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Stretchable Sensor-Based Glove for Hand Pose Recognition while Performing Activity of Daily Living (ADL) Tasks using Random Forest and K-Nearest Neighbors

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ABSTRACT

Hand movement analysis is gaining increasing attention across various fields of application. However, due to the complex dexterity and unrestricted range of motion of the human hand, developing a reliable and cost-effective method to monitor and capture hand motion remains essential. This study focuses on a stretchable sensor data glove designed to recognize hand poses during the performance of six Activities of Daily Living (ADL). The stretchable strain sensor is composed of three layers made from distinct materials, including conductive carbon ink, thermoplastic polyurethane, and a cotton/polyester fabric blend. The reliability of the strain sensor is assessed through testing, revealing mean values and standard deviations of 85kΩ ±12kΩ for the stretch stage and 25kΩ ±2.5kΩ for the relaxed stage. The developed stretchable sensors are integrated into gloves of various sizes. A custom module for reading the strain sensor data is designed using an Arduino Uno board system. A voltage divider circuit is implemented to determine the degree of finger and wrist bending, where the stretchable sensors function as unknown resistors connected in series with a 200kΩ known resistor. Twenty-three participants participate in validating the data glove's performance, with data acquisition conducted and processed offline. Each participant performs six ADL tasks three times while wearing the data glove. Machine learning algorithms, specifically Random Forest (RF) and K-Nearest Neighbor (K-NN), are employed to classify hand poses during the six ADL tasks, achieving accuracies of 82.47% and 70.31% for RF and K-NN, respectively.

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1. Introduction

Currently, clinical practice is transitioning to an era of continuous precision monitoring of physiological parameters through wearable or implantable electronic sensors, which is reducing healthcare costs and enhancing patient care [1]. Real-time monitoring of physiological signals is crucial for assessing functional recovery and aiding therapists in administering the necessary exercises to patients [2]. Recognizing Activities of Daily Living (ADL) is rapidly gaining attention, as it provides crucial information about individuals, their activities, and important contextual insights, thereby enhancing the effectiveness of mobile health and wellness delivery models [3]. Various applications, including physical fitness monitoring, diet tracking, assisted living, and remote health monitoring, benefit from the information provided by ADL recognition systems.

Hand pose recognition is a widely used technique for identifying hand gestures, with applications in sign language recognition, gesture-based interfaces, and human-robot interaction [4]. Hand gestures can be categorized into static and dynamic gestures, with the latter playing a crucial role in hand pose recognition for telerehabilitation [5]. Telerehabilitation has emerged as an effective method for delivering remote physiotherapy, enhancing patient recovery, and reducing the burden on physiotherapists [6][7]. Recent advancements in machine learning algorithms, such as Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), Decision Trees (DT), XGBoost, and Random Forest (RF), have improved hand pose recognition accuracy using wearable sensor data gathering micro-activities using wearable sensing for ADL recognition of home-care patients [8][9]. Wearable sensing technologies, including Inertial Measuring Units (IMUs), Electromyographs (EMGs), bending sensors, and stretchable sensors, provide valuable insights into ADLs [8]. IMUs, which consist of accelerometers and gyroscopes, are extensively used for hand pose and ADL recognition, enabling accurate assessment of motor functions [10][4]. EMG signals help monitor recovery levels and motor function but are susceptible to noise, affecting accuracy [11][12]. Bending sensors, commonly placed over finger joints in gloves, measure deflection angles, while stretchable sensors offer high dexterity and sensitivity, making them ideal for hand pose recognition [13][14]. The ability to accurately track individual finger movements, along with its enhanced convenience, has made instrumented glove-based hand tracking and hand pose recognition a preferred alternative to computer vision-based methods. However, the extremely intricate anatomy, small size, and 27 degrees of freedom of the hand make creating instrumented gloves a difficult task. Different wearable sensors were utilised by different researchers to design data gloves for various applications such as hand pose recognition[15].

Flex sensors, or bend sensors, are widely used for measuring angular displacement and have been extensively applied in data gloves for hand motion tracking and gesture recognition [16][17]. Several studies have explored their effectiveness compared to computer vision-based methods in virtual reality. For instance, the studies in [18] and[19] developed data gloves with flex sensors for dynamic gesture recognition. In previous research of [20], a data glove integrating ten flex sensors and a 9-axis IMU sensor achieved 90.66% accuracy in static China sign language recognition. Similarly, the study of [21] used ten flex and force-sensing resistor sensors for static gesture recognition in therapy, where machine learning models (SVM, KNN, and DT) attained up to 99.07% accuracy. Research in [22] combined bend and pressure sensors, reaching 98.48% accuracy using SVM. Additionally, research in [5] designed a data glove with five force and five flex sensors to recognize 13 static gestures, where Random Forest and Classification and Regression Tree (CART) achieved 96% and 81% accuracy, respectively. Despite their advantages, flex sensors face challenges such as durability, precision, and limited motion range, affecting their long-term reliability and accuracy.

IMU sensors are widely used in data gloves for tracking hand motion because they provide detailed movement data. These sensors usually include an accelerometer to measure movement speed, a gyroscope to track rotation, and sometimes a magnetometer to detect direction. Researchers have explored IMU sensors in hand pose recognition. For example, previous study in [23] used three IMU sensors and two bending sensors to measure finger joint angles, with errors between 0.81% and 5.41%. Other studies, such as in [24] and [25], achieved 92% and 91.11% accuracy in recognizing static hand gestures using machine learning and deep learning. Bin *et al*. [26] used an IMU-based glove to classify 10 sign language gestures, obtaining 79% accuracy with PCA+SVM and 81% with LSTM. Fang *et al*. [27] applied 18 IMU sensors for recognizing static and dynamic gestures, achieving 90% and 82.5% accuracy, respectively. Similarly, the research in [28] used 16 IMU sensors to capture finger and hand movements, achieving an average error of 3°. Despite high accuracy, IMU sensors face challenges such as drift over time, noise, and high computational demands that may affect real-time performance. Additionally, IMU-based gloves can be uncomfortable, particularly for patients, making it important to balance accuracy with user comfort.

