closely monitoring cognitive data and user behaviour. This essay examines the condition of information fusion and wearable technologies at the moment. The effect of sensor location on motion measurement is emphasised, and conventional machine learning is criticised for its poor feature extraction and generalisation powers. Deep learning, on the other hand, provides better performance and versatility by automatically picking up higher-level characteristics. Notwithstanding, several obstacles persist, specifically related to managing a wide range of user actions and the practicality of gathering copious labelled data for every user. In order to improve model performance, the paper proposes merging deep learning with transfer learning and offers open research questions for further investigation [2].

Zhang et al. have completed a research paper in order to facilitate the digital revolution of healthcare; smart and connected health, or SCH, improves the integration of information science and engineering. Using multi-position sensor data fusion, this research focuses on HAR and suggests a hybrid model (1DCNN-Att-BiLSTM) for multi-channel deep learning. Improved HAR performance via local and global feature extraction, the establishment of a multi-position sensor data pool from publicly accessible datasets, and a comprehensive analysis of sensor data fusion patterns are some of the major contributions. The suggested model performs competitively in HAR tasks when compared to deep learning and classical methods. The approach's efficacy for ambient assisted living and healthcare monitoring has been validated through extensive studies. By establishing a multi-channel 1DCNN-Att-BiLSTM model and demonstrating its efficacy on three datasets—Shoaib AR, Shoaib SA, and HAPT—this study greatly enhances HAR. Making use of spatial and temporal data, the model leverages a bidirectional long short-term memory and a one-dimensional CNN to improve classification accuracy. The outcomes demonstrate that, especially for data from belt positions, the AGM sensor combination achieves the maximum classification precision. Furthermore, the model achieves a precision of 98.76% on the HAPT dataset, outperforming conventional machine learning approaches. The results address issues with explainability in deep learning models for real-world applications while also highlighting the model's promise in health management and personalised services [11].

Krishna and Paneerselvam have completed a research paper. With HAR, movement data from sensors are used to anticipate an individual's activities. At the moment, wearable technology is used for this, such as cell phones and body-worn sensors. These gadgets make it easier to gather and analyse data in order to gain insights on day-to-day activities. Finding patterns in unprocessed data are the main goal of this study in order to obtain important insights into human behaviour. While current techniques, especially deep learning, have shown significant progress in identifying explicit activities, they still face difficulties in identifying transitions between different tasks. In order to improve HAR accuracy, this project uses a long short-term memory (LSTM) model for activity transitions and a CNN for activity recognition. The HAPT and HAR datasets are used to train the model, and hyperparameters are adjusted to evaluate performance and measure parameters like recall, F1-score, and precision, producing better results with adjusted parameters, and they came to this conclusion. This HAR study successfully illustrates how wearable technology, including smartphones and body-worn sensors, may be used to forecast a person's activity based on sensor data. Although current deep learning techniques have made strides in identifying explicit activities, they frequently have trouble identifying changes in activity. Hyperparameter tuning, which involves varying the number of neurones, batch size, and learning rate, is used to evaluate the model's performance. The results demonstrate that optimum parameters greatly improve HAR accuracy, indicating the model's potential for more efficient human activity monitoring [12].

III. Study and Analysis

HAR systems typically involve several stages: data collection, preprocessing, segmentation, feature extraction, feature selection, modelling, and classification [13]. Deep learning techniques [13], particularly CNNs, have proven to be effective in enhancing feature extraction and classification accuracy in HAR tasks. Traditional approaches such as symbolic representation, Fourier and wavelet transforms, and statistical analysis have been utilized to process time-series data, but they often lack robustness, are heuristic, and are not task-specific [14]. Additionally, conventional methods tend to struggle with heterogeneity within the same activity class and similarity between different classes, limiting their effectiveness [15].

To address these limitations, recent research has explored the integration of CNNs with attention mechanisms to improve feature extraction and selection [16]. The attention mechanism enables the model to focus on the most relevant features, filtering out unnecessary information and enhancing classification performance [18]. By incorporating attention into multi-head CNNs, the proposed method achieves higher accuracy in recognizing activities [2]. The study validated this approach using a dataset from the Wireless Sensor Data Mining (WISDM) lab, demonstrating that it outperforms previous methods in terms of accuracy.

Despite the advancements of deep learning in HAR, several challenges remain. Conventional HAR methods often face difficulties in feature selection, leading to suboptimal classification results and increased computational costs. Moreover, issues such as the dominance of the NULL class, the complexity of physical tasks, and the need to account for contextual factors such as user states and environmental conditions further complicate HAR tasks [11]. The paper also highlights transfer learning as a promising avenue for addressing these challenges, especially in scenarios where training data are limited.

