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EEG Feature extraction using DaubechiesWavelet and Classification using Neural Network

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Abstract— Electroencephalography (EEG) is a straightforward technique which gives thought regarding the potential produced on the outside of the mind which helps in understanding the usefulness of the cerebrum. EEG signals play a vital job in recognizing the human feelings. In feeling appraisal using EEG flags, the time span of EEG motions in given number of channels, enthusiastic upgrades, and recurrence groups, nature of statistical feature extraction techniques and highlights important job. In this paper, new highlights are removed using Discrete Wavelet Transform (DWT) and further the feelings are arranged using EEG signs of 10 subjects is gathered and using 24 anodes from the standard 10-20 Electrode Placement System which is set over the whole scalp. Feature Extraction is performed by using DWT and the Decomposition of EEG signals is separated for 8 levels using "db4" wavelet. The feature extracted signs are then grouped using Artificial Neural Network (ANN) and the neural framework which can be compared at for feeling passionate states classification.

Keywords-Electroencephalogram (EEG), Discrete wavelet transform, Feature extraction, Artificial Neural Network (ANN), Daubechies Wavelet.

I. INTRODUCTION

The capacity of emotion preparing, PCs and robots can't speak with human normally. Specialists are discovering approaches to concentrate on Human PC connection to enable PCs to comprehend human emotions Muruggappan.et.al [1].Emotion discernment identifies with comparative reasoning, learning and recalling a consequential complicated mind action. These distinguished emotions can be used as a client contribution to the cerebrum PC interface framework. Feeling is one of the major factors that impact our insight and our every day undertakings that request relational abilities and productive social connection. Scientists on human EEG flag uncover that cerebrum action assumes a noteworthy job in the evaluation of feelings. M.A.Khalilzadeh et.al [2]. Perceiving passionate states from neural reactions is a successful method for implementing full of feeling in computer PC interfaces. K.Schaaffet.al [3]. EEG signals uncover critical data on their working and functioning. The investigations identifies with a critical useful action of EEG signals. Numerous techniques are utilized for evaluating human feelings previously. Different scientists have completed distinctive techniques for highlight extraction and order which is been talked about

Mingyang et.al [4] proposed a novel methodology for the Classification of BCI signals. In their work Discrete Wavelet Transform (DWT) was implemented for highlight extraction using Daubechies wavelet db4, for a 5 level Decomposition of EEG signals. They have considered 100 examples in a solitary channel EEG at an inspecting rate of 173.61 Hz. The highlights registered were mean of the envelope range in each sub-band, vitality, standard deviation, most extreme estimation of the envelope range in each sub-band. The grouping of EEG signals was performed dependent on bagging technique. In this technique a Neural Network Ensemble (NNE) Algorithm was created for the Classification of EEG flag which uses the idea of changing the N-class arrangement into N autonomous 2-class order. Classification accuracy of about 98.78% was accomplished. Jasmin Kevric [5] implemented two component extraction techniques in particular Discrete Wavelet Transform and Wavelet Packet Decomposition for the disintegration of EEG motions in Brain Computer Interface. Both these techniques create a few sub-band signals from which six diverse statistical highlights, including higher request measurements were extracted. An inspecting rate of 100 Hz was considered by uting Symlet 4 Wavelet. The mix of Multiscale Principal Component Analysis (MSPA) was executed for noise removal. Classification of BCI signals was executed using K

nearest neighbor (K-NN) calculation and a normal characterization precision of 92.8% was accomplished.
Gilsang Yoo et.al [6] built up a framework that can perceive human passionate state from biosignal. The proposed strategy can have six emotion enthusiastic states, for example, delight, joy, dread, outrage, hopelessness and misery. The outcome demonstrates that the proposed technique can recognize one feeling contrasted with all other possible enthusiastic states. The technique is made out of two stages, Multimodal Bio-flag Evaluation and Emotion acknowledgment using Artificial Neural Network. To perceive the feeling design, the Back propagation neural system is proposed. The system contains 11 input layer hubs and 3 yield layer hubs. The yield layer hub is as two parallel yields for every one of the three feelings that should be recognized. After the example acknowledgment is finished, every feeling is arranged into happiness, bitterness, and despondency in a substantial scale and in 3-branch design. At last, the precision of Back Propagation is 85.9%, and the orders of every feeling were as per the following: bliss (86%), joy (91%), dread (79%), outrage (87%), lose hope (76%), and bitterness (94%).The examination results can help feeling acknowledgment concentrates to enhance acknowledgment rates for different feelings of the client notwithstanding fundamental feelings.

