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A REVIEW ON BRAIN LESION IMAGE DETECTION USING MRI IMAGES

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Abstract:

Brain tumor analysis is very challenging task in Magnetic Resonance Images because images of brain are complicated, because complexity of the location, shape, size and its texture of tissues which has suffered damage through injury. Brain tumor is recognized by magnetic resonance imaging (MRI) consists of several stages. Segmentation is notable and necessary step in medical imaging for assortment and dissection. Performing the brain MR images segmentation it is very problematic work to find out brain tumor by manually. In present era MRI is very useful tool which helps for brain diagnosis. By Image processing we can able to detect this type of undesirable cells and upbraids the amount it spreads. The image from MRI scan will tell the presence of tumor in the brain, but we have to find the size of that tumor. In this paper, modified image segmentation techniques by applying MRI scan will be able detect the brain tumors. This paper will show how the image from MRI scan is adjusted to suitable contrast and tumor is separated from the original image and in this paper we present a technique for automatic brain tumor diagnostic system by magnetic resonance images. This system made up of three stages to identify & segment of a brain tumor. In very first stage, Magnetic resonance image of brain is received and pre-processing is done to evaluate the noise and also to enhance the image. And the second stage, edges are observed by implementing Gabor filter. In the last stage, Thresholding is the simplest method of image segmentation on the brain tumor. This segmentation increase the brightness of the image of that segment tumor and segmented image more operation by morphological and it remove the extra pixels segments.

Keywords: Segmentation, Gabor Wavelet, Statistical feature, Thresholding, Brain Tumor.

1. Introduction:

Medical imaging is having very important role in finding brain tumors, which helps to look over and reduce the impact of the infections. MRI (Magnetic resonance imaging) is a standout amongst the most effectual medical imaging method. Here it is account of MRI uses no ionizations waves, and it fits for indicating different tissues having a great resolution with great differentiation. Benefit of MRI is that it creates variety of pictures of the identical tissue body with distinctive complexity representation ability by procedure for applying various picture securing rules and aspects. All this individual pictures give valuable extra anatomical knowledge about the same tissue body. Corresponding knowledge from various complexity procedures helps analysts with focusing on brain conditions and processes of a disease more clearly. In managing MRI, the most exacting issues is to segment some specific cells and tissues from whatsoever is there in the images that is why it proceed toward segmentation. The more specifically, image segmentation includes manual or automatic dividing the image into an arrangement of moderately homogeneous body with related attribute, so every one of which can be labeled with a isolated mark. Segmentation facilitate doctors to understand the diseased tissue more simply, so it is an most vital and severe approach in MR imaging. Whereas in manual segmentation, the tumor regions is manually situated on every single adjacent portion where the tumor is deliberate to exist, However this is a costly, long and very time consuming. Furthermore, it is very difficult to labialized tumor by manual variety. So for that purpose we need computerized strategy is required.

Although the fact that there are a few general division techniques, for e.g., thresholding, clustering and region growing methods, and they are not simply suitable to the area of brain lesions recognition. On account of consolidation likenesses between brain tumors and some typical tissues can actuate unsureness is in the applied algorithm. In this methodology we have four basic problems. Firstly, getting the information is not generally possible because of patient's state and the second one is, gathering of multi-spectral magnetic resonance image is high in cost. Whereas in Third more of data is collected which is redundant that grows data processing span and the probability of segmentation faults. And by last multi-spectral MRI information sustain the wrong effects of irregularity and improperly aligned, which needs image improvement and predisposition rectification preceding applying the segmentation implemented algorithm. In this paper we propose an automatic algorithm calculation for tumor recognition and segmentation is formed of 2D single-spectral anatomical magnetic resonance image. The purpose in this paper is to calculate tumor location, tumor segmentation, and efficacy assessment of capabilities. A tumor identification method is observed in view for examination of shared information of histograms of the two sides of brain. After recognition of an image, wherever the injured tumor tissue is, it is putted into the segmentation stage so as to portray the lesion region. We find the applicant tumor areas by using sliding windowing, which clears the entire brain tissue. Where we use proposed post-processing technique is implemented to remove the faulty positives and negatives. This is evident that the attributes of tumor which can be isolated in different class of tissue is immensely essential and depends, on the important decision of taking out the elements to depict the district of attentiveness or semi-homogenous areas. An extensive diversity in region, size, appearance, and apparent of tumor tissue makes quality Extraction a confusing job. In magnetic resonance brain image different tissues, for example, White matter and cerebrospinal fluid is having cumbersome structures that raise the problem of efficient quality/feature extraction. Whereas studies has concentrated on extracting the features that are helpful for tumor segmentation, the significant literary texts has not gave an contrast of which extraction technique is much better for this form of application. We are using the two most well-known type of firmly established and proficient texture form component extraction method. The very first is the Gabor wavelet feature extraction technique that apprehends persistence, area, and its inclination, giving multi-determination texture data for the spatial space and in addition to the frequency domain also. Second one is statistical features which are basically based on using texture based features extraction technique for example, GLRLM (Gray level run length matrix), HOG (Histogram of oriented gradient), LBP (linear binary pattern), and GLCM (Gray level co-occurrence matrix). Here all the given extraction technique shows the relation in between the force of two image pixels or variety of pixels.

