International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-4, April 2019

Classification of Magnetic Resonance Images Using Eight Directions Gray Level Co-Occurrence Matrix (8dglcm) Based Feature Extraction

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Abstract*: Classification of MRI images is very difficult due to the variance and various complexities of tumor cells. The proposed classification system is designed for differentiating the brain MRI images into three classes such as Malignant, Benign and Normal. The proposed probability based Support Vector Machine (SVM) includes characteristic Extraction, Best Feature Subset Selection and Classification. In Feature Extraction, most of researchers are using GLCM method for extracting the texture features from an image. Main limitation of GLCM is that, it is computationally very intensive and many of the calculations are done using unnecessary zero frequencies. To avoid the limitations of GLCM, this paper introduces the 8DGLCM for feature extraction. Performance of classifiers is reduced if many features are considered during object identification. Feature Selection method is used to deal with the issues in feature dimensionality by way of selecting the best features subset. Here, Ranking based Particle Swarm Optimization (PSO) is concentrates to choose the best feature subset from an extracted feature. Finally, the MRI images are classified using the probability based SVM classifier. The performance of this method is evaluated based on 7 MRI image sets. An expert radiologist observation is used as reference to evaluate the performance of this system. Final result shows the performance of proposed system is 95.65%.

Index Terms*: Feature Extraction, Selection, Classification, Swarm Optimization, Co-Occurrence Matrix.

I. INTRODUCTION

Tumour identification on brain from the Magnetic Resonance Images is a most important research area in image processing and significant improvement has been achieved during recent years. Early detection of brain tumor will improve the human survival rate and the classification is important for the clinical practice. The correct classification of brain tumor leads to give the correct treatment for the patient. Many techniques have been proposed for classification. This work introduces the probability SVM for tumour classification. It consists of Data pre-processing, Extraction of Features from an image, Feature Subset Selection, Classification and Similarity Measurement [5].

In classification system, preprocessing is the major step to increase the efficiency of tumor classification. The main intend of preprocessing is to remove the noise and irrelevant data from the data set. After preprocessing, the image characteristics are extracted from the images and it undergoes the process of feature reduction for identifying the best set of features to increase the efficiency of classification. During the process of extraction, images are studied using various color patterns, texture and shape features. Extraction is a technique to find out the characteristics of an image and it is used for object description. These features must be invariant to the distortions and variations [2].

An important feature of an image is texture. There are three approaches to analyze an image texture which are namely structured approach, transform approach and statistical approach. In structured approach, the image texture is viewed in the form of primitive texture in some regular or repeated patterns. Statistical approach is the widely used technique to find out the texture of an image. In which, the texture is viewed as a quantitative measure of a region. When compared to extraction, the selection is a method for selecting the best feature subset (‘K’) from an original set (‘M’). In subset selection, the size of ‘K’ is less than ‘M’. In feature selection, searching of feature subsets within reasonable time is very important for applying the feature selection algorithm on data containing large number of features. The image is classified or the set of objects are retrieved from the database using salient features such as image such as texture, shape and color.

This proposed brain tumour classification system uses8D-GLCM for feature extraction, Ranking based PSO method for feature selection and probability based SVM for classification.

II. RELATED WORKS

Image Texture is a significant characteristic for image identification and it provides the visual characteristics of a surface. Commonly used texture extraction techniques are fractals, co-occurrence matrix, gabor filters and variations of wavelet transform [10].The GLCM is used for obtaining texture characteristics of an image. Many features such as correlation, inverse difference moment, angular second moment and entropy can be taken out using GLCM.

Manuscript published on 30 April 2019.
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The collected texture features provide the high dimensional accuracy to find the patterns of an image[8]. Haralick proposed GLCM to extract the features from an image and the main limitation of GLCM is that, it is computationally very intensive and it produces only the global features of an image. Generally, the co- occurrence matrices are sparse matrix and many of the calculations are done using unnecessary zero frequencies [9].

Almuallim & Dietterich(1992) have proposed the exhaustive search to find out best feature subset using some criteria. In this method, the candidate feature set is generated based on some performance measures. Then, the exhaustive search is employed to find out the optimal feature set. This approach is applicable only for smaller feature set. If the feature set is very large, this approach becomes impossible. The problem which is discussed above can be addressed through the method of randomized or heuristic feature set selection. In heuristic approach, relevant features are added or irrelevant features are eliminated from the feature set vector [6].

