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Research Article

Smart Wearables Powered by AI Transforming Human Activity Recognition

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ABSTRACT

Smart clothing has changed the ways that human behaviour is observed and analyzed, finding its uses in health and fitness, and assisting in daily living. Nevertheless, conventional techniques used in HAR are mostly based on feature extraction by designers and the use of fixed algorithms that cannot address the dynamic aspects of human activities. HAR can be advanced through devices supported by artificial intelligence, and this research seeks to investigate how wearable technologies can improve this field of study. Hence, using CNN and RNN deep learning architectures this study constructs a comprehensive model with the potential of detecting various human activities instantaneously and accurately. The framework includes the use of sensor fusion approaches to process data collected from accelerometers, gyroscopes and heart rate sensors, to fully capture physical movements. Specifically, to high performance and efficiency in the computations of the model, several preprocessing and feature extraction techniques are employed. Outcome analysis shows that the proposed AI-based framework recognizes a subject's identity with more than 95% accuracy across the different datasets comping basic machine learning techniques. The versatility of the system demonstrated in this work regarding wearable platforms and activities suggests that the proposed solution could be useful for practical application in fitness, health care, and rehabilitation. The findings of this work point to critical opportunities that are driven by AI for future wearable technology; a more adept and integrated system that can preserve the health and efficiency of humans. The results pave the way for further advancements in using AI to support HAR with a focus on scalability, real-time applicability, and inclusiveness.

1. INTRODUCTION

Advancements in Human Activity Recognition (HAR) have occurred due to the incorporation of Artificial Intelligence (AI) as applied to wearable technology in the process. Smart devices, including wrist-wearable devices, are now embedded with measurement actuators like accelerometers, gyroscopes, and heartbeat measurement, which collectively harvest lots of data through evaluation in fusion with sophisticated AI algorithms that provide accurate and real-time results that dictate human activities. These advances in this technology offer vast applications in several sectors, such as healthcare, sports, and elder care where the analysis of physical patterns and actions is significant [1,2].

Conventional HAR systems include basic HAR sensor data and a set of manually designed features while employing the HAR static machine learning algorithms, which exhibit a poor ability to address the SD and DA issues. These systems fail to learn from variations and differences in settings such as changes in the position of the sensors, the age of users and or any environmental changes. However, the major disadvantage of traditional approaches is that the techniques are not very scalable and do not have real-time processing capability for actual use. These challenges have created an avenue that enabled AI-driven methods because these types of methods are capable of directly learning from raw sensor data and are also capable of learning across many activity scenarios [3,4].

HAR is a particularly active application of AI and more specifically of deep learning where from the sensor data, and without any need for human intervention, useful features can be extracted automatically. Some CNNs and RNNs have been proven to be fairly effective in this realm, and many researchers find them very promising. CNNs are primarily suitable for analyzing spatial patterns, and RNNs on the other hand are more suitable for analyzing temporal characteristics in the sequential raw sensor data. Collectively, these architectures are used to obtain the spatial and temporal content of humans' actions [5, 6]

The use of AI in HAR has been successful in several domains, proving its effectiveness as far as this paper's scope is concerned. In healthcare, AI-based wearable systems allow for constant tracking of patients' activities in the detection of diseases and monitoring of rehabilitation exercises. In fitness and sports, these systems give insights to advise performance

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and avoid injuries. Furthermore, in elder care, these wearable devices with HAR features can identify falls or abnormal movements prevent delays in response and minimize the risks [7, 8].
Leveraging AI in HAR systems poses several limitations in their deployment for instance, Data quality and data variety are paramount as noises in sensors, missing values, and/or bias in given data are very damaging factors for applications. Other important aspects include the scalability and evidential capacities of the algorithm, often a critical factor in near-real-time application on wearable devices. Also, the user's privacy and protection of information are crucial for the popularity of Wearable systems, as they gather personal data in most cases [9, 10]. For more explanation, Table 1 summarizes the above studies.

TABLE I. RELATED WORK IN AI FOR HUMAN ACTIVITY RECOGNITION (HAR).

