Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3, 2930-2940
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i3.5889

Analysis of the applicability of an artificial intelligence technology to classify hand movements of people with or without limited hand movement, using AI-motion SW: An observational study

Won-Jin Bae[1], Nam-Hae Jung[2], Young-Jin Jung[3], Kyung-Yoon Kam[4*]
[1]Department of Occupational Therapy, Donggang University, Gwangju, Republic of Korea.
[2]Department of Occupational Therapy, Dongseo University, Busan, Republic of Korea.
[3]Department of School of Healthcare and Biomedical Engineering, Chonnam National University, Yeosu, Republic of Korea.
[4]Department of Occupational Therapy, College of Healthcare Medical Science and Engineering, Inje University, Gyeongsangnam-do, Republic of Korea; kamlapa@inje.ac.kr (K.Y.K.).

Abstract: The purpose of this study was to analyze hand movements using artificial intelligence. From September 1, 2020, to December 30, 2020, a total of 200 individuals, including those with limited hand movements and healthy individuals, were included in the study. Photographs were acquired using a smartphone camera to establish a protocol for hand movements, targeting 100 healthy individuals and 100 individuals with limited hand movements due to central nervous system diseases. The protocol for hand motion video recording using a smartphone camera was as follows: During the hand movement, the participant sat on a chair sufficiently high to touch the floor and did not lean against the back. When the participant sat on the chair and placed the forearm on the desk, the elbow joint was bent at 90°, and the arm was placed on the desk to perform hand movements. The participant placed the forearm in a neutral position on the desk. The smartphone camera was positioned 45 cm in front of the palm at the same height as that of the hand, and then a video was recorded. The data collected to determine the hand movements of all subjects were used for artificial intelligence machine learning analyses. An independent t-test was performed to determine the difference between the two groups. Significant differences between the two groups were observed ($p < 0.001$). The motion analysis through images showed that the analysis of hand motions using artificial intelligence is feasible. The analysis of healthy individuals and those with limited hand movements confirmed that hand movement alone can be used to quickly and accurately predict hand functions.

Keywords: *Artificial intelligence, Hand function estimation, Hand movement, Hand, Machine learning, Occupational therapy.*

1. Introduction

In the field of occupational therapy, hand function evaluation provides an important information for the treatment of a patient [1]. A common approach to evaluate the hand functions is to measure the hand strength and range of motion. These are factors that directly affect the performances of functional tasks and are considered important in clinical practice [2]. In addition, activities such as grasping and pinching are important factors that allow the fingers to bend naturally to perform daily life activities [3]. Various evaluation tools are used in the field of occupational therapy to accurately evaluate the hand function. Among them, the hand function evaluation tools frequently used in clinical practice include the box and block test, Purdue pegboard test, Jamar dynamometer, and pinch gauge have been verified for validity and reliability [4-6]. Various studies have been conducted to track hand movements through artificial intelligence (AI) and images [7, 8]. The pattern of hand movements varies depending

History: Received: 16 January 2025; Revised: 4 March 2025; Accepted: 10 March 2025; Published: 29 March 2025
* Correspondence: kamlapa@inje.ac.kr

on the task being performed rather than being simple and repetitive. Therefore, the three-dimensional (3D) motion camera system, smart glove, and Inertial Measurement Unit (IMU)-based motion analysis system are used for quantitative and objective analyses of hand movements. However, these systems are expensive and there are limitations in installation and analysis, so that occupational therapists cannot easily access them. A glove that attaches a sensor to the palm and fingers to tract the movement of the hand can provide an accurate information about the movement. However, this is expensive due to the attachment of the sensors, and movement is not natural due to wearing gloves [9]. The method of recognizing hand movements based on images has the advantage of not wearing a separate device. A high-performance 3D camera is used for an accurate measurement of hand movements using a neural network. Using this method, extensive computations are required to predict coordinate values [10, 11]. However, with the development of the AI technology, software for tracking and analyzing hand movements is being developed and studies using deep learning and machine learning techniques to accurately analyze the hand using images have been carried out [12-15]. Among them, AI technologies that analyze motion using laptop cameras and smartphone cameras are being introduced [16, 17]. In the case of smartphone cameras and laptop cameras, a dual camera, higher lens, or camera function specialized for high-speed shooting are installed. They contain camera functions combined with future technologies, such as AI and augmented reality. Although it is relatively inexpensive, it maximizes the user's usability and has a high potential for a simple use in the clinical field. Such AI technology could be used for hand function evaluation in rehabilitation field. However, little research has been carried out on its practical application. Therefore, this study aimed to investigate the feasibility of using AI for hand function evaluation. The studies on AI and hands have been focused on whether they can improve performance or train faster. Most of the studies focused on analyzing hand movements. However, no study was conducted with the purpose of distinguishing between healthy people and those with limited hand movements.

