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EEG Signal Classification Using Feature Level Fusion

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***Abstract* - Human brain is a diverse creature, and unveils rich spatiotemporal dynamics. Among the noninvasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. Electroencephalogram is a signal produced in the human brain when there is an information flow among several neurons. Human brain contains millions of neurons which are responsible for information flow. We have classified the publically available dataset for testing between normal and epileptic persons. We have achieved accuracy of 99.88% which is highest accuracy on this dataset.**

Index Terms— EEG, SVM, Classifier, post processing.

I.INTRODUCTION

Human brain is a diverse creature, and unveils rich spatiotemporal dynamics. There are many noninvasive methods for investigating human brain dynamics. Electroencephalography (EEG) offers a through quantitative analysis of cortical movement with millisecond temporal resolution. In classical research, EEG analysis was limited to visual waveform examination of EEG values. As the certain specific parameters were undefined by experts of medical field, visual examination of EEG signals seems to be insufficient. For central alpha activity, corresponding delta waveforms and theta waveforms were not examined. Monotonous clinical scrutiny needs to analyze the EEG signals. Involuntary EEG handling, demonstrations with Fourier transform are normally efficient. Previous intrinsic observations prove that the EEG spectrum encompasses four frequency bands—delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz). These esteemed techniques are anticipated for numerous EEG descriptions, however Fast Fourier transform (FFT), undergoes great noise sensitivity. Investigational Parametric chi square power spectrum estimation methods such as AR, decreases the obvious spectral loss difficulties and produces higher frequency domain resolution. Parametric AR method has a benefit above FFT that, it requires squatter period information records as compared to FFT. An influential technique was recommended in 1980s to accomplish time-scale examination of signals: the discrete wavelet transforms (DWT). As DWT is appropriate for examination of non-stationary random signals and this exemplifies DWT a leading improvement over spectral investigation, it is best matched for discovering transient events, which may take place through epileptic seizures. Wavelet transform's feature extraction and representation properties are used to examine numerous transient events in biotic signals. This is summary of the discrete wavelet transform established for identifying, locating and measuring spikes, sharp waves and spike-waves. They have employed wavelet transform to investigate and illustrate epileptic-form expulsions in the form of 3-Hz spike as well as complex wave among patients with absence of seizure activity. With the help of wavelet decomposition of the EEG records, transient features are precisely apprehended and restricted in both time and frequency context. The competence of this mathematical formulation to analyze the signal at diverse scales of neural rhythms results as an influential contrivance for examining small-scale fluctuations in the brain signals. An improved exploration of the dynamics of the human brain with EEG examination can be attained with auxiliary analysis of such EEG waveforms.

Electroencephalogram is a waveform produced in human brain because of information flow between numerous neurons. Human brain comprises of masses of neurons that stand accountable for signal flow. As a result of this flow of data, a human body performances consequently. A neuron hits a new neuron and this iteration endures for numerous neurons, as a result a minor quantity of electric discharge is produced. Resultant electrical waveform is moderately minor in quantity and therefore it's problematic to measure the frequency. Thus, there are numerous electrodes positioned on the scalp. The electrode read electric flow and frequency is recorded by a machine. Recorded waveforms are very non-stationary in nature, since the frequency of waveforms vicissitudes swiftly with respect to time. Hence, the waveform examination must

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be done carefully to analyze it meticulously. At first, these signals should be logged before analyzing. There are predefined international criterions for placement of electrodes on human scalp EEG waveform logging. The electrodes are located on diverse scalp regions, namely frontal, Occipital, Parietal, and Temporal. With positioned electrodes, the EEG waveforms are logged and administered in a device. In general, these devices plot a graph of the logged waveform, which is subsequently examined by a medical professional. Furthermore, the analysis of logged waveforms is moderately essential for few major applications in medicine. Typically, FFT is preferred for continuous signals which are not appropriate for investigation of EEG signal which is discrete in nature. DWT is most competent approach for investigation of these types of waveforms. It is a waveform decomposition procedure that deploys two types of filters, low and high pass filter to distribute the waveform coefficients into low and high frequency bands. Subsequently after this wavelet decomposition, numerous features are extracted for every waveform. Resultant feature set is utilized for further processing. Upon investigating these waveforms, one can determine effective and hypothetically expedient data related to the human brain. This results in classifying diverse kinds of human brain functional disorder diseases. One of those diseases is acknowledged as Epilepsy. This disorder in human brain activity occurs due to irregular EEG signal flow. The duration of this disorder attack is known as epileptic seizure. This seizure happens for a small duration for which a very high fluctuation of EEG is generated.

