A Comparative Study on Different Techniques for Classification of Brain Waves From EEG Signals

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Abstract – The latest trends and research in Brain-Computer Interface (BCI) technology have been used for emotional sensing and researchers interested in neurons to analyse brain diseases and disorders. In particular, Brain-Computer Interfaces (BCIs) are used by machine learning approaches to either restore neural pathways or help the patient interact effectively through an electronic prosthetic, showing promising results in impairment and rehabilitation care. Emotion Recognition and prediction of sensations supported by electroencephalography (EEG) have generated interest in a number of ways to implement human-centered services. Emotion is an aspect of how people behave and it is a critical overall performance in BCI. Today, researchers in computational linguistic regions have an interest in emotional attention for the evaluation of feeling. The EEG is moreover extra efficient for the evaluation of brain signal that assists in the analysis of neurological disorder medicinal drug and additionally performs a critical function altogether the neurosurgery related to the mind. This work aims to review reported papers on emotion identification, recognition, and exceptional detection of brain sickness upon that paper, a research analysis is worked out again to outline and illustrate the Brainwave emotion referendum outcome, and the evaluation also covers a few recent works on these degrees such as acquisition of EEG signals, extraction of capacities, emotion category, and prediction of ailment from these degrees. The various techniques of computer vision applied and combined with BCI technologies show that perhaps the treatment of brain disease with the use of BCIs is a promising and constantly evolving field.

Keywords– BCI; EEG; ML; Prediction;

NOMENCLATURE

BCI- Brain Computer Interface, EEG- Electroencephalography, ML- Machine Learning, MRI- Magnetic Resonance Image, SVM- Support Vector Machine

I. INTRODUCTION

Machine learning, with its power to pass around, interpret and identify data easily, is a good approach for EEG analysis in patients with brain disease. The use of technology will lead to a quicker, more open and potentially reliable assessment of patient data, leading towards more timely and efficient treatment. [1] Emotions play a significant and vital role in human creatures' existence. A sign of psychosomatic problems is conveyed through impulsive behaviors. The variations in brain patterns and perceptions can be reflected in these disorders. BCI serves as a human brain channel to connect with a computer device. It facilitates its users to monitor digital signals with cognitive processes which are independent of cortical nerves and muscles. Image is a general representation of an artefact, idea, organisation of patterns, person or thing in art. Figure 1 explains how a EEG signal looks like.

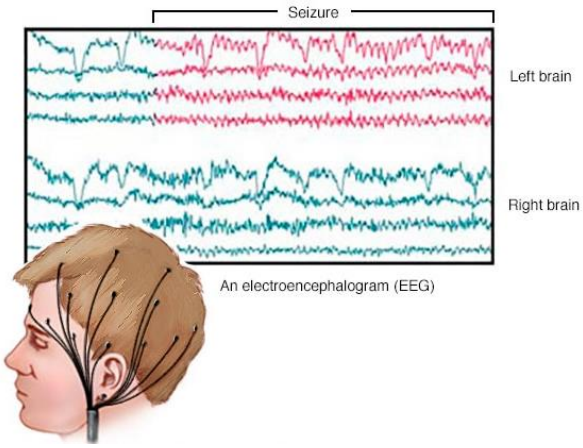

Fig.1. EEG Signal

Well humans have come so far that we have the technology to perceive the images that used be on papers on digital platforms. A digital image is an image that is depicted by the computer systems normally in a binary form generally in the 2-D matrix state. It can also be defined by mathematical function f(x,y) where x and y are axis. Generally, we broadly categorize the digital images in two forms depending on the image resolution is fixed or not, it can be called vector and raster. A vector image is a combination of 2D points connected by lines and curves to create unique polygons and other structures. Whereas raster images are bitmap images that are represented as the dot matrix image generating a series of rectangular dots with respective pixel colors [2].

The human brain is divided into two hemispheres. The left one is known to be "logical brain" which is mainly involved in language and for analysis purpose and the right one is the "creative brain," which involved in daydreaming and imagination. The right part of the body is still dominated by the left one, while the right part of the brain has power over the parts of the left body. Brain produces signals which reach the nervous system and make humans and animals to reciprocate what our brain wants to tell.

