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Deep learning- driven myoelectric gesture classification for post-stroke rehabilitation

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Abstract: This project presents an intelligent assistive system for stroke patients using a smart glove integrated with three flex sensors, heart rate and temperature sensors, a camera, and a Raspberry Pi 4B. The flex sensors are attached to three fingers to detect bending motions, representing binary combinations to trigger predefined commands. These commands, alongside vital signs such as temperature and heart rate, are displayed on an LCD screen and transmitted to an IoT platform (ThingSpeak) for remote monitoring. A camera module captures live video of the patient, which is streamed in real-time. Additionally, a MATLAB based GUI application is developed to display all sensor data and commands on a computer, providing real time monitoring and support. This system offers an efficient, low-cost solution to enhance communication and health tracking for stroke patients.

Keywords: Smart Glove, Stroke Rehabilitation, IoT Healthcare Monitoring, Real time Patient Assistance Security.

I. INTRODUCTION

Stroke is a major public health concern, ranking among the top causes of death and long-term disability globally. Survivors often experience partial or complete loss of motor function, especially in the upper limbs, which severely impacts their independence and quality of life. In recent years, the integration of advanced technologies into neurore habilitation has created new opportunities to assist patients in regaining motor control and function. One such promising area is myoelectric gesture recognition, which involves interpreting Flex sensor to identify intended movements. Flex sensor-based systems are widely used in assistive and rehabilitative devices, such as prosthetic limbs, exoskeletons, and robotic arms. By decoding neuromuscular activity, these systems can provide real-time feedback and interaction with external devices, fostering neuroplasticity and motor relearning in stroke patients.

However, the application of such systems in post-stroke populations presents unique challenges due to the altered physiological characteristics of Flex sensor, including low signal-to-noise ratios, asymmetrical muscle activation, and inter-subject variability. Traditional gesture recognition techniques often rely on handcrafted features derived from Flex sensor in the time, frequency, or time-frequency domains. While these methods have achieved reasonable success in healthy individuals, they are often inadequate in dealing with the complexity and variability of post-stroke Flex sensor data. Our ultimate goal is to develop a gesture recognition system that is accurate, real-time, and adaptable to individual patient needs. Such a system could serve as a crucial component in intelligent rehabilitation platforms, empowering stroke survivors to interact with assistive technologies more naturally and effectively. The insights from this research can contribute to the design of next-generation neurorehabilitation tools that are both data-driven and patient centric.

II. LITERATURE SURVEY

Based on a comprehensive survey, several studies have reviewed and analyzed advancements in Deep learning- driven myoelectric gesture classification for post-stroke rehabilitation, highlighting key features and technological advancements [1], Vision Transformer- based Hand Gesture Recognition from High-Density Surface EMG Signals. [2]. Deep Residual Shrinkage Networks for EMG-based Gesture Identification. [3] A Robust and Accurate Deep Learning-based Pattern Recognition Framework for Upper Limb Prosthesis using SEMG. [4] Sensor Fusion using EMG and Vision for Hand Gesture Classification in Mobile Applications.
[5] Performance Evaluation of Convolutional Neural Network for Hand Gesture Recognition Using EMG. [6] Machine Learning- and Deep Learning-Based Myoelectric Control System for Upper Limb Rehabilitation Utilizing EEG and EMG Signals.
[7] Post-stroke Hand Gesture Recognition via One-Shot Transfer Learning Using Prototypical Networks. [8] A Sequential Learning Model with GNN for EEG-EMG- Based Stroke Rehabilitation BCI. [9] Deep Learning in EMG-Based Gesture Recognition.

