Available *online* at : http://jitce.fti.unand.ac.id/

JITCE (Journal of Information Technology and Computer Engineering)

| ISSN (Online) 2599-1663 |

Research Paper

Hand Gesture to Control Virtual Keyboard using Neural Network

Arrya Anandika [1], Muhammad Ilhamdi Rusydi [2], Pepi Putri Utami [2], Rizka Hadelina [1], Minoru Sasaki [3]

[1] *Computer Engineering Department, Universitas Andalas, Limau Manis, Padang, 25163, Indonesia*
[2] *Electrical Engineering Department, Universitas Andalas, Limau Manis, Padang, 25163, Indonesia*
[3] *Department of Mechanical Engineering, Faculty of Engineering, Gifu University Yanagido, Gifu, 501-1193, Japan*

Article Information

Received: January 4th, 2023
Revised: February 9th, 2023
Available online: March 31st, 2023

Keywords

Virtual Keyboard, Disability, Hand gesture, Neural Network, Leap Motion

Correspondence

Phone: -

E-mail: rusydi@eng.unand.ac.id

A B S T R A C T

Disability is one of a person's physical and mental conditions that can inhibit normal daily activities. One of the disabilities that can be found in disability is speech without fingers. Persons with disabilities have obstacles in communicating with people around both verbally and in writing. Communication tools to help people with disabilities without finger fingers continue to be developed, one of them is by creating a virtual keyboard using a Leap Motion sensor. The hand gestures are captured using the Leap Motion sensor so that the direction of the hand gesture in the form of pitch, yaw, and roll is obtained. The direction values are grouped into normal, right, left, up, down, and rotating gestures to control the virtual keyboard. The amount of data used for gesture recognition in this study was 5400 data consisting of 3780 training data and 1620 test data. The results of data testing conducted using the Artificial Neural Network method obtained an accuracy value of 99%. This study also performed a virtual keyboard performance test directly by typing 20 types of characters conducted by 15 respondents three times. The average time needed by respondents in typing is 5.45 seconds per character.

INTRODUCTION

Disability is a condition that can prevent a person from communicating and carrying out daily activities[1]–[3]. based on data from WHO, there are approximately 15% of people worldwide with disabilities, and 2-4% of them experience functional difficulties[1], [3]. One form of disability is paralysis and speech impairment. Paralysis is a condition in which a person loses the ability to communicate verbally or to move. This is caused by loss of function of neurons in the brain or known as neurodegenerative disorders[2] or other causes such as physical accidents[1]. someone who is paralyzed and speech impaired will have difficulty communicating with people around them, so a medium is needed to communicate with people around them, one of which is by using a smartphone and computer[2]. However, it becomes a new problem if people with speech disabilities experience limited finger function due to certain neurological diseases or accidents[4]. So, we need special media in communication. One way to build communication is by using the concept of HCI (Human-computer Interaction).

HCI development has been carried out starting from the use of a keyboard and mouse as a medium of communication between humans and computers[5]. there are many developments in HCI for support communication each other, such as nose tracking cursor control[5], speech and movement recognition system[3], recognition of hand or finger gestures [4], [6]–[20], biosignals[1], [2], [21], [22], and others.

Hand gesture recognition has been developed for various purposes, such as wheelchair control[14], hand robots[23], virtual keyboards[6], [15], [24], [25], sign language recognition[26]–[29], alternative remote control[30], virtual mouse control[31], Touchless Exploration of Medical Images[12], and various other implementations.

Previous research in recognizing patterns of hand gestures is through image processing through taking pictures [16], [17], [19]. In research [19] it is limited to character recognition numbers 1 to 10. Research [17] is limited to character recognition numbers 1 to 20. Meanwhile, in the study [16] it is limited to character recognition of letters (A, B, C, D, G, H, I, L, V, and Y). In addition, all three studies were limited to static shooting and would have problems with dynamic hand gestures.

Leap motion sensors are an alternative in developing technology to recognize hand gesture patterns[9], [12]–[14], [20]. Li's research [9] conducted research on the introduction of hand gestures using leap motion for post-stroke rehabilitation. Seven gestures recognized as a method of rehabilitation for stroke patients. Hand gestures are recognized based on the pitch, roll,

 Attribution-NonCommercial 4.0 International. Some rights reserved

and yaw values on the sensor. Other research by Lu [20] to recognized hand gestures are ten gestures (poke, pinch, pull, scrape, slap, press, cut, circle, key tap, and mow) and are stored in the Handicraft-Gesture dataset. The classification method used is the Hidden Conditional Neural Field (HNCF).

Besides that, research [13] in recognizing Arabic numbers has been carried out. there are 10 recognized numbers (0-9) which are modeled and classified using the Radial Basis Function (RBF) neural network method. other studies [12] in recognizing 11 hand gestures in controlling DICOM Images without direct contact to avoid the risk of contamination. the method used in this study is the Support Vector Machines (SVM) method. The introduction of hand gestures based on pitch, roll, and yaw values was also carried out by Rusydi [14] using a leap motion sensor. Introduction Hand gestures are made to control a wheelchair. Recognition of wrist gesture is based on hand muscle fatigue analysis in order to provide comfort for wheelchair users.