The graphic examination is difficult; therefore abundant studies have been carried out for growth of semi-automatic seizure recognition techniques. Henceforth, most significant aspect of ongoing research is the classification of EEG signal. It is a procedure of allocating an unlabeled matrix into an explicit pre-defined class upon building a model using the training patterns and afterwards authenticating with a test set. In machine learning, there are either binary or multi-class problems. For this experimentation, we classify the EEG waveforms into two unique classes that are either epileptic or normal patient. Consequently, it's a two class binary problem. Supervised classification in machine learning is just like a small kid learning different activities by observing the actions taking place near him. The diverse machine learning techniques popularly utilized for classification are Artificial Neural Network, Support Vector Machine, Radial Basis Function Neural Network, etc. All of these techniques have their own applications in various areas and have own limitations.

II. LITERATURE SURVEY

Ma et al. [1] proposed a method that employs the particle swarm optimization algorithm to optimize the choice of together the kernel and penalty parameters so as to advance the classification quality of support vector machines. The throughput of the rigid optimized classifier was evaluated with motor imagery EEG waveforms for prediction. Obtained results validate that the optimized machine learning classifier effectively progress the absolute classification intrinsic accuracy of motor imagery EEG signals.

Subasi [2] stated that Mixture of experts (ME) is modular neural network architecture for supervised learning. The discovery of epileptic-form exonerations in the EEG is an imperative constituent in the finding of epilepsy disease. These sub-band frequencies were utilized as an contribution to a ME network with two discrete outcomes: normal and epileptic. For increasing overall accurateness, the outcomes of expert networks were joined as per collection of indigenous weights called the "gating function". The invariant revolutions of the ME probability density mappings comprise of the permutations of the expert labels and the transformations of the factors in the gating functions. The results established that the proposed ME network structure has certain value in noticing epileptic seizures. The ME network structure attained accuracy rates which were greater than that of the stand-alone neural network model.

Wang et al. [3] proposed a system that consists of following three stages: (i) unusual EEG signals exemplification by wavelet packet coefficients and feature extraction using the finest basis-based wavelet packet entropy technique, (ii) cross-validation process poised with k-N Neighbor classifier for internal training stage to hierarchical knowledge base (HKB) building, and (iii) in the testing stage, calculating classification accuracy and rejection rate using the top-ranked discriminative rubrics from the HKB. The data collection consists of a publicly available EEG database which intentions at differentiating healthy subjects and subjects suffering from epilepsy diseases. Investigational outcomes display the efficiency of their proposed system.

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Guo et al. [4] applied genetic programming (GP) to achieve automatic feature extraction from unique feature database with for improving the biased performance of a classifier and plummet the input feature dimensionality simultaneously. The branch structure of GP obviously characterizes the features, and a new function produced by this experimentation mechanically decides the quantity of the features extracted.

Jahankhani et al. [5] described the solicitation of neural network models for classification of electroencephalogram (EEG) waveforms. The enactment of the neural model was assessed for training performance and classification precisions and the results established that the proposed scheme has large potential in classifying the EEG signals.

Amin et al. [6] described an intrinsic discrete wavelet transform based temporal feature extraction for the EEG signal classification. Discrete wavelet transform is rational choice on EEG waveforms and the relative wavelet energy is measured in associations of detailed coefficients and the residue approximation coefficients of the last breakdown. (1) EEG signals were logged throughout the complex cognitive task—Raven's advance progressive metric test and (2) the EEG signals chronicled in eyes open situation. The accuracy was accomplished above 98 % by the support vector machine, multi-layer perceptron and the K-nearest neighbor classifiers with approximation (A4) and detailed coefficients (D4), which represent the frequency range of 0.53–3.06 and 3.06–6.12 Hz, respectively.

III. SYSTEM DESIGN AND OVERVIEW

A. Discrete Wavelet Transform (DWT)

Wavelet transform is a spectral estimation method that comes with a capacity that any general function can be expressed as an infinite series of wavelets. The straightforward notion for wavelet exploration contains articulating a waveform in linear amalgamation of a specific set of mappings, acquired with shifting and dilating singular function called a mother wavelet. This signifies that most of the energy of the wavelet is restricted to a finite time interval. When compared to STFT, the advantage of time-frequency localization is that wavelet analysis diverge the time-frequency aspect ratio, generating good frequency localization at low frequencies. The discrete wavelet transform (DWT) is a flexible signal processing tool that has many engineering and scientific applications. Each stage of this algorithm contains two digital filters and two down samplers by the factor of 2. The levels are singular that correlate well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients.