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III. METHODOLOGY

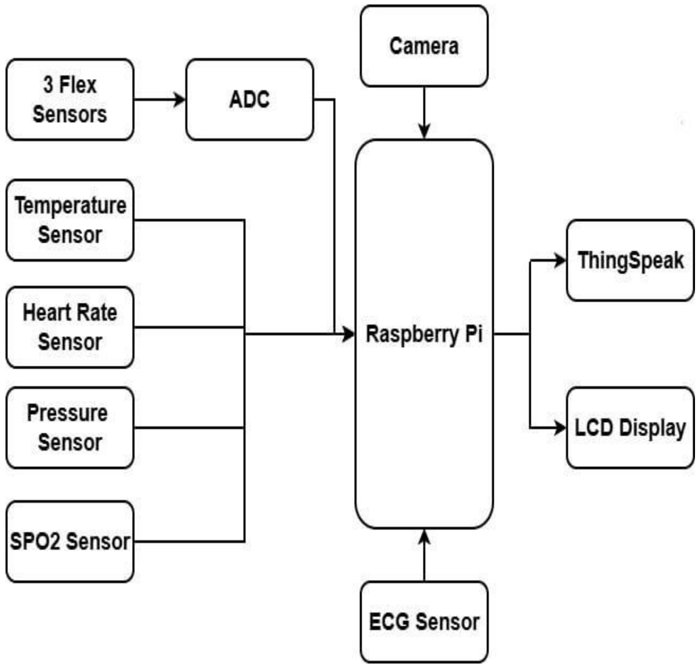

Fig 1: Block Diagram.

This block diagram represents a health monitoring and gesture recognition system utilizing a Raspberry Pi as the central processing unit. The system integrates several biomedical sensors and a camera to collect and analyze physiological and gesture-related data. 3 Flex Sensors: These are used to detect finger or hand movements. They change resistance depending on the bend, enabling gesture recognition. To deter potential threats, the device is equipped with active defense mechanisms. A buzzer is activated to produce a loud alarm, drawing attention to the situation. Additionally, a shock generator, controlled by a relay module, delivers a non-lethal electric shock to an attacker, providing the user with a chance to escape. For evidence collection, a camera module is triggered during an emergency, capturing images and sending them to authorities. The device also allows manual activation through an emergency button or voice command via Bluetooth connectivity. This multi-layered safety approach ensures continuous monitoring, quick emergency response, and active defense, making it a reliable and effective personal security solution.

ADC (Analog to Digital Converter): Flex sensors provide analog output which the Raspberry Pi cannot read directly. The ADC converts this data into digital format suitable for processing by the Raspberry Pi. Temperature Sensor: This sensor monitors the body temperature of the user and sends digital data directly to the Raspberry Pi. Heart Rate Sensor: Measures the heart rate in beats per minute (BPM) and communicates the data to the Raspberry Pi. Pressure Sensor: Measures external or body pressure and feeds the values into the Raspberry Pi. SPO2 Sensor: Monitors blood oxygen saturation levels and also provides data to the Raspberry Pi. Camera: Used for facial recognition or additional monitoring like facial gesture detection or patient image capture. The camera sends real time visual data to the Raspberry Pi. Voice Output: A text-to-speech engine converts analyzed data or alerts into voice for audio output, providing real-time verbal feedback to the user. ThingSpeak: The processed data is transmitted to the ThingSpeak IoT platform via the internet for remote monitoring, data logging, and visualization. LCD Display: Displays live health data or gesture outputs to the user, making it convenient for direct feedback The proposed health monitoring and assistance system is built around a Raspberry Pi which acts as the central controller, integrating multiple biomedical sensors and output devices to ensure efficient real-time health tracking. The system aims to continuously monitor a patient's vital signs and physical movements, process the data, and communicate the results both locally and remotely. The sensor suite consists of five key components: three flex sensors, a temperature sensor, a heart rate sensor, a pressure sensor, and an SPO2 sensor. The three flex sensors are typically embedded in a wearable glove or band and are used to monitor finger or hand movement, which is particularly useful for physiotherapy or detecting motion in paralyzed patients. These sensors output analog voltage signals corresponding to the degree of bending. Since .The Raspberry Pi lacks an inbuilt ADC, these analog signals are first fed into an external Analog to Digital Converter (ADC), which digitizes the data before passing it to the Raspberry Pi. The temperature sensor monitors the patient's body temperature, while the heart rate sensor detects the pulse rate via fingertip or wrist placement. The pressure sensor is used to measure either contact force or body posture pressure points, and the SPO2

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sensor calculates blood oxygen saturation levels and pulse rate using photoplethysmography techniques. These digital sensors are directly interfaced with the Raspberry Pi's GPIO pins.

