

Bidirectional GRU Neural Network for Simultaneous Human Activity Recognition and Localization Using WiFi CSI Signals

Sakorn Mekruksavanich[1] and Anuchit Jitpattanakul[2(✉)]

[1] Department of Computer Engineering, School of Information and Communication Technology, University of Phayao, Phayao, Thailand
sakorn.me@up.ac.th

[2] Intelligent and Nonlinear Dynamic Innovations Research Center, Department of Mathematics, Faculty of Applied Science, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand
anuchit.j@sci.kmutnb.ac.th

Abstract. WiFi-based human sensing has emerged as a viable alternative for activity recognition and indoor localization, owing to its broad deployment, non-invasive operation, and inherent privacy preservation. This paper proposes a unified framework for concurrent human activity recognition and indoor positioning using WiFi channel state information (CSI) signals processed by bidirectional gated recurrent unit (BiGRU) networks. The framework is evaluated on the WiARL-UIT dataset—the first publicly released CSI dataset employing wireless timing synchronization—comprising 1,500 samples spanning six activity-location combinations. The pipeline covers data acquisition via software-defined radio (SDR) platforms, followed by CSI extraction, amplitude sanitization, and normalization. Classification is performed using BiGRU, which processes temporal sequences in both forward and backward directions. Stratified 5-fold cross-validation is used for performance assessment. The BiGRU model achieves 98.33% (±0.30%) accuracy, 98.33% (±0.30%) F1-score, and a loss of 0.0864 (±0.0383), surpassing all baseline architectures: CNN1D (90.80%), LSTM (90.00%), BiLSTM (95.67%), and unidirectional GRU (98.13%). The consistently low standard deviation across folds indicates stable, dependable generalization. Confusion matrix analysis further confirms strong discriminative ability across all activity-location classes with low misclassification rates. The results presented here suggest that BiGRU is particularly well-suited to the demands of WiFi CSI processing, given its capacity to capture temporal dependencies in both directions while remaining computationally efficient. Furthermore, the proposed framework affirms that simultaneous activity and location recognition is not merely a theoretical possibility but an achievable and practical objective—one that holds considerable promise for real-world deployment across domains such as smart home systems, elderly care monitoring, context-aware computing, and intelligent building management.

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1 Introduction

Human activity recognition (HAR) and indoor localization have emerged as significant research domains in ubiquitous computing, propelled by applications in smart homes, healthcare, eldercare, context-aware services, and intelligent building management [1]. Wearables, cameras, and dedicated infrastructure are traditional ways to sense things, but each has significant problems [3]. Wearables require users always to follow the rules, camera systems raise privacy concerns by capturing visual data, and dedicated solutions like infrared sensors or pressure mats are expensive to install and do not work well when more units are added.

WiFi-based sensing has become popular as a useful alternative, mostly because the necessary infrastructure is already in place in most indoor spaces [17]. As Wi-Fi signals move through a space, they bounce off objects and people, causing multipath fading. Channel state information (CSI) records these changes by taking highly precise amplitude and phase measurements across many subcarriers. This gives a much better picture of the channel than the received signal strength indicator (RSSI) does, and it also makes it easier to determine whether someone is there, moving, or doing something [2].

Even though WiFi-based activity recognition and localization have both made steady progress, not much work has been done on combining the two [12]. This is a significant gap because context-aware systems need to know both what a person is doing and where they are simultaneously. In smart home scenarios, distinguishing whether a user is seated in the living room or the bedroom enables appropriate environmental adjustments. In elderly care, simultaneous detection of a fall and its location accelerates emergency response. Nevertheless, most prior work addresses these tasks independently.

The core difficulty lies in extracting two distinct feature types from the same CSI measurements: activity-specific patterns that generalize across locations, and location-specific cues that remain stable across activities. Handcrafted feature methods have proven insufficient for this joint problem due to the complexity of manual feature design. Deep learning offers a more suitable path by autonomously learning hierarchical representations from raw signals. However, identifying a network architecture that effectively models CSI temporal dynamics while preserving computational efficiency remains an open challenge.

This paper proposes a unified framework for concurrent HAR and indoor positioning using WiFi CSI signals and bidirectional gated recurrent unit (BiGRU) networks. The framework is built upon the WiARL-UIT dataset, the first publicly available CSI dataset with wireless timing synchronization for joint recognition tasks. BiGRU processes input sequences in both forward and backward directions, allowing the network to exploit past and future context simultaneously when learning features that encode both activity and location information.