Contribution

The methods which we discussed are depend on brain tumor segmentation, like multiple scales classification, local and global registration, multi- spectral MRI information. And in our paper we will discuss few shortcomings as followed. For illustration we can say that our proposed calculation is autonomous of map book enrollment, bunches, and former learning. We have to take care of our mistake in the predisposition stages form which our tumor division accuracy will straightforwardly influence. Further the learning of conditions and calculations that can be prepared to fuse such data. We can enhance some accuracy by our commitment towards computational efficiency, which is depends on single-spectral MRI.

We can say that gathering of multiple MR images is time-and cost-expending, otherworldly MRI information is a great deal and reasonable. No human intercession and additionally completely programmed is our strategy.

Moreover, in this work we utilize have viable composition based factual component extraction strategies for tumor division by utilizing the way that brain tumors frequently have extraordinary structures contrasted with brain tissues attributable to the impact of angiogenesis. Our commitment is correlation of components with the generally utilized

Gabor wavelet highlights. The remaining part of the paper is sorted out after, 2 component extraction techniques utilized. Our tested system (having information planning) are introduced in Section 3. Conclusion is in Section 4.

2. Texture-based Feature Extraction Techniques

In this paper, we are discussing on the two features that is (Gabor wavelet and Statistical feature). In Gabor wavelet feature it using a Gabor wavelet transformation technique. And in Statistical feature, it uses different texture-based feature technique. In this we are using some important methods to know more about the two main feature, those are GLCM, GLRLM, HOG, and LBP.

2.1 Gabor wavelet feature Extraction technique

Gabor wavelet highlight the basic structure of image and it relating to spatial frequency (scales), and the reference of a visual sensation, and still there are research going on it, which includes texture analysis and image segmentations. There are 2 main techniques; two-dimensional Gabor filter is a Gaussian kernel function inflection by a complex sinusoidal plane wave.

$$G(a,b) = \frac{f^2}{\pi\gamma\eta}\exp(-\frac{a^2+\gamma^2y^2}{2\sigma^2})\exp(a2\pi f a^{'}+\phi)$$

Where a and b defined as:-

$a^{'} = acos\theta + bcos\theta$

$b = asin\theta + bsin\theta$

here f is the density of the sinusoid (θ) is the introduction of the direction of the typical to the parallel stripes of a gabor wavelet operation, (ϕ) the stage counterbalance, (μ) is the standard deviation of the Gaussian envelope and (γ) is the spatial aspect ratio which indicates the ellipticity of the support Gabor functions. Ordinarily, analysts use Gabor wavelets channels in five unique scales and eight introductions.

