Pixel-Level Frequency and Stress Mapping in Brain Tumor MRI Using DWT and Clustering algorithm

Dr.S.Rani,
Assistant Professor
Department of Information Technology (BCA/IT)
Vels Institute of Science, Technology & Advanced Studies (VISTAS)
Chennai 600117 , India
Email: srani.scs@velsuniv.ac.in
Dr. A. Clementking,
Oprational Manager
Mount Carmel College Autonomous ,
Bengaluru-560052, India
Clementking1975@gmail.com

Abstract :
This research work attempted to determine the brain activation level influence of stress in tumor affected region using MRI data. By applying Discrete Wavelet Transform (DWT) to pixel slices, researchers identify active neurons and stress levels. The Equal Interval Method clusters pixel values to detect high-density regions, indicating tumor impact. Frequency analysis reveals stressed versus relaxed neurons, helping forecast tumor zones. Preprocessing of NRRD files enables accurate visualization, and clustering techniques enhance precision. The methodology combines neuron activity computation and density-based clustering to understand the relationship between brain stress and tumor presence.The research involves using slices of the raw raster data to generate frequency waves, which calculates the pixel position variation. Although the sliced pictures are employed for tumor-affected region identification, this is done utilising the approaches of the Equal Interval. Study the relationship between stressed/relaxed neurons in the tumor-affecting brain MRI and stress level in the tumor. Digital Number (DN) values from image frames represent pixel density, which helps identify active or inactive neurons. Frequency waves are generated from these values, showing different patterns based on neuron activeness. Stress levels are computed based on frequency variations, categorized as inactive, low, normal, stress, and high stress. The analysis revealed a high percentage of neurons under stress, indicating a malignant condition. This method effectively links high-frequency wave patterns to elevated stress levels in brain scans.

Keywords : *Clustering algorithm, MRI Analysis, Discrete Wavelet Transform, Discrete Wavelet Transform, Stress Mapping*

1. INTRODUCTION

MRI is one of the many well-known three-dimensional views of the brain and the accurate spatial connections between brain regions. Although the image resolution is low, the photos nevertheless look clear. On the other hand, there are typically spatial distortions associated with the staining process when stained sections are used. N-dimensional raster data visualisation and image processing involving N-dimensional raster data is supported by the nrrd library and file format. The NRRD stands for nearly raw raster data. The region of Interest (ROI) is a section of a picture that has a great deal of significance to the issue at hand. The photos might be filtered to obtain an extract, or the images could be operated on in some other way. As a frequency value is applied to every pixel of every slice, a Discrete Wave Transformation (DWT) is used to identify changes and stress levels.

2. METHODOLOGY

Converting the raster data file into a sequence of frames that contains the same number of two-dimensional data yields the result fetched almost raw. The digital value variations of each pixel sequence are utilised to create a wavelet function and to calculate its variations. Neurons must be in continuous varying mode if the variation in the signal is zero, and therefore the neuron is inactive else it is active. The initial and ending frame's high-frequency fluctuation is calculated. Changes in brain frequency are able to anticipate changes in brain activity and stress. Neuron activation is realised via the creation of a frequency curve using source pictures at each focal point. Brain MRI collects data from the activated neurons by the fluctuation in the frequency curve. The brain's active neuron is found by converting MRI images that have already been preprocessed and then calculating the resulting frequency wave.Clustering is the divided image results in five clusters, which are identified by digital values.

Equal range value [12] is used to compute the distance measurements. For any cluster between 0 and 255, the number of values is 256. Each pixel is assigned to one of the five clusters depending on its value. The values are estimated to be impacted clusters, and hence, the high-density values are assumed.Density analysis is used to determine the brain's stress level, based on the results of this analysis.

2.1 DATA DESCRIPTION

MRI (Magnetic Resonance Imaging) is one of the popular and well-known methods for the three-dimensional observation of the brain and structures. It is quite limiting when it comes to image resolution. In stained sections, the resolution is good, but spatial aberrations are inherent in the staining process. Fetching data from the slicer's 3D download data base, the nrrd file is read.

