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IDENTIFICATION OF SCHWANNOMA IN HUMAN BRAIN USING CROSS-CORRELATION-COMMON SPATIAL PATTERN ALGORITHM THROUGH IMAGE-SIGNAL BANDWIDTH ANALYSIS

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ABSTRACT

Neuroanatomy is a pertinent dimension in neoteric times due to the various dysfunctionalities that is associated with it. The periodical health analysis of the neural connectivity is most commonly effectuated for pregnant women to continuously monitor the structural development of the foetus' brain. However, in adults this can be comprehended by the symptoms that are evinced on a quotidian basis. The meticulous scrutinization of the neural signals forms to be the quintessential facet of Neuroscience, and thereby delivers a wholistic diagnostical cognizance of the entirety of functions involved. With the increasing competitive realm, rapid lifestyle changes and food habits that contributes to the sundry disorders, Schwannoma can be categorized as a malady that can turn fatal with neglected vigilance. The existing studies have largely pivoted on various domain-relevant algorithmic approaches to agnize the brain disorders in relevance to malignancy and benign characteristics of an observed tumor. While the previous research pivoted on unimodal approaches such as either image processing or signal analysis of detecting brain abnormalities, this paper focuses to render a novel approach of commingling the approaches of image and signal processing to effectuate a bimodal technique of corroborating the detected abnormality through a combined effort of medical imaging and respective brain signal generation. Techniques of pre-processing, filtering and the unrivalled application of Cross-correlation Common Spatial Pattern (CCCSP) algorithm aids to classify the dossier appropriately as normal and abnormal inorder to understand the underlying problem of vagus nerve detriment to their relationship with Schwannoma. This study also focusses on the Fast-Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) to sequester the wave bands, and subsequently accentuate the inconsistencies observed in the specific frequency modules to further corroborate the normalcy of the signal waves. The Delta-Beta frequency bandwidths from the generated Electroencephalogram (EEG) are specifically used in this paper inorder to cognize the abnormalities. The simulative implementation for this study is functioned in MATLAB, and the efficient results to corroborate the motivation of the research is procured.

Keywords: *Cross-Correlation-Based Common Spatial Pattern Algorithm, Delta-Beta Signal wave, Electroencephalogram (EEG), Fast-Fourier Transform, Discrete Time-Direct Form Filter, Schwannoma, MATLAB.*

1. INTRODUCTION

A rudimentary and assiduous analysis of the functionalities that an individual is occupied with can be largely impacted with a trivial alteration in the neural connections of the human brain. The paramount significance and the uniqueness of these connections is still an intricate conundrum even for the experts in the domain to explicitly detail in general. While studying the diverse methods through which tumors and associated diseases are studied, it is crucial to essentially analyse the various components of observation involved. A Medical imaging is a sought-after method when an individual goes through a health gremlin that necessitates swift solutions prior to a surgical approach. The techniques such as X-ray, Magnetic Resonance Imaging (MRI) and Ultrasound are some of the common methodologies that are sub-composed in

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medical imaging. The next approach to analysing the brain function is the signal processing technique that observes the communicative joints within the cranium through an Electroencephalogram (EEG). The spatiotemporal Neuroscience [4] renders an overall purview of the relationship between the brain signals and the behaviour of an individual. The World Health Organization (WHO) has established a survey that analyzed the approximation of brain disorders and neurological dysfunctionalities to be greater than half a century of human population [20]. Nonetheless, the idiosyncrasy of the neural connections, and the detriments that arise with it are gradually dissected through the trailblazing and progressively advanced technologies that can detect the minuscule change in the signals or connectivity of the neural system. The EEG signals in the brain hold vital data that helps in agnizing the variations in the frequency waves. This signal waveband is crucial for the detection of failed connectivity in the amplitude band, and the consequences it may have with the other vitalities in the human body. Schwannoma is most commonly ignored in most cases, due to its characteristic to remain benign for longer durations. However, the chances of the abnormality turning malignant can escalate when appropriate annihilation is not effectuated. The subsequent symptoms that can be observed when Schwannoma is triggered in an individual can be loss of appetite, vocal cord hoarseness, repression of blood vessels that can lead to numbness, paralysis and schwannomatosis. The EEG signals [6] helps in identifying the schwannomas in the nerves, through their multi-band frequency spectrums. The different bandwidths in the EEG signals are as follows:

- **Delta Waveband:** This bandwidth holds an amplitude in the range of 1-3Hz [16], with the amplitude range effectively recorded when the individual is sleeping.
- **Theta Waveband:** The amplitude range of this wave is recorded to be 4-7Hz [16], and is recorded when an individual holds no anxieties, with the brain function observed to be relaxed.
- **Alpha Waveband:** The dispersed, yet tranquil mode of the brain can record the best alpha signals which range from 8-12 Hz [16].
- **Beta Waveband:** The most dynamic and agile functionality by the brain is recorded at the amplitude of 13-38Hz [16]. Thus, instituting to be the most significant waveform to evince the anomaly in the neural system that could consequence the individual to become debilitated.

