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Intelligent Controlled Hand Assistive Device Based on Eeg Signals

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ABSTRACT:
This paper presents the design and development of an **intelligent, EEG-based hand-assistive device** aimed at supporting individuals with limited hand mobility. The system captures **electroencephalogram (EEG) signals** corresponding to user intention and processes them using machine learning algorithms for classifying multiple hand-movement tasks. The classified commands are then used to control a **robotic hand prototype**, enabling actions such as grasping, lifting, rotating, and releasing. The proposed approach integrates **real-time signal acquisition**, **feature extraction**, **task classification**, and **actuator control** to provide an intuitive, non-invasive human–machine interface. Experimental results demonstrate improved response accuracy and smooth motion assistance, highlighting the device's potential for **rehabilitation**, **assistive applications**, and **enhanced user independence**. The system offers a low-cost and scalable solution that can be further extended for personalized neuro-assistive technologies.

Keywords: EEG, Brain–Computer Interface, Assistive Device, Robotic Hand, Motor Imagery, Machine Learning

INTRODUCTION

Hand movement difficulties can affect a person's daily activities and independence. Assistive devices are commonly used, but many existing systems are not intuitive or require physical effort from the user. With advancements in Brain-Computer Interface (BCI) technology, it is now possible to control devices solely with brain signals.

This project developed an **intelligent hand assistive device controlled by EEG signals**. The system captures brain activity associated with hand-movement intentions and uses machine learning to classify these signals. Based on the detected task, a **robotic hand prototype** performs actions such as grasping, lifting, or releasing objects. This provides a non-invasive and user-friendly way to assist individuals with limited hand mobility.

The proposed system aims to offer a low-cost, efficient, and responsive solution that can support rehabilitation and daily activities for people with motor impairments.

LITERATURE SURVEY

Methods were later proposed to improve classification reliability. Comparative studies revealed that deep-learning architectures like CNNs and LSTMs outperform traditional models (SVM, KNN, RF) in capturing the complex temporal characteristics of EEG signals, especially for multi-class motor-imagery tasks [3].

- Clinical studies evaluating EEG-controlled hand-rehabilitation devices further showed measurable improvements in motor recovery for stroke patients, proving the therapeutic value of closed-loop assistive systems [4].
- Lightweight microcontrollers such as Arduino and ESP32 have also been integrated into BCI hardware to enable real-time, portable systems capable of decoding simple motor commands with minimal latency [5].
- Recent application-oriented works proposed deep-learning pipelines for real-time elbow, wrist, and finger rehabilitation, demonstrating high accuracy and robustness in decoding motor imagery under practical conditions [6].
- In parallel, convolutional neural networks have achieved superior performance in tasks such as grasp-and-lift detection using large public datasets, establishing benchmarks for movement-intent recognition [7].
- Studies on online BCI robotic-arm control also showed that EEG signals could differentiate multiple executed hand movements with moderate accuracy, laying the groundwork for continuous-control robotic applications [8].
- Broader systematic reviews in BCI-robotics reveal that although many prototype systems exist, only a few have progressed to clinical trials due to challenges like inter-subject variability and the need for standardized evaluation protocols [9].
- Low-cost designs have also gained attention, with several works demonstrating accessible EEG-controlled exoskeletons and 3D-printed robotic hands powered by affordable sensors and actuators [10].
- Beyond upper-limb rehabilitation, BCI research has extended to mobile robotics, including EEG-controlled wheelchairs and CNN- LSTM-based navigation systems integrated with ROS, showing the versatility of EEG-driven interfaces in assistive technology [11].

PROBLEM STATEMENT

- EEG-based Brain–Computer Interfaces (BCIs) have emerged as Powerful tools for restoring motor function and enabling Existing hand assistive devices require physical movement or complex communication for individuals with physical impairments. controls, making them unsuitable for individuals with severe motor Early foundational studies established that non-invasive EEG impairments. There is a need for a simple, non-invasive system that can provides high temporal resolution and can reliably capture interpret user intention directly from brain signals to control hand motor imagery patterns that correspond to user intention movements.

forming the basis for BCI-controlled assistive devices [1].

