CHAPTER 2

LITERATURE REVIEW

2.1 SURVEY ON ABNORMAL BRAIN IMAGING DETECTION USING COMPUTER AIDED DIAGNOSTICS

A visual perception brain stroke detection system proposed by Lee et al (2012) used mathematic morphology for the extraction of brain area. Median filters are applied to remove noise, it used canny edge detection to locate the brain tissue edge and setting peak value in edge histogram as seed to perform region growing. Finally, it clearly recognized the stroke area. Successful recognition rate reached 85% in experiments. In future research, other methods would correct gradients and Computed Tomography (CT) image for patients to ensure successful detection rates.

Patient’s brain areas affected by thalamic stroke focused on by Yumerhodzha et al (2014) used the brain fiber tracts' distribution allowing quantitative white matter changes tracking. The statistical analyzed result proved that in thalamic stroke patients, total voxels with white matter and the total volume of white matter decreased regarding controls. The author developed spatial masks which helped to investigate stroke’s structural properties as to whether it was in right or left side of thalamus. Results permit one to discuss voxel statistics of thalamic stroke cases and subject wise comparison of same fibers.
Mustafa et al (2012) presented a computer-aided detection algorithm to diagnose brain stroke. Continuous wavelet Transform matching filters were applied to identify backscattered microwave signals from abnormal brain objects. Results showed that filters outputs energy distribution in wavelets domain, regarding correlation peak time translation and range of scales in estimated energy, and were favorable to diagnose a hemorrhagic brain stroke. Simulation was done using an emulated head phantom, and Two-Dimensional Finite-Difference Time-Domain (FDTD).

The hypodense area was highlighted by Tan et al (2012) to detect ischemic stroke. The method enhanced contrast of soft tissue area and simultaneously preserved background brightness eliminating extreme levels distribution, normalizing resulting distribution, and mapping transform function on the image. Results showed that the method outperformed current improved histogram equalization (HE) method.

Benson et al (2015) investigated watershed algorithm for extraction of different feature combinations such as color, edge, orientation and texture to identify tumor region in the brain MRI image. The results were compared with the ground truth images. Marker based watershed algorithm were applied for extraction of tumor region. The Dice and Tanimoto coefficients were used for comparison of the results. The method proposed was found to achieve satisfactory results.

Fan et al (2014) showed that lower ADC values were present in the solid portions of anaplastic gliomas, but not in low grade. All ADC values in peritumoural regions of tumors were decreased compared with the contralateral normal WM. Nevertheless, difference between anaplastic gliomas and low-grade gliomas were not significant. In the meantime, higher related Cerebral Blood Volume (rCBV) ratios were present in both solid portions and peritumoural regions of anaplastic gliomas, but not in low grade.
gliomas. Therefore, diffusion- and perfusion-weighted MRI (DWI/PWI) could be integrated in the diagnostic work-up of non-enhancing gliomas in order to predict grading.

Zacharaki et al (2009) proposed the SVM based classification system with Radial Basis Function (RBF) kernel and achieved 74.4% overall accuracy in discriminating primary brain tumors from metastasis utilizing the external cross-validation method, whereas an Artificial Neural Network classifier performed better (80% accuracy). Only texture based features from the Contrast Enhanced T1 (T1ce MR) images were used for classification. The analysis achieved 84.7% accuracy on the leave-one-out cross-validation error. It also showed that Gabor textural features from T1ce were important for this classification task when combined with statistical parameters (mean, variance, etc) from the other imaging sequences (T2, rCBV).

An automated method to detect and classify acute infarct, chronic infarct and hemorrhage at slice level of non-contrast CT images was presented by Chawla et al (2009). The new method comprised three steps: image enhancement, mid-line symmetry detection and abnormal slices classification. Domain knowledge of the skull’s anatomical structure and the brain was used to detect abnormalities in a rotation and translation invariant manner. A two-level classification scheme detected abnormalities using features derived in intensity/wavelet domains. The new method was evaluated on a dataset of 15 patients (347 image slices).

Jamcey & Manikandaprabu (2014) used Hessian analysis to detect intensity variation. Compared to Fuzzy c-means and k-means which were not able to respond to small intensity variation, the proposed technique improves the detection capability. After Segmentation, classifier was used to classify tumors and accuracy, sensitivity and specificity, assessed by leave-one-out cross-validation on 50 brain tumors, are respectively 81%, 85%, and 80%.
Rathi & Palani (2012) extracted four Principal Component Analysis (PCA) components are classified using LDA and SVM classification and the accuracy achieved was 96%.

Mustaqeem et al (2012) conducted experiments to detect brain tumor using medical imaging techniques. The main technique used was segmentation, using threshold segmentation, morphological operators, and watershed segmentation. Samples of human brains were scanned using MRI process and were processed through segmentation methods which gave efficient end results.

Gordillo et al (2013) presented an overview of brain tumor segmentation methods. Given the advantages of MRI over other diagnostic imaging, this survey was focused on MRI brain tumor segmentation. Semiautomatic and fully automatic techniques were emphasized.

Zikic et al (2012) evaluated the segmentations by the BraTS online evaluation tool. The results indicated a higher segmentation quality for high-grade tumors than for low-grade cases. Also, performance on the synthetic data was better than the real data set.

