Calibrating Hand Gesture Recognition for Stroke Rehabilitation Internet-of-Things (RIOT) Using MediaPipe in Smart Healthcare Systems

Ahmad Anwar Zainuddin[1]*, Nurul Hanis Mohd Dhuzuki[2], Asmarani Ahmad Puzi[3], Mohd Naqiuddin Johar[4], Maslina Yazid[5]

Department of Computer Science-Kulliyyah of Information, and Communication Technology, International Islamic University Malaysia Kuala Lumpur, Malaysia[1, 2, 3]

Physiotherapy Unit, Rehabilitation Department, Hospital Putrajaya, Selangor, Malaysia[4]

Consultant Rehabilitation Medicine, Rehabilitation Department, Hospital Shah Alam, Selangor, Malaysia[5]

***Abstract*—Stroke rehabilitation is fraught with challenges, particularly regarding patient mobility, imprecise assessment scoring during the therapy session, and the security of healthcare data shared online. This work aims to address these issues by calibrating hand gesture recognition systems using the Rehabilitation Internet-of-Things (RIOT) framework and examining the effectiveness of machine learning algorithms in conjunction with the MediaPipe framework for gesture recognition calibration. RIOT represents an IoT system developed for the purpose of facilitating remote rehabilitation, with a particular focus on individuals recovering from strokes and residing in geographically distant regions, in addition to healthcare professionals specialising in physical therapy. The Design of Experiment (DoE) methodology allows physiotherapists and researchers to systematically explore the relationship between RIOT and accurate hand gesture recognition using Python's MediaPipe library, by addressing possible factors that may affect the reliability of patients' scoring results while emphasising data security consideration. To ensure precise rehabilitation assessments, this initiative seeks to enhance accessible home-based stroke rehabilitation by producing optimal and secure calibrated hand gesture recognition with practical recognition techniques. These solutions will be able to benefit both physiotherapists and patients, especially stroke patients who require themselves to be monitored remotely while prioritising security measures within the smart healthcare context.**

Keywords*—Internet-of-Things (IoT); RIOT; stroke rehabilitation; calibration; machine learning; MediaPipe; data security; smart healthcare

I. INTRODUCTION

In enhancing care quality, patients wellbeing, and healthcare efficiency, smart healthcare systems can be promising by the integration of IoT, Artificial Intelligence (AI), big data analytics, and wearable devices, with the collaboration and involvement of patients, healthcare providers, technology developers, and policymakers [1]. These real-time data collection, remote monitoring and personalised healthcare solutions manifested an acceleration of technological advancements from healthcare industry demands, especially during COVID-19 pandemic since it was driven to be implemented globally [2]. Across the globe, the goals of smart healthcare systems will always be the improvement of patient care, cost effective, and efficient deliverables through accurate diagnoses, timely treatments, and continuous monitoring [3].

"Immobility" terminology is always close to "movements". So do the struggles of the stroke patients who need to face the challenges who are not commuting freely? A stroke, as defined by the World Health Organization, is a sudden onset of focal or global neurological impairment presumed to be of vascular origin [4]. Stroke is a severe neurological disease with complex underlying pathological processes, leading to high rates of morbidity and mortality [5].

As a starting point, this study will investigate the hand gesture of the orientation of the palm, either having a landed wrist or upper limb, depending on the patient's ability during the rehabilitation session. Since stroke rehabilitation poses challenges such as imprecise progress tracking and assessment, along with concerns about sensitive data, highlighting the need for reliable and secure data handling, a framework was introduced to assist the healthcare community in improvising the rehabilitation sessions with the presence of the emerging modern technologies that is remotely accessible through the network. Therefore, a framework called RIOT is proposed to deliver affordable and efficient remote stroke rehabilitation.

Remote rehabilitation strategies, as highlighted by Tuli et al. [6] suggest favourable solutions and introduce privacy vulnerabilities and software reliability issues [7]. In response to these challenges, a RIOT framework was developed to enhance gesture recognition accuracy and ensure data security within smart healthcare systems to stand with the exploration of the calibration of hand gesture recognition using the RIOT framework and evaluating its effectiveness in improving home-based stroke rehabilitation [8], [9].

Blending IoT, Machine Learning [10], security and calibration can improve the recovery process for stroke survivors as a blueprint that a system development requires an advanced rehabilitation requires multidisciplinary collaboration [11]. Based on the issue, there was a need for a secure calibration approach for hand gesture recognition using a DoE methodology on a RIOT platform, which can inspect an accurate hand gesture recognition and precise rehabilitation assessment with well-calibrated parameters while considering potential security implications within a smart healthcare context. In addition, the implementation of MediaPipe by Python is necessary to capture the elements of hand gesture recognition that can execute the performance of the recognition [12].

Calibration is essential for accurate hand gesture recognition outcomes, as clinical models, algorithms, and scores must provide reliable and consistent readings [13]. Consequently, the incorporation of DoE can fine-tune and adjust the accuracy of the rehabilitation assessment with its analytical basis [14].

Hence, smart healthcare compromises better future with the developments of services, including the sensitivity towards the importance of data protection, affordability of the healthcare treatment, and widely nurturing the field of computer science [15]. The integration of various technologies has been explored in recent studies to enhance security and efficiency in different sectors [16]. Additionally, the security and privacy aspects of IoT in smart city applications have been comprehensively analysed, underlining the potential and challenges of such technologies [17]. Moreover, calibration process is one of the applications that can enable improvisation of the precision of the experiment as it is essentially supports the initial process of developing remote rehabilitation.

This paper is arranged as follows: Section I gives a brief introduction to the implementation of the calibration for gesture recognition using MediaPipe in the smart healthcare context. Section II focuses on the existing literature on the integration of IoT in stroke rehabilitation, the effectiveness of machine learning algorithms for gesture recognition, and the encounters related to data security and reliability in smart healthcare systems. Section III describes the proposed solution for this paper. Section IV showcased the results and discussion of the experiment. Finally, Section V concludes the content of this research.

II. Literature Review

This literature review segment provides an overview of existing knowledge, identifies research gaps, and highlights areas for future investigation, setting the foundation for this study. Key areas of focus include the integration of IoT in stroke rehabilitation, and the challenges related to data security and reliability in smart healthcare systems. The effectiveness of machine learning algorithms for gesture recognition.

A. *Smart Healthcare for Stroke Rehabilitation Internet-of-Things*

Smart healthcare systems for stroke rehabilitation empower Internet-of-Things (IoT) technologies to offer remote monitoring capabilities for patients undergoing rehabilitation [18]. These systems utilise advanced technologies such as cloud computing, machine learning, and wearable sensors to enable remote rehabilitation training for stroke survivors, reducing costs and burdens on both patients and healthcare providers [19]. By integrating big data, artificial intelligence, cloud computing, and IoT, smart healthcare enhances medical services' automation, informatisation, and intelligence, leading to improved healthcare efficiency and patient experience [3].

B. *Limitations of Current Stroke Rehabilitation Systems and Home-Based Solutions*

Incapabilities in tracking and monitoring the progress of stroke patients over time can hinder the effectiveness of traditional rehabilitation methods. Additionally, data security concerns arise caused of the sensitive nature of patient information which obviously displaying the need for innovative solutions for the quality and security of stroke rehabilitation programs [20].

Home-based solutions are a promising way to overcome traditional stroke rehabilitation limitations. Tele rehabilitation uses e-health platforms and digital technologies to provide convenient and cost-effective services to stroke patients at home. Research has shown that home-based programs enhance patient outcomes and improve access to care, particularly when in-person rehabilitation is not possible [21]. Technological advancements such as webcam monitoring and mobile apps provide cost-effective options for home-based stroke rehabilitation with remote monitoring and real-time feedback, increasing patient engagement. Inexpensive technologies can enhance outcomes for stroke survivors by optimizing home-based rehabilitation and overcoming current system limitations [22].

C. *Challenges in Data Security and Reliability*

Safeguarding data security in smart healthcare is critical, with the exchange of sensitive healthcare data among IoT-enabled medical devices necessitating secure data aggregation and transmission protocols [5]. Additionally, the implementation of secure IoT frameworks is essential to protect patient data and ensure the integrity of healthcare systems [6].

