# Deep Learning for Wi-Fi based Human Activity Recognition

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ABSTRACT: Wi-Fi-based human motion sensor technology has been broadly developed from time to time. By comparing with traditional human behaviour recognition system, the benefits of using Wi-Fi-based motion technology are that it had large coverage of signal with unconstraint by any obstacles in terms of dead angle and sensitivity of light. This paper proposes an improved Wi-Fi based human activity recognition (HAR) by using a deep learning method of Long Short-Term Memory (LSTM). In this work, feature extraction using discrete Wavelet transform (DWT) has been applied to preprocess the datasets to improve the recognition process. The results show that more than 25% improvement of the accuracy rate and processing time have been achieved with the proposed method compared to conventional method.

**Keywords:** Human Activity Recognition; Discrete Wavelet Transform (DWT); Bi-directional Long Short-Term Memory (Bi-LSTM).

# 1. INTRODUCTION

Wireless network is emerging and widely deployed with high demand of wireless data, the availability of wireless signal is bringing new opportunities to human activity recognition (HAR). Wireless sensing can reuse the wireless communication infrastructure in which it is easier to use and only required low cost when compared to sensor-based and vision-based human activity recognition system [1-2]. Besides, this technology also eliminates the constraint of Line of Sight (LoS) and light dependency of vision based HAR system. In term of privacy issues, wireless technology will be more secured than other method of human activity sensing [3]. One of the wireless technologies that contribute the growth of human activity recognition will be the Wi-Fi network. Fig. 1 shows how the Wi-Fi network works in HAR. The movements of the human body impact the wireless signals propagation, which make it possible to capture

human movements by analyzing the received wireless signals.



Fig.1. Human activity recognition through reflection of Wi-Fi signals [3]

# 2. METHODOLOGY

The general flow of this work is shown in Fig. 2. Firstly, the Hirokazu's dataset [4] is imported into MATLAB. Then, this dataset will be pre-processing using denoise function. This can help in showing significant features of human activity using spectrogram. Next, the feature extraction by using discrete wavelet transform (DWT) is used for reducing the dimension of signal while still maintaining the significant features. Lastly, the extracted features will be classified by using Bi-LSTM algorithm and result will be shown in the form of confusion matrix. Similar processing will be applied for second dataset - Ermongroup [5] to verify the effectiveness and generality of the proposed method.

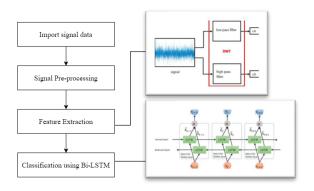


Fig. 2. Steps in processing HAR datasets.

#### 3. RESULT AND DISCUSSION

Table 1 demonstrates the result of LSTM's accuracy and processing time in term of confusion matrix. Bi-LSTM, which allow networks to have both backward and forward information about the sequence at every time step, has been used in this work. The proposed method has been applied to two datasets [4-5]. Table 1 shows 64.3% and 60.7% of accuracies that have been achieved using LSTM applied for Hirokazu's [4] and Ermongroup's [5] datasets respectively. By introducing DWT feature extraction pre-processing step, the accuracy has now been improved from 64.3% to 96.4% for Hirokazu's dataset while 60.7% to 89.3% for Ermongroup's dataset.

Table 1: Time processing and accuracy of different datasets during classification of LSTM.

