2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) | 979-8-3503-6908-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICEEICT61591.2024.10718430

# Flex Sensor Data Analysis for Hand Rehabilitation using Wearable Glove

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***Abstract*—Every day we encounter many people with unexpected situations where they suffer from many neuropathological diseases that cause a severe impact on the daily lives of individuals, especially about hand movements, thereby directly affecting the quality of their lives. Traditional methods often lack insights into personalized progress and optimal medication outcomes, which take longer to recover. We have designed an approach based on a novel concept using wearable technology to monitor and assess finger movements. The proposed solution of wearable device integrated flex sensor technology to enhance the rehabilitation process by providing real-time insights by the input of the flex sensors captured by the finger movements of the patients. By sensor data analysis, people get a chance to know their progress and the professionals gain accurate tracking of the progress so that they enhance identifying the areas of improvement and customize the treatment. This innovative approach to designing a wearable device serves as a helping aid to improve patient outcomes by categorizing the stages of improvement into Normal, Mild, and Severe Impairment for a better understanding and helps improve the rehabilitation experience.**

***Index Terms*—Wearable, Flex sensors, Hand Rehabilitation, Impairment, Finger movements, Neurological condition**

## I. Introduction

In today's technological world, effective healthcare solutions are more critical than ever. One of the great challenges that healthcare providers meet is the monitoring and rehabilitation of patients with motor impairments, such as stroke or other neurological disorders. Impairment of fine motor control is among the most serious consequences of these conditions, which make it difficult for a patient to carry out his or her daily activities, hence living a less fulfilled life. By recognizing the drawbacks of the present approaches, we seek to create a system that uses IoT technology to remotely monitor and classify finger movements in patients with motor impairments. Healthcare providers with objective and real-time data on motor function can use the system to help track progress, adjust treatment plans, and even intervene promptly when problems emerge for the best possible outcomes for patients.

In the proposed solution , the movement is monitored through flex sensors worn on patients' fingers. Data obtainable by the wearable sensors pass through processing at the central hub. The movements obtained are classified under three categories of movements: normal, mildly impaired, and severely impaired movements. Keeping this in mind, a lot of issues are taken into consideration as the system is in development. Among them are the means to make the collected data both accurate and reliable, means to design real-time processing techniques, and the matter of designing the user interface for the healthcare providers. We intend to have an effective design for remote monitoring and classification of finger movements for subjects with motor impairments. A system that will revolutionize the area of motor rehabilitation to offer a user-tailored, data-driven solution, thus empowering both the patient and health provider.

## II. Literature Review

Yanay et al. [1] work on the general established background of writing recognition, based on computer vision and motion sensors. Some of the previous works have used the ability of smart bands to capture the air-written letters, but authors coped with the limitations in the amount of data and a number of external devices used. Therefore, the authors implement a novel method that will make use of motion signals from the wrist in lieu of further hardware and may be able to permit richer data collection from a wider pool of subjects.

Lee et al. [2] deal with the fact that the development of the human–machine interface (HMI) has gone on to new skies, possible through the confluence of a host of innovative technologies. This is a fact against the background that low-power and potential self-sustainable devices could now become a reality for all sorts of applications, with the TENG sensors causing the most cacophony. This, in turn, will help in the creation of much smarter monitoring devices in the wearables and HMI to assure more funding in the field. More importantly, the two most critical words, AI and haptics, in relation to the development of HMI for intuitive and clever interaction with humans. With wearable exoskeletons to VR interfaces with haptic feedback, and with all kinds of other micro-motion sensors to touchpads, the world of HMIs is on the brink of significant improvement in concert with power-saving and enriched experiences.

According to Guo et al. [3], this technology is a part of HMI. The reasons for preferring the use of hand gesture in control applications over other approaches are explained in this section. After this, many potentials for making such a solution work in most parts of our daily life are shown. The authors have introduced body movement sensing, such as piezoelectric and optical accelerometers, sensing of the micromachined mechanical gyroscopes, and different methods for hand gesture recognition. The following sections of the work go deep into development, as well as the current challenges that the HGR technology is facing, and focus on the hybrid methods that are looking towards more robust recognition, using both inertial, visual, and electromyography (EMG) sensors.

A dynamic recognition framework for hand gestures was proposed by Pal et al. [4] for its use in dynamic conditions. The general concept of the framework relates to the information received by sensors regarding human-machine interaction. The paper addresses the 3D form of hand gesture recognition based on a machine learning model, with one of the focus areas being the 3D CNN approach for feature extraction and classification of hand gesture sequence coming from a sensor data stream. The general explanation for the framework includes the general method to be applied to the recognition of gestures, an algorithm for classification, and the analysis of datasets, along with an explanation of the comparison using different approaches.

Wang et al. [5] This paper designs a new hardware system for hand gesture recognition. The system comprises several motion sensors, probably IMUs, in that due to the manner it is inclined in capturing the movement of the hand. The prototype is built by off-the-shelf components, like the Arduino Nano board and Bluetooth module, and contains a total of 6 motion sensors. Hence offering better results of recognition than the usual methods describing the kinematics only by Euler angles. It has shown performance over 98% in gesture recognition, and thus it seems promising for HMI applications.