2. Materials and Methods

2.1. Participants and Duration

This study was carried out in the period of September 2020 to December 2020, targeting 100 healthy people and 100 stroke patients. The purpose and method of this study were fully explained to the subjects and the study was carried out with those who agreed to participate. The study subjects were required to have 18 years or more or limited hand movements in left side due to stroke. This study was approved after deliberation by the Institutional Review Board (IRB) of Inje University (Inje University approval number: INJE 2019-06-019-009).

2.2. Procedure

To measure the movement of the hand, videos were acquired for the general public and those with central nervous system diseases. A protocol was established to improve the accuracy and analysis of hand movements. The video image can be analyzed through fewer layers owing to the protocolized motion. If the input layer is large, the accuracy may be degraded because there are many input areas. However, in this study, as the input layer area is small, the accuracy can be improved and information on the intended motion of the researcher can be provided.

2.2.1. Protocol for Video Recording of Hand Movements

The protocol for hand motion video recording using a smartphone camera was as follows. During the hand movement, the participant sat on a chair sufficiently high to touch the floor and did not lean against the back. When the participant sat on the chair and placed the forearm on the desk, the elbow joint was bent by 90° and the arm was placed on the desk to perform hand movements. The participant placed the forearm neutral on the desk. The smartphone camera was placed 45 cm in front of the palm at the same height as that of the hand, and then a video was recorded. The participants performed flexion and extension of the metacarpophalangeal (MCP), proximal interphalangeal (PIP), and distal interphalangeal (DIP) joints with the abduction of four fingers, excluding the thumb (Figure 1). Example image comparing the hands of a healthy person and a stroke patient (Figure 2).

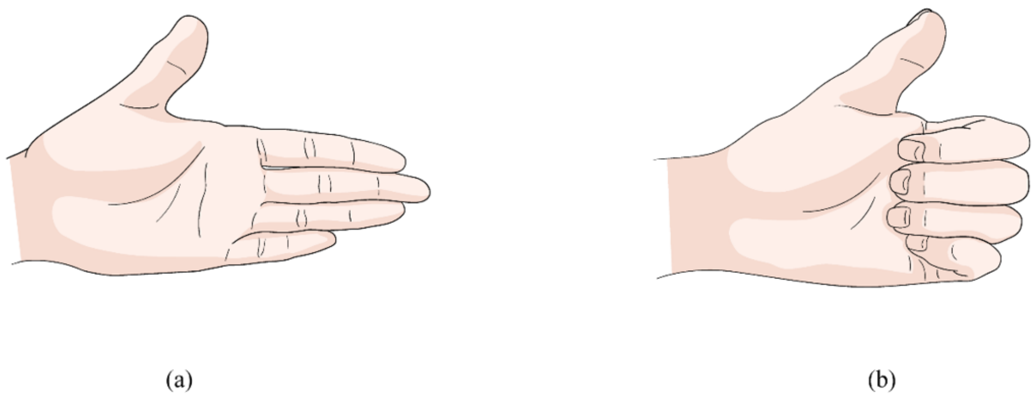

Figure 1.
(**a**) Extension of the second to fifth finger (starting position); (**b**) Flexion position of the second to fifth finger.

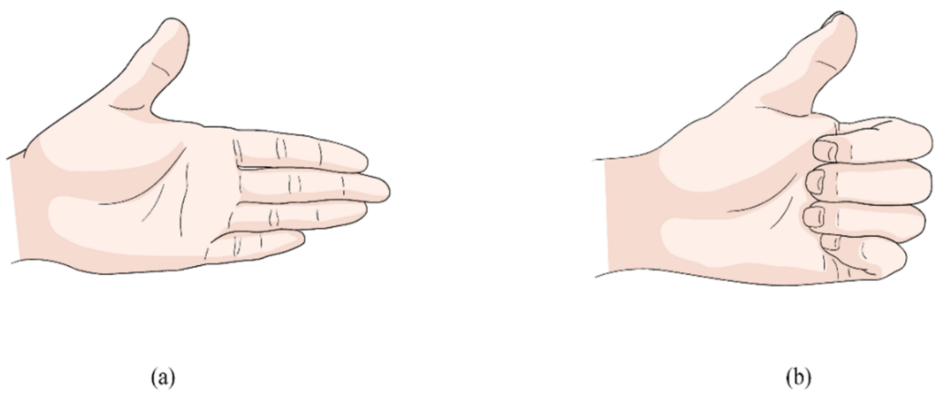

Figure 2.
Example image comparing the hands of a healthy person and a stroke patient.

