IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

BRAINWAVES DECODER: ENABLING AUTISM SUPPORT THROUGH EEG SIGNALS

[1]K.Linga Jothi,[2]T.C SubbuLakshmi

[1]PG Scholar,[2]Associate Professor

Information Technology

Francis Xavier Engineering college,Tirunelveli,India

***Abstract*:** Interaction problems, as well as unusually restricting and repetitive behaviours, are characteristics of autism spectrum disorder. In the US, 1 in 36 children has been diagnosed with autism, according to the CDC. Autism Spectrum Disorder affects around 75 million people worldwide, or 1% of the total population. Most autistic people have difficulty interacting with others, reacting to them, and utilising interaction to explain things to them or to be kind. They also commonly have problems with communication delays.EEG-based brain-computer interfaces have been developed to help solve this problem by allowing individuals with autism to engage with others by deciphering their EEG brain signals. Our goal is to enable brain typing, which will translate their ideas into writing. To address this, this study offers a unique method for feature extraction from EEG motor imagery data using a hybrid architecture that combines CNN and RNN.EEG recordings from patients with autism are used as a complete dataset for training and assessing the suggested model.Analysing their intentions reveals that they may be able to help those with autism as well as those with disabilities.Thus, in the near future, this might be a useful tactic with possible applications in neurology and medicine.

IndexTerms - Autism,Electroencephalogram,convolutional neural network,Recurrent neural network, Disabled people

Introduction

Autism spectrum Disorder 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 Autism spectrum disorder. 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

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 challenged people [1]. It serve as a automated 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 EEGsignals 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(Brain computer interface) system 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 ELECTROENCEPHALOGRAM 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 a true rate of around 76 percentage, and P3 and O2, with an prediction of rate around 74 percentage, 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] Evaluating the EEG and Eye Movements for Autism Spectrum Disorder. Using machine learning algorithms, this paper includes the movement of eyes for the analysis for autism patients. This paper consolidate Eye developments and EEG information to foster an effective procedure for determination. This paper presents a few models in light of EEG, and eye developments for the determination of AUTISM SPECTRUM DISORDER. The aim of this paper is to investigate the use of eye tracking and electroencephalography to identify autism spectrum disorder. Essential objective is to break down AUTISM SPECTRUM DISORDER utilizing EEG, Eye development and blend of both. This will be finished by ordering AUTISM SPECTRUM DISORDER utilizing three different list of capabilities,just EEG, just eye development, Mix of EEG and Eye. features.But this paper provides some issues such as large dataset should be used for implementation.Currently,only 34 members were participated ,therefore this results in less accuracy and prediction.In [5] Detection and Tracking of Anxiety Related Diseases for Autism Spectrum Disorder Using ECG. This paper presents about Tension related messes, Once in a while their approaches to conveying any side effects may not be unmistakable by the overseers, consequently developing a need of a painless, ceaseless, ongoing identification and following of their ECG signals for expectation of these illnesses giving potential meds. Here a framework structure in light of unscented Kalman channel (UKF) is created to consistently identify and follow the R stretch for tension expectation to make these erratic sicknesses unsurprising and diminishing losses of life with convenient therapy. A harmless strategy for following of ECG signal utilizing unscented Kalman channel (UKF) procedure is created and expectations from this persistent following are additionally used to foresee sicknesses.But additionally,this system can be improved by using sweat sensors and deep learning techniques to increase the accuracy and sensitivity of the system. In [6] Unsupervised Eye Blink Artifact Detection from EEG with Gaussian Mixture Model.Cascaded thresholding technique is used to first screen the EEG signal. Then, the channel connection of the two front facing anodes (FP1, FP2), the fractal aspect, and the mean of adequacy distinction somewhere in the range of FP1 and FP2, are extricated to portray the separated EEGs. Eye blink detection is carried out using the GMM that has been trained on these features.But still the dataset has to be improved further. In [7] Feature Extraction Algorithm based on CSP and Wavelet Packet for Motor Imagery EEG signals. To acquire better element accurate results, the strategy for EEG signal component extraction in view of wavelet bundle and Normal Space Example (CSP) is embraced in this paper. First and foremost, based on dissecting channels and recurrence groups firmly connected with occasion desynchronization, wavelet bundle decay was done for EEG signs to extricate the action creative mind EEG co-rhythms and beta rhythms. The CSP algorithm was used to extract features through spatial filtering, and the related nodes were chosen to determine the wavelet packet energy. Consolidating the benefits 32 of wavelet bundle and CSP technique, the connection data between various channels can be completely used, and the Help Vector Machine (SVM) can be utilized to order the two sorts of EEG signals.This algorithm requires more training in order to acquire better results and good accuracy.In [8] Channels Selection using Independent Component Analysis and Scalp Map Projection for EEG-based Driver Fatigue Classification. In this survey, gives an order of driver weariness electroencephalography (EEG) channels choice investigation. The framework utilizes autonomous part investigation (ICA) with scalp map back projection to choose the predominant of EEG channels. After channel choice, the highlights of the chose EEG channels were extricated in view of force ghostly thickness , and afterward grouped utilizing a Bayesian brain organization. ICA uses the maximally independent source time courses as the sole criterion for performing a blind source separation (BSS) on the EEGdata. The consequences of the Independent component analysis disintegration with the back projected scalp map and a limit showed that the EEG channels can be diminished from 32 channels into 16 dominants directs engaged with exhaustion evaluation as picked channels.This shows that this technique selects the EEG signals and development of EEG based fatique development. In [9] Deep Learning Enables Accurate Automatic Sleep Staging Based on Ambulatory