2.2 Statistical Feature extraction technique

- First-order statistical technique

Mean, entropy, average contrast, median energy, skewness and kurtosis are useful first-order statistical features. Mean is the average quantity of the intensity of image. Variance indicates the intensity variations around the mean. Skewness quantifiers are the asymmetry of the histogram around the mean. Kurtosis is the planeness of the histogram. Entropy reveals the randomness of intensity quantity. Formulae for these features are listed as follows

Mean, median, average contrast, energy and selective information, skewness and kurtosis are helpful first-request statistical features. Mean is the normal estimation of the power of the image. Fluctuation indicates the power fluctuation around the mean. Skewness determines the asymmetry of the histogram around the mean. Selective information uncovers the irregularity of force qualities. Some formulae are there for these elements as follows

In mean:

$$\mu = \sum_{i=0}^{G-1} iP(i)$$

In average contrast

$$\sigma^2 = \sum_{i=0}^{G-1} (i-\mu)^2 P(i)$$

In skewness:-

$$\mu_4 = \sigma^{-4} \sum_{i=0}^{G-1} (i-\mu)^4 Pi(i) - 3$$

In energy:-

$$E = \sum_{i=0}^{G-1} [P(i)]^2$$

In entropy:-

$$H = -\sum_{i=0}^{G-1} P(i) log_2[P(i)]$$

here G is the heights gray level of the image and P(i) is the fair chance of density to the intensity levels which is take out from.

$P(i) = h(i)/N$

The total number of pixels with intensity level is denoted by h(i), and the total number of pixels in the image is denoted by (i) and N.

2.3 Gray level co-occurrence matrix techniques

The gray level occurrence of the image properties which are connected to second order statistics, among in all the pixels or the bunch of the pixels (normally 2). In the GLCM is a 2D histogram which exposit the striking the couple of pixels which are distributed by the some distant d.

If we see our example in this $I(a,b)$ is an image and the size are$(M \text{ x } N)$ and it also having a some gray level G . In this $(a_1 b_1)$ and $(a_2 b_2)$ are the tow coordinate of the gray level intensities of i and j. If we take $\Delta a_1 = a_2 - a_1$ in the way towards j, and $\Delta b - b_2 - b_1$ in the way towards b, the it make a straight line and it has the direction θ that are comparable to function $\Delta b/\Delta a$. The simple modification of matrix $C_{\theta j}$ s determine as:

$C_{\theta d}(i,j) = (Num\{((a_1,b_1),(a_2,b_2))(M \text{ x } N) \text{ x } (M \text{ x } N)|\text{A}\}/K$ In this state A is given as$(\Delta a = d \sin\theta), (\Delta b = d\cos\theta,\ Ia1,b1=i,$ and $(Ia2,b2=j)$Furthermore, the number of elements are represented by Num in the matrix and total number of the set of pixels. Here d=1,2 and $\theta = 0°, 45°, 90°, 135°$ this degree is use for calculation. There are nearby eight variant texture characteristic which defines co-occurrence of the matrix. Those are defines as:-

Entropy:-

$$-\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} C_{ij} \log 2\, C_{ij}$$

Correlation:-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} \frac{ijC_{Ij} - \mu_a \mu_b}{\sigma_a \sigma_b}$$

Homogeneity:-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} \frac{C_{Ij}}{1+|i-j|}$$

Absolute value:-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} |i-j|\, C_{ij}$$

Inertia value :-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} (i-j)^2 C_{ij}$$

Inverse different:-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1} \frac{C_{Ij}}{1+(i+j)^2}$$

Maximum probability:-

$$\max_{ij} C_{ij}$$

Angular second moment(energy):-

$$\sum_{i=0}^{G-1}\sum_{i=0}^{G-1}(C_{ij})^2$$

Here C_{ij} is the (i,j) the element of the co-occurrence of the matrix.

2.4 Gray level length technical attribute.

GLRLM is a special space second-arrange statistical technical factual system quantitative constant to a spatial area which having a low level. In GLRLM base of the primitive also called gray level run length is thought to be the uttermost collinear supplement set of pixels with the same gray level. In the gray level they runs by differentiate the length and relatedness to the keep going through for a specific gray quality. To figure out the GLRLM, the gray level quantity which keeps going through of different lengths and it should be found out. In the gray level run length matrix of (R(equation), the component (equation) gives an approximate of the number of times a image contains a keep running with a length of l, for a gray level i, toward point h. The gray level run length matrix (equation) are measured for 0°, 45°, 90° and 135°. There are five techniques to measure the GLRLM.