Gyanendra [7] has played out the feature extraction of EEG signals using Daubechies Wavelet by thinking about 32 channels. The physiological signs were recorded at 512 Hz testing rate and down examined to 256 Hz, for a 5 level disintegration to acquire the point by point and rough co-efficients with an inspecting rate of 512 Hz to catch the data from signs as it gives great outcomes to nonstationary. The tests were performed to order unique feelings from four classifiers to be specific, Support Vector Machine (SVM), Multilayer Perceptron (MLP), K-Nearest Neighbor (K-NN) and Meta Multiclass (MMC).The normal exactnesses are 81.45%,74.37%,57.74% and 75.94% for SVM, MLP, KNN and MMC classifiers separately. A precision of 85.46% was accomplished for melancholy utilizing SVM.

Suwicha Jirayucharoensak et.al [8] executed a framework by gathering 32 subjects of EEG signals. The EEG signals were down tested from 512 Hz to 128Hz.The power spectral highlights of EEG motions on these channels were removed .The feeling acknowledgment was performed by using a profound Learning Network with 100 hidden hubs in each layer and it was diminished to 50 hidden hubs for researching the impact of concealed hub estimate in the DLN. The Principal Component Analysis (PCA) separated the 50 most essential segments. The extricated highlights were encouraged as into the DLN with 50 shrouded hubs in each layer. The motivation behind PCA is to lessen measurement of info highlights. The order exactness of the DLN with PCA and CSA is 53.42% and 52.05% to group three dimensions of valence states and three dimensions of excitement states.

Amjed S. Al-Fahoum[9] has depicted a scientific strategy for extracting highlights from EEG signals. Five distinctive EEG signals Extraction techniques are embraced condensing their qualities and weakness. The fundamental strategies for recurrence space and time-recurrence area techniques for straight examination of one-dimensional signs for EEG signal highlight extraction are looked at and the general favourable circumstances and disadvantages of these modalities are talked about. Noppadon Jatupaiboon et.al [10] considered a remote EMOTIV Headset for accumulation of EEG signals, which comprises of 14 channels. The inspecting rate is set at 128 Hz. The EEG signals were deteriorated by actualizing Discrete Wavelet Transform. This paper portrays a constant EEG signal to group upbeat and despondent feelings by giving an outside upgrade as pictures and established music. Distinctive frequencies were investigated, in that Gamma and Beta band gave a superior outcome than low recurrence groups. By using SVM as a classifier, power spectral density was examined as a component and a normal precision of 75.12% and 65.12 % was accomplished.

Umut Orhan et.al [11] proposed a Multilayer Perceptron neural system based characterization display for epilepsy treatment. The EEG information of around 100 single channel EEG signals were viewed as which was deteriorated into sub-groups by using Daubechies wavelet (db2).The decay was performed for 11 levels. The wavelet coefficients were grouped using the K-means calculation for every recurrence sub-band. Wavelet coefficients acquired from EEG portions with 4097 examples were bunched by K-implies calculation. In this work, the MLPP Model is supported by the Levenberg– Marquardt (LM) calculation by considering a single hidden layer of 5 hidden neurons resulting characterization of the EEG portions. Five distinct investigations were implemented by the MLPNN demonstrate. An all out Classification precision of 95.60% was accomplished for solid portions, seizure free sections and epileptic seizure fragments using the test information. In our Research, distinctive grouping calculations have been executed, to characterize three diverse enthusiastic states, in this paper one Classification of EEG signals is proposed using artificial neural system. In this work, usage of Feed forward Back-Propagation Algorithm is performed.

