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The Design of Stroke Rehabilitation Using Artificial Intelligence K.A.K.I (Kinesthetic Augmented Kinematic Inference)

Yong Saan Cern* & Yeoh Sheng Ze

Sekolah Menengah Jenis Kebangsaan Katholik,
Jalan 10/3, Seksyen 10, 46000 Petaling Jaya, Selangor, Malaysia

**Corresponding author: yong.saancern@gmail.com*

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ABSTRACT

Stroke is a major cause of disability worldwide that affects many people every year. Stroke rehabilitation is a process that helps stroke patients regain their lost function and improve their quality of life. However, the recovery process varies widely depending on the severity of stroke and other factors such as age, health and type of stroke. Many elderly patients face difficulties in attending rehabilitation centers due to various factors such as cost, distance and congestion. Therefore, this paper proposes methods to help stroke patients do rehabilitation exercises at home using the latest technology. Our project consists of interactive exercises that are customized to the skill level of the patients, hardware sensor inputs that can measure the strength of the hand movement of the patients, embedded processing board with camera that can detect and guide the movement of the patients and machine learning using convolutional neural network (CNN) that can analyze the movement data and provide feedback and motivation to the patients. The effectiveness of the proposed system is evaluated by the improvements in patients' conditions through pre- and post-exercise tests. Overall, our kinesthetic augmented kinematic inferencing methods appear to be more effective than conventional methods for post-stroke rehabilitation. This project demonstrates a promising solution to enhance stroke rehabilitation, recovery and quality of life.

Keywords: Machine learning; interactive exercises; convolution neural network; artificial intelligence

INTRODUCTION

Stroke is among the top three leading cause of death and disability-adjusted life-years lost (DALYs) in the world (GBD 2019 Stroke Collaborator, 2019). The estimated global cost of stroke is over US$721 billion, equivalent to 0.66% of the global GDP. From 1990 to 2019, there are 70.0% increase in incident strokes, 43.0% deaths from stroke, 102.0% prevalent stroke, and 143.0% DALYs with majority of the cases occur in lower-income and lower-middle-income countries (Feigin et al. 2022). Stroke is a brain attack that happens when blood supply to a part of the brain is cut off, causing the death of brain cells (Langhorne et al. 2011; Lo et al. 2005). The brain damage if not fatal, may result in paralysis, sensory impairment and disability. The severity of stroke complications and ability to recover vary widely among individuals (Dobkin 2004). Rehabilitation which involves a series of well-directed and repetitive practice, helps to promote the intrinsic ability of the brain to rewire its circuits and remodel healthy brain tissue to take on lost functions (Wieloch et al. 2006; Kleim et al. 2008). It has a vital role in helping the stroke survivors to relearn lost skills so that they will be able to regain the best possible level of independence and quality of life (Billinger et al. 2014; Sacco et al. 2006). Current rehabilitation system relies mainly on extended hospital stay and regular visits to specialized outpatient medical facilities that require physical interactions with healthcare practitioners (Dodakian et al. 2017). This hospital-centered approach faces challenges to cope with growing patient load, shortage of trained manpower, and pressure of healthcare cost control. Hence, stroke patients do not receive maximal therapy dose despite the evidence that intensive high-dose rehabilitation on a long-term basis has positive impacts on sensorimotor function recovery and maintenance of function gains (Daly et al. 2019; Ward et al. 2019). In order to achieve the therapy dose required for function recovery, the patients need regular hospital visits (Stinear et al. 2020). The frequent travelling for hospital appointments incurs additional expenses and poses an extra financial burden to the patients (Young et al. 2009). The journey to hospitals might cause pain and discomfort to the stroke survivors who are mobility compromised (Dickerson et al. 2007). This condition may result in poor patient compliance and motivation. The problems were further exacerbated during Covid 19 pandemic as the standard of post-stroke care was impacted when there was no access to physical hospital-based rehabilitation program (Bersano et al. 2020; De Sousa et al. 2020; Richter et al. 2021). All these challenges have highlighted the need of shifting the current hospital-centred model of stroke care towards a more home-based one. With the new approach, stroke patients spend less time in medical facilities and perform home-based rehabilitation therapy with various solutions provided. This helps to decrease dependency on hospital strained resources, reduce patients' travelling time as well as increasing the patients' physiotherapy dose through self-directed rehabilitation (Lambercy et al. 2021). Artificial intelligence has a vital role in supporting this model by providing patients with various rehabilitation solutions. There are complementary robotic systems designed for various parts of the upper limb such as H-man (Chua et al. 2018), tenoexo (Butzer et al. 2019), eWrist (Lambercy et al. 2011), and ReHaptic Knob (Ranzani et al. 2020). There are also virtual reality exergames using passive gadgets such as gloves and orthoses (Nijenhuis et al. 2017). The breakthrough in machine learning, the study of computer algorithms that improve automatically through experience, also helps researchers to make quicker and more accurate assessment by providing more resources for data handling and processing (Shailaja et al. 2018; Alsheikh et al. 2014). Machine learning techniques can be applied in image classification, object recognition, speech recognition, and hand gesture recognition (Al-Hammadi et al. 2020). Convolutional neural network (CNN) was the most used classification method for vision-based sign language recognition studies since 2017 (Johari, R.T. et al. 2023). There are various important criteria for a successful implementation of an artificial intelligence aided homebased rehabilitation model. The technologies involved ought to be safe, robust and user friendly as the devices are used under minimal supervision. The rehabilitation technologies must also be scalable for the model to be sustainable and impactful. All these factors are crucial to gain the stroke patients acceptance and active involvement in home-based therapy (Neibling et al. 2021).