- Subsequent research demonstrated successful decoding of hand- movement intentions—such as grasping, lifting, and releasing—using machine-learning models trained on EEG features, showing viability for robotic hand and prosthetic control applications [2].
- Advanced feature-extraction techniques such as wavelet transforms, power spectral density, and hybrid time–frequency

OBJECTIVES

- To use the **EEG sensor** to capture brain signals related to different hand-movement intentions.

- To preprocess and analyze sensor data for precise task identification.
- To map the sensor-classified outputs to control the robotic hand movements.

SYSTEM DESIGN

BCI -Brain Computer Interface System Analysis

BLOCK DIAGRAM

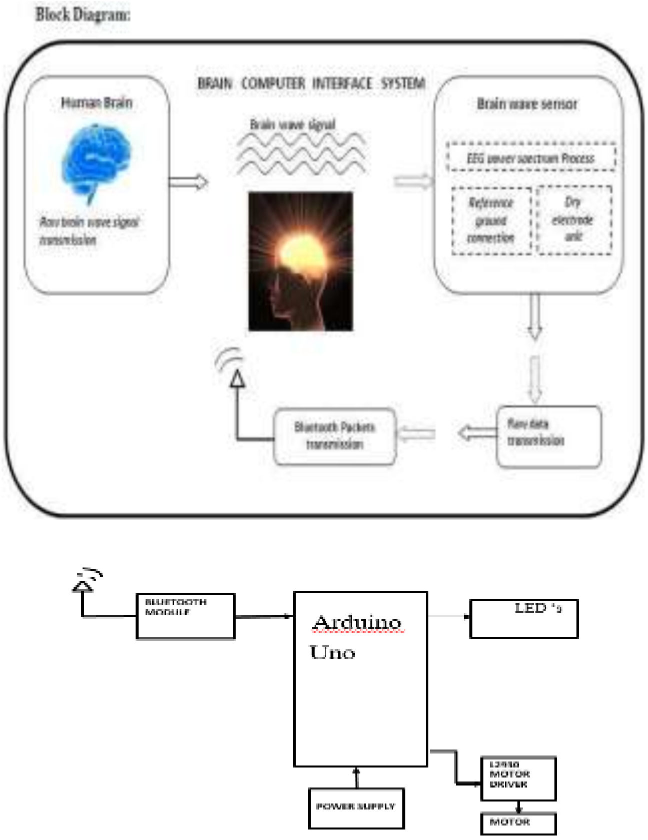


Fig 1: Block Diagram

RELATED WORKS

EXISTING SYSTEM	PROPOSED SYSTEM
1. No remote-control operation	1. Brain wave analysis
2. Depend on others to operate	2. Robot control using Human thoughts
3. No muscle contraction sensing	3. Self-controlled and operating facility
4. No Bluetooth communication	4. Bluetooth communication

- **System Analysis:**

BCI systems translate human intentions into commands for external devices, such as robots or assistive tools. Analysis involves breaking down requirements, structures, and system functions to ensure safe and effective operation. Feature extraction and classification are crucial for achieving high accuracy, as misclassification can lead to dangerous movements. Shared control methods reduce user workload by combining human intention with intelligent robot assistance (e.g., obstacle avoidance).

- **Feasibility-Analysis:**

The proposed system provides a cost-effective, independent control solution for disabled users. It enables users to operate devices (robotic hand/robot) without assistance, promoting independence.

- **Financial-Analysis:**

The components used are low-cost and affordable for most users compared to conventional robotic systems.

- **Technical-Analysis:**

The system starts with image-based tracking (faster) and can be extended to video-based operation. Integration of EEG signals with classification algorithms ensures real-time, safe control of robotic devices.