Apart from the above said few researchers concentrate on population based heuristic search and bio-inspired algorithm for selecting relevant features [11]. Yun et al (2011) has proposed the bio-inspired algorithm such as Particle Swarm Optimization (PSO) andGenetic Algorithm (GA) for feature selection. This algorithm behaves like organisms. It is mainly used to find out an optimal solution. GA is based on the fittest value of a feature and finding the solution using cross over and mutation. The behaviour of the PSO method is same as Swarm of creatures and finding the best solution by using swarm combination. The fitness function for the PSO is computed using several methods such as random selection, probability based methods, etc. At present, some of the researchers use random based methods to select the fitness function of PSO. Sometimes, this method tends to reduce the performance of feature selection. Some of the authors have proposed the Gabor filter approach for object segmentation [12].

III. METHODOLOGIES

The proposed classification system consists of Extraction, Subset Selection and Classification. In feature extraction, 8D-CGLCM is used for extracting the characteristics of the images.

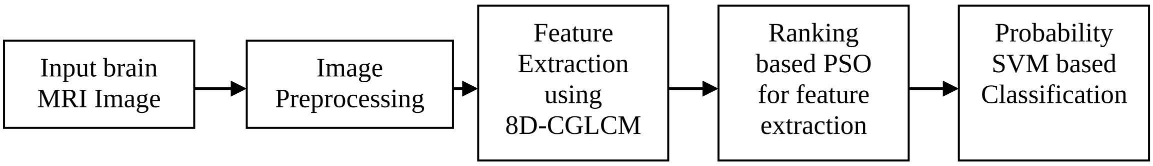

Fig.1. Work Flow Diagram of Classification System

This method solves the limitations of GLCM by using the Ranking based PSO to select the best subset of features from an extracted features and the probability based SVM for tumour classification. Figure 1 shows the work flow of this classification system.

A.8D-CGLCM Based Feature Extraction

The co-occurrence matrix is referred as GLCM, GLCH and spatial dependence matrix. The main purpose of GLCM matrix is to describe the distribution of co-occurrence values of an image. The matrix G is defined an array of ‘iX j’ of an image I.

$$C(i,j) = \sum_{n=1}^{i}\sum_{m=1}^{j}\begin{cases}1 & \text{if } I(n,m) = i \text{ and } I(n+m)\\ 0 & \text{Otherwise}\end{cases} \quad (1)$$

Where,

i , j - image intensity value,

n and m - spatial positions in an image I

Here, concentration is mainly focused on GLCM based texture extraction. GLCM is one of the most basic methods for extracting the image characteristics. GLCM stores the spatial relationship information of pixels. This information is denoted in the form of second order statistical moment. A small 4X4 sub images with 4 gray levels and the corresponding GLCM P (i, j/Δx=1, Δy=0) are shown in Figure 2.

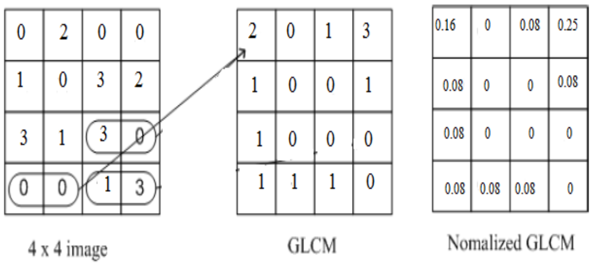

Fig.2.GLCM and Normalized GLCM

The texture feature extraction is mainly used to help the segmentation or classification of images into subparts. This research paper concentrates on a clustering algorithm withCo–occurrence matrix for capturing the numerical measures of a texture using spatial relations among pixels. This numerical measure can be used to compare, represent and classify the textures. In this paper, the combined 8D -GLCM with DENCLUE based algorithm is used for extraction. The purpose of this clustering is to reduce the number of relative zero frequencies among the pixels.Generally,the GLCM is computed using the probability distribution P (d, θ) of clustering image. Here, θ takes the values of 0°, 45°, 90° and 135°. To improve the efficiency of GLCM, the features are extracted from eight directions such as 0°,20°,45°,65°, 90°,110°,135 ° and 150 °. Using GLCM, Haralick proposed thirteen statistical features which are known as Haralick texture features.These characteristics are computed from the clustering image. The features are as follows:

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Angular second moment (ASM) feature

This feature is used to measure the uniformity or energy from an image. Angular Second Moment is very large, if the pixels are very similar.

$$\text{Angular Second Moment} = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} P(n,m)^2 \quad (2)$$

Contrast Feature

It gives the intensity values among pixels and this value will be calculated using colour and brightness of an image.

$$\text{Contrast} = \sum_{i=0}^{M-1} i^2 \left\{ \sum_{j=0}^{M-1}\sum_{k=0}^{M-1} P(j,k) \right\} \quad (3)$$

Entropy Feature

Entropy is a term used in thermodynamics to measure the proximity among the systems or it is used to define the disorder between systems. Higher entropy means greater disorder values. The following Equation is used to define entropy:

$$\text{Entropy} = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} P(n,m)\log\left((P(n,m)\right) \quad (4)$$

Variance Feature

Variance is one of the moments in the distribution. It is used to measure the variation between the pixels. It is similar to entropy measure. It is always a positive
value. If the value of variance is zero, then it says that the values are identical. If the variance is small, then the pixels are very close to the mean and the variance.

$$\text{Variance} = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} (k-\mu)^2 P(n,m) \quad (5)$$

Correlation Feature

It gives the linear dependency among the pixels in the form of matrix. It is used to refer the reference pixels with its neighbour. It takes the value of 0 for no correlation and 1 for perfect correlation.

$$\text{Correlation} = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} P(n,m)\frac{(1-\mu_x)(1-\mu_y)}{\sigma_x\sigma_y} \quad (6)$$

Where

μ_x , μ_y – Mean Value

σ_x, σ_y -Standard deviations

Inverse Difference Moment (IDM) Feature

It is usually called as the homogeneity which is used to measure the local homogeneity in an image. Small IDM value refers to small contributions in the non-homogeneous image and larger value refers to higher value for homogeneous image.

$$\text{IDM} = \sum_{n=0}^{N-1}\sum_{m=0}^{N-1} \frac{1}{1+(n-m)^2} P(n,m) \quad (7)$$

Sum Average

The sum average is defined as follows:

$$\text{Sum Average} = \sum_{n=0}^{2(N-1)} n.\,P_{j+k}(n) \quad (8)$$

(2)

Sum Variance

$$\text{Sum Variance} = \sum_{n=0}^{2(N-1)} (i - \text{Sum Average})^2 P_{m+n}(n) \quad (9)$$

Sum Entropy

$$\text{Sum Entropy} = -\sum_{n=0}^{2(N-1)} P(n)\log P(n) \quad (10)$$

Difference Variance

-

(11)

$$\text{Difference Variance} = \sum_{n-0}^{N-1} (n - \text{Variance})^2 P(n)$$

Difference Entropy

$$\text{Difference Entropy} = \sum_{n-0}^{N-1} P(n)\log P(n) \quad (12)$$

B. Normalization

Normalization is a process of converting all feature values into a specific range. It takes the values from 0.0 to 1.0. This chapter concentrates on min-max normalization method for normalizing all the feature values into a specific range. Equation 13 shows the formula for min-max normalization.

$$B = \left(\frac{A - \text{Min. Value of A}}{\text{Max. Value of A} - \text{Min. Value of A}}\right) * (D - C) + C \quad (13)$$

Where,

B – Min –Max normalization

A – Current feature value

C, D – Normalization range [0.0, 1.0].

C. Ranking based PSO for Feature Selection

In PSO, each particle coordinates are in the form of problem space. This problem space is stored with its best solution achieved using fitness function. This fitness value is called as ‘pbest’. The ~~next best~~ value is tracked by the PSO using its neighbourhood particles. The location of next best value is called as ‘lbest’. PSO considers all the ‘lbest’ and finally computes the global best called as ‘gbest’. PSO starts with random initialization and the swarm moves in the search space to find out best solution by updating the position of each particle using its own experience and neighbouring particles. During each movement of the particle, velocity is changed towards the ‘pbest’ and ‘lbest’.