II. BACKGROUND THEORY

2.1 Discrete Wavelet Transform (DWT):

Discrete wavelet transform is performed by continued separating of the info signals using two channels. The channels are a low pass channel (LPF) and a high pass channel (HPF) to disintegrate the signals into various scales. The yield co-effective picked up by the low pass channel is the guess co-productive. The scaling capacity yield is as:

$$\Phi(t) = 2\sum_{Q=0}^{M} \square(\quad (1)$$

The output of the high pass filter is the detailed co-efficient.

The wavelet function output is the in the form of:

$$w(t) = 2\sum_{q=0}^{M} g(q)\Phi(\quad (2)$$

The estimate co-effective is consequently isolated into new guess and point by point co-efficients. By picking the mother wavelet the co-proficient of such channel banks are determined. This decomposition procedure is rehashed until the required recurrence reaction is accomplished from the given information signals. The choice of a fitting wavelet work has been a test in this exploration. Among various wavelets, Daubechies wavelet has been picked as they have a maximal number of evaporating minutes and consequently they can speak to higher degree polynomial capacities. With every wavelet kind of this class, there is a scaling capacity known as "father wavelet" that produces a symmetrical multi-goals examination. Every wavelet has evaporating minutes equivalent to a large portion of the quantity of coefficients. For instance, D2 which is the Haar wavelet makes them evaporate minute, D4 has two, and so forth. The quantity of evaporating minutes is the thing that chooses the wavelet's capacity to speak to a flag. For instance, D2, with one minute, effectively encodes polynomials of one coefficient or consistent flag parts. D4 encodes polynomials with two coefficients, for example consistent and straight signal parts etc. Every goals scale is twofold that of the past scale. Daubechies group of wavelets has been picked due to their high number of evaporating minutes making them equipped for speaking to complex high degree polynomials. Along these lines Daubechies 4 wavelet gives a good signal result.

2.2 Daubechies 4 Wavelet

The Daubechies wavelet changes are characterized similarly as the Haar wavelet change by processing running midpoints and contrasts by means of scalar items with scaling signs and wavelets the main distinction between them comprises in how these scaling signs and wavelets are characterized. For the Daubechies wavelet changes, the scaling signs and wavelets have marginally longer backings, i.e., they produce midpoints and contrasts utilizing only a couple of more qualities from the signal.

The Daubechies D4 change has four wavelet and scaling capacity coefficients. The scaling capacity coefficients are:

$$\{ h_0 = \quad ; h_1 = \quad ; h_2 = \quad ; h_3 = \quad \} \quad (3)$$

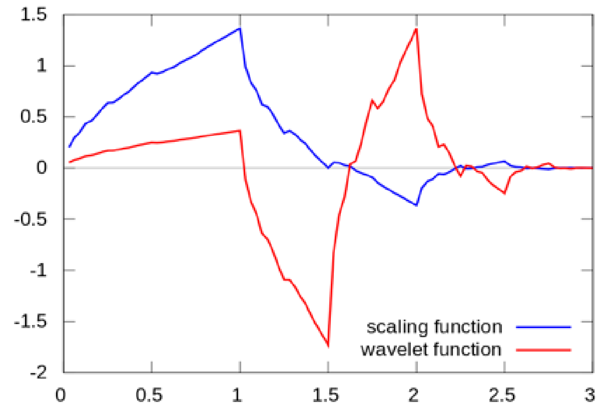

Fig.1 Daubechies Wavelet representing scaling and wavelet function

Each progression of the wavelet change applies the scaling capacity to the information input , if the first informational index has N esteems and the scaling capacity will be connected in the wavelet change venture to ascertain N2 smoothed qualities in the arranged wavelet change and the smoothed qualities are put away in the lower half of the N component input vector.

The wavelet function co-efficient values are:

$$\{g_0 = h_3 ; g_1 = -h_2 ; g_2 = h_1 ; g_3 = -h_0 \} \quad (4)$$

The wavelet change applies the wavelet capacity to the info information if the first informational collection has N esteems. The first informational index has N esteems and the wavelet capacity will be connected to figure N/2 contrasts. The scaling and wavelet capacities are determined by taking the inward result of the coefficients and four information esteems. The conditions are appeared:

Daubechies D4 scaling function:

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3} \quad (5)$$

$$a[i] = h_0 s[2i] + h_1 s[2i+1] + h_2 s[2i+2] + h_3 s[2i+3]; \quad (6)$$

Daubechies D4 Wavelet function:

ci = g0s2i + g1s2i+1 + g2s2i+2 + g3s2i+ 3 (7)

c[i] = g0s[2i] + g1s[2i+1] +g2s[2i+2] + g3s[2i+ 3]; (8)

Every cycle in the wavelet change step ascertains scaling capacity esteem and wavelet work esteem.

