Efficient Residual Neural Network for Human Activity Recognition using WiFi CSI Signals

Narit Hnoohom*
Department of Computer Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom, 73170, Thailand

Sakorn Mekruksavanich
Department of Computer Engineering, School of Information and Communication Technology, University of Phayao, Phayao, 56000, Thailand

Thanaruk Theeramunkong
School of Information and Computer Technology, Sirindhorn International Institute of Technology, Thammasat University, Pathum Thani, 12000, Thailand

Anuchit Jitpattanakul
Department of Mathematics, Faculty of Applied Science, King Mongkut's University of Technology North Bangkok, Bangkok, 10800, Thailand; Intelligent and Nonlinear Dynamic Innovations Research Center, Science and Technology Research Institute, King Mongkut's University of Technology North Bangkok, Bangkok, 10800, Thailand

ABSTRACT

The use of deep learning (DL) technology for the purpose of human activity recognition (HAR) is an important research area. Vision and sensor-based methods can provide good data but at the cost of privacy and convenience. Furthermore, Wi-Fi-based sensing has become popular for collecting human activity data, as it is ubiquitous, versatile, and performs well. The utilization of channel state information (CSI) obtained from Wi-Fi networks has the potential to facilitate the recognized activities. Traditional machine learning relies on hand-crafted features, but DL is more appropriate for automated feature extraction from raw CSI data. This work presented a generic HAR framework using CSI and studied various deep networks. We proposed a deep residual network that would automatically extract informative features from raw CSI. In this study, we conducted a comparative analysis of five fundamental deep networks; namely, convolutional neural network (CNN), long short-term memory (LSTM), bidirectional LSTM, gated recurrent unit (GRU), and bidirectional GRU. Experiments on a publicly benchmark dataset named the CSI-HAR dataset showed that the proposed recognition model performed the best for CSI-based HAR with the highest accuracy of 98.60%, thus improving the accuracy by up to 3.60% over prior methods. Therefore, deep residual networks would be considered to be a suitable option for HAR tasks that would encompass Wi-Fi CSI data.

CCS CONCEPTS

• **Artificial intelligence**;

*Corresponding author.

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KEYWORDS

Technology, channel state information, Wi-Fi, human activity recognition, deep residual network

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1 INTRODUCTION

Over the past years, research on human activity recognition HAR has advanced significantly with wide-ranging applications in smart homes, sports monitoring, healthcare, and human–computer interaction, among others. HAR has the primary objective of identifying and analyzing user behavior, so that systems can proactively provide assistance. Typically, there are two main HAR categories: vision-based (V-HAR) and sensor-based (S-HAR). V-HAR utilizes optical sensors and computer vision techniques to achieve positive results [1]. However, issues like illumination, occlusion, and privacy remain. On the hand, S-HAR uses data from accelerometers, gyroscopes, etc. to infer high-level behavior from low-level sensor readings. However, with respect to its environmental prerequisites, the S-HAR system has certain limitations [2].

V-HAR is susceptible to factors like lighting and background and has privacy concerns, whereas S-HAR sensors can be cumbersome for users. Nevertheless, Wi-Fi-based sensing has gained attention for ubiquity, versatility, and performance. Moreover, Wi-Fi sensing utilizes channel information for both communication and sensing. Additionally, Wi-Fi-based HAR offers advantages over V-HAR and S-HAR, as it is unaffected by lighting or anthropometrics and does not compromise privacy. Unlike S-HAR, this does not require wearing sensors. Thus, Wi-Fi-based HAR would be promising for smart homes and healthcare. In the past few years, research efforts have focused on the investigation and enhancement of HAR techniques that are based on Wi-Fi technology [3].

Wi-Fi-based HAR systems are economical and can easily be integrated with existing Wi-Fi infrastructure without much cost. Two distinct categories also exist - using the received signal strength indicator (RSSI) or channel state information (CSI). CSI characterizes how radio frequency signals travel between the transmitter and receiver, consequently undergoing effects like attenuation, phase shift, and delay. Additionally, prior work has shown that CSI-based systems outperform RSSI-based ones, as CSI provides more information.