II. LITERATURE SURVEY

The human brain is a complicated, interconnected device. Trillions of dollars of nerve fibers (synapses) with complex spatiotemporal neuron dynamics, along with non-invasive brain signal mapping methods, there are several aggressive versions. Among all the approaches to non-invasive. Direct cortical measure for the study of the human brain The temporary resolution of less than one millisecond EEG is provided. [3] The

A very good review on Deep Learning for Segmentation of Brain MRI: State of the Art and Expected Directions [4]. A quantitative analysis was done on MRI brain daily for neurological diseases and for segmentation types. Deep learning plays a vital role in this. A segmentation approach based on deep learning, evolving daily because of its self learning generalization capability. The study in this paper provides an overall overview of different techniques used by deep learning for MRI brain images. It has been concluded that in critical assessment, deep learning plays a vital role effectively.

This dissertation focuses on the automated segmentation of meningioma from the Magnetic Resonance Imagery of the multispectral brain. By proposing a completely automated system hierarchically organized into two stages, the authors address the segmentation task. The initial, unsupervised stage is formulated on the basis of Graph Cut. Initial segmentation outcomes are optimized in the second step using a supervised Support Vector Machine-based classification. The overall segmentation process is fully automated and adapted to non-volumetric information characterized by poor cross separation in an effort to facilitate insertion in clinical practice. The findings of this small survey are promising but indicate that classification profits from either the integrated a use of Graph Cut as well as SVM frameworks. [5].

Various methodologies are used for the image segmentation purpose and clustering is one of them. As far as the complexity of brain image edges is concerned, it is very difficult to perceive three different tissue segments accurately: white matter, grey matter and cerebrospinal fluid as well as different diseases that is affected in the brain. We have implemented a modified approach in this paper to bring forward a new process which means Modified C. The whole algorithm was used for the identification of brain image diseases such as the anomaly detection associated with tumor and gray matter. In this paper, colours are used for the detection of anomaly part. We have merged all the colours to get the final coloured image. With the help of the coloured pixels, we can easily calculate the percentages of white matter, grey matter and the percentage of cerebrospinal fluid. Then according to the colour percentage, we can predict the brain anomaly according to a dataset; which contains the name of the brain disease and the percentage of grey matter and white matter of the affected person. Segmentation of accurate brain tissue from magnetic resonance (MR) images is a crucial step in quantitative brain image analysis [6].

The nature is exclusivist, non-Gaussian, unpredictable, non-correlated, of EEG signals. Electroencephalography (EEG) may be used to identify brain damage, any other illness, or symptoms. In detecting, Many neurology-related conditions, including such psychiatric illnesses like epilepsy, sleep disturbances like crohn's disease, cancer, anxiety, and depression, are also used and numerous trauma (stress)-related issues. The traces are distinct different activities for the brain [7].

III. ANALYSIS

A. Machine Learning Review

Before you can even start to run your algorithm, four key components must be part of each Machine Learning algorithm. These components are the ingredients that the data you want to run, The model, the optimization method, and the algorithm of restriction. The data to be used is normally background information that is available to the public, but to create a data set that is specific to your particular research, you often need to add your own research. The next ingredient was the model we would prepare to be using the sample as part of the machine learning phase in your specific study. The third ingredient is the objective attribute that plays a part once you are

prepared to make your model give you a performance that is as similar as possible to truth. To evaluate the accuracy of the performance that your model has produced, the objective function is used [8].

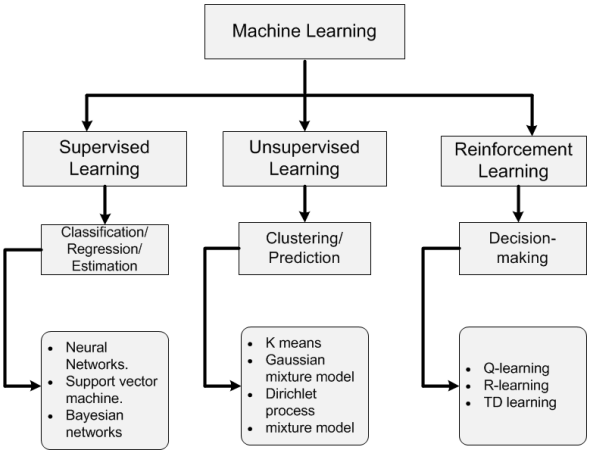

Fig.2. Machine Learning Algorithm Chart (Google Photos)