This paper pivots on assessing the schwannomas through a combined approach of image processing procured through medical imaging and signal wave analysis acquired from the EEG signal of the image. While several existing studies have pivoted on a single mode of approach to understand the detection of tumors, this study elaborates to bolster the classification of normal and abnormal schwannomas based on the processing techniques and the application of cross-correlation-based common spatial pattern algorithm through the image-signal scrutinization of the brain. The structure of the paper is organized with Section II elaborating the existing research relevant to the domain of interest used in this research, with the proposed methodology delineated in Section III, and the simulative results illustrated explicably in Section IV. The final section conjectures the implemented indagation, and elaborates the further study that could possibly be effectuated.

2. EXISTING METHODOLOGY - AN EMPIRICAL OVERVIEW

The study on Improved Brain–Computer Interface Signal Recognition Algorithm Based on Few-Channel Motor Imagery articulated by Fan Wang et al [8] elaborated on common spatial patterns based on phase space reconstruction, time frequency decomposition using a trimodal approach of wavelet packet transform, fast ensemble empirical mode decomposition and local mean decomposition to enhance the classifier accuracy and feature distribution on the limited channel motor imagery patients using the EEG data. This processing using the decomposition and reconstruction further enhances the proposed methodology and mitigates the computational complexity.

Naeem Ullah et al [9] in the study "An Effective Approach to Detect and Identify Brain Tumors using Transfer Learning" elaborated on the performance of pre-trained transfer learning networks to identify three different tumors such as glioma, meningioma and pituitary brain tumors. Hybrid approaches used with the transfer learning networks are the Convolution Neural Network (CNN) and the Support Vector Machine (SVM) [2, 3] to unsheathe the features from the MRI dataset, and then to subsequently classify them. The findings explored the pre-trained networks such as the Inceptionresnetv2, Inceptionv3, Xception, Resnet18, Resnet50, Resnet101, Shufflenet, Densenet201, and Mobilenetv2. The results further concluded that the Inceptionresnetv2 model rendered the highest accuracy classifying the tumor with an accuracy percentage of 98.91% over the other models.

N. Sravanthi et al [10] in their study Brain Tumor Detection using Image Processing distinctly explained the detection of brain tumors using a series of image processing mechanisms. The research utilized the preprocessing of the MRI images using noise removal, segmentation, feature extraction and classification of the benign and malignant tumors based on the SVM classifier. Their future work elaborated on the necessity to incorporate 3D models of the brain inorder to augment the tumor identification process on a facile platform.

Hafeez Ullah Amin et al [21], articulates the stratification of EEG signals based on a pattern recognition approach. The research entailed the Fisher's discriminant ratio (FDR) and the Principal Component Analysis (PCA), effectuated through the K-nearest neighborhood method, SVM, Multi-layer Perceptron (MLP), and Naïve Bayes (NB) to procure the accuracy percentages of the classification.

Each of the above research articulated have pivoted to provide a conclusive solution to detect and augment classification of brain functionalities. Nonetheless, a collateral verity on the obtained solutions to substantiate the findings is neglected.

3. PROPOSED INDAGATION

Medical imaging and the signal processing of the brain provides gargantuan information on the health of the organ, and in early detection of any abnormalities that may exist. The primary motivation of the indagation is to deliver verity on the procured examination of an individual's brain, along with establishing affordable and unwavering diagnostic modus operandi for patients. The proposed methodology for the study entails the data procured from the imaging domain and the signal waves to be effectuated through an algorithmic approach. The pre-processing techniques implemented on the images for narrowing the entropy, and augmenting the Signal-to-Noise Ratio (SNR) and Peak-Signal-to-Noise Ratio (PSNR) [11] enhances the quality of the input images. A detailed architecture of the proposed methodology is illustrated in the figure below.