The limitations of IMU sensors, such as drift and discomfort, have led researchers to explore alternative technologies like stretchable sensors, which offer greater flexibility and adaptability in data glove design. These sensors are made from materials that maintain functionality under deformation and can detect strain, pressure, temperature, and bio-signals. In previous research [14], a data glove with stretchable sensors was developed for hand pose reconstruction without an external optical setup, achieving a 35% improvement in reconstruction accuracy compared to commercial gloves. Similarly, Zhang *et al*. [29] designed a glove with 10 stretchable strain sensors for static sign language recognition, using a radial basis function neural network (RBFNN) to classify 26 letters with 86.5% accuracy. Another study [30] employed five piezoresistive strain sensors to measure finger joint angles, reconstructing two hand gestures with 80% accuracy. Dong *et al*. [31] developed a glove with five soft piezoresistive strain sensors for signal classification and robotic finger control. Additionally, Heo *et al*. [32] created a textile-based glove using AgNw strain sensors on a polyester-spandex fabric, which successfully detected hand gestures and controlled a 3D-printed prosthetic hand. These advancements highlight the potential of stretchable sensors for accurate and comfortable hand motion tracking.

Various sensor-equipped data gloves and classification methods have been used for hand pose recognition, with higher accuracy achieved in static gestures than dynamic ones [5][29]. Challenges remain in recognizing dynamic gestures, especially in ADL tasks, due to motion limitations and real-time computation demands. To address this, the study focuses on developing a data glove with stretchable strain sensors to recognize hand poses in 6 ADL activities, using RF and K-NN algorithms for evaluation. This research adapted the developed stretchable strain sensors in study [33] which evaluates the shape, material composition and the reliability of the stretchable strain sensors. This study focuses on the design of a module for sensor data collection, evaluation of the performance of the data glove in dynamic hand pose recognition and analysis on the accuracies of the two machine learning algorithms for the hand pose classification. It aims in evaluating the performance of the develop stretchable strain sensors-based gloves for potential telerehabilitation application. The rest of the paper is organized as follows. Section 2 describes the methodology, the results are presented in Section 3 and finally conclusion is drawn in Section 4.

2. Methodology

2.1 Stretchable Sensor Gloves Hardware Design

A stretchable strain sensor made of three layers from three distinct materials produced in [33] work has been utilized for the data glove production. Stretchable conductive carbon is printed onto a second layer of thermoplastic polyurethane (TPU) to form the top layer. A blend of polyester and cotton makes up the third layer. After printing the stretchy conductive carbon ink on the TPU, the cotton/polyester fabric was laminated onto it using the U-Shape strain sensor test design pattern. An automatic Micro-tec (MTP-1000) printer at MTI Lab, Jabil Circuit Sdn. Bhd., Penang was utilised to screen-print the strain sensor using a polyester mesh (200 threads/inch) with 20 microns of emulsion thickness and 25 N tension. The Stretchable Conductive Carbon Ink was blended prior to printing. The carbon has been printed with printing speed of 90mm/sec, squeegee and counter pressure of 0.280 and 0.132 MPa respectively [34].

The developed stretchable strain sensor has been attached to a commercially available PVC Dot knit gloves as shown in Figure 1. Four pieces of stretchable sensors have been attached to the glove using adhesive glue, at the phalanges of the thumb, index finger, middle finger, and the wrist of the glove. The sensor positions are determined based on a previous study using a commercial stretchable sensor to identify the best arrangement. Four different placements were evaluated while performing the six ADL activities, as listed below:

i. Thumb, Index finger, Middle finger, and Wrist (TIMW)
ii. Thumb, Index finger, Middle finger, and back of hand (TIMB)
iii. Thumb, Index finger, Wrist, and Back of hand (TIWB), and
iv. All fingers (All Fingers).

The TIMW achieved the best result and is adopted in this study.