To address security concerns in IoT-based healthcare systems, various frameworks and solutions have been proposed to safeguard patient data and privacy [7]. Security and privacy challenges in IoT healthcare systems are being studied to enhance robust security measures [8]. Furthermore, blockchain in healthcare improves security and privacy in tele-medical services by integrating technology for patient data transmission [9].

Security is important for IoT devices in smart healthcare to prevent breaches and the limitations in processing and battery life make it critical [10]. Studies found weaknesses in IoT healthcare apps and stressed blockchain's importance in reducing security threats, offering ways to boost security in healthcare systems [11]. Also, the development of secure and scalable healthcare data transmission frameworks based on optimised routing protocols is essential for ensuring data integrity and confidentiality in IoT applications [12].

D. *Effectiveness of Machine Learning (ML) and Deep Learning (DL) Techniques for Hand Gesture Recognition*

ML uses algorithms to learn from data for decisions or predictions while DL is a subset of machine learning, employing neural networks with multiple layers for automatic intricate data representations that is inspired by biological neural structures, excels in extracting complex patterns and features from data, outperforming traditional machine learning methods in different tasks [23].

Based on the related previous work, artificial intelligence and machine learning have been increasingly utilised in the healthcare sector to improve diagnostics and patient care, as reviewed by Rozario et al. [24] as well as the challenges of implementing IoT in educational domains have been discussed, providing insights into the potential applications and obstacles. The recent trends in AI and IoT have also been studied, suggesting future research prospects for enhancing networking systems [15].

TABLE I. Table I and Table II indicate the comparative analysis of various techniques used in gesture recognition. Specifically, Table I compares general techniques in gesture recognition, while Table II focuses on comparing techniques that utilises MediaPipe framework.

TABLE I. THE COMPARISON OF TECHNIQUES IN GESTURE RECOGNITION

Author /Year	Methods /Algorithms	Research Area	Feature Sets	Results	Type
Guo et al. (2023) [25]	Support Vector Machine (SVM), k-Nearest Neighbours (k-NN), Linear Discriminant Analysis (LDA), Neural Network (Electromyography), InceptionTime, 1D-CNN	Hand Rehab Equipment, sEMG-based Gesture Recognition	Mean Absolute Value (MAV), Root Mean Square (RMS), Variance of Average Values (VAV), Integrated EMG (iEMG), SSI, WL	90.89% Overall Gesture Recognition Accuracy	ML DL
Padilla-Magana & Pena Pitarch (2022) [26]	Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbours (k-NN) (Classification), Borderline-SMOTE (Balancing)	Post-Stroke ARAT Activities Classification	Finger Joint Extension/Flexion Angles	98% Precision (SVM Classifier)	ML
Ho et al. (2023) [27]	Support Vector Machine (SVM), Multilayer Perceptron (MLP), Random Forest, Logistic Regression, k-Nearest Neighbors (k-NN) (Leap Motion)	Gamified Rehab, Key Pose Identification	Skeleton Extraction, Hand Pose, Gesture Recognition	96.84% (SVM) & 96.47% (MLP) Accuracy	ML
Zaher et al. (2024) [28]	Bidirectional Long Short-Term Memory (Bi-LSTM), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), CNN-LSTM	Action Recognition (Deep Learning)	UI-PRMD & KIMORE Datasets (Pain/Posture)	93.08% Accuracy (KIMORE), 99.70% (UI-PRMD)	DL
Akmal et al. (2021) [29]	Electromyography (EMG) Signal, Support Vector Machine (SVM) (Classification)	Prosthetic Finger Movement Classification	Finger Movement Classification, True Positive Rate (TPR) Analysis	High Accuracy & Efficiency (SVM)	ML
Antonius & Tjahyadi (2021) [30]	Convolutional Neural Network - Recurrent Neural Network (CNN-RNN) (Electromyography)	Drone Control with Hand Gestures	Muscle Tension State Signals [74]	Successful Gesture Identification for Drone Control	DL
Copaci et al. (2022) [31]	Bayesian Neural Network, Artificial Neural Network (ANN), Local Response Normalization (LRN)	Surface Electromyography (sEMG) Gesture Recognition for Rehab Glove	Improvement on Patient Motivation	98.7% Gesture Recognition Accuracy	MLDL
Das et al. (2023) [32]	Support Vector Machine (SVM), Random Forest, Multilayer Perceptron (MLP), Convolutional Neural Network (CNN)	Real-time Hand Gesture Recognition (Vision-based)	Hand Detection, Tracking, Gesture Features	97.3% Accuracy (CNN)	MLDL
Tsokov et al. (2021) [33]	1D Convolutional Neural Network (1D CNN) Optimization (Evolutionary Algorithm)	Human Activity Recognition	Evolutionary CNN Architecture Optimization	Accurate Human Activity Recognition	DL
Jiang et al. (2022) [34]	Support Vector Machine (SVM), k-Nearest Neighbours (k-NN), Naïve Bayes, Discriminant Analysis	Spatio-temporal Hand Gesture Recognition	-	Achieved an average accuracy of 85% in hand gesture recognition	ML
Palanisamy & Thangaswamy (2023) [35]	Hough Transforms, Artificial Neural Networks (ANN)	Hand Gesture Recognition	Spatiotemporal Features	Detected hand gestures with an accuracy of 92% using spatiotemporal techniques and artificial neural networks	ML
Wei et al. (2021) [36]	CNNs	Surface Electromyography-Based Gesture Recognition	-	Achieved a classification accuracy of over 90% for a large set of gestures using CNNs.	DL
Lee & Bae (2020) [37]	Dual-channel ANN, DNN	Hand Gesture Intention Cognition	IMU sensor data	Explored deep learning techniques achieving an accuracy of 88% for hand gesture intention recognition.	DL

1) MediaPipe framework: The comparison of deep learning techniques in gesture recognition using the MediaPipe framework reveals significant advancements in sign language recognition for individuals. Various researches have demonstrated the effectiveness of combining modern computer vision and machine learning approaches, such as CNN [38], LSTM [39], and lightweight deep neural networks as GRU and 1D CNN [40], in accurately recognising sign language gestures. These techniques have shown high classification accuracies ranging from 98.8% to 99.95% on different datasets, including ASL alphabets, daily used signs, and static sign language letters and characters. By leveraging the MediaPipe framework for feature extraction and real-time processing, these models contribute significantly to bridging the communication gap between the physically impaired community and the general population, enhancing their quality of life with proper recognition.

Overall, there are two main hand gesture recognition approaches: vision-based (using cameras for features) with high accuracy, and sensor-based (using EMG or IMU) with moderate accuracy. ML/DL techniques (CNNs) achieve high accuracy in various applications, while MediaPipe Framework offers real-time recognition with comparable accuracy. In stroke rehabilitation, both ML/DL and MediaPipe are efficient with high accuracy. MediaPipe suits smart healthcare for immediate feedback, while traditional models are better for offline processing. Combining both can make sure accurate recognition in rehabilitation. Since gesture recognition field is rapidly evolving, best approach depending on specific requirements.

E. Technology Integration for Secure Calibration

In this section mentions calibration process involving the system accuracy recognises the equations application to the calibration analysis. Also, the gestures across different devices, environments, technical approaches, and user conditions with MediaPipe's hand tracking module due to its robust and real-time capabilities were meant to be achieved.

