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Differentiate Between Human and Non Human Fall Using Floor Vibration and Artificial Neural Network

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Abstract: Human falls is when a body loss its balance of standing and falling down where it can cause serious injury such as bone fracture, coma and death. Usually person at age 60 and above has highest death rate of falling due to weak physical body. There are various type of fall detection including wearable, non wearable device and sensor. In this research accelerometer were used to determine fell response. Various activity were chosen such as dummy falling with a weight of 26.48kg, sand bag dropping with the weight of 6 kg, ball dropping with a weight of 0.54kg dropping height of 1m, and mechanical movement. Sample data were averaged from each accelerometer and generated pattern graph of acceleration and peak acceleration. Then, three feature dataset which are maximum, mean and variance from total 385 test sample was chosen to analyze by using MATLAB software and using Artificial neural network to determine the training data prediction of performance. The testing result data prediction overall had great potential to classify human and non human fall with accuracy of 97.1%, sensitivity with 92.7% and specificity 97.1%. Therefore, Artificial neural network in MATLAB provide high accuracy of data prediction to the target data.

Keywords: Human Falls, Acceleration Graph, Peak Acceleration, Artificial Neural Network

1. Introduction

In 2050, World Health Organization predicted 2 billion of people will going through aging at 60 and older, representing 22 percent of the world's population[1]. However, the falls from elderly will be increased too. In Malaysia, falls among elder rate has risen 27.9 % from 19.1% to 47% and in Kuala Lumpur, 30 of the elderly experience prevalence of falls in nursing home [2,3]. Falls among older adult will causes serious injury such as bone fracture, coma and even death. For example, falling down occur for an instant which it has high velocity and head is getting hit by hard or shape object causes shock, bleeding and damage to the head. Thus, the person acquired medical help immediately otherwise the person will be dead. Therefore, fall detection is suitable for this problem.

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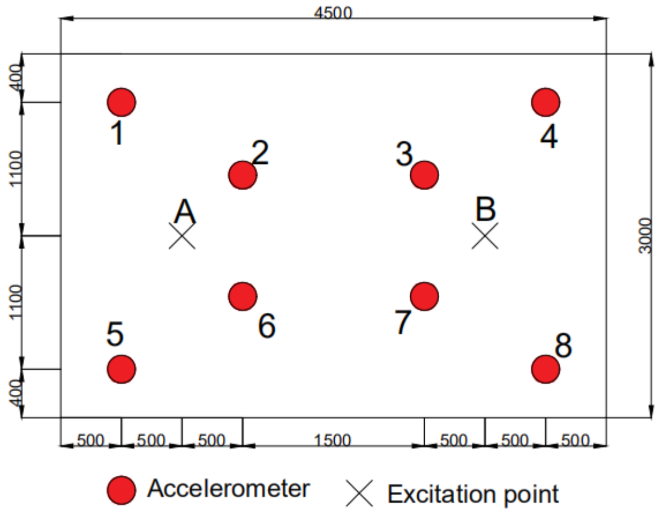
There are 3 type of fall detection methods which is user dependent, user independent and sensor. User dependent method is where a person relay on a wearable device to detect fall which as watch, hair clip, necklace, ring, bracelet and etc. When fall occur, the device either will detect automatically and trigger it signal, or the injured person should press the button of device that trigger it signal. However, there are some weakness on it where the device unable to differentiate fall detection and trigger false signal while no accident occur[4]. For user independent method is a technology that detect fall such as infrared camera and handphone where it can detect infrared energy and convert into infrared image in a computer or monitor. Even so, 2 this method provide visual to fall detection but still it can affect an individual privacy where a person feeling uncomfortable being watch from camera.

Thus, this research are proposed fall detection using floor vibration method to record the acceleration response from the falls from human and non human such ball, book etc. Then, the data was analysis using neural network method. Neural network are a set of algorithms that recognize pattern of data in sound, numerical, image and time, and predict the output [5].

