Brain Tumour Detection and ART Classification Technique in MR Brain Images using RPCA QT Decomposition

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Abstract: *In medical field, image fusion is a significant role to analyse the brain tumor which can able to classify cancerous or noncancerous region. It is the method in which many images are integrated to a similar view into single fused image. This image is to decrease the uncertainty and minimise the redundancy while extracting all the useful information through the input source images. The image fusion system is the combination of multi-images with relative data into single image. This method can be used to notice the brain tumor by combining T1 and T2 MRI slice images. In this proposed method, an efficient image fusion method using quad tree decomposition and robust principal component analysis. Tumor segmentation is done using the level set segmentation method. Then the feature extraction is done with the complete local binary pattern approach and pyramid HOG approach. ART classifier is also used to classify the brain tumor to malignant or benign.*

Key Words: MRI T1 and T2 Images, RPCA and QT based Image Fusion, Level set Segmentation, CLBP and PHOG Feature Extraction and ART Classifier.

1. INTRODUCTION

In medical field, image processing method has been developing the significant factors where as in normal medical applications is treatment planning and disease diagnosis. Due to the scientific limits, the feature of the medical-images is typically unacceptable; corrupting the efficiency of the human interpretations and analysis of the health images, needed a value of these images to improve [01]. Now a day's many of them facing the brain tumor disease, this brain tumor can be group of growing an abnormal cells in the head or brain. This is a cancerous or noncancerous. Unlike another cancers, where cancer arise starting from the brain tissues spreads rarely. All brain tumor whether malignant or benign were serious. The tumor grows eventually can compress also damage the other format in the head. There is two varieties of brain tumor such that primary tumor and secondary tumor. The primary tumor will begin in the brain tissues and secondary tumor spreads to the skull from other element of the body.

Tumor analysis will play a critical role as detect the size of the accuracy and position of brain tumor. The medical science has seen a radical growth in biomedical field analytical imaging. In present technologies in computer vision and also artificial intelligence has been effectively place into exercise in the applications are diagnosis disease such that cancer by medical imaging. The major important of the newest development in medical-imaging are to be build more dependable and competent algorithms are used diagnosis tumor in genuine time purpose. Image fusion can appropriate a multi modality images like computed tomography, position emission tomography, magnetic resonance of the image and single photon emission calculated tomography for recognition of brain tumor. However, to identify the tumor different image fusion approaches have developed.

Image fusion is divided into the three types such as pixel, region, and decision level. It has two methods for pixel stage like transform and spatial domain. Spatial domain fusion techniques are easy and fused image which can be achieved by apply the direct fusion rules on the source image of the pixel values like averaging, principal component analysis and linear fusion. However, the main weakness of spatial domain will establish the spatial distortion in fused images and does not supply any information of spectral. Transform domain approach were introduced to overcome the drawback of the fusion method of spatial domain. The pyramid-based and wavelet transform-based approach are mainly used for transform domain method of the fusion [02].

In this paper, proposes a robust method of principal component analysis with quad-tree decomposition based algorithms for image fusion. These algorithms are takes as an input is passed to feature extraction. Then extracted images and fused those images to the tumor detection. Pyramid histogram of the oriented gradient and also complete local binary pattern techniques is used to feature extraction of fused image. After extract the feature, this will apply to the classification using ART classifier then will get a malignant or benign image of brain tumor.

2. LITERATURE SUSRVEY

Zhenhua Guo et.al [03] has concluded modelling of local binary pattern operator and also projected it. They have analyzed a local binary pattern from point of vision, also the local dissimilarity of the sign magnitude transform and subsequently a novel method namely the CLBP. Established sign element is much more significant than the element of magnitude in reverse the local dissimilarity data can describes the conventional LBP_S features would be a more proficient than magnitude of CLBP features. At last, through fusing the CLBP_M, CLBP_S and CLBP_C codes, they could perform a best accuracy of the quality of the organization than the state-of-arts LBP techniques.

Huilin Gao et.al [04] proposed an efficient algorithm for image classification, on the basis of SVM and also fusion of the multi feature. This process of the image feature extraction and explanation are employing the integration process of the pyramid histogram of color (PHOC), pyramid histogram of words (PHOW) and pyramid histogram of oriented gradient (PHOG). A Caltech 101 database is confirmed a validation of this projected method for experimenting. Experimental outputs could be see that accuracy rate of classifier approach is enhanced by usual BOW approach.

