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Original Article

# Detection of Primary Brain Tumor Present in EEG signal using Wavelet Transform and Neural Network

**Sharanreddy[a], P.K.Kulkarni[b]**

[a]*Ph.D. Scholar, dept. of EEE, P.D.A.College of Engineering, Gulbarga, India- 585103*
[b]*Prof & HOD, dept. of EEE, P.D.A.College of Engineering, Gulbarga, India*

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ABSTRACT

The Brain tumor is life threatening disease of brain. The brain contains about 10 Billion or more working brain cells. Damazied brain cells are diagnosed themselves by dividing to make more cells. Normally, this turnover takes place in an orderly and controlled manner. If, for some reason, the process gets out of control, the cells will continue to divide, developing into a lump, which is called a tumor. Brain tumors are broadly categorized in to two types, primary and secondary brain tumor. The detection of primary brain tumor (Gliomas) is possible by analyzing EEG signals. This paper, proposes a technique to classification EEG signal for detection of primary brain tumor detection, which is combination of multi-wavelet transform and artificial neural network. Irregularity in the EEG signals is measured by using the Approximate Entropy. The proposed technique is implemented, tested and compared with existing method based on performance indices such as sensitivity, specificity, accuracy; results are promising with accuracy (96%).



## 1. Introduction

The brain is an incredibly complex organ. Like a true resident in an Ivory Tower, the brain lives apart from, and quite differently than, the rest of the body. The brain contains about 10 Billion (10,000,000,000) working brain cells. They are called neurons and make over 13 Trillion (13,000,000,000,000) connections with each other to form the most sophisticated organic computer on the planet -- maybe even the universe. By today's computer standards, the brain far exceeds any network of linked state-of-the-art computers. Although cells in different parts of the body may look and work differently, most repair themselves in the same way, by dividing to make more cells. Normally, this turnover takes place in an orderly and controlled manner. If, for some reason, the process gets out of control, the cells will continue to divide, developing into a lump, which is called a tumor.

Clinical neurologists use Computer Tomography (CT) imaging techniques for diagnosis of brain tumors because of it high accuracy in initial diagnosis of the primary pathology. However such scans stand short, when analyzing the physiological functioning of the brain as a whole, both at the time of initial diagnosis or as part of a long term management of the patient. For such purpose, EEG has been used to render a clearer overall view of the brain functioning at initial diagnosis stages. In brain Tumor diagnostics, EEG is most relevant in assessing how the brain responds to treatments (e.g. post operative).

Being a non-invasive low cost procedure, the EEG is an attractive tumor diagnosis method on its own. It is a reliable tool for the glioma tumor series. The EEG in vascular lesions is abnormal form the onset of symptoms where as a CT only become abnormal on the third or fourth day or after week. The EEG is, however less successful in detecting brain stem tumors and meningioma series.

Many researchers are working to develop an automated tool which easily analyses the EEG signal and revel information of existence of primary brain tumor. This paper proposes an automated tool to classification of EEG signal for brain tumor detection.

* Corresponding Author :
Sharanreddy.m@hotmail.com

## 2. Recent Research works: A Review

Numerous research works already exist in the literatures that make use of EEG signal for identification of brain tumor. Important papers are reviewed below, for detailed review refer [15].

Murugesan, M. Sukanesh, R [5] proposed a method for automated system for efficient detection of brain tumors in EEG signals using artificial neural networks (ANNs). The ANN employed in the proposed system is feed forward back propagation neural network. Generally, the EEG signals are bound to contain an assortment of artifacts from both subject and equipment interferences along with essential information regarding abnormalities and brain activity (responses to certain stimuli). Initially, adaptive filtering is applied to remove the artifacts present in the EEG signal. Subsequently, generic features present in the EEG signal are extracted using spectral estimation. Specifically, spectral analysis is achieved by using Fast Fourier Transform that extracts the signal features buried in a wide band of noise. The clean EEG data thus obtained is used as training input to the feed forward back propagation neural network. The trained feed forward back propagation neural network when fed with a test EEG signal, effectively detects the presence of brain tumor in the EEG signal. The experimental results demonstrate the effectiveness of the proposed system in artifacts removal and brain tumor detection.