By leveraging the strengths of CNNs and attention mechanisms, the proposed method enhances the precision and robustness of HAR systems, offering significant improvements over traditional approaches. This study is the first to combine multi-head CNNs with attention mechanisms for HAR, setting a new direction for future research in the field [20].

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The study investigates the use of attention mechanisms and multi-head CNNs in HAR. By utilising multiple processing layers, multi-head CNNs enhance feature extraction and facilitate more effective handling of intricate, multichannel input from wearable devices. The attention mechanism enhances accuracy even further by focusing on the most important components of the incoming data, highlighting salient characteristics, and eliminating superfluous information [22]. When combined, these methods offer a promising way to improve HAR systems, particularly when dealing with complex recognition jobs. Systems are able to evaluate user behaviour and activity trends by utilising the proposed HAR technique for real-time activity monitoring. This feature is beneficial to people as well as healthcare providers since it provides insightful information on everyday routines. Systems are able to evaluate user behaviour and activity trends by utilising the proposed HAR technique for real-time activity monitoring. Healthcare practitioners as well as users might both gain from this capability's insightful observations of daily activities.

TABLE I
EVALUATION OF VARIOUS DEEP LEARNING MODELS FOR RECOGNIZING HUMAN ACTIVITIES

Method	Merits	Demerits	Dataset
Fast Classification of EEG Artefacts	Improves classification performance significantly (2–9% for 1-channel data and 8–12% for 2-channel data)	This model was specially developed for the health care sector.	Public Dataset
Changed Inception Time Network Architecture	The model works better in terms of accuracy for ARIL, Stan Wi-Fi and SignFi	The proposed model may not work for the real-world dataset because the real-world data set has vast interference.	ARIL, StanWiFi, and SignFi
Binary Motion Image Deep learning	Binary Motion Image Deep learning model gives good accuracy for both 2D and 3D datasets consistent speed of action performed by a human.	The model fails to provide an accurate detection rate when multiple people are present in the 3D image.	MSR action 3D dataset
The complete deep learning model for Recognizing Human-to Human Interactions	The developed end-to-end deep learning model provides 86.3% accuracy for all human-to-human interactions recognition.	The proposed model is not developed for group-to-group interactions. This model will work only for Human-to Human Interactions.	CSI dataset of HHI
Inception ResNet deep transfer learning method for HAR using LSTM	It provides the best accuracy score of 92% and 91% for different data sets	It takes a tremendous amount of training time	UCI 101 and HMDB 51 data sets
Kernel principal component analysis	KPCA outperforms SVM and ANN	It provides less accuracy for the real-time data.	Public Dataset
Sparse Feature Learning for Human Activity Recognition	It provides long term dependencies	It provides less accuracy for the real-time data	UCI-HAR dataset
HAR using Ensemble Learning of Multiple CNN	It takes less amount of pre-processing time because the proposed model support automatic feature extractions	Model is not suitable for concurrent activity recognition	WISDM dataset
Unsupervised deep learning assisted reconstructed coder in the on-nodule wearable sensor for HAR	improves the feature selection and extraction using an unsupervised deep learning model	The performances degrade in large datasets with different types of human activities.	WISDM dataset
Multi-domain HAR based on Stepped-Frequency Continuous-wave radar using deep learning	Developed deep learning model increases the recognition accuracy by 1.3% by additionally introducing the range maps	The proposed model is not developed for group-to-group interactions.	Public Dataset

IV. PROPOSED HYBRID MODEL

Deep learning has revolutionized HAR by automating the feature extraction process, which traditionally required extensive manual intervention. Combining CNNs with LSTM or Gated Recurrent Units (GRUs) to build a hybrid model for tasks like HAR involves several stages:

A. Data collection and preprocessing
- *Collect Data:* Gather raw data from sources like sensors (accelerometers, gyroscopes) or images/video frames in the case of HAR.
- *Preprocessing:* Clean and preprocess the data. For time-series sensor data, this might include normalization, noise filtering, and segmentation. If working with video frames, the data may be transformed into image-like formats such as spectrograms.

B. Input Preparation
- *Data Structuring:* For time-series data, ensure the input is structured so that temporal dependencies can be captured. Each input sequence should consist of a series of time steps. For video data, frames are arranged in a time-sequenced manner.
- *Batching:* Split the data into batches and time windows, preparing it for input into the CNN and RNN models.

C. Spatial Feature Extraction (Using CNN)
- *Convolutional Layers:* Pass the input (either image-like spectrograms or raw sensor data) through convolutional layers. These layers apply filters to extract spatial features, like patterns, edges, and texture, from the input data.
- *Pooling:* Use max-pooling or average-pooling layers to reduce the spatial dimensions while retaining the most important information.
- *Feature Maps:* The result of the CNN is a set of feature maps, which represent the important spatial characteristics of the input data.