METHODOLOGY

In this project, we develop interactive exercises using artificial intelligence (AI) to help stroke patients engage in the exercises. The main component of the project is Kinesthetic Augmented Kinematic Inference (or in short, K.A.K.I). We use AI technology with machine learning capability via deep learning to evaluate post-stroke patients' rehabilitation performance using vision sensing. These images are then compared with trained datasets from a recommended rehabilitation healthcare practitioner or a normal person. The system can provide feedback and guidance to the patients based on the comparison.

Discipline and emotional aspect play a key part for a fast recovery. By using games and exercises guided by the artificial intelligent, this will allow a more stress free and fun factor that allows stroke patient to achieve a good and fast recovery. Vision sensing is used to feed the images into Deep Learning to evaluate post stroke patient's rehabilitation performance. In order to achieve large computational processing power which normal PC will have difficulty for real time image processing, we use Nvidia Jetson Nano single board computer to perform those Deep Learning neural networks.

FIGURE 1. Nvidia Jetson Nano single board computer with 128 CUDA or 128 GPU cores to perform large data processing in deep learning.

Nvidia Jetson Nano with 128 CUDA or Computational Unified Design Architecture has 128 GPUs similar to 128 CPUs that allows plethora of Deep Learning capability.

Deep Learning works with deep neural networks in two-stage processes:

1. First, a neural network used and trained, with its parameters determined using images as inputs and its desired output.
2. Then, the network is deployed to run inference, using its previously trained parameters to classify, recognize, and generally process unknown inputs.

This method is widely recognized within academia and industry that GPUs are the very suitable in training deep neural networks, due to speed and energy efficiency advantages compared to more traditional CPU-based platforms.

Nvidia Jetson Nano has ability to run a wide variety of advanced Deep Learning networks. We used convolution neural network (CNN) which is Resnet18 or Residual Network with 18 layers deep to balance between training time and effectiveness.

We applied our specific training on the CNN Resnet18 rather than the existing pre-trained datasets from the public cloud.

