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Human Activity Recognition System Using WiFi Sensing and Deep Learning

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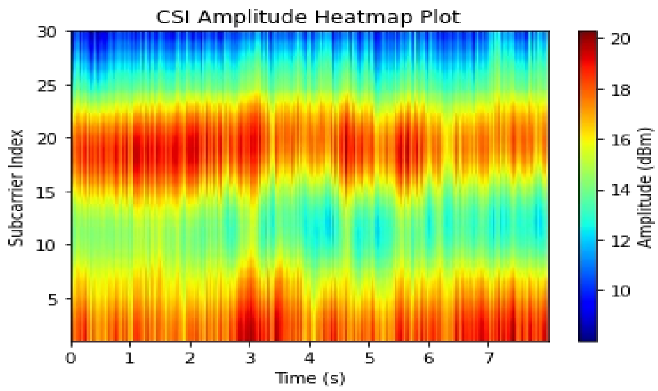
ABSTRACT



Human activity recognition systems can be used for various purposes such as monitoring, authentication, and telemedicine. In this research, a non-invasive, high privacy, easy to implement, and affordable human activity recognition system based on WiFi and deep learning is developed. Sixteen activities; including upper body, lower body, and whole body movement; were recognized by utilizing Channel State Information (CSI) contained in the WiFi signal. Measurements were carried out in an empty room with dimensions of 6×8 m with the distance between the transmitter and receiver being 1, 3 and 6 meters from the subject. Google Teachable Machine is used to recognize activities carried out. From the measurement result, the accuracy shows more than 97%. It is also evident that the further the measurement distance, the worse the recognition results. This is due to the increasing amount of noise in the radio channel as the distance increases.

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1. INTRODUCTION

Human activity recognition is a substantial research topic supporting Industry Revolution 4.0 and Society 5.0 [1]. This system can be implemented in various fields, such as smart home development [2], user authentication services [3], telemedicine [4], smart room management [5], healthcare [6], sport [7], and security [8].

Smart watches are one example of sensor-based human activity recognition systems [9]. It can recognize various users' activities. The advantage of this system is high accuracy. This is caused by the condition of the sensor which is connected directly to the user's body. However, this system is an invasive type. Users must continuously wear it in order for the sensor to be able to identify the activities being carried out. When the sensor is not directly connected to the user, the system can't recognize the activities anymore.

Camera-based system is one of the non-invasive human activity recognition systems that has been widely developed for security purposes [10]. The system is easy to install and the recognition result can be easily verified. However, this system is prone to privacy breach. In addition, the camera must be installed in Line-of-Sight (LOS) position. If the camera view is blocked, the system will no longer work. This system is also very dependent on lighting. If there is little light around the camera range, the accuracy will drop drastically. This can be overcome by using a special camera such as a night vision camera or infrared camera. But the price of these devices is not cheap.

Another non-invasive activity recognition system is a radar-based system [11]. In this system, radio waves are used for detection. The radar works by reading the reflected signal by the target. The radar will emit radio waves that propagate through the air. When the wave hits an object, the wave will be reflected back. It is the results of these reflections that will be received by the radar and will be interpreted using digital signal processing. The larger the object, the greater the amount of energy returned to the radar. By using radio waves, this system does not depend on light conditions. So that the detection process can be done in the dark. In addition, radio waves will radiate in all directions. So that the device and the object do not need to be in a LOS condition. Radio waves will also not interfere with user privacy because no visual data is required. The drawbacks of this system are the relatively expensive device price and complicated signal processing to interpret the information.

WiFi is the most widely available radio wave-based device [12]. It is possible to use this device to recognize human activity. Similar to radar, it uses radio waves. Thus no visual data is needed and provides high privacy. WiFi technology has been used to provide connections to desktops, laptops and mobile devices to enable Internet and network connectivity to smart devices and IoT. There are many types of devices that can connect via WiFi. This resulted in increasing the number of available WiFi devices and the coverage of WiFi networks.