(1) SRE:- Short Run Emphasis.

$$RF_1\big(R(\theta)\big) = \frac{1}{T_P}\sum_{i=0}^{G-1}\sum_{l=1}^{N_R}\frac{r'(i,l|\theta)}{l^2}$$

(2) LRE:- Long Run Emphasis.

$$RF_2\big(R(\theta)\big) = \frac{1}{T_P}\sum_{i=0}^{G-1}\sum_{l=1}^{N_R} j^2 r'(i,l|\theta)$$

(3) GLD:- Gray Level Distribution.

$$RF_3\big(R(\theta)\big) = \frac{1}{T_P}\sum_{i=0}^{G-1}\left[\sum_{l=1}^{N_R} r'(i,l|\theta)\right]^2$$

(4) RLD:- Run Length Distribution.

$$RF_4\big(R(\theta)\big) = \frac{1}{T_P}\sum_{i=0}^{N_R}\left[\sum_{i=1}^{G-1} r'(i,l|\theta)\right]^2$$

(5) RP:- Run Percentage.

$$RF_5\big(R(\theta)\big) = \frac{1}{T_P}\sum_{i=0}^{G-1}\sum_{l=1}^{N_R} r'(i,l|\theta)$$

In this G is the total number of gray level and total number of run length in the matrix is denoted by (Nr) and Tp is

$$T_P = \sum_{i=0}^{G-1} \sum_{i=1}^{N_R} r^{'}(i,l|\theta)$$

By doing this experiment we will deduct the above techniques of GLRLM.

2.5 Histogram of oriented gradient technique

In Histogram oriented gradient components are spotlight as frequently as possible utilized of the object and for image processing and for digital vision. The basic need of this technique is to find out the local object appearance and the shape can be represented by a distribution of intensity gradient or edge direction. The procedure ties up frequencies of angle, introduction in limited bits of an image. This is the feature framework of consistently separated cells, and uses covering nearby contrast standardization for higher exactness. In Histogram Oriented Gradient, a image is isolated into small, joined areas called cells, and for every cell a histogram of slope headings or edge introductions is ordered for the pixels inside the cell. The accumulation of these histograms then constitutes the information. For enhanced exactness, the local histograms can be complexity standardized by computing a measure the force over a bigger region called a block, afterward the utilizing this quality to standardize all cells inside of the block.

2.6 Linear Binary pattern features.

In Linear Binary Pattern function slumber a window over the image and offers names to important pixel of the window by thresholding its local with the important parameter and determining binary numbers for its neighbours. At that point the LBP measurement the sum of the double numbers increased by forces of two expanding clockwise or anticlockwise. The histogram of these 256 variant names is utilized as a texture descriptor. As we considered the locals can be in variant sizes. Any radius and any number of pixels are use in local variable can be used. In this we mention (L,O) for the local pixels, in which L is a pick point on s circle and O is a radius. The value of the LBP code of pixels are $(a_c b_c)$.

$$LBP_{L,O} = \sum_{L=0}^{L-1} S(g_p - g_c)\, 2^L$$

$$S(x) = \begin{Bmatrix} 1 & if\ x \geq 0 \\ 0 & otherwise \end{Bmatrix}$$

Here g is the pixel magnitude value, we have chosen P=2 and R=1 on this experiment.

3. Experimental techniques

3.1 System overview

The presented automating algorithm involve detection of segment carrying tumor, Magnetic resonance images severity normalization, feature extraction, windowing, dimensionality reduction and feature efficacy estimation. Our presented technique for tumor slice identification is depended on histogram asymmetry between two brain divisions. First we break the brain into two divisions by looking for the lengthy diameter like the brain midline. To detect histogram asymmetry, division are obtained for each of the histograms. After this, using collective data of their histograms, the slice possible to involve a part of the tumor is obstinate.After identifying of a slice, which contains tumor tissue,the slice is used for the segmentation level, which contains the tumor part. We find the candidate tumor area implementing the sliding window which ranges over the all brain tissue in the identified slice. Tumor analysis access explained below is implemented then to each of the window instance. In case the window is confidential to have tumor, the key pixel of the window will be determined as tumor, while on other hand, In case it is defined as healthy, the key pixel will be specified as healthy. The given post-processing technique is implemented to evaluate the faulty positives and negatives.