K.A.K.I. consists of a single board computer from Nvidia Jetson Nano with camera mounted on an adjustable pivot setup to monitor the progress of the stroke rehabilitation using artificial intelligence. K.A.K.I is using augmented learning from a camera and matches against normal trained person. We started off with simple hands and finger movement which are relatively easy for normal person but will pose a great difficulty for stroke patient which has affected muscle control disability in that area. K.A.K.I provides data information and allows analysis whether the stroke patients achieve the proper muscle control even for a simple thumbs up or down. More complex finger movement like displaying numbers in fingers are also evaluated and then augmented against trained data. K.A.K.I's deep learning capability allows not just simple thumb or finger coordination but has the ability to learn and inference any other complex hands and leg coordination. The components used in K.A.K.I are:

NVIDIA Jetson nano developer kit, MIPI CSI camera 5 megapixels, SD card class 10 extreme pro, Jetson nano casing, WIFI 8265AC NIC module, Mains 240VAC to 12V 5A adapter, 12V to 5V regulator XL4005 5A DC-DC step down voltage regulator, 5V relays 2 channel and short pieces of plastic Lego Technic are used as camera mount for camera.

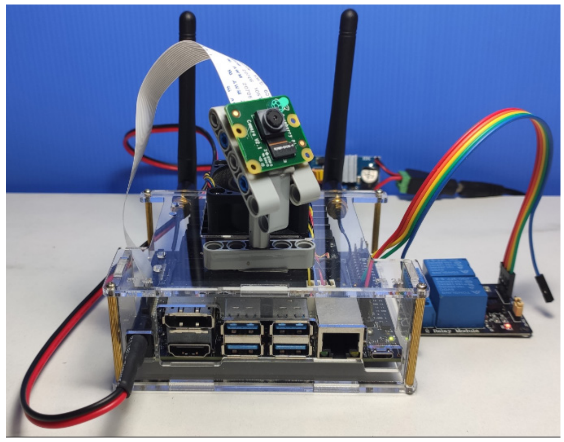


FIGURE 2. A fully setup Jetson Nano with camera ready to run K.A.K.I.

Stroke patient with disability on arms and hand may have difficulty to even raise thumbs up. Our rehabilitation methodology will gather all normal person thumbs up and thumbs down images from live camera to create the datasets for the neural network for classification. We train the Resnet18 CNN (convolution neural network) and feed into classification in order to differentiate a thumbs up or a thumbs down. Below is the flow chart of the training and classification.

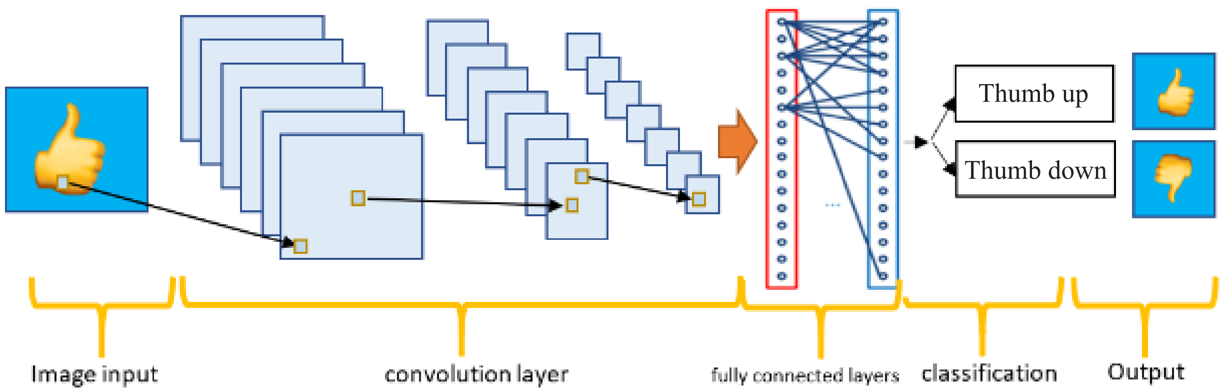


FIGURE 3. We use convolution neural network (CNN) to train and connect it to Resnet18 in fully connected layers for classifying a thumbs up or thumbs down.