Figure 2 explains about different algorithms used in Machine Learning. Machine learning algorithms are classified into categories of supervised learning, including the simple implementations shown in this category as well as the unsupervised learning classification, which contains the complex algorithms used for this segment. Issues will often occur for any machine and algorithm-based technology. Machine learning may lead to datasets or algorithms being. More generic and not sufficiently detailed for various topics of study [9]. Compared to the true model, In the general equation, the generalizability may be induced by a prejudice that could then create an error due to incorrect assumptions being made according to how the model appears.

A. EEG Signal & Machine Learning

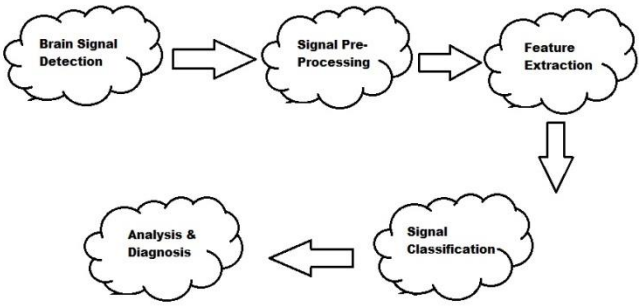

Fig.3. Diagram to describe how a brain signal is processed to detect and predict emotions and diseases respectively.

The above diagram Figure 3, explain clearly about the step by step process how a brain signal in analyzed. In this review paper, we have mainly focused on EEG Signals, how this signal is captured, how pre-processing is done, and then different features extraction methods of machine learning are used to detect the signal type and then moved to the classification processes that is also a part of machine learning and lastly the part goes to the doctor or different researcher for analysis and diagnosis purpose for emotion detection analysis as well as disease prediction.

B. EEG Signal Identification

At first, the brain's EEG is captured by the traditional approach known as the International 10-20 System globally. These signals are first amplified and then digitized within the Digital EEG system. By electric impulses, the neurons connect with each other. To measure the amplitude of electrical impulses, the electrodes are located on the scalp. Frequency range of a standard EG signal is 1 Hz-100 Hz but the 100Hz is very unusual and amplitude varies from 10 µV – 100 µV.

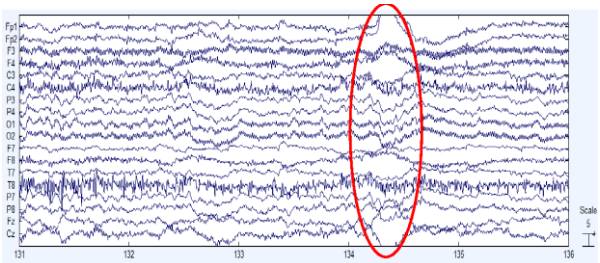

Fig.4. Represents the various types of emotions using EEG brainwaves. The circled area demonstrates the variations in pattern from which we can assess the emotion of any live individual.

EEG signals are an important indicator of the function of the brain and have an immense capacity for diagnosing brain diseases and disorders [10]. Figure 4 represents the various types of emotions using EEG brainwaves. The circled area demonstrates the variations in pattern from which we can assess the emotion of any live individual. Flashing of eyes during the process of signal acquisition, muscle activities, and activities occurring in the background are different forms of objects that influence the signal. Therefore, EEG signals are generated from extremely reliable, de-noised facilities and specialized intervention instruments, objects, and numerous other noise sources. EEGs have outstanding spatial resolution and less than a millisecond, regardless of their actual spatial resolution. The signal has a very low Hertz frequency range when measured. Based on the frequency bands, such signals can be categorized [11]. Our brainwaves shift in line with what we do and experience. When slower brain signals are dominant, we can feel tired,

slow, sluggish, or wistful. The longer wavelengths are dominant, as they sound activated, or neurotic.