2.2.2. Hand Movement Analysis Method

This study used a method of finding 21 points in an image (Figure 3) and analyzing the data using 3D coordinates. The movement distances and movement angles of the second to fifth finger were analyzed. The position of the hand was estimated using an analysis algorithm.

The position information on the motion input from the image was expressed as a 3D coordinate value through MediaPipe. It was possible to check the positions of 21 precise key points within the hand area. A list of 21 tracked coordinates is expressed as x, y, and z values as the output. MediaPipe Hands is Google's opensource framework that provides source code to create machine learning models from various data platforms regardless of platform .x is the horizontal movement(width), y is the vertical movement(height), and z is the depth.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3: 2930-2940, 2025
DOI: 10.55214/25768484.v9i3.5889

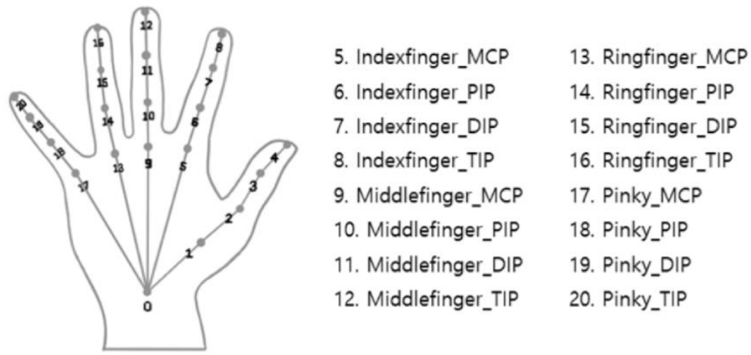

Figure 3.
21 markers expressed as 3D coordinate values.

Abbreviation: CMC, carpometacarpal; DIP, distal interphalangeal; IP, interphalangeal; MCP, metacarpophalangeal; PIP, proximal interphalangeal; TIP, fingertip.
(retrieved from https://google.github.io/mediapipe/solutions/hands.html)

2.3. AI-Based Motion Data Analysis Environment and Feature Selection

In this study, the location information acquired using MediaPipe was analyzed using AI-Motion (www.neurorehap.com, South Korea). AI-Motion software can calculate the Euclidean distance between the MCP and the fingertip and the vector inner product of the DIP joint. All processes were performed in an Intel(R) Core (TM) i7-9700K and 64.0GB RAM environment on a personal computer with Windows 10 operating system.

The AI technology was applied to the 3D location information data extracted from the video image captured by a smartphone camera to provide the 21-coordinate information from each viewpoint. This coordinate information provides not only the characteristics of the movement speed and acceleration of the hand over time, but also the range of motion of the hand. A quantitative analysis was carried out by selecting the angle according to the patient's hand function movement and distance between a specific area as one of the features identified with the naked eye.

2.3.1. Distance Evaluation Between the MCP and Fingertips (TIP)

The distance between the MCP and fingertips is one of the visual features that an occupational therapist can easily check between the patient and normal groups. The features can be confirmed with the naked eye. However, to use them as quantitative and objective indicators, a mathematical calculation was performed using MATLAB.

The numerical calculation was carried out to obtain the index by calculating the Euclidean distance using the coordinates of each MCP of the four TIPs (p), excluding the thumb, and coordinates of the TIPs (q)

$$\text{Distance}(p,q) = \sqrt{\sum_{i}^{n}(q_i - p_i)^2},$$

Where n is set to three because the3D space (x,y,z) is used. As the Euclidian distance is calculated at each time point, the difference between the maximum value (when the hand is open) and minimum value (when the hand is bent) is calculated. The difference between the two groups was analyzed by evaluating the change and selecting its maximum as an indicator. The maximum of the change at each time point calculated in this manner corresponds to one of the four fingers per subject. The average of the maximum distance change was calculated as an index of one subject.

2.3.2. Joint Angle at DIPs (Without the Thumb)

It was assumed that two lines (DIP to TIP and DIP to PIP) created based on DIP were two vectors. After calculating the values of the two vectors in the 3D space, the joint angle was calculated for each viewpoint by calculating the angles for the two vectors,

$$\mathrm{Vector_A} = \overline{TIP - DIP} = \vec{\mathrm{A}},$$

$$\mathrm{Vector_B} = \overline{TIP - DIP} = \vec{B},$$

where the operation of (TIP-DIP) is the calculation of the difference between the coordinate values in the rectangular coordinate system of two different points, which is then applied to the vector operation,

$$\vec{\mathrm{A}} \cdot \vec{B} = \left|\vec{\mathrm{A}}\right|\left|\vec{B}\right|\cos(\theta),$$

$$\mathrm{Angle}\left(\vec{A}, \vec{B}\right) = \theta = \arccos\left(\frac{\vec{\mathrm{A}} \cdot \vec{B}}{\left|\vec{\mathrm{A}}\right|\left|\vec{B}\right|}\right).$$

The angle at each time point calculated in this manner corresponds to each of the four fingers per subject. To use it as an index to evaluate the function of holding and opening of the hand, the change in the angle was calculated. After calculating the average of the changes in the four values, the value with the maximum change at all time points was used as an index.