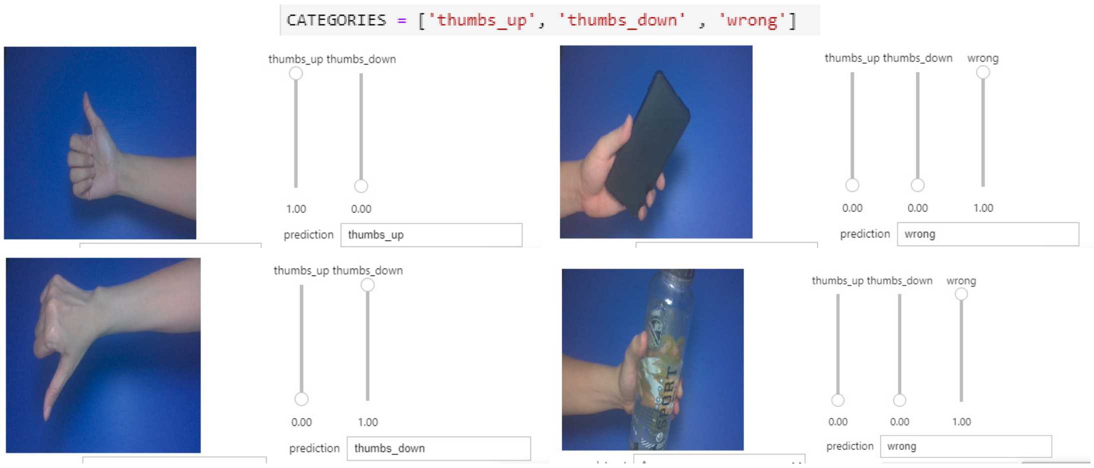


FIGURE 4. Training of difference gestures and object grasping.

We modified the codes from Jupyterlab notebook "classification.ipynb" to enable the training and classification. Using JupyterLab notebook, we collect trained images from 'Data Collection" function which will then store all the live images of 'thumbs up" and "thumbs down" images into classified folder. We used neural network model, Resnet18 CNN for Live Execution to observe the output of the Resnet18 classification. We turn on the Training capability so that all images that was collected will be feed into CNN Resnet18 for layer processing. We achieved 0.95 accuracy with 1.0 as highest accuracy number.

With the data collection from a normal person, training and successful classification, our CNN neural network deep learning is ready for evaluating on a stroke patient's hand coordination for thumbs up or down in comparison with a normal person. We extend the evaluation of the number gestures of 1, 2, 3, 4 and 5 using finger. When we prepared setup for K.A.K.I Deep Learning with CNN Resnet18 classification, a good lighting with flat color background is needed to ensure higher accuracy with good contrast of the subject.