Seenwasen Chetty, Ganesh K. Venayagamoorthy [7] proposed The ANN based EEG classifier to distinguish between the EEG signal of a normal patient and that of a brain tumor patient. The results show that an artificial neural network is able to distinguish between an abnormal and normal EEG signal, and classify them correctly as brain tumor and healthy patient respectively. This is possible with ANNs since they are able learn the patterns in a normal and abnormal EEG signal. ANN gives a 100% classification success rate with both normal and abnormal EEG.

Fadi N. Karameh, Munther A.Dahleh [8] focused on developing an automated system to identify space occupying lesions on the brain using EEG signals. EEG features are extracted using wavelet transform for different tumor classes and classification by self-organizing maps.

M. Murugesan and Dr. (Mrs.).R. Sukanesh [6] proposed a technique for classification of electroencephalogram (EEG) signals that contain credible cases of brain tumor. The classification technique support vector machine is utilized in the proposed system for detecting brain tumors. The artifacts present in the EEG signal are removed using adaptive filtering. Then the spectral analysis method is applied for extracting generic features embedded in an EEG signal. Precisely, Fast Fourier Transform for spectral analysis is used to separate the signal features which are buried in a wide band of noise. The radial basis function-support vector machine is trained using the clean EEG data obtained. With proper testing and training, they effectively classify the EEG signals with brain tumor.

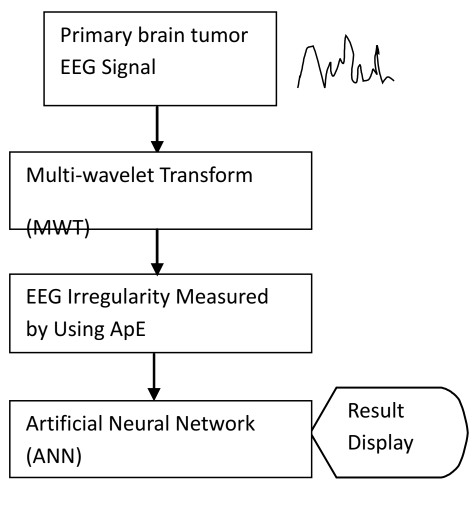
Rosaria Silipo, Gustavo Deco and Helmut Bartsch [9] proposed a brain tumor classification method on EEG signals. The classification done by applying a nonlinear analysis to the hidden dynamic of the F3 and F4 EEG leads, that describe the electrical activity of the left and right brain hemisphere, respectively. The hidden dynamic of the pair (F3, F4) is tested against a hierarchy of null hypotheses, corresponding to one- and two-dimensional nonlinear Markov models of increasing order. An appreciative measure of information flow, based on higher order cumulates, quantifies the hidden dynamic of each time series and is used as a discriminating statistic for testing the null hypotheses. The minimum order of the accepted Markov models represents a measure of the intrinsic nonlinearity of the underlying system. Rest EEG records of 6 patients with evidence of meningeoma or malignant glioma in lead F4, or without any pathology, are investigated. A high order hidden dynamic is detected in normal EEG records, confirming the very complex structure of the underlying system. Different inter-dependence degrees between the hidden dynamics of leads (F3, F4) discriminate meningeoma, malignant glioma, and no pathological status, while loss of structure in the hidden dynamic can represent a good hint for glioma / meningeoma localization.

Habl, M. and Bauer, Ch. and Ziegaus, Ch., Lang, Elmar and Schulmeyer, F [10] presented a technique to detect and characterize brain tumors. They removed location arifactual signals, applied a flexible ICA algorithm which does not rely on a priori assumptions about unknown source distribution. They have shown that tumor related EEG signals can be isolated into single independent ICA components. Such signals where not observed in corresponding EEG trace of normal patients.

## 3. Proposed Methodology for primary brain tumor Detection

The proposed method uses MWT and ANN to classify the EEG signal for primary brain tumor detection. The below block diagram shows flow of proposed methodology.