2.3 Filter Co-efficients

The channel coefficients for h and g which speaks to the low pass channel and high-pass channel, where n signifies the length of the channel. The wavelet coefficients are determined by turning around the request of the scaling capacity coefficients and afterward switching the indication of consistently one. The Filter coefficients for D4 wavelet is. {-0.1830127, - 0.3169873, 1.1830127, - 0.6830127}). Mathematically it is represented to by the condition:

$$b_k = (-1)^k a_{N-1-k} \qquad (9)$$

where k is the co-efficient index "b" is a coefficient of the wavelet sequence and "a" is the coefficient of the scaling sequence.

2.4 NEURAL NETWORK

A neural system comprises of formal neurons which are associated so that every neuron yield further fills in as the contribution of for the most part more neurons also as the axon terminals of a natural neuron are associated through synaptic ties with dendrites of different neurons. The quantity of neurons and how they are interconnected decides the engineering (topology) of neural system. The info and yield neurons speak to the receptors and effectors, separately, and the associated working neurons make the relating channels between them to proliferate the individual signs. These direct are called ways in the numerical model. The signal engendering and data preparing along a system way is acknowledged by changing the conditions of neurons on this way. The conditions of all neurons in the system structure the condition of the neural system and the synaptic loads related with all associations speak to the arrangement of the neural system.

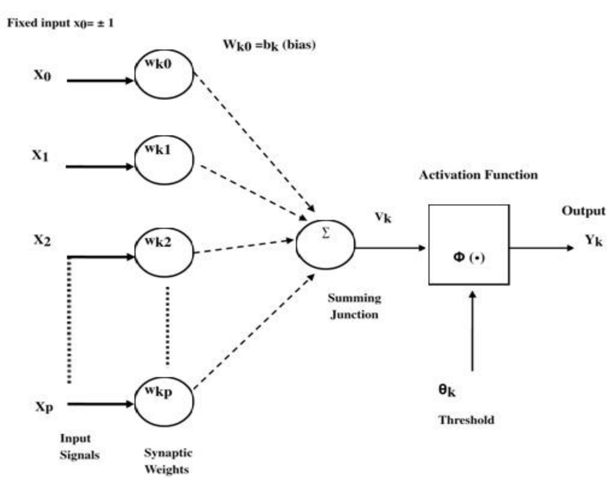

Fig.2. Mathematical Model of Neural Network

An Artificial Neural Network (ANN) is a data handling worldview that is motivated by the way organic sensory systems, for example, the biological system process data. The key component of this worldview is the novel structure of the data preparing framework. An ANN is arranged for a particular application, for example, design acknowledgment or information grouping, through a learning procedure. Learning in organic frameworks includes changes in accordance with the synaptic associations that exist between the neurons.

From the scientific model a artificial neuron has three essential parts are. The neurotransmitters of the natural neuron are displayed as a load which interconnects the neural system and offers solidarity to the association. All sources of information are summed together and are adjusted by the loads. This action is alluded as a straight mix. An actuation work controls the plentifulness of the yield. From this model the internal movement of the neuron is represented to as:

$$V_k = \qquad (10)$$

The output of the neuron, y_k will be the outcome of the activation function on the value of v_k.

III. PROPOSED WORK

The proposed work portrays the crude EEG which is obtained by utilizing 10-20 cathode position frameworks. In spite of the fact that there are different securing framework, the procurement is finished utilizing 10-20 terminal situation framework and it is discovered that 10-20 framework is the best for the information obtaining as for the information consistency. Since it is a standard framework for estimating the electrical movement of a mind concerning all the standard positions on the scalp in this way it is considered as most appropriate technique for EEG obtaining.