Zamel et al. [6] designed an innovative portable robotic hand with 5 DOFs for individuals with hand disabilities. This robotic hand aids in activities requiring finger agility, thereby restoring independence. The system combines a glove with flex sensors that translate finger bends into electrical signals to drive the robotic hand.

Kong et al. [7] developed a continuous user authentication system for smart homes using WiFi signals. This system ensures efficient user verification with 90.6% accuracy and a response time of 186.6 ms. It utilizes deep learning for login identification and lightweight classifiers for continuous authentication during interactions.

Husi et al. [8] developed a CPM device for finger and wrist rehabilitation, providing controlled passive motion for therapeutic purposes. The detailed discussion includes device specifications, power management, and control unit implementation using Kinovea motion analysis software for data analysis and system design.

Thangam et al. [9] showed that VANET routing protocols using metaheuristic EGAACO outperform conventional protocols like AODV, PSO, and ACO in real traffic situations. The integration of GA and ACO methods results in an improved routing algorithm for VANETs.

Thangam and Virupaxappa [10] optimized farming productivity by monitoring soil nitrogen levels and controlling pests using IoT technologies. This study combines sensor, wireless, and predictive technologies to improve efficiency and precision in farming processes.

Rishitha et al. [11] designed an IoT-based solar tracking system to optimize energy output from solar panels. The system uses sensors, microcontrollers, and stepper motors to adjust the panels' angles in real time, ensuring they remain perpendicular to the sun for increased energy production.

Thangam et al. [12] developed safety applications for automatic driver behavior recognition using deep learning techniques. They focused on recognizing distracted driver postures with CNN models like ResNet50 and VGG16, classifying behaviors into distracted and non-distracted categories.

Ananthan et al. [13] proposed an automated indoor hydroponic system based on IoT for real-time monitoring. The system uses Raspberry Pi and ESP 12E microcontrollers to control environmental factors such as pH, TDS, temperature, humidity, and lighting to maintain optimal growing conditions for plants.

Chuang et al. [14] enhanced finger gesture recognition by integrating flex sensors and GRU algorithms. Flex sensors measure finger movements, while GRU algorithms improve gesture classification by reducing noise and enhancing features.

Mitra et al. [15] improved gesture recognition using IMUs and LSTM-based deep networks. Their approach demonstrated enhanced recognition accuracy and efficiency for single-shot multiple gesture classification, showcasing the potential of IMU-specific deep learning methods.

Moulik et al. [16] focused on hand gesture recognition using flex sensors and machine learning algorithms. The study achieved high accuracy and precision, exploring the integration of IMU and EMG signals to develop robust recognition systems for real-life applications.

Pal et al. [17] enhanced dynamic hand gesture recognition using Kinect and OpenCV. This methodology allows real-time tracking and potential control applications for robotic arms, highlighting the use of hidden Markov models for effective classification of dynamic gestures.

Shravani et al. [18] developed gesture control systems for human-computer interaction using distance and accelerometer sensors. Their approach enables intuitive control of applications, providing low-cost, robust solutions for gesture based HCI applications.

Paul et al. [19] explored low-cost sensor gloves for humanrobot interaction, addressing issues like finger kinematics and position sensing. Their DAGLOVE integrates flex sensors, an IMU, and vibrotactile feedback, offering a low cost, wireless solution for enhanced interaction.

## III. Data Collection & Preparation

A complete idea of raw data collection from the sensor in Stage 1 to the Data preparation of the Final Stage for further analysis and result-making is discussed in the section.