Also we detail a study where we correlate the performance of Gabor wavelet method with statistical features, these both are successful and efficient method of texture based features in detecting tumor segmentation. There is different analysing method like SRC, KNN, NSC and K-means clustering are implemented for competence assessment of the two features. And then final results are correlated using three performance principle explained below.

3.2 Performance Criteria.

In both the feature the goal is to find the best capabilities for finding the exact MRI lesion segmentation. We are going to measure the capability of using a period’s algorithm. And also we are using three basic spectacular criteria.

- Sensitivity
- Specificity
- Accuracy

True Positives (TP) = correctly categorised positive example,

True Negative (TN) =correctly categorised negative example,

False Negatives (FN)=incorrectly categorised positive example,

False Positives (FP) = incorrectly categorised negative example.

Now we are going to allocate the values on True Positives, True Negative, False Negatives, False Positives by $x_{TP} x_{TN} x_{FN}$ and x_{FP}. And it defines as

Sensitivity=$\frac{x_{TP}}{(x_{TP}+x_{FN})}100\%$

Specificity= $\frac{x_{TP}}{(x_{TN}+x_{FP})}100\%$

3.3 Tumor cuts detection

The central concept of tumor cut detection depends on histogram asymmetry among the two brain fractions. Splitting the brain into two fractions is accomplished by discovering the longest distance across as the brain mid-line. So as to identify histogram asymmetry, histograms of every fraction is computed. At that point, utilizing common data and resolving the tumor by contain the possible cuts.

There are six stages in our algorithm. In the 1st stage we described the isolation of brain form background. The second uses the middle mass algorithm to discover brain's middle. The third discovers the mind's marginal. And the lengths of every conceivable brain width are decided in fourth stage. The fifth stage assigns the longest breadth as the brain mid-line. The 6th stage assumes the tumor cut taking common data between histograms brain division (any two). By utilizing brain mid-line force for every histogram side division is figured. So, we can say that in both blended and genuine databases we utilize, the quantity is same for all subjects in the cuts. For this situation, we can accept that the comparing cuts for to the same area of the brain, which is approximately comparative structure. This helps us to make high level histograms for the nutritive brain division for all cuts utilizing the preparation information. These high level histograms are thought about by the histograms of the verified information to discover the division consists of tumor and show histogram of nutritive and tumor divisions. This technique can get the exact tumor division, which encourages the division procedure to seek just in the division of hobby. In the event that the quantity of cuts is not reliable, another methodology is to figure the shared data between histograms of the two division of one brain image. For this situation, the entire brain is needed to be seeking by the segmenting algorithm.

The tumor span is identified by this technique relies on upon the edge for the measure of common data. Higher qualities make it less demanding to recognize little tumors, however just at the expense of a sure rate of false positives. Then again, a lower edge averts false positives, however the calculation won't have the capacity to recognize little tumors. This is an exchange off issue as a level of flexibility for the fashioner relying upon the application. In our test case, we picked the limit taking into account perceptions of the preparation information, enduring the framework's inability to identify little and barely apparent tumors.

3.4 Windowing

To create the practice set, we will automatically produce contingent windows containing tumor find each selected division. Here we will have the brain borderline and midline which helps us to bound the windows to only overlay the brain tissue and not its background. For this test, the equal sized window sliding sweeps by all the brain, eliminating the field outside the borderline. Here Gabor wavelet as well as statistical feature is extracted by implementing the feature extraction technique.

3.5 Magnetic Resonance Image Intensity normalization

Expected to inter and intra scan image variations in intensity, after identification of slices which involves tumor, we generalize the magnetic resonance image intensity. Image severity normalization is mandatory in quantitative texture review. There are many Magnetic resonance image intensity normalization techniques: Scaling, contrast stretch, histogram normalization and stretching, Gaussian kernel and at last histogram equalization. The histogram normalization technique gives the good performance in comparison to other normalization technique. For quantitative texture analysis we implement histogram normalization technique that is about shifting and stretching the original picture and histogram in procession to overlay all the level of gray scale in the image. It is defined as:

$$f(a,b) = (GWM - BWM)/(h\_max - h\_min\ )\ (h(a,b) - h\_min\ ) + BWM$$

We are using h(a,b) for histogram of the starting image. F(a,b) is new histogram and h_min and h_max is a small and big gray scale. Based on GWM and BWM, there is new minimum level and new maximum level of image.