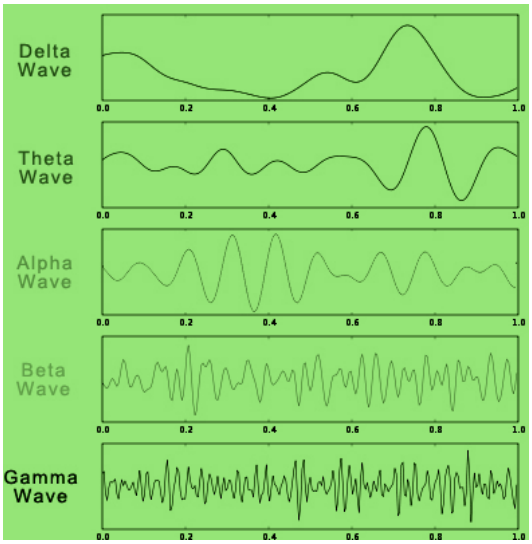

Fig.5. Different Types of Brain Waves.

Figure 5 explains how many types of waves are there that can be used. The EEG signals structure is very complex, random, and non-correlated. The attributes of the EEG rely on several variables, including the person, maturity and psychological condition of the object. Many solutions have been proposed in research to detect the secret performance metrics and unexpected changes that can take place. The study of the signal [12] includes three important factors. All prevailing wavelengths throughout the EEG are calculated by means of signal spectral data.

TABLE I. BRAIN WAVES CLASSIFICATION

Brain Waves Name	Frequency Range	Usually associate With
GAMMA	> 40 Hz	Greater cognitive performance, including perception, problem solving, and awareness
BETA	13–39 Hz	Active, intensive thought, active processing, active focus, awareness and arousal
ALPHA	7–13 Hz	Calm, comfortable but alert condition.
THETA	4–7 Hz	Extreme mindfulness /relaxation, Stage of sleep.
DELTA	< 4 Hz	Extreme restful sleep, lack of consciousness about the body

A number of states of consciousness, from sleep to active thought, are controlled by each type of brainwave. Table 1 describes about the brain waves classification [14].Though all brain signals work collectively, one brainwave may be more powerful and predominant than the others. Your present state of mind will be dictated by the dominant brainwave. So you would be known to be in a "alpha state of mind" if you are awake and comfortable since the maximum intensity of your Alpha brain waves would be the greatest.

C. Brain Computer Interface Model

Under BCI Model we have 3 phases of brain signal processing namely; Signal Preprocessing, Feature Extraction and Classification [13]. Different machine learning algorithms for EEG signals are currently being explored for identification, classification, and analysis. Fig.6. illustrates the working of BCI Model. Diagram is taken from Google images.

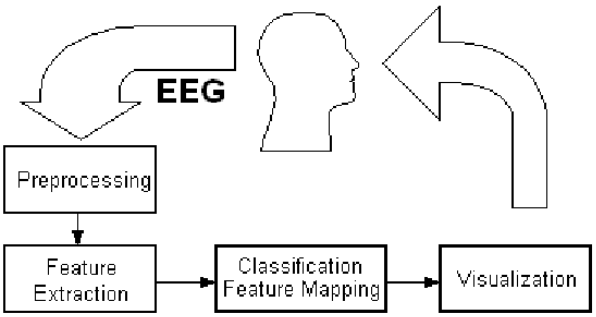

Fig.6. illustrates the working of BCI Model

I. Signal Pre-Processing

In BCI, at the initial level, data collection and filtering is carried out. Data collection is recorded with the aid of electrodes placed on the subject's scalp (EEG signal). In the context of an EEG sample, the 10-20 or Global 10-20 system would be an internationally accepted tool for the identification but application of scalp electrode position, polysomnograph sleep analysis or voluntary laboratory research. This technique was developed to maintain systematic testing procedures to ensure that the findings of the study (clinical or research) of a subject could have been compiled, replicated, and analyzed and compared accurately using the methodology [14]. Figure 7 shows 10-20 International System of Electrodes Placement. The method is focused on the correlation between an electrode's position and the brain's underlying region, specifically the cerebral cortex.