1) Formulas and equations: To precisely assess and calibrate the hand gesture recognition system, six key equations and references are employed for the analysis:

a) The Accuracy of Gesture Recognition and Euclidean Distance Formula

$$Accuracy = \frac{Distance\ of\ Correctly\ Recognised\ Gestures}{Total\ Distance\ of\ Gestures} \times 100\% \quad (1)$$

TABLE II. THE COMPARISON OF DEEP LEARNING TECHNIQUES IN GESTURE RECOGNITION USING MEDIAPIPE FRAMEWORK

Author /Year	Methods /Algorithms	Research Area	Feature Sets	Results
Lu & Peng (2023) [41]	Deep neural network architecture	Intelligent security system	Landmark prediction	Efficient and reliable gesture detection.
Giri & Patil (2023) [42]	GRU, LSTM neural network model	Sign language recognition	Hand segmentation, feature representation	99% accuracy achieved.
Sahoo et al. (2022) [43]	Fine-tuned CNN	Hand gesture recognition	-	Real-time gesture recognition.
Abdallah et al. (2022) [40]	Hybrid architecture involving MediaPipe for hand detection and tracking	Real-time gesture recognition	Hand and pose landmarks	Lightweight system for accurate recognition. Validation loss: 0.115
Ong et al. (2022) [44]	LSTM	Autonomous Vehicles (AV)	Pose extraction algorithm: MediaPipe	Achieved reliable results with traffic gestures in indoor environment.
Wang et al. (2020) [45]	Gaussian Mixture Model, Hidden Markov Model	Gesture recognition	Data gloves, position sensors	Recognition of over 93% of 280 gesture models
Ru et al. (2023) [46]	PCA, HMM, Particle Filtering, Condensation Algorithm	User guide application	Stochastic process, statistical modelling	Dynamic gesture recognition using statistical approaches.
Indriani et al. [47]	Transfer learning on DenseNet201 for gesture classification model.	Neural network architectures for training and classifying hand gestures	DenseNet201 for hand gesture classification using transfer learning"	Validation accuracy: 97.55%"
Wang et al. (2023) [48]	LTSM, Gated Recurrent Unit (GRU) neural networks	Sign language recognition	Visual sign language recognition. - sign language dataset 64 Argentine sign languages (LSA64)	Capture of 3D coordinates of hands for sign language recognition, LTSM: 94.0625% and GRU: 94.5312%
Padhi & Das (2022) [49]	Transfer learning on DenseNet201 for gesture classification model."	Neural network architectures for training and classifying hand gestures	DenseNet201 for hand gesture classification model	Validation accuracy: 97.55%"
Kumar et al. (2023) [39]	BlazePalm, Landmark model, Gesture recognition model	Virtual scene	Hand key point model for 3D hand joint coordinates	Effective hand key point localization and 3D hand joint prediction
Giri & Patil (2024) [42]	GRU, LSTM	Sign language recognition	Hand segmentation, feature representation	99% accuracy achieved
Suherman et al. (2023) [50]	CNNs, transformer	Gesture recognition	Image feature representation	Achieved over 95% accuracy in 2D or 3D gesture recognition tasks
Liu et al. (2022) [51]	Few-Shot Learning,	Continuous gesture sequences recognition	RWTH German fingerspelling dataset	Accuracy for 5-way 1-shot gesture recognition 89.73%, which randomly selected.

The distance between the camera and the hand is crucial for calibration. The distance was measured in centimetres (cm) using a metal ruler. Wang et al. [52] explored stress formulas from deformation equations to acquire spatial distances using mathematics. The Euclidean distance formula calculates 3D space distance when hand landmark coordinates are known

$$d = (x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2 \quad (2)$$

Where (x_1, y_1, z_1) and (x_2, y_2, z_2) are the coordinates of two points which are landmark 4 and 8.

b) Corner angle of the laptop: The corner angle of the laptop, measured using a 3D printed protractor (Xiphias), affects the range of capture for the webcam. This angle is decisive for recognising landed wrist gestures. The angle θ. θ can be measured and used to adjust the camera's field of view:

c) Mean (Average) and standard deviation calculation: The accuracy of different formulas demonstrated the importance of mean accuracy and standard deviation calculations in assessing formula performance [53].

$$\theta = \arctan\left(\frac{height}{distance}\right) \quad (3)$$

Measurement and accuracy assessment of angles aligns with the methodology of measuring and adjusting corner angles for webcam calibration [54].

$$Mean = \frac{\sum Accuracy\ Values}{n} \quad (4)$$

where n is the number of accuracy measurements.

$$\text{Standard Deviation} = \sqrt{\frac{\sum(\chi_{\mathrm{i}} - \mu)^2}{n}} \quad (5)$$

where χ_I is each accuracy value, μ is the mean accuracy, and n is the number of measurements.

d) ANOVA (Analysis of variance): To know the main features of similarity indices, which aligns with the statistical analysis required for accuracy assessment in gesture recognition [55] and ANOVA was used to determine if there are any statistically significant differences [56] between the means of independent (unrelated) groups.

$$F = \frac{Variance\ Between\ Groups}{Variance\ Within\ Groups} \quad (6)$$

2) Calibration procedure: Some factors such as camera type, whether using a laptop camera or an external camera with different resolutions, can impact the quality of gesture recognition [57]. Additionally, the distance between the camera and the hand, as well as the orientation of the palm, are essential factors that influence the ability of stroke patients to perform gestures accurately [58].

Moreover, repetitions and accuracy of gestures are fundamental for calibration in rehabilitation systems [59]. Also, lighting conditions need to be controlled to evaluate camera sensitivity and gesture recognition [60].

Thus, secure calibration methods with camera type, distance, palm orientation, accuracy, repetitions, and lighting are vital for optimising stroke rehabilitation systems. Advanced technologies can improve rehabilitation programs for stroke patients.

In summary, while significant progress has been made in integrating IoT and machine learning into stroke rehabilitation, challenges related to data security, system reliability, and the effectiveness of home-based solutions remain. Previous studies have demonstrated the effectiveness of machine learning for gesture recognition but have not addressed security concerns. Therefore, this research aims to address these gaps by calibrating hand gesture recognition using the RIOT framework and evaluating machine learning algorithms with MediaPipe, with a focus on enhancing data security and rehabilitation accuracy.

III. Methodology

The methodology outlines the process of integrating and calibrating MediaPipe for hand gesture recognition in stroke rehabilitation, addressing the limitations identified in the literature review. Fig. 1 and Fig. 2 visualise the flow of the data collection, and palm orientation testing as a part of data collection process.

A. Tool Selection

1) Python, MediaPipe framework and MediaPipe solutions: The convergence of MediaPipe with Python libraries is pivotal in pose detection and analysis for the creation of machine learning pipelines. MediaPipe framework offers hand tracking and gesture recognition solutions and provides a palm detector and hand landmark model for accurate gesture recognition [61], [62]. Using MediaPipe with Python allows access to hand landmark models and gesture recognition capabilities [63].

MediaPipe's BlazePose algorithm has been effective in single-camera human 3D-kinematics. BlazePose in physiotherapy exercise classification showed efficient performance with a frame rate of 32 frames per second [64], [62].

Additionally, MediaPipe's adaptability and dependability are evident in its performance across different areas of pose detection tasks. It has shown effectiveness in the identification of genetic syndromes and in reducing the likelihood of overfitting in contrast to other techniques [63], [65]. The framework's robustness and versatility make it a valuable tool for various applications, including sign language-based video calling apps and object detection for aspiring film directors [63], [66].

2) Gesture recognition procedure: Subsequently, Fig. 2 will explain further the process of palm gesture recognition during Palm Orientation Testing. To detect the palm, MediaPipe acquires landmarks, as shown in Fig. 3 to produce the coordinates of the gestures. The landmarks were generated in Fig. 3 and Fig. 4. A by MediaPipe and the purple label was the MediaPipe, between landmark 4 and 8 for the measurement of accuracies. Fig. 3. B is the initial visualisation of the 21 landmarks by MediaPipe.