Emmanuel J. et.al [05] proves that with some appropriate considerations, it is possible to improve both sparse and low rank components closely to solve very convenient of convex program. They discuss a technique for optimized problems and current applications in video observation of the area. The projected scheme is allowed to identify the objects in the background of the cluttered, and face recognized area, to remove the shadows and specularities in face images.

Atreyee sinha et.al [06] have proposed novel Gabor based shape, color, local and texture feature extraction approach encouraged by the pyramid HOG and fusing with the GLBP features with an optimal feature of the demonstration method. Such that PCA, to offer the GLP of robust and also calculate its performance in six-various color space and also in greyscale. By using three impressive challenges of the datasets are demonstrate that FC-GLP descriptor improve the presentation of the organization in excess of the GPHOG and GLBP descriptors and this can be successful when apply on the objects and view the image classifiers are carried out.

Sugata Banerji N et.al [07] have presented on the texture, color, wavelets and shape of the object and view of the image-classification and also H-descriptor of feature extraction can be developed by principal component analysis method and enhanced fisher model. By fuse the method of PCA feature of H-descriptor in seven-color space will use further integrated the color data. Experimental results were used 3 dataset, the Caltech 256 purpose category of the dataset, Scene MIT dataset and Event dataset of UIUC Sports shows a projected novel image descriptor accomplish a best presentation of image classification than the admired image descriptors such that are SIFT, PHOW, PHOG, C4CC, LBP, object bank and hierarchical matching pursuit.

3. METHODOLOGY

The proposed scheme includes training and testing phases. In training phase the segmented brain tumor samples are applied in to pre-processing step. This pre-processing step can used to resize the image, to convert an image RGB to greyscale and remove the noisy by using wiener filter. Then feature is extracted, once the pre processing stage is done and extracted feature is stored in knowledge base.

In testing phase two input sample images are given to the pre-processing step. This step will remove the unwanted noise and resize the input images also convert the image RGB to greyscale, and then fuse the input images by decomposition of the robust-principal component analysis and the quad tree technique. Fused image is subject to level set segmentation, and then an image is segmented. Where segmented image is gives to feature extraction. Extraction is used to extract the features of image; complete local binary pattern with pyramid histogram of oriented gradient process can apply to feature extraction. Then feature extraction is subject to the classification, ART classifier can be used here for final resultant of an image. Then the proposed block diagram of this paper is shows in Figure 1.

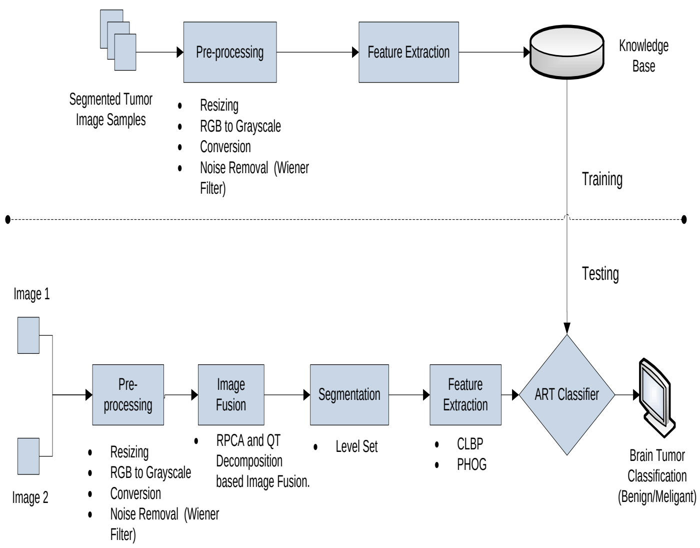

Figure 1 : Proposed Block diagram

3.1 Pre-processing:

This process can perform for filtered noisy; sharpen the edge of an image and artifacts in the image. Also takes place a conversion of RGB to gray and reshape the image. It has a medium filter for removal of noise [08]. The skull removing or stripping is complete by normalising an image which can be fused and fill the inner area of an image. With the use of maximum threshold, the mask process applied to load the mask of image fuses the image which also recovers the estimated original image with no portion of the skull and also noise.