**Figure 1: Block diagram of proposed Methodology.**



The EEG signal without any art affect is given as an input to MWT, the EEG signal is decomposed and the irregularities of the signal are determined by using the ApE process.  Then the ApE output is trained by using Feed Forward Neural Network (FFNN) and result is displayed.

The proposed system was evaluated with 325 samples of EEG data recorded from patients. Of which, 163 samples correspond to EEG data with brain tumor and the remaining 162 samples correspond to EEG data without brain tumor.

**Multi Wavelet Transform Decomposition:**

In MWT decomposition, the input signal is denoted as)($nx$. The decomposed low pass filter outputs are denoted as $A_1A_2A_3A_4$, and $A$ the decomposed high pass filter outputs are denoted $D_1D_2D_3D_4$. and D $_5$The following figure shows the decomposition structure of MWT. Using this structure, the decomposition stage of EEG signal is calculated

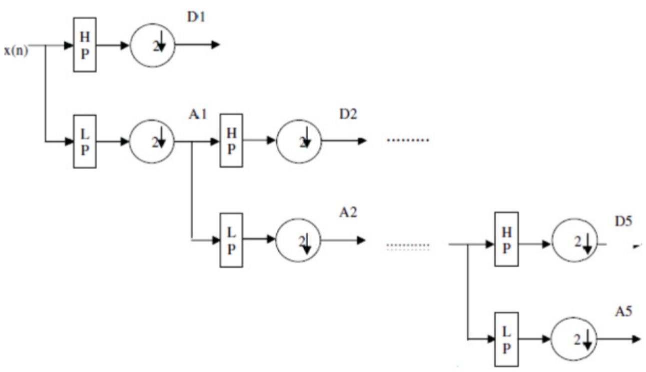



**Figure 2: Decomposition of MWT.**

The decomposition of MWT is calculated by using the following formulas. The decomposition of low frequency component is calculated as,

$$A_{i-1} = \sum_k H_k \, A_{i,2k+n}$$

**The decomposition of high frequency component is calculated as,**

$$D_{i-1} = \sum_k G_k \, D_{i,2k+n}$$

Using the above two formulas, the decomposition of MWT is calculated

**Approximate Entropy Method:**

Approximate entropy (ApE) is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time-series data. The output of ApE is denoted as

$$AD_1, AD_2, AD_3, AD_4, AD_5 \text{ and } AA_5$$

Then the irregularities of the EEG signal are calculated by following the below procedure.

1. Calculate N data points from the signal i.e.

$$n = [n_{(1)}, n_{(2)}, \ldots\ldots\ldots\ldots n_{(N)}]$$

2.Fix window length m and tolerance rr

3. Form a sequence of vector  $x(1), x(2), \ldots.. x(N-m+1)$
m dimensional vectors are  defined by
$x(i) = [u(i), u(i+1), \ldots\ldots.., u(i+m-1)]$ for $i$ = 1, 2,...... N- $m$ + 1

4. Using sequence $x(1), x(2), \ldots.. x(N-m+1)$ to construct, for each I $1 \le i \le N-m+1$ Calculate the absolute difference between their respective scalar components i.e.,
$d[x(i), x(j)] = \max_{k=1,2,\ldots m} |u(i+k-1) - u(j+k-1)| \le rr$ Calculate

$$C_i^m(rr) = \frac{d[x(i), x(j)]}{(N-m+1)}$$

5. Calculate natural algorithm for each value of $C_i^m(rr)$ and average it over $\phi^m(rr) = (N-m+1)^{-1} \sum_{i=1}^{N-M+1} In C_i^m(rr)$

6. Calculate $C_i^{m+1}(rr)$ and $\phi^{m+1}(rr)$ for increasing the m up to its fixed value ApE calculated by below formula

$$ApEn = \phi^m(rr) - \phi^{m+1}(rr)$$

The irregularities of signal depend on the ApE value. ApE value for each sub-signal of the decomposed data with MWT is calculated to form a feature vector. These ApE value is then applied as input to the neural network and the training dataset is generated.

**Training of Neural Network:**

In the present work, a feed-forward neural network (FFNN) is used for identifying the types of EEG signal.