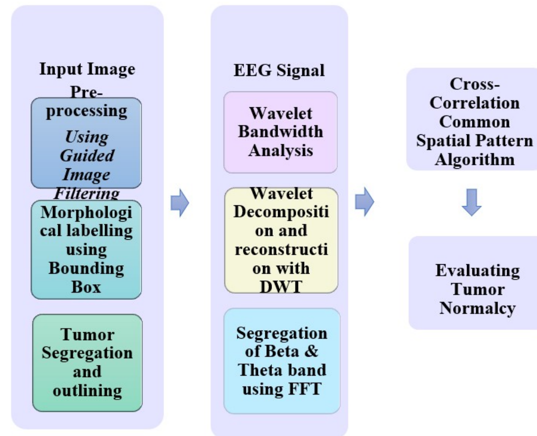

Figure 1. Process flow of the Proposed Methodology

The proposed model of indagation incorporates the various phases involved in enhancing the brain imaging and signal processing quality. The processing methodologies establishes a pre-processing method to filter the noise in the image through the guided image filtering technique. This technique optimizes the quality of the image by utilizing a guide in the form of another image, or the similar image before it was polluted with noise. The method potentially reinforces edge-preservation through its utilization of the Laplacian matrix to linearly filter the pixels that may hold higher entropy. The Gaussian filter function is combinedly used with the guided filter to further aggrandize the quality of the pixels for subsequent processing.

The morphological labelling operation is effectuated to comprehend the sub-components encompassed in the brain image such as the nerve structures and tumors. The 4-connected neighborhood defines the connected pixels through a 3 X 3 matrix to assess the varying pixel value in the binary image. The tumor thus identified through this sliding connectivity matrix is then accentuated through the bounding box component. The bounding box is a sub-element used with the 'regionprops' function, and aids in highlighting a specific object in an image. The size and position of the bounding box containing the region of interest is implemented as a 1-by-(2*M) vector, where 'M' is defined as the dimensionality of the image, and the order of M is hierarchical to the coordinate points from the minimal corner progressing toward the entire size of the box along the dimension. The subsequent phase of tumor segregation and outlining is effectuated through morphological operations of erosion and dilation. The image erosion is computed by dilating the bounded box through the subtraction of the entire range of the image. The EEG signal for the same image is obtained through the Brain Computer Interface (BCI) [17] machine. The electrodes placed at relevant positions establish the hybrid combination of odd-even connectivity in the cerebral cortex of the individual to capture the Frontal-Central-Temporal-Parietal-Occipital (FCTPO) signal bands [15,19]. It is observed that the EEG is a combination of varying bandwidths, and therefore necessitates explicit segregation of the differing amplitudes. This unsheathing of the wavebands is effectuated through a combined effort of Discrete Wavelet Transform (DWT) [13] and Fast-Fourier Transform (FFT) [1] inorder to first perform coupling that could filter the aggregated signal waveband into definite high and low-band groups. The discretization of the waves thus adopts a high and low-pass filter to segregate the higher and lower band signals identified in an EEG signal. The FFT is then used to further segregate the high and low wavebands into amplitude specific wavebands through time intervals [1,14] and the below equated formula.

$$\mathbf{I(g)} = \sum_{n=1}^{Q} l(n)\ \omega_Q^{(n-1)(g-1)} \qquad (1)$$

$$l(n) = \left(\frac{1}{Q}\right) \sum_{g=1}^{Q} h(k)\ \omega_Q \qquad (2)$$

Where $\omega_Q = e^{(-2\pi b)/Q}$ can be considered as the Qth root of unity.

Inorder to further analyse the degree of bandwidth dissemination precision [18], the Power Spectral Density (PSD) is evaluated. The computation of PSD is implemented by:

$$F(m,n) = g|j(m,n)|^2 \qquad (3)$$

Where g is obtained through the real-valued scalar definition, and is defined by the below equation.

$$g = \frac{2}{F_s \sum_{o=1}^{V} |b(o)|^2} \qquad (4)$$

Where the hamming function is represented by b(o). This b(0) is responsible for unsheathing the amplitude frequencies of the spectral bands, with F_s explicating the sampling approach through the factoring of Nyquist frequencies.

In this study, the beta and delta wavebands are specifically analyzed due to their significant qualities of extremity. The Beta bandwidth holds highly dynamic functional activity, while on the contrary, the delta waveband is a state of neurological indolence and relaxation. The signal waves thus segregated are used in the subsequent approach od entailing the cross-correlation common spatial pattern algorithm. The novelty of this research lies with the utilization of cross-correlative features along with spatial classifier technique which is unprecedented in previous research relevant to this field of study. The working of cross-correlation common spatial pattern algorithm is explicated in Table 1.