3.1.1 Wiener filter Method

The function of wiener has been derived from wiener filter approach which can be a categorized the linear filter. Apply this filter to an adaptive picture and also adapt itself to a variance of local image. At the low variance the image will get equalized. Similarly it is equalize the image more at high variance. Therefore this wiener filter can provide a best result compare to linear filter and also it's perform is healthy where noise can be constant power of the white noise additive is known as Gaussian noise [09].

Wiener filter represents a coefficient of *w* vector, $y(m)$ is a input filtered signal, $\hat{x}(m)$ is produces a signal output sample, this $\hat{x}(m)$is establishing a least mean square of desires otherwise target the signal of$x(m)$. The correlation between input and the output signal sample of a filter is shows in below equation 1,

$$\hat{x}(m) = \sum_{k=0}^{P-1} w_k y(m-k) \tag{01}$$

In common,

$$\hat{x}(m) = w^T y \tag{02}$$

Then discrete time index is representing with an m, the sample input signal of the filter is shown as $y^T = [y(m), y(m-1), \dots, y(m-P\_1)]$, the vector parameter of $w^T = [w_0, w_1, \dots, w_{P-1}]$ is gives a coefficient vector of wiener filter. In beyond equation is expressing the operation of filter into a two alternatives also corresponding form of the convolution sum with the profit of the inner vector. The signal error of wiener filter, $e(m)$ is define that the dissimilarity between a desired signal of $x(m)$ and the output sample signal of the $\hat{x}(m)$ is given by,

$$e(m) = x(m) - \hat{x}(m) \tag{03}$$

Therefore error filter is given by,

$$e(m) = x(m) - w^T y \tag{04}$$

Where above equation gives a desired signal $x(m)$ and an input sample signal $y(m)$, the error wiener filter $e(m)$ on the coefficient filter of the vector *w*. Then explore the correlation between the signal error $e(m)$ and filtered coefficient of *w* vector and also expand the beyond equation for the N number of sample signal. The compressed notation of vector matrix can be given as,

$$e = x - Yw \tag{05}$$

Where *x* represents a desired signal, *e* gives an error signal and *Y* is an input matrix signal. Then, final wiener filtered output signal is as follows;

$$Yw = \hat{x} \tag{06}$$

This will assuming an initial input sample signals *(P)* $[y(-1), \dots, y(-P-1)]$ can be known or else set this to zero.

3.2 Image Fusion

In this part, we proposed the system on RPCA and QT decomposition method. The two source input images of the tumor are considered and are pre-processing. Then the pre-processed images are fused by using decomposition techniques as described below.

3.2.1 RPCA

Robust-principal component analysis is one of decomposition based method, which can be proved an effective mode to improve both sparse component and low rank component. Closely from the higher dimension information by determine a principal component of pursuit. Where, the matrix of input information $D \in i^{M \times N}$ has been subjected to the property of low rank. To recover a structure low rank of D, D will be decomposed as,

$$D = A + E, \;\; rank(A) = \min(M, N) \tag{07}$$

Where, '*E*' represents a spare matrix and '*A*' represents principle matrixes. This can be identified the problems to solve the difficulty. Hence Wright has been demonstrating when sparse matrix *E* is sufficient to spare, which can accurately recovering a principal matrix of *A* from the decomposed *D* while solving the optimal problem as follows:

$$\min_{A,E} \|A\|_* + \lambda \|E\|_1 \;\; i.e \; A + E = D \tag{08}$$

The λ is a parameter of the positive weighted, $\|A\|_*$ represents a nuclear model of matrix *A* and $\|E\|_1$ is a first norm of *E* matrix [10].

To solve the semi-definite program of robust the PCA is having a possibility approaches. Interior point process is suggest to the accurate and convergence of rate [John Wright]. This method is used to solve, slight relax version of equation (8), equal constraint is replace with the penalty expression as shown below,

$$\min \mu \|A\|_* + \lambda_\mu \|E\|_1 + \frac{1}{2} \|D - A - E\|_F^2 \tag{09}$$

Where, μ is denoted as a small constant. This method is minimizing a function by designing separable quadratic approximation to an information term $\|D - A - E\|_F^2$ at $(\tilde{A}_k, \tilde{E}_k)$ and is obviously select to achieve junction rate of $O(k^{-2})$. Then those sub problems of the solution is efficiently calculated by soft thresholding (*E*) and singular threshold value.