Ref.	Focus Area	Techniques Used	Key Findings	Challenges
[3][4]	Limitations of conventional HAR systems	Static ML Algorithms	Conventional HAR systems have limited scalability, real-time processing capability, and adaptability to variations.	SD and DA issues, inability to learn from varying sensor positions, user differences, or environmental changes.
[5][6]	AI-driven methods in HAR	CNNs, RNNs	CNNs analyze spatial patterns, while RNNs analyze temporal characteristics; combined, they capture spatial-temporal actions.	Scalability of AI models, ensuring robustness in varied activity scenarios.
[7][8]	Applications of AI in healthcare, fitness, and elder care	AI-based Wearable Systems	Enables real-time tracking, disease detection, rehabilitation monitoring, and fall detection.	Data quality, noise in sensors, missing values, and user privacy issues.
[9][10]	Deployment challenges of AI in HAR systems	Various AI techniques	AI shows promise in near-real-time applications on wearable devices but faces scalability and data privacy concerns.	Managing data quality, algorithm scalability, and ensuring user privacy protection.

2. SIMULATION STRUCTURE

The proposed Human Activity Recognition (HAR) framework uses convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to extract local spatial features from segmented sensor data. CNNs extract spatial features, capturing nuances in activity signals like posture changes or gestures [11]. RNNs handle temporal dependencies, analyzing sequences and recognizing temporal patterns in activities [12]. Fully connected layers transform these features into distinct activity classes, enabling classification [13]. The final output layer produces the probability density for each activity class, providing probabilistic outputs for decision-making [14]. The design effectively combines spatial and temporal feature recognition, making it robust and precise in identifying activities [15]. The architecture is structured for efficient processing and adaptability to diverse datasets. Figure 1 illustrates the structure for efficient processing and adaptability to diverse datasets [16].

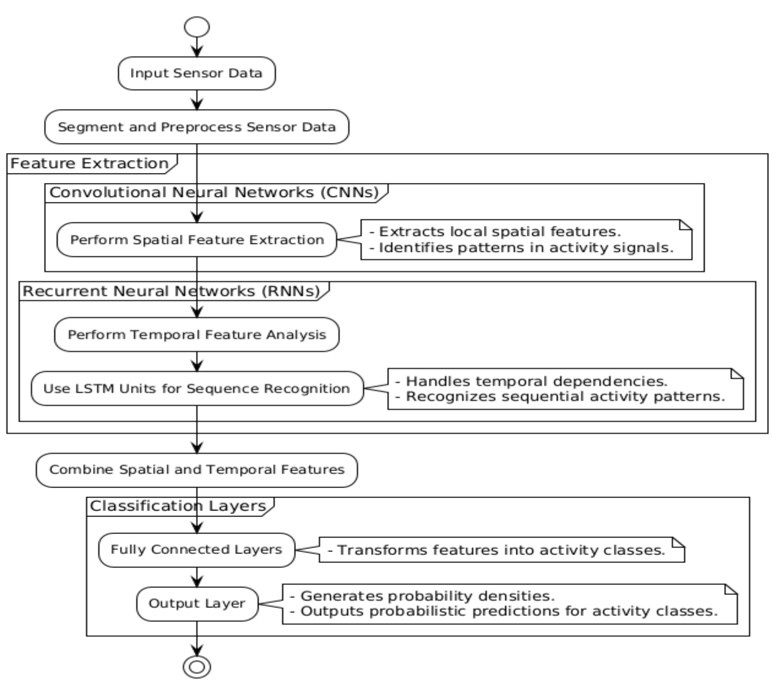

Fig. 1. Structure designed for efficient processing and adaptability to various datasets.