2 Related Works

This section surveys prior research in WiFi-based human sensing across three areas: activity recognition using WiFi signals, indoor positioning techniques, and the emerging joint task of simultaneous activity and location recognition. Relevant publicly available datasets are also discussed.

2.1 WiFi-Based HAR

WiFi-based activity recognition has drawn growing research interest due to its non-invasive operation and reliance on existing wireless infrastructure. Early studies demonstrated the feasibility of detecting human presence and basic motion using fluctuations in WiFi signal strength. More advanced methods use CSI to detect small multipath distortions that occur when a person moves, which helps recognize activities such as walking, sitting, and falling [15]. Later work used deep learning architectures, such as convolutional and recurrent networks, to automatically extract spatio-temporal features from CSI data to improve classification accuracy. Bidirectional long short-term memory (BiLSTM) networks, often used with convolutional neural networks (CNNs), have been especially good at modeling complex temporal dependencies in activity sequences [7]. Their ability to process sequences in both directions allows them to capture long-range dependencies, which are necessary for identifying subtle activity patterns [16]. A comparative analysis of BiLSTM and CNN with GRU models across various WiFi CSI datasets revealed that BiLSTM is superior in extracting long-term temporal structures from high-resolution data [15]. This temporal awareness enables reliable differentiation of activities, even when movement patterns are highly similar.

2.2 WiFi-Based Indoor Localization

A lot of research has been done on using WiFi to navigate indoors instead of GPS, which does not always work or can be wrong in enclosed spaces. Some methods use fingerprinting to compare observed signal patterns to a pre-made radio map, while others use trilateration and angle-of-arrival techniques based on geometric signal calculations. The use of CSI has greatly improved localization accuracy, enabling centimeter-level performance by leveraging fine-grained phase and amplitude data that RSSI-based methods cannot provide [4]. CSI gives a more detailed picture of the wireless channel than RSSI does. This makes sensing tasks like localization and activity recognition more stable and useful [7]. CSI also lets you see tiny changes in signal oscillations across subcarrier frequencies, which are important for accurate positioning and activity detection because they show changes in amplitude and phase [4]. Deep learning, especially convolutional networks, has improved localization by learning direct mappings from CSI features to spatial coordinates without requiring explicit signal-propagation models [9]. Recurrent architectures, especially LSTM networks, have also enabled modeling temporal dependencies in CSI streams. This makes localization more reliable in changing environments [8].

3 The HAR Framework

This section describes a unified framework for concurrent HAR and indoor positioning using WiFi CSI signals. As illustrated in Fig. 1, the framework comprises four sequential stages: data acquisition, preprocessing, classification, and evaluation. This structured pipeline enables systematic extraction and analysis of CSI patterns to predict human activities and their corresponding indoor locations jointly.

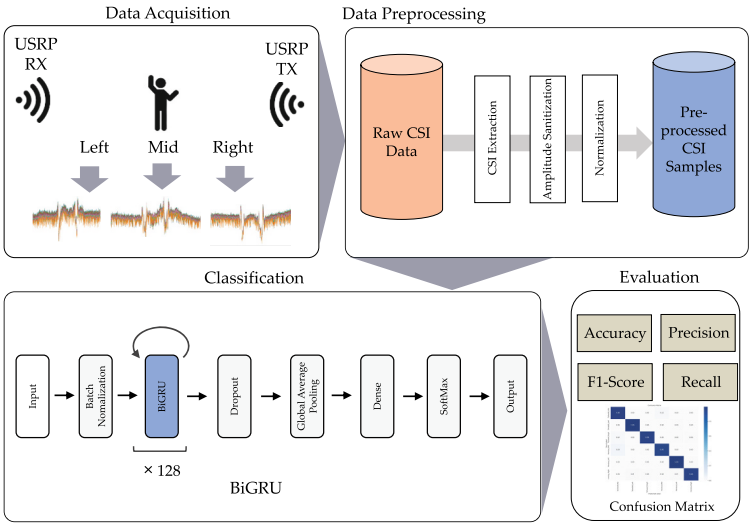

Fig. 1. The HAR framework based on CSI data used in this work.

The data acquisition stage employs a software-defined radio (SDR) platform with universal software radio peripheral (USRP) devices to capture raw WiFi CSI measurements from volunteers conducting various activities at different spatial positions. The pre-processing stage converts these raw measurements into clean, standardized time-series sequences via CSI extraction, amplitude normalization, and sanitization, preparing the data for model training.