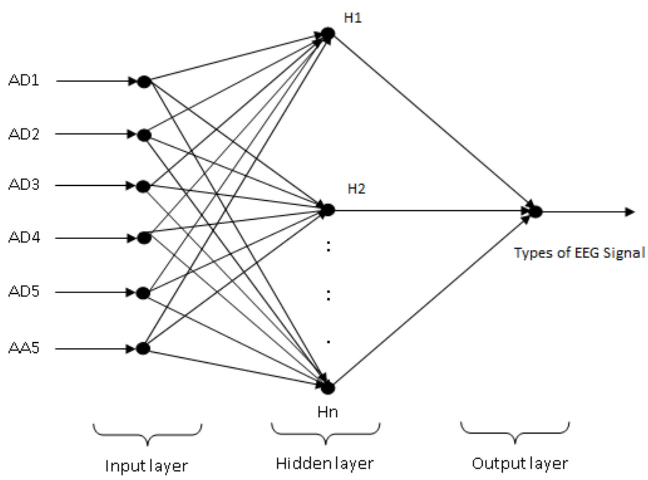



**Figure 3: Neural network training structure**

FFNN consists of three layers namely input layer, hidden layer and output layer. The input to input layers of neural network are $AD_1, AD_2, AD_3, AD_4, AD_5$ and $AA_5$ The $n$ numbers of hidden layers and $H_1, H_2, \ldots\ldots H_n$ are nodes of hidden layer, the neural network process takes place in this hidden layer. The training of the neural network is performed by back propagation algorithm. The output of neural network is used to determine the types of EEG signal. Figure. 3 show the neural network training structure. The multi-wavelet output is trained and the training dataset is generated for primary brain tumor detection. The weight between input and hidden layer is denoted as $W_1$, the weight between hidden and output layer is denoted as $W_2$. The weight adjustment depends on the output requirement.

The formula for weight adjustment between the layers is $W_{ji}(n+1) = W_{ji}(n) + \Delta W_{ji}(n)$ The neural network output is calculated by using the formula $\sum_{j=i=1}^{n} W_{ji}AD$ . Once the training process is completed, then, the network is trained for classifying the EEG signal. After the training process, the next process of neural network is testing. In this testing phase, an input signal is applied and then the types of EEG signal are calculated. From these types of EEG signal, the primary brain tumor can be detected.

**4. Result and Discussion**

The proposed multi-wavelet based primary brain tumor detection technique is implemented using MATLAB 7.11 on windows 7 PC with Intel i5 processor. Here, the wavelet level was chosen as 5 for extracting the feature of the signal and for ApE calculation value of m = 4 and rr = 5 is considered. The hidden layer neuron was set as 20. The results are compared with existing methods [6].

The true positive, true negative, false positive and false negative values are calculated from the results obtained. The above four values are used to calculate a few important criterions as specified in the equations given below.

Specificity: Number of correctly detected negative patterns/total number of actual negative patterns. A negative pattern indicates a detected normal/non-seizure.

$$Specificity = \frac{TN}{(FP+TN)}$$

Sensitivity: Number of correctly detected positive patterns/total number of actual positive patterns. A positive pattern indicates a detected seizure

$$Sensitivity = \frac{TP}{(TP+FN)}$$

Accuracy: Number of correctly classified patterns/total number of patterns. Then the determined values are tabulated and it is shown in the below table

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

$$precsion = \frac{TP}{(TP+FP)}$$

Using the above formulas, the values of specificity, sensitivity, accuracy and precision are determined.

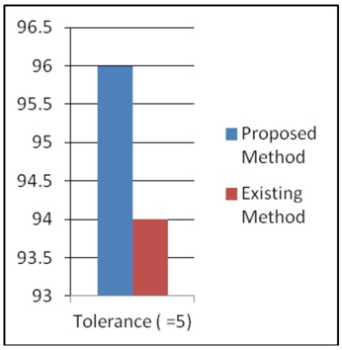
**Table 1: Performance evaluation table**

| Parameter | Proposed Method | Existing Method |
|---|---|---|
| Sensitivity | 78 | 70 |
| Specificity | 88 | 78 |
| Accuracy | 96 | 94 |
| Precision | 83 | 66 |

Graph 1 and Graph 2 reveals the accuracy and precision of proposed and existing method [6]. From the charts, it is clear that the proposed method is better than the existing method. Figure.4 shows the GUI of the proposed system.