$$A_{k+1} = \arg\min_A \mu\|A\|_* + \left\|A - \left(\tilde{A}_k - \frac{1}{4}\nabla_A\|D-A-E\|_F^2|_{\tilde{A}_k\tilde{E}_k}\right)\right\|_F^2 \quad (10)$$

$$E_{k+1} = \arg\min_E \lambda_\mu\|E\|_1 + \left\|E - \left(\tilde{E}_k - \frac{1}{4}\nabla_E\|D-A-E\|_F^2|_{\tilde{A}_k\tilde{E}_k}\right)\right\|_F^2 \quad (11)$$

Sub-gradient is having sufficient frobenius norm which can be terminated in the form of iteration. The convergence speed is radically improved via employing the continuation strategy that can be started with the relatively more and geometrically decreases at every iteration until it reach a lesser bound.

$$\left(\tilde{A}_k - A_{k+1} + E_{k+1} - \tilde{E}_k, \tilde{E}_k - E_{k+1} + A_{k+1} - \tilde{A}_k\right)$$
$$\in \partial\left(\mu\|A\|_* + \lambda_\mu\|E\|_1 + \frac{1}{2}\|D-A-E\|_F^2\right)|_{A_{k+1}E_{k+1}} \quad (12)$$

3.2.2 QT Decomposition

Quad tree is an important data construction whereas in each node, leaf is not having children in the tree and single internal node is having exact four children. This decomposition is the technique which can analysis the partition of image to the block that will be large homogenous than that image. In the traditional decomposition quad tree of square image is partition into a four equivalent size of an image and also block will evaluating with certain threshold conditions of the homogeneity sector. Where the block will meet the threshold circumstances that do not sub divide into further, while block will not meet the threshold circumstances can be sub divide into a block of four. Then that blocks will be evaluated by repeating iterative until meet the threshold circumstances.

The complete image can represent the source node where it is separated into four blocks and the homogeneity will not meets the threshold circumstances. Therefore the homogeneity block image will meet the threshold a circumstance is representing with a leaf node. I_0 is a level 0 image. Then the first part $I(k = 1, \ldots \ldots, 4)$ related into a sector of level 1. In level 1, the level0 and level3 blocks of I_1 and I_3 can sub divide into a lesser blocks and are I_{1k} and I_{1k} $(k = 1, \ldots, 4)$ at second level.

$I_0 \ldots \ldots \ldots \ldots \ldots \ldots level\ 0$

$I_1\ \ I_2\ \ I_3\ \ I_4 \ldots \ldots \ldots \quad \ldots \ldots level\ 1$

$I_{11} I_{12} I_{13} I_{14} I_{31} I_{32} I_{33} I_{34} \ldots \ldots \ldots \ldots \ldots \ldots \ldots level\ 2$

In decomposition of quad tree rule, I_{1k} and I_{3k} were later subdivided once they meet the threshold circumstances [10]. Similarly the next step will also be subdivided. In the scheme of the quad tree decomposition, first division will perform based on lowest resolution image then the sub division will perform based on the highest image resolution. This can proved as the decomposition having an advantage of the self adaptation with high speed.

3.3 LEVEL SET SEGMENTATION

The segmentation of level set is presented by osher and sethian for face propagation and can apply to the blurry frames and ocean waves. Malladi applied, this level set to medical imaging field. We describe the boundary segmentation as section of surface where the formed level is zero that known as zero level set. Where, $\emptyset$ correspond to the contained surface as shown below,

$$\emptyset(x,t) = \pm d \quad (13)$$

Where x denotes the position of our image, t represents a time and d denotes the distance between level set zero and x position. If x is level set zero outer, d represents the positive values otherwise it gives a negative sign. Let mark the curve by the location when $\varphi = 0$, to the φ more than time by the chain rule is as given below:

$$\varphi_t + \varphi_x x_t + \varphi_y y_t = 0 \quad (14)$$

$$\varphi_t + (x_t, y_t).\nabla_\varphi = 0 \quad (15)$$

Consider $(x_t, y_t) = n + s$ where the vector normal (n) in the front by the x point and s is several arbitrary vectors. Therefore the s and n describes the complete field of x, in fact those are the real vector domains. Then, this can be written as;

$$\varphi_t + (n+s).\nabla_\varphi = 0 \quad (16)$$
$$\varphi_t + n.\nabla_\varphi + s.\nabla_\varphi = 0 \quad (17)$$
$$\varphi_t + V_n|\nabla_\varphi| + s.\nabla_\varphi = 0 \quad (18)$$

Therefore, V_n and s are representing a two forces which are independent that will progress the surface, where V_n is a scalar vector. The scalar vector of V_n will manage how the surface can faster and shift in regular direction. The s vector can be the other force that dictates in both directions and growth of speed. Then, equation of incomplete differentiation can solve the primary condition $\varphi(x, t = 0)$. Since, the segmentation will get reduce into the initial value to solve a problem.