In the MRI scans, SVDC - Lab, Chennai, collects the pictures. The MRI brain pictures are identified as normal, whereas the Data sets are identified as having an abnormality status. There are 60 patient's samples that are retrieved for the analysis . The individual pictures are composed of ranges from 122 to 148 images. Since cancer stages are divided into five, each picture is assigned to one of the five clusters. Nearly Raw Raster Data(NRRD) format MRI data was gathered from the lab. This file format was developed to convey data in N-dimensional form as well as visualisation in the scientific sector. This is also a good choice for converting and extracting various file formats.

The neural analysis was done by Modha, et. al., who studied the MRI three-dimensional coordinated image to find out how far and how quickly the neuron was moving.[3] [2] The procedure to improve the speed of the neuron process utilises a similar method. MRI scans process the pictures, which are obtained, using Matlab, and convert them to two-dimensional images and values shown in figures 1 and 2

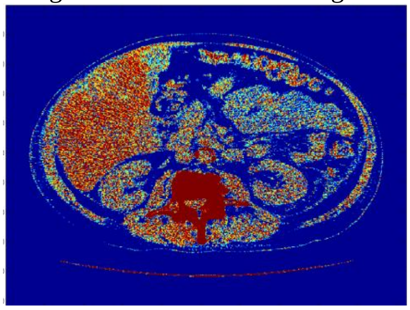

Figure 1 Converted MRI

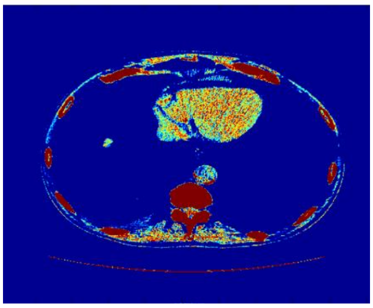

Figure 2 MRI layer Image

Because of the nature of the MRI file, the image is sequenced into a 1: 120 ratios. For the purpose of calculating the frequency of changes, the files corresponding to digital values are converted and presented. The activation of the neuron is determined by the changes in the digital number that occur.A pixel is a component of a picture [9]. It is the tiniest point on the image that is used to construct it. In order to create a complete image, pixels were organised into rows and columns. It is the number of bits that have been made accessible in the digital system to represent each pixel in the image that is referred to as the pixel bit depth. When the bit depth of a pixel is extended to eight bits, a pixel can have a total of 256 possible values (brightness levels, shades of gray, etc).

The image represented by a single bit per pixel can only have two possible values: BLACK and WHITE, because there are only two available bits per pixel. If a pixel has 4-bit values, the image can only have 16 different brightness levels if the pixel has four bits (shades and gray). The eight-bit pixels can display 256 different brightness levels, which is sufficient for the human eye to distinguish between the colours.The digital numbers are extracted, and the data set is formed as macroarray . Each pixel is represented with *five* values (X, Y, R, G, B), where X, Y represent the location of the pixel or pixel coordinates R, G and B are DN values of the pixel in Red, Green and Blue bands respectively. The layer values represent the spectral attribute reflection of the object, which may vary in different layers of the same pixel in the image.

The ROI represented in the multi-dimensional layer representing the spectral values of objects as recorded by the sensor as Digital Numbers (DN). DN of the pixel values of each layer presented in a two-dimensional matrix data set. The DN values are preprocessed and converted into 8-bit resolution with the minimum value starting from 0 to a maximum value of 255. To further augment the processing capability, these DN values are again converted into a cubical macro array format. This would facilitate easy processing by the machine while implementing desired algorithms. Macro array format adheres to a standard format –{X, Y,L1,L2,L3,F1} where X, and Y are pixel position of the image and L1,L2 and L3 are DN values of B, G and R band values respectively. The F1 is the representation of the frame presented in the table 1. From the three layers, the same coordinated pixel values are represented with three digital values of respective three layers that have been selected for the analysis by forming a macro array. Converted sequences of images are processed in each frame and its results are analyzed together as per the nature of the problem.

Table 1. Macro array of DN values

X	Y	R	G	B	Frame
1	1	125	134	137	1
1	2	134	141	132	1
1	3	143	147	139	1
1	4	146	128	139…	1

Macro-array values are constructed, resulting in a large array size. A pixel's location and the number of it are both cubically represented. With respect to the ROI, the macro-array data set values serve as a big data set, with the numerical data compiled into it. When using a Very Large Data Base, memory and processing problems may emerge. In the current study, the picture is examined utilising custom-developed algorithms and running them on the Matlab platform.