The classification stage applies a BiGRU network to model temporal dependencies in sequential CSI data by processing input in both forward and backward directions. The evaluation stage then quantifies framework performance using accuracy, precision, recall, F1-score, and confusion matrix analysis under stratified 5-fold cross-validation.

The subsections below detail each component: the WiARL-UIT dataset, preprocessing procedures, the BiGRU architecture, and evaluation criteria.

3.1 WiARL-UIT Dataset

The WiARL-UIT dataset, introduced by Thanh et al. [13], is the first publicly available WiFi CSI dataset using wireless timing synchronization for joint activity recognition and indoor positioning. It fills a significant gap in the literature, as prior datasets were either withheld from public release or relied on wired synchronization, which constrained their real-world applicability. Data collection used an SDR framework built on two USRP B200-Mini devices equipped with VERT-2450 Wi-Fi antennas, running GNU Radio and implementing the IEEE 802.11 protocol.

Signal transmission and reception relied on orthogonal frequency division multiplexing (OFDM). Each OFDM frame included two synchronization words for timing and frequency offset correction, followed by a payload of BPSK pilot signals for CSI extraction. Each OFDM symbol contained 64 subcarriers: 4 pilot subcarriers, 49 data symbols, and 11 guard bands for interference suppression. Wireless timing synchronization was achieved through a dedicated algorithm enabling precise transmitter-receiver coordination without physical cable connections, improving practicality over cable-dependent approaches used in earlier work.

The dataset covers two activities—"HandUp" and "ToTheLeft"—performed at three indoor positions: "Right", "Mid", and "Left". This yields six class labels combining activity and location: HandUp-Right (A), HandUp-Mid (B), HandUp-Left (C), ToTheLeft-Right (D), ToTheLeft-Mid (E), and ToTheLeft-Left (F). Each class contains 250 samples, producing a balanced total of 1,500 CSI samples. Representative CSI samples are shown in Fig. 2.

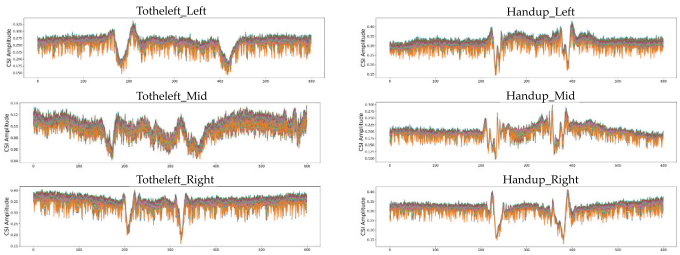

Fig. 2. Some samples of CSI data for the WiARL-UIT dataset.

The CSI measurements capture amplitude and phase variations in WiFi signals caused by human presence and motion. These variations result from multipath propagation, where signals reflect off the human body and surrounding objects, generating distinctive fingerprints for each activity-location combination. Accurate timestamping through wireless synchronization ensures proper alignment between transmitter and receiver, which is essential for temporal feature extraction. Together, the SDR-based collection setup and synchronization capability make the WiARL-UIT dataset a valuable benchmark for WiFi-based human sensing in smart environments and Internet of Things (IoT) applications.

3.2 Data Preprocessing

Preprocessing is an essential stage that converts raw WiFi CSI signals into a format suitable for deep learning training and evaluation. The raw CSI data from the WiARL-UIT dataset consists of complex-valued channel coefficients encoding amplitude and phase information across multiple subcarriers. If we do not handle these measurements correctly, noise, outliers, and inconsistencies can degrade the model's performance. A structured preprocessing pipeline is used to improve the signal and find useful features for classifying joint activity and location.

The first step is to get the CSI and break it down. The USRP device gets raw OFDM signals and uses GNU Radio demodulation blocks to get CSI from pilot subcarriers. Extraction is all about the pilots because each OFDM symbol has 64 subcarriers and 4 pilot positions. This helps you get the right channel estimates. The resulting coefficients are divided into two groups: phase and amplitude. Each part gives you a different piece of information about how the signal moves. Phase shows very small changes over time between channels, while amplitude shows how the signal strength changes when people are nearby and moving.

Next, amplitude sanitization is used to correct measurement errors and incorrect values. Hardware problems, interference, or packet loss can cause sudden changes in CSI amplitude data. We use a median filter with a 5-pixel-wide sliding window to smooth out sudden changes while preserving the signal's general shape. After that, a threshold-based method is used to remove outliers. This means that values more than 3 standard deviations away from the local mean are replaced with estimates from nearby subcarriers. This step ensures that the inputs are identical and that measurement noise has less effect during training.