Apart from hand gestures, more specifically development using Leap Motion Sensor has been carried out on the recognition of finger gestures[4], [11], [15], as in Li's Research [4] about finger motion reconstruction. Finger motion generated by angle of finger joint and it calculated. Other studies [11] compared the recognition of finger movements based on leap motion sensors and glove data. the data glove consists of flex sensors, gyroscopes, and vision data. comparisons are seen based on position, orientation, velocity and acceleration from the angle of the finger bend. Then, then finger gestures recognition research was also carried out to control the virtual keyboard[15], where there are two algorithms designed with each different finger gestures. Finger gesture patterns obtained based on the angle of the index finger and thumb. Based on that research, hand gesture pattern recognition can be done using a leap motion sensor, but this becomes a problem if someone has limited finger function.

One of the developments of communication media with persons with disabilities is carried out using a virtual keyboard. Virtual keyboard was developed in various shapes and types[6], [15], [21], [24], [25], [32]. based on research [6], [15], [25], the virtual keyboard that is being developed is still in a static form which each consists of letters and numbers in the qwerty type and alphabet type[15], [24]. Other type has been developed by [32] with the layout similar to mobile phone key layout. Other static form is designed based on a GUI (Graphics User Interface) with two types of display, namely in the form of words that are equipped with pictures and letters arranged in qwerty and alphabet form[6]. Another form that has been developed is the dynamic form[21]. The virtual keyboard is designed in a 7x7 pattern. There are 6 zones. The first and second zones consist of central point and four function. That zones do not change position adaptively. The third to sixth zones consist of letters and numbers arranged alphabetically and can adaptively switch positions based on frequently used characters.

This paper describes the design of a virtual keyboard that is controlled using a leap motion sensor based on hand gestures for persons with disabilities without fingers using an artificial neural network method. Hand gestures are identified based on the pitch, roll, and yaw values for each hand gesture (up, down, left, right, and rotate). Each gesture is classified using an artificial neural network as input on the virtual keyboard.

The paper consists of five sections. Part 1 explains the background, related work, and primary contribution. Section 2 describes the research methodology which consists of a virtual keyboard design, hand gesture patterns, and classification of hand gestures using artificial neural networks and experimental designs. The research results and discussion are presented in section 3. Section 4 describes the conclusions of the research.

METHOD

2.1. Virtual Keyboard Design

The virtual keyboard is designed using IDE processing software. The designed virtual keyboard consists of two parts. The left section consists of the word or character button, and the right section displays the selected word or character. The virtual keyboard is designed in two types, namely general word (GW) and custom word (CW) as shown in figure 1. GW Virtual keyboard is built based on common and frequently spoken words. GW Virtual Keyboard consists of the words I, you, want, eat, and other words. Each word is accompanied by a picture that represents that word.

Meanwhile, the CW Virtual keyboard consists of the letters A-Z and numbers 0-9. Letter characters are arranged based on the type of the alphabet. Each type of virtual keyboard provides a button to switch to another type of virtual keyboard. In addition, there are also buttons for delete, send, and space. The virtual keyboard is controlled by moving your hands up, left, right, and down. Meanwhile, selecting a word or character is done by rotating the hand 90°.

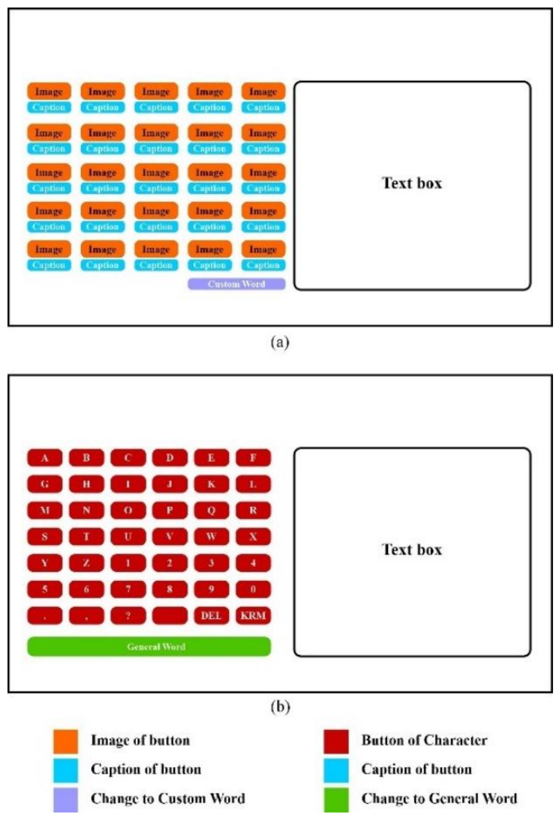


Figure 1. Virtual keyboard design; (a) general words (GW), (b) custom words (CW)

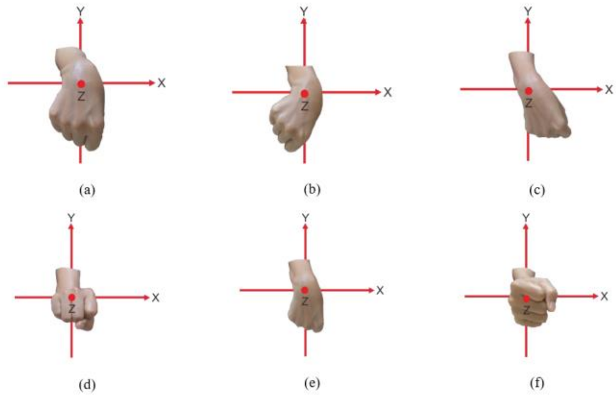


Figure 2. Hand Gesture Patterns; (a) Normal, (b) right, (c) left, (d) up, (e) down, (f) rotate

Figure 3. Hand position and Leap Motion Sensor

2.2. Hand Gesture pattern

The hand gestures recognized in this study were especially the right hand which had no fingers. Figure 2 shows the pattern of hand gestures consisting of gestures up, down, left, right, and rotating. Every Gesture is detected using the Leap Motion sensor. The normal hand position is based on the user's comfortable position by placing the hand directly above the leap motion sensor. The distance between the hand and the leap motion sensor is set at ±15 cm as shown in Figure 3. The reading of the leap motion sensor will produce Pitch values (change in direction of hand on the x-axis), Yaw (change in direction of hand on the y-axis), and Roll (change in direction of hand on the x-axis). z). Each Move results in a different Pitch, Roll, and Yaw value.

