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Deep Learning Wi-Fi Channel State Information for Fall Detection

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***Abstract*—It is common that the elderly may fall and injure severely. This problem has attracted worldwide attention and becomes a major challenge in the public health care. In the past decade, extensive studies have been conducted to detect fall using wearable sensors and cameras. Given the pervasive WiFi penetration in our daily life, behavior recognition based on the channel state information (CSI) of WiFi signals has shown its potentials in detecting falls for the elderly with less constraint compared with clumsy sensors. In this paper, we conducted a performance evaluation study of three deep learning methods on a public dataset to detect falls. The experiment results show that the accuracy of the deep learning algorithms on Wi-Fi datasets achieves beyond 95% which may generate notable market values. Nevertheless, the long training time of deep learning models is likely to be the hampering factor before commercialization. Our study may stimulate further research on accelerating deep learning methods in a software/hardware co-design approach.**

***Index Terms*—Channel State Information, Wi-Fi, Deep Learning, Fall Detection**

I. Introduction

In recent years, the falls of the elderly have attracted worldwide attention. According to the World Health Organization (WHO) report, 30% of the elderly over the age of 65 and 50% of the elderly over the age of 85 have fallen at least once a year. Nowadays, there are many studies on the fall detection for the elderly. The current mainstream method for fall detection is to collect data from different sensors and then apply the algorithmic approach to determine occurring falls [1]. With the development of the Internet of Things, smart devices will appear more in our lives, and it is of significant potentials for fall detection.

Wi-Fi has a wide range of applications in the field of gesture recognition [2] due to its easy deployment, low price and wide application. In this paper, deep learning methods are applied to study Wi-Fi datasets containing a large number of daily activities. To our best knowledge, we are the first to comprehensively compare the effects of different neural networks on the same Wi-Fi datasets for fall detection. Based on our experiments, deep learning methods are able to achieve very good results on the Wi-Fi datasets for different performance metrics.

II. Deep Learning for Fall Detection

Previous work on CSI was mostly based on wireless signal denoising, feature extraction and classification, mainly because wireless signal is difficult to gather, and wireless signals have no structure and regularity compared to images and text. [3] collects CSI information about different daily activities in an indoor environment and released on public. Yousefi et al. leveraged the long-term short-term memory (LSTM) method to classify different daily activities, and finds deep learning can also get good performance on this dataset. Neural networks are more convenient than normal machine learning algorithms since they combine feature extractions and classification. Based on [3], we explore the CSI datasets further and uses more deep learning methods to detect the fall events.

A. CNN based fall detection

The CSI collected with [4] contains information on 30 sub-carriers collected by three antennas. For each data point, there are 90 dimensions of information. In order to detect a continuous action, it is necessary to collect information for a certain period of time. Convolutional Neural Networks (CNN) can then be applied to extract its features since an action is determined by two dimensions: carriers and time series.

Since the “2D image” of each action is not very complicated, the LeNet structure is used for classification [5]. The first layer is a 5×5 patch, 32 convolution kernels, followed by the max-pooling layer. The second layer of convolution is a 5×5 patch, 64 convolution kernels also followed by the max-pooling layer.

B. RNN based fall detection

Since the collected CSI is sequential, Recurrent Neural Networks (RNN) can also be used to solve the fall detection problem. The activity recognition is somewhat similar to speech recognition and RNN is widely used in speech recognition [3]. However, it is difficult to train RNNs due to gradient disappearance and gradient explosion. [6] proved that speech recognition can achieve better accuracy using LSTM instead of RNN. In addition to LSTM, Gated Recurrent Unit (GRU) for sequence modeling can also yield good results [7]. Both LSTM and GRU can catch time status information, which helps for the classification of different activities in the indoor environments.

