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Convolutional Neural Network Based Human Activity Recognition using CSI

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Abstract—**Human activity recognition (HAR) has the potential to significantly impact applications such as health monitoring, context-aware systems, transportation, robotics, and smart cities. Because of the prevalence of wireless devices, the Wi-Fi-based approach has attracted a lot of attention among other existing methods such as sensor-based and vision-based HAR. Wi-Fi devices can be used to distinguish between daily activities such as "walking," "running," and "sleeping," which affect Wi-Fi signal propagation. This paper proposes a Deep Learning method for HAR tasks that makes use of channel state information (CSI). We convert the CSI data to RGB images and classify the activity recognition using a 2D-Convolutional Neural Network (CNN). We evaluate the performance of the proposed method on two publicly available datasets for CSI data. Our experiments show that converting data into RGB images improves performance and accuracy compared to our previous method by at least 5%.**

This paper is the extended version of our previously accepted paper in ICCKE 2021.

Keywords: Activity Recognition, Channel State Information, Convolutional Neural Network, Deep Learning, WiFi.

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I. Introduction

Human activity recognition (HAR) techniques have attracted many researchers due to their high potential in academic and industrial applications such as smart homes, health diagnosis, transportation, security, robotics, and indoor pedestrian tracking [1]. HAR includes sensor-based, image-based, and Wi-Fi-based methods. In sensor-based methods, users need to install sensors that limit the application environments and long-term surveillance impossible [2]. Image-based systems are hampered by the consistency and stability of the light source [3]. Wi-Fi-based methods are gaining popularity because they enable more precise monitoring without disturbing participants in sensor-based methods or introducing privacy issues in image-based processes. Furthermore, because indoor spaces are usually full of wireless signals, Wi-Fi systems do not impose any additional costs. Meanwhile, new HAR techniques, such as light-based and radio-frequency [4], are constantly emerging due to their device-free nature.

The idea behind Wi-Fi-based HAR is that two activities, such as Walking and Falling, have different effects on the reflected signals. The human body's motion affects the surrounding Wi-Fi signals, and signals received during a specific activity have different characteristics. Analyzing signal models can help distinguish between different human activities [5]. To determine a user's activity, the physical layer characteristics of the channel, including the Received Signal Strength (RSS) and Channel State Information (CSI), could be measured. RSS can be easily captured with the majority of devices, whereas CSI requires specialized hardware such as Intel 5300 network interface cards (NIC), raspberry pie (Nexmon tool), Atheros 9580, and Atheros 9390 (Atheros tool) [6, 7].

While carrying-on device location estimation has historically been one of the most representative RSS-based applications, it is unreliable in HAR due to the inability to capture small signal fluctuations caused by movement. CSI is generally preferred to obtain more accurate and reliable HAR systems because it represents more information about dispersion and discoloration [8]. As shown in Figure 1, different movements have different effects on CSI values, resulting in different patterns.

Deep learning (DL) algorithms excel at exploiting the received signal schema [9]. Because there are various types of DL algorithms, selecting a suitable neural network is dependent on the tasks implemented and the types of features. For example, depending on the dataset's quiddity, bi-directional Long Short-Term Memory (BLSTM) could be used [10]. In a multi-model sensor-based task, Simple Recurrent Units and Gated Recurrent Units networks were used [11], and Jichao Liu et al. used deep CNN-LSTM for video-based group activity recognition [12].

In [13], the background scene framework in an image-based HAR is statistically distinguished using pixel intensities redundancies. The model obtains an initial video frame that separates the moving humans from the background. Following training, they create boxes for each part that corresponds to behavior, in which the object filters the detected foreground. When motion is detected, the proposed method in [13] only records and analyzes video frames. The authors of [14] used CNN to estimate three arm movements while wearing a wrist accelerometer sensor (a sensor-based HAR). Many open-source sensor-based HAR databases relied on a single smartphone accelerometer with a low sampling rate. Training an accurate classifier with these data is difficult because they require more quantity and have an asymmetric distribution. To address this issue, participants' contributions must be increased.