2. Experimental procedure

2.1 Test layout

Experiment was conducted in Jamilus Research Center (JRC) laboratory FKAAB. Figure 1 shows the location of the eight (8) accelerometers to record the floor acceleration responses where 4 accelerometer placed at the edge of the lab and other 4 accelerometer were place at near middle of the lab. Two (2) excitation points were place in the waling for activities take place. The location in the experiment represent as a small room.



All unit in mm

Figure 1: Proposed plan

2.2 Fall test

In this research, several fall test were conducted which are ball dropping, sand bag dropping, mechanical movement and human falling. Table 1 below show the summary of total sample obtained for each activity.

Table 1: Sample obtained in each test

Activity	Description	Sample
Falling test	26.48kg of dummy free falling	110
Ball dropping	0.54kg of basketball drop from height 1.0m	110
Sand bag dropping	6kg of sand bag free falling	110
Mechanical movement	3.8kg of chair experience free walking	55

2.2.1 Dummy falling

A rescue dummy with a weight of 26.48kg was used for falling test. Due to excessive weight of dummy it is too heavy lift the dummy by hand, therefore wooden pulley frame was built for support dummy weight and using pulley for lifting and releasing for experience free fall show in Figure 2. In each excitation point were repeated 55 times, therefore total of 110 fall sample with 10 seconds of duration each fall sample were tested out (55 repeat x 2 excitation point).

Figure 2: Preparation dummy fall

2.2.2 Ball dropping

A basketball shown in Figure 3 below was prepared for dropping test. The weight of the ball is 0.54kg and dropping height is 1.0m. In each excitation point were repeated 55 times of dropping, therefore total of 110 fall sample with 10 seconds of duration each fall sample were tested out (50 repeat x 2 excitation point).

Figure 3: Ball dropping

2.2.3 Sand bag dropping

A sand bag with a weight of 6 kg were prepared for dropping test. Wooden pulley frame were used for support the weight of sand bag and lift and release to experience free fall show in Figure 4. In each excitation point were repeated 50 times of dropping, therefore total of 110 fall sample with 10 seconds of duration each fall sample tested out (50 repeat x 2 excitation point).

Figure 4: Sand bag dropping

2.2.4 Mechanical movement

A chair were prepared for free moving test. The weight of the chair is 3.10 kg and performed free movement(pulling) in the testing area show in Figure 5. This activities were repeated 55 times for moving randomly with 10 seconds of duration each moving sample tested out.

Figure 5: Chair movement

2.3 Data analysis using MATLAB

All data were converted from ME-Scope software to MATLAB file and load into workplaces shown in Figure 6. Each type of testing had consist of 55 data sample including acceleration data from accelerometer 1 to 8. In Figure 7, each type of testing were averaged with their 55 data for every accelerometer and obtained acceleration graph on each accelerometer. Peak acceleration were obtained using highest peak acceleration point from each type of testing in each accelerometer.