When a WiFi signal propagates through space, it interacts with objects or human bodies in that environment. The phenomena includes reflection, diffraction and scattering which cause changes in signal's amplitude and phase. When the human body moves through this wave, the propagation of radio waves will be affected. By exploiting this phenomenon, WiFi devices can be used to recognize human activity.

The WiFi signal contains information about the amount of the received power. This information can be obtained from the Received Signal Strength (RSSI) and Channel State Information (CSI) values. RSSI shows the sum of signal energy from several paths which include the LOS path between the transmitter and receiver, as well as several reflection paths caused by walls, furniture and people in the room [13]. The research conducted by Wassila, et al showed that by using RSSI, the activity can be recognized with accuracy of 94% [14].

CSI is information that can be used to determine the value of the power received [15]. It consists of a complex number of amplitudes and phases of the WiFi signal. CSI contains information on all thirty Orthogonal Frequency Division Multiplexing (OFDM) subcarriers used in WiFi technology. Therefore CSI can provide more detailed information than RSSI. Therefore, information from CSI can provide more accurate information to develop human activity recognition systems..

Further signal processing is needed to interpret the data provided by CSI. Therefore, in this research deep learning is proposed to classify the CSI data to recognize the activity. Deep learning techniques have advantages such as being able to handle big and complex data, high performance, and easy implementation.

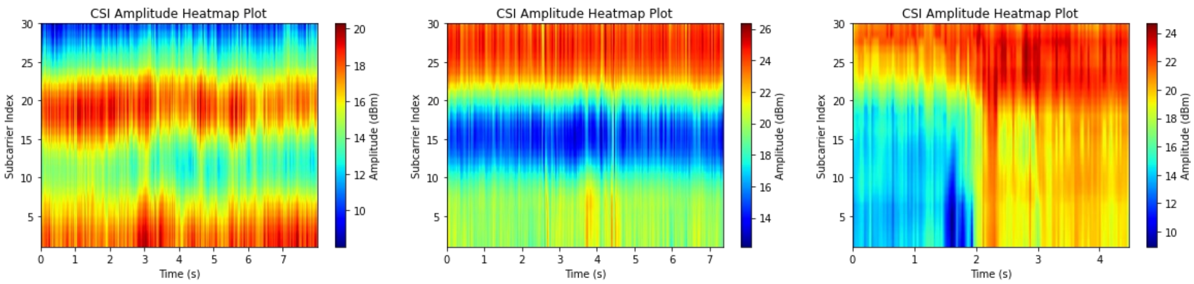
2. METHODS

To be able to recognize the activity, a dataset is needed by deep learning. In this research, the dataset collected by Guo, et al [16] is used. The data is collected from ten volunteers doing sixteen activities involving three types of activities: upper body movement, lower body movement, and whole body movement. The measurement took place in a 6×8 m empty room with the transmitter and receiver are placed 1, 3, and 6 meters apart from the volunteers. Table 1 showed the sixteen activities performed.

Table 1 Sixteen Performed Activities

No	Types	Activity	No	Types	Activity
1		Horizontal Arm Wave	11	Lower Body Movement	Forward Kick
2		Two Hand Wave	12		Side Kick
3		Toss Paper	13	Whole Body Movement	Squat
4		Draw Tick	14		Sit Down
5	Upper Body Movement	Phone	15		Bend
6		Draw X	16		Walk
7		Hand Clap			
8		High Arm Wave			
9		Drink Water			
10		High Throw			

After obtaining the dataset, preprocessing is performed. In this step, a python library called CSIKit is used to extract the CSI data [17]. Then the data is visualized in heatmap format. Three filters are used to preprocess the heatmap: a lowpass filter to isolate frequencies below 10 Hz, a Hampel filter to reduce high frequency noise, and a running mean filter for smoothing. Figure 1 showed three examples of converted heat maps for different activities measured from various distances.



(A) (B) (C)

Figure 1. Sample of three activities heatmap (a) Horizontal arm wave measured from 1m, (B) Forward kick measured from 3m, (C) Bend measured from 6m

In order to be able to classify the activities, the dataset is trained using deep learning. Since the activities are measured from 1, 3, and 6 meters, different dataset is trained and tested based on the distance. Then the dataset is divided into sixteen classes representing sixteen activities. For training and testing the dataset, Google Teachable Machine is used. Google Teachable Machine is a web-based tool provided by Google that can be used to recognize images, sounds, or poses based on deep learning algorithms [18]. Learning rates, batch sizes, and epochs are three parameters used for tuning the model.