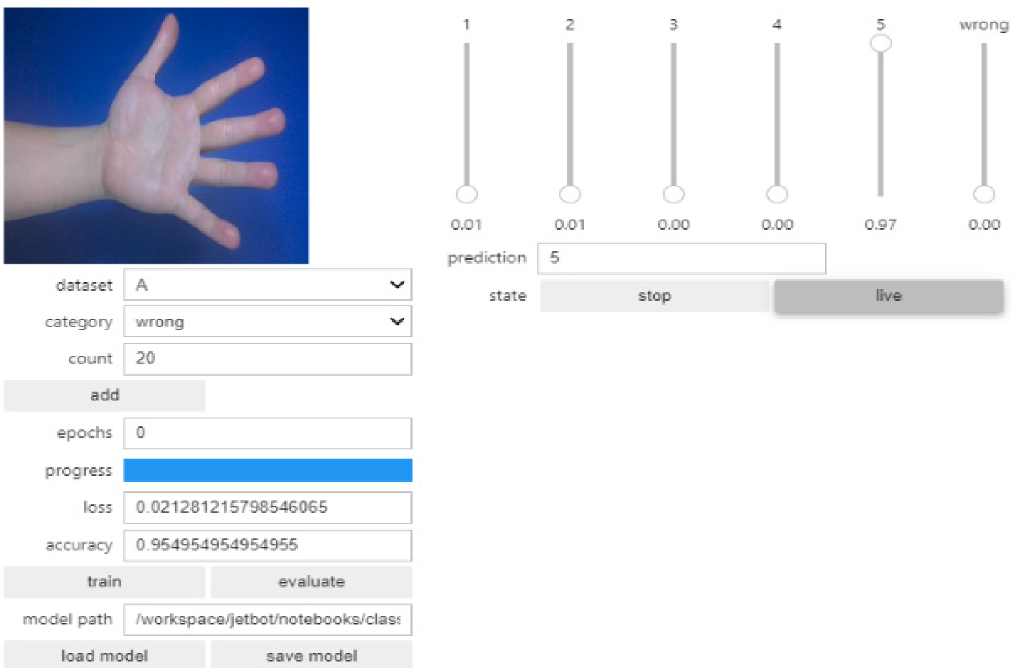


FIGURE 5. Data recorded for the Number gesture "5" in the evaluation.

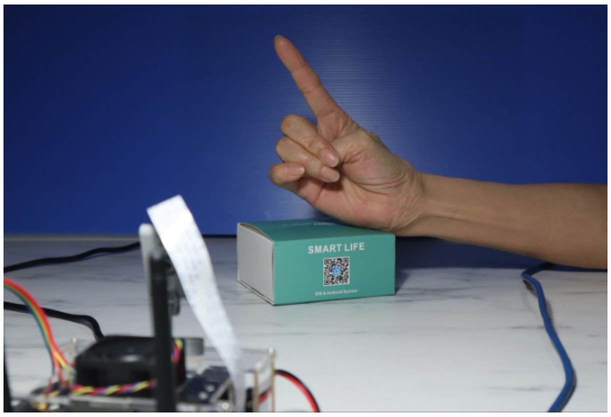


FIGURE 6. Here is how it looks like doing the number gesturing with K.A.K.I.

FIGURE 7. Improper staging of the hand position away from the small platform may cause error in classification due to image out of frame.

A small platform stage up to allow hand position for proper camera view.