The cross-correlation features such as mean absolute error, Signal-to-noise ratio and PSNR are computed using the following equations. The frequency peaks are computed by summating the delta and beta signal bands taken for this study. The PSNR value [12] is procured by:

$$PSNR = 10 \log 10 \left(\frac{Peakval^2}{MSE}\right) \qquad (7)$$

Where peakval [12] is the zenith of the slope generated through the EEG signal, and Mean Square Error (MSE) [14] is calculated by the following formula:

$$MSE = \frac{1}{xy} \sum_{i=1}^{x} \sum_{j=1}^{y} [\hat{D}(x,y) - B(x,y)]^2 \qquad (8)$$

Where B(x,y) and $\hat{D}(x,y)$ are the beta and delta frequency signals respectively.

The SNR computation is facile with analysing the compounded signal and noise ratios through the below formula:

$$SNR = 20 \log\left(\frac{S}{N}\right) \qquad (9)$$

The subsequent results procured for the above implementation of the algorithmic process and image processing methodology is implemented in the subsequent section.

Table 1. Cross-Correlation Common Spatial Pattern Algorithm

1. Start
2. Select the input EEG signal respective to the brain image.
3. Normalize the signal waves using linear transformation.
4. Position the transitioned regions and effectuate the same through a passband and attenuation frequency spectrum to segregate them into distinct class band spectrums.
5. Incorporate the average of cross-correlation features such as mean-absolute error, SNR and PSNR value to utilize them as weights in the spectrum bandwidths.
6. The ratio of normalcy in signal bandwidths is observed post approximation, in either of the classes, with the entailing of covariance used on the trace of the inputted sample vector using the below formula:

$$S_W = \frac{N_x \, A_y^i}{\text{Trace}\,(M_X M_y^n)} \qquad (5)$$

Where S_W is the inputted signal waveband, N and A are the two distinct classes denoted as Normal and Abnormal respectively. x and y denote the matrix vectors of the inputted EEG signal, and 'i' is the total number of samples in the signal bandwidth.

7. The normalized covariance of $\overline{S_W}$ is computed by averaging the trials of the entire group of matrices, with the spatial covariances calculated through the incorporation of eigen vectors and the transformation matrix.

$$S = \overline{S_W} + H_0 \sum H_0^i \qquad (6)$$

Where H_0 is the eigenvector matrix which are aggregated to the summated value of all sample matrices.

8. The linear whitening transformation is then used to further distinctly accentuate the incongruity quotient using independent variances on both classes.
9. End

The proposed technique of combined processing strives to overcome the flaws of the existing research throughputs through contriving a bimodal approach of compounding the image and signal parameters of the brain to analyze the functionality in relevance to agnizing the presence of schwannoma in the brain. The phase-wise operations in image and signal processing are effectuated in MATLAB to obtain a juxtaposed waveband analysis to corroborate the dysfunctionality further. The cross-correlative common spatial algorithm helps to institute the region-based indication of the tumor, along with explicitly elucidating the type of tumor through the summated spatial covariances and eigen vectors implemented in this study.

4. RESULTS

This section of the study presents the various implementation results obtained from MATLAB. Figure 2 through 6 are the throughputs of the benign or normal schwannomas observed in an individual. The imaging of the brain along with the subsequent generated signal is depicted in the below list of figures. Figure 7 through to 14 illustrates the abnormal class of images, and distinctly highlights the tumor and respective bandwidths with respect to the cross-correlation spatial patterns that illustrate the vagus nerve detriment that triggers schwannomas on the nervous system. Figure 15 and 16 explicates the comparative feature analysis procured from the cross-correlative spatial pattern analysis respectively.

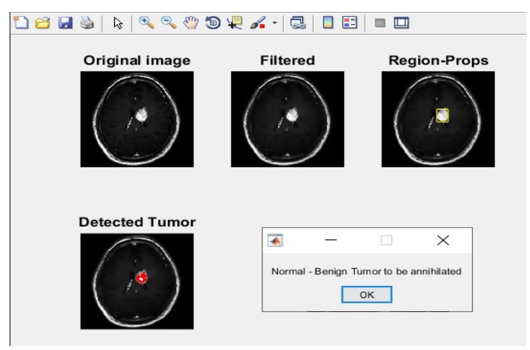

Figure 2. Identified Tumor categorized as Benign.

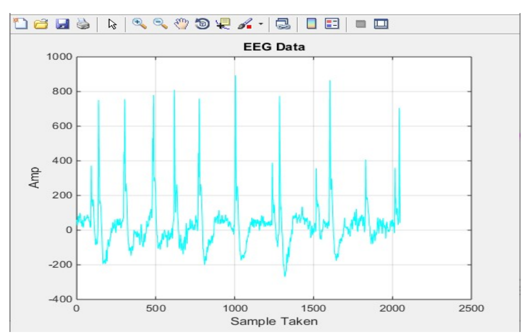

Figure 3. EEG Data of Inputted Brain Image.