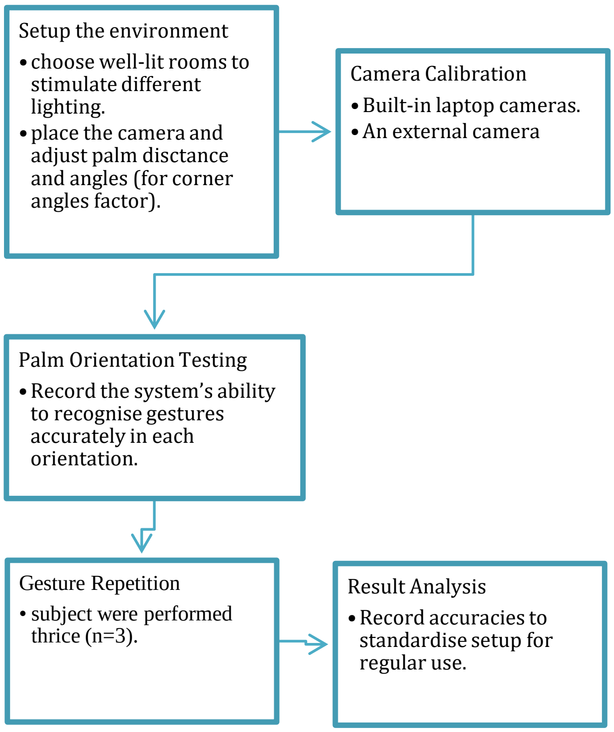


Fig. 1. Calibrating process flow for data collection.

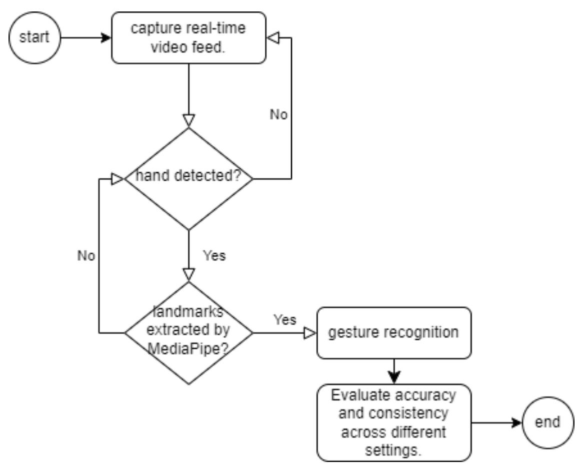


Fig. 2. The palm orientation testing of hand gesture recognition flowchart using MediaPipe during calibration data collection.

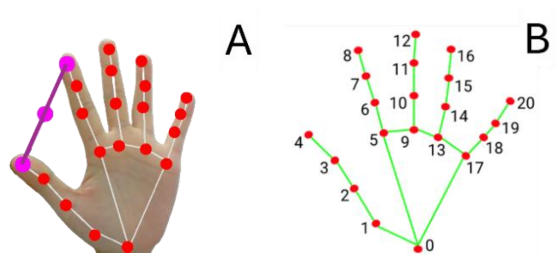


Fig. 3. The key point localisation of 21 hand-knuckle coordinates within the detected hand regions by MediaPipe with red points.

0.	MIDDLE_FINGER_DIP	10.	WRIST
1.	MIDDLE_FINGER_TIP	11.	THUMB_CMC
2.	RING_FINGER_MCP	12.	THUMB_MCP
3.	RING_FINGER_PIP	13.	THUMB_IP
4.	RING_FINGER_DIP	14.	THUMB_TIP
5.	RING_FINGER_TIP	15.	INDEX_FINGER_MCP
6.	PINKY_MCP	16.	INDEX_FINGER_PIP
7.	PINKY_PIP	17.	INDEX_FINGER_DIP
8.	PINKY_DIP	18.	INDEX_FINGER_TIP
9.	PINKY_TIP	19.	MIDDLE_FINGER_MCP
		20.	MIDDLE_FINGER_PIP

Fig. 4. Hand Landmarks list by MediaPipe with numerical labelling.

3) Evaluation of MediaPipe for hand gesture recognition: Using an open-source framework, for hand gesture recognition [73]. MediaPipe offers a suite of pre-trained models and pipelines specifically designed for real-time hand tracking and gesture recognition. The evaluation of MediaPipe's performance in this context focuses on its built-in accuracy metrics.

a) Accuracy measurement: The built-in accuracy evaluation includes the confidence score indicating the probability that the detected hand landmarks correspond to a hand gesture and the percentage of gestures correctly classified by MediaPipe's pre-trained models. The measurement of the distance was set in between the perpendicular point of camera to the base, and palm location at 0.00 cm, as displayed in Fig. 5. According to Fig. 6, the attached ruler was placed right by the side of the laptop screen to record the angle between the web camera and the base or keyboard of the laptop. The angles were measured by placing Xiphias at the side of the laptops, respectively, as shown as in Fig. 6. A. Meanwhile Fig. 6. B is how the angles was examined on the devices.

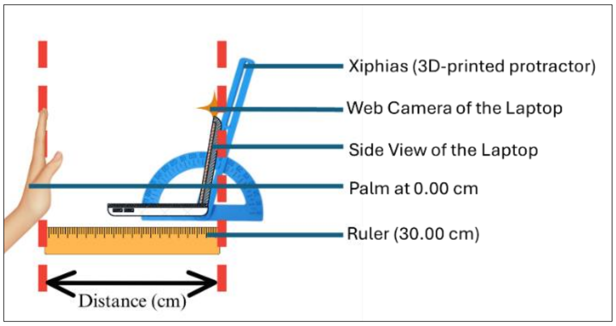
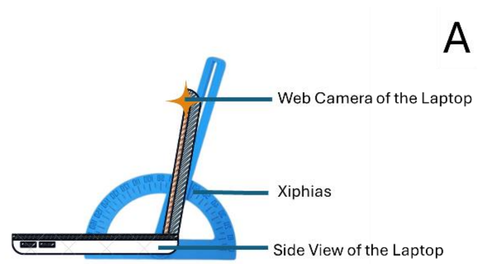


Fig. 5. Experimental setup showing the distance measurement between the laptop webcam and the hand using a metal ruler and a 3D printed protractor (Xiphias) to determine the corner angle of the laptop.



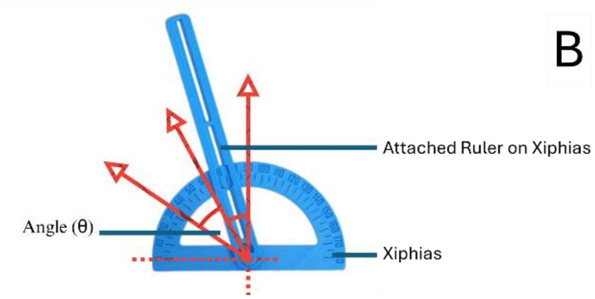


Fig. 6. The coordination of Xiphias to get the angles and then the distances started to be examined was perpendicular to the laptop webcam.

B. Calibration with DoE

1) Calibration process: The calibration process involved optimising factors to enhance the accuracy of hand gesture recognition within the stroke rehabilitation context. This step focused on fine-tuning parameters such as camera type, camera distance, palm orientation, and lighting conditions to ensure precise and reliable gesture recognition outcomes [67], [68], [69].

a) Calibration setup: Strategically placing the external camera at a specific distance from the hand minimises occlusions and distortions that may arise with a laptop camera, resulting in more reliable gesture detection. Gesture recognition has gained traction due to advancements in computer vision and AI. Hand-gesture recognition for Human-Machine Interaction (HMI), enabled effective interpretation of user intent by machines [70]. Besides, calibration process is aligned with research focused on enhancing gesture recognition systems through cutting-edge technologies and methodologies [71]. Likewise, scholars have recorded developments in real-time hand gesture recognition through the use of deep learning models from MediaPipe and sensor fusion strategies [72]. For reliable results, calibrating a gesture recognition system is important. It benefits in developing systems for various purposes, which supports this approach.

C. Data Collection and Result Analysis

Data gathering under various conditions was recorded to ensure robustness and accuracy. The comparison was made based on factors as mentioned in Table III statistical method was implied for evaluation and optimal settings identification.