Variables - DA14

DATATEST | avgBallA15 | MAXIMUM | MEAN | Acc1DA | DA14

2000x8 double

	1	2	3	4	5	6	7	8
1	-1.1889e-04	-1.6203e-05	4.7549e-06	8.0449e-05	-4.2853e-05	7.1079e-05	2.6720e-06	-4.1096e-04
2	-1.7188e-04	3.7411e-05	-2.5043e-05	2.0651e-05	3.4676e-05	1.0645e-04	-6.8760e-05	1.2083e-04
3	-6.9970e-05	6.6972e-05	5.8385e-05	1.6338e-04	-7.2035e-06	7.0290e-05	8.9660e-06	3.5767e-04
4	7.9057e-05	9.6459e-05	2.2340e-05	2.5701e-05	-5.4694e-05	8.1958e-05	2.1712e-04	-1.5506e-04
5	3.1084e-05	4.2410e-05	-1.6812e-04	-1.6468e-04	8.8294e-05	1.7676e-04	-4.0742e-06	2.8573e-04
6	-8.7963e-05	-1.9574e-04	-1.4360e-04	1.1571e-04	-8.4713e-05	-8.5862e-05	-2.9547e-04	-4.0578e-04
7	-9.3549e-05	-1.7110e-04	-1.0141e-04	1.6859e-04	-1.9134e-04	-1.3293e-04	-1.4488e-05	-1.6863e-05
8	-1.6451e-04	-1.0501e-04	-9.5060e-05	-5.8135e-05	-7.7541e-05	3.4083e-05	2.3531e-04	1.4329e-04
9	-9.0344e-06	-9.3801e-06	-2.9230e-05	3.1387e-05	-1.1293e-04	-1.0886e-04	-2.7523e-05	-1.6033e-04
10	1.2187e-04	9.1771e-05	2.4431e-05	-4.5241e-06	6.5949e-06	2.8495e-05	-9.2657e-05	2.6849e-04
11	2.4046e-04	1.5089e-04	1.2548e-04	1.9365e-05	7.1942e-05	1.1158e-04	2.3497e-04	-3.3953e-04
12	2.8106e-04	1.4427e-04	1.2491e-04	8.4662e-05	8.9575e-05	9.3303e-05	1.5647e-04	1.4418e-04
13	1.8153e-05	8.6305e-07	7.0893e-05	8.4338e-05	8.3169e-05	7.5013e-05	-1.5346e-04	5.9761e-05
14	-7.1055e-05	-8.8389e-05	1.2417e-04	1.2559e-04	-1.2537e-04	-8.0000e-05	-1.5855e-05	-1.2443e-04
15	-1.3028e-04	-1.5347e-04	1.6529e-04	2.9861e-05	1.7145e-07	-4.9872e-05	1.7453e-04	2.6250e-04
16	-1.7132e-04	-5.1655e-05	1.5864e-04	-1.7874e-05	2.9822e-05	8.1190e-05	6.6636e-05	-1.4303e-04
17	-6.9455e-05	1.9854e-05	3.3028e-05	-1.3085e-04	4.7596e-05	9.2688e-05	-1.5969e-04	2.9197e-04

Figure 6: Raw acceleration data

Variables - Acc1DA

DATATEST | avgBallA15

2000x1 double

	1	2	3
1	-7.3745e-06		
2	-9.5139e-06		
3	-2.0176e-05		
4	6.7674e-07		
5	-8.9645e-06		
6	-2.4241e-06		
7	1.2718e-05		
8	1.0722e-05		
9	9.4872e-06		
10	4.8003e-06		
11	-9.7248e-06		
12	-3.2932e-05		
13	-5.8537e-06		
14	1.2872e-05		
15	1.3683e-05		
16	2.0969e-07		
17	-1.2921e-06		

Figure 7: Average acceleration data in each accelerometer

2.4 Analyze data using Artificial Neural Network

There were total of 385 sample data to analyze, in a sample consist of data from 8 accelerometer (2000 x 8), each sample were averaged into 1 accelerometer (2000 x 1). Maximum, mean and variance value were used as feature set that determined from averaged acceleration data, and set as input data. Then, target data was determined as a classify for human and non human fall. Next, data can be analyzed using artificial neural network in MATLAB. Validation and data test randomly divide up the sample with Training 70% (269 samples), Validation 15% (58 samples) and Testing 15% (58 samples) of 385 samples. In network architecture a total of 10 hidden neuron was setup in the pattern recognition network's hidden layer. Data were trained and retrained data are necessary until it good performance if the result was bad.

3. Results and Discussion

3.1 Acceleration response

In Figure 8 show the result run by MATLAB and generated formed acceleration graph pattern for dummy falling, ball dropping, sand bag dropping and chair movement at accelerometer 1. Each type of testing has different acceleration graph pattern. Based on Figure 9 shows the graph of peak acceleration against time for each sample events at each accelerometer. The highest peak acceleration was sandbag dropping.