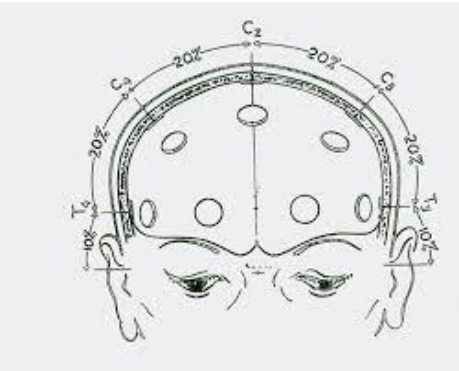

Fig.7. 10-20 International System of Electrodes Placement

Effective identification and removal involves artifacts and noise in the signal. Then the signal obtained serves as an input to the filter. The noise signal is filtered out of the signal by the filter and avoids signal distortion. For rejection of anomalies and noise, Notch filters are used. Medav Filter is also there [15]. To reject components with very low frequencies. With both the aid of low-pass filters with 40-70 Hz as a cut-off frequency, high-frequency noise components are eliminated.

II. Signal Feature Extraction & Classification

A feature reflects a property that is exclusive. Several feature extraction techniques have been developed and the choice of both appropriate characteristics and electrode position is typically based on neuroscientific observations [16]. Many linear and non-linear approaches have been documented in the literature for feature extraction. Linear techniques include ICA, FFT, Eigenvector, AR, Wavelet transform, Wavelet Packet Decomposition, Principal Component Analysis The factor of correlation, Hurst exponent (H), largest exponent of Lyapunov (LLE), different entropies, Higher Order Spectra (HOS), Fractal Dimension (FD), complication charts and spatial stage graphs are non-linear techniques. BCIs depend, through signal processing and other feature analysis, Gathering data and extracting characteristics from EEG impulses from the brain. The input data will gradually be represented as a machine result by operation of extracted data through a predetermined machine learning model.

Collection and measurement by means of a sensor, such as EEG data. To addition to digitally manage things,, these signals are magnified and electromagnetic distortion and other unwanted signal features are extracted out. The signal is analyzed to identify important features until this signal, along with a technique called feature extraction, is changed and transmitted to a computer. Amplitude and latencies of time-triggered EEG response, including such P300 waves, 20 or power within Resonant frequencies, like those from sensor motors patterns, may be commonly derived features of EEG operation. Such collected signal characteristics serve to decipher the intent of the user. The extracted data would undergo function conversion by the use of a supervised machine learning method to convert the features into some kind of function required by the user.

With their merits and de-merits, the EEG signal detection and feature extraction methods have been evaluated in a highly thorough and extensive survey [6-14]. Time-frequency methods for epilepsy detection and assessed frequency analysis (FFT), time-frequency analysis (STFT) over several electrodes were studied by Alexandros et.al. It was found that the classification outcomes were better for STFT. Another paper compared their shortcomings to FFT, AR, TF and WT and according to the author, the WPD approach generates a redundant signal representation and achieves better accuracy. For epileptic seizure detection, a DWT and SVM based expert model has been developed. The issue of improving the extraction of features was discussed in [17]. The adaptive feature extraction process, i.e. adaptive common spatial patterns, was also reviewed in this paper.

D. Diagnosis & Analysis

In the classification of brain diseases, any use of computer intelligence has continued to expand the number of observations of advanced diagnostic imaging identification, their ability to manage the period of occurrence, the optimization of the tumour, the condition of repairable tissue, and eventually the effects of the patients prior. The potentially long-term challenges they will have to endure. The key diagnostic class of disease is focused on medical (two-dimensional) imaging and one-dimensional) signal processing. In the identification, control, and prediction of diseases, certain methods have been used. Machine Learning has been applied to biomedical signal function extraction, such as electroencephalography (EEG), for one-dimensional signal processing. Recent results demonstrate the feasibility of EEG recordings predicting seizures; the transition from preictal to paroxysmal states consists of a "buildup" that can be monitored using advanced techniques of extraction of features and ML.

I. SVM

EEG is a relatively useful method for disability detection, but it can be very difficult to extract features from these signals. For higher dimensional and nonlinear issues, In pattern recognition, the SVM, that utilizes kernels that transfer specimens from one function space to another, has been shown to be extremely strong. All in all, though LDA is an effective classification technique, it is restricted to linear analysis. Consequently, however versatile, neural networks involve large amounts of data. Consequently,

for nonlinear analysis, SVM is a good preference for small data sets. Even then, SVM is a successful approach for accurately classifying stroke-related EEGs, selecting the correct kernel for a given task can be difficult. First to enhance the general efficiency of the signal, raw EEG signals were pre-processed. Next through wavelet packet entropy and Granger causality flow, features were extracted. The defined weights within and kernel are accounted for by this approach to retain a much more effective procedure [18].