Forehead EEG. This study expected to use a profound learning based mechanized rest organizing approach for EEG signals procured with the AES. A combination of convolutional and recurrent neural networks makes up the current architecture of the neural network. It has previously been demonstrated that a single standard EEG channel can achieve excellent sleep scoring accuracy (F4-M1). 135 AES-recorded EEG signals were used to retrain and test the model in this study. The accounts were led for subjects associated with rest apnea or rest bruxism. The exhibition of the profound learning model was assessed with 10-overlay cross-approval utilizing manual scoring of the AES signals as a source of perspective. Therefore, the automatic scoring algorithm that can be usedwith a self-applicable EEG electrode set could significantly facilitate the arrangement of type II in-home PSGs.In [10] Brain EEG Time-Series Clustering Using Maximum-Weight Clique. This paper proposes to deal with the issue of unlabeled EEG time-series grouping and propose a clever EEG bunching calculation, that we call mwcEEGc. The thought is to plan the EEG bunching to the most extreme weight coterie (MWC) looking in a superior Fréchet closeness weighted EEG diagram.24 Instead of calculating the cluster centroids, the mwcEEGc takes into account the weights of both vertices and edges in the constructed EEG graph, as well as the EEG of clusters based on their similarity weights. Supposedly, it is the principal endeavor to bunch unlabeled EEG preliminaries utilizing MWC looking. The mwcEEGc accomplishes high-qualityclusters concerning intracluster conservativeness as well as intercluster disperse. Using 14 real-world brain EEG datasets and detailed experiments with the standard clustering validity criteria, we show that mwcEEGc is superior to ten cutting-edgeunsupervisedlearning/clustering approach. It is another orientation to apply mwcEEGc for these signal clustering .

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.

Proposed System

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

Dataset:

Public EEG dataset is used in proposing deep learning algorithm. It recorded the signals from 109 participants at the frequency rate of 160 Hz. The participants were performed five actions which are labelled as 0-4.The main actions were performed such as left or right fist and opening and closing both fist and feet.34560 samples were taken and recorded.There are 16 elements are there.Whereas 1-14 data elements are denoted as EEG raw signal,15^{th} denotes the label of the corresponding participants sampling rate is 128HZ.The actions recorded are up,down,left,right,middle and eyes closed are labelled as 1,2,3,4,5,6.

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.

Preprocessing

When analyzing EEG signals,a type of signal processing filter called butterworth filter is employed to perform particular frequency domain operation 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 signals 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.