For recognition models, learning approaches like machine learning (ML) are powerful classification and prediction tools. Some works use ML techniques like random forest [4], hidden Markov models [5], support vector machines [6], and k-nearest neighbor [7] for Wi-Fi CSI-based HAR. Furthermore, traditional approaches rely on manually extracting statistical or structural features from sensor data, thus requiring domain expertise to obtain the relevant features. While these handcrafted features work well with limited data, feature extraction has become very complex as sensors increase.

- The architecture for deep learning (DL) that we proposed was termed CSI-ResNeXt, and it was a ResNet. It could automatically extract spatial features from raw Wi-Fi CSI signals using residual connections and multibranch aggregation transformations. This improved the efficiency and accuracy for recognizing human worker activities.
- The efficacy of the CSI-ResNeXt network was substantiated through empirical investigations conducted on a publicly available dataset encompassing CSI data pertaining to diverse human activities.
- We conducted a comparative analysis of the experimental results obtained from our proposed methodology with those of the leading approaches in the field of HAR as documented in the CSI-based literature.

The subsequent sections of the paper are structured in the following manner: In Section 2, an overview of advanced research conducted on the HAR through the utilization of Wi-Fi CSI data is provided. Section 3 presents the HAR framework that is being discussed in this study, which focuses on the automatic learning of the features and the recognition of the activities. This is followed by the introduction of the CSI-ResNeXt model that is being proposed in this research. Section 4 provides a comprehensive account of the conducted experiments and the corresponding experimental setup. The results are subsequently displayed for diverse scenarios. In conclusion, Section 5 serves as the final segment of this study by providing a summary of the results and suggesting prospective avenues for further research.

2 RELATED WORKS

This section begins by presenting a review of prior research in CSI-based HAR. Subsequently, an examination of the DL approaches for CSI-based HAR was conducted.

2.1 CSI-based HAR

Given the widespread availability of the Wi-Fi signals, much research has explored Wi-Fi-based HAR. Abdelnasser et al. [8] proposed WiGest using WiFi RSS for gesture recognition, consisting of primitive extraction, gesture identification, and action mapping. The technique proposed by Gu et al. [9] utilized an RSS-based methodology, which entailed the manual extraction of features from raw RSS data. Subsequently, a fusion algorithm was employed to identify fundamental activities, such as sitting, standing, and walking.

However, RSS is noisy and unstable due to multipath fading, hence limiting the performance even for simple activities. RSS provides coarse-grained channel state information, while CSI offers finer-grained details. Consequently, the CSI field has garnered significant interest due to its enhanced stability and provision of valuable information. In their study, Zhang et al. [10] conducted an analysis on the sensing capability of Wi-Fi, presenting a Fresnel zone model that achieved high accuracy detecting centimeter-scale respiration and decimeter-scale walking direction. Likewise, Wang et al. [11] introduced a recognition system that was based on CSI and focused on location-oriented applications.

Nonetheless, hand-crafted features require expertise and could lose implicit information. Therefore, DL was applied to the automatic learning of the significant features from Wi-Fi CSI for the recognition of the activities.

2.2 Deep Learning Approaches for CSI-based HAR

Recently, CSI has been used for localizing and classifying human activities via DL, as it provides fine-grained wireless link information. Yang et al. [12] proposed an indoor localization and HAR system by creating a dataset of six activities and using 1-D CNN architecture to achieve 95.68% accuracy. Moreover, Moshiri et al. [13] converted CSI data to images for 2-D CNN architecture by comparing it to ML methods with 95% best accuracy. Chahoushi et al. [14] also proposed an indoor localization and HAR system by creating a dataset of six activities and using 1-D CNN architecture that used a MIMO autoencoder to classify the activities with 94.49% accuracy from only 50% of the training data.

Since CSI is time-series data with temporal dependency, recurrent neural network (RNN) and long short-term memory (LSTM) have been applied more than other DL approaches for HAR. RNN and LSTM process sequences, but struggle with long sequences due to vanishing gradients. LSTM also requires a high memory bandwidth. Despite proficiency in the time series, LSTM cannot learn long sequences. It only considers past CSI, so it is unable to distinguish similar start-different end activities.