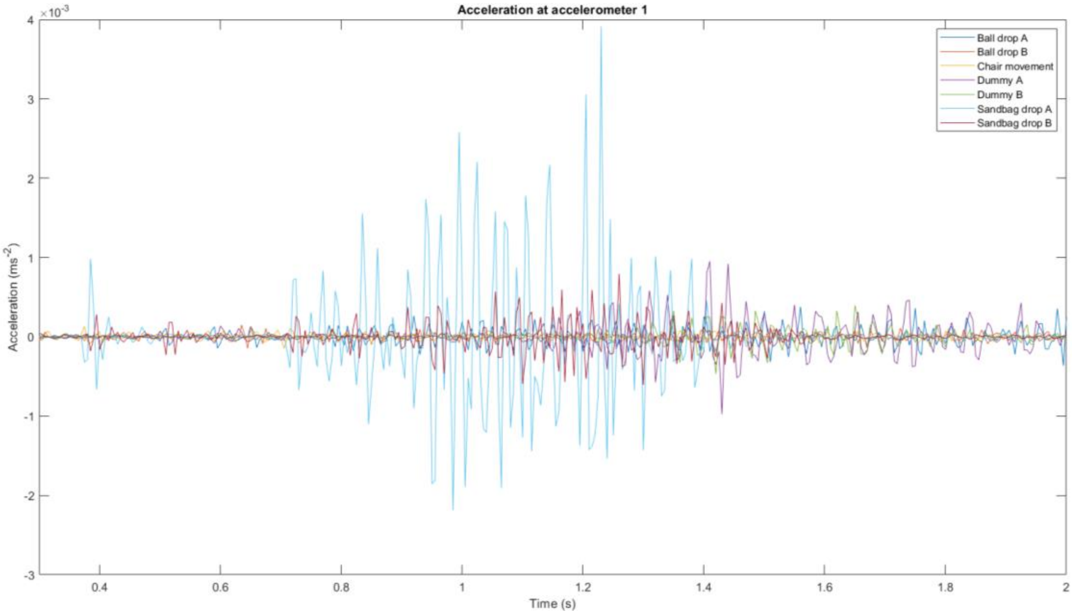


Figure 8: Acceleration signal generated from accelerometer 1

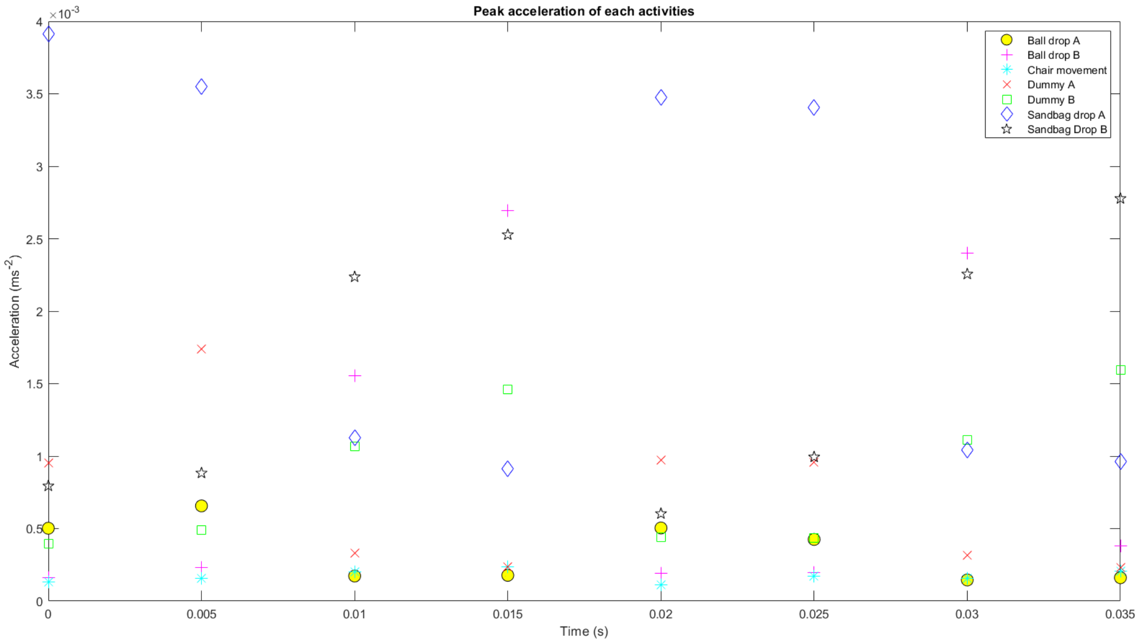


Figure 9: Peak acceleration signal from each activities

3.2 Artificial neural network analysis

A total of 385 sample data were used to analyze using artificial neural network (ANN) to differentiate human and non human fall. Validation stop when epoch was reached 28 where epoch is a process where dataset require to run a forward and backward to complete a cycle (1 epoch). Figure 10 show the result performance graph of train data, validation data, test data and best