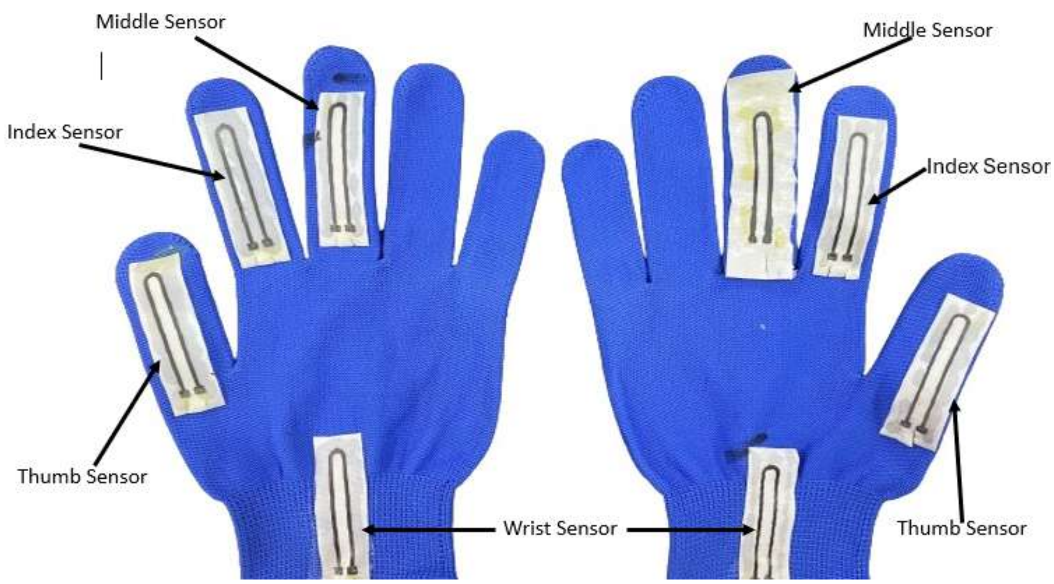


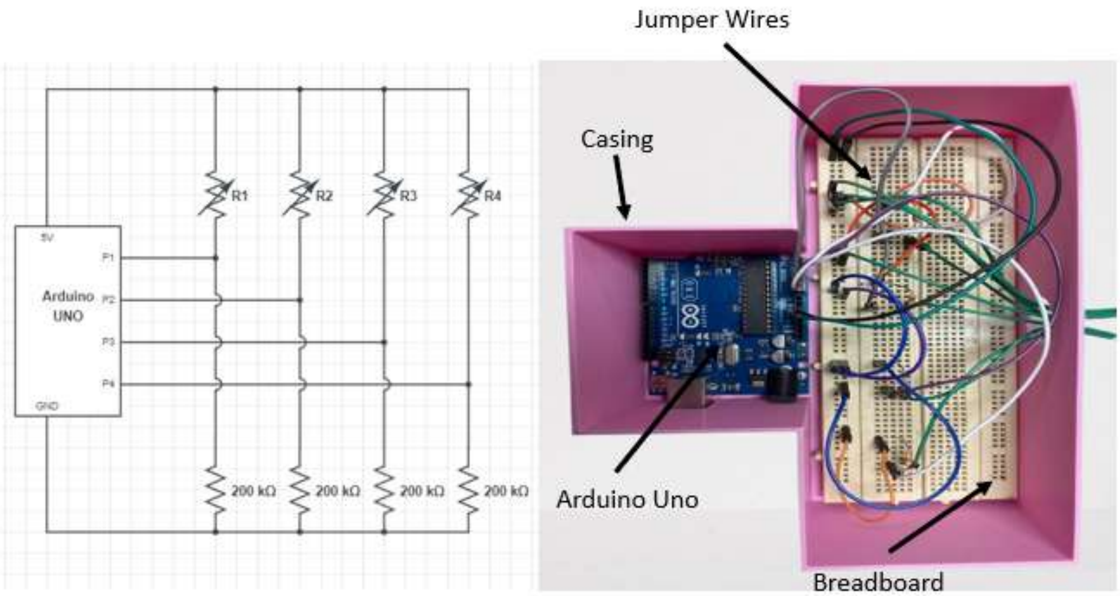
Fig. 1. Stretchable strain sensor- based glove with the developed sensors

The module for reading the stretchable strain sensor has been designed with Arduino Uno board system. The sensors have been connected to the Arduino board with crocodile connectors onto the two ends of each sensor. The voltage divider circuit has been used to determine the amount of bending of the fingers and wrist as the values of the stretchable sensors which are labelled as the unknown resistor connected in series with 200kΩ resistor as the known resistor according to Eq. (1)

$$Vo = Vs(Ru/(Rk + Ru)) \tag{1}$$

where Vo is the output voltage, Vs is the supply voltage which is 5V, Ru is the resistance of the stretchable sensor and Rk is the known resistance of the fixed sensor, which is 200kΩ.

Figure 2 (a) and (b) show the schematic circuit diagram and the Arduino circuit module respectively. The 5V supply and the ground (GND) pins of the Arduino Uno board has been connected to the breadboard. The 200kΩ resistors have been connected to the power and in series with the developed stretchable strain sensors which are connected via crocodile connectors at one end. The second ends of the developed sensors have been connected to the GND via jumper wires. The value of the output voltages of the circuit is read via analog pins of the Arduino as shown in Figure 2. Table 1 presents the Arduino technical configuration for the data acquisition. The input and output wires from the Arduino board are connected to the data glove via crocodile clips attached at both ends of each sensor. The Arduino board has been connected to a Dell DESKTOP-ELG9H9H with an Intel® Core ™ i7-6700 CPU @ 3.40GHz, which stores the data using Excel Data Streamer. Figures 3 and 4 illustrate the stretchable sensor data glove system and its block diagram respectively.



(a) (b)

Fig. 2. (a) Schematic circuit module (b) Arduino module circuit

Table 1
The Arduino Uno technical configuration

Parameter	Value
ATmega328P	8-bit
Operating Clock speed	16MHz
Operating Voltage	5v
ADC Resolution	10-bit
Input Pin 1	Thumb sensor
Input Pin 2	Index Finger sensor
Input Pin 3	Middle Finger sensor
Input Pin 4	Wrist sensor
Sampling Frequency	9.6kHz
Connectivity	USB interface Type-B