2.3. Design of Artificial Neural Networks

Artificial neural networks are used to classify hand gestures. The design of an artificial neural network consists of an input layer (Xi), a hidden layer (Zj), and an output layer (Yk) as shown in Figure 4.

Table 1. ANN output and hand gestures

No.	Hand Gesture	Output Layer (biner)
1	Normal	001
2	Right	010
3	Left	011
4	Up	100
5	Down	101
6	Rotate	110

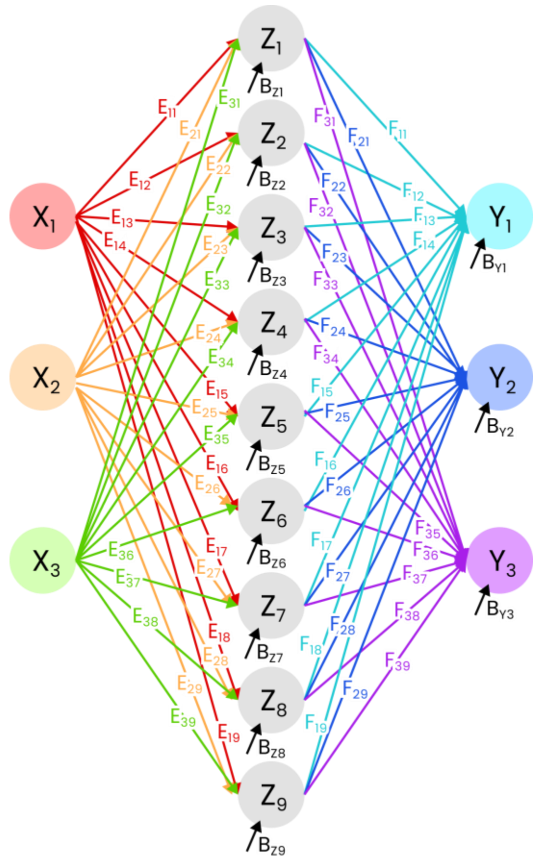


Figure 4. Design of Artificial Neural Networks

The input layer consists of 3 neurons (X1, X2, X3) which are the pitch, yaw, and roll values. The recognition process is carried out in the hidden layer which consists of 9 neurons (Z1 – Z9). The input layer and the hidden layer are connected by the input weight (Eij). Then it is processed at the output layer which consists of 3 neurons (Y1, Y2, Y3). The hidden layer and output layer are connected by layer weights (Fjk). The three resulting neurons are in the form of binary numbers representing each gesture according to table 1. The output in the hidden layer is calculated using equation (1) and the activation function used in the hidden layer is the Sigmoid function in equation (2). While the output in the output layer is calculated using equation (3) and the activation function used is the purelin function as in equation (4).

$$AZ_j = B_{Zj} + \sum_1^n E_{ij} * X_i \tag{1}$$

$$Z_j = Sigmoid\ (AZ_j) \tag{2}$$

$$AY_k = B_{Zk} + \sum_1^n F_{jk} * Z_j \tag{3}$$

$$Y_k = purelin\ (AY_k) \tag{4}$$

RESULTS AND DISCUSSION

3.1. Retrieval of Hand Gesture Direction data

Direction data collection for hand gestures is carried out by placing the hands parallel to the leap motion sensor 15 cm as shown in Figure 3. Directional data is read in the form of pitch, yaw, and roll values for each gesture. gestures that are read are

 https://doi.org/10.25077/jitce.7.01.40-48.2023

wrist up, down, left, right, and rotate. The reading results can be seen in Figure 5.

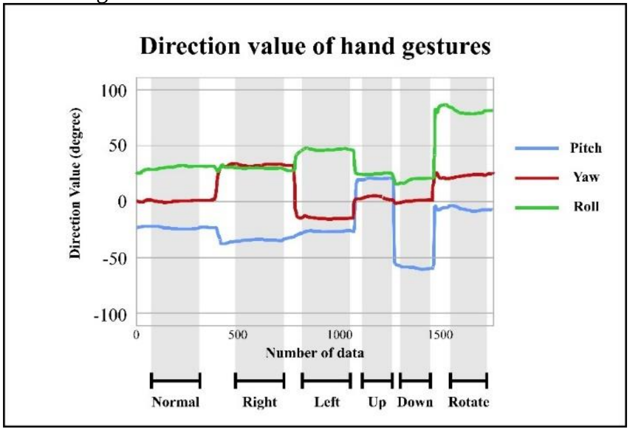


Figure 5. Direction value of leap motion sensor based from gesture.