CSI-based HAR is also used in elderly-care systems to detect user falls [15, 16]. Furthermore, researchers believe that CSI signals can be used to diagnose users' typing states on their smartphones [17]. CSI signals are used for hand sign recognition in [18, 19]. Recently, researchers have been interested in applying DL algorithms to WiFi-based HAR assisted by signal processing techniques, as DL-based HAR methods can automatically improve feature extraction, thereby improving recognition performance [20]. Researchers in [21] used CSI fingerprints for HAR and indoor localization tasks by using 1-D CNN to extract temporal information from CSI signals. The authors used the Short-time Fourier Transform for feature extraction and the Random Forest (R.F.) and Hidden Markov Model (HMM) for classification [22]. Furthermore, in [23], the authors used recurrent neural networks (RNNs) for feature extraction and proposed a feature enhancement scheme to improve the quality of CSI data. To obtain high-level features, [24] created an autoencoder long-term recurrent convolutional network. These systems are susceptible to phase shifts caused by timing offsets. To more precisely calculate and recoup the timing offset, the authors of [25] proposed a CSI-based HAR system that employs an activity filter-based DL network with improved correlation features on the CSI. Their scheme can also improve the accuracy of similar activities by incorporating an Activity Filter (A.F.). To recognize similar activities, the method employs the enhanced correlation features obtained through CSI compensation and enhancement. Their experimental results showed that their method is faster and more accurate than comparable state-of-the-art HAR research. The specific hardware/software combination for CSI data collection is one of the main issues in Wi-Fi-based HAR. As a result, there are few datasets available.

Sequential processing is used by LSTM and RNN, which means that long-term information must pass through all cells before reaching the current cell. When we need to multiply RNNs by small numbers, their structure cannot perform efficiently, resulting in vanishing gradients. Even the LSTM network's multiple switch gates and large memory can only solve some vanishing gradient problems. Furthermore, because it has a more complicated sequential path and MLP layers in each cell require more memory bandwidth, this module could be more hardware-friendly. Although LSTMs are excellent for time series prediction and classification, they can only learn a few hundred terms [26]. The period of each activity is important in real-time activity monitoring, especially for older adults; we consider two approaches: 2D-CNN and Attention-based BLSTM. Using 2D-CNN allows us access to future-step information, which is impossible in LSTMs. Convolutions process input in parallel, as opposed to RNNs and LSTMs, which process long-term input

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sequentially. Because LSTMs perform slightly better over longer training times than CNNs, they require more memory bandwidth for computation.

We consider an improved CSI-based HAR, which takes advantage of CNN's high potential in the classification task because wearing sensors is inconvenient for users, the image-based approach is dependent on light constancy, and LSTM cannot work correctly in the long term. The CSI-based HAR combined with the 2D-CNN model produces promising activity recognition results. In other words, our model is based on a signal conversion concept and proposes an image processing model based on a deep learning network. The following are the main contributions of this study:

- We apply the image processing concept to CSI data by converting smoothed CSI data amplitudes into RGB images. This is an extension to our previously presented method in [29], in which we convert the CSI data into gray-scale images.
- We examine the propoed method on two publicly available CSI datasets collected by authors in [22] and [28].
- We compare the performance of our new method to that of our previous method, in which we converted data collected by [22] into gray-scale images and fed them into the same CNN used in this study. Our evaluations confirm that the RGB conversion, improves the accuracy at-least by 5%.

The remainder of this paper is structured as follows. Section II describes the system model and how to obtain CSI for classification. Section III summarizes the main contributions of this research, including how we generate RGB images from CSI data and use them as the input layer for our proposed CNN. The experimental results are reported in Section IV, and the conclusions are discussed in Section VI.