	Dataset				Classification								Processing Time					Accuracy			
a	[4]				Bi-LSTM Bi-LSTM with DWT								13m23s 6m25s					64.3%			
b																		96.4%			
c	[5]				Bi-LSTM								12m55s					60.7%			
d					Bi-LSTM with DWT								7m31s					89.3%			
	а		2		Confusion Matrix						Confusion Matrix										
	Bed	7.1%	7.1%	0.0%	0.0%	0.0%	3.6%	0.0%	60.0%		b Bas	14.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100%		
	Fall	3.6%	3.6%	0.0%	0.0%	0.0%	0.0%	0.0%	50.0%		Full	0.0%	14.3%	0.0%	0.0%	0.0%	0.0%	0.0%	100%		
	Piak Up	0.0%	0.0%	14.31	0.0%	0.0%	0.0%	0.0%	100%		Pick Up	0.0%	0.0%	4 14.3%	0.0%	0.0%	0.0%	0.0%	100%		
Dutrait Class	Run	3.6%	0.0%	0.0%	3 10.7%	0.0%	0.0%	3.6%	60.0% 40.0%		Run	0.0%	0.0%	0.0%	4 14.3%	0.0%	0.0%	0.0%	100%		
Organia	Sit Down	0.0%	3.6%	0.0%	0.0%	3 10.7%	0.0%	0.0%	75.0% 25.0%	Outras Class	Sit Down	0.0%	0.0%	0.0%	0.0%	4 14.2%	3.0%	0.0%	80.0% 20.0%		
	Stand Up	0.0%	0.0%	0.0%	0,0%	3.6%	2 7.1%	0.0%	88.7% 33.3%		Stand Up	0.0%	0.0%	0.0%	0.0%	0.0%	3 10.7%	0.0%	100%		
	Welk	0.0%	0.0%	0.0%	3.6%	0.0%	3.6%	3 10.7%	60.0% 40.0%		Walk	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4 14.3%	100%		
		50.0% 50.0%	25.0% 75.0%	100%	75.0% 25.0%	76.0% 25.0%	50.0% 50.0%	75.0% 25.0%	64.3% 35.7%			100%	100% 0.0%	100%	100%	100%	75.0% 25.0%	100%	96.4% 3.6%		
	day day			NA US	IN SE STORE SHEETS SER.				*			of the spirit set with the				ard IR	S NP				
	Target Class											Target Class									
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	Fall	0.0%	2 7.1%	0.0%	0.0%	0.0%	0.0%	0.0%	100%		Fed	14.3% 0 0.0%	3.6%	0.0%	0.0%	0.0%	0 0.0%	0.0%	100%		
	Plak Up	0.0%	0.0%	3 10.7%	3.6%	0.0%	3.6%	0.0%	60.0% 40.0%		Pick Up	0.0%	0 0.0%	4 14.3%	0.0%	0.0%	1 3.6%	0.0%	80.0% 20.0%		
Class	Run	0.0%	0.0%	0.0%	3 10.7%	3.6%	0.0%	7.1%	50.0% 50.0%	Jass	Run	0.0%	0.0%	0 0.0%	4 14.3%	0 0.0%	0 0.0%	0.0%	100%		
Output Class	Sit Down	0.0%	0.0%	0.0%	0.0%	3.6%	0.0%	0.0%	100%	Output Class	Sit Down	0 0.0%	0 0.0%	0.0%	0.0%	4 14.3%	0.0%	0.0%	100%		
8	Stand Up	1 2.6%	3.0%	3.0%	0.0%	2 7.1%	3 10.7%	0.0%	37.5% 62.5%		Stand Up	0.0%	0.0%	0.0%	0.0%	0.0%	2 7.1%	0 0.0%	100%		
	Walk	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.1%	100%		Walk	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.3%	100%		
		78.0% 25.0%	50.0% 50.0%	75.0% 25.0%	75.0% 25.0%	25.0% 75.0%	75.0% 25.0%	50.0% 50.0%	60.7% 39.3%			100%	75.0% 25.0%	100% 0.0%	100%	100%	50.0% 50.0%	100%	89.3% 10.7%		
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In term of time processing of LSTM, time taken for processing is very crucial since this aspect is highly demanded in deep learning. Table 1 illustrates the time taken for each dataset when same training parameters have been applied. It shows that the time elapsed using LSTM for Hirokazu's dataset is 13 minutes 23 seconds while the time elapsed for Ermongroup's dataset is 12 minutes 55 seconds. However, by introducing DWT feature extraction pre-processing step, this significantly improve the time elapsed to 6 minutes 25 seconds and 7 minutes 31 seconds, respectively. The reduction in

recognition time is due to dimensionality reduction by the DWT in feature extraction process. When the data size is small, the processing of the classification will be reduced at the same time.

### 4. CONCLUSION

In conclusion, a deep learning-based recognition system for improved Wi-Fi based human activity recognition system has successfully been developed. In the proposed method, DWT has been used in feature extraction to reduce the dimension of signal while still maintaining the significant features. The best performance that has achieved with the accuracy of 96.4% and half the recognition time comparing to without DWT pre-processing. The work demonstrates the possibility of human's behavior recognition using unobtrusive method of authentication, with low hardware cost and power demands.

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