3 METHODOLOGY

This section presents a framework for HAR that was based on CSI and utilized the CSI-ResNeXt model. First, raw Wi-Fi CSI data was collected. Second, the CSI data were pre-processed with denoising and segmentation. Next, a five-fold cross-validation was performed on the processed data before it was divided into the training and test sets. Then, we mapped the data samples into a high dimensional embedding space and classified the human activities using the DL models. Finally, the evaluation of model performance was conducted based on the parameters, such as accuracy, precision, recall, and F1-score. The overall structure of the CSI-based HAR framework is shown in Figure 1.

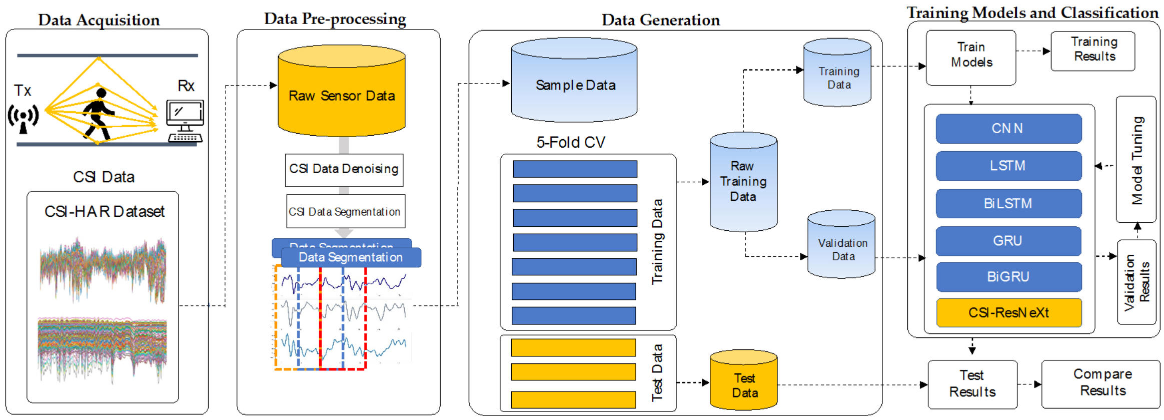


Figure 1: A CSI-based HAR framework used in this study.

3.1 Data Collection

In this work, we conducted our experiment on a publicly available dataset named the CSI-HAR dataset [13]. This dataset was used to evaluate the proposed model and comparable Wi-Fi-based HAR baselines. The dataset was collected through the utilization of the Nexmon, which was installed on a Raspberry Pi 4GB with the purpose of capturing and storing CSI data from both broadcast and received signals. A total of 4,000 samples of CSI were gathered throughout a time span of 20 seconds, where each line of data corresponded to a duration of 5 ms. Raw CSI associated with the activities was segmented and stored as CSV matrices. Each matrix consisted of 52 columns representing subcarriers and the number of rows varied between 600 and 1,100 based on the duration of the respective activity. Label files separated the lines per activity. There were seven distinct activities contained in the CSI-HAR dataset: walking, running, sitting, lying, standing, bending, and falling. Each activity was repeated 20 times with the participation of three volunteers of varying ages, all within a home environment.

3.2 Data Pre-processing

Raw CSI data can be noisy without distinctive features for different activities. As a consequence, it was necessary to filter the noise before extracting the features for classification. Low-pass filters are one noise filtering method, but CSI noise contains high bandwidth bursts and impulses that are not smoothed by low-pass filters. More effective techniques like principal component analysis (PCA) denoising have been shown for CSI data. PCA reduces high-dimensional data's dimensionality by concentrating most on the signal information in fewer features. The first principal component containing noise was discarded, while the next five were used for the feature extraction. Mobile target reflection information was also not lost since it was captured in other components. After the PCA denoising, the features were extracted from the CSI data to enable classification. In summary, the CSI data required pre-processing like PCA denoising before the feature extraction, so the noisy raw data could be effectively classified.