1) DoE methodology for statistical optimisation: Calibrating factors in Table III enhances the accuracy and reliability of gesture recognition:

TABLE III. FACTORIAL DOE DESCRIPTION

Factors		Levels/SI Unit	Description
Primary	***Camera***	Laptop camera External camera	Cameras with different resolutions[a].
	Camera distance	Centimetre (cm)	Measurement in cm using a metal ruler (up to 30 cm) to determine the distance between the camera and the hand.
	Palm orientation	Upper limb Landed wrist	Stroke patients' ability to move parts of their hands.
Secondary	***Lighting***	Controlled: Bright Dim	Evaluating the camera's sensitivity to gesture recognition under different indoor lighting scenarios.
	Personal computer (PC)	Laptop models A: HP Envy Laptop 13 B: ASUS Vivobook A542U C: ACER Aspire E 14	Laptop models vary in size and specifications, impacting gesture recognition software performance[b]. Laptop size affects camera positioning and stability, potentially affecting gesture recognition accuracy. Hardware differences such as processor speed, RAM, and graphics impact efficiency and accuracy of gesture recognition algorithms.
	Corner angle of the laptop	Degrees (θ): 50°, 60°, 70°	Measuring from a 3D printed protractor to determine the range of capture for the webcam in recognising landed wrist gestures.
	Accuracy	Percentage (%)	Percentage of correctly recognised gestures[c](i.e. pinch extension).
	Repetitions	n = 3	Conducting each gesture n = 3 times to ensure consistency and reliability.

The DoE approach optimises gesture recognition systems by adjusting elements and levels, aiming to determine optimal parameters for accurate recognition, particularly in stroke patients and different lighting conditions.

The factors clearly provided some IoT devices used in the experiment in the description in Table III. In Section IV, the comprehensive analysis of IoT security and privacy will be discussed further to ensure that the best practices were identified in recent research [17].

a Romeo et al. [73] has experimented different resolutions and abled to receive the best results for 3D calibration procedures.

b The assertion regarding the impact of laptop models on gesture recognition software performance is supported by research that specifically addresses the interaction between hand gestures and laptops, emphasizing the importance of considering laptop specifications in the context of gesture recognition systems.

c According to Hu et al. [74] the effectiveness of proposed method can be measured through accuracy to reduce training burden of the system.

IV. Results and Discussions

This part presents the outcomes of implementing MediaPipe for gesture recognition, the experimental setup, calibration process, and statistical analysis of DoE approach in optimising calibration parameters in enhancing hand gesture recognition for RIOT, and the argument on security measures with smart healthcare awareness. The visual representation of the results was also showcased in graphs and the process of data collection is displayed in Fig. 7.

A. *Descriptive Statistic and Overview*

The dataset comprises measurements of accuracy at different distances, camera types, and lighting conditions. Basic statistics are summarised in Table IV.

TABLE IV. Descriptive Statistic

Metric	Value
Sample Size	84
Mean Accuracy (%)	Varies by distance and lighting (refer Table V, Table VII, Table VIII, Table IX, Table X, and Table XII).
Standard Deviation	

From TABLE IV. (from 10.00 cm to 30.00 cm) and each distance has multiple conditions for Bright and Dim lighting. For example, Bright and Dim conditions are repeated twice, so there are four measurements per distance. So, the sample size appeared to be 84 meanwhile the mean accuracy and standard deviation were explained in the next subtopic (refer to *B. Experimental Setup and Calibration Results*).

B. *Experimental Setup and Calibration Results*

In this section, the presentation of results of gesture recognition experiments, focusing on the accuracy, the relationships between factors were displayed and discussed. Sample of calculations of mean accuracy and standard deviation were shown as the following.

a) Calculation of average accuracy: To calculate the average accuracy at a specific distance, the sum the accuracy percentages of multiple measurements at that distance and divide by the number of measurements (refer to Formula (3)). For example, at 10 cm:

$$Average\ Accuracy = \frac{\sum Accuracy\ Measurements}{Number\ of\ Measurements}$$

$$= \frac{10.31}{1} = 10.31\%$$

b) Calculation of standard deviation: The standard deviation is calculated to understand the spread of accuracy measurements around the mean (average) accuracy (refer Formula 5). For example, at 10 cm with sample measurements (hypothetical values):

$$Accuracy\ Measurements = [8,12,10,11,10]$$

$$Mean\ Accuracy(\mu) = 10.20$$

Step-by-step calculation:

First, each measurement's deviation was calculated from the mean, square it:

$$(8 - 10.20)^2, (12 - 10.20)^2, (10 - 10.20)^2,$$
$$(11 - 10.20)^2, (10 - 10.20)^2$$
$$= 4.84, 3.24, 0.04, 0.64, 0.04$$

Next, the calculation of standard deviation (SD) was finalised:

$$SD = \sqrt{\frac{4.84, 3.24, 0.04, 0.64, 0.04}{5}}$$

$$= \sqrt{1.76} = 1.33$$

Given the provided data in Table V, if the SD is given directly as 21.946, then it was directly used in the report:

$$SD = 21.946$$

c) Distance and accuracy: To begin with, the determination of the impact of camera distance on gesture recognition, the accuracy was examined at various distance from 10.0cm to 30.0cm towards the palm placement. Moreover, the reliability and consistency of gesture recognition accuracy were analysed the standard deviation of accuracy measurements at different distances. The results are presented in Table V TABLE V. and Fig. 7.

TABLE V. Accuracy and Standard Deviation at Different Distances

Distance (cm)	Average Accuracy (%)	Standard Deviation
10.00	10.13	21.946
11.00	13.88	22.635
12.00	29.25	32.766
13.00	40.77	33.187
14.00	54.29	41.415
15.00	64.17	32.778
16.00	74.27	29.884
17.00	82.04	15.265
18.00	85.27	14.596
19.00	86.90	12.842
20.00	88.08	12.266
21.00	83.79	13.639
22.00	85.00	12.360
23.00	82.85	12.751
24.00	83.04	13.152
25.00	81.85	14.856
26.00	81.52	16.114
27.00	79.85	17.471
28.00	76.27	19.254
29.00	75.24	21.120
30.00	72.04	23.297

For distances of 10 to 15 cm, the standard deviation is high (21.946 to 41.415), indicating significant variability in accuracy. This suggests that at these distances, the system's performance is inconsistent.

Next, the distances of 16 to 20 cm, the standard deviation decreases (12.266 to 29.884), suggesting more consistent performance. The accuracy is higher, and the lower standard deviation indicates that the system is more dependable at these distances.

Finally, beyond 20 cm, the standard deviation remains moderate to high, indicating that the accuracy becomes more variable again as the distance increases. This suggests that the system's performance is less stable at greater distances.

Subsequently, a trend of accuracy was manifested across different distances and with variability based on the error bars in Fig. 7.

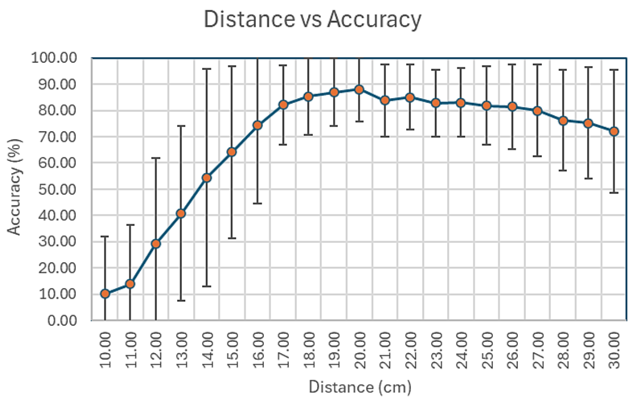


Fig. 7. Line graph shows the trend of accuracy across different distances with error bars representing standard deviation. Error bars show higher variability at shorter distances, decreasing up to 20 cm.

Therefore, from the line graph, the optimal distance is 20 cm for the highest accuracy and stability. Meanwhile, the variability is high at 10-15 cm, low at 16-20 cm, and increases beyond 20 cm. Now, a histogram with 10% bin width visualises accuracy distribution across distances for clear view in Fig. 8. show that the accuracy values are most frequently distributed between 70% and 90%, with the highest frequency around 80-90%.