2.4. Statistical Analysis

A total of 200 data were analyzed for the normal group and hand dysfunction group. The results were used to analyze the statistical significance between the two groups using an independent *t*-test. A total of 200 data were analyzed for the normal group and hand dysfunction group. The results were used to analyze the statistical significance between the two groups using an independent *t*-test. The data set provided *x*, *y*, and *z* coordinate values for each joint of the hand. The minimum and maximum values for the distance of motion, angle of motion, and space between points were calculated and the two groups were compared.

3. Results and Discussion

3.1. Estimation of 3D Coordinate Information of the Smart Phone Camera Image

Using AI-Motion SW, the 3D coordinate information was derived from the image captured by the smartphone camera. Figure 4(a) shows a skeleton model that connectsthephotographed3D coordinates by superposing on the hand. The label number of each position is provided. Figure 4(b) shows the 3D coordinate information estimated when the fist is clenched by superimposing it on the image, while Figure 4(c) shows the 3D coordinate information when the hand is opened. Figure4 confirms that the 3D position estimation algorithm based on the AI technology derives fairly accurate results when are judged with the naked eye.

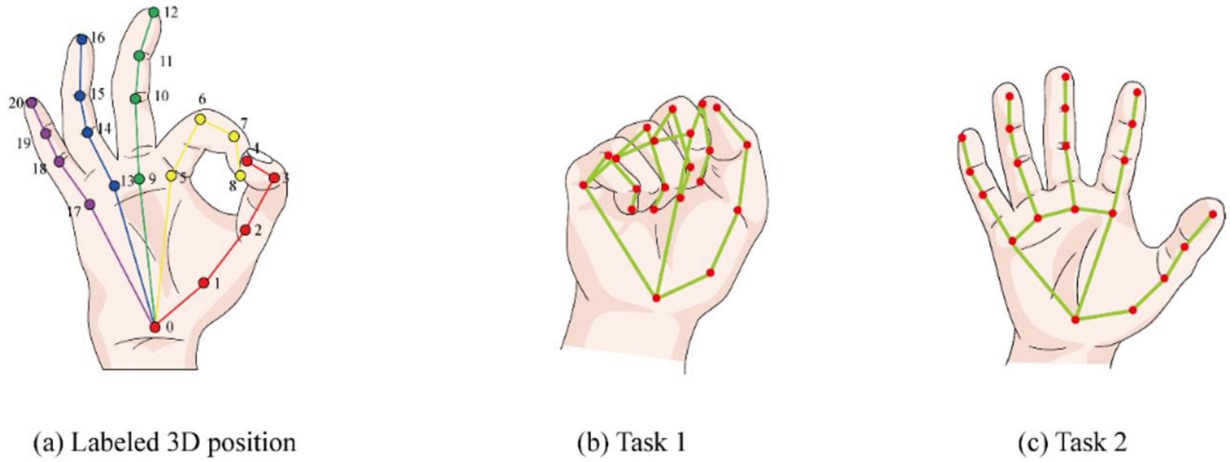

Figure 4.
Estimation of 3D coordinate information of smartphone camera images.

3.2. Distance Evaluation Between MCP and TIP

The analysis of the image showing the distance difference between the MCP and TIP for each finger over time confirms a pattern in which the distance change was constant when the four fingers clenched the fist and when they opened the hand. However, for the group with the impaired hand function, we can estimate that the strong tremor is added to the pattern. The pattern of the change in movement is not clear. In addition, graphs showing the difference between the maximum and minimum values of the four fingers are presented. The graph shows that the healthy person exhibits a slightly larger change than that of the patient group (Figure 5). In the independent *t*-test, the *p* value is smaller than 0.01, indicating a significant statistical difference.