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The fitness function is represented as $P = F_1F_2F_3....F_N$, where N = 1, 2, 3...., m. The parameter 'P' represents a particle, which belongs to the fitness function of each feature subset. A Value '1' and '0' indicates the selection and '0' rejection of feature subset. In fitness function, the features are selected based on its ranking.

This ranking is performed using gain ratio. The classes are denoted as 'C' and number of images denoted as 'N' for a particular class respectively. The values of M represent the mean of corresponding classes and it can be calculated as follows:

$$\mathrm{Mi} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} M_i, \mathrm{i} = 0,1,2,3, \dots\dots, \mathrm{L} \qquad (14)$$

The grand mean is calculated from the weight factor as follows:

$$\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{Mi} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{L}} W_iF_i, \mathrm{i} = 1,2,3, \dots\dots, \mathrm{L} \qquad (15)$$

Where,

F_i – Features of an image and

Wi – Weight factor.

The scatter function or class separate function 'F' is computed using the following fitness function.

$$\mathrm{F} = \sqrt{\sum_{i=1}^{L}\left((M_i - M_0)^t\,(M_i - M_0)\right)} \qquad (16)$$

The steps involved in the Feature subset selection is shown in Figure 3. This process using the Fitness function and scatter function to find the Global best value using the frequent updating of P_best value. The P_best is updated using velocity and also the position. The current P_best is compared with nearest P_best and it is updated based on velocity and position.

D. Probability Support Vector Machine for Classification

It is one of the methods for classification of both linear and nonlinear data. SVM method uses nonlinear mapping to transform the original data into a higher dimension. In this new dimension, it searches the linear optimal separating hyper plane [1]. This hyper plane is called as a decision boundary for the classes. The probability is included with the SVM for increasing the efficiency of SVM classification.

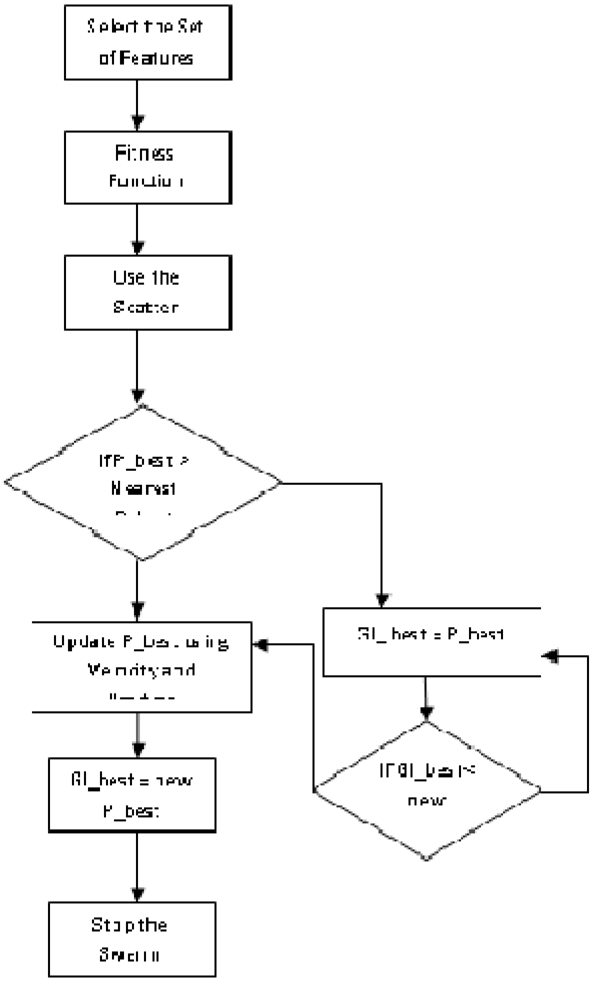

Fig.3. Flowchart of Ranking based Particle Swarm Optimization

Here the conditional probability value is calculated for the input and the output values. Based on these values, the MMH is separated from the hyper plane. The conditional probability is using the following Equation to predict the probable value.

$$P\left(\frac{\mathrm{A}}{\mathrm{B}}\right) = \frac{\mathrm{P(A \cap B)}}{\mathrm{P(B)}} \qquad (17)$$