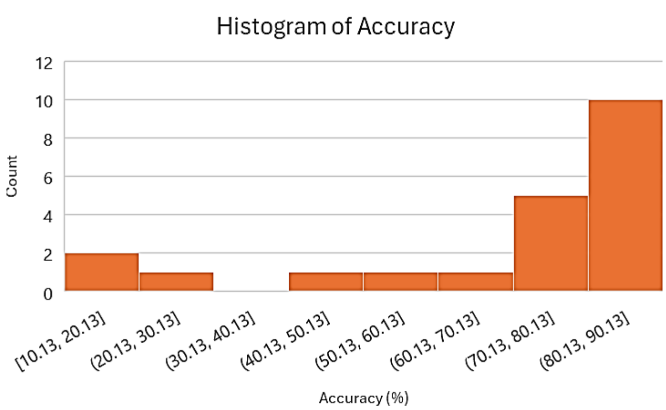


Fig. 8. Histogram depicts the frequency distribution of accuracy across different distances.

d) Percentile analysis of accuracy: The 25th, 50th (median), and 75th percentiles were calculated to comprehend the distribution of accuracy. So, percentiles helped to summarise the central tendency and variability of the data from Table VI.

TABLE VI. PERCENTILE VALUES OF ACCURACY

Percentile	Value (%)
25th Percentile	64.17
50th Percentile	79.85
75th Percentile	83.04

The 25th percentile indicates that 25% of the accuracy values are below 64.17%. The median (50th percentile) is 79.85%, showing that half of the accuracy values are below this value. The 75th percentile indicates that 75% of the accuracy values are below 83.04%. Next, a bell curve in Fig. 9 was generated based on the calculated mean and standard deviation. This visualisation helps in understanding the normal distribution of the accuracy data and provides insights into the performance and consistency of the gesture recognition system.

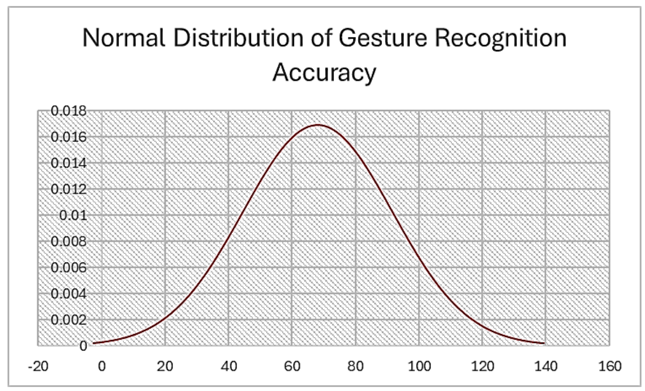


Fig. 9. Bell curve peak indicates most scores are close to the mean, which is around 70% and illustrates the normal distribution of gesture recognition accuracy.

The mean accuracy in Fig. 9 represents the central value of accuracy scores. The graph demonstrates a balanced variability in accuracy scores, with a moderate spread with the highest concentration around the mean and a balanced spread shown by standard deviation manifesting reliability and consistency, essential for its intended use.

e) Camera and laptop model, lighting, and accuracy: The accuracy of gesture recognition was evaluated using different cameras under bright and dim conditions. The outcome was summarised in TABLE VII. TABLE VIII.

TABLE VII. ACCURACY BY CAMERA TYPE AND LIGHTING CONDITION

Model	Bright	Dim
External	70.83	69.29
Laptop A	70.83	67.67
Laptop B	63.74	62.42
Laptop C	73.4	66.78

TABLE VIII. STANDARD DEVIATION FOR ACCURACY LIGHTING CONDITIONS

	Lighting	
Camera/ Model	**Bright**	**Dim**
External	13.334	14.827
Laptop A	8.059	12.515
Laptop B	1.223	12.15
Laptop C	7.879	15.309

By the comparison from Fig. 10 indicates the accuracy evaluation within lighting condition and camera types.

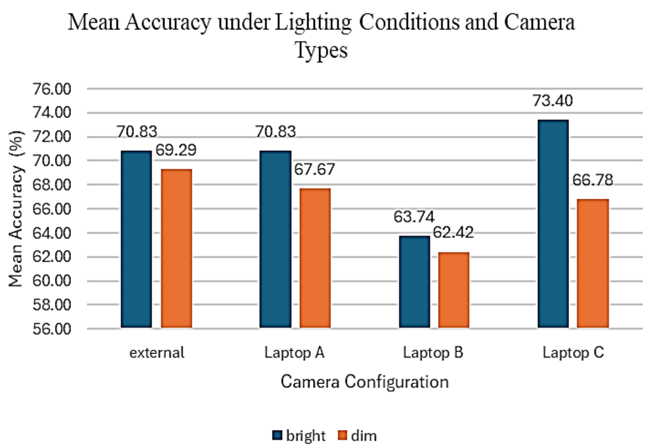


Fig. 10. Bar chart compares accuracies affected by different laptop models and an external camera.

To sum up, Fig. 10 gesture recognition accuracy varies by camera type and lighting conditions. The best performance is from Laptop C under bright lighting achieves the highest accuracy (73.40%), while Laptop B under dim lighting has the lowest performance (62.42%).

f) Palm orientation and accuracy: The accuracy of gesture recognition was also calculated for different palm orientations, as shown in Table IX.

TABLE IX. ACCURACY BY PALM ORIENTATION

Palm Orientation	Average (%)	Standard Deviation
Upper Limb	62.96	27.30
Landed Wrist	7.900	11.548

Table IX specifies that the accuracy for the upper limb orientation is significantly higher (62.96%) compared to the landed wrist orientation (27.30%). The standard deviation is also lower for the upper limb orientation, suggesting more consistent performance. The scatter plot, Fig. 11, reveals those error bars of standard deviation at various distances, highlighting accuracy variability.

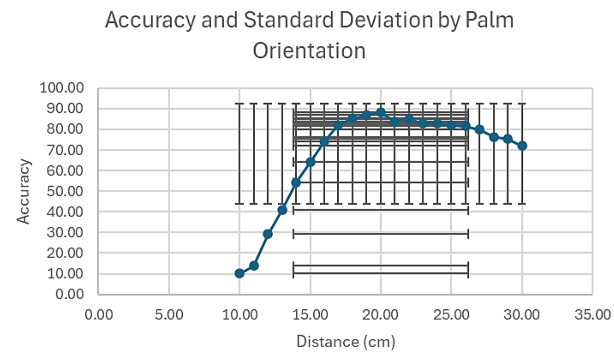


Fig. 11. The scatter plot visualises the relationship between distance (cm) and accuracy (%) for different palm orientations. The upper limb orientation consistently outperforms the landed wrist orientation.

Accuracy sharply increases between 10 cm and 15 cm was revealed in Fig. 11 meanwhile accuracy peaks at 88% at 20 cm, then drops to 72% at 30 cm. High standard deviation at 10-15 cm shows inconsistent performance, while from 16-20 cm it decreases, indicating more consistent accuracy. Standard deviation rises after 20 cm, showing less stable performance. Thus, the optimal distance for gesture recognition in this system was around 20 cm, where it achieved the highest accuracy and consistency, making it the most reliable range for practical applications in remote stroke rehabilitation.

g) Corner angles and accuracy: The impact of the corner angles of the laptop on the accuracy of gesture recognition was investigated and summarised in Table X.

TABLE X. ACCURACY BY CORNER ANGLES

Corner Angle (°)	Average (%)	Standard Deviation
50	61.31	8.02
60	69.95	3.66
70	51.58	12.92

Based on Fig. 12Fig. 12, a corner angle of 60° gives the highest accuracy (69.95%), while the lowest accuracy is observed at 70° (51.58%).

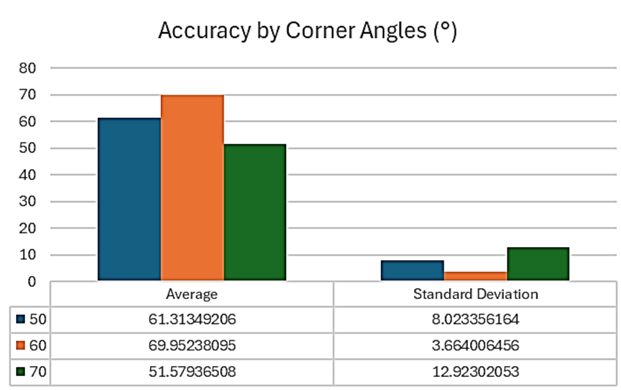


Fig. 12. Accuracy and standard deviation at different corner angles (50°, 60°, 70°).