Table 2. Data training input weights

	X_1	X_2	X_3
Z_1	0.24	0.19	0.08
Z_2	-1.84	0.00	0.75
Z_3	0.04	0.43	-0.02
Z_4	0.52	-0.06	0.09
Z_5	-0.12	-0.83	0.02
Z_6	-0.08	-1.76	0.03
Z_7	0.10	0.42	0.01
Z_8	0.21	0.30	-0.27
Z_9	-0.29	0.41	-0.17

Table 3. Data training layer weights

	Y_1	Y_2	Y_3
Z_1	0.85	0.38	-0.63
Z_2	-0.15	0.88	-0.63
Z_3	-1.14	1.05	-1.76
Z_4	-0.89	0.02	0.1
Z_5	0.41	-0.99	0.92
Z_6	-0.19	0.41	0.37
Z_7	0.66	-1.27	1.27
Z_8	-0.18	-0.07	-0.03
Z_9	-0.03	-0.58	0.44

Table 4. Layer bias and data training output bias

	Bias	Value
Hidden Layer	B_{Z1}	-1.74
	B_{Z2}	-0.27
	B_{Z3}	-13.95
	B_{Z4}	16.73
	B_{Z5}	19.94
	B_{Z6}	-14.47
	B_{Z7}	-12.49
	B_{Z8}	7.6
	B_{Z9}	-2.8
Output Layer	B_{Y1}	0.8
	B_{Y2}	0.7
	B_{Y3}	-0.38

Each gesture produces a different pitch yaw and roll value so that it can be used as input for virtual keyboard controls.

3.2. Artificial Neural Networks

3.2.1. Training Data

Artificial neural network design is trained using 3780 data. Each data has a target for each gesture which has been defined with a binary number. Data training is carried out to see the performance of the artificial neural network based on the Mean Square Error (MSE) value. MSE is determined based on a comparison between the targets given and the output generated in the training data. The results of the data training show that the MSE value stops at 0.013 at the 1265th epoch. The data training produces weight and bias values to calculate the output value. The resulting weight values consist of input weights in table 2 and layer weights in table 3. Meanwhile, layer bias and output bias are shown in table 4. There are 27 input weights, 27 layer weights, 9 layer biases, and 3 output biases.

3.2.2. Testing Data

The test was carried out using 1620 data. Each data is divided based on each gesture. Based on the tests carried out, there were 1601 data that were declared in accordance with the classification of gesture, while 19 data experienced differences between the target and the resulting output. The details of the data result are described in the confusion matrix in table 5. so that the accuracy can be calculated from the total amount of data. based on the performance of training data and test data in table 6, it was found that the average precision of each gesture was 97.83% and 98.83%. while the average data accuracy in the training data is 96.19% and in the test data is 98.82%. The test results also show that the gesture data to the right and down has a smaller value than other gestures. This is due to the less ideal position of the user's hand so that the read value is similar to other gestures.

Table 7 shows several methods of classifying hand gesture patterns that have been used by previous researchers. in studies [16] and [17] use the same features, namely image processing using edge detection and the same method, namely Support vector machines (SVM). However, the number of recognized gestures is different. in research [16] the recognized gestures are numbers (0-9) where the resulting performance reaches 92%. whereas in research [17] the gestures that are recognized are sign language numbers (1-20) and classified based on database, but from a testing point of view the test results are not included in the form of percentages.

Another study [12] detected hand gestures based on Skeleton hand and finger data with coordinates (X, Y, Z) using two methods, namely SVM and multilayer perceptron, each of which obtained an accuracy of 91.73% and 89.91%. Another method, namely neural networks, can also classify hand gestures. in research [13] the Radial Basis Function (RBF) Neural network method is used to recognize hand gesture patterns based on Hand motion dynamic features, including spatial position and direction of finger. performance in recognition was obtained at 95.1%. Lastly, research [33] recognizes hand gestures based on Doppler radar using the deep convolutional neural network (DCNN) method. based on this method obtained system accuracy with 10 hand gestures of 85.6% and 7 gestures of 93.1%.

Based on previous research with several methods and compared with the proposed research, it can be seen that the performance produced in other studies is not more than 96% and the proposed research obtains a performance of 99%. it can be said that the ANN method can recognize given hand gestures with very good results and can be implemented.

Table 5. Confusion matrix of data results

Data	Prediction Gesture	Actual result gesture							Total
		Normal	Up	Down	Left	Right	Rotate	Unknown	
Training data	Normal	609	0	8	7	6	0	0	630
	Up	0	626	0	0	0	2	2	630
	Down	10	0	617	0	2	1	0	630
	Left	9	0	0	619	1	0	1	630
	Right	1	1	5	0	600	9	14	630
	Rotate	0	1	0	0	2	627	0	630
					Number of Data				3780
Testing data	Normal	269	0	1	0	0	0	0	270
	Up	0	269	1	0	0	0	0	270
	Down	1	0	264	3	0	2	0	270
	Left	0	0	0	266	0	0	4	270
	Right	1	0	0	0	263	5	1	270
	Rotate	0	0	0	0	0	270	0	270
					Number of Data				1620

Table 6. Performance of Neural Network Method (%)

Data	Gesture	Performance				
		TPR	FPR	Precision	F1 Score	Accuracy
Training data	Normal	97%	3%	97%	97%	94%
	Up	99%	1%	99%	100%	99%
	Down	98%	2%	98%	98%	96%
	Left	98%	2%	98%	99%	97%
	Right	95%	5%	95%	97%	94%
	Rotate	100%	0%	100%	99%	98%
Mean		98%	2%	98%	98%	96%
Testing data	Normal	100%	0%	100%	99%	100%
	Up	100%	0%	100%	100%	100%
	Down	98%	2%	98%	99%	98%
	Left	99%	1%	99%	99%	99%
	Right	97%	3%	97%	99%	98%
	Rotate	100%	0%	100%	99%	100%
Mean		99%	1%	99%	99%	99%