After denoising, segmentation refers to the process of division of a signal into small sections or windows. Segmentation was employed for two primary objectives in our research. First, the length and subjectivity of the captured CSI signals could be a bit different, which could make identification difficult. Second, the processing of long CSI data sequences necessitated a significant amount of time and computation resources.

To effectively deal with this issue, a fixed window size was applied to divide the denoised CSI signals into segments that were smaller and could be treated as independent instances for training the CSI-ResNeXt model. Segmentation improved the efficiency by enabling parallel training on the segments. This also enhanced the accuracy by normalizing the input length across varying CSI sequences. In summary, segmentation standardized the CSI data and allowed more efficient parallel training, thus overcoming variability in the raw signals.

3.3 Data Preparation

Samples of data were categorized into training data for the purpose of model learning and test data for the purpose of model validation. The method that is most commonly used for separating data into a training set and a test set is cross-validation. There are techniques for dividing the data, such as k-fold cross-validation. Evaluating how well the algorithm for learning could be applied to new data as the goal. In this particular framework, a five-fold cross-validation approach was employed, wherein the dataset was partitioned into five distinct folds. The training dataset consisted of four folds, while the testing dataset comprised one-fold. The aforementioned process was iterated five times with each iteration utilizing a distinct fold for the purpose of testing. Cross-validation helped evaluate the model's ability to generalize the new data rather than just memorize the training data.

3.4 Training Models and Classification

An end-to-end DL model was the CSI-ResNeXt network, which was constructed using the deep residual architecture principle. This used convolutional blocks along with multi-kernel residual blocks Figure 2.

Convolutional blocks, (ConvB) are a set of four layers used to uncover low-level features from raw CSI data. These layers were

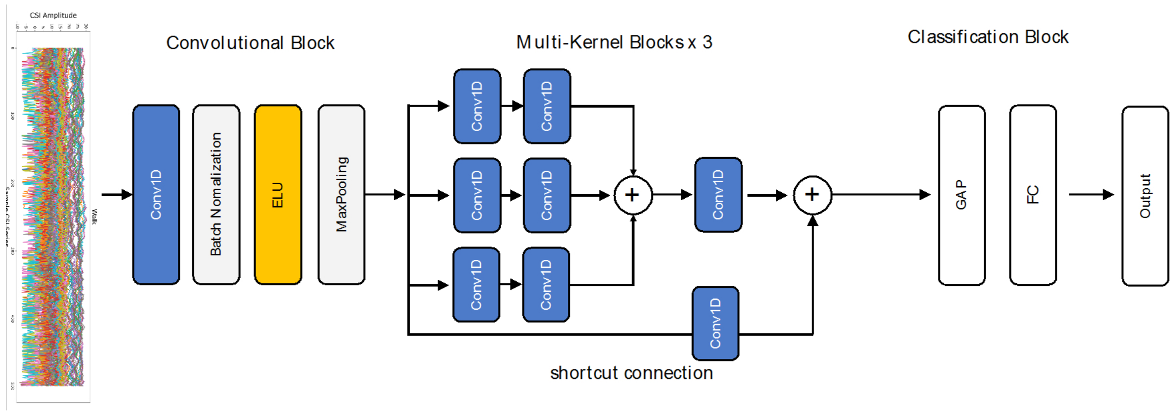


Figure 2: Structure of the proposed CSI-ResNeXt

Table 1: Performance results of the proposed CSI-ResNeXt model and the five baseline models on the CSI-HAR dataset.