Where,

P(A)- Probability of Current Feature Value

P(B) - Probability of Predicted Feature Value

The separating hyper plane can be written as follows:

$$\mathrm{W.X} + \mathrm{b} = 0 \qquad (18)$$

Where,

W – Weight Vector and b – Scalar or Bias Value

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IV. SIMILARITY MEASUREMENTS

Similarity measurement is a measure to find out similar images from a database using distance metrics. Here, the Euclidean distance is used to measure such similarities between the images. The following formula shows the Euclidean distance to measure the similarities between images.

$$ED = \sqrt{\sum_{i=1}^{n} (FQ_i - FD_i)^2} \qquad (19)$$

In Equation 19, FQ_i and FD_i represent the features of query and the database images. The objects in an image are identified using this distance metrics. The object that has less distance between them is identified. Similarly all identical objects are identified from an image.

V. EXPERIMENTAL RESULTS

A. Image Database

The proposed classification system is implemented in MATLAB with 7 set of brain MRI image. The MRI images are collected from the BIRN and MR-TIP database. Each database contains 250 brain images for classification. In which, 190 images are used for training and 60 images for testing.

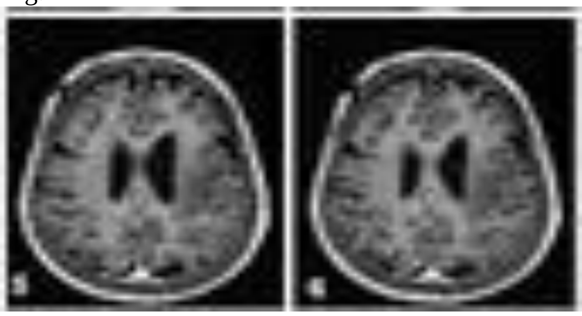

Fig.4. Sample Brain MRI Image

B. Results of Classification System

This work considers thirteen Haralick features from CGLCM at eight directions such as 0º, 20º, 45º, 65º, 90o, 110o; 135o and 150º.This feature is applied on each cluster for obtaining the local descriptors of an image. 416 features from each image are considered. Hence, the total number of features for each training dataset is 2912 and the testing dataset is 2080 for global descriptors of an image. The local descriptors are processed by features in each cluster. Here, the total number of features is 22,880 for training dataset and 8320 for testing dataset. These features are formulated using the offset Δx and Δy in the co-occurrence matrix. Table 1a and 1b shows the extracted values of the brain image.

Fitness function generates 363450 feature subsets for 104 features with 8 combinations. This combination of features is achieved using ranking based feature selection with the threshold value of more than 0.5. Here, the PSO is used to find out the optimum feature subset from various combinations of feature subsets. A fitness function is generated using the weight factor (w). This weight factor (w) is given as w = 0.1, 0.2, 0.3, 0.4... N. This factor is used to find out the mean value of features in an image. The number of selected features is shown in table 3. Figure 3 shows the brain image affected by the tumor.

Table 1.a. Texture Feature Extraction Values for MRI Images using 8DGLCM

GLCM Features	Energy	Contrast	Entropy	Variance	Correlation	IDM	Sum Average	Sum Variance	Sum Entropy	Difference variance	Difference Entropy	Information Measure of Correlation Feature 1	Information Measure of Correlation Feature 2
0º Degrees	0.0732	0.8465	7.6762	143.7472	0.8786	0.7682	188.285	145.4235	7.6792	33.96	7.6923	3.794	3.742
	0.0584	1.7078	7.0281	142.9561	0.7552	0.6986	184.285	146.3621	7.8342	26.78	7.8943	3.482	7.417
	0.0536	2.2202	6.2065	145.6453	0.6821	0.6712	178.934	158.4572	9.0453	56.89	6.2263	3.382	3.51
20º Degrees	0.0508	2.5357	5.0189	138.924	0.6373	0.6545	183.421	154.943	7.4832	48.35	5.1943	4.092	4.618
	0.0486	2.7363	7.8104	142.5834	0.609	0.6417	176.783	162.4329	7.431	42.47	7.4091	4.834	4.382
	0.0496	2.8706	7.9023	141.7652	0.5903	0.6313	186.343	143.452	8.0216	35.57	7.9201	4.612	4.418
45 º Degrees	0.0683	1.04	8.2054	153.5296	0.8505	0.746	178.376	142.6731	8.7267	37.83	8.2054	5.639	4.646
	0.058	1.7471	7.432	147.5432	0.7491	0.6958	181.326	147.2632	8.9265	40.92	7.4331	5.62	4.723
	0.0536	2.2196	5.7203	138.6239	0.6816	0.6702	172.482	162.5622	7.4524	54.43	5.6521	4.852	4.276
65º Degrees	0.0507	2.5289	6.9398	153.654	0.6376	0.6531	174.583	147.5298	7.8231	54.02	6.9332	4.035	4.143
	0.0486	2.7282	7.5407	148.3762	0.6094	0.6414	183.034	138.6392	6.3723	46.78	7.5412	4.821	4.542
	0.0469	2.863	8.832	147.3674	0.5906	0.639	169.403	146.2672	8.5472	46.29	8.0219	5.342	4.754