Normalization is used to ensure that amplitude values are consistent across all samples and recording sessions. When the transmission power, receiver gain, or environment changes, the amplitude between sessions can vary significantly. Min-max normalization changes all the numbers so that they are all between 0 and 1, as shown below:

$$\mathrm{CSI}_{\mathrm{normalized}} = \frac{\mathrm{CSI} - \mathrm{CSI}_{\mathrm{min}}}{\mathrm{CSI}_{\mathrm{max}} - \mathrm{CSI}_{\mathrm{min}}} \tag{1}$$

where $\mathrm{CSI}_{\mathrm{min}}$ is the lowest amplitude value in each sample and $\mathrm{CSI}_{\mathrm{max}}$ is the highest amplitude value in each sample. Normalizing at the sample level keeps the relative structure of the amplitude signal intact and makes sure that all samples share a common scale. This is a trait that usually leads to more stable convergence during training.

3.3 BiGRU Network

Recurrent neural networks (RNNs) are a class of neural architectures well-suited to processing sequential data, making them a good fit for time-series signals like CSI measurements. RNNs, on the other hand, have an internal hidden state

that keeps track of temporal context across input sequences of different lengths [11,14].

The GRU, introduced by Cho et al. [5], is an improved version of the RNN designed to address the problem of gradient disappearance in regular RNNs. This is achieved through a gating mechanism that governs information flow across time steps. The GRU comprises two gates: an update gate, which controls how much the hidden state is refreshed, and a reset gate, which determines how much prior information is discarded. Together, these gates enable efficient modeling of long-range temporal dependencies in signals with complex sequential structure [6].

The BiGRU extends the standard GRU by processing input sequences in both forward and backward directions, allowing the network to incorporate both past and future context at each time step [10]. As shown in Fig. 3, a BiGRU layer consists of two parallel GRU hidden layers: one traversing the sequence left-to-right and the other right-to-left. Their outputs are concatenated to form the final layer representation.

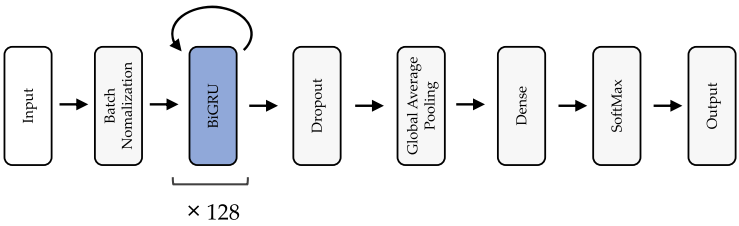

Fig. 3. Architecture of a BiGRU network used in this work.

For WiFi CSI-based joint recognition, BiGRU offers four key advantages. First, it captures both short- and long-term temporal dependencies in sequential signal patterns. Second, bidirectional processing allows the model to identify features that depend on both preceding and subsequent signal characteristics. Third, GRU's reduced parameter count relative to LSTM leads to faster training and lower overfitting risk, particularly valuable with limited data. Fourth, the bidirectional structure supports comprehensive automatic feature extraction, reducing reliance on manual feature engineering.

4 Experimental Results and Discussion

This section presents an evaluation of the proposed BiGRU-based framework for concurrent human activity recognition and indoor positioning using WiFi CSI signals. The experiments are designed to validate the BiGRU architecture and assess its advantage over alternative deep learning approaches in modeling temporal CSI patterns.

4.1 Experiments

All experiments were conducted on Google Colab Pro+, utilizing a Tesla V100 GPU for high-performance neural network training. Python 3.6.9 was used to build the software environment, and TensorFlow 2.2.0 served as the deep learning backend, with Keras 2.3.1 as the high-level modeling interface. Scikit-Learn was used for metric computation and validation; NumPy 1.18.5 for numerical and array operations; and Pandas 1.0.5 for data management and preprocessing. This stack provided a solid foundation for building and testing all the models.

To get an accurate estimate of performance, a stratified 5-fold cross-validation approach was used. The dataset was split into five equal parts, and the class and location distributions remained the same across all parts. In each iteration, four folds were utilized for training and one for testing. This process was performed five times, such that each fold was used as the test set once. The final performance measurements were reported as mean values with standard deviations, making it easy to see both overall performance and consistency across partitions.