line. Blue line represented as training value, green line represented as validation data, red line represented as test value and dotted line represented as best line. The best validation performance was 0.070325 at epoch 22.

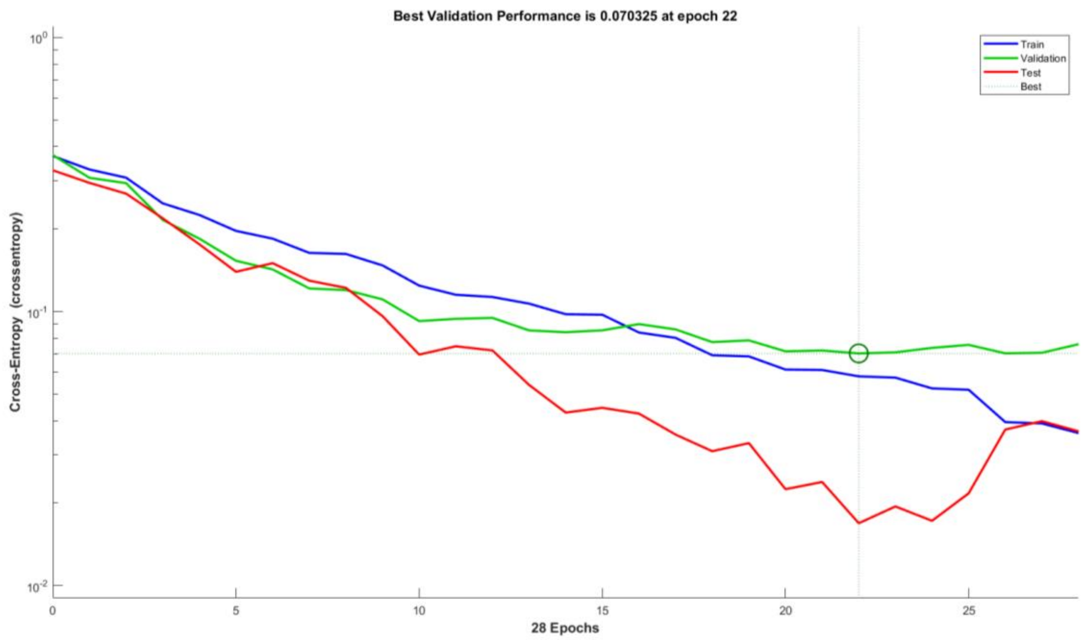


Figure 10 Best validation graph

Figure 11 show the result of error histogram, it consist of 20 bins represented as the bar. Blue line represented as training value, green line represented as validation data, red line represented as test value and yellow line represented as zero error. The nearest value to the zero error was -0.04975 and 0.04975 bin.