Electroencephalogram (EEG):

- Measures brain activity through surface electrodes.
- Requires no physical movement, enabling direct brain-to-device communication.
- Also called Mind-Machine Interface (MMI).

EEG can be invasive (electrodes under skull/brain surface) or non-invasive (scalp electrodes).

- Invasive BCI: High-resolution electrodes placed inside the brain, used when seizures or brain activity require precise localization.
- Non-Invasive BCI: Scalp electrodes (EEG) record brain activity without surgery, are safer, and widely used for assistive devices.

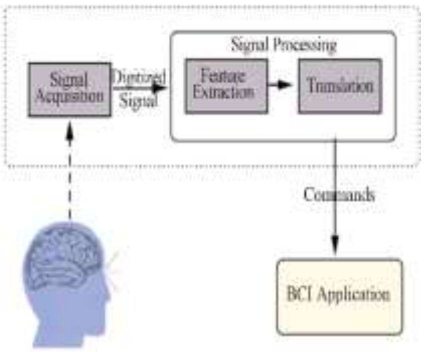


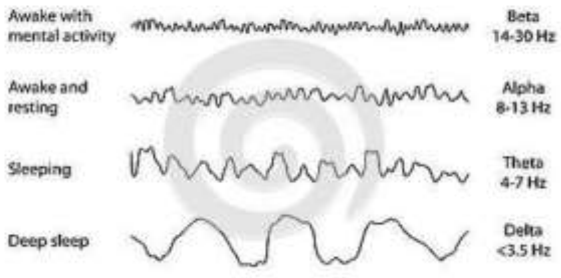
Fig 2: BCI Unit

Classification of EEG Waves

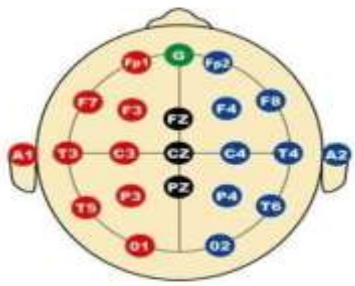
EEG waves are classified by frequency, amplitude, and scalp location.

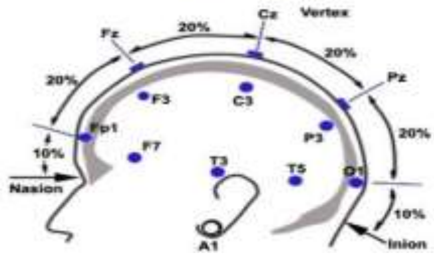
The main types are:

- Alpha (8–13 Hz): Rhythmical waves in relaxed, awake adults; strongest in the occipital region.
- Beta (>14 Hz): High-frequency, low-voltage waves during active mental tasks; mainly in frontal and parietal regions.
- Theta (4–7 Hz): Occur in children, emotional stress, or certain brain disorders; found in parietal and temporal regions.
- Delta (<3.5 Hz): High-voltage waves during deep sleep, infancy, or serious brain conditions. These waves are used in BCIs to interpret brain activity and control external devices.



ELECTRODE PLACEMENTS:





- Non-invasive EEG headset captures brain signals during motor imagery tasks.
- **Signal Processing & Feature Extraction:**
  - Filters noise and artifacts from raw EEG data.
  - Extracts features (time-domain, frequency-domain, or wavelet features) for classification.
- **Classification Module:**
  - Machine learning model (Random Forest, SVM, etc.) maps extracted features to hand-movement commands such as LEFT, RIGHT, UP, and DOWN.
- **Robotic Hand Control:**
  - Microcontroller receives commands and drives servo motors to perform the corresponding hand movements.
  - Optional feedback sensors improve accuracy and

In our experiments to get the signals, we set the electrodes according to standard 10-20 systems for electrode placement used for EEG tests as we weren't aware of exact origin of corneal- retinal potential signals initially.