We used the Adam optimizer with a starting learning rate of 1×10^{-3}. This made convergence faster and more stable than normal stochastic gradient descent. The batch size was set to 32 to balance training stability and computational cost. Models were trained for up to 200 epochs, with early stopping triggered when validation loss failed to improve for 15 consecutive epochs. The weights yielding the lowest validation loss were retained as the final model—categorical cross-entropy served as the loss function, appropriate for multi-class settings. Dropout regularization with a rate of 0.5 was applied to fully connected layers, randomly turning off half the neurons at each step to promote generalization and reduce overfitting.

To assess the BiGRU architecture's effectiveness, four baseline models were included for comparison: (1) CNN1D, a one-dimensional convolutional network extracting spatial features from CSI amplitude sequences; (2) LSTM, a standard recurrent network modeling temporal dependencies in sequential CSI data; (3) BiLSTM, a bidirectional LSTM processing sequences in both directions; and (4) GRU, a unidirectional gated recurrent network. All baselines were configured with comparable network depth and hidden unit counts to ensure a fair architectural comparison. Identical hyperparameters and cross-validation procedures were applied across all models to isolate the effect of architectural design on classification performance.

4.2 Experimental Results

The experimental findings confirm that the proposed BiGRU architecture outperforms all other tested models in jointly recognizing human activities and determining locations through WiFi CSI data. Table 1 summarizes the full set of evaluation metrics for every deep learning architecture examined. These metrics include accuracy, loss, and F1-score, along with their standard deviations computed across the 5-fold cross-validation.

Table 1. Performance metrics of deep learning models

Model	Performance		
	Accuracy	Loss	F1-score
CNN1D	90.80% (±8.37%)	0.58 (±0.57)	90.68% (±8.51%)
LSTM	90.00% (±11.19%)	0.28 (±0.23)	89.76% (±11.60%)
BiLSTM	95.67% (±1.30%)	0.18 (±0.05)	95.67% (±1.29%)
GRU	98.13% (±0.62%)	0.13 (±0.05)	98.13% (±0.61%)
BiGRU	98.33% (±0.30%)	0.09 (±0.04)	98.33% (±0.30%)

A noticeable trend emerges when comparing models of increasing complexity. Simpler designs yield lower performance, while more advanced recurrent architectures consistently achieve better results. The CNN1D architecture achieved 90.80% accuracy (±8.37%) but suffered a comparatively high loss of 0.58 (±0.57). This suggests that one-dimensional convolutional networks can derive meaningful spatial representations from CSI data. However, they fall short in modeling temporal variations, which are critical for reliable activity classification and position estimation. The conventional LSTM network produced a similar accuracy of 90.00% (±11.19%). Its higher variance across folds, however, points to less dependable training behavior when evaluated on different data subsets.

Introducing bidirectional processing into the LSTM framework led to a notable performance gain over the single-direction variant. The BiLSTM model attained 95.67% accuracy (±1.30%) alongside a considerably reduced loss of 0.18 (±0.05). This enhancement highlights the value of incorporating context from both forward and backward temporal directions when interpreting WiFi CSI patterns. In such data, information both preceding and following a given time step contributes to more precise classification outcomes. The smaller standard deviation further reflects more stable results across different validation splits.

The GRU architecture delivered strong results, achieving 98.13% accuracy (±0.62%) with a loss of 0.13 (±0.05). These figures surpass those of both the CNN1D and the standard LSTM models. This advantage likely stems from the GRU's streamlined gate structure. It effectively models extended temporal relationships while using fewer trainable parameters than the LSTM. This reduction in parameter count may help mitigate overfitting and improve the model's generalization.

Among all architectures tested, the proposed BiGRU model produced the highest overall performance. It achieved 98.33% accuracy (±0.30%), the lowest loss at 0.09 (±0.04), and an F1-score of 98.33% (±0.30%). The notably small standard deviation reflects highly stable and dependable outcomes across all data partitions. These results indicate that combining the GRU's efficient gate design with bidirectional sequence processing yields the most effective feature representation for concurrent activity recognition and localization from WiFi CSI signals.

