MINDWAVE NEUROSPECTRUM: EMPOWERING AUTISM ASSISTANCE THROUGH EEG-ENHANCED MACHINE LEARNING

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Abstract

Autism Spectrum Disorder exhibits interaction disorders and abnormal restrictive and repetitive behaviors. According to the CDC, around 1 in 36 children in the US has been diagnosed with Autism. Around 75 Million people have ASD (Autism Spectrum Disorder), which is 1% of the world population. The majority of autistic individuals struggle with social contact, responding to others, and using interaction to demonstrate things to others or to be sociable. They also frequently have communication delay issues.

In order to overcome this we have used EEG EEG-based brain-computer interface to enable autistic people to communicate with the outside world by interpreting EEG signals of their brains and interacting with the people. We hope to enable a brain typing system means converting their thoughts to text form. In this project, we use the Butterworth filter and Least square Template matching for preprocessing the signal, and for enhancing the quality of the signal we are using common average reference and wavelet convolution for extracting the features and ANN classifier is used. Finally, GPT-4 is used to automatically write the explanation this could be beneficial for autism patients as well as disabled people.

Index Terms:

Autism, EEG, Butterworthfilter, ANN, GPT-4, Disabled people

I Introduction

ASD is a complex neurodevelopmental condition that affects individuals in many ways, often impairing their ability to communicate effectively. A core challenge faced by many individuals with autism is the limited or nonverbal expression of their thoughts, emotions, and needs. As we embark on this technological journey, the potential to harness electroencephalogram signals to convert the intricate neural patterns of individuals with autism into text-based communication emerges as a beacon of hope.

In order to overcome this problem, the intersection of neuroscience and assistive technology opens new vistas. EEG, a non-invasive approach that records electrical activity from the brain's surface, provides a unique window into the neural processes underpinning our thoughts and intentions. Furthermore, this technology can serve as a powerful tool for researchers and clinicians, offering unprecedented insights into the cognitive processes of individuals with ASD. we hope to contribute to a future where individuals with autism can express their thoughts, connect with others, and navigate the world with newfound clarity and independence.

II Related Work

There are a variety of ways that are defined and implemented for face detection and identification and we have looked at a few of them, which are listed in the following survey.

EEG-based load control system for those with physical disabilities in [1]. They signify a brain-controlled EEG system for home automation intended to assist those with disabilities in this survey. Some microcontrollers are also used to decode the raw signals. The EEG signals from the Neurosky headset are detected by this system. The ability to identify attention level with the 90% accuracy and blink rate accuracy among 60% & 70% outperforms performance. This survey provides an overview of concerns including how this device's functionality may be expanded by adding more features and improving the environment. Zero-shot learning for EEG categorization in a BCI system based on motor imagery is discussed in [2]. This study employs a new kind of motor imagery task that combines standard tasks with an innovative zero-shot learning approach to transform human intents into computer instructions. Our zero-shot approach's classification accuracy is 91% accurate compared to the standard method which includes all data categories. This poll provides an overview of the problems, including the need to enhance the system's accuracy. Choosing the best EEG channels for classifying mental activities is discussed in [3]. The strategy used in this study to choose the best electroencephalography channels for three different mental activities is based on a systematic approach to BCI categorization. The two EEG channels that performed the best were O1 and C4, with an accuracy of 76.4 percent, and P3 and O2, with an accuracy of 74.5 percent, according to the categorization of the two-channel combinations. P3 and C4 had a 71.9 percent accuracy rate, whereas O1 and O2 had a 70% accuracy rate. Issues like "Dataset is not adequate for this system" are summarised in this survey. In [4] EEG-based emotion recognition via feature transfer learning. This approach suggests a feature-based transfer paradigm for EEG-based emotion identification in this survey. Findings indicate that the TCA-based approach yields the greatest mean accuracy of 58.49 percent, outperforming the 52.06 percent found in the prior research. The viability and effectiveness of subject transfer emotion recognition are confirmed by the experimental findings. This survey provides an overview of problems, including the need for the system to enhance its characteristics in order to better reflect emotional EEG data. Thoughts to words using EEG waves [5]. The BCI solution offered by this system in this survey will convert the user's active intent into text displayed in Morse code. RNN learns the temporal information, whereas the model (CNN) achieves a very high accuracy of 97.7% in capturing the spatial data. There are no issues with bias or variation, and the learning rate is suitable. This survey provides an overview of the difficulties, including the need to enhance the project's cost efficiency. This review examines methods for preprocessing EEG data, extracting features, classifying them, and detecting aberrant activity to diagnose ASD based on the power spectral density of EEG signals by utilizing machine learning models. Some topics are summarised in this survey, such as the comparison and analysis of mainly Asd patients and healthy patients. At [7] An optimized categorization approach for ASD based on EEG data. A 93 percent accuracy rate was reached in this survey using correlation-based feature selection and random forest. An improved automated decision support system may be achieved by extending the system via the use of thermal image processing methods and sophisticated learning models, as this survey summarises. Assessing eye movements and the eeg for autism spectrum disease in [8]. In this survey, the technology integrates EEG data with eye movements to provide an effective diagnosing process. This study uses a number of models based on eye movements and electroencephalograms to diagnose ASD. This survey provides an overview of the problems that need to be fixed in many sections of the system, and further comparisons need to be done. When [9] EEG correlative analytics with eye tracking: a trend in autism spectrum disorder research. This survey's system integrates a number of technologies that might be useful in determining how a certain visual pattern in realistic environments affects cognition. The concerns that must be planned to compare the link among gaze patterns and neurophysiological parameters in various developmental disorders are summarised in this survey. Consequently, using this technology to apply ET-EEG correlative analytics to a population with severe autism symptoms is not appropriate. Detection &tracking of anxiety-related disorders for ASD by (ECG) [10]. In order to make these unexpected illnesses predictable and lower death tolls with prompt treatment, this survey's method employs a framework based on an unscented Kalman filter to constantly identify and monitor the R-R interval for prediction of anxiety. The concerns listed in this survey are summarised as follows: to boost the sensitivity of the system, image processing algorithms for ocular pictures and motions and sweat sensors should be included.