3.4 FEATURE EXTRACTION

After segmenting an image, it can be subject to the feature extraction. This extraction is carried out with the CLBP and pyramid histogram of the oriented gradient methods, explained as follows.

3.3.1 Complete Local Binary Pattern (CLBP):

The CLBP defines a complete local binary pattern. This is used to improve an effective texture analysis. The complete local binary pattern will representing a local area with central pixel and differentiated among the values by the central local pixel with the magnitude is known as difference sign magnitudes transform and it denotes as LDSMT. Figure 2 represents a general flow chart of complete local binary pattern. The CLBP is having a three various mechanisms such as CLBP-S, CLBP-M and CLBP-C. Whereas the CLBP-S illustrates the sign values like positive or negative differences among a local pixel and centre pixel. CLBP-M gives dissimilarity among the magnitude of centre pixel and local pixel. CLBP-C implies the difference among the average central pixel and local pixel values. CLBP-S is a normal LBP as follows,

$$LBP\_S_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c)2^P, \tag{19}$$

$$where\ s(x) = \begin{Bmatrix} 1, if\ x \geq 0 \\ 0, if\ x < 0 \end{Bmatrix}$$

CLBP-M is calculated and is as similar as the CLBP_S, but this will contract with the magnitude differences as shown as,

$$CLBP_{M_{P,R}} = \sum_{p=0}^{p-1} t(m_p, c)2^P \tag{20}$$

$$where\ t(x,c) = \begin{Bmatrix} 1, if\ x \geq c \\ 0, if\ x < c \end{Bmatrix}$$

Then the threshold is to be resolved adaptively with the magnitude component. The centre image pixel is having a discriminate data. The CPBP_C [11] is as follows;

$$CLBP\_C_{P,R} = t(g_c, c_t) \tag{21}$$

The equation 21 defines the threshold to compute the average gray level of complete the image.

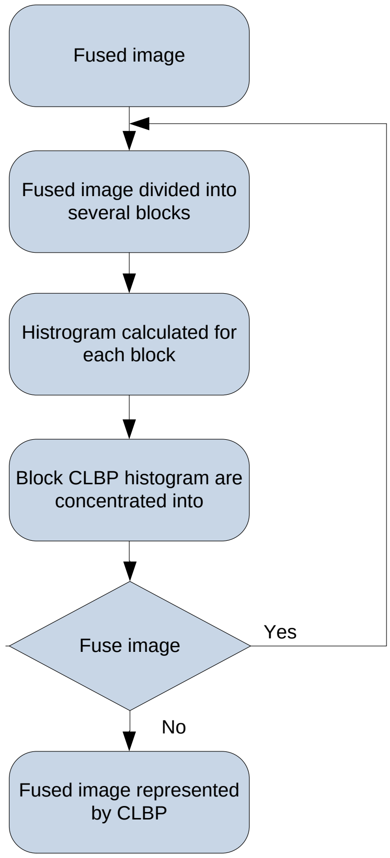

Figure 2 : Flow Chart of CLBP

3.3.2 Pyramid Histogram of oriented Gradient (PHOG)

HOG is proposed for the pedestrian identification in the static videos or the images. The approach will count the amount of times; the oriented gradient is arrived in local images. Therefore it is an effective process to explain the shape which is having the information of an image.

The data allocation of the gradient or edges is extracted only for the local area of the image that is best characterization of an arrangement that supposed to be an edge or the gradient of an object in local region. Therefore it achieves to show the shape of an object. Initially the complete image has to segment the image into dense grid of the consistent where the spaced cell and gradient path will divide in to K bins. Therefore all pixels of the gradient in any cell can be calculated to generate an oriented gradient which can be measured as K-dimension feature vector into a model of descriptor for each cell. Finally, all cells of the oriented gradient descriptor will interconnecting to represents the vector feature of sub images. The histogram of an oriented gradient is having a better robustness beside the illustration and also changes in geometric.