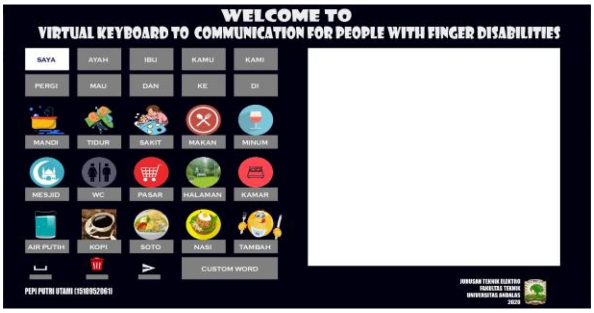
Table 7. Hand gesture patterns methods from previous research compared to the proposed method

Feature	Number of Gesture	Classifier	Result
Image processing based on Canny edge detection[17]	20	Support Vector Machines (SVM)	testing is done using a webcam and can be classified based on the database. however, the percentage of the results of the tests performed was not explained.
Image processing based on Canny edge detection[16]	10	Support Vector Machines (SVM)	The percentage of performance up 92% for recognizing based on gesture set.
Skeleton hand and finger data with coordinates (X, Y, Z)[12]	11	Support Vector Machines (SVM) and Multilayer Perceptron	Accuracy of testing data using SVM is 91.73% and with multilayer perceptron is 89.91%
Hand motion dynamic, including spatial position and direction of finger[13]	10	Radial Basis Function (RBF) Neural Network	Performance of recognition is 95.1%
Pitch, yaw and roll values[6]	7	Threshold	the rules for each hand movement have been determined threshold values based on pitch, yaw and roll values so that an accuracy of 100% is obtained.
Doppler Radar by micro-doppler signatures[33]	10	Deep Convolutional Neural Network (DCNN)	Accuracy of classification is 85.6% with 10 gestures. But with 7 gestures it becomes 93.1%
Proposed: Pitch, yaw and roll values	6	Artificial Neural Network (ANN)	This method has 99% accuracy and 99% precision.

3.3. Virtual keyboard

The virtual keyboard is designed in two types, there are GW Virtual keyboard, and CW Virtual Keyboard. The results of the virtual keyboard design are shown in Figure 6. On the GW Virtual keyboard, words used in Indonesian are generally used like *saya, kamu, kami, ayah, ibu, pergi, ingin, dan, untuk, di*. Then there are also words that represent daily activities (*mandi, makan, tidur, minum*), *sakit, lokasi*(*masjid, pasar, pekarangan, toilet, kamar*), foods and drinks (*air, kopi, sup, nasi*) and *tambah*. At the bottom left, there are several main buttons such as (space, delete, and send) and the button to switch to the CW Virtual keyboard.

 https://doi.org/10.25077/jitce.7.01.40-48.2023



(a)

(b)

Figure 6. Virtual Keyboard Display; (a) GW Virtual Keyboard, (b) CW Virtual Keyboard

Meanwhile, on the CW Virtual keyboard display, it consists of the letters A-Z followed by the numbers 1-0, full stop (.), comma (,), question mark (?), space, delete and send. Meanwhile, the bottom row contains buttons to switch to the GW Virtual Keyboard.

3.4. Performance of Virtual keyboard

Virtual keyboard testing using a leap motion sensor is carried out based on hand gestures. Hand gestures have been recognized by leap motion sensors and classified by type of gesture using artificial neural networks. Tests were carried out on 15 respondents as shown in table 8 by typing words or sentences using the CW Virtual keyboard and GW Virtual keyboard. For each type of virtual keyboard, there are 10 trials consisting of predetermined words in Indonesian. Word or sentence testing was carried out three times for each respondent. From each test performed, the average time consumption required by the respondents was calculated and shown in Figure 7. From the results obtained, there is no significant difference in the time required for each test with the same character or word with an average standard deviation of 2.65 seconds.

Tests were conducted to determine the average time required to type each character or word according to the type of virtual keyboard used. Based on the results of the tests conducted, the average time needed to select a character or word is 5.45 seconds.

Table 8. Virtual keyboard performance testing

No.	**Words/Sentence**	**The number of buttons selected**	**Average of time comsumption of Test (s)**			**Average of time (s)**	**Average to select one character/word (s)**	**Deviation Standar**
			1	**2**	**3**			
CW Virtual Keyboard								
1	Zimbabwe	8	36.91	36.49	36.60	36.66	4.58	1.76
2	Kapal	5	31.36	30.97	30.53	30.96	6.19	2.24
3	Dokter	6	31.80	32.12	31.57	31.83	5.30	2.44
4	Soekarno	8	38.70	37.54	37.81	38.02	4.75	2.78
5	Randang	7	34.22	34.69	33.39	34.10	4.87	2.24
6	Universitas Andalas	18	95.37	95.22	95.53	95.37	5.30	1.79
7	Bukittinggi Kota	21	112.57	111.43	110.59	111.53	5.31	5.72
8	Wisata	10	46.01	45.17	44.25	45.14	4.51	2.40
9	17.08.1945	10	45.15	44.79	44.61	44.85	4.48	2.32
10	1510952061	10	54.20	54.25	53.63	54.03	5.40	2.33
GW Virtual Keyboard								
11	Saya Mau Makan	3	18.47	18.25	17.06	17.93	5.98	3.50
12	Ibu Pergi ke Pasar	4	23.28	22.89	23.30	23.16	5.79	2.54
13	Ayah Minum Kopi	3	22.74	21.45	20.84	21.68	7.23	2.68
14	Saya Mau ke WC	4	21.46	21.65	21.03	21.38	5.35	1.81
15	Saya Mau Tambah Soto	4	22.44	21.97	22.79	22.40	5.60	1.84
16	Ayah dan Ibu Pergi ke Masjid	6	30.84	30.76	30.54	30.71	5.12	3.37
17	Ayah Tidur di Kamar	4	20.86	20.68	21.20	20.91	5.23	2.00
18	Saya Minum Air Putih	3	20.23	19.52	20.01	19.92	6.64	2.68
19	Ibu Sakit dan Tidur di Kamar	6	28.33	28.35	27.86	28.18	4.70	2.44
20	Kami Minum Kopi di Halaman	5	33.05	33.09	32.43	32.85	6.57	2.26
			Total of Average				**5.45**	**2.56**