MATLAB is a programming language used for data analysis, visualisations, and number computation In the current study, the pictures are imported into Matlab, where they are then transformed into digital numbers. The preprocessed loaded picture file is transformed into two-dimensional array format digital values for the data variable.

2.2 FREQUENCY ANALYSIS

All pictures have the same location in this multidimensional array created with Digital Numbers. Each have their own individual values, serve as correlatives for the different levels of neuron density. As each pixel value represents the change in the density of the neuron activations, the neuron densities are represented by the pixel values. Wavelet decomposition is accomplished via a continuous wavelet transform. It is possible to create a time and frequency representation of a signal that gives great time and frequency localisation with the use of the continuous wavelet transform. Completed in the area of numerical analysis and functional analysis.

Alfred Haar[4] first suggested this sequence in 1909. To show that an orthonormal system may be given for the space of square integrable functions on the real line, Haar utilised these functions shown in figure 3. It is also the simplest conceivable wavelet, known as the Haar wavelet. The Haar wavelet has a technical drawback in that it is discontinuous, which prevents it from being differentiated

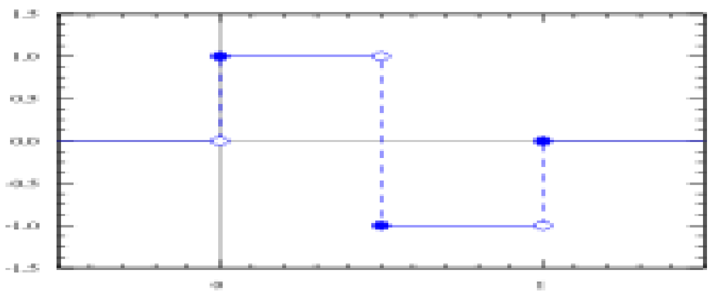

Figure 3. Haar Wavelet

The Haar wavelet's mother wavelet function ψ(t) can be described as

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

and its scaling function φ(t) can be described as

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

The data that has been translated can then be sorted at a resolution that corresponds to its scale. Because of the differences in digital values, it is possible to distinguish between little and significant characteristics.As per the selection of sequence of digital values a discrete transformation wavelet is constructed, and analysis of the neuron activation is computed.

2.3 CLUSTERING

When run a clustering process, related components are grouped together into one cluster, and separate clusters are formed that are extremely distinct from one another. Determining the existing values based on selective attributes using "distance" for the clustering procedure. The clusterby-variance approach is generally employed for the same reason. [6][7][1][8][10]. Variance values for the clustering process implemented using Equal Interval Method for this application.

2.3.1 Equal Interval Method (EIM)

The Equal Interval Method (EIM) is used to explore the unprocessed or processed dataset for analysis. Equal interval technique is usually active to cluster the pixels in a picture based on the input dataset, without relying on any reference data or other assessment criteria. The numeric values often active in clustering are integers, not whole numbers. To split attribute values into a number of intervals, the interval must have the same width (Range/n). Using this approach helps in finding the range of attribute values that are accessible [11]

In this study, cluster counts define the range values. According to the current research, a five-cluster model is used. To compute the interval, we apply the unique values technique. The last step is dividing the range of minimum value of 0 (in increments of 0) and maximum value of 255 (in increments of 255) into five ranges (256/5 = 51.2 rounded to 51) presented in table 2

Table 2. Pixels are classified according to the range values.