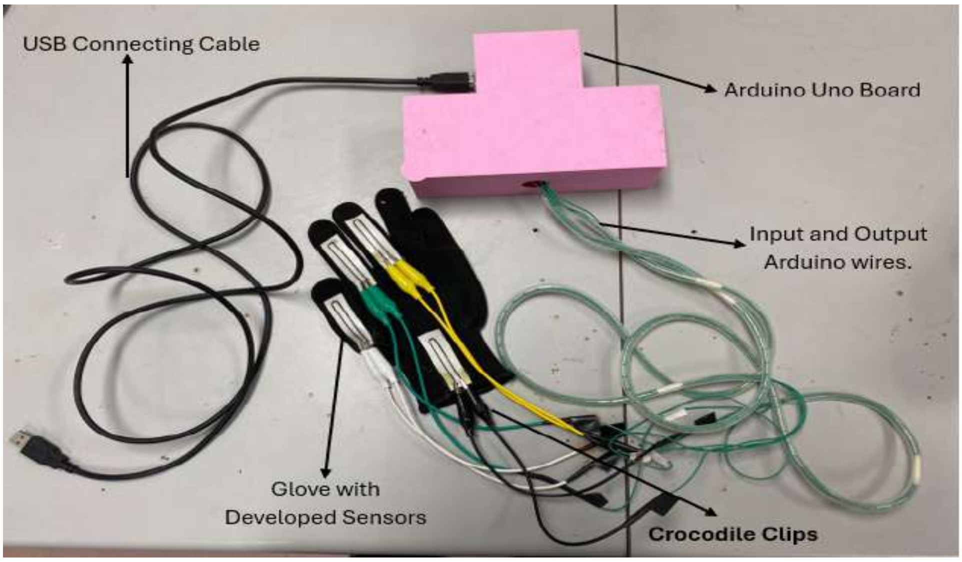


Fig. 3. Developed sensor system

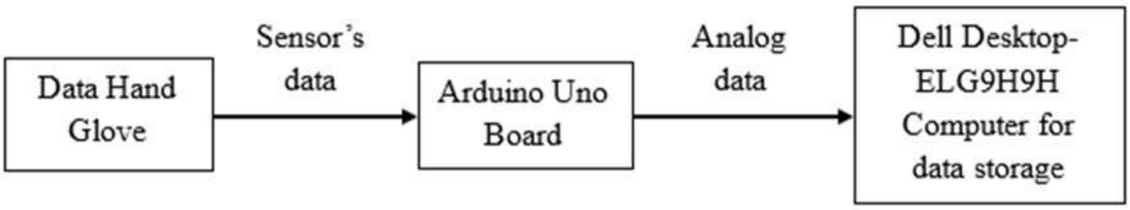


Fig. 4. Developed sensor system block diagram

2.2 Data Acquisition

Twenty-three healthy participants have been recruited to assess the performance of the developed data glove with stretchable strain sensors. The subjects comprised of 3 females and 20 males with mean age of 27 ± 8 years, 91.3% of the subjects are right-handed and 8.7% uses left hand for daily activities. Participants are recruited from a diverse group of Asians and Africans ethnicities.

All participants have received a written and verbal information about the study and have given written informed consent. The protocol for the study was approved by the International Islamic University Malaysia Research Ethics Committee (IREC), under approval number IREC 2023-079. The study focuses on recognizing hand poses during six activities of daily living (ADL), which include:

i. Turning the doorknob (Task 1)
ii. Turning the water tap (Task 2)
iii. Sliding the door latch (Task 3)
iv. Removing the plug head from the plug (Task 4)
v. Turning the padlock key (Task 5)
vi. Pressing the switch (Task 6)

The subjects are requested to sit in front of the manipulation board. The board is placed on the table 65cm height and a chair without armrest place opposite the manipulation board. The subject receives a brief explanation on the experiment procedure and conduct a trial session. The procedure for the data collection are as follows:

i. The subjects place their dominant hand on the table at the home position (starting or ending point).
ii. The subject performs Task 1 and moves his / her hand back to the home position which indicates the completion of the first cycle of Task 1.
iii. The same task is repeated 3 times with an interval 10s for validation.
iv. After each task, the data are saved before the starting of the next task and the subject rests to avoid fatigue.
v. The next task cycle commences when the subject is ready to continue.
vi. The procedure is repeated for remaining Task 2, Task 3, Task 4, Task 5, and Task 6.
vii. The experiment ends after the subject completes the 6 ADL tasks on the manipulation board.

All rotational tasks (Tasks 1, 2, and 5) are standardized as clockwise rotations to ensure the consistency in performing the ADL-based tasks. Participants have been instructed to turn the doorknob or water tap or key in a clockwise direction to maintain uniformity. For Task 3, they are required to slide the latch lock linearly to open it. Additionally, in Task 4, participants are instructed to remove the plug head from the socket, while in Task 6, they use their index and middle fingers to switch on the light. Figure 5 shows the data acquisition setup. The sensor signals are sampled continuously at 9.6kHz. The acquired data is stored in computer as excel file using excel data streamer and processed offline.

2.3 Data Processing

The data from the 23 participants have been collected and stored for offline pre-processing. Each participant has a dataset comprising of four sensors and six tasks (4 × 6) which makes it twenty-four datasets. The size of training dataset is 552 × 250 for the 23 participants. The data has been processed using MATLAB version 2023a. The outliers caused by circuit disconnection or partial connection have been removed to ensure the data quality. Additionally, the dataset contains varying window lengths, requiring the application of different smoothing techniques, including moving average, moving

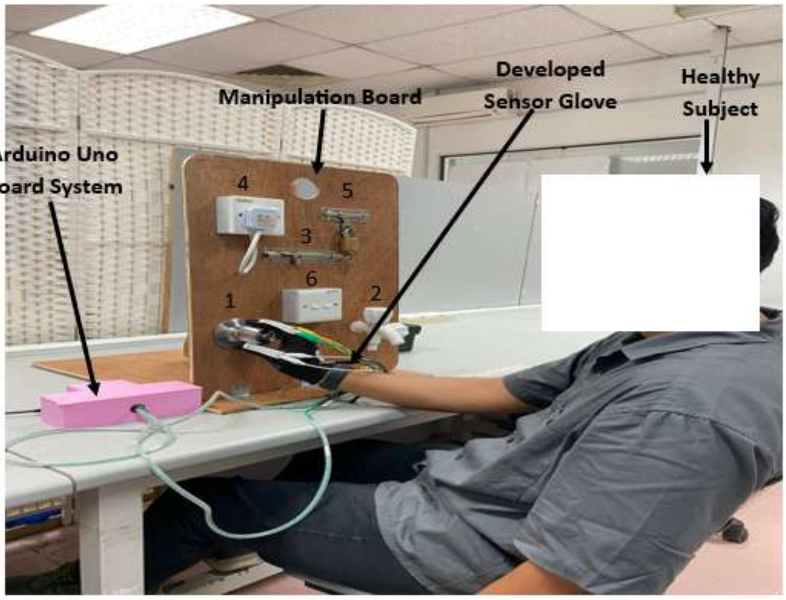


Fig. 5. Data acquisition setup

median, moving median absolute deviation and Gaussian filter. The most suitable technique, which minimized data distortion, has been selected. MATLAB's Data Cleaner app has been used for both smoothing and outlier removal, with a Gaussian filter applied using a smoothing factor of 0.25, as defined by the Gaussian formula

$$G(X_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{X_i^2}{2\sigma^2}} \tag{2}$$

where $G(X_i)$ is i^{th} filtered data value, Xi is the i^{th} data value, σ is the standard deviation value of the dataset (smoothing factor).