Each finger over time confirms a pattern in which the distance change was constant when the four fingers clenched the fist and when they opened the hand. However, for the group with the impaired hand function, we can estimate that the strong tremor is added to the pattern. The pattern of the change in movement is not clear. In addition, graphs showing the difference between the maximum and minimum values of the four fingers are presented. The graph shows that the healthy person exhibits a slightly larger change than that of the patient group (Figure 5) (Table 1). In the independent *t*-test, the *p* value is smaller than 0.01, indicating a significant statistical difference.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 3: 2930-2940, 2025
DOI: 10.55214/25768484.v9i3.5889

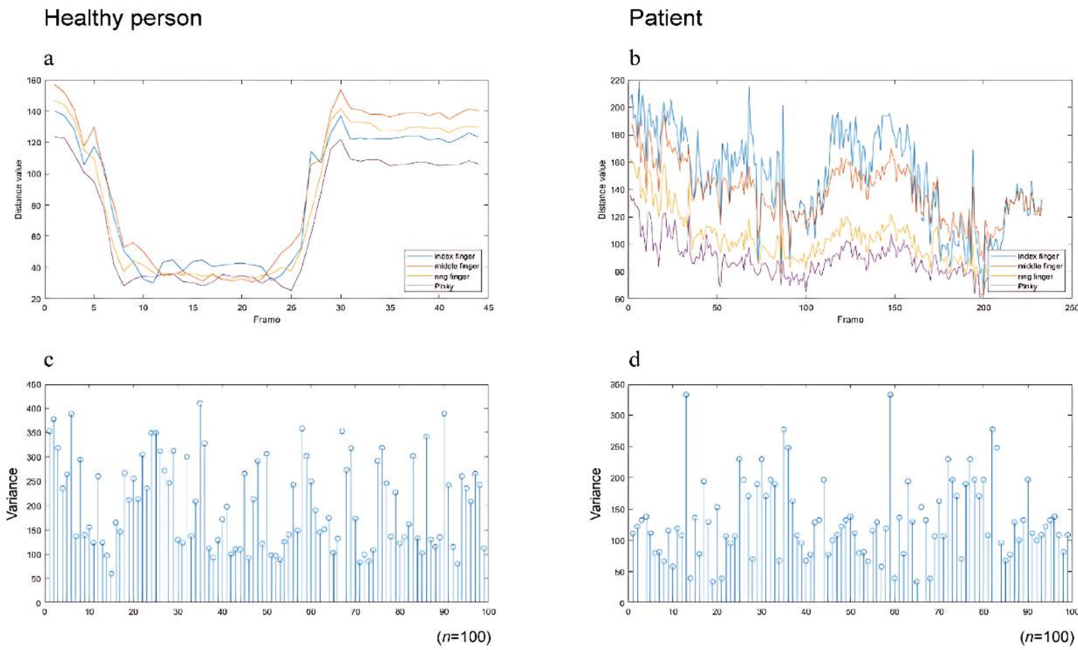

Figure 5.
Result of Distance evaluation between MCP and TIP.
Note: *** P-value = 5.0122e-10.

Table 1.
Difference in MCP and fingertip distance between healthy people and patients.

	Healthy people (n=100)		Patients (n=100)		t
	M	***SD***	***M***	***SD***	
Distance between MCP and fingertip	204.11	±91.79	131.99	±62.44	6.464***

Note: ***p<.001

3.3. Joint Angles at DIPs

The pattern of change in the DIP joint angle of the four fingers was different between the healthy and patient groups (Table 2). The vertical value of the graph is expressed in radians. The maximum value of the change during the movement is slightly larger in the healthy group than in the patient group. In Figure 6, the difference between the values is shown in the stem plot, which lists the absolute difference of the maximum change between the two groups as data from 100 people.

Table 2.
Difference in DIP joint angle between healthy people and patients.

	Healthy people (n=100)		Patients (n=100)		t
	M	***SD***	***M***	***SD***	
DIP joint angle	1.04	±.31	0.76	±.36	5.918***

Note: ***p<.001.