D. Flattening or reshaping
- *Flatten:* After feature extraction, the CNN’s output (spatial features) is reshaped or flattened to prepare it for sequential processing. This step converts the 2D or 3D output into a format suitable for input into the LSTM/GRU layers.

E. Temporal Feature Extraction (Using LSTM/GRU)
- Recurrent Layers: Pass the reshaped CNN output through LSTM or GRU layers to capture temporal dependencies. These layers process the sequence of feature maps, understanding how spatial features evolve over time.
- Memory Cells: LSTMs have memory cells that help store and forget information over time, allowing the network to learn both short-term and long-term dependencies in the sequence. GRUs, while simpler, performs a similar role with fewer parameters.

F. Fully Connected Layers
- After the recurrent layers, the output is typically passed through fully connected (dense) layers to map the temporal and spatial features to the final output space, such as activity labels in HAR.
- These layers aggregate the learned information and prepare it for classification.

G. Classification
- Output Layer: The final layer is a softmax or sigmoid activation layer that classifies the activities based on the extracted spatial and temporal features. This layer assigns probabilities to the possible activity classes.

H. Training the Hybrid Model
- Training Process: We train the hybrid model using back-propagation through time (BPTT) for LSTM/GRU and standard back-propagation for CNN layers. The model learns by minimizing the loss function (e.g., cross-entropy loss) using optimization techniques like Adam or SGD.

I. Evaluation and Optimization
- After training, we evaluate the model's performance on validation or test data. Further fine-tuning of hyper-parameters (e.g., learning rate, number of layers) might be necessary to improve accuracy.

J. Prediction
- Once the hybrid model is trained and optimized, it can predict the activities from new, unseen data by recognizing both the spatial and temporal patterns learned during training.

This combination of CNN for spatial features and LSTM/GRU for temporal dependencies ensures a robust model capable of handling complex tasks that require both static and dynamic pattern recognition, like HAR.

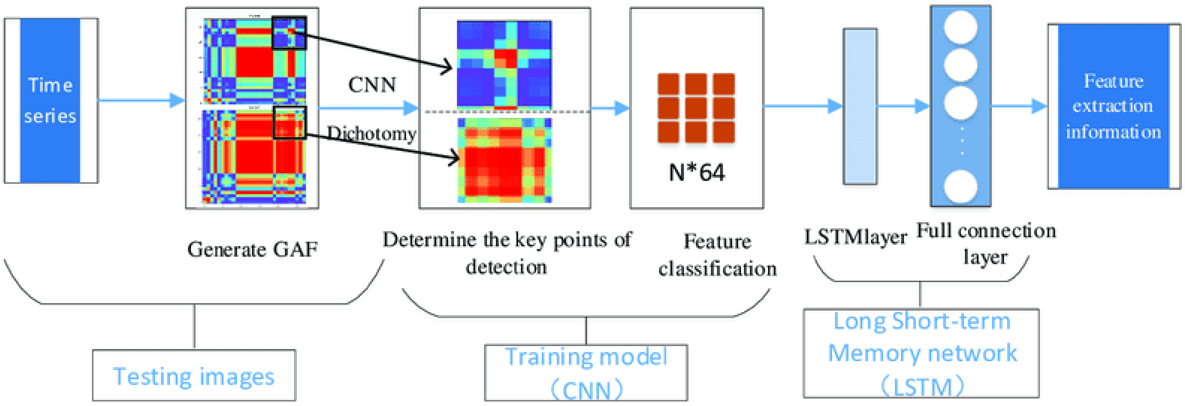

Fig. 1 Workflow of Hybrid Model (CNN+LSTM)

The proposed IoT-based HAR system has significant implications for various sectors, particularly in healthcare, where it can facilitate remote monitoring and support for elderly or disabled individuals. By utilizing deep learning, the system can adapt to new activities and environments, improving its robustness and applicability across different scenarios. In conclusion, the integration of deep learning with IoT technologies in HAR systems presents a promising avenue for enhancing human-computer interaction and automating activity recognition in real-time environments. The proposed methodologies aim to address current challenges in HAR, such as the need for extensive labelled datasets and the complexity of feature extraction, ultimately leading to more efficient and user-friendly applications.

V. Conclusion

In conclusion, the integration of deep learning with IoT technologies in HAR systems presents a promising avenue for enhancing human-computer interaction and automating activity recognition in real-time environments. The proposed methodologies aim to address current challenges in HAR, such as the need for extensive labelled datasets and the complexity of feature extraction, ultimately leading to more efficient and user-friendly applications.

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