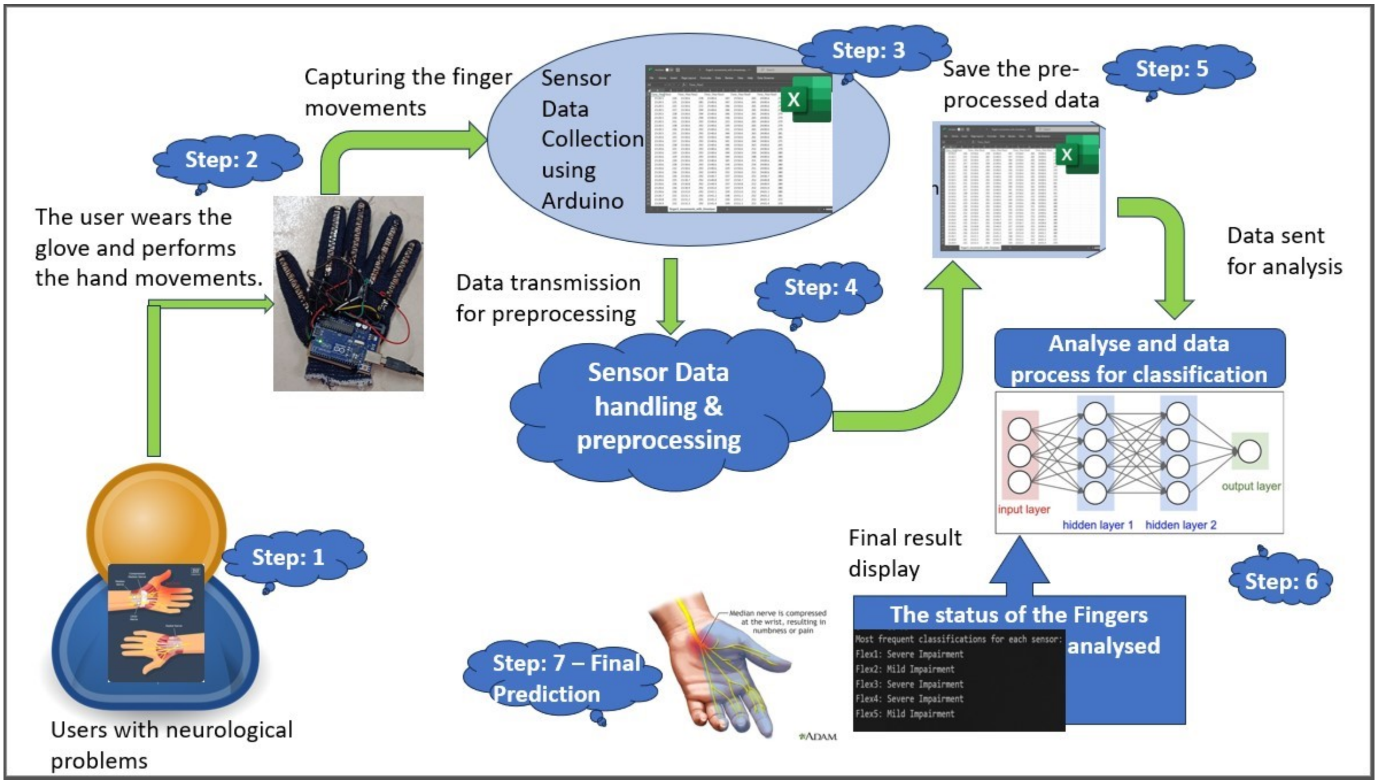


Fig. 1. System Design of the Proposed Solution

| Time_Flex | Flex1 | Time_Flex | Flex2 | Time_Flex | Flex3 | Time_Flex | Flex4 | Time_Flex | Flex5 |
|---|---|---|---|---|---|---|---|---|---|
| 00:37.9 | 6 | 00:47.8 | 242 | 00:57.8 | 336 | 01:07.8 | 264 | 01:17.8 | 165 |
| 00:37.9 | 0 | 00:47.8 | 242 | 00:57.8 | 335 | 01:07.8 | 265 | 01:17.8 | 165 |
| 00:37.9 | 0 | 00:47.8 | 242 | 00:57.8 | 335 | 01:07.8 | 264 | 01:17.8 | 166 |
| 00:37.9 | 0 | 00:47.8 | 242 | 00:57.8 | 336 | 01:07.8 | 264 | 01:17.8 | 168 |
| 00:37.9 | 0 | 00:47.8 | 243 | 00:57.8 | 334 | 01:07.8 | 264 | 01:17.8 | 170 |
| 00:37.9 | 6 | 00:47.8 | 243 | 00:57.8 | 336 | 01:07.8 | 263 | 01:17.8 | 180 |
| 00:37.9 | 0 | 00:47.8 | 243 | 00:57.8 | 335 | 01:07.8 | 264 | 01:17.8 | 198 |
| 00:37.9 | 2 | 00:47.8 | 243 | 00:57.8 | 334 | 01:07.8 | 264 | 01:17.8 | 215 |
| 00:37.9 | 3 | 00:47.8 | 244 | 00:57.8 | 335 | 01:07.8 | 263 | 01:17.8 | 228 |
| 00:38.0 | 2 | 00:47.8 | 244 | 00:57.8 | 334 | 01:07.8 | 264 | 01:17.8 | 237 |
| 00:38.1 | 1 | 00:47.8 | 247 | 00:57.8 | 334 | 01:07.8 | 264 | 01:17.8 | 243 |
| 00:38.2 | 1 | 00:47.8 | 258 | 00:57.8 | 336 | 01:07.8 | 264 | 01:17.8 | 247 |
| 00:38.3 | 0 | 00:47.8 | 264 | 00:57.8 | 335 | 01:07.8 | 265 | 01:17.8 | 251 |
| 00:38.4 | 0 | 00:47.8 | 268 | 00:57.8 | 335 | 01:07.8 | 264 | 01:17.8 | 255 |
| 00:38.5 | 0 | 00:47.8 | 268 | 00:57.8 | 336 | 01:07.8 | 265 | 01:17.8 | 257 |
| 00:38.6 | 3 | 00:47.8 | 270 | 00:57.8 | 335 | 01:07.8 | 265 | 01:17.8 | 256 |
| 00:38.7 | 4 | 00:47.8 | 272 | 00:57.8 | 335 | 01:07.8 | 265 | 01:17.8 | 258 |
| 00:38.8 | 0 | 00:47.8 | 276 | 00:57.8 | 336 | 01:07.8 | 264 | 01:17.8 | 258 |
| 00:38.9 | 0 | 00:47.8 | 277 | 00:57.8 | 336 | 01:07.8 | 266 | 01:17.8 | 258 |
| 00:39.0 | 205 | 00:47.8 | 280 | 00:57.8 | 336 | 01:07.8 | 266 | 01:17.8 | 258 |
| 00:39.2 | 192 | 00:47.9 | 281 | 00:57.9 | 336 | 01:07.9 | 267 | 01:17.9 | 259 |
| 00:39.3 | 182 | 00:48.0 | 280 | 00:58.0 | 336 | 01:08.0 | 267 | 01:18.0 | 259 |
| 00:39.4 | 178 | 00:48.1 | 278 | 00:58.1 | 334 | 01:08.1 | 266 | 01:18.1 | 260 |
| 00:39.5 | 182 | 00:48.2 | 274 | 00:58.2 | 328 | 01:08.2 | 266 | 01:18.2 | 259 |
| 00:39.6 | 186 | 00:48.3 | 267 | 00:58.3 | 317 | 01:08.3 | 265 | 01:18.3 | 259 |