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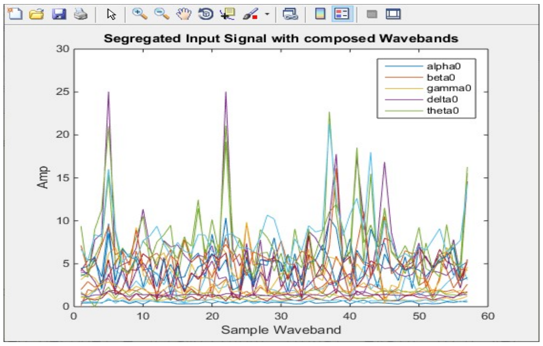

Figure 4. Summated Frequency Bands

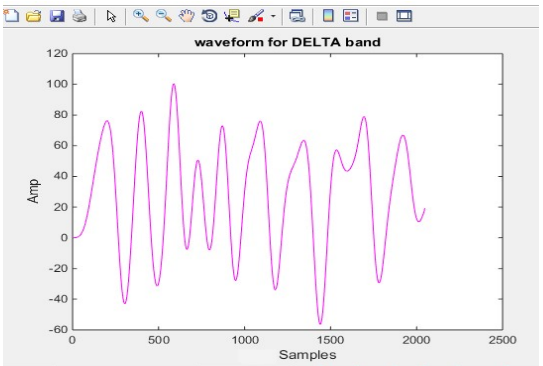

Figure 5. Delta Band Segregated from EEG.

