CHAPTER 2

REVIEW OF LITERATURE

The most important aim of medical image analysis in general, and brain magnetic resonance image (MRI) analysis in particular, is to extract clinical information that would improve diagnosis and treatment of disease. Brain tumors are one of the most common brain diseases, so classification of brain tumors in MRI is important in medical diagnosis. The aim is to provide information about normal and abnormal images necessary to treatment planning and patient follow-up. Despite numerous efforts and promising results in the medical imaging community, accurate classification of abnormalities are still a challenging and difficult task because of the variance and complexity of tumors.

2.1 LITERATURE SURVEY ON MR BRAIN IMAGE CLASSIFICATION TECHNIQUES

Gering (2002) in his research has applied the Expectation Maximization (EM) algorithm in the detection of abnormalities. These algorithms proved to be capable of distinguishing large tumors from the surrounding brain tissues by training exclusively on normal brain images in healthy people in order to recognize deviation from normality. This requires high computational effort.

AN Artificial Neural Network (ANN) approach for melanoma detection has been used by Tomatis (2003). Multivariate Discriminant
Analysis (MDA) is compared with the above said ANN approach. The ANN approach gave more stability and high diagnostic scores when compared with MDA.

Lukas (2004) shows a comparative study of brain tumor classification based on long echo proton magnetic resonance spectroscopy (MRS) signals. Linear discriminant analysis (LDA), support vector machines (SVM) and least squares SVM (LS-SVM) with a linear kernel and LS-SVM with a Radial Basis Function (RBF) kernel. Kernel-based methods performed well in processing high dimensional data. The major limitation was the limited number of available spectra for the tumor types which resulted in inferior classification accuracy.

Majos (2004) has classified four different types of tumor using Linear Discriminant Classifier (LDA) technique, but the classification accuracy reported was 80%. Various reasons for misclassifications were also suggested. As higher level of accuracy would assist physicians, as well as minimize the process of diagnosis this classifier was proved to be less useful.

Sandeep (2006) proposed a novel method using wavelets as input to neural network self-organizing maps and support vector machine for classification of Magnetic Resonance (MR) images of the brain. Classification rate was high for a support vector machine classifier compared to self-organizing map-based approach and major drawback was the low convergence rate.

The application of Kohonen neural networks for image classification has been explored by Messen (2006). Some modifications of the conventional Kohonen neural network were implemented which proved to be much superior to the conventional neural networks.
Ulacl Bagcl (2007) utilized Support Vector Machines (SVM) with linear, sigmoid, RBF kernel functions to classify the images into normal and abnormal groups. SVMs were trained using wavelet features and Gabor wavelet features for linear, RBF and sigmoid kernels. Gabor wavelets perform better than Daubechies wavelets in classification.

Selvaraj (2007) used Least Squares Support Vector Machines classifier as linear and nonlinear Radial Basis Function (RBF) kernels and compared it with other classifiers like SVM Multi Layer Perceptron and K-NN classifier. The LS-SVM classifier outperformed all the other classifiers. LS-SVM had a higher accuracy of classification over other classifiers. The number of false negative in LS-SVM was very low compared to others. The LS-SVM classifier results showed a high degree of sensitivity of the classifier to abnormal images.

Chalabi (2008) compared Self Organization Map (SOM), Linear Vector Quantization (LVQ), combination of SOM and LVQ. The combined approach gave more reduced quantification error and higher rate of recognition classification rate. The execution time of the combined approach was shorter compared to that of LVQ.

The modified Probabilistic Neural Network (PNN) for tumor image classification was used by Georgiadis (2008). Abnormal images such as metastase, glioma and meningioma were differentiated using the least square feature transformation based PNN. A comparative analysis was also performed with SVM. The inference was that the transform based PNN was superior to the SVM in terms of classification accuracy.

A time efficient neural network such as PNN was used by Ibrahiem (2008) for pattern classification problems. Emphasis was given for convergence time than the classification accuracy. The results concluded that
the PNN was superior over conventional neural networks in terms of training time period.

EL-Sayed (2009) compared feed forward back-propagation artificial neural network and k-nearest neighbor (k-NN). The experimental results showed that classification accuracy, sensitivity and specificity was high for k-NN when compared with feed forward networks. The limitation of the work was that it required fresh training each time whenever there was an increase in image database. This method required less computation time due to the feature reduction based on the Principal Component Analysis (PCA)

An enhanced ART neural network for classification applications was implemented by Palaniappan (2009). This employed the Genetic Algorithm (GA) approach to select the order of training patterns to enhance the classification performance. Experiments were conducted on various datasets. But the classification accuracy results were different for different datasets which was one of the drawbacks of this approach.