II. System Model

CSI is one of the wireless channel metrics used in Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) communication systems to describe how a signal deflects, reflects, fades, and scatters during transmission. Knowing this information allows us to tailor the transmission state to the channel's properties to achieve the best bit rate and reliable communication with a low bit error rate [28]. Let $T(f_n, t)$ and $R(f_n,t)$ denote the sequence transmitted from the transmitter and the *nth* signal received the receiver at subcarrier frequency f_n at time t, respectively:

$$R(f_n,t) = T(f_n,t) \times CSI(f_n,t) + W \tag{1}$$

Where $R(f_n,t)$ is the received vector, $CSI(f_n,t)$ is the CSI matrix, and $T(f_n,t)$ is the transmitted vector, respectively, and W is an additive white Gaussian noise. According to (1), $CSI(f_n,t)$ with t transmitter and r receiver can be described as:

$$CSI = \begin{pmatrix} h_{1,1} & \cdots & h_{1,r} \\ \vdots & \ddots & \vdots \\ h_{t,1} & \cdots & h_{t,r} \end{pmatrix} \tag{2}$$

where, $h_{t,r}$ is a complex number, containing both amplitude and phase of the pagated signal from t_{th}transmitter and t_{th} receivual $h_{t,r} = |h| \times e^{i\angle h}$where $|h|$ is amplitude and $\angle h$ is its phase response.

III. Proposed Method

A. Pre-processing

We use the CSI dataset provided by Yousefi et al. [22] and Moshiri et al. [28]. Yousefi et al. collected CSI for seven activities at a 1 kHz sample rate [22], whereas Moshiri et al. collected data at 50 Hz using a raspberry pi four and Nexmon Tool [28]. The recorded activities include "bed," "fall," "walk," "pick up," "sit down," "run," and "stand up" for [22] and "Bend," "Walk," "Stand up," "Sit down," "Fall," "Run," and "Lie down" for [28]. We apply the CSI amplitude matrices to both datasets. In both datasets, a person completed each activity within 20 seconds, while no action was taken at the beginning or end of the period. We export activity rows and save them in matrices using the labeled files provided by these researchers. Smoothing methods remove random variations that appear as abrasiveness in a raw data plot because CSI data is noisy and time-series. We use the average method and the exponential method as the two smoothing methods. Based on the fact that close-in-time CSI data typically has similar values, the moving average approach is applied to raw data to remove random variation or noise. Smoothed data values are normalized to create 128x128 RGB images for all activities. This is because the numeric values in RGB image pixels are uniformly changed from zero (black pixels) to 255 (white pixels). Figure 2 shows sample-converted images of CSI data presented by the dataset in [22] and Figure 3 illustrates sample-converted images of CSI data presented by the dataset in [28]. The proposed post-processing technique is presented in Fig. 4.

B. CNN architecture

CNN is a type of neural network that is commonly used in vision-based tasks. Unlike traditional classification algorithms, which require human assistance in preprocessing steps, CNN can perform those tasks autonomously. Furthermore, CNN can automatically extract image features by applying filters to pixels. A CNN is typically made up of several layers, including Convolution, Max or Average Pooling, and Dense. Convolution layers are responsible for extracting features from pixels in a given image. The first Conv layer captures features such as color, edges, and angles, and adding the Conv layer allows it to extract more intricate details from images. Because the exact locations of the extracted features are not critical, each Conv layer is typically followed by a Max or Average Pooling layer. The main benefit of using this layer is that it reduces the number of trainable parameters and gives the network translation invariance, which means that regardless of how the input is shifted or translated, the output and response will be unique [28]. The final main layer is known as the Dense or fully connected layer, and it is similar to the network used in

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conventional models in which each neuron is connected to others in the next layer.

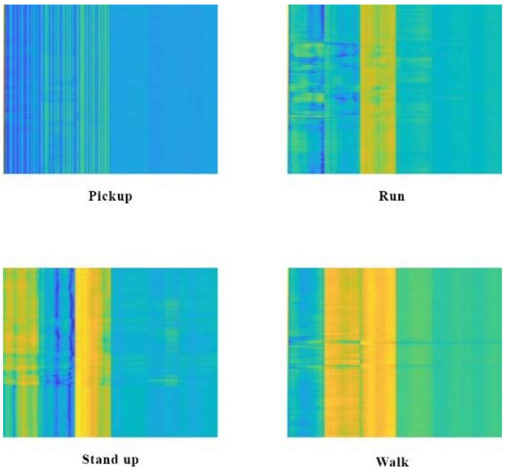

Figure 1. Sample RGB images of the CSI dataset presented by Yousefi et al [22].

