ICIC Express Letters ICIC International ©2023 ISSN 1881-803X
Volume **17**, Number **12**, December **2023** pp. **1375–1383**

DEEP LEARNING FOR RECOGNIZING DAILY HUMAN ACTIVITIES USING SMART HOME SENSORS

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Received March 2023; accepted May 2023

Abstract. *One of the vital purposes of health-related studies is to enhance people's living conditions and well-being. Solutions for smart homes could offer occupants preventive care based on the identification of regular activities. Recent advancements and developments in sensor technology have raised the demand for intelligent household products and services. The rising volume of data necessitates the development of the deep learning domain for the automated identification of human motions. Moreover, networks with long short-term memory have been used to represent spatio-temporal sequences recorded by smart home sensors. This study proposed ResNeXt-based models that learn to identify human behaviors in smart homes to increase detection capability. Experiment findings generated on a publicly available benchmark dataset known as CASAS data demonstrate that ResNeXt-based techniques surpass conventional DL approaches, achieving improved outcomes compared to the existing research. ResNeXt outperformed the benchmark approach by an average of 84.81%, 93.57%, and 90.38% for the CASAS Cairo, CASAS Milan, and CASAS Kyoto3 datasets, respectively.*
Keywords: Human activity recognition, Deep learning, Smart home sensor, Spatio-temporal sequence

DOI: 10.24507/icicel.17.12.1375

1. **Introduction.** Technological breakthroughs in sensing devices, especially in energy usage, affordability, and interoperability, have accelerated the creation of intelligent settings, such as smart homes. With an increasing number of new buildings containing smart sensors and actuators, concentrate on enhancing the quality of life, health, and well-being of the elderly and handicapped in smart homes [1, 2]. In addition, smart homes could offer various other incredible opportunities, including energy management and security systems. To deliver both automatic and personalized experiences, a smart home must be able to comprehend the occupants' everyday tasks.

Utilizing sensor traces, smart homes could be used to identify human behaviors such as food preparation, eating, resting, and bathroom usage without being intrusive [3]. Various sensors (movement, opening door, or heat) incorporated into the home's surroundings or items gather these traces [4]. Event-triggered sensors record human behaviors in smart home automation systems. This technique produces irregularly sampled and sparse data, unlike video-based action recognition. Consequently, we must continually face obstacles in pattern recognition and temporal sequence analysis [5]. This results in designing and implementing systematic machine learning (ML) algorithms to acquire knowledge from data and deliver accurate human behavior predictions [6, 7].

It has been commonplace to perceive the human activity recognition (HAR) challenge as a categorization issue in recent years. Several classification techniques, including Naive Bayes (NB) [8], random forest (RF) [9], k-nearest neighbor (k-NN) [10], and support vector machine (SVM) [11], have been applied. Most contemporary ML algorithms result in static models that are not required to evolve and adapt to a constantly changing environment.

Recently, there has been a significant focus on deep learning (DL) approaches for HAR situations [6, 12, 13], which can learn different, non-linear interpretations of raw data through many hidden layers [14]. This enables the DL system to extract and manipulate features without previous knowledge. Deep neural network (DNN), convolutional neural network (CNN), recurrent neural network (RNN), and long short-term memory (LSTM) are the most widely exploited deep learning (DL) approaches in HAR [15, 16].

This paper proposes ResNeXt, a deep residual neural network for improving HAR in smart home circumstances. In contrast to earlier DL techniques for video and wearable-based HAR, this study contextualizes the issue in the smart home environment, where a typical house is supplied with several sensors, and the collected data is massive and structurally dense. Applying widely dispersed Center for Advanced Studies in Adaptive Systems (CASAS) standard datasets [17], the proposed HAR technique's dependability is examined in a smart home context. Although the CASAS datasets are frequently utilized and studied by researchers employing supervised ML algorithms, there is, to the greatest of the authors' awareness, a lack of HAR papers on the utilization of DL techniques that consider temporal data. The efficacy of the proposed residual network has been evaluated and compared against commonly used one-dimensional CNN and traditional LSTM methods in the field of HAR.

The remainder of this article is structured in the following manner. Section 2 presents recent related literature. Section 3 outlines the specifics of the deep learning models implemented in this study. Section 4 displays our experimental outcomes. Lastly, Section 5 offers a conclusion of our findings and potential future directions.