Fig. 2. Raw Sensor Data Collection

| Classification_Flex1 | Classification_Flex2 | Classification_Flex3 | Classification_Flex4 | Classification_Flex5 |
|---|---|---|---|---|
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Severe Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
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| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Severe Impairment | Severe Impairment | Mild Impairment |
| Normal | Severe Impairment | Mild Impairment | Mild Impairment | Mild Impairment |
| Normal | Severe Impairment | Mild Impairment | Mild Impairment | Mild Impairment |
| Normal | Severe Impairment | Mild Impairment | Mild Impairment | Mild Impairment |
| Normal | Severe Impairment | Normal | Normal | Mild Impairment |
| Normal | Severe Impairment | Normal | Normal | Mild Impairment |
| Normal | Severe Impairment | Normal | Normal | Mild Impairment |
| Normal | Severe Impairment | Normal | Normal | Mild Impairment |
| Normal | Severe Impairment | Normal | Normal | Mild Impairment |

Fig. 3. Class labels of sensor data using Absolute difference

The flex sensor generates the resistance values for different angles that are made to be bent and it is highly difficult to be sure to map the values telling the values will be the same for the same angle bent. It is not possible to analyze the sensor that easily.

How the proposed solution address this challenge is that, we collect the data from the sensor to an excel or csv file in timestamps for each finger to move (as described in the Algorithm IV.B). The collected data just looks like the Fig. 2. (one sample instance).

After this, we further refine the data to address the issue of missing values. After the all of the preprossing, each and every sensor value is labeled by either one of the class labels (Normal, Mild Impairment, Severe Impairment) by considering first few rows as the reference point and all others in the same column are labeled using the absolute difference value with the reference as shown in Fig. 3. Finally, we assign the finger's status with the most repeated label in the entire column.

## IV. Proposed Methodology

The proposed methodology addresses the pseudocode, sequence or the flow of the proposed solution with its system architecture in detail.

### *A. System Architecture & Sequence Flow of the Proposed Solution*

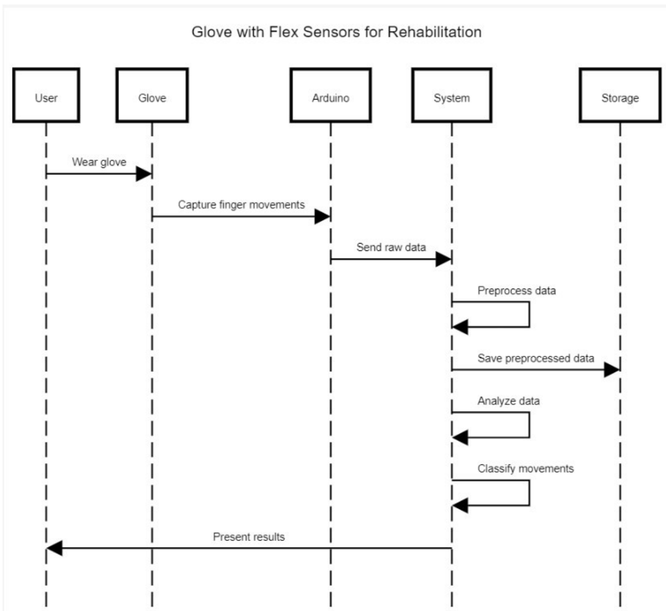


Fig. 4. Sequence Flow of the proposed solution

Fig. 1., is the System Design of the solution proposed in this entire study, and below gives a detailed description of the Sequence Flow shown in Fig. 4.

The architecture and execution flow are as follows: subsubsectionUser Interaction

The target user wears this specially designed glove with flex sensors. This step is essential because user interaction forms the basis of data collection.