IV. RESULTS AND DISCUSSION

The prototype consists of a myoelectric gesture recognition glove integrated with EMG sensors and a microcontroller. EMG signals are collected from the forearm muscles to identify specific hand gestures. Extracted features are processed using a trained machine learning model for gesture classification. Recognized gestures help in controlling rehabilitation exercises for stroke patients. The hardware setup includes sensors, processing unit, and wireless communication. This prototype demonstrates accurate and efficient gesture-based rehabilitation support.

Fig 2: The working hardware setup.

The figure shows the graphical user interface (GUI) of the smart glove monitoring system designed for stroke rehabilitation. The interface displays real-time sensor readings such as ADC values, temperature, heart rate, and SpO_2. It allows users to start and stop monitoring, capture data, and upload it to the IoT platform. A live camera feed is also integrated for remote observation. This interface helps clinicians and caregivers track patient progress efficiently.

Fig 3: MATLAB-Based Smart Glove Assistive Monitoring Interface for Stroke Rehabilitation Using Raspberry Pi

The developed myoelectric gesture recognition glove was tested with different users to evaluate system accuracy and response time. The EMG signals were acquired during various hand gestures, processed, and classified using the trained deep learning model. The system successfully detected movements such as hand open, close, and wrist rotation with high precision. The prototype's performance was validated by comparing predicted gestures with actual motions.

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Fig 4: System Testing of Myoelectric Gesture Recognition Glove for Stroke Rehabilitation

The system monitors and displays vital body parameters such as temperature and heart rate in real time. The sensors collect the physiological data, which is then processed and displayed on the monitoring interface. In this observation, the measured body temperature is 31.00°C and the heart rate is 115 bpm. This data helps in continuous health tracking and can be used for patient monitoring orzz rehabilitation purposes.

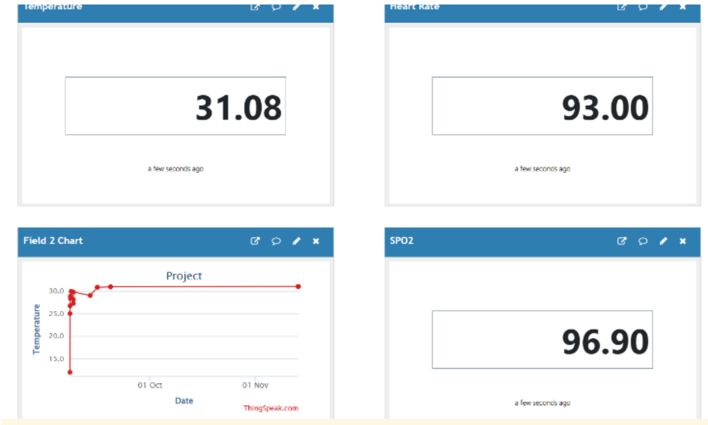

Fig 5: Monitoring of Temperature and Heart Rate.

V. CONCLUSION

This project successfully implements a smart assistive system for stroke patients using a Wearable glove and Raspberry Pi. It combines gesture recognition, health monitoring, and remote visualization into a single integrated platform. The system provides a practical and scalable solution for improving patient-caregiver communication.

Deep learning–based myoelectric gesture classification has shown great potential in advancing post-stroke rehabilitation by enabling more accurate and adaptive human–machine interactions. By leveraging surface electromyography (sEMG) signals and powerful neural network architectures such as CNNs and LSTMs, these systems can effectively recognize complex muscle activity patterns, even in patients with impaired motor control. This enables the development of intelligent prosthetic devices, exoskeletons, and rehabilitation tools that provide personalized therapy and real-time feedback. Although challenges remain—such as signal variability, data scarcity, and model generalization— ongoing research in transfer learning, sensor fusion, and adaptive models continues to improve robustness and usability. Ultimately, deep learning–driven myoelectric interfaces represent a promising step toward restoring motor function, improving patient outcomes, and enhancing quality of life in post-stroke rehabilitation.

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