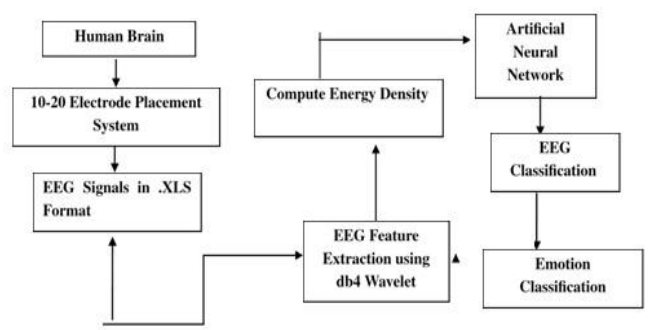

Fig.3 Block diagram of Emotion recognition system

The obtained EEG signal which is in the organization of .xls is stacked to the MATLAB workspace and changed over to .csv design for further handling. The organized EEG dataset is broke down by utilizing Daubechies wavelet change to separate all the principal recurrence segments of EEG flag for example alpha, beta, gamma, delta and theta. EEG recurrence groups which identifies with different cerebrum states. The removed EEG groups are additionally decayed. After further disintegration, conspicuous highlights like Energy and Power Spectral Density are registered. The highlights separated are encouraged as contribution for Classification utilizing Artificial Neural Networks. The proposed Block outline is appeared in Fig.3

IV. IMPLEMENTATION

Feature Extraction is the way toward recognizing a specific data structure EEG which is been estimated by the neuronal movement from the mind. Features are attributes of a signal that can separate feelings The primary undertaking of feature extraction is to infer the remarkable highlights which can map to EEG information into subsequent emotion states. As the EEG signal is non stationary the most reasonable route for feature extraction from the raw information is the utilization of the time-recurrence space strategies like discrete wavelet change (DWT) which is a spectral estimation procedure in which any broad capacity can be communicated as a limitless arrangement of wavelets. Subsequent to getting the noise free signals from the signal improvement stage. The wavelet decomposition of any flag x(t) is spoken to as far as its decomposition coefficients given by the condition:

$$X(t)= \qquad \varphi_k(t) + \qquad \sum_{j=0}^{\infty} \quad {}_{j,k}(t) \qquad (10)$$

In this work, "db4" (Daubechies wavelet) is picked for deterioration , db4 wavelet is known for its symmetry property and its smoothing highlights and it is helpful for recognizing the adjustments in EEG signals.

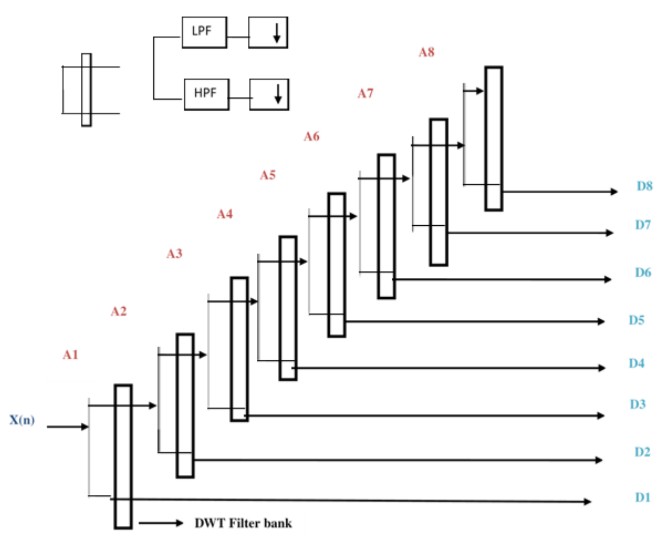

Fig.4. Decomposition of input signal into its detailed and approximation Co-efficient for 8 levels

The Multi resolution decomposition of the raw EEG information x(n) is disintegrated with an inspecting recurrence of 500Hz is appeared in Fig.4, each stage yield gives a point by point co-effective and an estimate co-proficient. Discrete wavelet change is performed utilizing continued separating of the info signal using two channels. The channels are low pass channel and high pass channel which is deteriorated into various scales. The low pass channel is the guess coefficient. The estimation coefficient is separated into new guess and definite coefficients. The disintegration levels are decayed as A1, A2, A3, A4, A5, A6, A7 and A8 as the estimated coefficients and D1, D2, D3, D4, D5, D6, D7 and D8 as the definite co-effective acquired after progressive deterioration. The multi-goals examination is deteriorated using "db4" for eight dimensions of disintegration, which yields five separate EEG sub-groups. The primary goal of the proposed strategy is the division of the first EEG signals into various recurrence groups. Table I, demonstrates the deteriorated EEG groups lying at their frequencies after decomposition.