*1) Movements are Captured:* While the user carries out a hand movement, the flex sensors worn on the glove are capturing finger bending or flexing. It is this information that is very crucial in determining the range of motion and the effectiveness of movement against the set rehabilitation goals. *2) Data Collection:* The data from sensors which is collected by the Arduino seems to be raw, capturing every slight movement or bending in the fingers that is considered. This data is then relayed from the Arduino onto a system, most probably a computer or a cloud system, for storage and then further processing.

*3) Preprocessing:* Before the raw data can be analyzed for any meaningful activity, it has to go through a preprocessing stage, which filters out any noises and corrects any errors in capturing the data. This might entail data-smoothing or trimming outliers so that only relevant data will be passed through for evaluation.

*4) Storage:* The pre-processed data is thus saved, maybe onto files in CSV format, so that it can later be used again, maybe in extraction or some kind of analysis, or for future comparisons. This is salient in holding the record of data being revisited upon further examination or in future comparisons.

*5) Analysis and Classification:* Advanced data processing techniques process the pre-processed data. This phase involves an analysis of the data after the pre-processing process. With the help of machine learning models or other analytical algorithms, the system classifies movements into classes such as normal, mild impairment, and severe impairment, based on some predefined criteria. Again, this would be very fundamental for a health worker to better understand the progression or needs of the patient.

*6) Results Prediction:* The outcome of the analysis is presented to the user or health provider: therefore, this is a detailed classification of the quality of the movement of the single fingers. The feedback could serve to inform further medical choices or rehabilitation adjustments.

The architecture nicely blends interactions with hardware and some sort of high-in-the-sky software for the analysis to give real-time, actionable feedback regarding the rehabilitation status of a patient. This flow from physical data collection through digital processing back to human-readable feedback forms a closed loop of continuous improvement in personalized healthcare.

### *B. Algorithm & its Explanation of the Proposed Solution*

The developed system first initiates a connection serially to the Arduino board with a pre-set configuration that is capable of transmitting over a specified port with a baud rate of 9600. After initializing the connection, a slight pause is given so that the system stabilizes before the start of data collection. The system then allows the user to move each finger, one by one, capture, and record the flex sensor data of each finger individually for 8 seconds.

The system captures and records this data, along with the associated timestamp information, to form a data frame for each finger, thereby accurate finger movement with time tracking. After all the fingers are done, the collected data is aggregated in one CSV file. This file is used further not only as a permanent record of raw data but also as an input file for the next processing stage. Each reading is juxtaposed against the immediately preceding value so as to identify and rectify the magnitude of abrupt changes in excess of a fixed threshold. This step actually reduces noise in the readings and prepares them further for an analysis with increased accuracy. Each movement is then classified against some previously determined baseline or reference value, as obtained in the earlier data points. Movements such as severe impairment,

**Algorithm 1** Data Collection and Processing for Finger Movement Classification

```
Initialize and connect to the serial port at a 9600 baud rate
Delay 2 seconds to establish a connection
Initialize an empty DataFrame for data collection
Display "Get ready!" and delay 2 seconds
for each finger index from 0 to 4 do
    Prompt user: "Move finger index+1"
    Collect data for 8 seconds:
        while data available and time ¡ 8s do
            Read, decode, and split data into sensor values
            if valid data for current finger then
                Append value and timestamp to lists
            end if
        end while
    Store lists in DataFrame and display "Relax."
    Delay 2 seconds
end for
Save DataFrame to an Excel file
Print "Data collection complete."
Process data:
Read data and filter columns with "Flex"
Initialize list to track previous valid sensor readings
for each row in the Excel file do
    for each sensor value do
        Handle empty values and convert to integer
        if change exceeds 200 then
            Use previous valid value
        end if
        Append current or previous value to list
    end for
    Write list to a new Excel file
end for
Classify movements in data:
Load data and use first row as reference
for each 'Flex' column do
    Calculate difference from reference
    Classify based on difference:
    if difference ¡ 50 then
        Record 'Severe Impairment'
    else if difference ¡ 100 then
        Record 'Mild Impairment'
    else
        Record 'Normal'
    end if
end for
Print most frequent classification for each sensor
```

mild impairment, or normal are identified depending on the deviation from this reference. Such classifications actually help to realize the motor ability of the patient and how the patient gets improved, over time. The system thus consolidates the data collection, preprocessing, and classification methods all into one framework and shapes them into a complete solution for monitoring and assessment of finger movements of patients with impairments of neurological origin. At this multistage process, all the work is methodical and assures accuracy and reliability, with the potential of offering many insights valuable in therapeutic interventions and rehabilitation progress tracking.

## V. Implementation Details

The section provides information on all the hardware components required to implement the project and the sequence of implementation from hardware to software.

### *A. Hardware Details*

Below is the table of required hardware components.