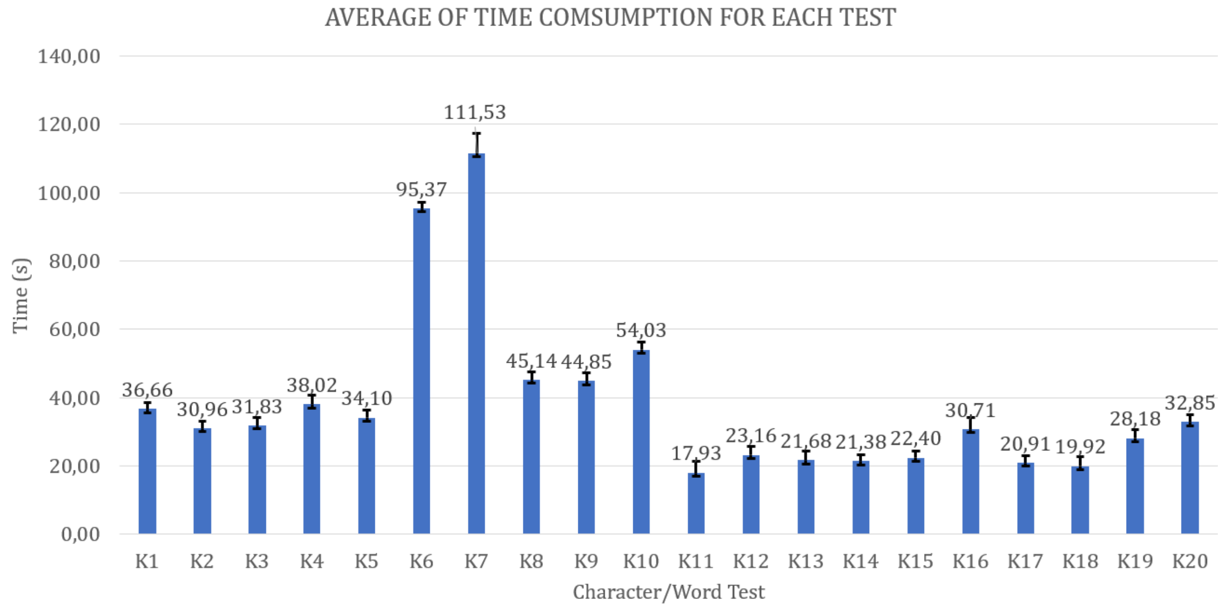


Figure 7. Average of time comsumption for each test

CONCLUSIONS

In this research. a virtual keyboard control process has been carried out using hand gestures by applying artificial neural networks in its classification. Recognized gestures are normal hand gestures. hand gestures up. down. left. right. and rotating. Based on the tests that have been carried out. it was found that the system can recognize the type of hand gesture with a success rate of 99%. In the tests carried out there were two gestures. namely gesture to the right and down which had a lower accuracy value than other gestures due to the less-than-ideal position of the hand gesture detected by the leap motion sensor. Tests were carried out on 15 respondents using two types of virtual keyboards. The test was carried out with three attempts on the same character or word. where each trial did not have a significant time difference with an average time difference of 2.56 seconds. The test was carried out to see the average typing time for each given character or word with the result that it takes 5.45 seconds for each character or word.

REFERENCES

[1] D. F. V. Anaya and Mehmet. R. Yuce. “A Hands-free Human-Computer-Interface Platform for Paralyzed Patients Using a TENG-based Eyelash Motion Sensor.” *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. 2020. doi: 10.0/Linux-x86_64.

[2] G. Jialu *et al.*. “Offline Analysis for Designing Electrooculogram Based Human Computer Interface Control for Paralyzed Patients.” *IEEE Access*. vol. 6. pp. 79151–79161. 2018. doi: 10.1109/ACCESS.2018.2884411.

[3] K. A. S. V Rathnayake. W. K. I. L. Wanniarachchi. and W. H. K. P. Nanayakkara. “Human Computer Interaction System for Impaired People by using Kinect Motion Sensor : Voice and Gesture Integrated Smart Home.” *Proceedings of the 2nd International Conference on Inventive Communication and Computational Technologies (ICICCT)*. pp. 531–536. 2018.

[4] X. Li. K. Wan. R. Wen. and Y. Hu. *Development of Finger Motion Reconstruction System Based on Leap Motion Controller*. 2018.