Table I: Decomposition of EEG Signals with the Sampling Frequency of 500 Hz

Decomposition Levels	EEG Bands	Frequency Range (Hz)
D5	Gamma	37-56 Hz
D6	Beta	11-37 Hz
D7	Alpha	6-11 Hz
D8	Theta	4-6 Hz
A8	Delta	0-4 Hz

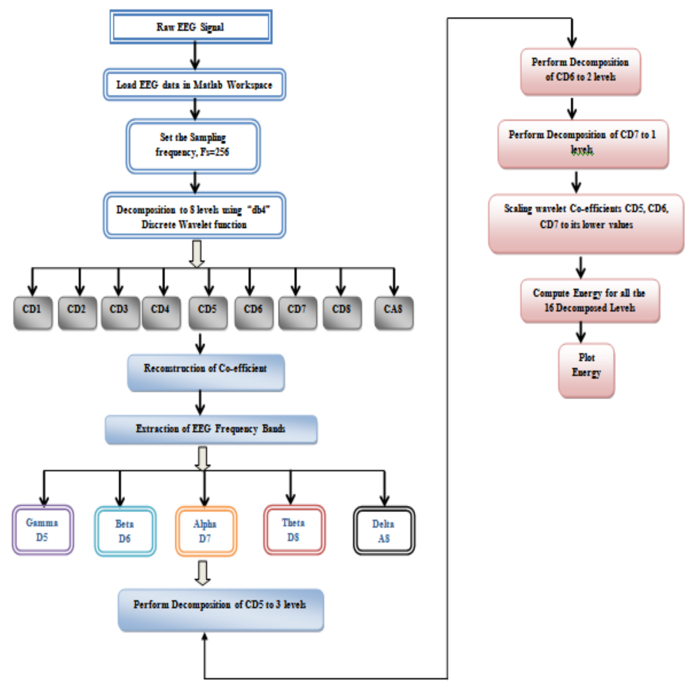

Fig.5 Flow chart of feature Extraction

4.2 Classification using Artificial Neural Networks

A multilayer perceptron (MLP) is a class of feedforward artificial neural system. A MLP comprises of somewhere around three layers of hubs. Aside from the information hubs, every hub is a neuron that uses a nonlinear actuation work. MLP uses a managed learning system got back propagation for preparing. Its various layers and non-straight initiation recognize MLP from a direct perceptron. This class of systems comprises of different layers of computational units, typically interconnected in a feed-forward manner. Every neuron in one layer has guided associations with the neurons of the hidden layer. In numerous applications the units of these systems apply a sigmoid capacity as an enactment work. The widespread estimation hypothesis for neural systems expresses that each ceaseless capacity that maps interims of genuine numbers to some yield interim of genuine numbers can be approximated self-assertively intently by a multi-layer perceptron with only one concealed layer. This outcome holds for a wide scope of enactment capacities, for example for the sigmoidal functions.

Multi-layer systems utilize an assortment of learning procedures, the most well known being back-engendering. Here, the yield esteems are contrasted with the right answer with register the estimation of some predefined mistake work. By different methods, the mistake is then nourished back through the system. Utilizing this data, the calculation changes the loads of every association so as to decrease the estimation of the mistake work just barely. In the wake of rehashing this procedure for an adequately extensive number of preparing cycles, the system will as a rule join to some state where the mistake of the counts is little. For this situation, one would state that the system has taken in a specific target work. To alter loads appropriately, one applies a general strategy for non-straight optimization that is called gradient descent.