TABLE I
HARDWARE REQUIREMENTS

| Hardware Components | Specification | Quantity |
|---|---|---|
| Flex Sensors | 5.6 CM Bend Sensor for Hand Recognition | 5 units |
| Microcontroller | Arduino Uno Board | 1 unit |
| Connecting Wires | Jumper Wires | Variable |
| Power Supply | Either external battery supply or through USB | Variable |
| USB | To connect Arduino to a system | 1 unit |
| Resistors | 10 KOhm resistors | 5 units |

TABLE I lists out all the required hardware components. Below is a description of how it works and is used in the proposed solution.

*1) Hardware Components usage in the proposed solution:* Flex Sensor: A flex sensor (Fig. 5.) detects movement or bending of the joints, by generating a resistance value due to the bend. Since the sensor is a analog sensor it generates a value between 0-1023 as the analog input. The device is placed at several predetermined positions on the patient's body and provides therapists with essential data about joint displacement. Such information is necessary for customizing tasks to fit different people's needs.

Arduino Uno: The Arduino Uno acts as the central processing unit of the proposed solution.It manages data collection and analysis from flex sensors and other components. It provides live feedback which is a critical role in real-time data processing.

Jumper Wires: Jumper wires are essential for connecting different flex sensors to the Arduino Uno and other electronic parts. They make communication efficient between components for data transfer and overall system operation.

Power Supply: A constant, stable power supply is vital for powering the Arduino Uno and other system components. It enhances that the system keeps operating by providing the necessary power, ensuring continuous monitoring and analysis.

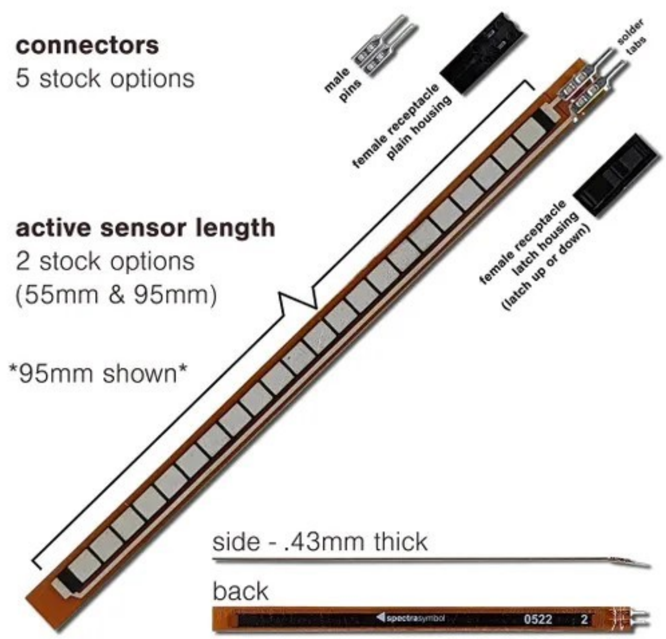


Fig. 5. Flex Sensors

If you are connecting the device to the system directly through USB then an external power supply is not required.

Resistors: Resistors control the electrical current and voltage flowing through the circuit. They are particularly important for setting up voltage divider circuits, which are crucial for accurate sensor data measurement and joint motion assessment. USB Cable: The USB cable connects the Arduino Uno to external devices, enabling software updates, data logging, and interaction during development and testing. It ensures that the system is well-integrated and functions seamlessly.

*B. Circuit Diagram & Glove Designed*

The hardware setup on the wearable glove and connections to establish the device is shown below.