Histogram of oriented gradient is measured as the spatial distribution image information, but it will not take a description on classification performance that causes a spatial scale division in different directions of an images. Since the Bosch proposes a shape feature that describes both the spatial with local image and is known as the Pyramid histogram of oriented gradient.

Initially an image is needed to generate a pyramid image which can be hierarchically partitioning to quad tree of the multiple stages of sub blocks. Then, extract a feature of HOG from each cell in each levels of the pyramid image. Then combine the multilevel HOG of various stages from the lowest resolution to highest resolution to form the image feature of the PHOG. To explain the shape and edge of the image for the PHOG with the increase of the partition stages is more refining and localized.

Algorithm steps for Pyramid Histogram of Oriented Gradient:

Step.1. Initially, the pyramid of the hierarchical images has built for the grid partitioned.

Step.2. Source images are partitioned the hierarchical form to multistage sub blocks of the quad tree.

Step.3. By edge detection, algorithm is extracting the contour edge of images into every partition level.

Step.4. Compute the gradient way, amplitude of every pixel edges and also the gradient scope direction $\theta(i,j)$ is [0,360] or [0,180] this is separated into k-intervals.

Consider the number of pixels of the gradient direction $\theta(i,j)$ will get the values in each interval. The gradient amplitude of every pixels in every interval of weight will corresponds to an interval that can be represents the gradient ways of histogram as shown below,

$$M(i,j) = \sqrt{I_i^2 + I_j^2} \tag{22}$$

$$\theta(i,j) = \tan^{-1}\frac{I_j}{I_i} \in [0,360] \tag{23}$$

Histogram of the all partition levels of the images are normalised, those normalised weight of the HOG in l th stages is $2^{\frac{1}{L-l+1}}$. Successively, concentrate on those histograms to achieve the final shape of pyramid of HOG description of the histograms.

3.5 ART Classifier

ART defines an adaptive resonance theory will build decision tree and can be used greedy algorithm but every decision should not revoke at once. Therefore this can employ an association-rule of mining algorithm to powerfully construct partial classification models and also it has a requirement of the typical user. The specified thresholds are using in minimum support for frequent item-sets, association mining rule and association of minimum confidence rule. In this theory min-support threshold gives a percentage of present size of the data set and it inhibits the factor of the branch tree. Since, the primary keys or student keys in input of dataset do not selected with ART.

4. EXPERIMENTAL RESULTS

The result is done by the database of the dataset. Initially pre-processing step is done by the conversion of RGB to greyscale and filtered, then fusing this filtered image by using RPCA and QT technique. The fuse image provides the level set segmentation. Then segment image can extract the feature by the ART classification; finally will get the detection of tumor in a brain image that is malignant or benign. The figure 3, figure 4, will gives a complete dataset of the brain tumor detection. The Figure 3 (a) and (b) shows an input two images and once pre-processing is done, will get filtered images is shown in figure (c) and (d). Figure (e) will give a fuse image with the help of RPCA and QT decomposition method. Then fusing an images to get the segmented images is shows in figure (f) and figure (h) is the tumor segmented image, then checks the detection of brain tumor image and gives information either it is malignant or benign that is shows in (i).

Similarly, in Figure 4 same functional steps are repeated with another datasets. In which each functional output of corresponding given dataset is pictorially presented.

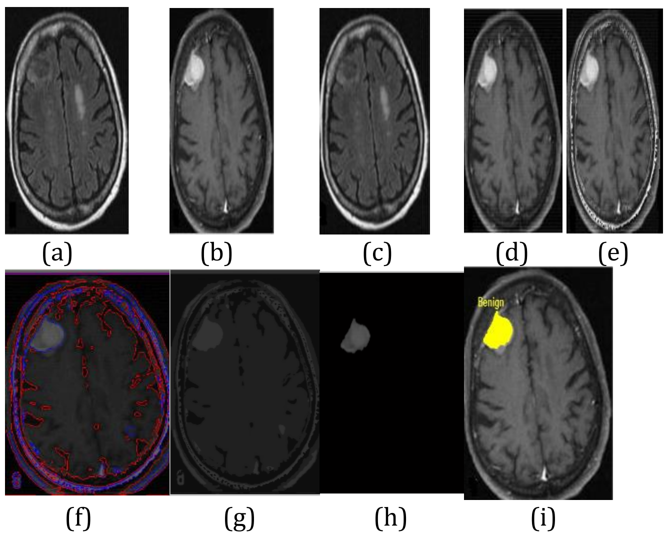

Figure 3: (a) Input T1 Image (b) Input T2 Image (c) Filtered T1 Image (d) Filtered T2 Image (e)198 Iterations in Fuse Image (f) Level Set Segmented Image (g) Segmented Tumor Parts (h) Validated Tumor Part (i) Selected Region of Tumor