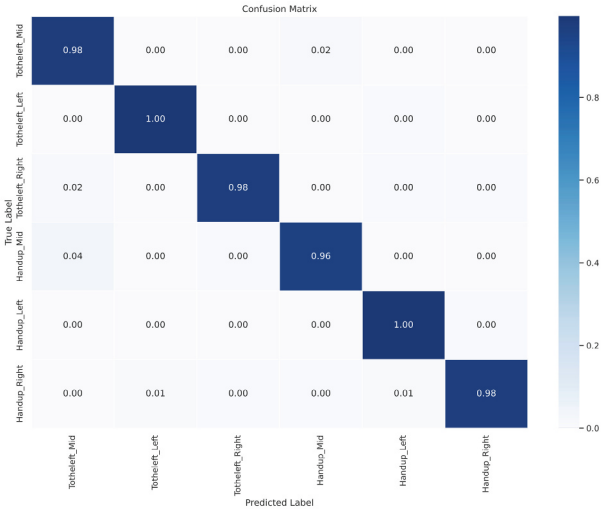

Fig. 4. Confusion matrix of the BiGRU.

The confusion matrix depicted in Fig. 4 provides additional insight into the BiGRU model's classification behavior. Nearly all diagonal entries approach perfect values, while off-diagonal elements remain minimal. The model demonstrates a strong ability to distinguish between all activity types and location categories, with very few misclassifications. Such reliability is especially valuable in real-world scenarios. Accurate joint inference of both activity and location is essential for context-sensitive systems and intelligent environment applications.

These findings support the hypothesis that BiGRU networks are particularly effective for analyzing WiFi CSI signals. This effectiveness arises from several key properties: (1) they efficiently model both brief and extended temporal dependencies introduced by human movement patterns in the signal; (2) bidirectional processing allows them to interpret full activity sequences by considering context in both directions; (3) they maintain lower computational demands due to fewer parameters compared to BiLSTM architectures; and (4) they deliver robust, consistent outcomes across varying data distributions. The slight yet steady improvement of BiGRU over the unidirectional GRU (98.33% versus 98.13%) confirms that the added computational overhead of bidirectional processing is warranted. It enables a richer interpretation of temporal structures within CSI data.

5 Conclusion and Future Works

This study has introduced a unified framework for jointly recognizing human activities and estimating indoor positions using WiFi CSI data. The system is built upon the BiGRU neural network architecture. Our work tackles a key problem in WiFi-based human sensing. Specifically, we show that both activity types

and spatial locations can be inferred simultaneously from identical CSI measurements. This removes the requirement for independent detection pipelines.

The proposed system is trained and evaluated on the WiARL-UIT dataset. This dataset is the first publicly accessible WiFi CSI collection that incorporates wireless timing synchronization designed for joint recognition tasks. It comprises 1,500 CSI samples spanning six unique activity-location pairings, offering a well-balanced basis for deep learning model development and assessment. A systematic preprocessing pipeline turned raw OFDM signals into clean, normalized time-series inputs. To get the data ready for use by a neural network, this pipeline included CSI extraction, amplitude correction, and value normalization.

The experimental results show that the BiGRU design works well. It had an F1-score of 98.33% (±0.30%), the smallest loss of 0.09 (±0.04), and an accuracy of 98.33% (±0.30%). The BiGRU outperformed several reference designs, such as CNN1D (90.80%), LSTM (90.00%), BiLSTM (95.67%), and the single-direction GRU (98.13%). These results support our hypothesis: integrating bidirectional sequence analysis with efficient gating mechanisms produces optimal feature learning from WiFi CSI data. The very minimal standard deviation across cross-validation repetitions shows that the behavior is steady and reliable. For real-world system deployment, this kind of consistency is very important.

The confusion matrix analysis shows that the model is quite good at classifying all activity-location groups. The diagonal values are almost perfect, and the misclassification rates are still quite low. These findings show that the BiGRU design can accurately capture temporal correlations in CSI signal variations caused by human mobility, both over short and long time periods. In the meantime, bidirectional processing enables the model to understand entire activity sequences by using input from both before and after the activity.

The results of this study are promising, but many areas need further research. First, the dataset needs to be expanded to include more activities, other locations, and a greater variety of people. This expansion would allow for a more comprehensive assessment of the framework's generalizability across diverse individuals and contexts. Second, the current method mostly uses amplitude data. Future work should explore more advanced methods for incorporating phase measurements via multimodal integration to improve recognition performance. Third, problems that make it hard to put these ideas into practice need to be solved. These include changes in the environment, interference from many users, and changes in the properties of wireless channels.

Also, we should explore ways to reduce model size, such as network pruning, weight quantization, and knowledge distillation. These techniques enable real-time inference on devices with minimal computing power and on embedded platforms, making them suitable for use in IoT environments. Finally, sensor fusion of WiFi CSI data with other sensing technologies, like accelerometers or radar systems, could lead to more reliable and accurate recognition frameworks. This is especially important in tough conditions because depending on just one sense modality might not be enough.

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