Popular spatial pattern performance relies heavily on predetermined spatial-spectral filtering circumstances; but these conditions for brain disease patients are often difficult to recognize. For identification after extracting features, a static SVM has been used, and the analysis revealed that the combination typical spatial-spectral pattern boosted and SVM system surpassed all other techniques and, following a 2month turnaround time, it was able to reach 70% precision.

II. NEURAL NETWORK

To differentiate between EEG and control info, which would be more easily accessible than CT scans, a convolutional neural network has previously been used. The classification model of the community was accelerated by the implementation of early stopping and batch normalization techniques. Using CNN, F ratings are been shown that it contributes to greater performance than the comparative classifiers and is capable of outclassing neural networks with a smaller number of steps than the Naive Bayes model. Compared to the Naive Bayes model, this CNN has a stochastic component [19]. When classifying brain damaged patients, problems occur due to varying stage stages of disease this limits the consistency of categorization throughout the classification of mental disorder for stroke victims.

Accuracy assessment has shown that Deep CNN accuracy has declined with reduced training time, with the maximum attainable performance after one minute. When binary and more fine-tuned diagnoses are still limited, the detection of brain disease, development of a deep CNN to determine EEG signals for disease may help. Enhanced deep CNNs, which could cause normal and patho-physiological changes in EEG to be properly established, can help real-time diagnosis.

III. OTHER ML METHODS

Quantifying the degree Movement disorder in an effective quality management system as this has a direct effect on the individual's subsequent quality of life. One approach to achieve was to use ERS as an exam function for both the level of motion impairment in an injured individual. These were observed that there had been a statistically important difference and in strength of ERS and the frequency of the incidence of ERS between such two groups. For chronic cases, the strength of ERS was smaller, and the timing was delayed. Cerebral system activities then revealed that this delay and low ERS power could be seen as the clinical team would have to devote more work into conducting the hand action, as ERS shows a reduction in cortical activation. Additionally, ERS was again found in stroke patients with mild motor disability and severe cognitive impairments, and the same response was found. GMM (Gaussian Mixture Model) is used for comprehensive feature analysis, since it is a probabilistic model that describes the existence of sub-populations inside a bigger population using Gaussian distribution. In a preprocessing module and as a classifier in a classification module, they implemented the model both as a filter. GMM as a filter and as a classifier outperforms in terms of accuracy as compared to CSPSVM, reaching a high reliability of 80% in the scenario of one of the research subjects.

Sensorimotor rhythms (SMR) paradigms are another technique Used only for assisting with stroke diagnosis in machine learning. The need for a sensorimotor rhythm paradigm has become one of the most popular motor imagery concepts. [20]. The movement that is being imagined in an SMR paradigm is characterized in the interpretation of large parts of the body's kinesthetic motions, such as our arms, that can be interpreted as harmonics of cognitive function. In studies between healthy patients and patients who have had brain disorders, this model was also used.

IV. CONCLUSION

EEG is a non-invasive procedure, i.e. The signals are collected via the scalp electrode is itself one of the causes of noise induction. The identification and removal of objects is the biggest ongoing problem for engineers these days. A rapidly expanding and developing sector is BCI technology for application in the diagnosis and recovery of brain diseases. When combined with BCI technology, When it comes to proper diagnosis, diverse variations of feature extraction and classification approaches for machine learning show increasing precision. These eeg-based BCI paradigms were tested in the current analysis in compliance with the application classification for the diagnosis of brain disease. Machine learning strategies such as CNN, SVM, GMM, etc. were reviewed within the diagnosis classification.

EEG signals are of a highly subjective, non-Gaussian, non-correlated, random type and are known as chaotic signals. In order to create a framework that can be run in real environments, a lot of development needs to be done, according to the study. Multiple linear and nonlinear signal processing strategies were discussed, including Time domain, frequency, time-frequency, as well as frequency domain methods for space-time.

Using non-linear methods helps to clarify the complex physiological activities that take place in the brain, such as chaotic actions and abrupt changes. Conclude, this review shows that when combined with various combinations of machine learning techniques, the use of BCI technology for brain disease care is a promising area that shows increased precision in both classification and differentiation of clinical purpose while implemented to prediction.