Classification:

In this paper ,CNN and RNN is used as classifier.A convolutional tool that automatically extracts the features of the signal is called as feature extraction.The feature extraction technique consists of many number of layers is called convolutional or pooling layers.A fully connected layer automatically extracts the features from previous stages and predicts the output.Therefore it creates a new features.Recurrent Neural Networks(RNN) can be used as feature extractors for classifiying EEG motor imagery data by leveraging their ability to capture temporal dependencies in sequential data.After training,the RNN's internal states or activations can be considered as featuresbthat capture relevant temporal information.These features can be extracted from the hidden layers of the RNN for each time step.XGBoost serves as a robust and efficient classifier that,when combined with features extracted by CNN and RNN,can effectively classify EEG motor imagery signals.The ensemble nature of XGboost contributes to the model's accuracy and interpretability.

System Architecture

Firstly, we have collected motor imagery dataset is called eegmmidb is used to evaluate our proposed deep learning model.Then we have created convolutional neural network that automatically learns the higher level representations from raw EEG signals.We are utilizing CNN and RNN machine learning models as feature extractor.Combining these architecture allows the model to capture both spatial and temporal aspects of motor imagery eeg data.Therefore combined features from CNN and RNN are used as input features for the XGBOOST(Extreme Gradient Boosting) classifier.Therefore by combining CNN and RNN for feature extracting with ensemble learning capabilities of XGBOOST.

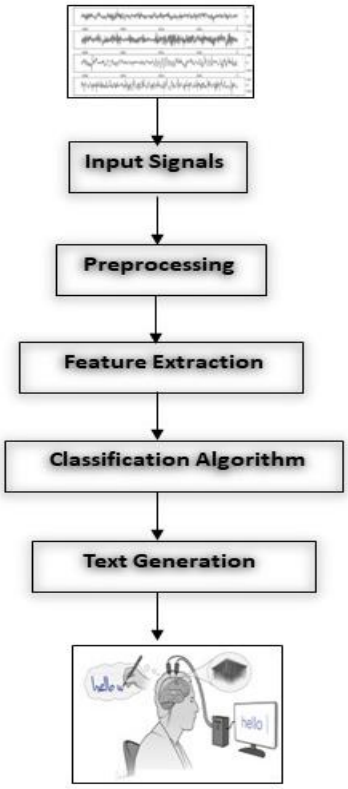

Fig 4.1 Workflow diagram

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.

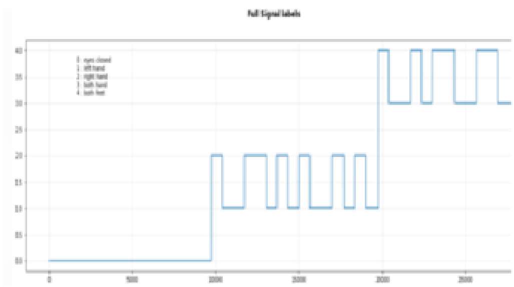

Fig 5.1 Full signal

The above figure shows the signals of actions of participants.Totally there are five actions are performed such as eyes closing,raising the left hand and right hand,both hands and both feet signals are visualized in an efficient manner.

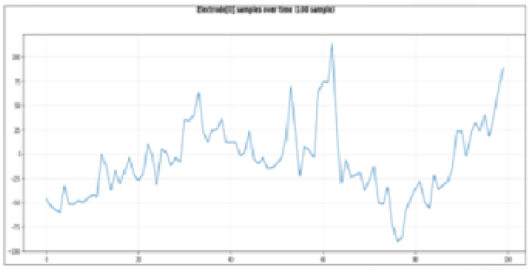

Fig 5.2 Signals of 100 samples

The above figure depicts the visualization of over 100 samples of the participants of brain signals.These signals are preprocessed in an efficient manner such as removing artifacts and reducing the high noise etc.