2. **Related Works.** The process of HAR using sensors involves utilizing a system of interconnected sensors and devices to observe and monitor an individual's actions [18]. The sensors produce a sequence of changes in state or characteristic values over time. Different types of sensors, such as touch detectors, RFID, accelerometers, motion sensors, noise sensors, and radar can be directly placed on a person, objects, or in the environment.

As a result, sensor-based techniques can be classified into three main categories: Wearable [19], Sensor on Objects [20], and Ambient sensors [21].

In order to address privacy concerns related to the use of cameras in our personal spaces, sensor-based systems have become more prevalent in tracking our daily activities [22]. With the development of intelligent technology and the Internet of Things (IoT), sensor-based smart homes have become a feasible and practical option. However, in order to fully utilize the potential of these systems, there is a need to further develop human motion analytics.

With the development of ML in recent years, many excellent ML classification algorithms have emerged, the most representative of which is the DNN algorithm. Especially in the field of image classification, DL methods, such as VGG [23] network, Google Inception [24] network, and ResNet [25] network, have powerful automatic feature extraction capabilities [26], which have been completely completed in some fields beyond traditional ML and statistical methods and shallow artificial neural network methods, it can even identify targets that are difficult to distinguish with the naked eye, surpassing humans. In addition, many large companies have also adopted the DL method as one of their core competencies [27, 28, 29].

Liciotti et al. [30] conducted research on movement recognition using various LSTM architectures and found that LSTM outperforms traditional HAR methods in terms of classification accuracy without the need for manual feature engineering, as LSTM can create features that represent temporal patterns. Singh et al. [31] compared LSTM's performance to other conventional machine learning methods such as NB, hidden Markov model (HMM), hidden semi-Markov model, and conditional random fields and found LSTM to be superior. Similarly, Alshammari et al. [32] demonstrated that LSTM outperforms other machine learning methods such as AdaBoost, HMM, multi-layer perceptron, and structured perceptron. LSTM also showed better performance compared to decision trees, SVM, stochastic gradient descent of linear SVM, logistic regression, and regression functions. However, to effectively utilize LSTM, an appropriate time frame needs to be established to balance long-term and short-term temporal relationships, which has been addressed by some studies. For instance, Park et al. [33] used a topology with multiple LSTM layers, residual connections, and an attention component to mitigate the issue of gradient vanishing and identify significant events in time series. Medina-Quero et al. [34] combined the LSTM with a fuzzy window to instantly interpret the HAR, enabling them to adjust their time frames duration dynamically and handle various time scales. However, these improvements' accuracy falls below 96%, so consideration of their activity-based classifiers combination and further enhancement is necessary.

3. **Methodology.** As illustrated in Figure 1, the HAR methodology based on smart home sensors employed in this study consists of five fundamental steps: data acquisition, pre-processing, data generation, model training, and classification.

3.1. **Data acquisition.** Washington State University provided the CASAS datasets during the data gathering procedure [17]. The intelligent apartment utilized for the CASAS smart home project consisted of three units with three bedrooms, one bathroom, one kitchen, and one living room/dining area. Each unit was connected with various sensors and actuators (e.g., motion sensors, temperature sensors, and door sensors) for monitoring the surroundings and giving details to residents. Among all accessible CASAS datasets, three annotated datasets with the names Milan, Cairo, and Kyoto3 were chosen. These three datasets were chosen to provide simple instances of operations for the following scenarios: 1) solely residents as a baseline (Kyoto3), 2) a more sophisticated dataset in which a pet can bring more noise (Milan), and 3) a complicated situation with two residents