With the help of the survey of these papers, a notion for the concept emerges, which aids in the selection of a better model. In addition, this survey offers an overview of the general concept and suggestions for execution, as well as what our project's obstacles are and what technologies are required, resulting in an overall concept for our application.

III Proposed System

EEG signals are frequently fainted with noise of several kinds, including electrical interference and signals unrelated to the brain.

Dataset:

The dataset used here is BS-HMS dataset which is an online dataset. The EEG data recordings from the Neurosky headset and the matching hand movement recordings from the motion sensors of the Sony wristwatch make up the Neurosky-based dataset. It was recorded from thirty-two willing participants. Depending on which hand they preferred, the users wore their smartwatches—left or right.

Filtering:

When analyzing EEG signals, a type of signal processing filter called butterworth filter is employed to perform particular frequency domain operations on EEG data. We have created a Butterworth filter that reduces or removes noise outside of the selected frequency range while keeping the frequency components of the EEG signal by choosing suitable cutoff frequencies..cutoff frequency is chosen to isolate the desired frequency band. Filter order determines the sharpness of the filter transition between the passband and stopband. Therefore it increases the quality of EEG data and helps to improve the signal-to-noise ratio

Removing Artifacts:

Any undesired,non-neural interference or disturbance that taints the recorded EEG data is called an artifact. EEG signals are frequently tainted by a variety of artifacts, including muscular contractions, eye blinks, and other background noise. ICA is a blind source separation technique that works especially well for removing artifacts from EEG data since it can divide these mixed signals into their individual sources. Generally, artifacts display particular qualities. For example, there are usually unique spatial patterns surrounding the eyes in the blinks and movements of the eyes. Muscle artifacts typically have distinct spectral characteristics and large amplitudes. We have recognized and classified components as either neural or artifact-related by looking at these features. Once the artifacts are identified, we can remove them by zeroing out or attenuating the corresponding independent components. Therefore this is suitable for removing a wide range of artifacts.

Feature Extraction:

Since the signal of EEG is non-stationary, the approach at the frequency domain is typically used to determine the suitable feature extraction, and Wavelet Transform(WT) is one of these methods. WT features an infinite wavelet for its frequency domain. The old WT window is utilized to acquire improved low-frequency resolution; a small time window is employed in place of gathering high-frequency information. The wavelet, a basic building component, is used in the WT technique to represent the original signal, which is the recorded EEG signal. The mother wavelet is a derivative function that is stretched and shifted along the time axis by translation and widening. There are two categories of signals on wavelets: approximate and detailed. An approximation is a signal that is received from the original signal's convolution procedure to the time axis of the high-pass filter, while an actual signal is a signal that is acquired from the original signal's convolution process to the low-pass filter.

Formula

$H(z) H(z^{-1}) + H(-z) H(-z^{-1}) = 1$

Where H(z) represents hz transform filter.

Basic statistics features, like maximum deviation, minimum mean, and standard are computed for the above factor

Classification:

An Artificial Neural Network (ANN) classifier is a machine learning model designed to classify patterns within EEG data. We suggested filtering the EEG signals using a low-pass filter with various cutoffs in order to further optimize the ANN. We show that removing high-frequency spectral components improves classification performance greatly (up to 90 ± 5% accuracy with only 8 electrodes). The creation of brain-computer interfaces for people who are not trained is particularly interested in the outcomes gained

Text Generation:

Finally, we are using GPT-4 to automatically write the explanation for the behavior of neurons. Therefore GPT-4 generates human-readable text based on the input it receives.