For a discrete sequence $x[n]$ defined for $n = 0,1,2,\ldots$ the final coefficients in the wavelet series expansion are called as Discrete Wavelet Transform of $x[n]$. The wavelet series coefficients are indicated in equations (1) and (2).

$$W_{\varphi}(J,k) = \frac{1}{\sqrt{M}} \sum_{n} x[n] \varphi_{J,k}[n] \quad (1)$$

$$W_{\psi}(j,k) = \frac{1}{\sqrt{M}} \sum_{n} x[n] \psi_{j,k}[n] \quad (2)$$

Here, $j > J$ and $x[n], \psi, \varphi$ are functions with discrete variables $n = 0,1,\ldots,M-1$.

An illustrative decomposition using DWT is shown in Fig.1.

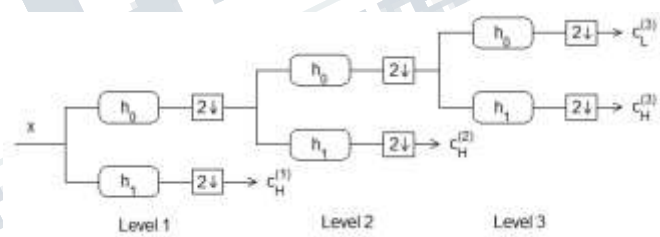

Fig.1. DWT decomposition

Stationary wavelet transforms (SWT)

The Stationary wavelet transform (SWT) is alike DWT excluding fact that the waveform is never sub-sampled and filters are up sampled at every step of decomposition. Each step's filters are up-sampled versions of the previous as shown in Fig.2.

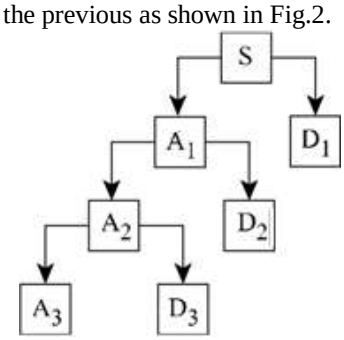

Fig.2. SWT decomposition

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The SWT is a key distinctive redundant data scheme, as each collection of EEG coefficients covers the equivalent numeral of samples as the input. Therefore for a forward decomposition at N levels, there is a data redundancy of 2N. A signal, f, is mapped upon dyadic-spaced set of scales or levels using a set of level dependent quadrature mirror decomposition filters, that have respective band-pass and low-pass characteristics specific to every wavelet mother basis. The comprehensive scale, or approximation, coefficients are convolved distinctly with low pass and high pass filters. This process ruptures the frequency data coarsely in half, partitioning it into a set of fine scale, or detail coefficients and a coarser set of approximation coefficients. For the following step of decomposition, a zero is added among each successive value found in the filters to achieve the next value of filtered data.

Principal Component Analysis

Principal component analysis (PCA) is a customary contrivance in contemporary data analysis - in miscellaneous fields from neuroscience to computer graphics. With token application PCA provides a roadmap for signal specific dimensionality reduction. The theory of principal component analysis is based on the notion that the signal $x[n]$ is zero average random process that is been deduced by the correlation $R_x = E[x \cdot x']$. After applying orthonormal linear mapping $\Psi = [\Psi_1, \Psi_2, \ldots, \Psi_N]$ to original signal $x[n]$.

$$P = \Psi' \cdot x \quad (3)$$

Here, $P = [P_1, P_2, \ldots, P_N]'$ is a principal component vector. The equation (3) ensures that all components of vector P are mutually uncorrelated.

$$E[\Psi_1' x x' \Psi_1] = \Psi_1' R_x \Psi_1 \quad (4)$$

Equation (4) signifies that Ψ_1 and maximum variance are interrelated.

IV. PROPOSED SYSTEM

The input signals which are essentially EEG waveforms are very transient and non-stationary in nature. The proposed system is depicted in Fig.3. Some samples from set A (Normal) and set E (epileptic) are shown in Fig.4 and Fig.5. The input EEG waveform is low pas filtered and subjected to 4 level DWT and SWT decomposition using coiflets. PCA Eigen components are also added to the fused feature vector. The feature vector is submitted to classifier for training. During testing the same process is repeated to compute feature vector.

We have used standard EEG dataset which is publically available [7]. We perform the classification between normal and epileptic person. The EEG waveform is containing 4096 values. EEG is subdivided into windows of 256 length for training the SVM classifier.