In this research, ten volunteers performed sixteen activities measured from three different distances. Therefore there are 480 images used in the dataset. 80% of the data from each activities is used for training, while the rest is used for testing. The tuning parameters used for training the models are: epochs 100, batch size 32, and learning rate 0.001.

For classification result analysis, a confusion matrix is used. Since there are three measurement distances, there are three multiclass confusion matrices presented. In every matrix, the actual and predicted activities result are shown in percentage. Then accuracy, precision, and recall are calculated from the confusion matrix [19]. Accuracy showed the rate of correct prediction made by model. The higher the accuracy, the better the prediction. To calculate accuracy from the confusion matrix, equation (1) is used.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

Precision presented a metric indicating the fraction of positive class predictions that accurately correspond to actual positive value. The higher the precision, the better the model. Equation (2) is used to calculate precision.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall is a parameter that shows the proportion of positive samples were correctly predicted as positive by the model. The higher the recall, the better the classifier. Equation (3) is used to calculate recall.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

3. RESULT AND DISCUSSION

In this section, the prediction results made by deep learning are presented. The confusion matrices show the comparison of actual and predicted of 16 performed activities in percentage. The following image shows the measurement from 1 meter.

From Figure 2, it can be seen that of the sixteen activities measured from 1m, 9 activities had TP value higher than 70% with activity 13 squat had the highest TP value of 97%. Out of seven activities with TP below 70%, five activities are correctly recognized while the other two are wrong. Figure 3 showed the confusion matrix for activities measured when the transmitter and receiver are separated by 3m from the volunteer. There are 8 activities that have TP higher than 70% with the highest percentage being 99%. Out of 8 activities with TP below 70%, 2 activities are incorrectly recognized. Figure 4 showed the confusion matrix for activities measured from 6m. From the matrix, there are nine activities with TP below 70% having activity 13 squat with the lowest percentage being 1%.

Based on the result shown from the three confusion matrix, the number of activities having TP lower than 70% increased as the distance increased. It could happen because of the higher noise due to distance. The farther the distance traveled, the more noise the signal will pass through. The more noise that is passed through, the greater the possibility of errors occurring in the received signal. Table 2 showed the quality evaluation of the classification result. The highest accuracy is found from the 1m measurement result with 97.78%. While the precision and recall highest percentage found from the 3m measurement result. Generally, the evaluation results tend to deteriorate with greater distances. This phenomenon could be attributed to increased noise levels as the measurement distance extends. Table 3 shows the comparison of the accuracy achieved in this research with previous research. From the table, it is evident that the model used in this research outperforms others. However, there is still room for improvement to increase the accuracy.