Model	Total Parameters	Recognition Performances (Mean +/- STD.)			
		Accuracy	Precision	Recall	F1-Score
CNN	1,040,231	95.19246% (+/- 1.80461%)	95.54061% (+/- 1.52075%)	95.21566% (+/- 1.77281%)	95.12646% (+/- 1.78832%)
LSTM	203,807	92.68241% (+/- 3.05481%)	92.78344% (+/- 2.91641%)	92.55934% (+/- 3.18249%)	92.46782% (+/- 3.10541%)
BiLSTM	407,607	93.78493% (+/- 1.78873%)	93.90208% (+/- 1.74999%)	93.58918% (+/- 1.84673%)	93.56045% (+/- 1.81109%)
GRU	153,807	95.18844% (+/- 1.13333%)	95.48618% (+/- 1.29807%)	94.92261% (+/- 1.10402%)	95.04041% (+/- 1.24139%)
BiGRU	307,607	96.38995% (+/- 1.86342%)	96.33798% (+/- 1.90958%)	96.17072% (+/- 1.98155%)	96.20565% (+/- 1.98093%)
CSI-ResNeXt	28,519	98.59598% (+/- 1.02267%)	98.63458% (+/- 1.04627%)	98.51800% (+/- 1.09494%)	98.52550% (+/- 1.11084%)

1-D convolution, batch normalization, exponential linear unit (ELU) activation, and max pooling. Multiple convolutional kernels extracted distinct features, hence producing feature maps. Batch normalization stabilized and speed up the training. ELU boosted the expressiveness, whereas max pooling compressed the feature maps by keeping the most important elements.

Three modules contained within the multi-kernel blocks (MKs) comprised kernels of varying sizes: 1×3, 1×5, and 1×7, respectively. Each module used 1×1 convolutions to reduce the complexity and parameters before applying the kernels.

With the use of a technique called global average pooling (GAP), the feature map averages were transformed into a 1-D vector by the classification block. The output of the fully connected layer was converted into probabilities through the use of the SoftMax function. Network losses were also computed utilizing cross-entropy loss function, which was prevalent in the classification applications.

In summary, CSI-ResNeXt used residual blocks and MKs for feature extraction from the Wi-Fi CSI signals, followed by GAP and SoftMax for classification.

4 EXPERIMENTS AND RESULTS

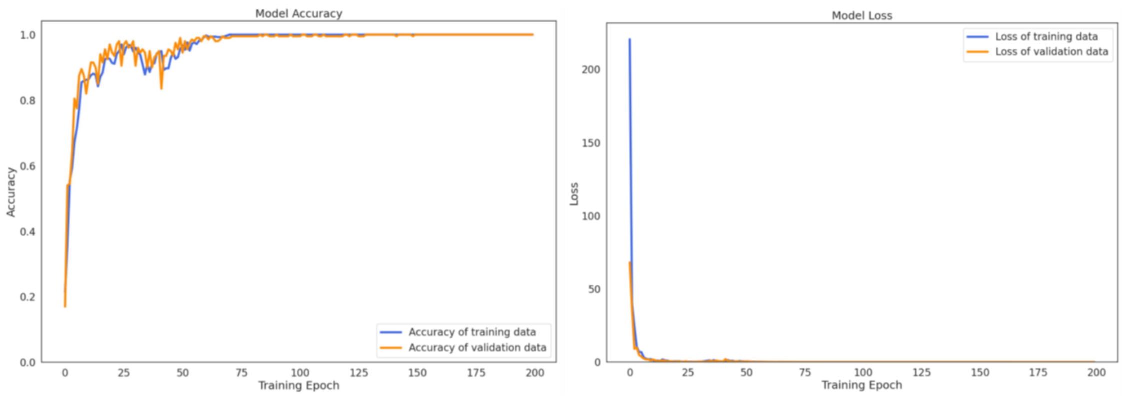
This section presents the experimental details and results using the proposed CSI-ResNeXt model on the CSI-HAR. In addition to the performance of CSI-ResNeXt, we also conducted a comparative analysis with five default DL models; namely, convolutional neural network (CNN), LSTM, bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and bidirectional GRU (BiGRU). Moreover, we made comparisons to the other DL models currently available on the benchmark dataset.

In this study, all DL networks were programmed and trained using Google Colab Pro+ in conjunction with a Tesla V100 GPU to accelerate the training. The CSI-ResNeXt model was proposed along with other basic models that were implemented in Python with TensorFlow backend (v3.9.1) and CUDA (v8.0.6).