4.3 Feed Forward Back Propagation Training

Back-Propagation neural system shapes a mapping among sources of info and wanted yields from the preparation set by adjusting the weighted associations inside the network. FFNNs are fitting for taking care of issues that include learning the connections between a lot of information sources and known outputs. They are a regulated learning strategy as in they require a lot of preparing information so as to get familiar with the connections. The neural system must be prepared on information arrangement of information, yield sets are separated from information arrangement, where info and yield are vectors rise to in size to the quantity of system data sources and yields, individually. Characterization of feelings is performed utilizing feed forward back engendering preparing calculation actualized utilizing neural system Toolbox. Back spread preparing calculation is utilized for preparing two subjects to be specific typical and unusual subjects.

4.3.1 Multi-Layer Feedforward Neural Networks using matlab NN Toolbox

With Matlab tool kit you can configure, train, envision, and recreate neural systems. The Neural Network Toolbox is intended to permit numerous sorts of systems. Neural system configuration stream is clarified in the accompanying flowchart, which speaks to the total technique of NN structure. The main conclusions of the study may be presented in a short Conclusion Section. In this section, the author(s) should also briefly discuss the limitations of the research and Future Scope for improvement.

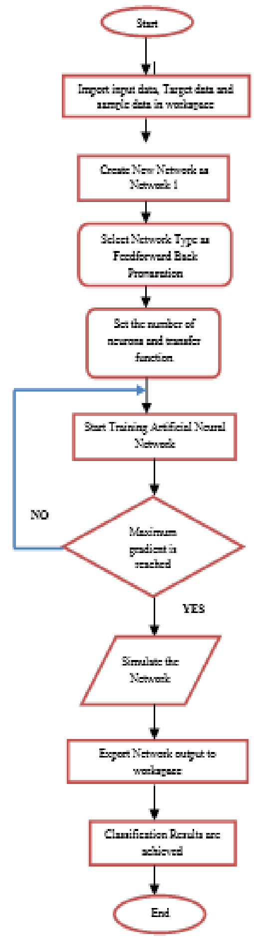

Fig. 6 Flowchart of Neural Network Design

V. RESULTS AND DISCUSSION

Vitality Graph of six unique anodes is appeared in Fig. 7, which speaks to the differing Energy estimations of all the five EEG groups taken from an ordinary subject. From the investigation, P4-O2 is having a higher Energy Density, contrasted with other Electrodes.P4-O2 is a district which lies the Parietal and Occipital flaps of the mind. The feelings relating to these projections produce signals which are in a casual perspective and are dynamic in the frontal areas of the cerebrum.

The correlation of Energy esteems is spoken to in Fig.7, which demonstrates the decay dimensions of six anodes. Fig. 8 represents the fluctuating Energy estimations of Abnormal subject. From the Energy chart , F3-C3, demonstrates a more noteworthy vitality thickness esteem contrasted with other electrodes.F3-C3 is a district which lies in the Frontal and

Central parts of the cerebrum flaps .The frontal projection is situated at the front of each cerebral half of the globe and situated before the parietal flap or more and before the fleeting flap. It is isolated from the parietal flap by a space between tissues called the focal sulks. The feelings relating to frontal flap experience frontal projection injury where a fitting reaction to a circumstance is shown yet shows an unseemly reaction to those equivalent circumstances, "in actuality", they experience ridiculous presentations of feeling. The vitality thickness of these two subjects is determined and nourished to the NN tool compartment for order to investigate its execution. The execution of neural system is broke down by considering the info esteems and the objective qualities which are set. In this work, a topology of 16-10-16 is considered as the system topology.

The execution chart, relapse plot is accomplished, which gives an ideal answer for better order exactness as far as proficiency. The feed forward back proliferation preparing system models have been coded into a MATLAB program utilizing neural system tool kit. The MATLAB programming empowers preparing with various intermingling criteria, resistance level, initiation capacities and number of ages. The neural system models considered in this examination utilizes exchange work = 'TANSIG' as actuation work. After this the system demonstrates is prepared for expectation of wanted yield. The plots specifically plot Performance, Plot Regression are appeared in Fig.9.The Plot Performance demonstrates the best approval execution with 16 ages. The plot train state demonstrates the framework state in the wake of preparing dependent on the Plot relapse which demonstrates the plot between and preparing tests, between yield information and approval tests and between yield information and test tests (R esteem demonstrates the connection amongst yield and target esteems).