Therefore, the accuracy and standard deviation of 60° angle as the optimal angle for highest accuracy is proven from the reading.

h) Comparison of accuracy between factors: ANOVA Single-Factor

An ANOVA single-factor analysis was conducted to compare the accuracy of gesture recognition across distinct factors. The results are presented in Table XI, Table XII and Table XIII.

TABLE XI. COMPARISON OF ACCURACY BETWEEN FACTORS

Distance (cm)	Lighting, Camera, and Palm Orientation	Corner Angle
10.00	10.13	26.11
11.00	13.88	26.00
12.00	29.25	40.94
13.00	40.77	50.61
14.00	54.29	49.00
15.00	64.17	60.06
16.00	74.27	77.33
17.00	82.04	76.44
18.00	85.27	74.50
19.00	86.90	79.28
20.00	88.08	77.28
21.00	83.79	73.50
22.00	85.00	72.83
23.00	82.85	72.61
24.00	83.04	69.17
25.00	81.85	66.11
26.00	81.52	64.89
27.00	79.85	60.83
28.00	76.27	57.50
29.00	75.24	56.06
30.00	72.04	48.56

TABLE XI. Table XI had shown the accuracy of gesture recognition at various distances, considering lighting conditions, camera types, palm orientations, and corner angles. Two sets of factors are considered: one combining lighting conditions, camera types, and palm orientations, and the other focusing on corner angles. The accuracies of the factors were generally increased with distance up to 20.00 cm and then declined. It also established different performance trends based on corner angles.

TABLE XII. SUMMARY OF RESULTS

Groups	Count	Sum	Average	Variance
Lighting, Camera, and Palm Orientation	21.000	1430.510	68.120	582.860
Corner Angle	21.000	1279.614	60.934	255.719

An overview of the total count, sum, average accuracy, and variance, in TABLE XII. for the two groups of factors: "Lighting, Camera, and Palm Orientation" and "Corner Angle", were signifying that the average accuracy is higher for the combined group of lighting, camera, and palm orientation compared to the corner angle group.

TABLE XIII. ANOVA TABLE

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-Value	P-value	F critical
Between Groups	542.134	1.000	542.134	1.293	0.262	4.085
Within Groups	16771.586	40.000	419.290			
Total	17313.720	41.000				

F-Value: 1.29 (less than the F-Critical value of 4.08), indicating no significant difference. Similarly, P-Value: 0.26 (greater than 0.05), failing to reject the null hypothesis. In short, the ANOVA test indicates that there is no statistically significant difference across settings.

C. Hand Gesture Recognition Accuracy Calibration Outline

1) Key findings by settings: Table XIV reveals the concise version of the experimental products after the observation and analysis.

TABLE XIV. SUMMARY OF ANALYSIS

Setting	Key Finding
Distances and Accuracy	• Optimal distance: 20 cm (accuracy: 88.08%). • High variability at 10-15 cm, low at 16-20 cm, increases beyond 20 cm.
Camera and Lighting	• Best performance: Laptop C under bright lighting (accuracy: 73.40%). • Lowest performance: Laptop B under dim lighting (accuracy: 62.42%).
Palm Orientation	• Higher accuracy with upper limb orientation (62.96%).
Corner Angle	• Optimal angle: 60° (accuracy: 69.95%).
ANOVA Analysis	• No significant differences across settings (F-Value: 1.29, P-Value: 0.26).

A concise summary of the key findings from the analysis was provided Table XIV to highlight the optimal settings for distance, camera, lighting, palm orientation, and corner angle for achieving the highest gesture recognition accuracy. The ANOVA analysis confirms that there are no significant differences across the settings tested.

2) Comparative analysis and unique contributions of current research in hand gesture recognition: The comparison of the obtained results on hand gesture recognition to other studies in the field, it is evident that this experiment on calibration outcomes provide valuable insights that surpass the relevance and accuracy of many existing works. While various studies have explored different aspects using technologies such as deep learning algorithms, data gloves, and EMG sensors, this calibration findings stand out for its specific focus on key factors that significantly impact accuracy and performance in hand gesture recognition systems.

Luo et al. [75] and Yılmaz [76] had previously investigated the use of CNNs and deep learning algorithms for gesture recognition, which are common approaches in the field. However, by pinpointing the optimal distance for accuracy at 20 cm and highlighting the impact of camera and lighting conditions on performance, has already surpassed their products. This specificity in identifying the ideal conditions for accurate gesture recognition sets this current research apart from these more general approaches such as altering genetic algorithms for the recognition under the same lighting alone.

Similarly, Gao et al. [77] had emphasised the reliability of data-glove-based methods for gesture recognition, which can indeed yield high accuracies. In addition, exploration on the binary serial image implied image extraction calculation with depth-sensor-based gesture recognition, showcasing the diversity of approaches in the field. does not seem practical when it comes to investigating the skin colour [78]. Nonetheless, this calibration study abled to provide more practical insights by focusing on the impact of palm orientation and corner angle on accuracy, offering tangible guidance for improving recognition rates beyond just the choice of recognition method, especially while considering the ability of stroke patients, to enable a layer of real-world applicability.

Moreover, while studies as per Farid et al. [79] discuss the application of vision-based systems for gesture recognition. Conversely, by conducting a detailed analysis of how different factors such as distance, lighting, and hand orientation affect accuracy the optimal settings for these variables, these calibration findings proposed a more comprehensive understanding of the nuances involved in achieving high accuracy rates in gesture recognition systems.

Furthermore, ANOVA analysis conducted has revealed no significant differences across settings, contrasts with the emphasis on specific methodologies and algorithms [80], [81]. While these studies contribute valuable insights into the technical aspects of gesture recognition. According to DoE factors that were implemented in this research, it was certain that focusing on the has been impactful compared to the environmental settings of the existing literature.

The outcomes of the experiment were recorded by observing the accuracy as shown in Fig. 13. The provided images in Fig. 13 demonstrate the performance of a gesture recognition system under various conditions. Fig. 13(A) shows a fist gesture in upper limb orientation with landmarks, achieving 22% accuracy for pinch extension at a close distance to the camera, indicating clear recognition. Fig. 13(B) depicts a fist gesture slightly further from the camera, resulting in 8% accuracy, highlighting the impact of increased distance on the system's performance. Fig. 13(C) illustrates a pinch gesture with 71% accuracy, measured by the distance between specific landmarks in a bright setting, underscoring the importance of good lighting for accurate recognition. Fig. 13(D) shows a fist gesture at 30 cm distance in landed orientation under dim lighting, with 7% accuracy, demonstrating the challenges of maintaining high accuracy at greater distances and under poor lighting. Fig. 13(E) presents a fist gesture at a closer distance in landed orientation under dim lighting, achieving 0% accuracy for pinch gesture recognition, highlighting the system's limitations in dim lighting conditions. Fig. 13(F) demonstrates perfect accuracy for the pinch extension gesture in upper limb orientation under dim lighting, indicating that the system can achieve high accuracy with proper calibration even under suboptimal lighting. These observations suggest that gesture recognition accuracy is influenced by distance, lighting conditions, and the specific gesture being performed.

D. MediaPipe Framework Implementation

MediaPipe provides a robust solution for real-time, on-device machine learning, particularly hand gestures, facial landmarks, and pose detection. One of its primary benefits is that it does not require extensive training, unlike many traditional machine learning models. MediaPipe's pre-trained models facilitate immediate recognition capabilities, making it an efficient and practical choice for works that demand quick and accurate results without the need for a deep understanding of machine learning algorithms or the resources required for training datasets.