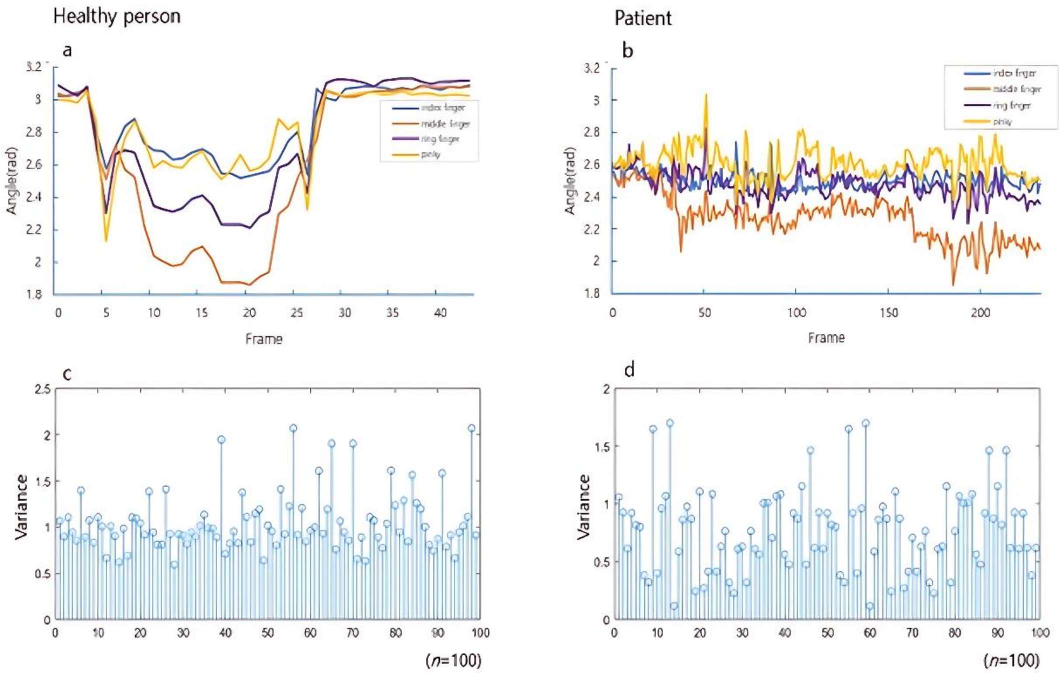

Figure 6.
Results of Joint angle at DIPs.
Note: *** P-value = 7.34903e-09.

3.4. Discussion

In this study, hand movements were analyzed using hand movement images captured with a single camera using artificial intelligence. It was possible to determine the difference in movement between the healthy and patient groups. This result supports previous studies that revealed that the analysis using AI for hand movements is effective [18-21]. The significance of this study is that a quantitative analysis was performed and classification was carried out by using AI-Motion to images of hand movements of healthy people and patients without the hand function evaluation tool commonly used in occupational therapy. The image analysis using AI-Motion showed that the healthy person had more constant hand movement angle and distance than those of the patient. These results are similar to the results of previous studies that demonstrated that the angle and distance of hand movements are not constant for people with limited hand functions, compared to the general population [22-24].

There are differences in hand function between the general population and that with limited hand functions [25, 26]. However, existing studies have only been able to explain the relationship with the normal range using the hand function evaluation tool, while no studies have been carried out to classify hand functions using machine learning.

In medical settings, it is inevitable to use hand function evaluation tools to accurately evaluate hand functions in general. Only evaluation tools with demonstrated reliability and validity among the hand function evaluation tools should be used to accurately measure functions. This finding suggests different results [1, 27]. The studies on hand movements using AI generally focused on tracking hand movements through learning, maximizing visual effects by removing noise, reproducing movements, or recognizing movements [10, 21, 28]. While no studies on classification of healthy people and persons with limited hand movements have been carried out. Therefore, the aim of this study was to analyze the function of the hand after photographing protocolized movements of a general person and person with limited hand functions using a smartphone camera. The effectiveness of the hand motion analysis using AI-Motion was demonstrated. As a limitation of this study, there were cases in which the AI could not recognize the motion information because the photographing was performed using one camera. To accurately recognize the movement distance and movement angle with respect to time in the future, improvements are required through the development of an engineering algorithm. Analyses of the movement speed, movement trajectory, and movement direction through the development of the algorithm are considered possible. In this study, adults over 18 years and patients who could understand and follow the instructions of the researcher were selected as subjects. Non adults may not have fully developed hand functions. Patients with cognitive impairments were excluded owing to limitations in following the instructions. However, if the limited information of the frame for an accurate learning is considered in the selection of the subject, a more accurate analysis will be performed. The size of the motion information extracted based on the deep learning algorithm of the general population and those with limited hand functions showed different results for each video, which hindered the extraction process. Thus, an optimal frame design is needed. The function of the hand is an important factor representing the physical ability [29]. The approach using AI along with the hand function evaluation tool is a science-based method, reflecting the academic characteristics. The deep learning and machine learning have been used as such techniques of AI. Analysis of the movements of the general persons and persons with limited hand functions through the AI-Motion showed significant differences in the moving distance over time and angle at which the flexion occurs. We demonstrated that the hand movement analysis using AI is feasible. The effectiveness of hand movement analyses using AI and computer techniques has been verified by several studies [30]. However, studies targeting the general public and those with limited hand functions were lacking. This study showed that hand movements can be quickly and accurately analyzed using AI. In addition, we showed that it is possible to quickly and accurately predict the function of the hand with the movement of the hand through AI. In this study, only the 3D coordinate information was extracted using the AI technology. A system that can identify and classify meaningful features from the coordinate information using AI is required. As a limitation in this study, since the shooting was carried out using one camera, when the frame length was less than 1 second, AI-Motion could not recognize the motion information.