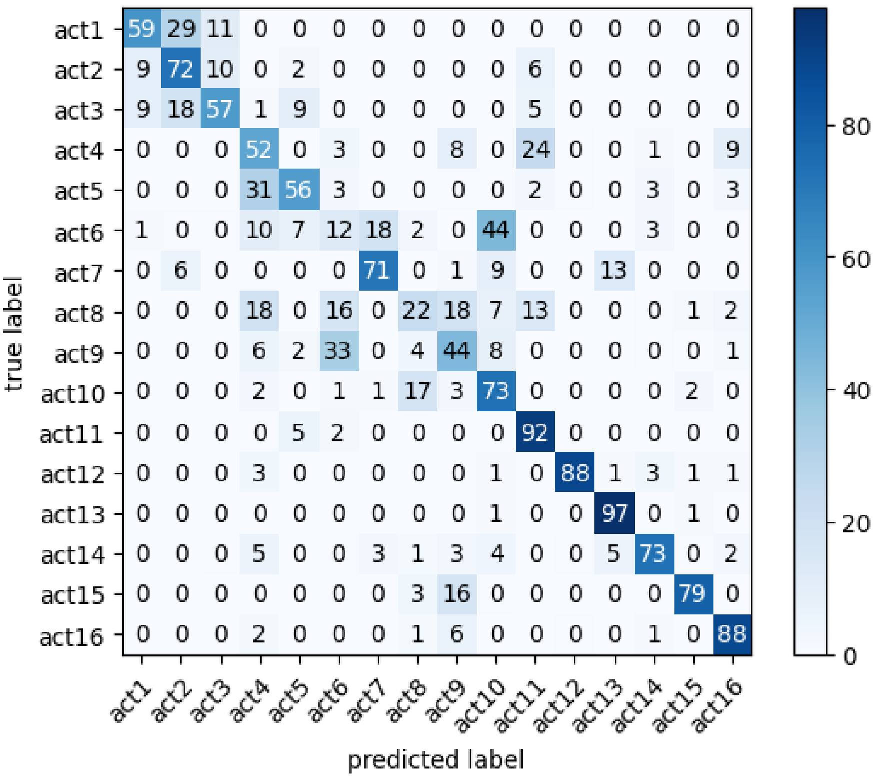


Figure 2. Confusion matrix for activities measured from 1m

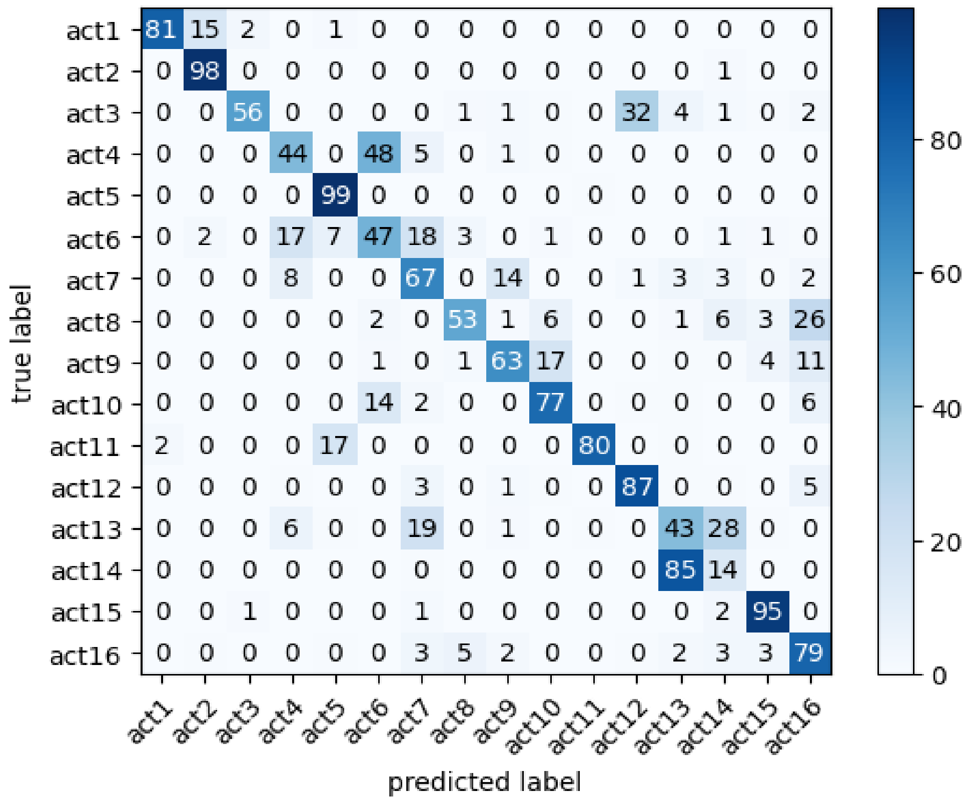


Figure 3. Confusion Matrix for Activities Measured from 3m

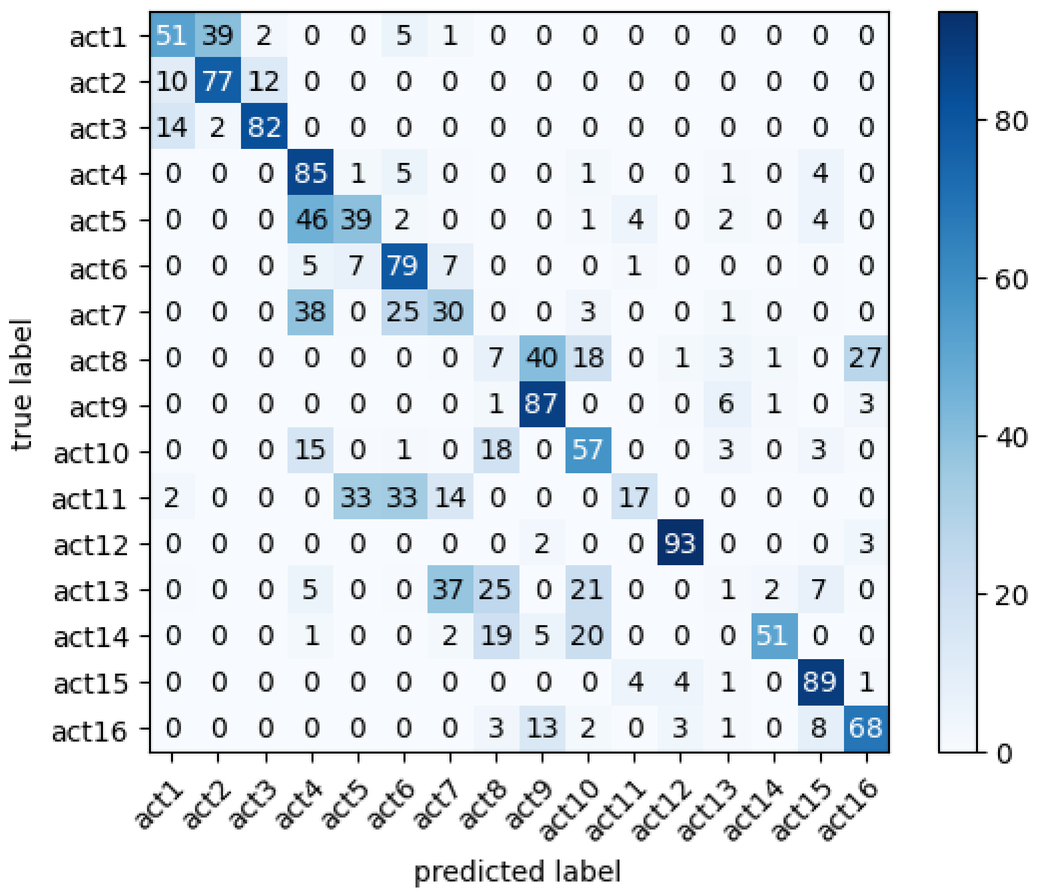


Figure 4. Confusion Matrix for Activities Measured from 6m

Table 2. Classification Evaluation Result

Distance	Accuracy	Precision	Recall
1m	97.78%	30.25%	64.97%
3m	97.77%	30.51%	67.97%
6m	97.73%	27.52%	57.33%
Overall	97.76%	29.43%	63.42%

Table 3. Comparison of Accuracy Result with Previous Research

Ref	Algorithms	Accuracy
L. Guo, et al [16]	CNN	90%
M. G. Moghaddam, et al [20]	Random Forest	94.16%
W. Huang, et al [21]	Temporal Spatial Convolutional Neural Network (TSCNN)	94.6%
M. G. Moghaddam, et al [22]	K Nearest Neighbors (KNN) classifier	97.5%

4. CONCLUSIONS

In this research, a human activity recognition system is developed based on WiFi sensing and deep learning. From the confusion matrices, the number of activities having TP below 70% increased as the distance increased. It is because of the higher noise level due to distance. The more noise that is passed through, the greater the possibility of errors occurring in the received signal. As for classification evaluation, 1m measurement has the highest accuracy while 3m has highest precision and recall. Even though there are some errors in measurement, the result shows that it is possible to develop a non-invasive, low privacy breach, cheap, and easy to install human activity recognition systems by combining WiFi sensing and deep learning.

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