The segmentation of level set algorithm endure 200 iterations to find the tumor region part is shows in (f) and finally gives an output of it shows in (g). This segmented region can be whether malignant or benign, therefore it detects the feature extraction of brain tumor is using a technique of CLBP and PHOG then it passes to the ART classifier to classify either it can be malignant or benign. The detected area is shows in (i)

The algorithm is evaluated on various MRI images consisting of tumor regions. Experiments gives that the projected system gives better results when compared than the previous systems.

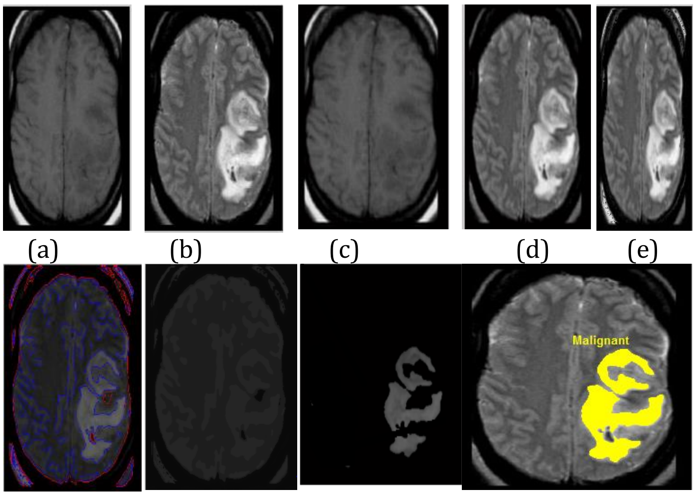

Figure 4 : (a) Input T1 Image (b) Input T2 Image (c) Filtered T1 Image (d) Filtered T2 Image (e)198 Iterations in Fuse Image (f) Level Set Segmented Image (g) Segmented Tumor Parts (h) Validated Tumor Part (i) Selected Region Of Tumor (j) Detection either Malignant or Benign

The evaluation metrics of accuracy, precision, sensitivity, specificity and recall are assured in terms of the T_p,T_n, F_p and F_n. Sensitivity is the ratio of true positives that can be correctly recognized with the analytic trial. It denoted that how the test image is detecting a disease.

$$Sensitivity = \frac{T_p}{T_p + F_n} \tag{24}$$

The Specificity defined as the ratio of true negatives exactly recognized with the analytic trial. It denoted that how best the test is detecting normal (negative) case.

$$Specificity = \frac{T_n}{T_n + F_p} \tag{25}$$

Accuracy can be defines as the ratio of true results, either true negative or true positive, in a population. It can evaluate degree of the veracity of analytic test on the shape.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{26}$$

The Precision and recall formula is shows in below,

$$Precision = \frac{T_p}{T_p + F_p} \tag{27}$$

$$Recall = \frac{T_p}{T_p + F_n} \tag{28}$$

Table 1 : Proposed Confusion Matrix

	T_p	T_n	F_p	F_n	Total
Dataset 1	24	12	1	1	38
Dataset 2	20	11	1	1	33
Dataset 3	23	9	1	1	34
Dataset 4	19	13	1	1	34
Dataset 5	28	11	1	1	41
Total	114	56	5	5	180

Table 2 : Different datasets for the

	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Recall (%)
Data set 1	94.73	96	96	92.30	96
Data set 2	93.93	95.23	95.23	91.6	95.23
Data set 3	94.11	95	95.83	90	95.83
Data set 4	94.11	95	95	92.85	95
Data set 5	95.12	96.55	96.55	91.66	96.55
Average	94.4	95.55	95.72	91.682	95.72

Table 3: Comparison table for proposed and existing method of Accuracy

Paper	Year	Methods	Accuracy (%)
Comparative Analysis of Classifier Performance on MR Brain Images [12]	2015	Association Rule (AR) based NN classifier	83.7
Brain Tumor Detection Using Hybrid Techniques and Support Vector Machine [13]	2015	C-means Segmentation algorithm	88
Implementation of	2016	Adaptive K-	88.67