Range number	Starting	End
1	0	51
2	52	102
3	103	153
4	154	204
5	205	255

Using above schemes, clustering is done with individual layer using equal interval (slice) values.
The similarity measure on clustered object is attempted using the following procedure.
Step 1: Fetch the MRI image
Step2 . Convert the fetched image into the nrrd file format.
Step 3 : Convert and represent the images into cubical data set.
Step 4 : Adopt the liner data set and compute the cluster index.
Step 5 : Generate clusters using equal interval algorithm.
Step 6 . Determination of similarity between different levels of clusters

2.3.2 Procedure for Equal Interval Method

i. Additionally, collect the pre-process MRI and process-able images together.
ii. Two layers of the integrated image need to be converted into the Digital values.
iii. Two-dimensional array is obtained by converting the cubical values (Number of Pixel ,5)
iv. Each row indicates values for (X,Y,R,G,B).
v. The goal of the NC was to process the number of categorizations targeted at.
vi. Having Determined the Min and Max values from the Digital data, find the range (Rng).
vii. Max minus Min yields dx, which is the difference between maximum and minimum.
viii. The range is equal to the product of the distance travelled and the velocity. "For every classification, find the range values, and start and end pixel values for each classification are then adjusted accordingly.
ix. Process all row values and make sure that the range is correct. Classification data and sub-image may be constructed by using individual and combinational range values.
x. until all the categorization to be processed has been repeated.

For the equal Intervals classification technique, each interval gets assigned the same width (width=Range/n). The initial values and the given intervals 'n' are applied to the input matrix.

3. RESULT AND ANALYSIS

3.1 Frame **STRUCTURE**

The converted frames are used to extract the digital values of each pixel and constructed a macro array as described in the methodology. The frames are extracted for gray scale image similarly the RGB images also extracted based on the .nrrd file attribute and its structure.

The selected source. nrrd format file contains the following properties.

File name : brain_1. Nrrd;Dimension: 3;Encoding : raw;Sizes : 304 x 493x 139;Type: uchar

The Converted sequence of RGB frames for 1 to 56 is shown in figure 4.

Figure 4 Converted RGB frame 1…56 from .nrrd file.

The Converted sequence of RGB frames for 57 to 105 are shown in figure 5.

Figure 5 Converted RGB frame 57…105 from .nrrd file.

The Converted sequence of RGB frames for 106 to 139 are shown in figure 6.

Figure 6. Converted RGB frame 06 …139 from .nrrd file.

The converted image frames are selected one after another to process further to construct a multi-dimensional array.

3.2 GENERATION OF FREQUENCY WAVE USING DWT FROM DN VALUES

As per the observation on the converted digital values, it represents the values as per the density of the pixels. The values 0 represent the low level of the density and the value 255 presents the high-level density. The Digital values are presented variation of the neuron process and frequency wave formation processed further. The frames1 consist of 256 rows and 256 columns pixels and the first file has 112 frames.The focal point values selected and constructed as a single dimensional array. Focal point values for 1,1 of sequence frames values are presented in the table 3.

Table 3. DN values for the focal point 1,1

S.No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
DNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S.No	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
DNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S.No	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**
DNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S.No	**61**	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**
DNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S.No	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
DNs	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S.No	101	102	103	104	105	106	107	108	109	110	111	112								
DNs	0	0	0	0	0	0	0	0	0	0	0	0								

The focal point DN values are 0 for all the sequence values. The constructed frequency waves are presented below figure 7.

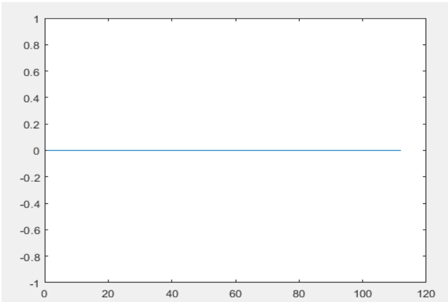

Figure 7 Frequency wave for the focal point 1,1

Although the wave in figure 7 does not have a variation, as shown in the horizontal line at the 0 value, the neuron in the line depicted in figure 7 views that section as an inactive section. Table 4 presents 50/50 focal point values for sequence frames.