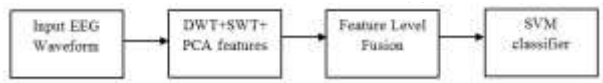

Fig.3. Proposed System

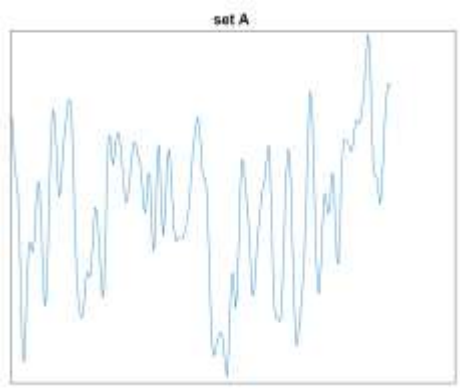

Fig.4. EEG logged waveform from Set A

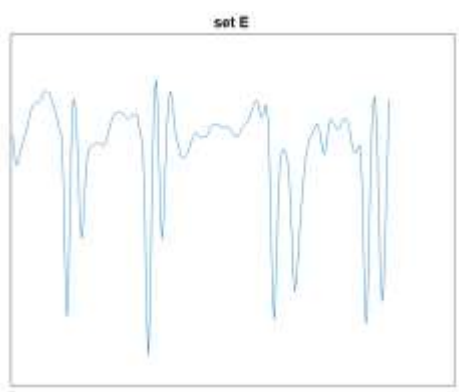

Fig.5. EEG logged waveform from Set E

The training to testing dataset ratio is 50%. The results indicating importance of fusion are summarized in table 1 and depicted in Fig.6. The formulas for calculating

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performance parameters are indicated in equation (5), (6) and (7).

Table 1: Fusion effect on recognition classification rate

Sr.No.	Case	Accuracy	Sensitivity	Specificity
1	DWT	99.50	99.50	99.50
2	SWT	99.69	99.62	99.62
3	DWT+SWT	99.81	99.62	99.62
4	DWT+Skew+SWT	99.81	99.62	99.62
5	DWT+Skew+SWT+PCA	99.88	99.75	99.75

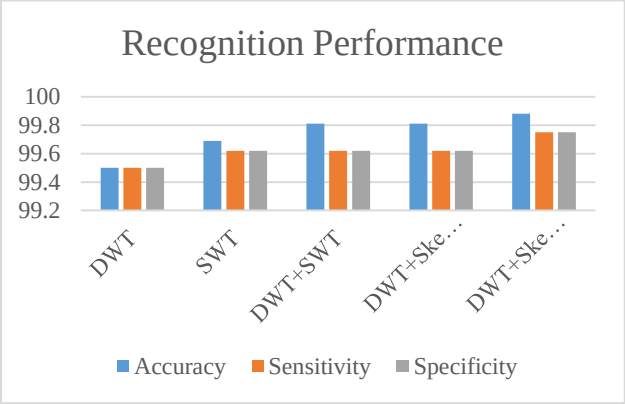

Fig.6. Effect of fusion on recognition performance

Benchmarking with other approaches is shown in table 2 and illustrated in Fig.7. It indicates that proposed approach gives higher recognition parameters.

Table 2: Benchmarking with other approaches

Sr. No.	Case	Accuracy	Sensitivity	Specificity
1	RBFNN+ABC [8]	72.5	66.4	85.7
2	RBFNN+MABC[8]	73.5	66	88.1
3	Proposed Approach	99.88	99.75	99.75

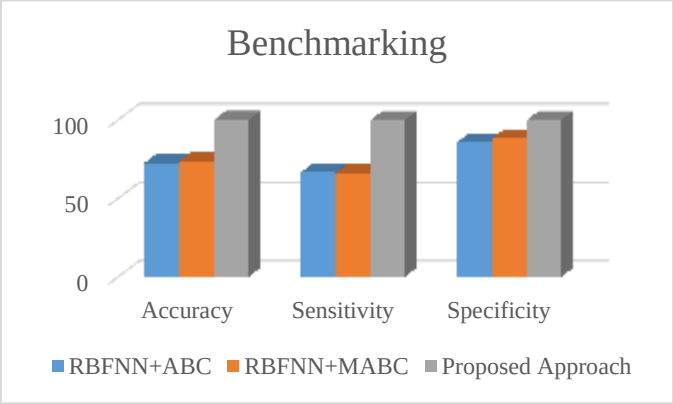

Fig.7. Benchmarking analysis

Therefore, we have achieved accuracy of 99.88%, Sensitivity of 99.75% and specificity of 99.75% using this EEG Classification system.

CONCLUSION

Electroencephalogram is a signal generated in human brain when there is an information flow among several neurons. Human brain contains millions of neurons which are responsible for information flow. We have classified the publically available dataset for testing between normal and epileptic persons. We have achieved accuracy of 99.88% which is one of the highest accuracy on this dataset

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