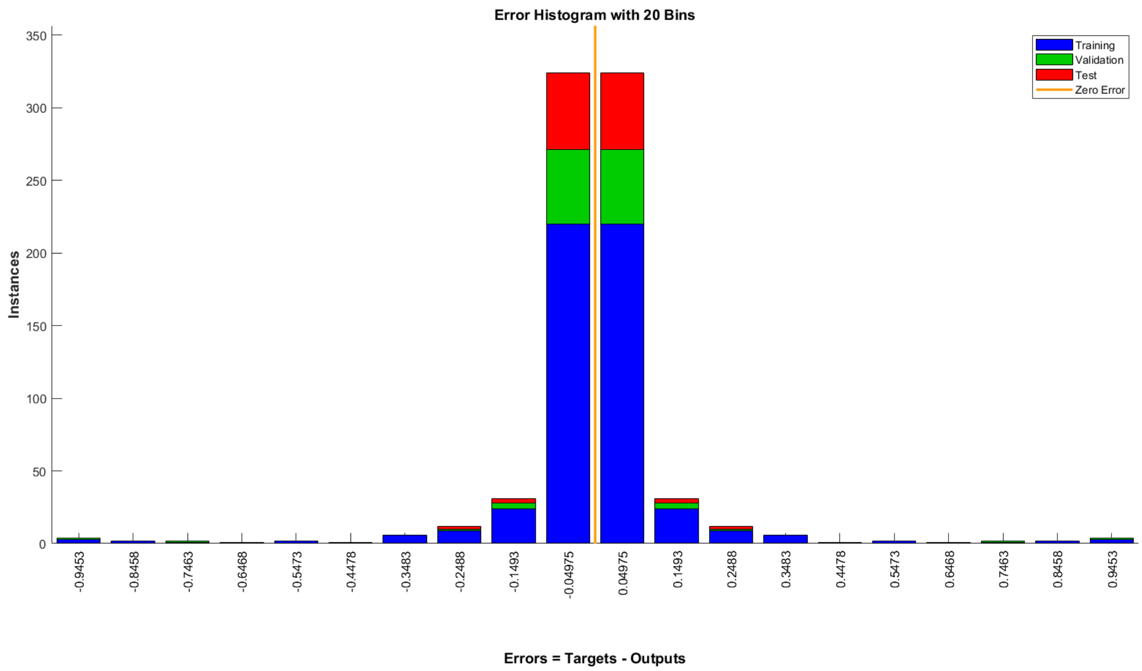


Figure 11: Error histogram

In Figure 12 show the result confusion matrix, output class represent as prediction data and target class represented as target data. In training confusion matrix had 96.7% accuracy to classify human fall and non human fall. In validation confusion matrix had 96.6% accuracy to classify human fall and non human fall. In test confusion matrix had 100% accuracy to classify human fall and non human fall. In overall confusion matrix had 97.1% accuracy to classify human fall and non human fall.

Figure 12: Confusion matrix

In Figure 13 show the result receiver operating characteristic graph, training, validation and overall were typical curve. From the graph obtained, area under curve can be obtained where the maximum area under curve was 1 represent as a perfect curve meaning the output data = target data. In test result, graph pattern was perfect curve, and area under curve value was 1, therefore it has perfect accuracy true positive rate.