Table 4 DN values for the focal point 50,50

S.No	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
DNs	**10**	**10**	**13**	**11**	**13**	**10**	**15**	**18**	**14**	**10**	**11**	**7**	**9**	**12**	**8**	**8**	**9**	**12**	**14**	14
S.No	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
DNs	**16**	**14**	**27**	**15**	**25**	**28**	**11**	**20**	**28**	**12**	**13**	**26**	**12**	**7**	**15**	**9**	**9**	**11**	**14**	13
S.No	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**
DNs	**8**	**13**	**11**	**8**	**10**	**9**	**8**	**11**	**10**	**8**	**13**	**11**	**11**	**14**	**6**	**11**	**9**	**6**	**9**	13
S.No	**61**	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**	**76**	**77**	**78**	**79**	**80**
DNs	**8**	**6**	**10**	**7**	**9**	**8**	**7**	**10**	**7**	**10**	**11**	**7**	**6**	**8**	**10**	**8**	**7**	**7**	**13**	9
S.No	**81**	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**	**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**100**
DNs	**12**	**13**	**12**	**11**	**8**	**7**	**6**	**8**	**6**	**11**	**11**	**6**	**8**	**10**	**8**	**9**	**7**	**7**	**8**	7
S.No	**101**	**102**	**103**	**104**	**105**	**106**	**107**	**108**	**109**	**110**	**111**	**112**								
DNs	**10**	**11**	**7**	**9**	**8**	**8**	**7**	**12**	**9**	**8**	**12**	**11**								

The focal point for 50,50 have a non – zero DN values .It shows that the neurons are active . The non-zero elements are used to form the frequency waves and presented in the below figure 8.

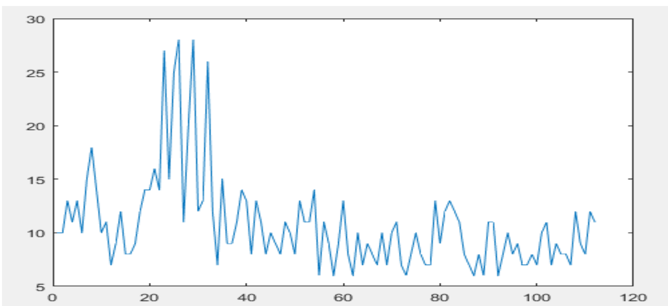

Figure 8 Frequency wave for the focal point 50,50

3.3 ANALYSIS OF NEURON ACTIVENESS USING DWT

As per the apex points the neuron activation attempted to classify as per its density. The constructed active neuron DWT wave forms are presented in figure 9 as follows.

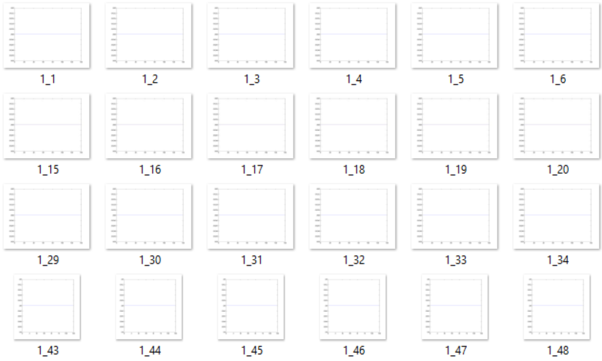

Figure 9 In Active Neuron Discrete Wave Transformation

The above wave shows that the neurons are in active based on continuous Digital values presented in different frames. The coordinate points on the first row of sequence of column generated in active waves, It shows the straight line on zero point values.

Figure 10 Active Neuron Discrete Wave Transformation with single mode

Waves changes figure 10 show that the pixel location of row 109 and column 131 varies across successive pixels. The coordinates for these waves are calculated using the single-mode waves. Only once did the waves' frequency alter during the whole set of observations. In the basic mode, neurons are highlighted, and single point variation is shown in figure 11.

Figure 11 Active Neuron Discrete Wave Transformation with high density and high frequency mode

A visualisation of the waves that go through row 28 and the column 247 forward is given in figure 4.13. The coordinates in this example were created by the waves that had numerous high density, high frequency modes. In the whole observations, the wave's frequency fluctuated regularly. The active neuron display features a higher density of active neurons in several locations shown in figure 12.