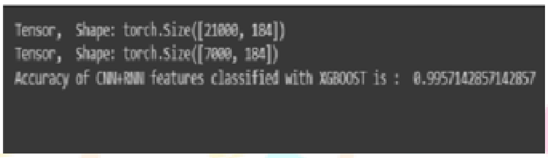

Fig 5.3 Models results

From the above figure,it shows that brain signals are trained using cnn and rnn algorithm as feature extractor and the output of feature extraction are given as input to the XGBoost classifier and it classifies the signals with an accuracy rate of 99%.

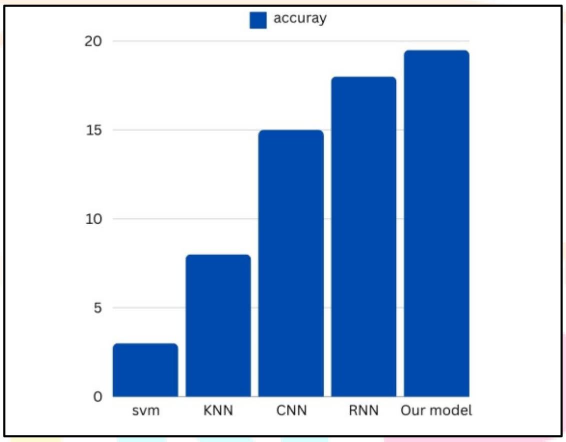

Fig 5.4 accuracy of our model

From the above graph,Our model's accuracy is compared with all other models and results are visualized in a bar graph in an efficient manner.

Feature learning	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	average
CNN	0.9021	0.5932	0.9392	0.9031	0.9013	0.9941	0.9721	0.6177	0.912	0.6321	0.83669
RNN	0.9004	0.8021	0.9402	0.9254	0.9486	0.9426	0.9098	0.9293	0.9643	0.8948	0.91575
CNN+RNN	0.939	0.9186	0.9784	0.9736	0.9967	0.9832	0.9675	0.9245	0.9758	0.8954	0.95527
Improvement	0.0379	0.0258	0.0278	0.0077	0.048	-0.011	0.0402	-0.0048	0.0115	0.0456	0.02287

Fig 5.5 Recognition accuracy of 10 subjects

From the above table,ten subjects signals are classified using cnn and rnn models and its prediction value is also mentioned and average and standardised value is also mentioned.

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.

Future scope:

Just as any technology that emerges and it evolves to new ideas and new market standards to meet the public need.Therefore "Brainwaves Decoder:Enabling Autism support through EEG signals" is also created and trained in order to meet with technological standards.For EEG based classification or analysis basic requirement is quality of the signal,accuracy of the model and efficiency which all are met.In near future,it could be the promising approach with potential application in healthcare sector and neurology department.And also by collecting the realtime data from autism patients and disabled people and trained their data using the model and user intents could be converted into voice commands in future.So,therefore it could be beneficial for caretakers for understanding them more efficient.

References:

[1] Pritam Bala,Redowan Amob,Mahbubul Islam,Fayaed Hasan, "EEG-Based Load Control System for Physically challenged people",2nd International conference on Robotics,electrical and signal processing,2021.

[2] Lili Duan,Jie Li,Hongfei Ji,Zilong pang,Xuanci Zheng, "Zero-shot Learning for EEG classification in Motor imagery-Based BCI System", IEEE Transactions on Neural systems and Rehabilitation Engineering,2020

[3] K.Tavakolian,A.M. Nasrabadi,S.Rezaei, "Selecting better EEG channels for classification of mental tasks",IEEE International symposium on circuits and system,2004

[4] Sashi Thapaliya, Sampath Jayarathna, Mark Jaime,"Evaluating the EEG and Eye Movements for Autism Spectrum" ,IEEE International conference on Big data,2018

[5] Abhirami A , Sudheesh P, "Detection and Tracking of Anxiety Related Diseases for Autism Spectrum Disorder Using ECG",International conference on communication and electronics system,2019.

[6] Long Chen, Dinghan Hu, Fang Dong, Tiejia Jiang,Weidong Gao, and Feng Gaoy, "Unsupervised Eye Blink Artifact Detection from EEG with Gaussian Mixture Model", IEEE journal of Biomedical and Health Informatics,2021.