Accuracy

**Graph 1: Accuracy Comparison of Proposed and Existing Methods.**




Precision

**Graph 2: Precision comparison of Proposed and Existing Methods.**

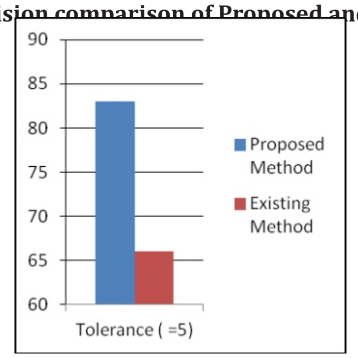
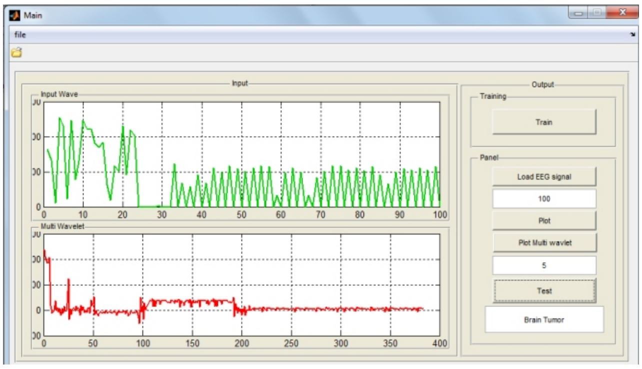


**Figure 4: GUI of proposed method system**




## 5. Conclusion

This paper, proposes a technique to classify EEG signal as normal and primary brain tumor, which is combination of multi-wavelet transform and artificial neural network. Irregularity in the EEG signals is measured by using the Approximate Entropy. The proposed technique is implemented and tested on data obtained from 335 EEG signals, proposed and exiting methods compared. Work is progress to enhance implemented method to achieve 100% accuracy for identification of primary brain tumor.

## 6. References

[1] J.D. Bronzino, "Biomedical Engineering Handbook", New York: CRC Press LLC, Vol. I, 2nd edition 2000

[2] D.Bradbury, "Volunteer's Guide to an EEG", Institute Of Neurology Wellcome Department Of Imaging Neuroscience,

[3] http://www.fil.ion.ucl.ac.uk/EEGvolunteerguide.pdf

[4] http://www.brain-surgery.com/primer.html

[5] Murugesan, M. Dr. (Mrs.). Sukanesh, R "Automated Detection of Brain Tumor in EEG Signals Using Artificial Neural Networks", IEEE Conference on Advances in Computing, Control, & Telecommunication Technologies, 2009. Act 09. Trivandrum, Kerala

[6] M. Murugesan and Dr. (Mrs.).R. Sukanesh "Towards Detection of Brain Tumor in Electroencephalogram Signals Using Support Vector Machines" International Journal of Computer Theory and Engineering, Vol. 1, No. 5, December, 2009

[7] Seenwasen Chetty, Ganesh K. Venayagamoorthy "An investigation into the Detection of brain tumours using electroencephalography (EEG) signals with Artificial neural networks" Computational Intelligence Group, Department of Electronic Engineering M L Sultan Technikon

[8] Fadi N. Karameh, Munther A.Dahleh "Automated Classification of EEG Signal in Brain tumour diagnostics" IEEE Proceeding of the American Control Conference, Chiago, llinois. June 2000.

[9] Rosaria Silipo, Gustavo Deco and Helmut Bartsch "Brain Tumour classification Based on EEG hidden dynamics" Elsevier Inc journal Intelligent Data Analysis, Vol 3, Issue 6, Pages 413-514 (December 1999).

[10] Habl, M. and Bauer, Ch. and Ziegaus, Ch., Lang, Elmar and Schulmeyer, F. "Can ICA help identify brain tumor related EEG signals?" Proceedings / ICA 2000, Second International Workshop on Independent Component Analysis and Blind Signal Separation: Helsinki, Finland, June 19 - 22, 2000. Unspecified, pp. 609-614. ISBN 951-22-5017-9.