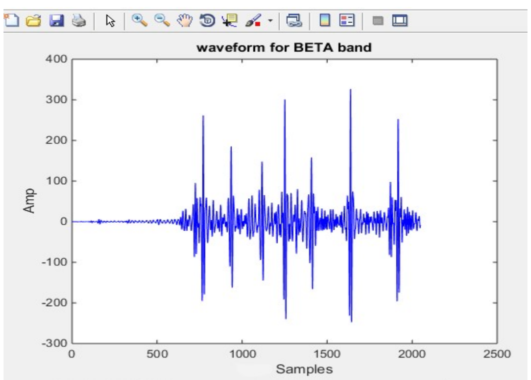

Figure 6. Beta band segregated from EEG

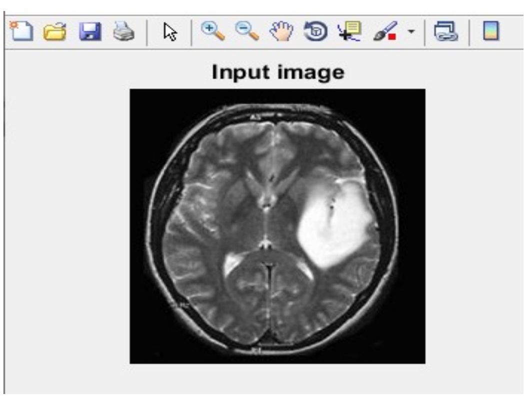

Figure 7. Input Image – Tumor

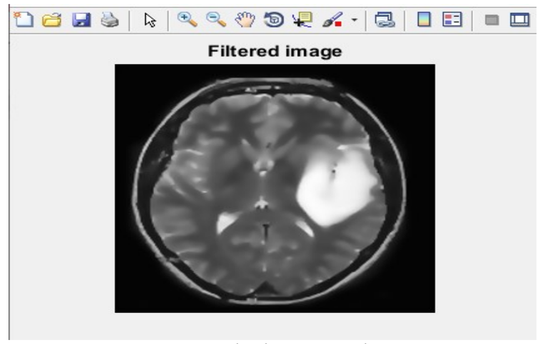

Figure 8. Guide d Image Filtering

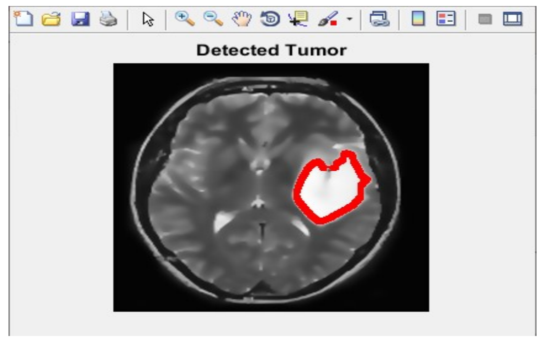

Figure 9. Morphological Labelling

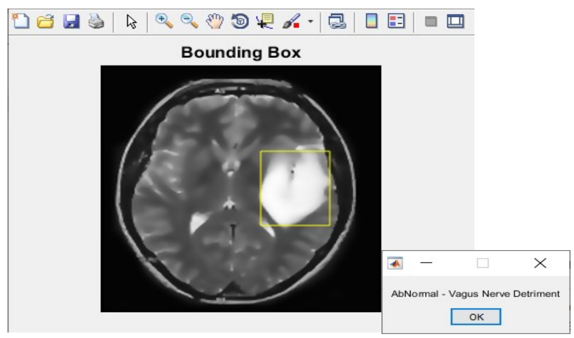

Figure 10. Bounded Box

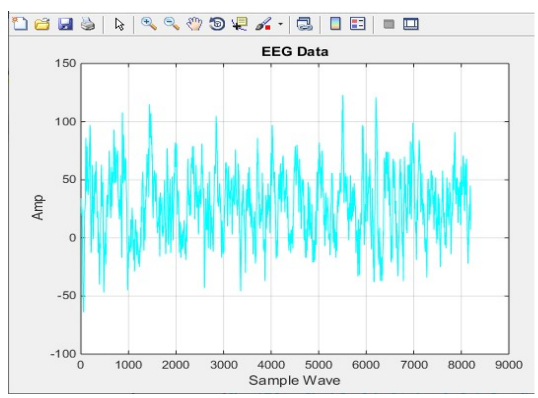

Figure 11. EEG of the Input Signal

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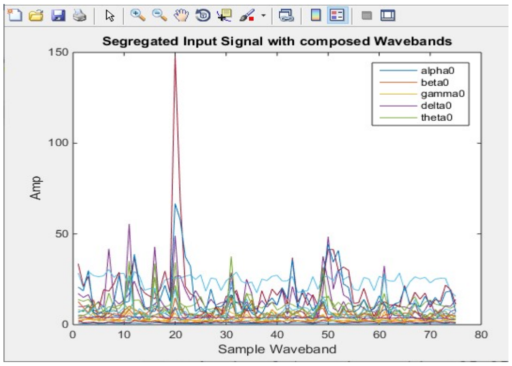