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Table 1.b. Texture Feature Extraction Values for MRI Images using 8DGLCM

GLCM Features	Energy	Contrast	Entropy	Variance	Correlation	IDM	Sum Average	Sum Variance	Sum Entropy	Difference variance	Difference Entropy	Information Measure of Correlation Feature 1	Information Measure of Correlation Feature 2
90 ^{0} Degrees	0.0844	0.5419	7.3641	139.5287	0.9221	0.8112	162.321	173.6328	6.3614	46.04	7.3439	4.942	4.65
	0.0675	1.0229	6.4198	153.4792	0.8527	0.7437	183.52	143.2135	8.6371	56.73	6.4194	6.723	4.721
	0.0615	1.3481	7.8289	151.3295	0.8057	0.7144	175.326	139.4218	6.7234	56.35	7.8231	4.179	4.943
110° Degrees	0.0576	1.6322	7.3145	143.6734	0.7645	0.6942	183.492	156.3742	7.4327	53.91	7.3127	4.623	4.034
	0.0545	1.8708	8.3672	138.4328	0.7298	0.6764	182.437	145.6297	7.2765	38.58	8.3298	4.672	4.853
	0.0522	2.0712	8.0372	137.5723	0.7006	0.6634	173.492	142.7392	7.3782	43.52	8.3852	4.343	4.905
135 ^{0} Degrees	0.0679	1.0104	8.7209	138.2476	0.0679	0.7447	174.736	148.3747	7.4537	42.83	8.5486	5.624	4.174
	0.0559	1.8421	7.619	143.2509	0.0559	0.6838	169.329	153.7231	8.9354	46.92	7.2549	6.539	4.607
	0.0509	2.3808	6.3954	142.6043	0.0509	0.6543	168.276	146.7256	6.3836	54.49	8.9403	4.628	6.93
150° Degrees	0.048	2.6845	5.2013	139.0378	0.048	0.6366	175.248	153.6237	6.9435	47.89	5.0432	4.567	5.372
	0.046	2.8712	6.8264	143.6092	0.046	0.6241	168.528	143.7245	7.8431	43.65	8.0539	4.543	5.624
	0.0447	2.9986	7.6274	135.3675	0.0447	0.6162	174.261	148.6043	6.4521	44.53	8.952	6.723	4.352

Table 2. Number of Features Selected by Ranking Based PSO

Directions	No. of Features	No. of Selected Features
0o Degrees	104	35
45o Degrees	104	32
55o Degrees	104	30
75o Degrees	104	34
90o Degrees	104	34
135o Degrees	104	28
225o Degrees	104	30
315o Degrees	104	32

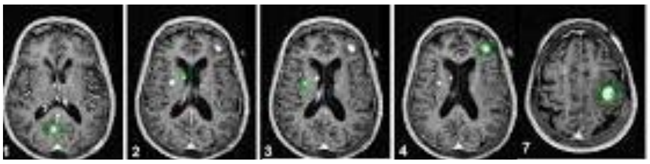

Fig.5. Brain Tumour Classification

VI. PERFORMANCE ANALYSIS

The performance of an algorithm is analyzed using a ground truth. The ground truth refers to the accuracy of the training set in supervised learning technique. This truth is used in statistical models to prove or disprove the research hypothesis. It uses set of measurements to measure the accuracy of object identification system.