Table 1 shows the performance results of the proposed CSI-ResNeXt model for the CSI-based HAR on the CSI-HAR dataset. The CSI-ResNeXt model achieved an excellent classification performance with 98.60% accuracy, 98.63% precision, 98.52% recall and 98.53% F1-score that averaged across all activities.

Table 2: Comparison of the CSI-HAR dataset-based proposed CSI-ResNeXt model to other existing works.

Classifier	Accuracy	Precision	Recall	F1-Score
2D-CNN [13]	95%	-	-	-
MIMI-AE [14]	94.49%	-	-	-
CSI-ResNeXt	98.60%	98.63%	98.52%	98.53%



(a) (b)

Figure 3: The accuracy and loss metrics of the CSI-ResNeXt model on the CSI-HAR dataset: (a) Train and validation accuracy curves; (b) train and validation loss curves.

These results demonstrated that the proposed CSI-ResNeXt model had significantly fewer parameters (28,519 parameters) compared to the other baseline DL models, such as CNN (1,040,231 parameters), LSTM (203,807 parameters), etc. This indicated that CSI-ResNeXt was a much more lightweight and efficient model in terms of parameter usage. Less parameters typically led to the reduced risk of overfitting as well. Despite having far fewer parameters, CSI-ResNeXt still achieved the best performance overall with 98.60% accuracy, thus outperforming even much larger models like CNN. This showed CSI-ResNeXt was able to extract more representative and useful features from the CSI data compared to other baseline models. In addition, the architectural optimizations allowed it to learn effectively with fewer parameters. The parameter efficiency and high performance of CSI-ResNeXt demonstrated that it was an optimal DL method to use for the CSI-based HAR application.

Based on the CSI-HAR dataset, our work presented the best recognition results compared to other existing models with an average accuracy of 98.60%, a precision of 98.63%, a recall of 98.52%, and an F1-score of 98.53% using the proposed CSI-ResNeXt model on the same dataset (Table 2). Our proposed model increased the accuracy by 3.60% more than existing state-of-the-art CSI-HAR datasets.

Figure 3 shows the accuracy and loss metrics obtained by the CSI-ResNeXt model during the training. The accuracy graph in Figure 3a demonstrates the model converged quickly within 100 epochs for both the training and validation data. The training loss in Figure 3b was higher compared to the validation loss, which was expected. The higher training loss was due to the multi-stage learning process needed to understand the varied properties of the CSI signals that corresponded to the many diverse activities carried out by humans. Overall, the fast convergence and steady improvement of the accuracy and loss metrics highlighted the efficiency of CSI-ResNeXt in learning effective representations of CSI data for HAR. As such, the model was able to rapidly extract distinguishing informative features from the Wi-Fi CSI inputs that enabled the accurate classification of human actions. Therefore, the accuracy and loss curves indicated fast and stable training of the CSI-ResNeXt model. The higher training loss arose from learning the CSI signal patterns but progressively decreased, while accuracy saturated close to 100% within 100 epochs, thus demonstrating the efficient learning of the discriminative CSI features for HAR by the proposed architecture.

The confusion matrix in Figure 4 for the CSI-ResNeXt model on the CSI-HAR dataset demonstrates excellent overall performance, with an average accuracy rate of 98.60% across all activities. This indicates that it possesses a consistent ability to differentiate across different human activities. The model demonstrates outstanding performance in accurately classifying the actions of "bend", "run", "stand up", and "walk", achieved accuracy rates of 99-100%. This implies that these activities generate very distinguishable patterns in the WiFi CSI data. The model demonstrates an occasionally greater extent of difficulty in some activities when compared to others. Specifically, the accuracy rates are marginally diminished for the actions "bend" (97.1%), "fall" (96.2%), and "stand up" (96.9%). Nevertheless, these are highly esteemed. Confusion often arises when there are activities that have comparable characteristics in terms of physical movement. There is significant ambiguity between the