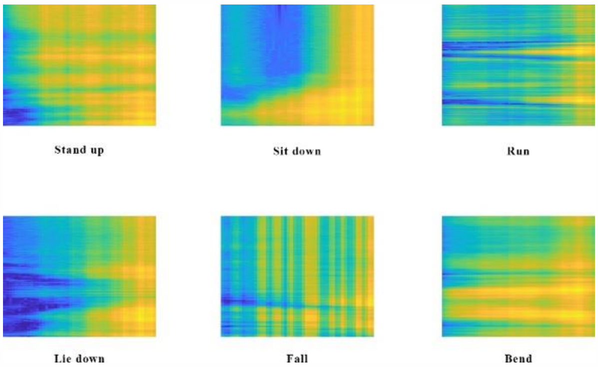

Figure 2. Sample RGB images of the CSI dataset presented by Moshiri et al [28].

The output of the first stage (the output of the Conv and Pooling layers) is fed into a fully connected layer, and the final output is calculated by taking the dot product of the weight vector and the input vector. Aside from these layers, some parameters are used for tuning and preventing overfittings, such as the Activation Function (A.F), Dropout layer, and Batch Normalization (B.N). The dropout layer is one of the methods that can be used to prevent the network from overfitting by randomly dropping and inactivating some neurons in each epoch. B.N. is used to improve network stability during the training process. The number of layers used varies according to the complexity of the classification task.

The proposed CNN architecture is made up of five different types of layers:

1. An input layer, the RGB images made from CSI data
2. 2D-Convolutional layers for feature extraction with kernel size 3x3
3. Max-pooling layers with pool size 2x2 as an applied filter to feature maps, resulting in features size reduction and improvement in the robustness of analyzed features
4. Fully connected layer (dense) to integrate all non-linear combinations of extracted features
5. An output layer with a SoftMax as an activation function representing a categorical distribution over seven different activities.

We apply ReLU (Rectified Linear Unit) after each Conv Layer to avoid the vanishing gradient problem. The result of negative input quantities is zero, according to this function (meaning that these neurons are deactivated). Following each ConvLayer, we apply the max-pooling layer. When features are detected in the Conv Layer, the max-pooling layer convolutionally down-samples feature maps and aids in the extraction of low-level features. Batch Normalization (B.N.) is used after the first Conv Layer with ReLU activation function and max pooling to make the network more stable during training. B.N. makes the variable mean and standard deviation estimations more stable across mini-batches and closer to 0 and 1, respectively. Dropout layers have been used between hidden layers to reduce overfitting. The last layer's output (pooled features) should be flattened before the fully-connected layer, resulting in a long feature vector (1-dimensional array). This single-column matrix is passed through a dense layer, and the output layer returns our predicted classes. In this study, we did not use transfer learning, and the proposed CNN architecture is shown in Fig.6.

IV. Experimental Results

In this study, we evaluate two publicly available datasets presented in [22] and [28] for seven daily activities such as walking, standing up, running, falling, and sitting down. For the experiment purpose, we utilized GeForce RTX 3060 and implemented TensorFlow 2.9. First, data from each dataset were preprocessed by the PCA technique with three components to omit the undesired values, which were then normalized between 0 and 255 to be in the range of RGB image intensity. During 200 epochs, the model could achieve an accuracy of 89.6% for [22] and 91.2% for [28]. To compare the result of the proposed method, we repeated the classification task by one of the NN architectures called 1D-CNN proposed by [21] and with our previous preprocess technique in [29], in which we converted the data into a gray-scale representation. As shown in Figure.6, with 1-D CNN, we could achieve an accuracy of 88.4% and 87.3% for [28] and [22], respectively. Also, compared to our previous approach, we witnessed an increase in the model performance and accuracy by just over 4% and 5%, respectively. Figure. 7 and Figure. 8 show the Confusion matrix for the proposed method. As can be seen, the model could discern the activity type ideally for data gathered by Moshiri. et al. [28] while, on the other hand, Yousefi. et al. [22], there is uncertainty between the activities of picking up and falling, and it is worth mentioning that compared to the previous approach, this confusion has degraded.