Figure 12. Summated Frequency Bands

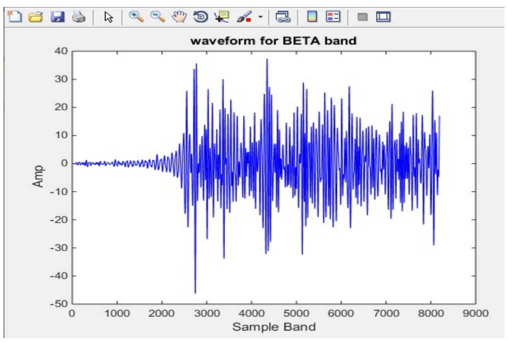

Figure 13. Beta Wave Form

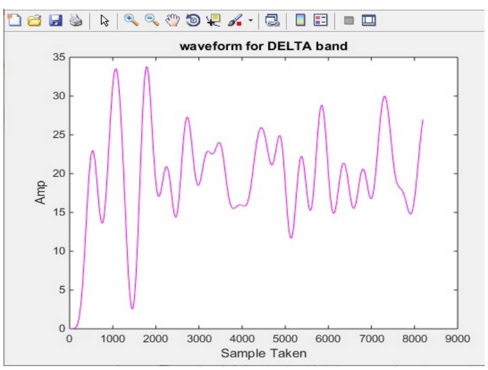

Figure 14. Delta Waveform

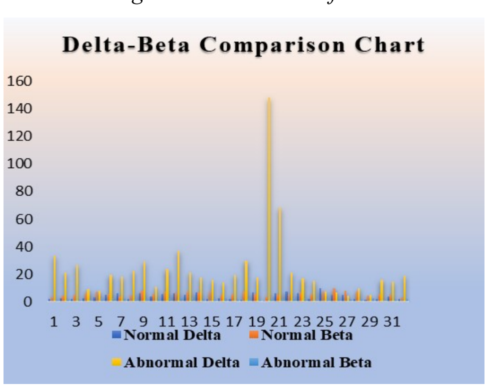

Figure 15. Delta-Beta Comparison Chart of Normal and Abnormal Data

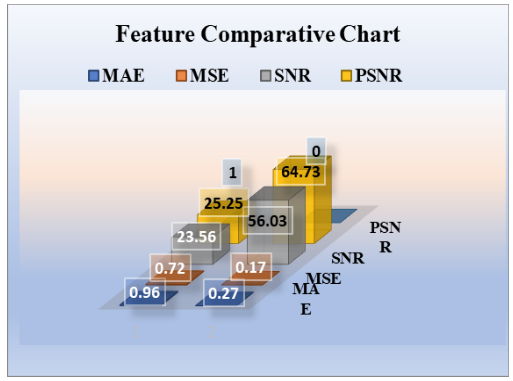

Figure 16. Comparative Chart of Normal and Abnormal Data

The results implemented in MATLAB, with using Excel to plot graphs as shown in the above figures evince the comparative analysis of wave signals for a normal and abnormal data with the emphasis on the delta-beta waveband. Thus, indicating that the delta and beta wave signals are subsequently lower and higher in a normal brain function respectively, and the vice-verse for an abnormal neural function that evinces higher delta amplitude, and lower beta function. The subsequent juxtapose of correlative features are represented by 1 for abnormal, and 0 for normal data. These features of cross-correlation spatial pattern indicate that there is a significant increase in the SNR and PSNR value, while depicting a down slope in MAE and MSE for normal brain functions. In abnormal brain functionality, the results are inversely proportional with the increase in MAE and MSE values, and a clear decline in the SNR and PSNR values.

5. CONCLUSION

An intrinsic responsibility in recent years is the rudimentary analysis of neural functions that play an utmost role in identifying the inconsistencies at an earlier stage. While the previous studies have largely focused on one of the domains to identify malignancy or benign characteristics of tumor in an individual, this research pivots to authenticate the acquired results based on both medical image processing and the relevant signal processing methods to substantiate for any inaccuracies in the comprehension of identification is resolved through this novel approach. The importance to entail the relationship between schwannoma and vagus nerve detriment [7] is to provide patients with an earlier stage of treatment thereby evading higher costs of treatment, and a more compatible and feasible solution. The delta-beta waveband segregation is vital in indicating the variations between a normal and abnormal data band. The FFT and DWT processing methods entailed in this study are established to enhance the quality of image and signal recognition of the brain with respect to the identified tumor. This indagation establishes impeccable results in terms of classifying and identifying the schwannoma in an individual's brain based on the cross-correlation common spatial pattern algorithm to narrow down the error rate, and in establishing successfully segmented frequency-amplitude ratio. The challenges of the research pertain to obtaining real-time data, along with establishing correlative analysis between the image and signal-based domains of the brain data. Cost optimization is another aspect that can be further pivoted on with further work directed toward employing machine learning algorithms and automated sensors to aid patients collaborate more closely with the features of interest, thereby enhancing the scope and development toward brain dysfunctionalities and schwannoma identification.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization and formal analysis have been done by the first author, methodology, software, validation, investigation, resources, data curation has been done by first and second author, Writing—original draft preparation has been first author, writing—review and editing, visualization had been done by second and third author.

REFERENCES:

[1] Dian Candra Rini Novitasari, Suwanto Suwanto, M. Hasan Bisri, Ahmad Hanif Asyhar, "Classification of EEG Signals using Fast-Fourier Transform (FFT) and Adaptive Neuro-Fuzzy Inference System (ANFIS)", Jurnal Matemmatika MANTIK, 5(1), May 2019, Pg: 35-44, DOI:10.15642/mantik.2019.5.1.35-44.

[2] Maria Camila Guerrero, Juan Sebastián Parada, Helbert EduardoEspitia, " EEG signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks", Heliyon, Science Direct, Vol 7, Issue 6, June 2021, https://doi.org/10.1016/j.heliyon.2021.e07258.

[3] Nitendra Kumar, Khursheed Alam and Abul Hasan Siddiqi, "Wavelet Transform for Classification of EEG Signal using SVM and ANN", Biomedical & Pharmacology Journal Vol. 10(4), 2061-2069 (2017), http://dx.doi.org/10.13005/bpj/1328.

[4] Chao Jiang, Yingjie Li*, Yingying Tang, Cuntai Guan, "Enhancing EEG-Based Classification of Depression Patients using Spatial Information", IEEE transactions on neural systems and rehabilitation engineering, February 2021 DOI: 10.1109/TNSRE.2021.3059429.

[5] Khatereh Darvish ghanbar, Tohid Yousefi Rezaii, Ali Farzamnia, Ismail Saad, " Correlation-based common spatial pattern (CCSP): A novel extension of CSP for classification of motor imagery signal", https://doi.org/10.1371/journal.pone.0248511, March 2021.

[6] Hamid Khodakarami , Navid Shokouhi , Malcolm Horne, "A method for measuring time spent in bradykinesia and dyskinesia in people with Parkinson's disease using an ambulatory monitor", Journal of Neuroeng Rehabil, July 2021, 18(1):116, DOI: 10.1186/s12984-021-00905-4.