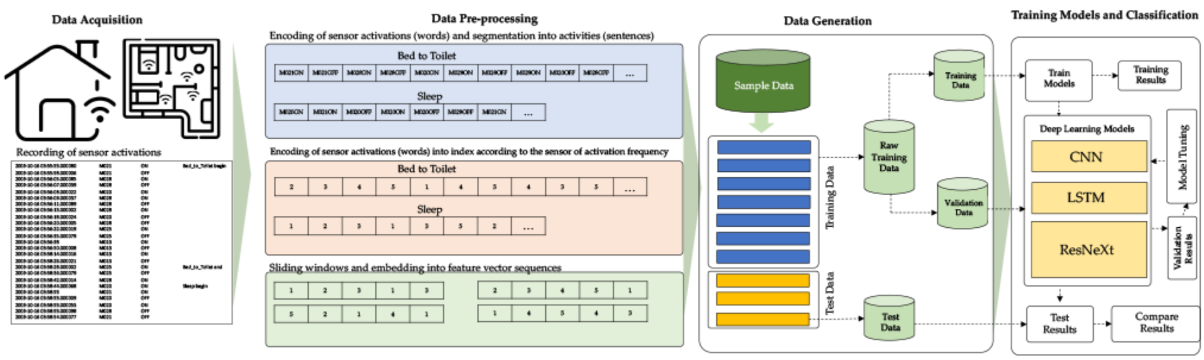

FIGURE 1. The HAR methodology based on smart home sensors used in this work

TABLE 1. Details of the three datasets used in this work

Detail	Cairo	Milan	Kyoto3
Number of residents	2 & pet	1 & pet	3
Number of sensors	27	33	86
Number of activities	13	15	12
Number of days	56	92	64

(Cairo). See Table 1 for specifics on how the three chosen datasets differ depending on the layout of the dwelling and the number of residents.

3.2. **Data pre-processing.** From the sequence of sensor activations, the dataset is segmented into event sequences as part of the pre-processing phase. Every sequence relates to a specific action, and the occurrence timestamp order is maintained within the sequences. The encoded occurrence sequences are subsequently utilized inputs for the pre-trained embeddings.

In order to capture all possible sensor activations, we create a collection of sensor activations and classify them into categories, assigning a distinct value to each one. By converting the sensor activations into categorical values, the model can learn about the frequency of a sequence of activations. This also allows the model to consider the relationship between two consecutive activations. These categories comprise the vocabulary used to represent a smart home comprehensively.

As in natural language processing for words in sentences, each sensor activation in sequences is converted into an index to be utilized as an entry to a neural network. The index begins at 1, with 0 allocated for sequence padding. This ordinal encoding represents the frequency of sensor activation. Depending on the sensor activation frequency, a series of words such as [M004ON M005OFF M007OFF M004OFF M007ON M005ON M004OFF M007ON M005ON M004OFF] becomes the sequence of indexes [1 4 8 2 1 2 7 1 8 7 3 2]. Figure 2 depicts the process of stream segmentation and encoding.

3.3. **Data generation.** For this task, data samples are taken and used as training data. The signals are divided into temporal windows, which are then used to build a model and test its effectiveness. The standard method for testing involves dividing the data into training and testing sets, known as cross-validation. There are different ways to split the data, such as using k-fold cross-validation. This step helps to assess how well the learning algorithm can adapt to new information. In this HAR methodology, we use 5-fold cross-validation during this phase.

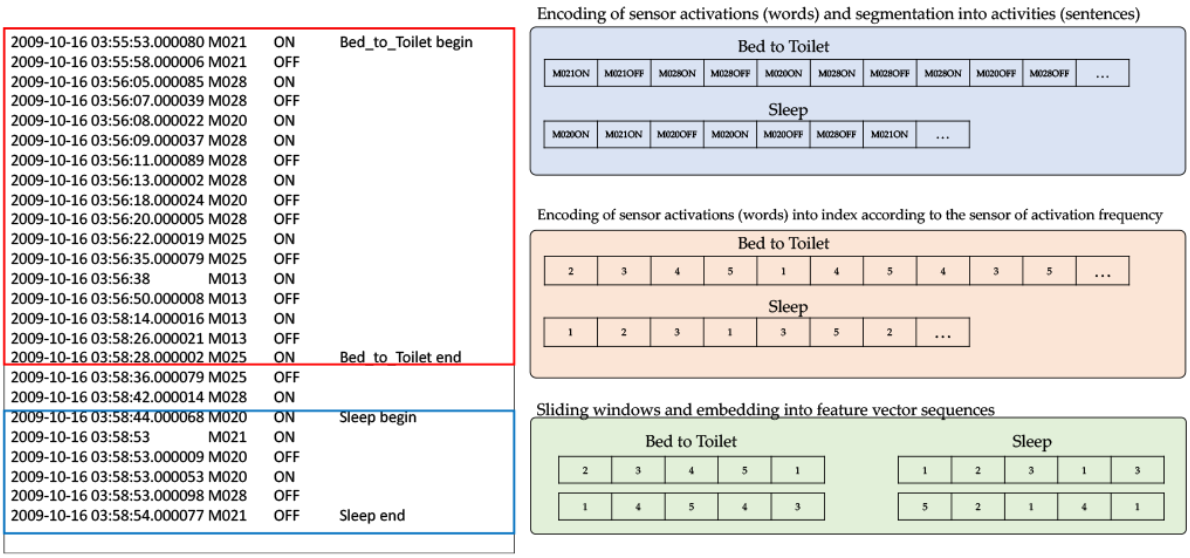

FIGURE 2. Stream segmentation and encoding

3.4. **ResNeXt model.** The proposed ResNeXt network is an end-to-end DL network based on convolutional blocks and multi-kernel residual blocks of the deep residual layout. Figure 3 depicts this proposed model's general design.