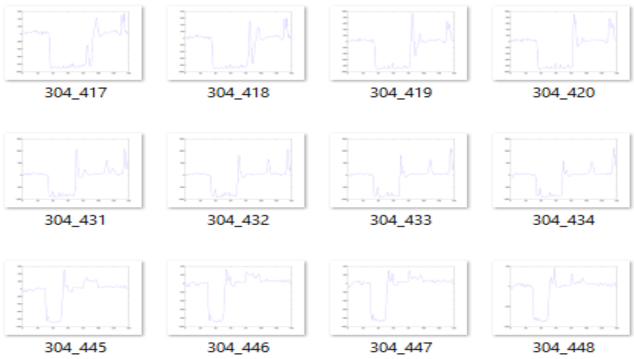

Figure 12 Active Neuron Discrete Wave Transformation with low density and high frequency mode

Low density and high frequency fluctuations are seen in the active state of the neuron shown in figure 12. These coordinates are generated by a set of multi-frequency waves with lower density and higher frequency oscillations. However, the variances are large. Active neurons are located in unusual locations in the low-density frequency mode.

Figure 13 Active Neuron Discrete Wave Transformation with low density and partial high frequency mode

Low density and high frequency fluctuations are seen in the active state of the neuron shown in figure 13. These coordinates are generated by a set of multi-frequency waves with lower density and higher frequency oscillations. However, the variances are large. Active neurons are located in unusual locations in the low-density frequency mode.

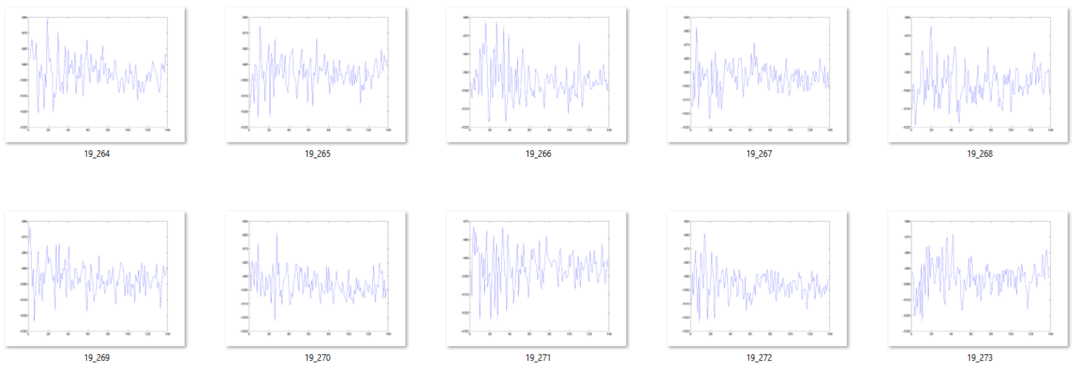

Figure 14 Active Neuron Discrete Wave Transformation with high density and medium frequency mode

The waves transformations of row 19 and the column 264 onwards presented in figure 14, the high density and average level frequency variations on the neuron active state. These coordinates are produced the waves with high density and average frequency variations. The waves are unstable, and the activeness shows the variations. The high-density frequency mode shows active neurons in multiple positions as parts of the transformations.

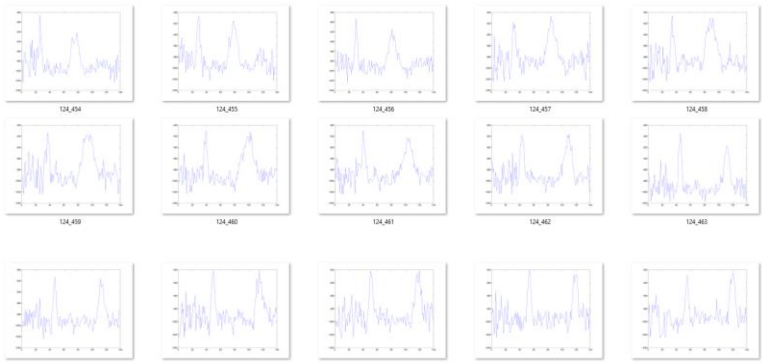

Figure 15 Active Neuron Discrete Wave Transformation with high density and low frequency mode

Figure 15 presents the high density and low-level frequency changes in the neuron's active state as the wave moves along the length of row 124 and down the column 454. The points generated with these coordinates are on the high-density, low-frequency waves. Active neurons are seen in few locations as components of the transformations in the high frequency mode.