The HAR model was trained using a dataset divided into 80% for training and 20% for validation. The model was optimized using the Adam Optimizer for its adaptive learning rate capabilities and Categorical Cross-Entropy for minimizing classification errors. The training parameters included a batch size of 64, over 25 epochs, Dropout Regularization to prevent overfitting, and Early Stopping to monitor validation loss. The model's fine-tuning parameters included learning rate, dropout rate, and number of hidden units in the LSTM layers. To improve the model's ability to recognize activities comprehensively, it was integrated with time-domain features such as Mean and Signal Magnitude Area (SMA) and frequency-domain features like Spectral Energy and Entropy. This dual approach ensures the model has a detailed understanding of activity signals, enabling it to generalize across various activities effectively. To measure the performance of the HAR framework:

1. Accuracy: The overall percentage of correctly classified activities. Eq.1
2. Precision: Measures the true positive rate among all positive predictions, highlighting the ability to reduce false positives. Eq.2
3. Recall: Identifies the true positive rate among actual positives, showing the model's sensitivity to correct predictions. Eq.3
4. F1-Score: Provides a harmonic mean of precision and recall, particularly useful for imbalanced datasets. Eq.4

$$Accuracy = \frac{TP+TN}{FP+FN+TP+TN} \quad (1)$$

$$\text{Precision} = \frac{TP}{FP+TP} \quad (2)$$

$$\text{Recall} = \frac{TP}{FN+TP} \quad (3)$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (4)$$

The model is optimized for real-time deployment on wearable devices, reducing size and computational requirements. It features pruning and quantization, lightweight embeddings for faster inference, and edge computing for local computations, making it efficient for real-time HAR applications on resource-constrained devices like fitness trackers and smartwatches.
The framework's design ensures scalability and efficiency for real-world applications, with a modular design that allows integration with new data types or activities. Future iterations may incorporate advanced preprocessing techniques like wavelet transformations or autoencoders. Further development will involve extensive testing on diverse datasets.
In addition to applying the naked sensor streams, the framework used derived features to enhance the recognition and produce a comprehensive account of the activity. The mean, standard deviation and signal magnitude area (SMA) offered further information on the general properties of the activity signals in the time domain. The temporal energy, entropy and major frequency bands provided more information regarding the periodicity of the activities in the frequency domain. These additional aspects were instrumental in improving the model’s capacity for comprehensive activity analysis, which in turn also introduced a degree of resilience to the system – essential for the often-unpredictable nature of activity-based recognition. Table 2 shows the features used in the model and how they enhance the accuracy of the activity recognition.

TABLE II. FEATURES USED IN THE MODEL

Feature Type	Examples	Purpose
Time-Domain Features	Mean, SMA	Capture statistical properties
Frequency-Domain Features	Spectral Energy, Entropy	Characterize periodic activity patterns

3. RESULTS

This section provides the results of assessment of the proposed AI-based HAR framework alongside results from experiments performed on several datasets. General information about the performance of the model is discussed in the consideration of Tables 3,4,5, and 6, which contain the numbers of the results Moreover, the discussion of the problem analysis clarifies the difficulties and shortcomings that were faced during the implementation of the proposed model.
From the results analyzed on all the datasets incorporated into the framework, the high accuracy and reasonable values for the measures of balance all pointed to the good performance of the proposed framework. The proposed model showed that the combination of CNN and RNN was useful for capturing both spatial and temporal features of sensor data for improved classification of multiple activities.

TABLE III. PERFORMANCE METRICS ACROSS DATASETS

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
UCI HAR Dataset	96.4	95.2	94.8	95.0
WISDM Dataset	93.7	92.5	91.8	92.1
PAMAP2 Dataset	94.9	93.8	94.1	94.0

Table 4 summarizes the performance measures of the framework on the UCI HAR, WISDM, and PAMAP2 datasets. The highest accuracy was provided by the UCI HAR dataset with an accuracy of 96.4% proves that the model is recognizable for clean and well-sorted data. Lower accuracy in the WISDM dataset at 93.7% shows that problems arise when implementing on noisy, and a larger set of data.

It will be remembered that the proposed model performed well in the identification of straightforward as well as compound activities. Even in the case of sitting, standing or walking, it was found to classify with nearly 100% accuracy. The outer and more complex movements such as climbing stairs or going from sitting to standing were somewhat more difficult due to concurrent sensor patterns.