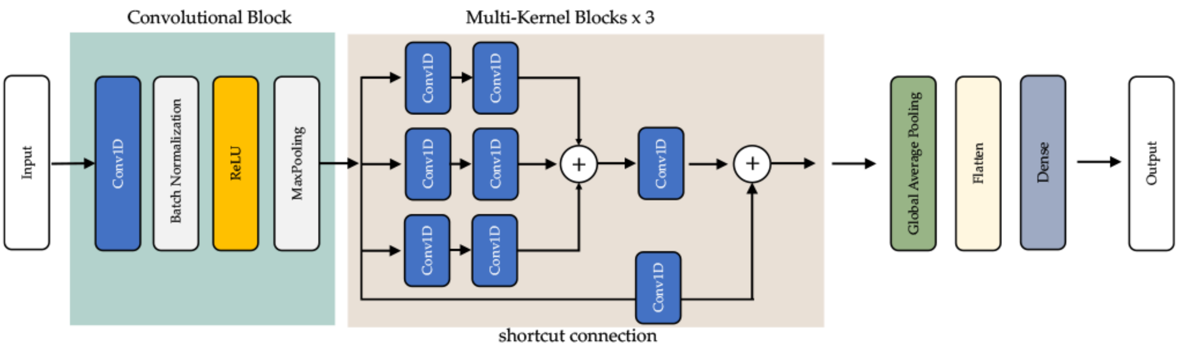

FIGURE 3. The ResNeXt network architecture

The MK block, illustrated in Figure 3, incorporates the cross-layer connection design concept of ResNet while also combining elements of the VGG and Inception networks. This structure addresses the limitations of the VGG network, which experiences degradation when too deep, by utilizing the ResNet cross-layer connection structure. In the proposed ResNeXt, a transformation set replaces the Inception network's transformation structure. Since each aggregated topology is identical, the network requires fewer adjustments to hyperparameters when dealing with different datasets, resulting in increased robustness.

This work uses the convolutional block to extract low-level characteristics from raw sensor data. This block consists of four layers, as shown in Figure 3: 1D-convolutional (Conv1D), batch normalization (BN), rectified linear unit (ReLU), and max-pooling (MP) layers. Multiple convolutional kernels that can be learned obtain particular characteristics in the Conv1D, and each kernel generates a feature map. The BN layer was selected to maintain and accelerate the training process, and the ReLU layer was applied to enhancing the expressiveness of the model. The MP layer was applied to compacting the feature map while preserving its most vital components.

The Multi-Kernel Blocks (MK) have three components with convolutional kernels of different sizes: 1×3, 1×5, and 1×7. Each module employs 1×1 convolutions before employing these kernels to reduce the proposed network's overall complexity and several parameters. Utilizing Global Average Pooling algorithm and flattened layers, the averages of each feature map were transformed into a 1D vector in the classification block (GAP). The outcome of the utterly connected layer was translated into probabilistic reasoning utilizing the softmax function. The network's losses were computed using the cross-entropy loss function, frequently employed in classification issues.

3.5. **Performance measurement criteria.** Researchers analyze HAR solutions using measures including Accuracy, Precision, Recall, and F1-score, considering HAR is a multi-class identification issue. Four characteristics of activity class C_i determine these measurements: true positive $TP(C_i)$, true negative $TN(C_i)$, false positive $FP(C_i)$, and false negative $FN(C_i)$. The F1-score estimates the accuracy of a model on a dataset. At row i and column j, an element C_{ij} of the confusion matrix specifies the number of cases for which the actual class is i and the signified class is j. The F1-score is a technique for combining the Precision and Recall of a model, and it is specified as the cumulative average of the Precision and Recall of the model. It should not be overlooked that most housing databases are class-imbalanced. In other words, specific actions have more instances than others and constitute the majority. In an unbalanced dataset, a minority class is more difficult to forecast since, by definition, there are fewer instances of this class. This implies that it is more difficult for a model to learn the properties of instances from this class and to distinguish them from examples from the majority class. Consequently, it would be more acceptable to employ measures weighted by the dataset's class experience, including balanced Accuracy, weighted Precision, weighted Recall, and weighted F1-score.