[7] Albertyna Osinska, Andrzej Rynkiewicz, Marek Binder, Tomasz Komendzinski, Anna Borowicz and Antoni Leszczynski, "Non-invasive Vagus Nerve Stimulation in Treatment of Disorders of Consciousness – Longitudinal Case Study", Frontiers in NeuroScience, https://doi.org/10.3389/fnins.2022.834507, May, 2022.

[8] Fan Wang, Huadong Liu, Lei Zhao, Lei Su, Jianhua Zhou, Anmin Gong and Yunfa Fu, "Improved Brain–Computer Interface Signal Recognition Algorithm Based on Few-Channel Motor Imagery", Frontiers in Human Neuroscience, https://doi.org/10.3389/fnhum.2022.880304, May 2022.

[9] Naeem Ullah, Javed Ali Khan, Mohammad Sohail Khan, Wahab Khan, Izaz Hassan, Marwa Obayya, Noha Negm and Ahmed S. Salama, "An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning", Journal of Applied Science, https://doi.org/10.3390/ app12115645, June 2022

[10] N. Sravanthi, Nagari Swetha, Poreddy Rupa Devi, Siliveru Rachana, Suwarna Gothane, N. Sateesh, "Brain Tumor Detection using Image Processing", International Journal of Computer Science, Engineering and

Information Technology, DOI : https://doi.org/10.32628/CSEIT217384, ISSN:2456-3307, Volume 7, Issue 3 Pg No: 348-352, June 2021.

[11] https://in.mathworks.com/help/images/ref/psnr.html

[12] Feng Li, Fan He, Fei Wang, Dengyong Zhang, Yi Xia and Xiaoyu Li, "A Novel Simplified Convolutional Neural Network Classification Algorithm of Motor Imagery EEG Signals Based on Deep Learning", 28 February 2020, Journal of Applied Sciences, 2020, 10, 1605; doi:10.3390/app10051605.

[13] Jie Sun, Rui Cao, Mengni Zhou, Waqar Hussain, Bin Wang, Jiayue Xue and Jie Xiang, "A hybrid deep neural network for classifcation of schizophrenia using EEG Data", Scientifc Reports, (2021) 11:4706, https://doi.org/10.1038/s41598-021-83350-6.

[14] M Beudel, E Roosma, O E Martinez Manzanera, T van Laar, N M Maurits, B M de Jong, "Parkinson bradykinesia correlates with EEG background frequency and perceptual forward projection", Parkinsonism Relat Disord, 2015 Jul;21(7):783-8, DOI: 10.1016/j.parkreldis.2015.05.004. Epub 2015 May 6.

[15] Diah P. Wulandaria, Nomala G. P. Putria, Yoyon K. Supraptoa, Santi W. Purnamib, Anda I. Junianic, Wardah R. Islamiyahd, "Epileptic Seizure Detection Based on Bandwidth Features of EEG Signals", Procedia Computer Science 161 (2019) 568–576.

[16] Levent Aksoy, Cristiano Lazzari, Eduardo Costa, Paulo Flores, "Design of Digit-Serial FIR Filters: Algorithms, Architectures, and a CAD Tool", March 2013, IEEE Transactions on Very Large Scale Integration (VLSI) Systems 21(3):498-511, DOI:10.1109/TVLSI.2012.2188917.

[17] Dipali Bansal, Rashima Mahajan, "EEG-Based Brain-Computer Interfacing", Cognitive Analysis and Control Application, 2019, Pg: 21-71, DOI.org/10.1016/B978-0-12-814687-3.00002-8.

[18] Janko Slavic, Matjaz Mrsnik, Martin Cesnik, Jaka Javh and Miha Boltezar, "Vibration Fatigue by Spectral Methods", Signal Processing, Science Direct, 2021, Pg:51-74, DOI.org/10.1016/B978-0-12-822190-7.00009-8.

[19] Adithya Valli Nettem, D. Elizabeth Rani, "Modified PWNLFM Signal for Side Lobe Reduction", International Journal of Engineering & Technology, 7(4):4-7, Nov 2018, DOI:10.14419/ijet.V7i4.20.22110.

[20] https://www.who.int/news-room/fact-sheets/detail/epilepsy

[21] Hafeez Ullah Amin, Wajid Mumtaz, Ahmad Rauf Subhani, Mohamad Naufal Mohamad Saad, Aamir Malik "Classification of EEG Signals Based on Pattern Recognition Approach", Frontiers in Computational Neuroscience, DOI:10.3389/fncom.2017.00103.