There are two ways to generate the ground truth such as generating the ground truth using high accuracy instrument and generating the ground truth manually by human expert for the case in which the results cannot measure by a device. In image processing, the results cannot be measured by a device and it is often measured by human experts or user in the corresponding fields.

The ground truth can be calculated using the measures such as precision and recall. Recall and precision are defined as follows:

Precision is referred as a positive predictive value. It is the number of relevant images that are retrieved from the total number of retrieved images. Equation 20 shows the formula for calculating precision. The recall is a measure of relevant images retrieved from the total number of relevant images from a database. Equation 21 shows the formula for calculating recall. Accuracy of the classification algorithm is calculated as shown in Equation 22 as below.

$$\text{Precision} = \frac{\text{Relevant Image}}{\text{No. of Image}} \quad (20)$$

$$\text{Recall} = \frac{\text{Relevant Images Retrieved}}{\text{No. of Relevant Image}} \quad (21)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (22)$$

Where,

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TP- True Positive

TN – True Negative

FP- False Positive

FN – False Negative

Accuracy is calculated using confusion matrix as shown in Figure 6. Figure 7 and 8 shows the performance of classification system using precision, Recall and Accuracy.

		Predicted Class		
		+	-	
Actual Class	+	4	1	C = 5
	-	2	1	D = 3
		A = 6	B = 2	T = 8

Fig.6. Example of Class Prediction (Confusion Matrix)

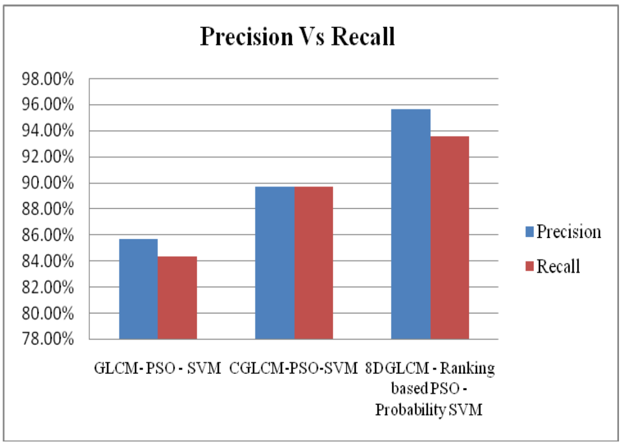

Fig.7. Performance of Classification System (Precision Vs Recall)

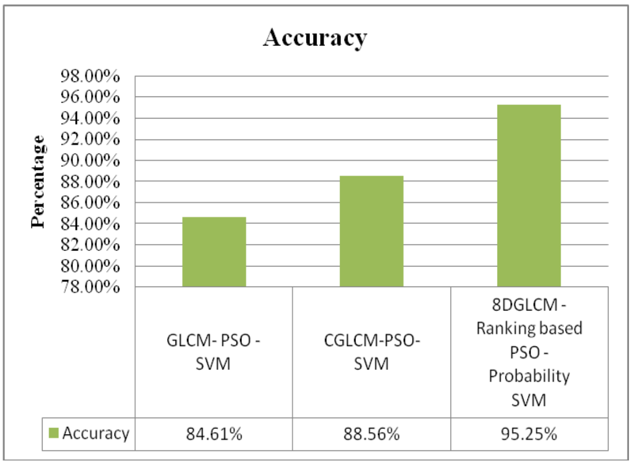

Fig.8. Performance of Classification System (Accuracy)

VII. CONCLUSION

Image classification system is an active research area for the past few decades. Image classification is a process of identifying similar objects in an image based on visual features such as colour, texture and shape. This classification system has got huge impact on diagnosis, object detection, education and research. This research work basically identifies the issues associated with the methods such as Gray Level Co-occurrence Matrix (GLCM) for feature extraction, PSO for feature selection and SVM. The GLCM stores more zero elements in the matrix which consumes more memory space and more computation time. PSO is the most commonly used algorithm for efficient image feature selection. Randomly selected features make the PSO to reduce classifier accuracy during the search process. These problems are solved by 8DGLCM, Ranking based PSO and Probability based SVM. The performance of this proposed system is increased to 95.65% for precision and 93.51% for recall when compared to the existing system such as GLCM-PSO-SVM and CGLCM-PSO-SVM.

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