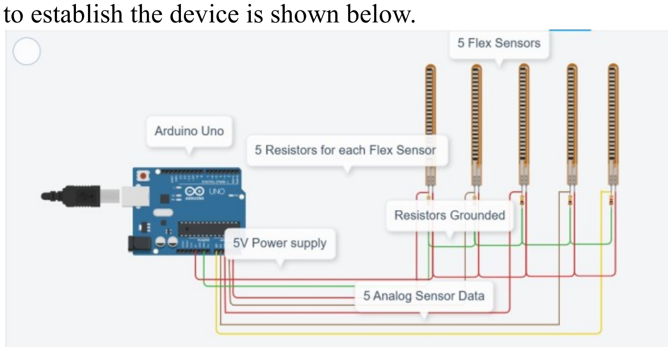


Fig. 6. Circuit Diagram of the Design

Fig. 7. Glove setup

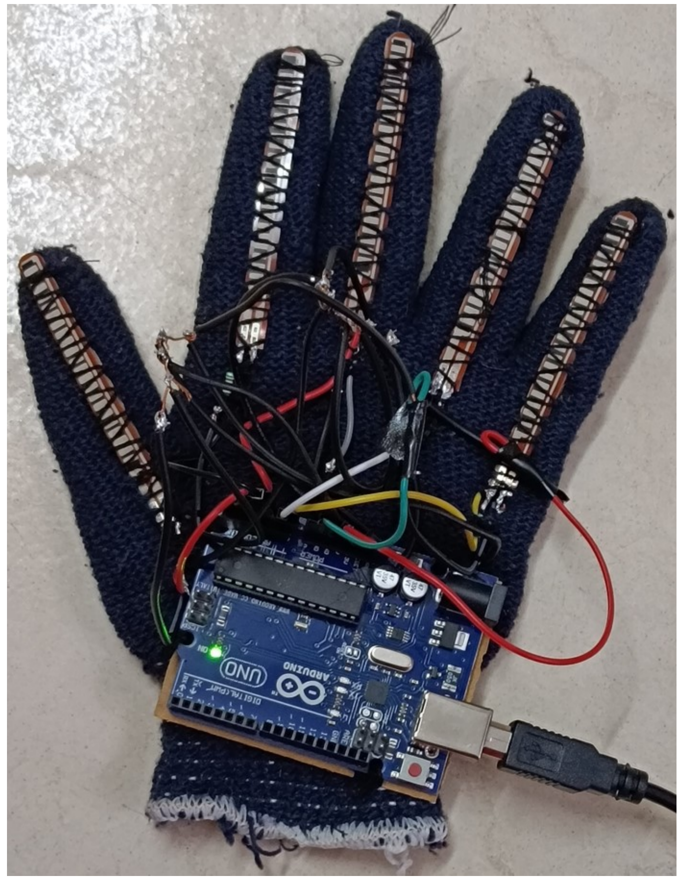

Fig. 7. Glove setup

Flex sensors have two terminals: one for data collection and the other for power supply. From the above Circuit Diagram Fig. 6., we can see that one common terminal of all the 5 Flex sensors is connected to a 5V power supply to the Arduino Uno board. The other terminal is connected to resistors to make sure that no fluctuations occur due to the voltage supply and resistance created by the sensor, from this terminal, where the resistor and the flex sensor terminal are connected, we made a connection for the analog sensor data for further processing requirements in Analog pins (A0, A1, A2, A3, A4) respectively to Arduino. The connection that comes out from the resistor is grounded to the ground pin of the Arduino.

Through the USB connected to Arduino, we acquire the analog data of all the five flex sensors by powering up the microcontroller and inputting the sensor data. These sensor data are stored and further processed based on the project necessity.

Fig. 7., shows the device designed as part of the project implementation. This device serves as the key aspect to collect the raw data and further process it. The connection setup is explained under the section Circuit Diagram & Explanation.

## VI. Results

The presented solution with a wearable glove with flex sensing is tested through three different scenarios.

Each scenario shown in Fig. 9,10,11. , demonstrates the three possible and different classifications that are applied based on the finger. The scenarios are addressed in detail reasoning the final decision of the class label assigned for the Flex values (Finger movements).

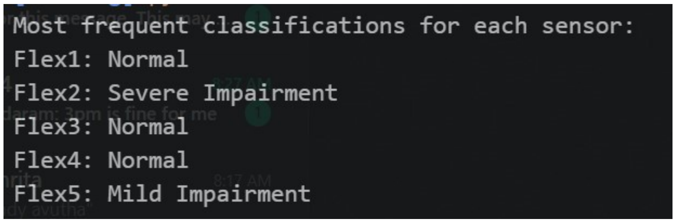


Fig. 8. Classification made for the above Scenario

These results, presented by the terminal output in the Fig. 8., confirm that the provided system differentiates normal from mild and severe impairments.

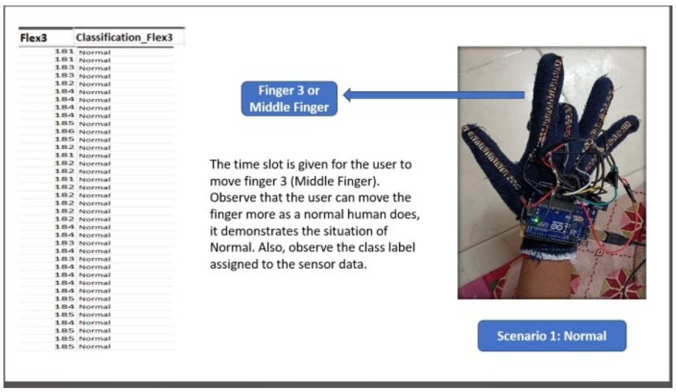


Fig. 9. Scenario 1: Normal

Scenario 1: Normal(Fig. 9.) - The user is performing the motions with Flex3; the system processes these movements with obtained sensor data, and the final output is as follows: The class is ”Normal,” for Flex3. This is indeed so because the performed motion of the finger was nice and within all the possible ranges to be expected by the healthy, normal finger. The classification output is rightfully predicting this, explaining Flex3 as ”Normal,” which confirms that the system can identify the correct state of using the normal finger.
Classifying Flex3 as ”Normal”