Clustering Techniques For Brain Tumor Detection [14]		clustering	
Gender classification from an iris images by using uniform LBP fusion [15]	2010	Histogram LBP	91.33
Brain Tumor Detection Using Image Segmentation [16]	2016	Particle Swarm Optimization	92.8
Proposed Method	2018	RPCA + Quad tree Decomposition + CLBP, PHOG+ ART	94.4

Table 4: Comparison table for proposed and existing methods of Sensitivity and Specificity

Paper	Year	Method	Sensitivity (%)	Specificity (%)
Comparative Analysis of Classifier Performance on MR Brain Images [12]	2015	Association Rule (AR) based NN classifier	90.27	88
Analysis And Evaluation Of Brain Tumor Detection From MRI Using F-PSO And FB-K Means [17]	2016	Fuzzy Bisector K-means clustering	77	80
MRI Brain Image Segmentation Using Combined Fuzzy Logic and Neural Networks for Tumor Detection [18]	2013	Level Set, Neural Networks, Fuzzy logic	94	93
Proposed Method	2018	RPCA + Quad tree Decomposition + CLBP, PHOG+ ART	95.72	93.682

Table 3, Table 4 represents the comparison for the proposed systems and the existing systems and this gives that proposed system has better results when compared than the previous systems with accuracy, sensitivity and specificity of 94.44%, 91.68%, 95.72% and respectively. Figure 5 and Figure 6 shows the comparison graph of the previous system with proposed method of accuracy, sensitivity and specificity.

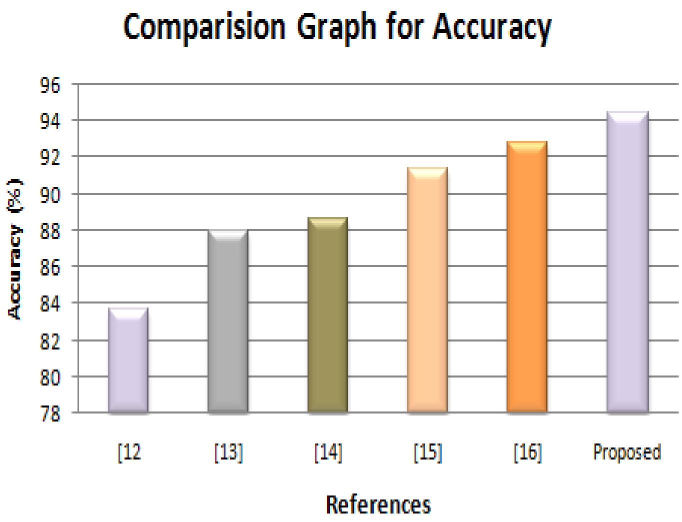

Figure 5: Comparison graph for Accuracy

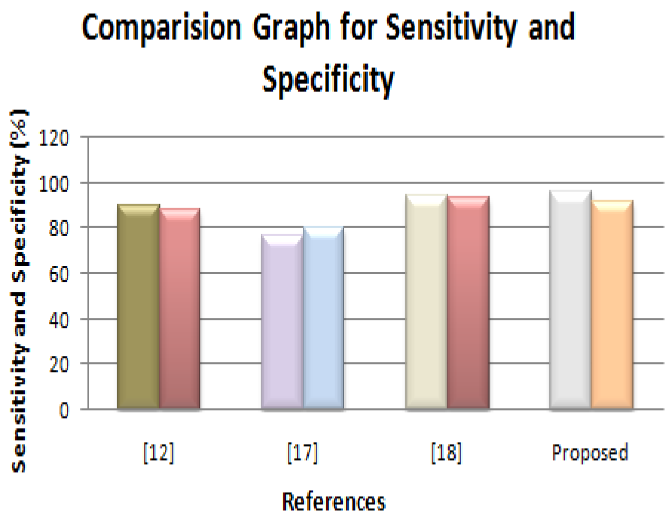

Figure 6: Comparison graph for Sensitivity and Specificity

CONCLUSIONS

In this work, we proposed the technique for the detection of tumor is using a fusion process on the robust principal component analysis, quad tree decomposition and ART classifier that will detect the brain tumor part. Before applying the ART classifier the fuse image will get extracted. The Complete local binary pattern and pyramid HOG approach can be extract the feature. Finally obtaining the cancerous or non cancerous brain images, this provides a better accuracy than the previous methods.

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