IV System Architecture

Firstly, the EEG signals from BS-HMS dataset is given as input signals and then EEG signals have to be preprocessed because it contain noises and artifacts. So, first, we have to apply butterworth filter and set the parameters such as cutoff frequency and filter order. This will enhance the quality of the signal and remove the noises. And then Independent component analysis is used for removing artifacts and extracting meaningful brain signals from EEG recording. Then wavelet Transform is used for extracting the features from the signals. Then ANN classifier is used to classify the specific patterns from the signals. Finally using GPT-4 method we could translate neuron signals into text.

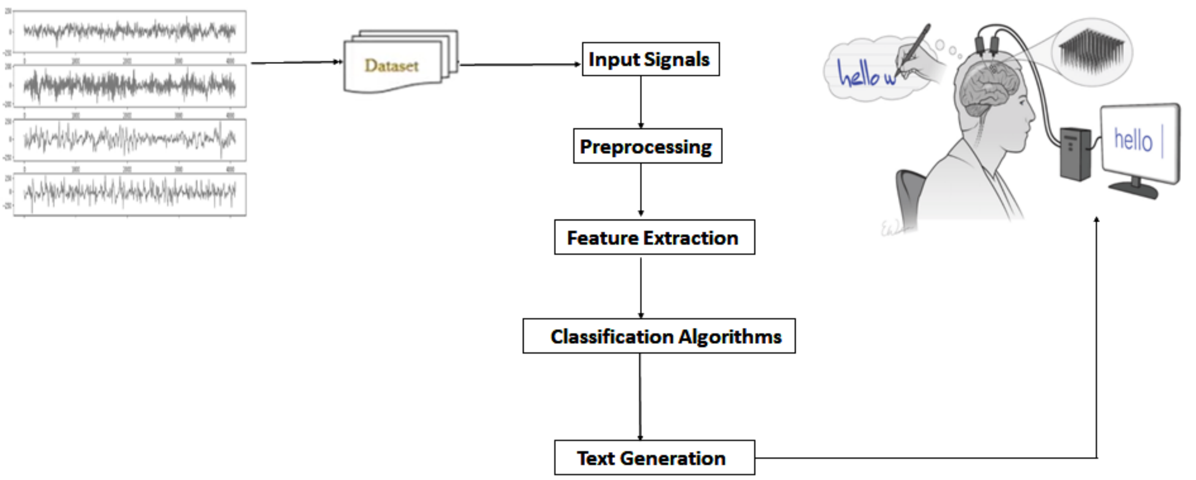

Fig 1. System diagram

V Results and Discussions:

In our study, EEG signals were collected from 32 volunteer participants, their brain signals were recorded using the Neurosky dataset. First, we cleaned the data and preprocessed their signals, and the preprocessed results are shown below.

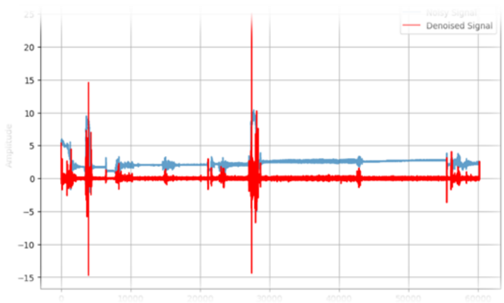

Fig 2. Denoised signal

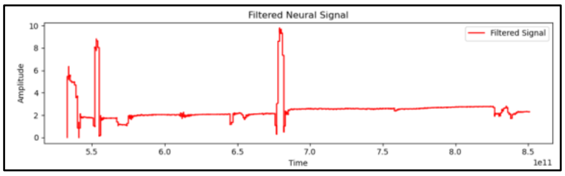

Fig 3. Filtered signal

Conclusion:

The use of EEG signals for converting thoughts into text is a captivating and promising area of research that holds the potential to significantly impact the fields of neuroscience, assistive technology, and human-computer interaction. The ability to harness the electrical activity of the brain to facilitate communication is a groundbreaking development that can empower individuals with motor disabilities or those facing challenges in traditional means of expression and for an autism patients. However, it is essential to recognize that the journey from EEG signals to text generation is a multifaceted one, involving interdisciplinary collaboration and a deep understanding of both the intricacies of the brain and the capabilities of machine learning models. Challenges such as noise reduction, real-time processing, and user adaptation must be addressed to make these systems effective and user-friendly.In Future this system has a potential gives voice out based feature for the patients.

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