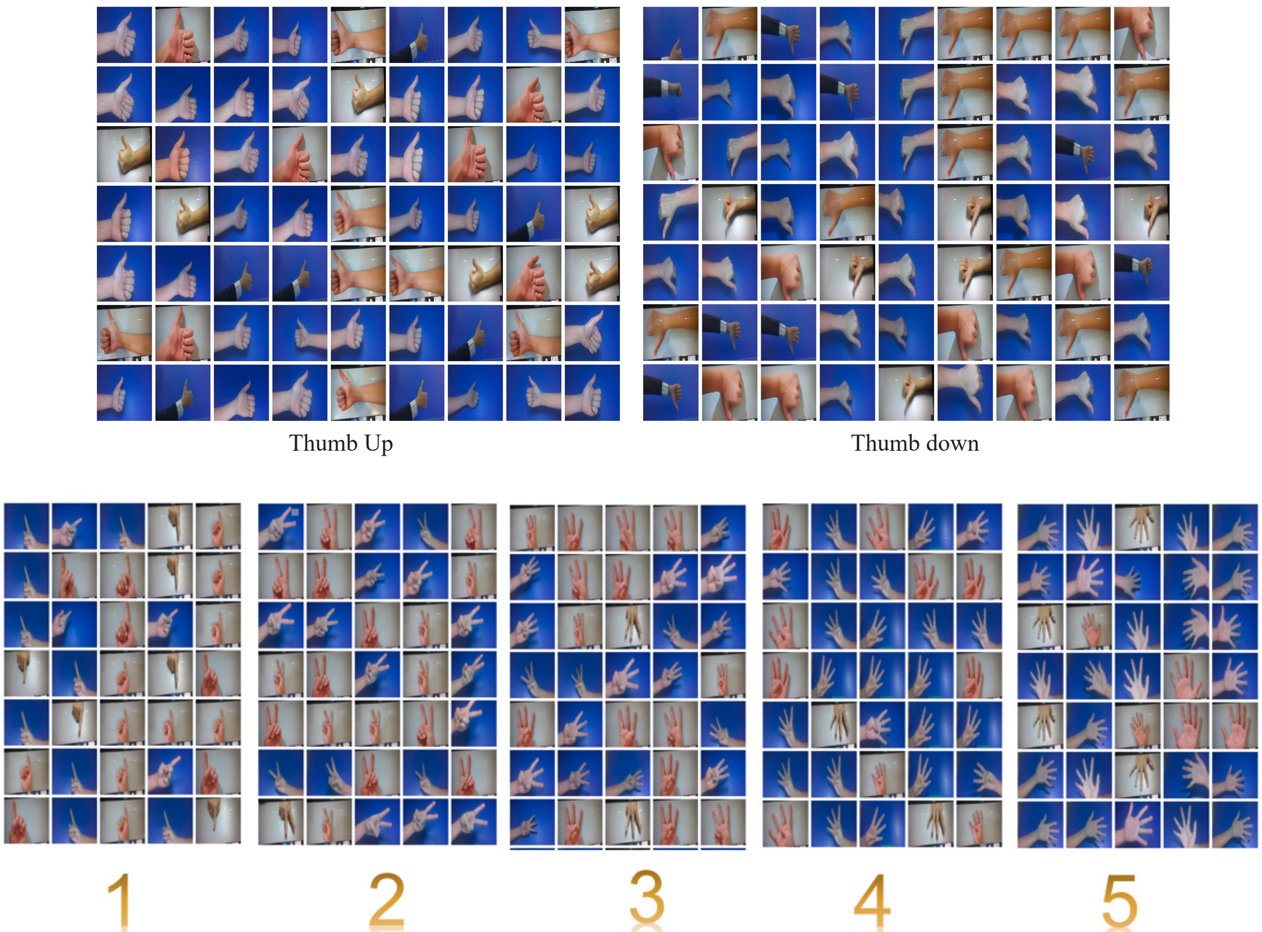


FIGURE 8. Evaluate the accuracy of various correct and wrong hand gestures against trained datasets for thumbs up, thumbs down, 1, 2, 3, 4 and 5

RESULTS AND DISCUSSION

We have collected the data for 9 adults and the results, 3 young adults (aged 16-21), 4 adults (aged 45-55) and 2 elderly (aged 70, one of them is a post stroke patient). A probability of 1.0 is the max. accurateness for that gesture where as a probability with 0.0 is the least for that gesture. The charts are generated based on the data collected.

The K.A.K.I Deep Learning CNN Resnet18 is pretrained with thumbs up and down. Multiple images are capture and trained to test the convolution neural network's classification accuracy versus human observation. The test is successful and has ability to differentiate improper thumbs up and hands position. Once the test is considered accurate, it is time to test it out on several persons. Participant H is 70 years old, a post stroke patient since 4 years ago and has fully recovered. His thumbs up and thumbs down which require wrist twisting of arm muscle group is working well.

However to our surprise, Participant I, 70 years old, who is healthy and without stroke condition, is having slight lower thumbs down coordination despite she scores well on thumbs up. Thumbs up is a natural arm coordination with more relax arm muscle as compare to thumbs down. After several attempt, it was revealed that Participant I's thumb is longer than all the persons in the evaluation. Since the ratio of thumb is longer than the pretrained thumbs down, this has been detected by the K.A.K.I classification. With thumbs down, which required arm muscle twisting, this has further exaggerates the ratio and is detected.