E. Overcoming Data Security and Reliability Downsides with Smart Healthcare

Ensuring data security and reliability is paramount due to the sensitive nature of patient information being transmitted across networks. Several strategic approaches can be employed to overcome these challenges effectively. The implementation of IoT in this study, which was included in the factorial DoE, aligns with the trends and challenges identified in by Zainuddin et al., [24] by demonstrating the practical applications and potential hurdles of integrating advanced technologies in healthcare.

Firstly, implementing robust encryption protocols, such as end-to-end encryption, ensures secure data transmission and storage [82]. Encryption plays a crucial role in protecting patient data from unauthorised access during transfer between devices and servers. Incorporating blockchain technology, data integrity and security were enriched through providing a decentralised and immutable ledger for recording transactions [83]. Once patient data is stored in the blockchain, it becomes tamper-proof, ensuring its accuracy and reliability.

Moreover, an advanced machine learning algorithms can significantly improve the reliability of smart healthcare systems by enabling accurate data analysis and predictions [84]. These algorithms can detect anomalies in data transmission, flag security threats in real-time, and predict system failures to enhance reliability.

Furthermore, utilising multi-factor authentication (MFA) adds an extra layer of security by requiring multiple forms of identification for system access [85]. This approach reduces the risk of unauthorised access, even if one factor is compromised.

In addition, regular security audits and vulnerability assessments are essential for identifying and addressing potential security weaknesses in smart healthcare systems [86]. By evaluating the system's security posture routinely, necessary updates and patches can be implemented to safeguard against emerging threats.

In short, by employing encryption, blockchain technology, machine learning algorithms, multi-factor authentication, and security assessments smart healthcare systems can effectively manage data security and reliability, ensuring the secure and reliable transmission of patient information.

F. *The Impact of Secure Calibration with DoE*

Calibration methods improve recognition accuracy and system reliability. Technology integration is important for securing the calibration process and optimising performance.

Tanwar et al. [87] conducted a study on secure calibration methods and technology integration in gesture recognition. The research emphasised the importance of preserving privacy in sign language recognition using deep learning for encrypted gestures. Hence, the encryption techniques are crucial for ensuring the security, integrity, and reliability of gesture recognition systems.

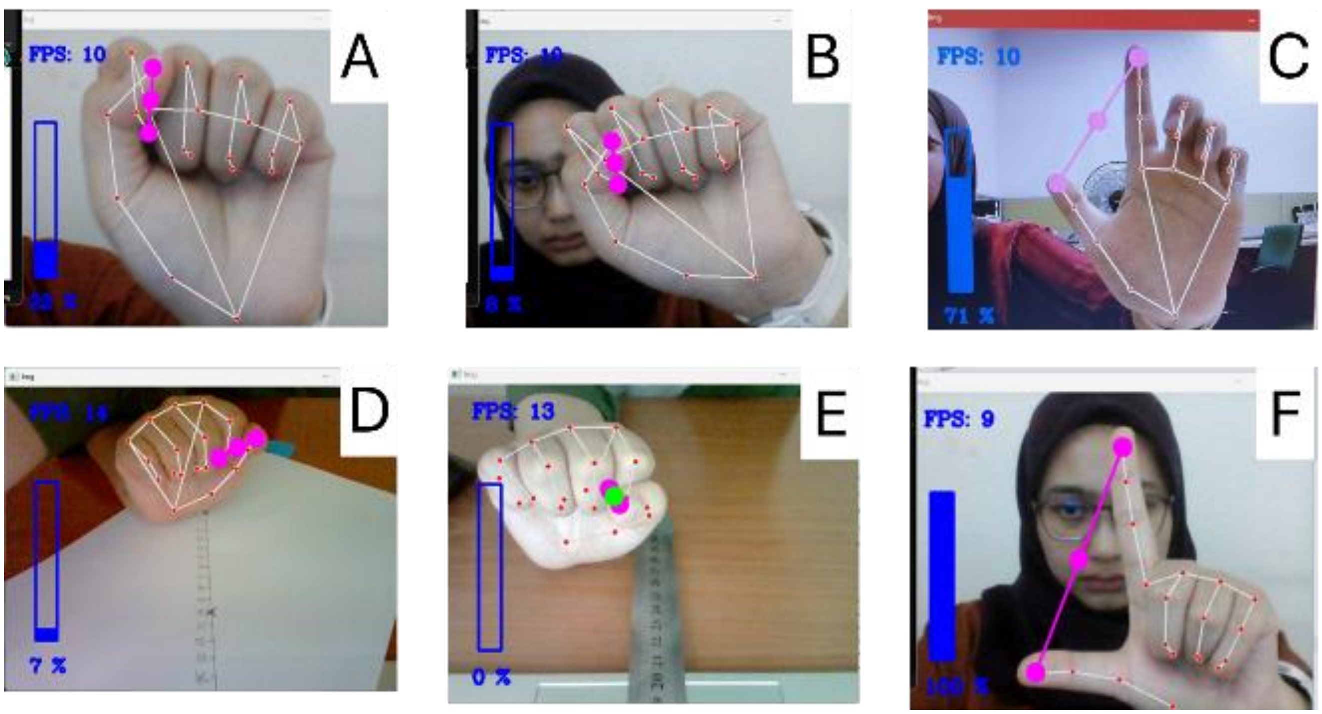


Fig. 13. Screenshots of hand gesture recognition accuracy for calibration.

Fig.13. A. Fist gesture in upper limb orientation with landmarks manifested 22% accuracy for pinch extension in a close distance between camera and palm where the gesture was fully and clearly recognised in the window. In this scenario, the gesture was fully and clearly recognized in the window, highlighting the system's potential for precise recognition at short distances.

Fig. 13. B. A demonstration of the fist gesture slightly further from the camera yielded an accuracy of 8%. This reduction in accuracy emphasises the impact of distance on the system's performance, with closer distances generally providing better recognition.

Fig. 13. C. The accuracy of the pinch gesture (71%) was calculated by measuring the distance between landmark 4 and landmark 8 in a bright setting. This high accuracy underscores the importance of bright lighting conditions for optimal gesture recognition.

Fig. 13. D. At 30.00 cm, the system recorded an accuracy of 7% for recognising a fist gesture in landed orientation under dim lighting conditions. This result illustrates the challenges of maintaining high accuracy at greater distances and under poor lighting.

Fig. 13. E. A closer distance of the fist gesture in landed orientation under dim lighting conditions resulted in an accuracy of 0% for pinch gesture recognition. This scenario highlights the limitations of the system in dim lighting, even at closer distances.

Fig. 13. F. Perfect accuracy was measured for the pinch extension gesture in upper limb orientation under dim lighting conditions. This indicates that the system can achieve high accuracy in certain gestures and orientations, even under suboptimal lighting, demonstrating the potential for robust performance with appropriate calibration.

Overall, the investigation on hand gesture recognition stands out for its meticulous examination of the impact of distance, lighting, palm orientation, and corner angle on accuracy. By providing specific recommendations for optimal conditions and highlighting the practical implications of these discoveries offer a valuable contribution to the field of gesture recognition that surpasses many existing studies in terms of relevance and applicability.

V. CONCLUSION

In conclusion, this research has demonstrated the potential of integrating the MediaPipe framework with the Rehabilitation Internet-of-Things (RIOT) to enhance the accuracy and security of hand gesture recognition in smart healthcare systems by applying strong methodologies, the DoE for calibration and this study has also addressed the critical challenges of data security, reliability, and accurate assessment in stroke rehabilitation. The results denote that optimising factors such as camera distance, lighting conditions, and palm orientation could significantly improve gesture recognition accuracy. Furthermore, the implementation of advanced encryption protocols and blockchain technology ensures the secure transmission and storage of sensitive patient data. These advancements are not only facilitating more effective and precise remote rehabilitation but also underscore the importance of multidisciplinary collaboration in developing smart healthcare solutions. Ultimately, this research paves the way for future innovations in healthcare technology, promoting better patient outcomes and more efficient rehabilitation processes. In growing body of research on the combination of IoT and AI in healthcare, building on the foundational work [15], [16]. Future research should continue to explore the intersection of these technologies to further enhance their efficacy and security.

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