3.6 Aggregation of Features

The Gabor wavelet components and statistical components are separated utilizing Gabor wavelet affect, first-arrange statistical caption, GLRLM, HOG, GLCM and LBP systems, as alleged in 2^{nd} section. Gabor-wavelet features are separated due to addition of Gabor-wavelet portions with eight introductions and five other scales on three diverse window sizes as 38x38, 50x50, 70x70 windows. The Gabor highlight vector length is 48, 565, 81, 005, 169,005, as to 38x38, 50x50, 70x70 window area, individually. In the brain MR image Fig. 4 shows the genuine after effects of Gabor wavelet filter on an appendix window.

In the first place request measurable elements incorporate middle, mean, normal differentiation, entropy and force vitality, kurtosis & skewness. By using GLCM quoted in our experiment we applied few angles i = 0°, 50°, 95° and 140°. In every introduction, GLCM lattice and eight inferred components are computed. GLRLM components are computed for 0 °, 50° , 95°& 140°. Separated components are LRE, LRE, RP, GLD, and SRE in different (four) ways. HOG components measure the events of slope introductions in the provincial zones of image. Utilizing 8 introductions and two scale, eighty HOG highlight qualities are removed.

3.7 Features Classification

As classification, there are four managed prosperous methods which are applied and the outcomes are compared. These methods are NSC, KNN, SVM and SRC as well as one separate clustering technique is k-means.

In comparison, count of healthy windows is basically much more than the count of tumor windows, that makes the set of training cumbersome. So to evade the basic problems known to be happen by cumbersome sets of training, we endorsed to avail the same count of healthy window like that of tumor windows. Sample of training are selected on random basis and then a cross validation 10 folded is used to verify the prosperousness in our model. This cross validation also helps to avoid overfitting.

Table-I: Algorithms wise run-time.

Algorithm step	Time(min)
Tumor slice detection	11
Gabor wavelet feature extraction	16
Statistical feature extraction	17
PCA on Gabor wavelet feature	57
PCA on Statistical feature	10

This table shows the run time of the each and every steps of the algorithm of all the features.

4. Conclusion:

A combining robotized system that has the capacity to recognize MR images accommodate tumor and after that accommodate the tumor is executed on T1-w and FLAIR arranged (independently). The uncommon exactly of the calculation in tumor division working together with its low figuring elaboration exhibits the effectiveness of our proposed system. One more important objective is its freedom from map book enrolment, earlier anatomical learning, or tilt revising that limit the general utilization of numerous class systems. One more advantage of the proposed technique is in the utilization of single-spiritual MRI. And when utilizing multi-spiritual MR images location the intensity identified in the middle tumor and active tissues, in various other clinical circumstances stand out kind of material in MR images is gathered because of time, expense, and patient circumstance restrictions. What's more, utilization of multi-spiritual information suggests the need to guarantee that each of the spectra(series) must be accurately enlisted. Furthermore, regardless of some other strategies' requirement for beginning theory, for example, a provided number of tissue classes or an multi-scale division, such inputs is not required in our algorithm. Such things are required for making our algorithm more powerful, as compare to others. We also analyzed the ability and capacity of two other feature sets – Gabor wavelets and statistical features – in programmed division of brain tumor sores in MRI images. Also, the capacity of statistical feature is much lesser than Gabor wavelet-based element. Our correlated results show the accuracy of Gabor wavelet feature is good but statistical features have more accuracy. Our correlated results show the accuracy of Gabor wavelet feature is good but statistical features have more accuracy. An extensive measure of memory is involves by Gabor wavelets elements, these are exceptionally excess and lead to high computational expenses. These perceptions appear to demonstrate that statistical element is adequately sufficient to separate tumor tissues from other tissue sorts in T1-w and FLAIR images.