The standardized placement of scalp electrodes for a classical EEG recording has become common since the adoption of the 10/20 system. The essence of this system is the distance in percentages of the 10/20 range between Nasion-Inion and fixed points. These points are marked as the Frontal pole (Fp), 15Central(C), Parietal(P), occipital(O), and Temporal(T). The midline electrodes are marked with a subscript, which stands for zero. The odd numbers are used as subscripts for points over the left hemisphere and even numbers over the right.

ARCHITECTURE

The proposed system architecture consists of four main modules:

1. EEG Signal Acquisition:

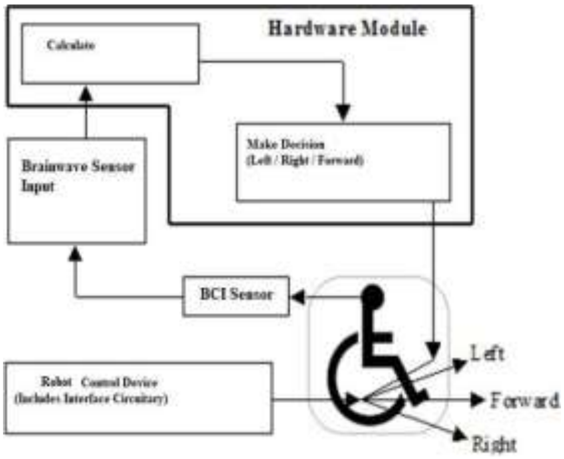


Fig 3: System Design-Architecture

Sequence Diagram:

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development.

Sequence diagrams are sometimes called event diagrams or event scenarios. A sequence diagram shows, as parallel vertical lines (lifelines), different processes or objects that live simultaneously, and, as horizontal arrows, the messages exchanged between them, in the order in which they occur. This allows the specification of simple runtime scenarios in a graphical manner.

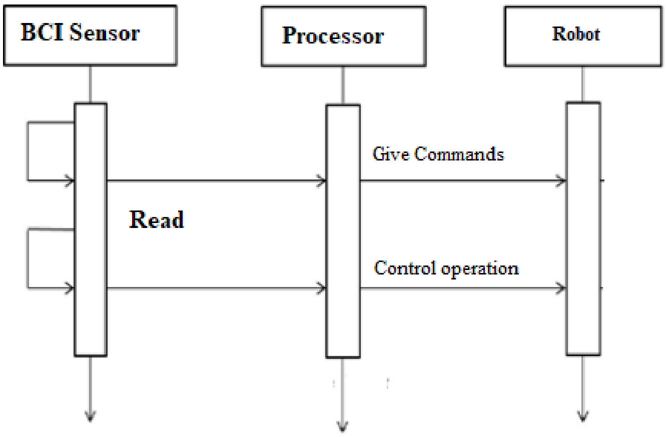


Fig 4: Sequence Diagram METHODOLOGY

The developed intelligent brain-controlled system uses EEG signals to control the movement of a robotic hand/robot. The Neurosky EEG headset captures brainwaves, and the α and β wave ratio is used to determine the user’s attention level.

Signal Classification:

- EEG signals are classified using an Adaptive Neuro-Fuzzy Inference System (ANFIS).
- Frequency ranges are mapped to commands:

- <7 Hz → Stop
- 7–12 Hz → Left
- 12.1–17 Hz → Forward
- 17 Hz → Right

Robot Control:

- Commands are sent via HC-05 Bluetooth to an Arduino microcontroller.
- The Robot uses ultrasonic sensors (two front, two sides) for obstacle detection.
- If an obstacle is detected, the stop command overrides other movements.
- Arduino converts commands into PWM signals to control DC motor speed and direction.

Attention-Level Mapping:

- 0–40% → Move forward
- 41–70% → Turn right
- 71–90% → Turn left
- 90% → Move backward

PROCEDURE

- Here, we analyze the brain wave signals. The Human brain consists of millions of interconnected neurons.