4. Conclusion

The purpose of this study was to analyze hand movements using AI for healthy people and those with limited hand functions. We demonstrated that the hand movement analysis using AI is feasible. An image analysis through AI was performed to determine the difference in hand movement in a standard position. Significant differences in hand movements were observed between the healthy people and those with limited hand movements.

This study showed that hand function can be predicted quickly and accurately just by analyzing hand movement. In addition, we propose a method to evaluate hand function using artificial intelligence in the clinical field. This strategy can be applied in the whole field of rehabilitation including occupational therapy in the future.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] H.-M. Chen, C. C. Chen, I.-P. Hsueh, S.-L. Huang, and C.-L. Hsieh, "Test-retest reproducibility and smallest real difference of 5 hand function tests in patients with stroke," *Neurorehabilitation and neural repair*, vol. 23, no. 5, pp. 435-440, 2009. https://doi.org/10.1177/1545968308331146

[2] I. Faria-Fortini, S. M. Michaelsen, J. G. Cassiano, and L. F. Teixeira-Salmela, "Upper extremity function in stroke subjects: relationships between the international classification of functioning, disability, and health domains," *Journal of Hand Therapy*, vol. 24, no. 3, pp. 257-265, 2011. https://doi.org/10.1016/j.jht.2011.01.002

[3] Z.-M. Li and J. Tang, "Coordination of thumb joints during opposition," *Journal of biomechanics*, vol. 40, no. 3, pp. 502-510, 2007. https://doi.org/10.1016/j.jbiomech.2006.02.019

[4] V. Mathiowetz, N. Kashman, G. Volland, K. Weber, M. Dowe, and S. Rogers, "Grip and pinch strength: normative data for adults," *Arch Phys Med Rehabil*, vol. 66, no. 2, pp. 69-74, 1985.

[5] D. K. Lindstrom-Hazel and N. VanderVlies Veenstra, "Examining the Purdue pegboard test for occupational therapy practice," *The Open Journal of Occupational Therapy*, vol. 3, no. 3, p. 5, 2015. https://doi.org/10.15453/2168-6408.1178

[6] J. V. Bellace, D. Healy, M. P. Besser, T. Byron, and L. Hohman, "Validity of the Dexter Evaluation System's Jamar dynamometer attachment for assessment of hand grip strength in a normal population," *Journal of hand therapy*, vol. 13, no. 1, pp. 46-51, 2000. https://doi.org/10.1016/s0894-1130(00)80052-6

[7] O. K. Oyedotun and A. Khashman, "Deep learning in vision-based static hand gesture recognition," *Neural Computing and Applications*, vol. 28, no. 12, pp. 3941-3951, 2017. https://doi.org/10.1007/s00521-016-2294-8

[8] O. Koller, H. Ney, and R. Bowden, "Deep hand: How to train a cnn on 1 million hand images when your data is continuous and weakly labelled," in *In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3793-3802)*, 2016.

[9] M. Schröder, C. Elbrechter, J. Maycock, R. Haschke, M. Botsch, and H. Ritter, "Real-time hand tracking with a color glove for the actuation of anthropomorphic robot hands," presented at the In 2012 12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012) (pp. 262-269). IEEE, 2012.

[10] M. Oberweger, P. Wohlhart, and V. Lepetit, "Hands deep in deep learning for hand pose estimation," *arXiv preprint arXiv:1502.06807*, 2015. https://doi.org/10.48550/arXiv.1502.06807

[11] J. Wang, Z. Liu, Y. Wu, and J. Yuan, "Learning actionlet ensemble for 3D human action recognition," *IEEE transactions on pattern analysis and machine intelligence*, vol. 36, no. 5, pp. 914-927, 2013. https://doi.org/10.1109/TPAMI.2013.198

[12] C. Keskin, F. Kıraç, Y. E. Kara, and L. Akarun, "Real time hand pose estimation using depth sensors," *Consumer Depth Cameras for Computer Vision: Research Topics and Applications*, pp. 119-137, 2013. https://doi.org/10.1007/978-1-4471-4640-7_7

[13] S. Melax, L. Keselman, and S. Orsten, "Dynamics based 3D skeletal hand tracking," in *In Proceedings of the ACM SIGGRAPH Symposium on Interactive 3D Graphics and Games (pp. 184-184)*, 2013.

[14] I. Oikonomidis, N. Kyriazis, and A. A. Argyros, "Full dof tracking of a hand interacting with an object by modeling occlusions and physical constraints," presented at the In 2011 International Conference on Computer Vision (pp. 2088-2095). IEEE. https://doi.org/10.1109/ICCV.2011.6126483, 2011.