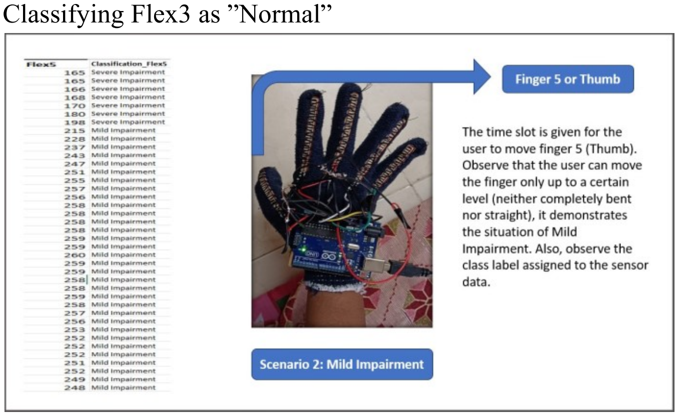


Fig. 10. Scenario 2: Mild Impairment

Scenario 2: Mild Impairment(Fig. 10.) - The user performs the motions with Flex5. From the data of the actual flex sensor in this scenario, there is a slight indication of difficulty but not as much that it falls into either the ”mild” or the ”severe” category. The system classified the scenario as ”mild impairment” when the range of motion was slightly restricted. The output from performing the classification is in line with the user’s trend of the performed movements, which shows that the system is sensitive to the tiniest restrictions in the flexibility of the finger and, what is more, it shows low severity. Classifying Flex5 as ”Mild Impairment”.

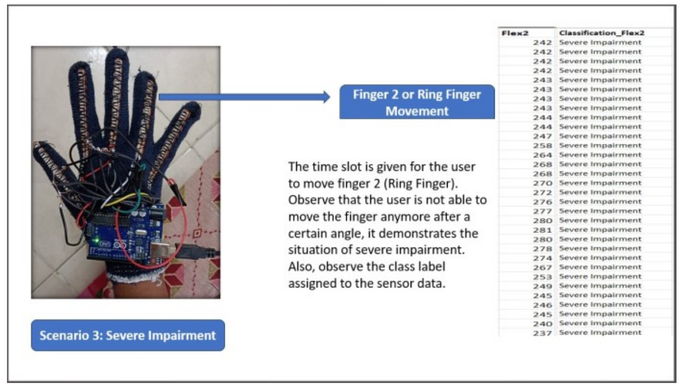


Fig. 11. Scenario 3: Severe Impairment

Scenario 3: Severe Impairment The user attempted to perform exercises with Flex2. Thus:. The system has correctly classified Flex2 to be under ”Severe Impairment.” This is justifiable since the performed movements showed a failure of the finger to reach any normal flexion angles. From the test scenario, the system was sensitive enough to detect severe impairments.

According to these test scenarios, it can be concluded that the proposed solution for the classification of finger movements into categories like normal, mild impairment, or severe impairment worked effectively. The system could classify the level of impairment correctly based on sensor data, and the results were clear and consistent in each of the considered test scenarios. Such classification would aid in the monitoring of patient performance and the adaptation of rehabilitation plans; thus, this proves its clinical and therapeutic resultant usefulness. Correct classifications in each of the scenarios again validate the system reliability and effectiveness in neurological and rehabilitation assessments.

## VII. Conclusion and Future Enhancements

The developed IoT-based wearable glove, embedded with flex sensors, holds potential to monitor and classify finger movements for patients with neurological impairments. The system provides information that is valued on the rehabilitation progress of patients using the real-time collection, processing, and classification of data. In this work, the system was evaluated using both normal, mild impairment, and severe impairment scenarios for the identification and classification of a different condition of states of finger movement. Thus, personalization of the rehabilitation protocols and assurance to afford the right interventions to the right patients.

The performance of the solution for detecting impairments of varying degrees positions it to be a useful tool applicable not only in clinical but also in therapeutic research. It promises to be an approach of noninvasive and continuous monitoring that improves the quality of detection and efficiency of the rehabilitation program through real-time feedback. It puts this solution at a place where the change can be adjusted in time and probably fasten the recovery process, thus improving the overall outcomes of the customer.

Future Work Future possible improvements might be added further to enhance the capability and utility of the current developed project:

Advanced Integration with Machine Learning Models: Deeper machine learning implementation for enhanced accuracy and robustness of the classification system. This will include training models with more significant datasets to recognize more subtle differences in patterns of motion.

Wireless Data Transmission: The comfort of patients to a great extent can be provided by making the system wireless, thus providing more mobility. This could be made possible with the help of a Bluetooth or Wi-Fi module, getting rid of the computer's physical connection.

Mobile Application Development: Development of a mobile application that interfaces with the glove so that the patients and therapists can monitor the progress on the go. The app may integrate features of real-time feedback, data visualization, and remote consultation.

Improved Data Analytics: Users should get insights about movement patterns and the rehabilitation progress with sophisticated data analytics and visualization tools. This will allow therapists to make better judgments since they will have full control over the data sets.

The developed wearable glove system with the integration of flex sensors is very useful for monitoring and rehabilitation of a neurological impairment patient. It permits the proper real-time classification of finger movements in the triggering of tailored rehabilitation programs and enhancement in the general quality of care to be given to patients. With an increase in the scope in the future, coupled with machine learning and integration, wireless connectivity, mobile application, and advanced analytics, this application will be the best-assisted tool in the field for physical therapists and patients in rehabilitation.

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