The choice of smoothing factor affects the degree of smoothness of the data with large smoothing factor resulting to more smoothing results and the opposite with smaller smoothing factor. In this study, the smoothing factor has been selected based on trial with 0.25 achieving good result without distorting the raw data features. Next, the smooth data has been normalised according to the Z-score equation for data normalisation and the Root Mean Square (RMS) features has been extracted according to.

$$Zi = \frac{Xi - \mu}{\delta} \tag{3}$$

where Zi is i^{th} normalized data value, Xi is the i^{th} data value, μ is the mean value of the dataset and δ is the standard deviation of the dataset, and

$$Xrms = \sqrt{\frac{1}{N}\sum_{i=1}^{N} Xi^2} \tag{4}$$

where $Xrms$ is the RMS value of the data, Xi is the i^{th} data value, and N is the numbers of data in the dataset.

2.4 Machine Learning

Various machine learning (ML) algorithms have been proposed in the literature to evaluate the performance of wearable sensors in hand pose recognition. In this study, the Random Forest (RF) and K-Nearest Neighbors (K-NN) algorithms have been used in recognizing hand poses while performing six activities of daily living (ADL) tasks using the developed stretchable sensor data glove. The processed datasets have been used for model development, with these two algorithms achieving the best results. PyCharm has been utilized to develop and validate the ML algorithms for recognizing the hand poses during the six ADL tasks.

The dataset for ML model development consisted of 537 × 250 data points, with 15 × 250 data points removed from the initial processed dataset of 552 × 250 due to sensor disconnection during data collection. The dataset is randomly split into 80% for training and 20% for testing and evaluation. A total of 108 × 250 datasets are used for testing, with Task 1, Task 2, Task 3, Task 4, Task 5 and Task 6 having 16, 23, 21, 17, 14, and 17 data points, respectively. The training data include the readings from 4 stretchable sensors for each of the 23 participants as input to the model, with the 6 ADL tasks as the output classes for ML classification.

The Random Forest (RF) model has been developed by optimizing its hyperparameters, where the number of decision trees in the ensemble was adjusted, and the Gini impurity criterion is employed to assess the quality of feature splitting at each stage of the tree-building process, as described by

$$G_c = 1 - \sum_{i=1}^{k} (\rho^2 T_i) \tag{5}$$

where G_c is the Gini impunity for c^{th}epoch and ρT_i is the proportion of elements of class T_i in the subset.

Furthermore, the K-NN algorithm model has been developed with *k* = 12-neighbors node after turning the node number and Minkwoski distance to determine the distance between data points. Generally, the accuracy score and the classification report which comprises of the precision, F1-score, and recall (sensitivity) has been deployed to evaluate the ML algorithms model in recognising the hand pose while performing the 6 ADL tasks. Moreover, the training/testing time for the ML algorithms model has been determined to illustrate the possibility of real-time performance of the models.

3. Results

3.1 Data Processing

Figures 6 and 7 illustrate the raw data of the four developed sensors attached on the data glove while performing Task 1 and 2 respectively. The three spikes on the graphs indicate the period when the tasks were performed by the participance with relaxing period at each cycle. The initial values of the sensors vary because the index and middle sensors are stretched to span the distal interphalangeal and proximal interphalangeal joints on the fingers. However, normalizing the data nullified the effect of the amplification. The raw data have been smoothened and normalized for the model development.