Brain tumor classification using pruned association rule with Mining Association Rule in Image database (MARI) algorithm was presented by Rajendran (2009). The approach was compared with naive Bayesian classifier and associative classifier. The experimental results showed that the author’s method achieved high sensitivity (up to 96%), accuracy (up to 93%) and less execution time and standard error in the task of support decision making system.

Jude (2010) used Particle Swarm Optimization (PSO) as the optimization algorithm and also used it along with the modified Counter Propagation Neural Network (CPN) classifier. Conventional CPN, Modified CPN, PSO based CPN were analyzed in terms of classification accuracy and convergence time period. Experimental results showed promising results for the PSO based modified CPN classifier in terms of the performance measures
Vijay Kumar (2010) suggested a neuro fuzzy classifier for predicting early brain cancer cells using texture features and neuro classification. A Neuro-fuzzy classifier provided better classification during the recognition process. The considerable iteration time and the accuracy level is found to be about 50-60% improved in recognition compared to the existing neuro classifier.

Jude Hemanth (2010) used first order Sugeno model based Adaptive Neuro Fuzzy Inference System (ANFIS) for brain tumor image classification. The performance measures of ANFIS was compared with the results of the back propagation neural network and fuzzy nearest center classifier respectively. The error rate of fuzzy classifier and the neural classifier was high since they suffered from the drawbacks of random initial cluster center selection and requirement of large training data set. The classification accuracy of ANFIS was comparatively higher than the fuzzy and neural classifiers. The convergence time period of ANFIS was ten times better than the neural and the fuzzy classifier.

Ahmed Kharrat (2010) suggested a hybrid technique designed by the Wavelet Transform (WT), genetic algorithm (GA) and supervised learning methods (SVM). The result of classification of this approach was better than the other ones which were lacking the decomposition stage for classification of the MRI brain, benign or malignant tumor. High sensitivity, specificity and accuracy rates were obtained as well as lesser computation time was observed due to the feature extraction based on Wavelet Transform. The approach was limited by the fact that it necessitates fresh training each time whenever there was a change in image database.

Support Vector Machine based classification of various levels of MR glioma images was performed by Li (2006). Advantage of SVM is automatic discovery of required pattern in the data rather than the manual
experimentation and intuition. This method claimed to be better than rule based systems but the accuracy reported was low. It dealt with only glioma images and thus the lack of generalizing capability was another drawback of the system.

Satish Chandra (2009) demonstrated that the results obtained by using SVM classifier are superior to other classifiers. The author compared the results of SVM with AdaBoost, a machine learning algorithm, for image classification and showed that SVM produced better results. Experiments conducted by Mazzara (2004), Garcia (2004) and Selvaraj (2007) using SVM classifier proved to produce improved results than other existing classifiers.

2.2 FUSION OPERATION IN BRAIN MRI

Dou et al. (2007) presented a work to segment the tumor areas of human brain from MRI (Magnetic Resonance Imaging), based on fuzzy information fusion. For a type of MRI sequence, fuzzy model is constructed at initial stage that describes the tumor characteristics. Fusion operation is executed on the basis of fuzzy fusion operators, which involves different fuzzy information captured from different types of MRI sequence. The segmentation result obtained from the fuzzy fusion of images produces better segmented sequence information, but suffers from poor definition on the tissue distribution.

Another fusion method for automatic segmentation of MRI brain images based on probabilistic model was proposed by Sabuncu et al. (2010). From the given training set of images, training labels were obtained and are then transferred to the test image, which is convolved to calculate the final segmentation of the tested images. This kind of label fusion techniques on MRI produces segmentation result more accurately. This is because of probabilistic framework deployed in this work. Even though the segmentation
is effective in this label fusion method, the label relationship considered is not clearly told.

In general, appearance of brain tumors has a large diversity in shape. To resolve the ambiguities in images, it is necessary to acquire complementary information. Multi spectral images encompass the favor in affording such complementary information. Even though the ambiguity is resolved, redundant information in data processing is effectuated that leads to segmentation errors.

In order to effectively use multispectral MR images fusion of these images is required. Zhang et al. (2009) fused the data using Support Vector Machine (SVM) combined with feature selection in a kernel space. The classification step includes learning of brain tumor and feature selection, automatic segmentation of tumor in new data with the help of SVM, tumor contour refinement using the region growing technique. Even though fusion of data using SVM for the extraction of features yields the improved segmentation results with low cost, time taken to obtain the inputs for the whole process spreads over a long period which is more than a year (Zhang 2011).

Similar to the aforementioned technique of data fusion, Ruan et al (2011) introduced another feature selection based data fusion technique for brain tumor evolution. The difference is that earlier data fusion method used SVM along with kernel space for feature selection but here only SVM is used for classification. Moreover, the system was tested with six feature selection methods to obtain the best segmentation result.