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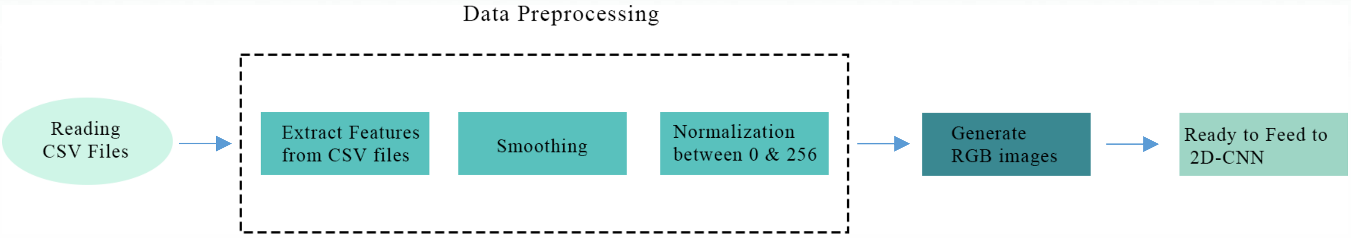

Figure 3. The pre-processing technique used in the proposed CNN-based *HAR*.

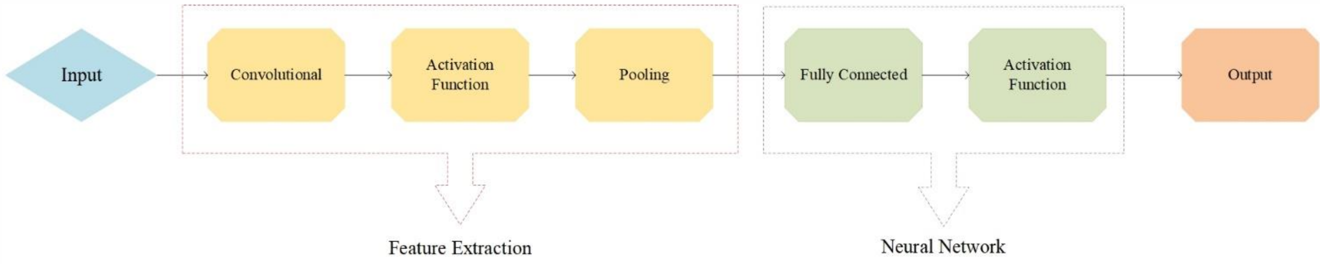

Figure 4. Main CNN architecture

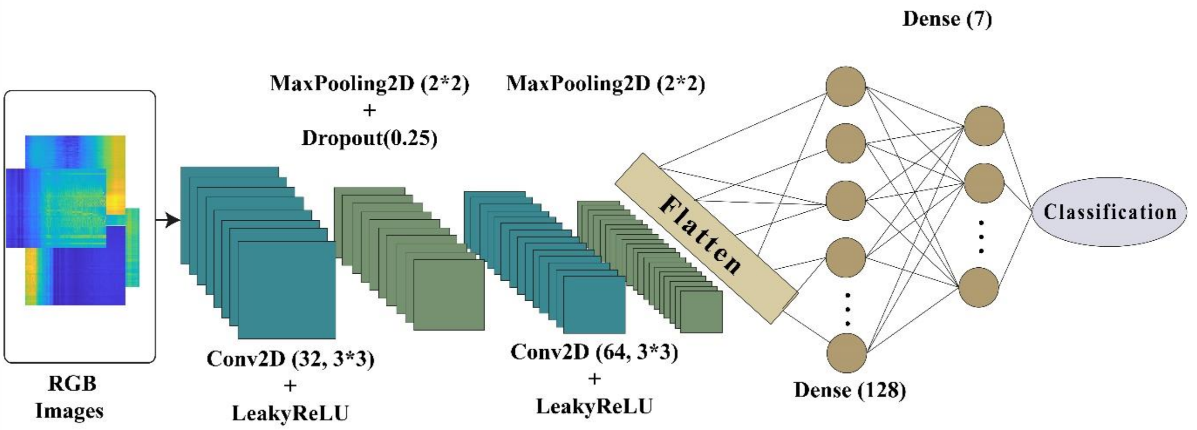

Figure 5. The proposed CNN architecture

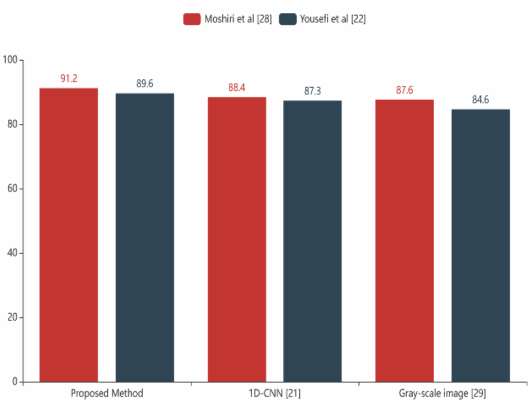

Figure 6. Comparison of activity recognition results' in various methods.

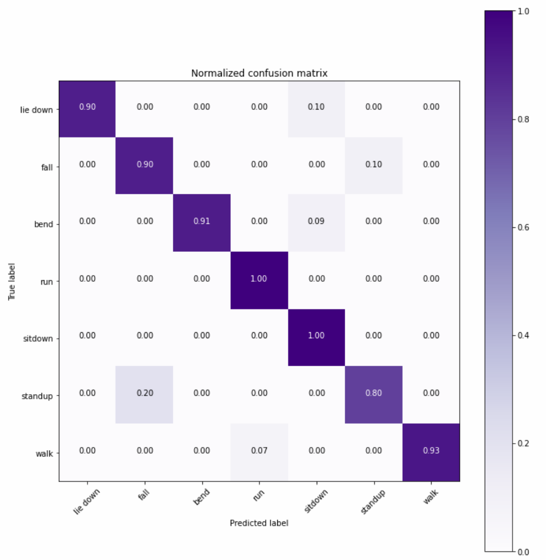

Figure 7. Confusion matrix of proposed CNN for the CSI dataset presented by moshiri et al. [28].

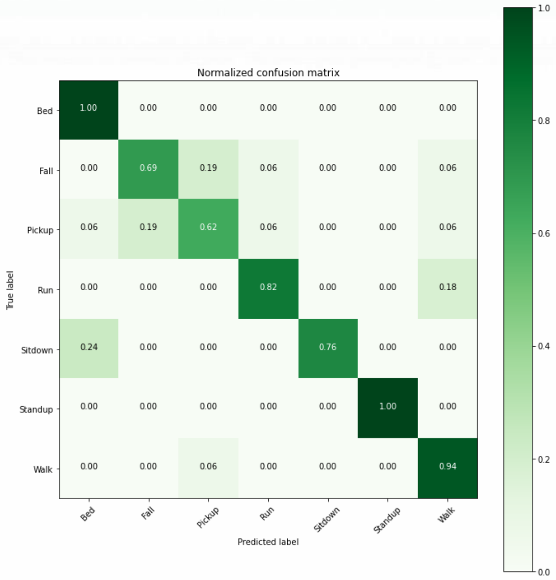

Figure 8. Confusion matrix of proposed CNN for Yousefi et al. [22].

V. CONCLUSION

The ubiquity of Wi-Fi devices in recent years and their best performance in activity recognition, combined with CNN's outstanding performance in classification tasks, motivate us to develop a new CSI-based HAR method. The novelty of this work is the conversion of Wi-Fi signals to images and the high-performance CNN method within the image class. To this end, raw CSI data for each activity has been analyzed and converted into RGB images. These images were fed into a two-dimensional convolutional layer. The proposed method in this paper improves the performance by at least 5% compared with our previous method. The impact of other data conversions and transformations on the raw CSI data may be studied in the future. Other DL models can be investigated, such as hybrid and low-dose learning.

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