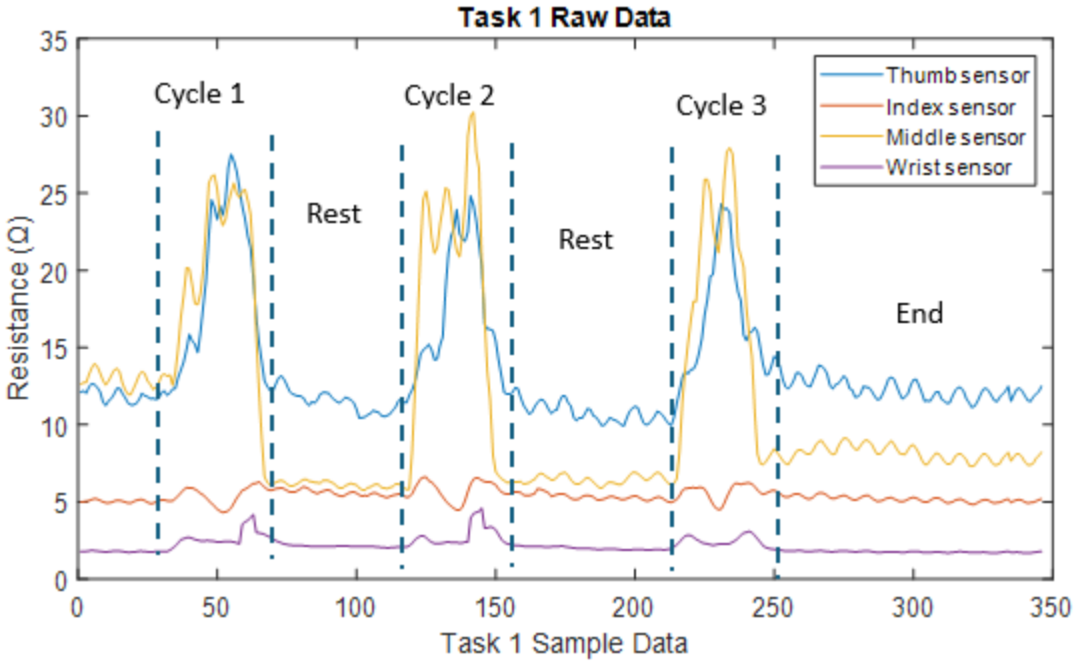


Fig. 6. Sample of raw data plot for Task 1

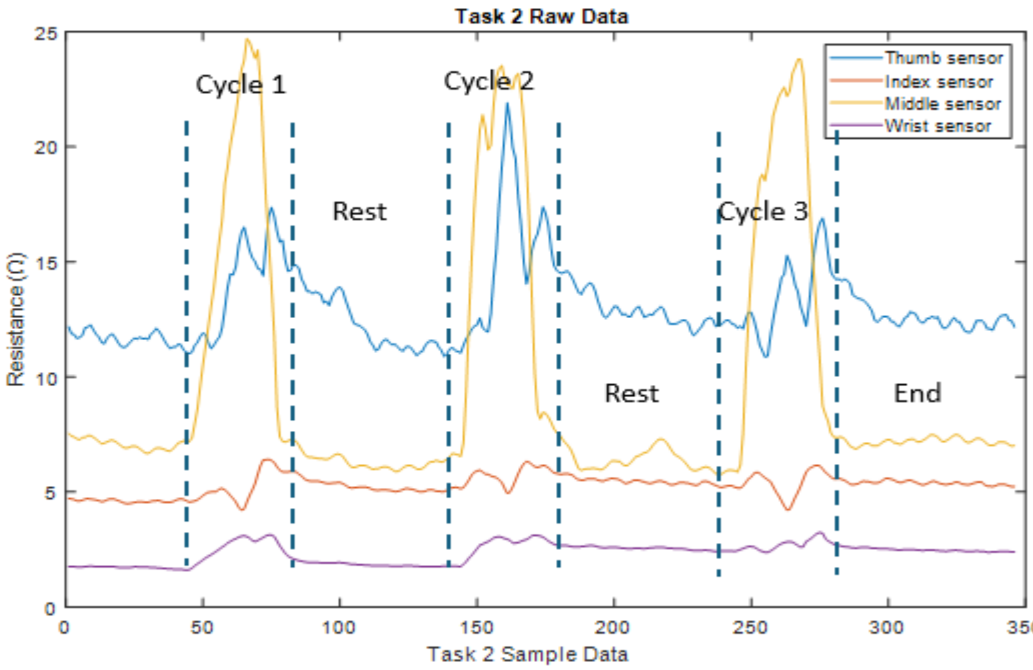


Fig. 7. Sample of raw data plot for Task 2

Figures 8 and 9 illustrate the sample data plot for the smoothen, normalised and extracted feature dataset of Task 1 and 2 respectively. The processed data have been used as the input for the ML model development. The smoothing factor has been selected to be 0.25 to preserve the features of the data so that the ML able to recognise the different hand pose while performing the six ADLs. The plots illustrate the effect of normalising the raw data as the four sensors are within same resistance range.