[5] S. S. Khan. Md. S. H. Sunny. M. S. Hossain. E. Hossain. and M. Ahmad. “Nose Tracking Cursor Control for the People with Disabilities: An Improved HCI.” *3rd International Conference on Electrical Information and Communication Technology (EICT)*. Dec. 2017.

[6] M. I. Rusydi. Oktrison. W. Azhar. S. W. Oluwarotimi. and F. Rusydi. “Towards hand gesture-based control of virtual keyboards for effective communication.” in *IOP Conference Series: Materials Science and Engineering*. Institute of Physics Publishing. Sep. 2019. doi: 10.1088/1757-899X/602/1/012030.

[7] N. Wang. Y. Chen. and X. Zhang. “Realtime recognition of multi-finger prehensile gestures.” *Biomed Signal Process Control*. vol. 13. no. 1. pp. 262–269. 2014. doi: 10.1016/j.bspc.2014.05.007.

[8] I. A. S. Filho *et al.*. “Gesture Recognition Using Leap Motion: A Machine Learning-based Controller Interface.” [Online]. Available: https://drive.google.com/open?id=

[9] W.-J. Li. C.-Y. Hsieh. L.-F. Lin. and W.-C. Chu. “Hand Gesture Recognition for Post-stroke Rehabilitation Using Leap Motion.” *IEEE International Conference on Applied System Innovation (IEEE-ICASI 2017)*. pp. 386–388. 2017.

[10] R. Zaman Khan. “Hand Gesture Recognition: A Literature Review.” *International Journal of Artificial Intelligence & Applications*. vol. 3. no. 4. pp. 161–174. Jul. 2012. doi: 10.5121/ijaia.2012.3412.

[11] P. D. S. H. Gunawardane and N. T. Medagedara. “Comparison of Hand Gesture inputs of Leap Motion Controller & Data Glove in to a Soft Finger.” in *IEEE 5th International Symposium on Robotics and Intelligent Sensors : proceedings*. 2017. pp. 62–68.

[12] S. Ameur. A. Ben Khalifa. and M. S. Bouhlel. “Hand-Gesture-Based Touchless Exploration of Medical Images with Leap Motion Controller.” in *Proceedings of the 17th International Multi-Conference on Systems. Signals and Devices. SSD 2020*.

 https://doi.org/10.25077/jitce.7.01.40-48.2023

Institute of Electrical and Electronics Engineers Inc.. Jul. 2020. pp. 1116–1121. doi: 10.1109/SSD49366.2020.9364244.
[13] Q. Wang. Y. Wang. F. Liu. and W. Zeng. "Hand Gesture Recognition of Arabic Numbers Using Leap Motion via Deterministic Learning." in *Proceedings of the 36th Chinese Control Conference*. 2017. pp. 10823–10828.
[14] M. I. Rusydi *et al.*. "Electric Wheelchair Control using Wrist Rotation based on Analysis of Muscle Fatigue." *IEEE Access*. vol. 10. pp. 1–1. Sep. 2022. doi: 10.1109/access.2022.3208151.
[15] M. I. Rusydi *et al.*. "The Use of Two Fingers to Control Virtual Keyboards with Leap Motion Sensor." *2017 5th International Conference on Instrumentation. Communications. Information Technology. and Biomedical Engineering (ICICI-BME)*. pp. 255–260. 2017.
[16] M. H. Rahman and J. Afrin. "Hand Gesture Recognition using Multiclass Support Vector Machine." 2013.
[17] N. R. N. S. Michahial. A. G. N. B. H. Azeez. J. M. R. and R. K. Rani. "Hand gesture recognition using support vector machine." *The International Journal Of Engineering And Science (IJES)*. vol. 4. no. 6. pp. 42–46. 2015. [Online]. Available: www.theijes.com
[18] Y. Zhou. G. Jiang. and Y. Lin. "A novel finger and hand pose estimation technique for real-time hand gesture recognition." *Pattern Recognit*. vol. 49. pp. 102–114. Jan. 2016. doi: 10.1016/j.patcog.2015.07.014.
[19] Z. H. Chen. J. T. Kim. J. Liang. J. Zhang. and Y. B. Yuan. "Real-time hand gesture recognition using finger segmentation." *Scientific World Journal*. vol. 2014. 2014. doi: 10.1155/2014/267872.
[20] W. Lu. Z. Tong. and J. Chu. "Dynamic hand gesture recognition with leap motion controller." *IEEE Signal Process Lett*. vol. 23. no. 9. pp. 1188–1192. Sep. 2016. doi: 10.1109/LSP.2016.2590470.
[21] M. I. Rusydi. A. Anandika. R. Adnan. K. Matsuhita. and M. Sasaki. "Adaptive Symmetrical Virtual Keyboard Based on EOG Signal." pp. 22–26. 2019.
[22] M. I. Rusydi. D. Saputra. D. Anugrah. S. Syafii. A. W. Setiawan. and M. Sasaki. "Real Time Control of Virtual Menu Based on EMG Signal from Jaw." *3rd Asia-Pacific Conference on Intelligent Robot Systems : ACIRS*. pp. 18–22. 2018.
[23] J. Hossain Gourob. S. Raxit. and A. Hasan. "A Robotic Hand: Controlled With Vision Based Hand Gesture Recognition System." in *2021 International Conference on Automation. Control and Mechatronics for Industry 4.0 (ACMI)*. 2021. pp. 1–4. doi: 10.1109/ACMI53878.2021.9528192.
[24] Y. Zhang. W. Yan. and A. Narayanan. "A Virtual Keyboard Implementation Based on Finger Recognition." in *International Conference on Image and Vision Computing New Zealand (IVCNZ)*. 2017.
[25] T.-H. Lee and H.-J. Lee. "Ambidextrous Virtual Keyboard Design with Finger Gesture Recognition." in *IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE. 2018.
[26] X. Chu. J. Liu. and S. Shimamoto. "A sensor-based hand gesture recognition system for Japanese sign language." in *LifeTech 2021 - 2021 IEEE 3rd Global Conference on Life Sciences and Technologies*. Institute of Electrical and Electronics Engineers Inc.. Mar. 2021. pp. 311–312. doi: 10.1109/LifeTech52111.2021.9391981.
[27] M. R. Islam. U. K. Mitu. R. A. Bhuiyan. and J. Shin. "Hand Gesture Feature Extraction Using Deep Convolutional Neural Network for Recognizing American Sign Language." in *4th International Conference on Frontiers of Signal Processing (ICFSP)*. 2018. pp. 115–119.
[28] S. Chaman. D. D'souza. B. D'mello. K. Bhavsar. and J. D'souza. "Real-time Hand Gesture Communication System in Hindi for Speech and Hearing Impaired." in *International Conference on Intelligent Computing and Control Systems (ICICCS)*. 2018. pp. 1954–1958.
[29] M. I. Rusydi. Syafii. R. Hadelina. E. Kimin. A. W. Setiawan. and A. Rusydi. "Recognition of sign language hand gestures using leap motion sensor based on threshold and ANN models." *Bulletin of Electrical Engineering and Informatics*. vol. 9. no. 2. pp. 473–483. Apr. 2020. doi: 10.11591/eei.v9i2.1194.
[30] M. S. Verdadero. C. O. Martinez-Ojeda. and J. C. Dela Cruz. "Hand Gesture Recognition System as an Alternative Interface for Remote Controlled Home Appliances." in *IEEE 10th International Conference on Humanoid. Nanotechnology. Information Technology. Communication and Control. Environment and Management (HNICEM)*. 2018.
[31] V. V. T. Reddy. T. Dhyanchand. G. V. Krishna. and S. Maheshwaram. "Virtual Mouse Control Using Colored Finger Tips and Hand Gesture Recognition." in *Proceedings of 2020 IEEE-HYDCON International Conference on Engineering in the 4th Industrial Revolution. HYDCON 2020*. Institute of Electrical and Electronics Engineers Inc.. Sep. 2020. doi: 10.1109/HYDCON48903.2020.9242677.
[32] Vi. I. Saraswati. R. Sigit. and T. Harsono. "Eye Gaze System to Operate Virtual Keyboard." in *International Electronics Symposium (IES)*. 2016. pp. 175–179.
[33] Y. Kim and B. Toomajian. "Hand Gesture Recognition Using Micro-Doppler Signatures with Convolutional Neural Network." *IEEE Access*. vol. 4. pp. 7125–7130. 2016. doi: 10.1109/ACCESS.2016.2617282.