[7] Gao Feng, Lu Hao, Gao Nuo, "Feature Extraction Algorithm based on CSP and Wavelet Packet for Motor Imagery EEG signals",IEEE 4th International conference on signal and image processing, 2019.

[8] Rifai Chai, Ganesh R. Naik, Sai Ho Ling,Yvonne Tran, Ashley Craig and Hung T. Nguyen,"Channels Selection usingIndependent Component Analysis and Scalp Map Projection for EEG based Driver Fatigue Classification", International conference of IEEE Engineering in Medicine and Biology society,2017.

[9] Akseli leino , Henri korkalainen , Laura kalevo , Sami nikkonen ,Samu kainulainen , Alexander ryan, Brett duce , kirsi sipilä,Jari ahlberg,"Deep Learning Enables Accurate Automatic Sleep Staging Based on Ambulatory Forehead EEG"volume 10,2022.

[10] Chenglong Dai , Jia Wu ,Dechang Pi,Stefanie I. Becker,Lin Cui , Qin Zhang , and Blake Johnson,"Brain EEG Time-Series Clustering Using Maximum-Weight Clique", IEEE Transaction on Cybernetics,2022.

[11] Rui Zhang,Ningling Zhang,Danyang Lv, "Motor Imagery EEG classification with self-attention-based convolutional Neural Network" International conference on Intelligent Informatics and Biomedical Science,2022.

[12] B S Vivek, A Adarsh, J Gubbi, Kartik Muralidharan, " ST-GNN for EEG Motor Imagery Classification" International conference on Biomedical and Health Informatics , 2022

[13] Manasi Saxena,Ekansh Sareen,Anubha Gupta, "Understanding Functional Brain Activation using Source Localization of EEG signals in Motor imagery Tasks", International Conference on Communication systems and Networks,2020.

[14] Syed Umar Amin,Hamdi Altaheri,Ghulam Muhammad,Mansour alsulaiman, "Attention based inception model for robust EEG motor imagery classification" ,International Instrumentation and Measurement Technology conference, 2021

[15] L. Kalevo, T. Miettinen, A. Leino, S. Kainulainen, K. Myllymaa,J. Toyras, T.Leppanen, and S. Myllymaa, ``Improved sweat artifact tolerance of screen-printed EEG electrodes by material selection-comparison of electrochemical properties in arti_cial sweat," *IEEE Access*, vol. 7, pp. 133237_133247, 2019.

[16] P. J. Arnal, V. Thorey, E. Debellemaniere, M. E. Ballard, A. B. Hernandez, A. Guillot, H. Jourde, M. Harris, M. Guillard, P. Van Beers, M. Chennaoui,and F. Sauvet, ``The dreem headband compared to polysomnography for electroencephalographic signal acquisition and sleep staging," *Sleep*,vol. 43, no. 11, pp. 1_13, Nov. 2020.

[17] C. Lord, T. S. Brugha, T. Charman, J. Cusack, G. Dumas, T. Frazier, E. J. H. Jones, R. M. Jones, A. Pickles, M. W. State, J. L. Taylor, and J. Veenstra-VanderWeele, ``Autism spectrum disorder," Nature Rev. Dis- ease Primers, vol. 6, no. 1, p. 5, Jan. 2020, doi: 10.1038/s41572-019-0138- 4.

[18] I. B. Slimen, ``EEG epileptic seizure detection and classication based on dual-tree complex wavelet transform and machine learning algorithms," J. Biomed. Res., vol. 34, no. 3, p. 151, 2020, doi: 10.7555/JBR.34.20190026.

[19] L. A. W. Gemein, R. T. Schirrmeister, P. Chrab¡szcz, D. Wilson, J. Boedecker, A. Schulze-Bonhage, F. Hutter, and T. Ball, "Machinelearning- based diagnostics of EEG pathology," NeuroImage, vol. 220, Oct. 2020, Art. no. 117021

[20] Y. Yao, J. Plested, and T. Gedeon, "Information-preserving feature Filter for short-term EEG signals," Neurocomputing, vol. 408, pp. 9199, Sep. 2020.