The data fusion process of brain MRI for tumor segmentation resolved the difficulties in tumor segmentation using an improved SVM algorithm, which is integrated with data fusion process. This algorithm
acquires three types of input sources for the process of learning and classification. The MRI sequences given as inputs are T2, FLuid-Attenuated Inversion-Recovery (FLAIR) and PD (Proton Density). Region growing technique was exploited for the process of tumor contour refinement. The empirical results demonstrate the effectiveness of this data fusion method wherein the advanced setting of SVM algorithm increases the cost.

Another fusion of novel fractal features for brain tumor segmentation was introduced by Iftekharuddin, et al. (2009) integrated with intensity values in multi modal MR images. The two novel fractals along with the features of fractal wavelet segment the tumor regions and generate the tumor region from non tumor region through classification.

From the normalized images, three kinds of features were extracted namely, fractal, intensity and fractal wavelet. Later, these features are fused and SOM (Self Organizing Map) neural network was applied in order to obtain the segmented tumor clusters. When the segmentation is over, clusters were labeled as tumor or non tumor segments. MR imaging in this technique lacks a standard interpretation for the intensity value in MR image.

2.3 LITERATURE SURVEY ON IMAGE PREPROCESSING TECHNIQUES

Image pre-processing is one of the preliminary steps which are highly required to ensure the high accuracy of the subsequent steps. The raw MR images normally consist of many artefacts such as intensity inhomogeneities, extra cranial tissues, etc. which reduces the overall accuracy. Several researches are reported in the literature to minimize the effects of artefacts in the MR images.
Yong yang et al. (2006) has used modified curvature diffusion equation as pre-processing technique to enhance and preserve edges in brain MRI.

Ben George (2012) has done the removal of artifacts and modified tracking algorithm as a preprocessing step. The removal of artifacts was used to remove high intensity values from the image and the modified tracking algorithm was used to remove the insignificant portion of the image. Noise reduction is done as pre-processing step in image classification according to Sebe et al.(2000). The author has analysed the use of Gabor and Quadrature Mirror Filter (QMF) for noise reduction purpose.

Sonali Patil et al. (2012) has emphasized the need for pre-processing. The author says the process is needed in order to remove artifacts which hinder further processing of MRI. Pre-processing of images is needed for processing them using Computer-Aided Diagnosis (CAD). The author has used median filtering and square shaped structuring element as a pre-processing step.

Jaya et al. (2009) have used removal of artifacts as a pre-processing step. The author has set a threshold value of 255 for artifacts removal and a threshold value of 200 for the removal of unwanted portion of the image. Author Ratan (2009) has used a different type of pre-processing for reducing the processing amount of data. A total of 128 images were processed into 3 clips.

In Stefan Bauer et al. (2013) survey paper, the author has analysed many papers that had dealt with image preprocessing technique. The author says that even though many techniques remove noise, they introduce a negative effect on the segmentation of the image.
Jiang (2004) implemented colour ray casting method in order to differentiate the region of interest from the background as a preprocessing step. But this technique was image dependent and not applicable for gray level images.

Greenspan (2006) used a fully automated technique of Expectation Maximization Segmentation (EMS) software package for image preprocessing. But this technique did not reduce the size of the image considered.

Fuzzy connectedness based on intensity non uniformity correction has been implemented by Zhou (2006) as a preprocessing step on brain MRI. A sequential approach with fuzzy connectedness, atlas registration and bias field correction has been followed. Limited range of intensity value variations was a drawback. To overcome this drawback weighted least square estimation method was used by Morris (2006). Here again the selection of weights was a major disadvantage.

Wavelets and curvelets were used for preprocessing step by Zhang (2007). The author also makes use of Hybrid approaches involving Variance Stabilizing Transform (VST). But the approach is restricted to only those images with Poisson noise.

A contrast enhancement is done as preprocessing for contrast agent accumulation model by Prastawa (2009). This improved only the contrast of the image and the unwanted tissues were not eliminated.

Apart from noise removal, several other pre-processing steps are also reported in the literature. This includes image format conversion, image type conversion etc. The combination of three modalities of MR images as a basic preprocessing was suggested by Ratan (2009).
All the above mentioned techniques remove only specific artefacts which is not sufficient for high classification accuracy and segmentation efficiency. Apart from eliminating the noises, techniques for the removal of unwanted tissues such as the skull tissues in MR images are highly essential for accurate identification of the diseases.

Co-occurrence texture features were used for accurate identification of diseases in brain MRI.