AUTHOR(S) BIOGRAPHY

Arrya Anandika

He finished bachelor degree in Computer Engineering and master degree in Electrical Engineering Universitas Andalas. He had been a young lecturer since 2022 and become Head of Laboratory Digital System and Computer Architecture in Computer Engineering Department. Universitas Andalas. He is interested in biosignal and Human Computer Interaction research especially in developing assistive technology to help disable people.

Muhammad Ilhamdi Rusydi

He received the bachelor's and master's degrees in electrical engineering from the Institute of Technology Bandung. Indonesia. and the Ph.D. degree from Gifu University. Japan. in 2014. He had been a Young Lecturer at the Universitas Andalas. since 2005. and became an Associate Professor. in 2018. He teaches biosignal. robotics. and control classes. He has been the Head of the Digital Electronics Laboratory. since 2016. and also the Head of the Electrical Engineering Department. since 2020. His research interest includes developing assistive technology to help disabled people.

Pepi Putri Utami

She is received the bachelor's degree in electrical engineering from the Universitas Andalas. Indonesia. During college. she focused on electronics. robotics. and control system. She was an Assistant with the Digital Electronics Laboratory. in 2016. and completed his research on assistive technology to help people with disabilities. in 2019. She has been active in several non-academic student organizations.

Rizka Hadelina

Rizka Hadelina received her bachelor's degree in computer engineering and master's degree in electrical engineering from Universitas Andalas in 2017 and 2021. She was a Biomedical Engineering Research Group member from 2018 to 2021. She currently works as a lecturer at Computer Engineering Department. Universitas Andalas. and teaches intelligent systems and embedded systems. Her main research interests are artificial intelligence and embedded systems. especially for medical purposes. (e-mail: rizkahadelina@it.unand.ac.id)

Minoru Sasaki

He earned a bachelor's degree in mechanical engineering at Yamagata University in 1980. Then. he continued with master's and doctoral degrees at Tohuku University in 1982 and 1985. He started his academic career at Tohuku University in 1985 and became a full professor at Gifu University in 2003. His Researches that have been carried out include industrial automation. robotics. vibration control. sound engineering and bioengineering. On the basis of this contribution. he received many awards in Japan and became the best professor at Gifu University in 2016. He has also been a visiting professor outside of campus in Japan. including the University of California Los Angeles in the USA. University of Dar-El-Salaam in Brunei. and Pan africa university of science and technology in Africa.

 https://doi.org/10.25077/jitce.7.01.40-48.2023