V. REFERENCES

[1] Shiliang Sun and Jin Zhou," A Review of Adaptive Feature Extraction and Classification Methods for EEG-Based BrainComputer Interfaces," in IEEE Joint Conference (IJCNN) on Neural Networks International, pp. 1746 – 1753, 2014.

[2] Marler, John R., Pamela Winters Jones, and Marian Emr. Setting new directions for stroke care: proceedings of a national symposium on rapid identification and treatment of acute stroke. No. 97. The Institute, 1997.

[3] Alpaydin, E. (2004). Introduction to Machine Learning[PowerPoint slides].Retrieved from https://camino.instructure.com/courses/44637/files/folder/Slides?preview=2485276

[4] Pari Jahankhani, Vassilis Kodogiannis and Kenneth Revett," EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks," IEEE John Vincent Atanasoff JVA International Symposium on Modern Computing, pp. 120 –124, Oct. 2006.

[5] Akkus, Z., Galimzianova, A., Hoogi, A. et al. J Digit Imaging (2017) 30: 449. https://doi.org/10.1007/s10278-017-9983-4

[6] S. Bauer, L.-P. Nolte, and M. Reyes, "Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization, in Medical Image Computing and Computer-Assisted Intervention" , pp. 354361-MICCAI, Springer, 2011.

[7] Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains," ISRN Neuroscience, Hindawi Publishing Corporation, Article ID 730218, 2014.

[8] D. Puthankattil Subha, Paul K. Joseph, Rajendra Acharya U, Choo Min Lim," EEG Signal Analysis: A Survey," Springer Science vol.34, pp.195–212, 2007.

[9] N.A. Md Norani, W. Mansor, L.Y. Khuan," A Review of Signal Processing in Brain Computer Interface System," IEEE EMBS Conference on Biomedical Engineering & Sciences, pp. 443 – 449, Nov. 30 2010-Dec. 2 2010.

[10] Gupta, Sayantan, and Sukanya Roy. "Medav filter—filter for removal of image noise with the combination of median and average filters." Recent Trends in Signal and Image Processing. Springer, Singapore, 2019. 11-19.

[11] Roy, Sukanya, et al. "Brain Anomaly Prediction Using Modified Clustering (MC)." 2019 6th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2019.

[12] Hoffmann, U., Vesin, J. M., Ebrahimi, T., & Diserens, K. (2008). An efficient P300-based brain–computer interface for disabled subjects. Journal of Neuroscience methods, 167(1), 115-125.

[13] Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. Clinical neurophysiology, 113(6), 767-791

[14] JR. Panda, P.S. Khobragade, P.D. Jambhule, S. N.Jengthe, P.R.Pal, T.K. Gandhi," Classification of EEG Signal Using Wavelet Transform and Support Vector Machine for Epileptic Seizure Diction",IEEE International Conference on Systems in Medicine and Biology, pp. 16-18, December 2010.

[15] Alexandros T. Tzallas, Markos G. Tsipouras and Dimitrios I. Fotiadis," The Use of TimeFrequency Distributions for Epileptic Seizure Detection in EEG Recordings," IEEE Annual International Conference EMBS Cité Internationale, August 2007

[16] Suwannarat, A., Pan-ngum, S., & Israsena, P. (2018). Comparison of EEG measurement of upper limb movement in motor imagery training system. Biomedical engineering online, 17(1), 103.

[17] Cheng, D., Liu, Y., & Zhang, L. (2018, April). Exploring Motor Imagery Eeg Patterns for Stroke Patients with Deep Neural Networks. In 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 2561-2565). IEEE. https://ieeexplore.ieee.org/document/8461525

[18] Keirn, Z.A.; Aunon, J.I. A new mode of communication between man and his surroundings. IEEE Trans. Biomed. Eng. 1990, 37, 1209– 1214.

[19] Roy, Sukanya, et al. "Predictive Analysis & Classification of Diseases in Organs using Modified-C Clustering Technique." 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom). IEEE, 2020.

[20] Roy, Sukanya, et al. "Identification of medical disorders in eye and biometric authentication analysis with iris retina scan using machine learning." Biotechnology and Biological Sciences. CRC Press, 2019. 29-33.