TABLE 1. Data Records and Observation for Participant H (70 years old, post stroke patient)

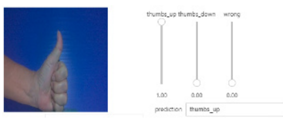
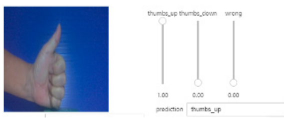
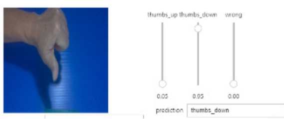
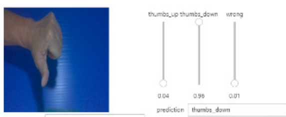
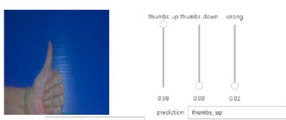
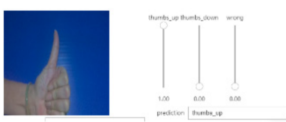
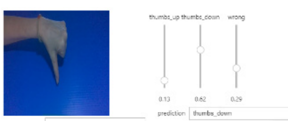
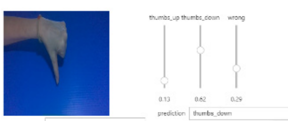
No	Images	Thumbs Up Probability	Thumbs Down Probability	Wrong Probability	Observation
1		1.0	0.0	0.0	Classification ok. Correct position.
2		1.0	0.00	0.00	Classification ok. Correct position.
3		0.05	0.95	0.00	Classification ok. Correct position.
4		0.04	0.96	0.01	Classification ok. Correct position.

TABLE 2. Data Records and Observation for Participant I (70 years old)

No	Images	Thumbs Up Probability	Thumbs Down Probability	Wrong Probability	Observation
1		0.98	0.00	0.02	Classification ok. Correct position.
2		1.00	0.00	0.00	Classification ok. Correct position.
3		0.13	0.62	0.29	Classification ok. Correct position. Slightly lower Thumbs down probability.
4		0.13	0.62	0.29	Classification ok. Correct position. Slightly lower Thumbs down probability.

Data records from various thumbs up and down position reveals classification results and observation which is useful for stroke patient even from this simple thumbs up and thumbs down exercise. Its observation provides insight and meaningful medical observation, from weak thumbs up finger muscle, unable to open fingers despite able to twist, to totally unable to coordinate the wrist and fingers. This data records allows on target evaluation of fingers and wrist muscle as though there is a medical rehabilitation officer at home conducting the wrist and fingers evaluation. As the patient uses this K.A.K.I, the patient will be able to adjust his or her fingers coordination as according the right gesture. Along time this will improve and the patient can do proper hand gesture in a very short time.

Our data collection and observation analysis has reveals that Participant H who was a post stroke patient since 4 years ago, has fully recovered. In addition, our data reveals that Participant I has difficulty in coordinating her thumbs gesture due to her occupation as tailor which has stiffened her wrist arm muscles. The Deep Learning Resnet18 classification is able to identify such attributes.