In 5-fold cross-validation, four standard assessment measures, Accuracy, Precision, recall, and F1-score, are generated to assess the effectiveness of the proposed DL model. Following are the mathematical formulae for the four measures:

$$Accuracy = \frac{\sum_{i=1}^{n} TP(C_i)}{\sum_{i=1}^{n} \sum_{j=1}^{n} C_{ij}} \tag{1}$$

$$Precision = \frac{1}{n} \sum_{i=1}^{n} Precision(C_i) \tag{2}$$

$$Recall = \frac{1}{n} \sum_{i=1}^{n} Recall(C_i) \tag{3}$$

$$F1\text{-}score = \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

where,

$$Recall(C_i) = \frac{TP(C_i)}{TP(C_i) + FN(C_i)} \tag{5}$$

$$Precision(C_i) = \frac{TP(C_i)}{TP(C_i) + FP(C_i)} \tag{6}$$

4. **Research Experiments and Findings.** In this part, we provide the experimental data designed to directly assess two evaluation DL models (CNN and LSTM) and the proposed ResNeXt model for the identification of human motions in a smart home environment.

Five-fold cross-validation was utilized to assess the three models employed in this study. The experiment findings show that the proposed ResNeXt model performed satisfactorily

Table 2. Recognition effectiveness of DL models using the Cairo dataset

Model	**Parameter**	**Recognition effectiveness**		
		Accuracy	**Loss**	**F1-score**
CNN	8,268,359	83.08%(±2.00%)	1.43(±0.23)	82.55%(±1.80%)
LSTM	93,703	83.59%(±2.98%)	0.79(±0.06)	82.93%(±2.71%)
ResNeXt	89,871	84.81%(±2.86%)	0.64(±0.10)	83.49%(±2.14%)

Table 3. Recognition effectiveness of DL models using the Milan dataset

Model	**Parameter**	**Recognition effectiveness**		
		Accuracy	**Loss**	**F1-score**
CNN	8,465,674	83.40%(±0.50%)	1.60(±0.38)	82.45%(±1.67%)
LSTM	251,402	92.55%(±0.70%)	0.45(±0.03)	90.09%(±3.80%)
ResNeXt	247,634	93.57%(±0.55%)	0.32(±0.06)	92.11%(±2.15%)

Table 4. Recognition effectiveness of DL models using the Kyoto3 dataset

Model	**Parameter**	**Recognition effectiveness**		
		Accuracy	**Loss**	**F1-score**
CNN	8,346,501	85.67%(±1.21%)	1.54(±0.20)	85.95%(±3.21%)
LSTM	156,293	89.92%(±2.54%)	0.92(±0.04)	88.51%(±2.77%)
ResNeXt	152,461	90.38%(±1.28%)	0.54(±0.34)	89.47%(±1.52%)

with the highest accuracies based on sensor data from three different datasets, as indicated in Tables 2, 3, and 4.

The results of the experiment indicate that the ResNeXt model has fewer parameters compared to other models like CNN and LSTM. This is significant for the proposed ResNeXt model since it can be a less complex and lightweight option for recognizing human movements in smart home systems.

5. **Conclusion and Future Works.** This study investigated human movement detection using smart home sensor data and DL techniques. ResNeXt is a deep residual network proposed to enhance HAR effectiveness. To assess the DL models, including ResNeXt, three CASAS datasets were included (Cairo, Milan, and Kyoto3). Based on experimental findings, ResNeXt surpasses CNN and LSTM models in terms of accuracy and F1-score. ResNeXt employing smart home sensors achieved the best interpretation, with accuracy scores of 84.81%, 93.57%, and 90.38% for the CASAS Cairo, CASAS Milan, and CASAS Kyoto3 datasets, respectively. Future research is suggested to generalize the model to function well in multi-user households.

Acknowledgment. This research project was supported by the Thailand Science Research and Innovation Fund and the University of Phayao (Grant No. FF66-UoE001). The authors also gratefully acknowledge the financial support provided by Thammasat University Research fund under the TSRI, Contract No. TUFF19/2564 and TUFF24/2565, for the project of "AI Ready City Networking in RUN", based on the RUN Digital Cluster collaboration scheme.

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