Co-occurrence texture features ware combined with bidirectional associative memory-type artificial neural network to classify the soft tissues in brain CT images (Sharma, 2008). It was combined with grey level and new edge features and classified using SVM for brain CT images (Padma Nanthagopal, 2012). Rajendran (2009) combined co-occurrence texture features with Naive Bayesian classifier to classify benign and malignant tumor images. Kharrat (2010) combined co-occurrence texture features with SVM classifier to classify normal, benign and malignant tumor images. Padma (2011) combined co-occurrence texture features with probabilistic neural network (PNN) classifier to classify brain CT images.

Choplet (2006) combined wavelet based co-occurrence texture features with SVM classifier to classify the magnetic resonance images. Padma (2011) combined co-occurrence texture features with bidirectional associative memory type artificial neural network to classify the brain tumor in CT images.

Padma (2011) combined dominant run length texture features with support vector machine (SVM) classifier to classify the brain CT images.

In all the above said methods co-occurrence texture features had the disadvantage of choosing the angle and direction and the number of features
were very large. Only some features were selected for further processing. In this thesis the use of 2D-DWT reduces the overall image size thereby reducing the feature space and increases the accuracy in classifying the image.

2.4 CLASSIFICATION BASED ON LOCAL TEXTURE FEATURES

A local feature descriptor describes the visual features of regions or objects which describe the image.

Ahonen (2008) proved that the Local Binary Pattern (LBP) operator could be seen as a filter operator based on local derivative filters at different orientations and a special vector quantization function. A new unified framework for texture descriptors such as LBP and Maximum Response 8 (MR8) based on histograms of local pixel neighborhood properties was presented and showed that when the filter responses were quantized for histogram computation, codebook based vector quantization yields slightly better results than the threshold based approach.

Liao et al. (2009) proposed a novel approach that helped to extract the image features for texture classification. The proposed features were robust to image rotation and also they were less sensitive to histogram equalization and noise. It comprised of two sets of features, dominant local binary patterns (DLBP) in a texture image and the supplementary features extracted by using the circularly symmetric Gabor filter responses. The dominant local binary pattern method made use of the most frequently occurring patterns to capture the descriptive textural information, while the Gabor-based features aimed at supplying additional global textural information to the DLBP features. It was experimentally demonstrated that the proposed method achieved the highest classification accuracy in various texture databases and image conditions.
LBP was used for MR image search and retrieval by Devrim Unay (2008) and the results were encouraging. Zhenhua Guo (2010) developed the completed LBP (CLBP) scheme for texture classification. Further, they (Yimo, 2012) integrated representation capability of texture features with local ternary pattern (LTP) to derive new image features for texture classification.

LBP and intensity histograms were combined by Lauge Sorensen (2010) for showing an improvement in quantitative measures of emphysema in CT images of the lungs and were successful.

Subrahmanyam (2012) integrated the Binary Wavelet Transform (BWT) and LBP for feature extraction and called it Directional Binary Wavelet Patterns (DBWP). It was used for biomedical image retrieval.

However, LBP provided all directional first-order derivatives. To address this problem, Local Derivative Pattern (LDP) (Zhang, 2010) was proposed for face recognition. Here the authors considered LBP as non-directional first-order local patterns collected from the first-order derivatives and extended the same approach for nth-order local derivative patterns. This was used for texture classification.

The versions of LBP and LDP available in the literature could not deal with the range of appearance variations that usually occurred in unconstrained natural images due to illumination. In order to address this problem, local ternary pattern was introduced by Tan (2010) for face recognition under different lighting conditions. LBP, LDP and LTP extract the information based on the distribution of edges which are coded using only two directions (positive direction or negative direction).
A variation of LBP version was developed by Suruliandi (2008) named as Local Texture Patterns where there was no splitting of patterns for the sake of dimensionality reduction but only three transitions were considered.

Extensions of LTP, namely Elongated Ternary Patterns (ELTP) and Improved Local Ternary Patterns (ILTP) were used by Nanni (2010) to classify the pain states from facial expressions. Hussain (2010) combined LTP with Histograms of Gradients (HOG) for detecting objects whereas Zheng (2011) used a Center-symmetric Local Ternary Patterns, texture feature based on LTP, for detection of a pedestrian.

This thesis considers the features of LTP and enhances by obtaining a global feature descriptor which describes the whole image for brain MRI classification.

2.5 SUMMARY

This chapter has discussed different types of algorithms available in the literature and the efficient algorithm adopted for our approach. Moreover, techniques for image fusion are also presented.

We also described the classification techniques available in the literature for classification of brain MRI. Preprocessing techniques and texture features for image classification was also discussed. The proposed methods for tumor identification in MRI with SVM classifier using orthonormal operators and Sobel operator for edge detection are also discussed.