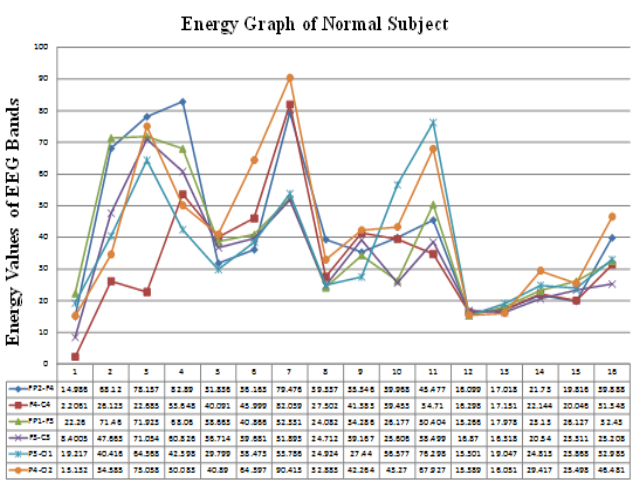

Fig. 7 Energy plot of normal subject considering six electrode

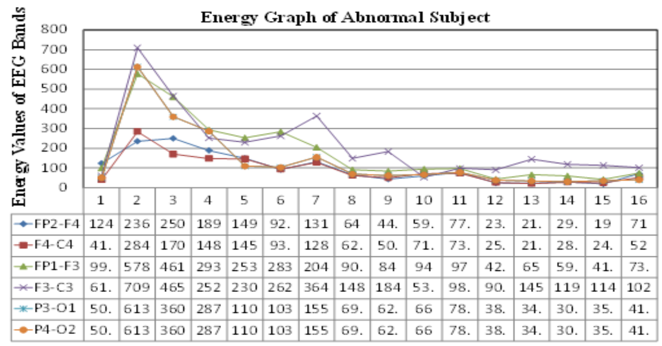

Fig. 8 Energy plot of abnormal subject considering six electrode

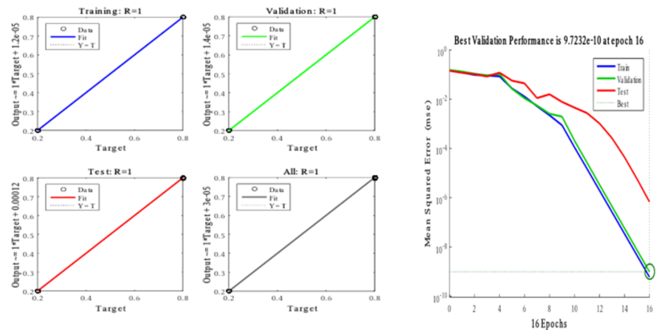

Fig. 9 Snapshots of best validation performance and training states

In the Neural system preparing stage, input information and test information are bolstered to the neural system Classifier, where the objectives are set as 0.2 for typical and 0.8 for anomalous subjects. A system topology of 16-10-16 is viewed as the execution chart; relapse plot is accomplished, which gives an ideal answer for better characterization exactness as far as effectiveness. Table II speaks to the execution esteem, the number blunders and the quantity of ages for two unique systems. The arrangement exactness for each kind of system is accomplished which can be contrasted and each other. System 1 gives an ideal precision of 88% contrasted with Network Type 2, which is shown in the below Table.

Table II Training and Simulated output results

Network Type	Performance	Epochs	Gradient	Mu	Errors	Classification Accuracy (%)	
						Normal Subject	Normal Subject
Network1	0.00044	16	0.00096	$8.3*10^{-7}$	4	100%	88%
Network2	0.00069	31	$7.4*10^{-8}$	$1.12*10^{-7}$	5	100%	86%

VI. CONCLUSION

The novel technique is proposed in this paper characteristics the performance of ANN Classification. This strategy is implemented by picking a superior wavelet for feature extraction. The implementation of categorization is performed by accomplishing an ideal accuracy of 88% for system 1 for unusual subject and system 2 accomplishes a precision of 86% . Later on increasingly number of emotions states can be actualized with various classification algorithms.

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