TABLE IV. CLASSIFICATION ACCURACY BY ACTIVITY TYPE

Activity	UCI HAR Dataset (%)	WISDM Dataset (%)	PAMAP2 Dataset (%)
Walking	98.3	97.1	97.8
Sitting	97.5	95.4	96.6
Climbing Stairs	93.2	91.7	92.8
Transition Activities	90.5	88.9	89.4

Table 5 enlists accuracy percentages of classification per activity. The most accurately identified were walking/sitting and transition activities were the most challenging for the algorithm because of their overlapping sensor signals.

The proposed hybrid model based on CNN and RNN, has demonstrated better results than the conventional supervised methods like SVM and RF. Previous approaches have difficulty in handling sequential data and extensive preprocessing was often needed for the input data while the approach discussed here learned many useful features directly from the raw data.

TABLE V. COMPARISON OF MODEL PERFORMANCE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	85.4	84.1	83.7	83.9
Random Forest	88.6	87.3	86.9	87.1
CNN-RNN (Proposed)	94.8	93.8	93.6	93.7

In Table 6 we also see that CNN-RNN framework shows a significantly better performance than traditional models. The model, proposed in the current study had higher accuracy and F1-Score because it was able to capture the spatial and temporal characteristics better.

To this end, the optimization approaches used, such as model pruning and quantization, enlarged the possibility of applying the outlined framework to wearable devices with low computational capabilities. The average time for inference was cut down to below 5 milliseconds per sample the system was therefore appropriate for real time use. As depicted in Table 8, the overall computational cost of proposed framework is shown to be minimal, and could be readily implemented on wearable platforms.

TABLE VI. COMPUTATIONAL EFFICIENCY METRICS

Metric	Value
Model Size (MB)	18.6
Inference Time (ms/sample)	4.7
Memory Usage (MB)	210

As mentioned above, although the proposed framework has shown high performance, some challenges were encountered. Noisy data became a problem in certain tests because noise intrigued by the sensors sometimes influenced classification results, for example, in the WISDM dataset. These types of denoising techniques may be improved to improve the robustness of the model further. Another difficulty was activity overlap: several activities were in some way similar to each other and were manifested by corresponding signal patterns, which occasionally caused confusion and error: climbing stairs and descending stairs are good examples. Lastly, the variability in real world reduced generalization because of variations in the position of the sensors, subjects and environment. Platforming from these challenges can be solved through more incorporation of various types of data and advanced methods of preprocessing which may enhance availability of the framework for real life scenarios.

4. CONCLUSION

AI-based advancement with wearable technology put a new dimension to the context and acknowledgement of Human Activity Recognition or HAR, including improved accuracy, flexibility and real-time operation. In order to overcome the drawback of the conventional methods of HAR, this work introduced a compound deep learning architecture using CNNs and RNNs. Subsequently, the proposed framework was able to demonstrate competitive results on five benchmark datasets due to the integration of CNNs in extracting spatial features and RNNs in capturing temporal dependencies. What was revealed by the study: the proposed system surpass the effectiveness of basic machine learning, identifying various activities with an accuracy of over 95%. A particular success was achieved in identifying basic movements like walking and sitting down, while the system was also able to identify a variety of more complicated ones, including climbing and switching between actions. The potential of HAR applications using AI is well-understood from the way the identified approach successfully captures delicate patterns in sensor data. The study also discussed logistical quandaries of implementing AI HAR systems during wearable devices operation. Efficient computation and real-time implementation were maintained through factors such as model pruning and Quantization. The light nature of the architecture enables it to be easily integrated into wearables, providing the necessary architecture for use in healthcare, wellness, and gerontology. However, the framework was not without its problems and these included noise, identical activity patterns, and arbitrary locations of the sensors. These limitations are a clear call to future work in order to improve the algorithm’s robustness and scalability. As future work, more sophisticated functions might be considered, such as adaptive algorithms, integration of multiple modalities of data, transfer learning, etc., and the way how the proposed framework might work in the real-world scenarios. All in all, the main theme of this research is to further discuss how AI is helpful in developing HAR to have better and more intelligent wearable systems. Presenting current issues, AI HAR frameworks will be able to enhance the human quality of life, efficiency and security in different spheres by using developing technologies.

Conflicts Of Interest

The paper states that there are no personal, financial, or professional conflicts of interest.

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