III. Performance Evaluation

A. Dataset

In this paper, we use the dataset collected in [3]. This data set uses Intel 5300 NIC [4] with the sampling frequency 1kHz. It contains 7 types of actions, 657 of lying, 443 of falling, 495

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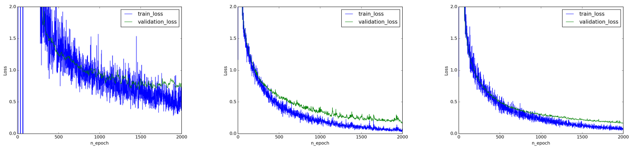
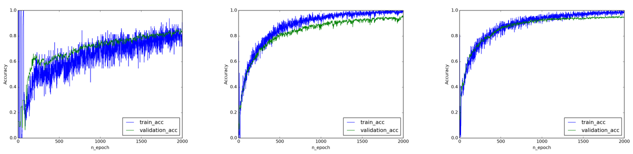


(a) CNN (b) LSTM (c) GRU

Fig. 1: Loss of three neural networks



(a) CNN (b) LSTM (c) GRU

Fig. 2: Accuracy of three neural networks

of bending, 1295 of running, 400 of sitting, 304 of standing up, and 1395 of walking, each of which lasts 0.5s, which means each action has 500-dimensional data in the time dimension.

B. Results

We trained our network on a server with Intel(R) Core i7-8700K CPU@3.70GHz, 64G memory and 12 cores. It should be mentioned that we have not used GPU to accelerate the process. CNN, LSTM and GRU are tested on the dataset. Since our target here is fall detection, not activity recognition, it is simplified into a two-category classification problem. In this paper, multi-classification is applied in our algorithms, but with other metrics to evaluate the performance in the fall detection applications. These metrics are listed as **Precision**, **Recall**,**Specificity** and **Specificity**, full definitions are reported in [10].

Based on the above definitions, the higher precision, recall, F1-score and the lower specificity indicate better performance. Fig.1 and Fig.2 show the performance of three networks. Loss captures the gap between the ground truth and the detected results while the accuracy captures the percentage of correct detected falls. Blue and green are results respectively on the training set and on the verification set. These results show that CNN curve still fluctuates while the other two already have converged. The poor performance of CNN indicates that CNN which means "weight sharing" and "local connection" is not proper in this task since the CSI has no local similarity. Comparing LSTM with GRU, GRU converged more quickly because GRU has fewer parameters than LSTM.

As shown in Table I, RNN achieves better results over all dimensions. In addition, GRU achieves better results for specificity and achieves similar results for the other three standards. One reason for this may be that the dataset is not balanced, which means the positive samples for "fall" are much less than the positive samples so that specificity are all very small which leads to more relative difference. Besides, the results of GRU are more stable than LSTM mainly because GRU has fewer parameters.

The time complexity of the three networks is also considered in [7]. The training process of LSTM lasts for 18.47 hours, while GRU lasts for 17.23 hours. However, CNN lasts for four days since it has most parameters. These results show that GRU performs best of all three algorithms in this task.

	CNN	LSTM	GRU
Precision	0.875	0.96	**0.97**
Recall	0.92	**0.96**	0.95
F1-score	0.90	**0.96**	**0.96**
Specificity	0.013	0.004	**0.0026**
Training time(h)	96	18.47	**17.23**

TABLE I: Performance evaluation of different algorithms

IV. Conclusion

As the number of elderly grows rapidly, the fall detection and protection has increasingly attracted the attention of in both the academia and the industry. In this paper, we have evaluated popular deep learning methods, including CNN, GRU and LSTM, based on the public dataset to analyze Wi-Fi signals for fall detection. Our results show that neural networks can not only capture the time series information of Wi-Fi, they can also achieve very good classification results. Provided with sufficient data, deep learning methods are very valuable in processing wireless signals for health-care applications. The training of these deep leaning algorithms can be offloaded at the edge for reducing delay and preserving privacy [8] with algorithm acceleration in a software/hardware co-design approach [9].

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