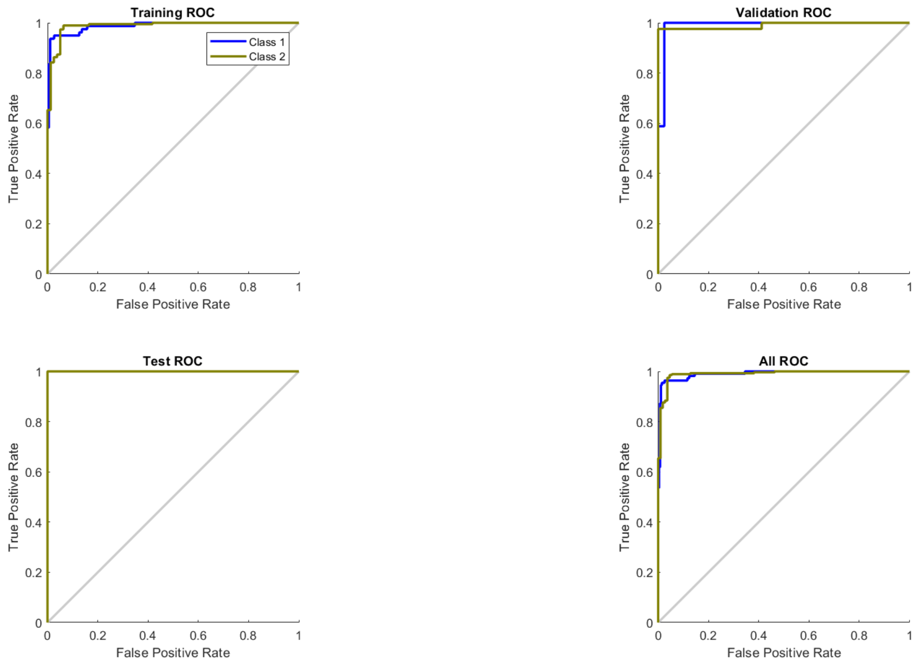


Figure 13: Receiver operation characteristic

In matlab analysis, highest peak acceleration was sand bag dropping from every accelerometer due to had a highest dropped height. Also from the acceleration graph ball dropping and dummy falling had similar pattern graph of falling impact force. The result epoch stop at 35 iteration the result where the data trained achieved optimum repetition, therefore best validation performance was at 29 with 6

validation check, also training and test were near to the best line. Excessive or less trained data result bad generalization due to overfitting and underfitting. In error histogram, the nearer the value of bin bar to the zero error, the better the graph performance. Value of bin bar in -0.04895 and 0.04895 had the highest instances (number of test) and nearest to the zero which mean the output prediction data was near to the target data, therefore the graph performance was good. In confusion matrix, all confusion matrix had over 95% accuracy to classify human fall and non human fall. Confusion matrix was formed based on comparing output data and target data show in Figure 3.5. From the confusion matrix, the value of true positive (TP) which are the prediction data correctly predicted human fall was 102, true
43 negative (TN) which are the prediction data correctly predicted non human fall was 272, false positive (FP) which are prediction data wrongly predicted human fall was 3 and false negative (FN) which are the prediction data wrongly predicted non human fall was 8. With these value of obtained, accuracy, sensitivity and specificity were determined. Below the shows the formula and calculation of accuracy, sensitivity and specificity.

Accuracy, % = $\frac{TP + TN}{TP + TN + FP + FN} X\ 100\%$

$= \frac{102 + 272}{102 + 272 + 3 + 8}\ X\ 100\%$

$= 0.971\ X\ 100\%$

$= 97.1\%$

Sensitivity, % = $\frac{TP}{TP + FN} X\ 100\%$

$= \frac{102}{102+8} X\ 100\%$

$= 0.927 X\ 100\%$

$= 92.7\%$

Specificity, % = $\frac{TN}{TN + FP} X\ 100\%$

$= \frac{272}{272+8} X\ 100\%$

$= 0.971 X\ 100\%$

$= 97.1\%$

4. Summary and Conclusion

The type of activities generate different result pattern of acceleration signal when impact force through the floor and produced vibration that received by the accelerometer. Highest peak acceleration in this research was sand bag dropping in every accelerometer due to it has highest dropping height by using wooden frame pulled it to the top. Therefore height of dropping affect acceleration.

Based on the result, artificial neural network in MATLAB software was used to analyze dataset and
46 determined accuracy of prediction data. Therefore, output data were generated and compared with target to create a matrix confusion consist of true positive, true negative, false positive and false negative. From confusion matrix, accuracy, sensitivity and specificity were determined. The value of accuracy was 97.1% as for overall classification, the value of sensitivity represent the accuracy to classify human fall was 92.7% and the value of specificity represent the accuracy to classify non human fall was 97.1.

In conclusion, this software gives high accuracy to differentiate human and non human. Therefore, objective in this research was achieved as the fall testing were conducted using floor vibration and differentiate the accelerations response between human fall and non-human fall using artificial neural network.

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