3.4 NEURON ACTIVENESS AND STRESS LEVEL COMPUTATION

The stress level of the brain and the activation of the neurons is in direct proportion, which means the total count and its maximum value must be justified, as well as the stress level. In Active, Normal, Low stress, Stress, and High stress are categories used to classify stress levels. If the overall frequency of a particular insight is zero, then the neuron stress level of that neuron is also zero. Between 0 and 13, the overall frequency impression is zero to 13. The stress level is Low when the total frequency intuitions are between 13 and 17. Stress can occur when the overall frequency intuition (above 17, below 25) is above 17 or below 25. The stress level is high if the amount of stress reaches 25 percent. For a better understanding of how the below technique was created and implemented, keep in mind the whole process.

3.5 STRESS ANALYSIS

In light of the investigation, table 5 summaries the computed pixel's DWT waves and related stress levels.

Table 5 Neuron Measures

Frequency Measures			**Activeness Measures**		
Frequency	**Count**	**Percentage**	**Active Stress Level**	**Count**	**Percentage**
High Frequency	48605	74.17	High Stress	46955	71.65
			Stress	1650	2.52
Low Frequency	1164	1.78	Low Stress	577	0.88
			normal	587	0.90
Not Active	15767	24.06	Inactive	15767	24.06
Total	65536			65536	

As per the observation and the analysis of captured brain image has 74.17 % of High Frequency and 1.78 % of low frequency. The remaining 24.06 % neurons are inactive. The high frequency neurons are generated 71.65 % of high stress level activation and 2.52 % of stress level. At the Low frequency, it is found that 0.88 % on the low stress level and 0.9 % is normal. The variation is presented as curve below figure 16.

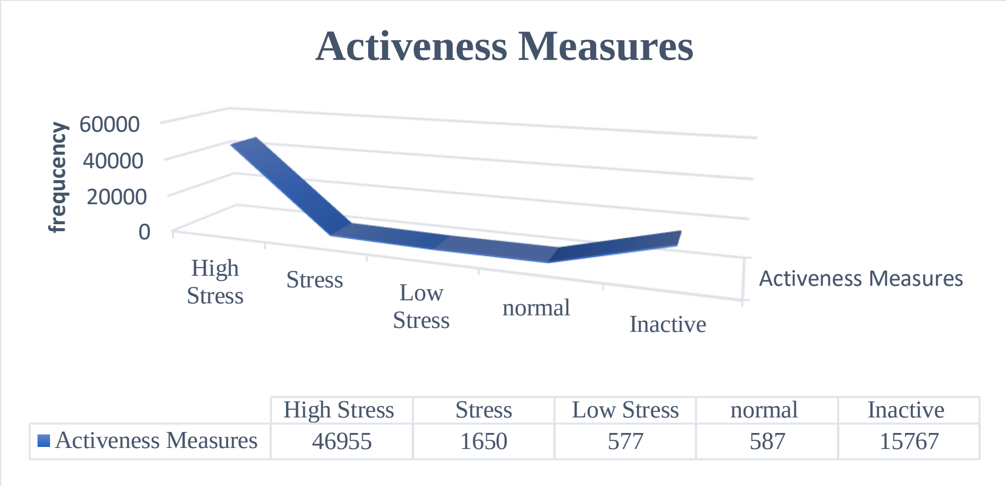

Figure 16 Stress level curve

As per the analysis of the fetched neuron activation and the computed stress level, the values show that 46,955 active neurons are at the high level of stress and 1650 neurons are stress level. Out of 1164 low frequency neurons, 577 neurons are at low stress level and 587 neurons are normal level. The In active 15,767 neurons are not in active therefore it does not create any influence of the stress level. As per observation, the high stress level is high therefore the patient is having high stress level. The above stress level is identified from the malignant patient.

4. SUMMARY

This work presented about the capturing the brain tumor images, conversion of captured images into a sequence of frames, formation of Discrete Wavelet Transformation frequency waves and its analysis. A sample process of conversion and the measures of the activeness discussed. The results of neuron activeness and its stress level determined and presented in the tables and figures. The computation process relationship between the high-level frequency and the stress level also presented. The neuron cluster and stress level computation should be strengthen using other clustering algorithm.

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