[15] D. Tang, H. Jin Chang, A. Tejani, and T. K. Kim, "Latent regression forest: Structured estimation of 3d articulated hand posture," in *In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3786-3793). https://doi.org/10.1109/CVPR.2014.490*, 2014.

[16] M. Hu, F. Shen, and J. Zhao, "Hidden Markov models based dynamic hand gesture recognition with incremental learning method," presented at the In 2014 international joint conference on neural networks (IJCNN) (pp. 3108-3115). IEEE, 2014.

[17] H. Lahiani, M. Elleuch, and M. Kherallah, "Real time hand gesture recognition system for android devices," presented at the In: 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA), Marrakech, Morocco, 2015, 591–559. https://doi.org/10.1109/ISDA.2015.7489184, 2015.

[18] L. Liu, J. Xing, H. Ai, and X. Ruan, "Hand posture recognition using finger geometric feature," in *In Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012) (pp. 565-568). IEEE*, 2012.

[19] M. A. Livingston, J. Sebastian, Ai, Z., and J. W. Decker, "Performance measurements for the Microsoft Kinect skeleton," presented at the In 2012 IEEE Virtual Reality Workshops (VRW) (pp. 119-120). IEEE, 2012.

[20] P. Trigueiros, A. F. Ribeiro, and L. P. Reis, "A comparative study of different image features for hand gesture machine learning," presented at the In: 5th International Conference on Agents and Artificial Intelligence (ICAAI), Barcelona, Spain, 2013, 51–61. DOI: https://doi.org/10.5220/0004200100510061, 2013.

[21] A. Moin *et al.*, "A wearable biosensing system with in-sensor adaptive machine learning for hand gesture recognition," *Nature Electronics*, vol. 4, no. 1, pp. 54-63, 2021. https://doi.org/10.1038/s41928-020-00510-8

[22] J. A. Franck, R. J. E. M. Smeets, and H. A. M. Seelen, "Changes in arm-hand function and arm-hand skill performance in patients after stroke during and after rehabilitation," *PloS one*, vol. 12, no. 6, p. e0179453, 2017. https://doi.org/10.1371/journal.pone.0179453

[23] A. Roby-Brami, A. Feydy, M. Combeaud, E. Biryukova, B. Bussel, and M. F. Levin, "Motor compensation and recovery for reaching in stroke patients," *Acta neurologica scandinavica*, vol. 107, no. 5, pp. 369-381, 2003. https://doi.org/10.1034/j.1600-0404.2003.00021.x

[24] B. C. Vermillion, A. W. Dromerick, and S. W. Lee, "Toward restoration of normal mechanics of functional hand tasks post-stroke: subject-specific approach to reinforce impaired muscle function," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 8, pp. 1606-1616, 2019. https://doi.org/10.1109/TNSRE.2019.2924208

[25] K. Allgöwer and J. Hermsdörfer, "Fine motor skills predict performance in the Jebsen Taylor Hand Function Test after stroke," *Clinical Neurophysiology*, vol. 128, no. 10, pp. 1858-1871, 2017. https://doi.org/10.1016/j.clinph.2017.07.408.

[26] B. P. Cunha, S. M. S. F. de Freitas, and P. B. de Freitas, "Assessment of the ipsilesional hand function in stroke survivors: the effect of lesion side," *Journal of Stroke and Cerebrovascular Diseases*, vol. 26, no. 7, pp. 1615-1621, 2017. https://doi.org/10.1016/j.jstrokecerebrovasdis.2017.02.023

[27] E. Croarkin, J. Danoff, and C. Barnes, "Evidence-based rating of upper-extremity motor function tests used for people following a stroke," *Physical therapy*, vol. 84, no. 1, pp. 62-74, 2004. https://doi.org/10.1093/ptj/84.1.62

[28] P. Trigueiros, F. Ribeiro, and L. P. Reis, "A comparison of machine learning algorithms applied to hand gesture recognition," presented at the In 7th Iberian conference on information systems and technologies (CISTI 2012) (pp. 1-6). IEEE, 2012.

[29] V. K. Ranganathan, V. Siemionow, V. Sahgal, and G. H. Yue, "Effects of aging on hand function," *Journal of the American Geriatrics Society*, vol. 49, no. 11, pp. 1478-1484, 2001. https://doi.org/10.1046/j.1532-5415.2001.4911240.x

[30] M. Oudah, A. Al-Naji, and J. Chahl, "Hand gesture recognition based on computer vision: A review of techniques," *Journal of Imaging*, vol. 6, no. 8, p. 73, 2020. https://doi.org/10.3390/jimaging6080073