[11] Lawrence J. Hirsch "Continuous EEG Monitoring in the Intensive Care Unit: An Overview" Journal of Clinical Neurophysiology, Volume 21, Number 5, October 2004

[12]. Small, Joyce Graham Bagchi, Basu K.Kooi, Kenneth A. "Electro-clinical profile of 117 deep cerebral tumors" Elsevier Inc Electroencephalography and Clinical Neurophysiology, Vol 13, Issue 2 , Pages 193-207, April 1961

[13]. I.Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic "Energy Distribution of EEG Signals: EEG Signal Wavelet-Neural Network Classifier" International Journal of Biological and Life Sciences, 6:4 2010

[14]. David A. Peterson, James N. Knight, Michael J. Kirby, Michael H. Thaut and CharlesW. Anderson "Feature Selection and Blind Source Separation in an EEG-Based Brain-Computer Interface" EURASIP Journal on Applied Signal Processing, 2005:19, 3128–3140

[15]. Sharanreddy and Dr.P.K.Kulkarni "Review of Significant Research on EEG based Automated Detection of Epilepsy Seizures & Brain Tumor", International Journal of Scientific & Engineering Research, Volume 2, Issue 8, Aug-2011, ISSN 2229-5518

[16]. Sharanreddy and Dr.P.K.Kulkarni "Literature Survey on EEG based Automatic Diagnosis of Epilepsy seizures & Brain Tumor using WT and ANN" International Conference on Biomedical Engineering (ICBME 2011), Dec 10-12, 2011, Manipal, India.

[17]. Sharanreddy and Dr.P.K.Kulkarni "Necessity for Automated Analysis of EEG Signal for Detection of Multiple Neurological Disorders" International Conference on Evolutionary Trends in Information Technology (ICETIT 2012), Sep 15-17, 2012, VTU Belgaum, India.

[18]. Sharanreddy and Dr.P.K.Kulkarni "Multi-Wavelet Transform Based Epilepsy Seizure Detection" Proceedings – 2012 IEEE EMBS Conference on Bio Engineering & Sciences (IECBES 2012) Dec.17-19, 2012, Langkawi, Malaysia. ISBN - 978-1-4673-1666-8

[19]. Forrest Sheng Bao, Donald Yu-Chun Lie, and Yuanlin Zhang, "A New Approach to Automated Epileptic Diagnosis Using EEG and Probabilistic Neural Network", in Proceedings of the 2008 20th IEEE International Conference on Tools with Artificial Intelligence, Vol. 02, pp. 482-486, 2008.

[20]. Steven Walczak and William J. Nowack, "An Artificial Neural Network Approach to Diagnosing Epilepsy Using Lateralized Bursts of Theta EEGs", Journal of Medical Systems, Vol. 25, No. 1, pp. 9-20, February 2001

[21]. M. Teplan "Fundamentals of Eeg Measurement" Measurement Science Review, Vol 2, Sec 2, 2002

[22]. Maan M. Shaker, "EEG Waves Classifier using Wavelet Transform and Fourier Transform", International Journal of Biomedical Sciences, Vol 1, No 2, 2006, ISSN 1306-1216.

[23]. Nick Yeung, Rafal Bogacz, Clay B. Holroyd and Jonathan D. Cohen "Detection of synchronized oscillations in the electroencephalogram: An evaluation of methods" Psychophysiology, 41 (2004), 822–832. Blackwell Publishing Inc. Printed in the USA.

[24]. Edward B. Bromfiled " EEG in Brain Tumor" Medscape Reference.

[25]. Samhita P, Venkataraman V, Radhakrishnan, Kurupath Radhakrishnan, Ravi M, and Sankara P. "Electro-clinical characteristics and postoperative outcome of medically refractory tumoral temporal lobe epilepsy" Vol 53, Issue 1, Neurology of India, March 2005.

[26]. Dr. YW Fan and Dr. Gilberto KK Leung "Management of seizure associated with brain tumour" Vol. 11, No 4, April 2006, Medical Bulletin, The Hon g Kong Medical Diary.