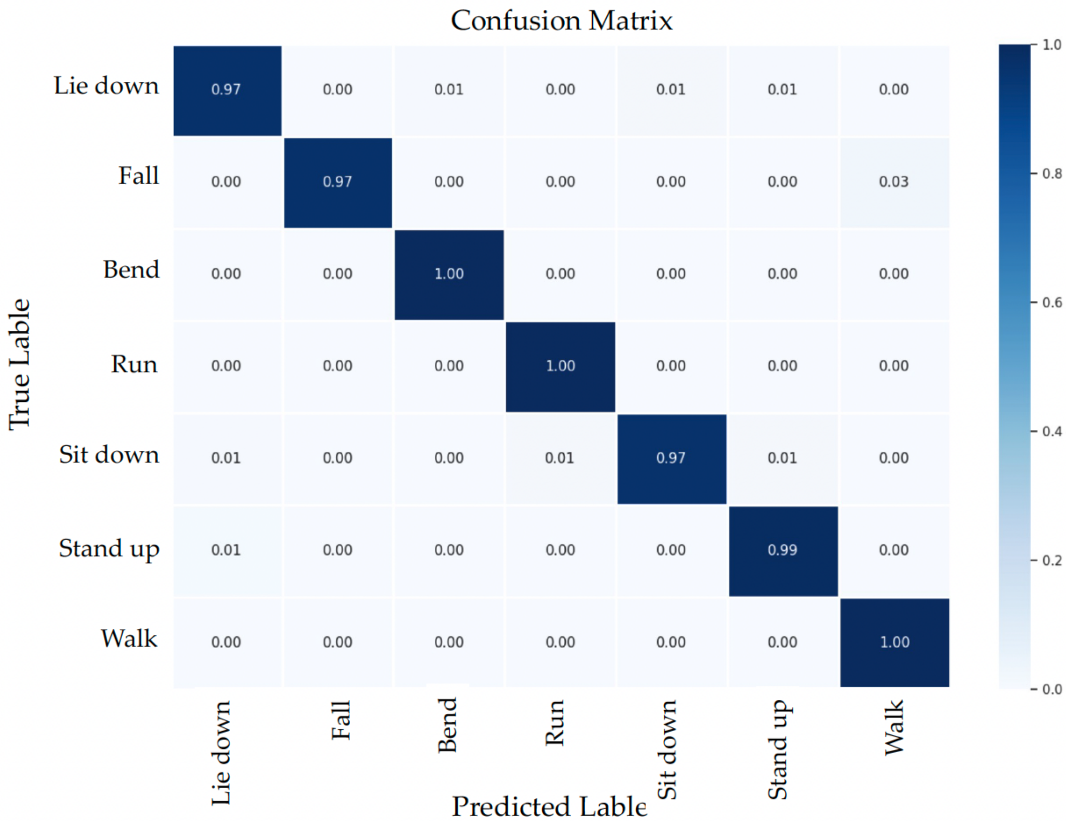


Figure 4: Confusion Matrix of the CSI-ResNeXt model

terms of the action's "bend" and "stand up" since both refer to changes in vertical body alignment. The terms "lie down" and "sit down" are sometimes conflated, probably due to the resemblance in the beginning and end of both actions.

In summary, the proposed CSI-ResNeXt model achieved state-of-the-art performance on the CSI-HAR dataset, consequently outperforming the baseline DL approaches for Wi-Fi CSI-based HAR.

5 CONCLUSION

This work proposed a DL model called CSI-ResNeXt to automatically recognize human activities from Wi-Fi CSI signals. Wi-Fi CSI-based activity recognition involved time-series data with spatial and temporal features. The proposed model achieved high recognition accuracies of 98.60% on CSI-HAR that was used as a benchmark dataset, thus outperforming existing methods by up to 3.60%. Although it performed well in the line-of-sight environments, performance was lower in non-line-of-sight conditions, hence needing further investigation.

Future work could include real-world datasets with high interference. Recognizing multi-user activities would also be more realistic and challenging than a single user. Furthermore, we could extend this work to multi-user recognition. Collecting a dataset of daily activities in indoor environments would also be valuable future work, as publicly available datasets have common but limited activities.

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