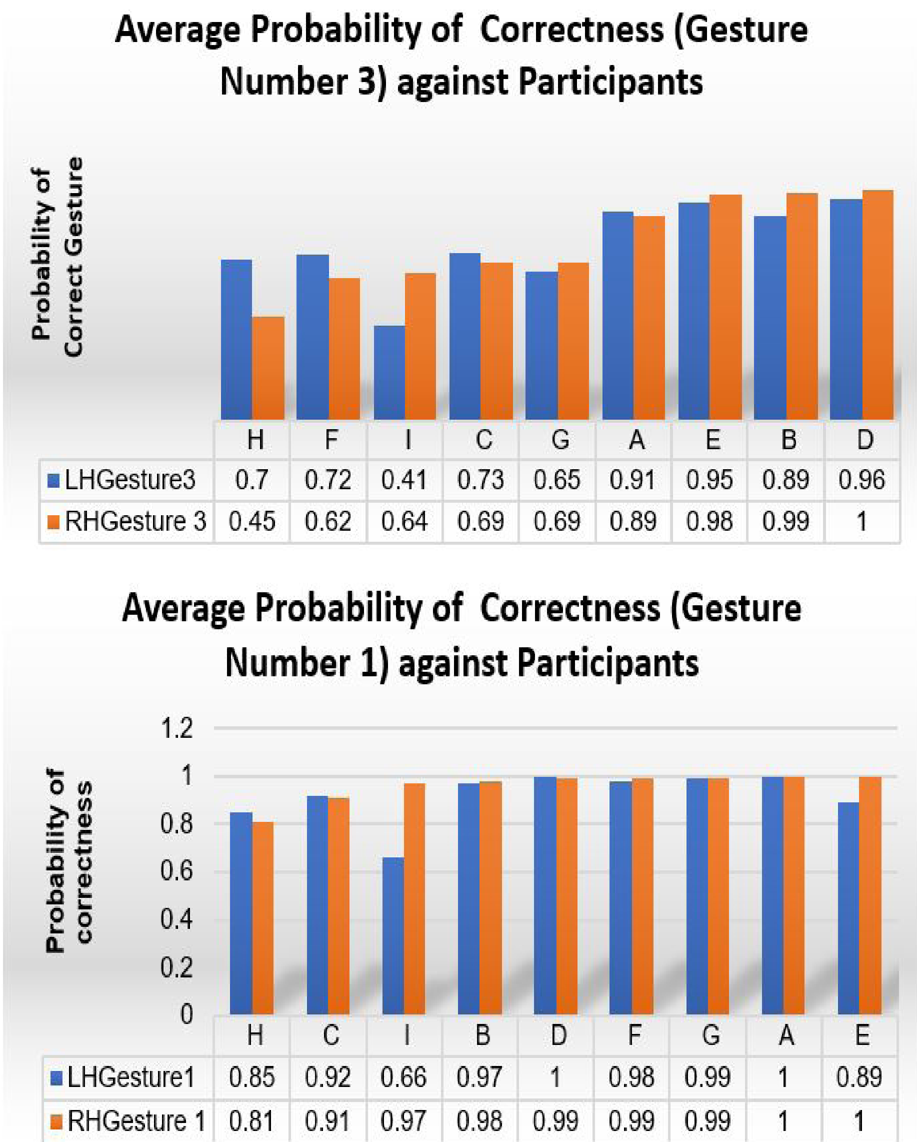


FIGURE 9. Average probability of correctness for gesture number 1 (left) and number 3 (right) against participants.

All the other participants aged between 16 to 55 have no difficulties to coordinate their fingers in the number gesturing exercise as reveal by our finger classification exercise. It is observed that older persons, has higher coordination issue on Middle, Index and Ring finger for gesturing number 3 and 4 as compare to younger persons.

Data records from various number fingering revealed classification results and observation which is useful for stroke patient on finger muscles. Its observation provides insight and meaningful medical observation, on which fingers are weak and unable to coordinate as how we are able to identify Participant I with stiffed fingers. This data records allows on target evaluation of fingers and muscle as though there is a medical rehabilitation officer at home conducting the wrist and fingers evaluation.

CONCLUSION

Overall, our kinesthetic augmented kinematic inferencing methods, K.A.K.I has potential to be a solution providing high dose home-based rehabilitation as the system is safe, robust, user friendly and scalable. The setup is relatively simple and space saving involving a desktop/laptop, Nvidia Jetson Nano with an attached camera, Wi-Fi, a table and a good lighting. This device with machine learning, is trained and can assess finger gestures when fed with an input of image. It is an interactive exercise where stroke patients are able to see the score as a feedback to keep improving on their finger gestures. This feature helps them to be engaged in self-directed rehabilitation exercise under minimal supervision in the comfort of their own home. Despite having home-based therapy, the patients' performance and progress can be monitored by the healthcare providers via cloud data.

The interactive exercise using K.A.K.I in this project is targeted at the fingers and wrist. More game-based exercises targeting different components of the upper extremities as well as the lower extremities can be explored and developed in the future.

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DECLARATION OF COMPETING INTEREST

None

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