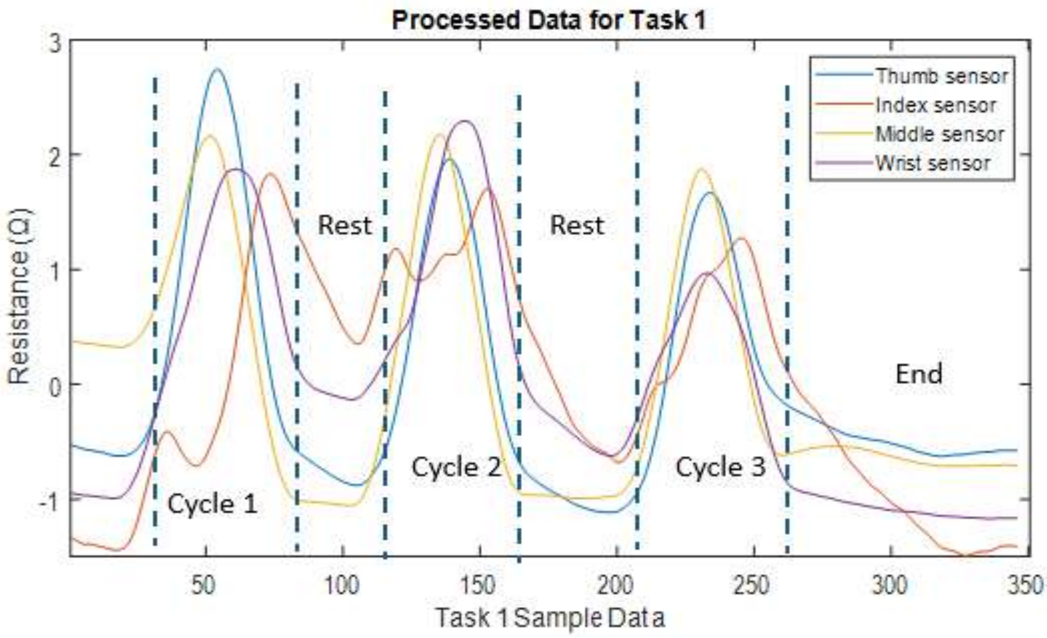


Fig. 8. Sample of the processed data for Task 1

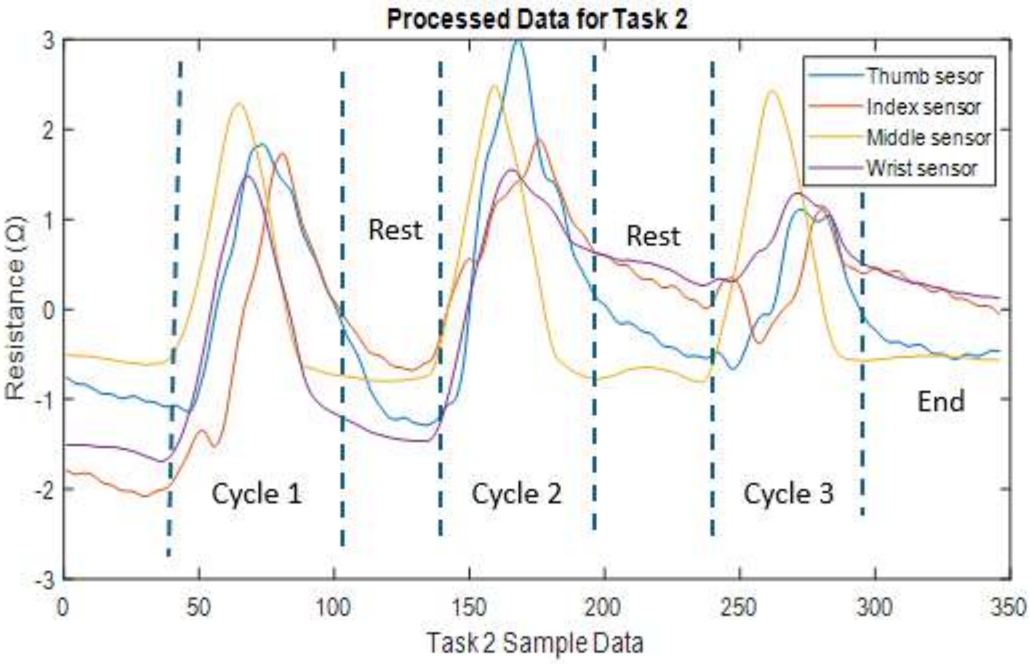


Fig. 9. Sample of the processed data for Task 2

3.2 Hand Pose Recognition Using ML based on Stretchable Sensor Data

The hand pose recognition models have been developed by adjusting key hyperparameters for the K-NN and RF models as shown in Table 2. For the K-NN model, different values of *k* (number of nearest neighbors) have been explored, including *k*= 6, 12, and 15. The highest validation accuracy of 70.37% was achieved with *k*= 12, corresponding to a training accuracy of 94.41%. However, increasing *k* to 15 led to a decline in both training and validation accuracy, indicating a potential underfitting issue.

Similarly, in the RF model, the number of estimators (n_estimatorsn) have been varied across 50, 100, and 150. Validation accuracy improved from 75% with 50 trees to 76.85% with 100 trees, reaching the highest validation accuracy of 82.41% with 150 trees, while maintaining 100% training accuracy. This show that the model's learning capability enhances with more estimators. However, the training time increased from 0.46s (50 trees) to 1.25s (150 trees), demonstrating a trade-off between accuracy and computational cost. Notably, the RF model significantly outperformed the K-NN model in test time efficiency, achieving 0.01s compared to 0.42s, reinforcing its suitability for real-time applications.

The confusion matrix results in Figures 10 and 11 show a validation accuracies of 70.37% for the K-NN algorithm and 82.41% for the RF algorithm. These accuracies indicate how well the models perform in recognizing hand poses during the six ADL tasks. The diagonal elements represent the correctly classified instances for each task, while the off-diagonal elements indicate the misclassification. The models correctly classified most data, as seen in the high values along the diagonals. However, some misclassification occurred particularly between Tasks 3 and 4 for K-NN model where 6 data from Task 4 have been classified as Task 3. Additionally, Task 2 data have been misclassified as Task 1 for RF model. This indicates a degree of overlap between those tasks. Despite the misclassification, the RF model demonstrates a strong overall performance, with minimal error in other tasks compared to the K-NN model.

Table 2
Hyperparameters of the models.

ML	n_estimator	k-value	Training accuracy (%)	Validation accuracy (%)	Train time (sec)	Test time (sec)
K-NN	-	6	89.98	61.11	0.01	0.42
K-NN	-	12	94.41	70.37	0.15	0.42
K-NN	-	15	82.28	63.89	0.01	0.42
RF	50	-	100	75	0.46	0.01
RF	100	-	100	76.85	0.87	0.01
RF	150	-	100	82.41	1.25	0.01

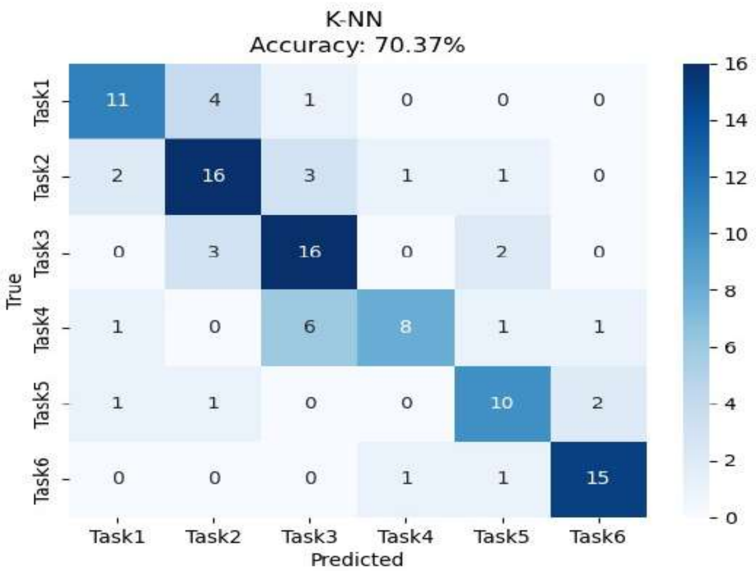


Fig. 10. The Confusion matrix for the hand pose recognition using stretchable sensor under K-NN algorithm

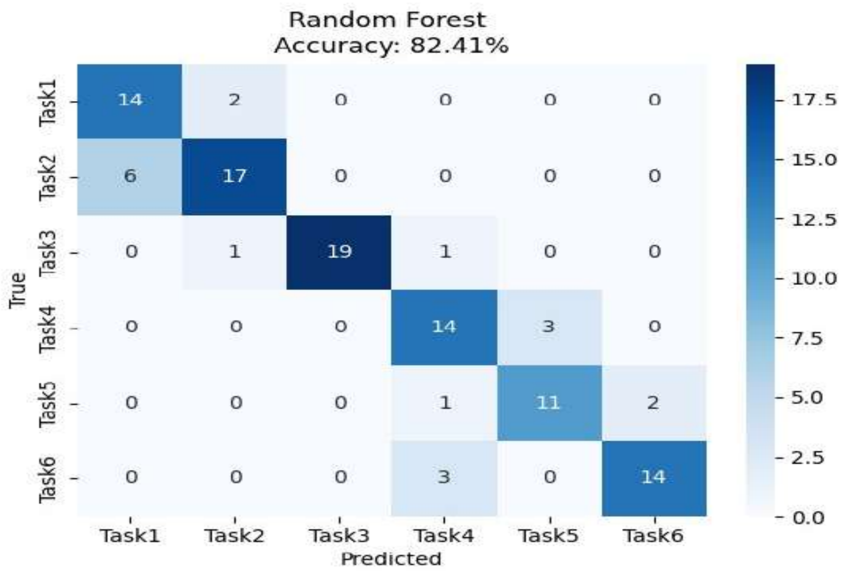


Fig. 11. The Confusion matrix for the hand pose recognition using stretchable sensor under RF algorithm