References:

1. D.P. Acharjya, 2009, Comparative Study of Rough Sets on fuzzy approximation spaces and Intuitionistic fuzzy approximation spaces, International Journal of Computational and Applied Mathematics (IJCAM), Vol. 4 (2), pp. 95-106.
2. A. Kharrat, N. Benamrane, M. Messaoud, M. Abid, 2009.Detection of brain tumor in medical images, 3rd IEEE International Conference on signal, circuits and System.
3. C.L. Chowdharyand D.P. Acharjya, 2016. A Hybrid Scheme for Breast Cancer Detection using IntuitionisticFuzzy Rough Set Technique, International Journal of Healthcare Information Systems and Informatics. Vol. 11(2), pp. 38-61..
4. D. Mortazavi,A.Z. Kouzani,H. Soltanian-Zadeh, 2011. Segmentation of multiple sclerosis lesions in MR images: an analysis, Neuroradiology .
5. C. L. Chowdhary, P. G.Shynu, 2011. Applications of Extendable Embedded Web Servers in Medical Diagnosing,International Journal of Computer Applications, Vol. 38 (6), pp. 34-38.
6. G. Lemiux G., K. Krakow, F. Woermann 1999.Accurate and Reproducible automatic segmentation of the brain in the weighted volume MRI data, Fast. Magnreson Med 1999.
7. Y. Yang, H. Liu, J. Carbonell, W. Ma, 2015. Concept Graph Learning from Educational Data, In Proceedings of the Eighth ACM International Conference on Web Search and Data Mining, pp. 159-168.

8. Y.H. Muftah, M.T. Das, L. Bai, K. Robson, D. Auer 2011. Classification of MR tumor images based of Gabor wavelet analysis. Analysis by Liu 2011.
9. H. Liu, W. Ma, Y. Yang, J. Carbonell, 2016. Learning Concept Graphs from Online Educational Data, Journal of Artificial Intelligence Research, Vol. 55, pp. 1059-1090.
10. C. L. Chowdhary, 2011. Linear feature extraction techniques for object recognition: study of PCA and ICA,Journal of the Serbian Society for Computational Mechanics,Vol. 5 (1), pp. 19-26.
11. Y. Kabir,M. Dojat, B. Scherrer, F. Forbes, C. Garbay, Multimodal MRI segmentation of ischemic stroke lesions.
12. U. C. Sekhar, L. D. Dwivedi and C. L. Chowdhary, 2013. Classification of ECG- Beats using Features from TwoStageTwo-Band Wavelet Decomposition, Journal of Theoretical and Applied Information Technology, Vol. 49(3), pp. 922-928.
13. H. Tang,E. Wu, Q. Ma, D. Gallagher, G. Perera, T. Zhuang 1999. MRI brain image segmentation by multi-resolution edge detection and region selection.Comput Med.
14. C. L. Chowdhary, G. V. K. Sai and D. P. Acharjya, 2016. Decrease in False Assumption for Detection usingDigital Mammography, In Springer Proceedings under AISC series, International Conference on ComputationalIntelligence in Data Mining (ICCIDM-2015), Vol. 2, pp. 325-333.
15. A.W.C. Liew, H. Yan 2003. An adaptive spatial fuzzy clustering algorithm for 3D MR image segmentation IEEE Trans Med imag.
16. C. L. Chowdhary and D. P. Acharjya, 2016. Breast Cancer Detection using Intuitionistic Fuzzy Histogram Hyperbolization and Possibilitic Fuzzy c-mean Clustering algorithms with texture feature based Classification on Mammography Images, AICTC '16 Proceedings of the International Conference on Advances in Information Communication Technology & Computing, August 13-14, 2016.
17. V. K. Leemput, F. Maes, D. Vandermeulen, A. Colchester 2001. Automated segmentation of multiple sclerosis lesions by model outlier detection. IEEE Trans Med imag.
18. C. L. Chowdhary, 2016.A review of feature extraction application areas in medical imaging, International Journal of Pharmacy and Technology, Vol. 8 (3), pp. 4501-4509.
19. C. L. Chowdhary, K. Muatjitjeja, D. S. Jat, Three-dimensional object recognition based intelligence system for identification, Proceedings of 2015 International Conference on Emerging Trends in Networks and Computer Communications, ETNCC 2015, pp. 162-166.