- The pattern of interaction between these neurons is represented as thoughts and emotional states.
- According to human thoughts, this pattern will be changing, which in turn produces different electrical waves.
- A muscle contraction will also generate a unique electrical signal.
- All these electrical waves will be sensed by the brain wave sensor, and it will convert the data into packets and transmit them through the Bluetooth medium.
- Arduino will receive the brain wave raw data, and it will extract and process the signal.
- Then the processed signal is used to move the Robot in the desired direction.
- The Robot is also equipped with ultrasonic sensors for obstacle avoidance, which stop the Robot.

HARDWARE COMPONENTS

Fig 5: EEG Sensor

- Single electrode placed on the forehead with ear-clip reference.

- Detects multiple mental states simultaneously.
- Built-in noise-removal filters (50/60 Hz).
- Bluetooth wireless signal transmission.
- Suitable for real-time BCI applications.

Fig 6: Arduino Uno

- Microcontroller: ATmega328P
- Operating Voltage: 5 V
- Recommended Input: 7–12 V
- Digital I/O Pins: 14 (6 PWM)
- Analog Inputs: 6
- Flash Memory: 32 KB
- SRAM: 2 KB
- EEPROM: 1 KB
- Clock Speed: 16 MHz

Fig 7: Bluetooth (HC-50)

- Bluetooth protocol: Bluetooth Specification v2.0+EDR
- Frequency: 2.4GHz ISM band
- Modulation: GFSK (Gaussian Frequency Shift Keying)
- Emission power: ≤4dBm, Class2
- Sensitivity: ≤-84dBm at 0.1%BER
- Speed: Asynchronous: 2.1Mbps (Max) / 160 kbps, Synchronous: 1Mbps/1Mbps
- Security: Authentication and encryption
- Profiles: Bluetooth serial port
- Power supply: +3.3VDC50mA
- Working temperature: -20 ~ +75 °C
- Dimension: 26.9mm x 13mm x 2.2 mm

- Runs on DC power or AC line voltage with a rectifier
- Operating speeds of 1,000 to 5,000rpm
- 60-75% efficiency rate
- High starting torque
- Low no-load speeds

Fig 10: LCD Display

- Operating Voltage is 4.7V to 5.3V.
- Current consumption is 1mA without backlight.
- An Alphanumeric LCD display module, meaning it can display letters and numbers.
- Consists of two rows, and each row can print 16characters.
- Each character is built by a 5×8-pixelbox.
- Can work on both 8-bit and 4-bit modes.
- It can also display any custom-generated characters
- Available in Green and Blue Backlight

SOFTWARE COMPONENTS

1. Arduino IDE

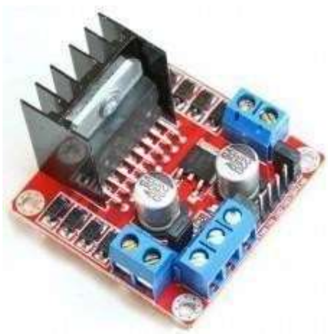


Fig 8: Motor Drive(L298N)

- Wide supply voltage: 4.5 V to 12V.
- Max supply current: 600 mA per motor.
- The driver has two holes of 3 mm dia.
- Male burg-stick connectors for supply, ground, and input connections.
- Screw terminal connectors for easy motor connection.
- High noise immunity inputs.

Fig 9: DC Motor

- Used to write, compile, and upload code to the Arduino Uno.
- Supports serial communication and motor control programming.
- Provides real-time debugging through the Serial Monitor.

2. EEG Signal Processing Software

- Used to visualize and monitor raw EEG data (e.g., NeuroSky ThinkGear software or equivalent).
- Handles initial signal filtering and packet formation before transmission.

3. Python / MATLAB (Optional for Analysis)

- Used for offline signal processing, feature extraction, and plotting EEG waveforms.