Tables 3 and 4 illustrate the classification report, summarizing the performances for the two developed models in terms of precision, recall, and F1-score for each task. The K-NN model illustrates similar result with Task 4 achieving the lowest F1-score of 0.59 and the highest F1-score of 0.86 for Task 6. The macro average and the weighted average scores of 0.68 for the K-NN model. The results for the RF model achieve the higher macro average precision and recall, with a macro average F1-score of 0.82. The highest F1-score of 0.95 was observed for Task 3, showing that this task has been well recognized by the model. Conversely, Tasks 1 and 4 have the lowest F1-score of 0.78, suggesting that some data were misclassified.

Table 3
Classification Report for K-NN algorithm Model

Task	Precision	Recall	F1-score	Support
1	0.73	0.69	0.71	16
2	0.67	0.70	0.68	23
3	0.62	0.76	0.68	21
4	0.80	0.47	0.59	17
5	0.67	0.71	0.69	14
6	0.83	0.88	0.86	17
Macro Avg	0.75	0.70	0.60	108
Weighted Avg	0.75	0.70	0.60	108

Table 4
Classification Report for RF algorithm Model

Task	Precision	Recall	F1-score	Support
1	0.70	0.88	0.78	16
2	0.85	0.74	0.79	23
3	1.00	0.90	0.95	21
4	0.74	0.82	0.78	17
5	0.79	0.79	0.79	14
6	0.88	0.82	0.85	17
Macro Avg	0.83	0.83	0.82	108
Weighted Avg	0.83	0.83	0.82	108

Table 5
Comparison the recognition accuracies of other researchers' data gloves with that of this study

Literature	Sensor	Type of Hand Gesture	ML/DL Algorithm	Accuracy
Maitre *et al* [5]	5 Force, 5 Flex	13 Static	RF/CART	96%/81%
Lei *et al* [20]	10 flex sensors, IMU	5 Static	ARM9 central processor	90.66%
Chen *et al*[21]	10 flex sensors, 10 force sensors	16 Static	SVM, K-NN, RF	Average recognition 94.87%
Dong *et al* [22]	5 flex sensors, 5 pressure sensors	10 Static	SVM	98.48%
Mummadi *et al* [24]	5 IMUs	22 Static	SVM, NB, MPL, RF	92%
Oleg *et al* [25]	5 IMUs	8 Static	RNN	91.11%
Bin *et al* [26]	IMU	10 Static	PCA+SVM/ LSTM	79%/ 81%
Fang *et al* [27]	18 IMUs	10 Static 16 Dynamic	ELM	90% 82.0%
Zhang *et al* [29]	10 Stretchable strain sensors	26 Static	RBFNN	86.5%
This Study	**4 stretchable strain sensors**	**6 Dynamic**	**RF/K-NN**	**82.41%/70.37%**

Table 5 compares the recognition accuracies of the data gloves examined in various studies with the work in this paper. Several studies focused on recognizing hand poses in static gestures, which generally resulted in higher accuracies compared to studies focused on dynamic gestures. For static gesture recognition, the highest accuracy achieved was 98.48% for 10 static gestures [22], while the lowest was 79% for 10 static hand poses using a different classification algorithm [26]. This highlights the influence of the machine learning algorithms, showing that the number of gestures has a minimal effect on recognition accuracy. The data glove developed in Fang *et al*.'s study [27], equipped with 18 IMU sensors, recognized 16 dynamic gestures with an accuracy of 82%, which is slightly lower than the 82.41% recognition accuracy achieved by the data glove in this study for 6 dynamic hand poses. A comparison between the data glove in Zhang *et al*.'s study [29] and the current study's data glove, both equipped with stretchable sensors, shows a slight difference in accuracy. Zhang *et al*.'s glove achieved 86.5% for 26 static hand poses [29], while the data glove studied in this paper achieved 82.41% for 6 dynamic hand poses. The data glove is expected to perform better if it is used to recognize the 26 static hand poses in Zhang *et al*.'s study [29]. It can be concluded that the data glove in this study performs effectively in recognizing the hand poses while performing 6 ADL activities, which are 6 dynamic hand gestures. At this stage of study, the data have been collected from healthy individual to evaluate its performance in recognising the dynamic hand poses. However, in future, the study needs to be extended with the data collected from the patients for the real telerehabilitation application.

4. Conclusions

This paper presents the classification of hand pose while performing 6 ADL based on the data collected using glove equipped with stretchable sensor using RF and K-NN algorithm. Data has been collected from 23 healthy individuals to evaluate the data glove's effectiveness in recognising hand pose while performing the 6 ADL activities on a manipulation board for upper limb rehabilitation. Two machine learning algorithms have been used for hand pose recognition while performing the six ADL tasks, yielding promising results of classification accuracy at 82.41% under RF algorithm and 70.37% accuracy under K-Nearest Neighbors (K-NN) algorithm. However, additional data are needed to further improve the model's classification accuracy. Remote recognition of hand poses during ADL is advantageous for providing rehabilitation exercises remotely, enhancing convenience, accessibility, cost savings, real-time monitoring, and feedback, thereby improving patient care and satisfaction. At this stage of the study, the performance of the designed stretchable strain sensor data glove has been evaluated on 23 healthy subjects and there is a need for more data from a higher number of subjects to improve the ADL hand pose classification accuracy. In the future study, the efficacy of the stretchable strain sensor data glove will be tested on stroke patients in assessing hand functional ability during the rehabilitation process. Additionally, the Arduino Uno board module will be replaced with more robust electronic modules, such as the Raspberry Pi, to achieve a higher sample frequency and potentially enhance the data glove's performance.

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