- Helps in model training, noise removal, and performance evaluation.

4. Bluetooth Communication Module Driver

- Enables wireless connection between the EEG headset and Arduino.
- Used to receive data packets and interpret mental commands.

CIRCUIT DIAGRAM

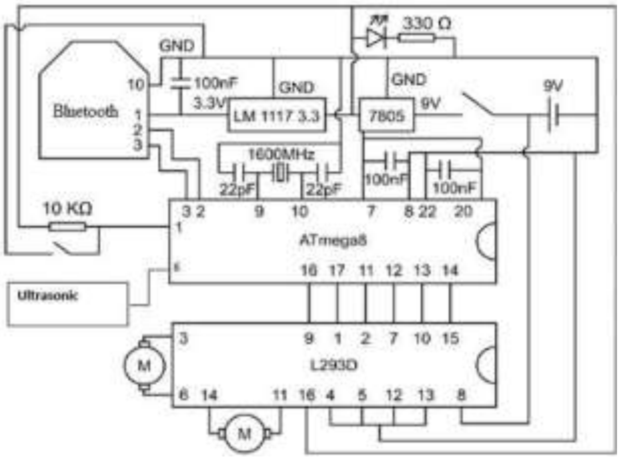


Fig 11: Circuit Diagram

FLOW CHART

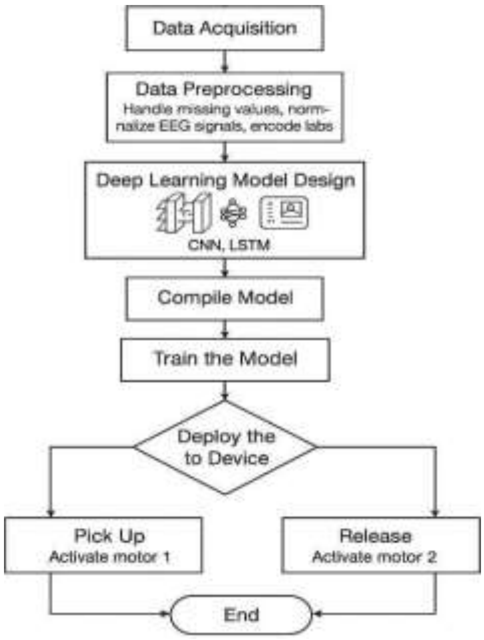


Fig 12: SOFTWARE PART

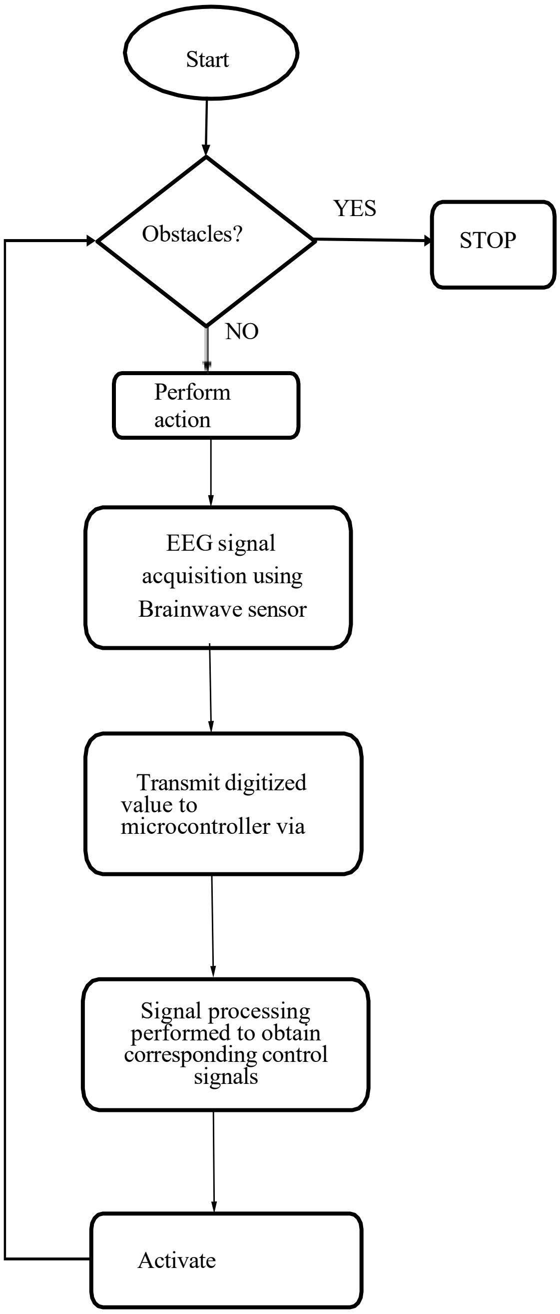


Fig 13: HARDWARE PART

EXPECTED OUTCOME AND RESULTS:

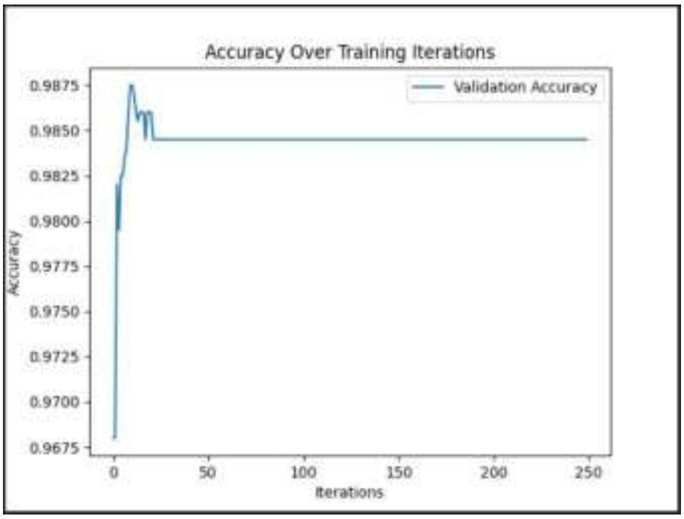


Fig 14: EEG Signal Graphical Representation

	precision	recall	f1-score	support
close	0.97	1.00	0.99	390
down	0.98	0.98	0.98	391
open	0.99	0.98	0.98	412
other	1.00	0.99	0.99	418
up	0.99	0.98	0.99	389
accuracy			0.99	2000
macro avg	0.99	0.99	0.99	2000
weighted avg	0.99	0.99	0.99	2000

Fig 15: Classification Report

Fig 16: UI web page (Manual Mode)

PROTOTYPE:

Fig 17: Sensor

Fig 18: Prototype(Hand Device)

Fig 19: Working in Auto Mode

CONCLUSION

The EEG-based intelligent assistive device developed in this project demonstrates an effective, low-cost, and user-friendly approach for restoring hand movement support in individuals with motor impairments. By utilizing a non-invasive Nuerosky EEG headset, the system accurately interprets mental states and attention levels to generate real-time control commands for the robotic hand. The integration of Arduino

Uno, Bluetooth communication, and ultrasonic sensors ensures smooth operation, reliable wireless data transmission, and enhanced safety through obstacle detection.

The experimental results confirm that the system can successfully translate brainwave patterns into directional movements with reasonable accuracy, enabling hands-free operation even for users with severe physical limitations. The modular hardware and easily programmable software also make the system highly scalable, allowing additional sensors or machine-learning models to be incorporated in future work.

Overall, the proposed BCI-assisted device demonstrates strong potential for rehabilitation therapy, independent movement assistance, and personalized mobility solutions. The work highlights that affordable EEG-based control systems can significantly improve user independence, provide better accessibility, and serve as a foundation for next-generation neuro-assistive technologies.

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