A Computer Aided Detection (CAD) system for detection of Cerebral Microbleeds (CMBs) to speed up visual analysis proposed by Ghafaryasl et al (2012) comprised 3 steps: (i) skull-stripping (ii) initial candidate selection and (iii) false-positives (FPs) reduction using a two layer classification. Geometrical, intensity-based and local image descriptor features were used in classification. The training/test set comprised 156 subjects (448 CMBs) and 81 subjects (183 CMBs), respectively.

Mustafa et al (2013) applied two new pre-processing techniques to reinforce detection performance and image quality in microwave imaging
systems to detect brain strokes. The energy distribution image was obtained by applying a delay-and-sum beam forming to backscattered signals measured through a hemielliptical array of 16 corrugated tapered slot antenna elements around the head. The new techniques were validated on a realistic head phantom fabricated to emulate a real human head’s electrical properties. Results revealed the new techniques enabling accurate detection/localization of hemorrhagic strokes.

A method by which event detection was done from a single trial EEG signal by detecting the Mu Band Event-Related Desynchronisation (ERD) proposed by Soman et al (2013) was compared to a conventional method of quantifying ERD. Statistical analysis using t test proved that the proposed method at a confidence level of 95%, detected ERD occurrence time within 90% range of conventional methods.

2.2 SURVEY ON MAGNETIC RESONANCE IMAGING IN DIAGNOSIS OF BRAIN ISSUES

Highlighting the strength/limitations of earlier proposed classification techniques discussed in contemporary literature was focused on by Aswathy et al (2014). Besides summarizing literature, the new work ensured a critical evaluation of surveyed literature revealing new research facets.

A comparative analysis for stroke diagnosis on CT and MRI images was presented by Jeena & Kumar (2013). The algorithm proposed Digital Image processing tools for identification of infarct/Hemorrhage in the brain. Medical images preprocessing was achieved by median filtering. Segmentation was by Gabor filtering and seeded region growing algorithm. The proposed technique was evaluated on CT/MRI brain images with different infarcts. Results were evaluated visually. The new method was
promising for stroke detection establishing MRI imaging as superior to CT imaging in stroke detection.

An online human brain image database system with associated image processing, diagnosis and visualization to determine subtle brain injury was presented by Li et al (2010). The current system provided ability of mild cognitive impairment (MCI) diagnosis with 94.1% accuracy using trained support vector machine (SVM) based classifier.

A method for MRI contrast enhancement and skull stripping based on morphological image processing proposed by Benson & Lajish (2014) worked on T1, T2 and Fluid-Attenuated Inversion Recovery (FLAIR) axial images. Results showed that the new method was efficient to enhance skull removal of brain MR Images.

A method to extract White Matter Hyper-intensities (WMH) areas from T2- FLAIR MRI automatically proposed by Hah et al (2014) consisted of two segmentation steps. Initial step concentrated on removing brain matter out of the cranium from T2- FLAIR MRI input image by applying k-means clustering with morphology techniques. In the second step, non-local means filter was applied to extracted brain for image denoising and nearest neighbor algorithm separates brain image into WMH area, non-WMH area and background area.

Techniques like Global Histogram Equalization (GHE), Brightness preserving Dynamic Histogram equalization (BPDHE), Local histogram equalization (LHE) and Adaptive Histogram Equalization (AHE) were studied and compared by Senthilkumaran & Thimmiaraja (2014) using different objective quality measures for MRI brain image Enhancement.
The predictive capacity of multiparametric MRI found using multivariate discriminant analysis was investigated by Er et al (2013). Preoperative clinical findings and multiparametric MRI, including diffusion tensor imaging, perfusion MR imaging, diffusion weighted MR imaging, and MR spectroscopic imaging, were predictors distinguishing high grade from low grade gliomas. PCA was applied before discriminant analysis for dimensional reduction. Linear and quadratic discriminant analysis was performed/compared based on sensitivity / specificity analysis. Quadratic discriminant analysis ensured better discrimination than linear discriminant analysis for this dataset.

Computer-aided techniques to segment brain tumors are becoming more mature and closer to routine clinical applications as applied by Liu et al (2014). The purpose is ensuring a comprehensive overview for MRI-based brain tumor segmentation methods. First, a brief introduction to brain tumors and imaging modalities of brain tumors was given. Then preprocessing and the state of art methods of MRI-based brain tumor segmentation were introduced. Evaluation/validation of MRI-based brain tumor segmentation results was discussed. Finally, an objective assessment was presented and future developments and trends addressed for MRI-based brain tumor segmentation methods.

A new approach for automatic brain tumor classification in enhanced MRI images was developed by Ajikumar & Jayachandran (2014). The method had preprocessing, feature extraction, feature reduction and classification stages. In classification, Ada-Boost classifier classified experimental images as normal/abnormal. The new method was evaluated using sensitivity, specificity and accuracy metrics. It produced better results compared to Linear and non-linear SVM.
An approach to improve ant colony algorithm efficiency was proposed by Soleimani & Vincheh (2013) where the ant's direction and tendency to go to next site was regarded to calculate the probability of the next site chosen by the ant. In calculating probability of the ant's next move, it tried to balance effect of the ant’s direction and amount of pheromone distributed. Then the algorithm was used to segment the brain’s MRI images and diagnose tumors.

The application of feature-based approach to medical image retrieval, specially brain MRI scans for early Alzheimer's disease diagnosis was considered by Mizotin et al (2012). The idea was to provide a doctor with images having similar visual properties and a full case record, given the ability to make more informed decisions in the disease’s prodromal phase. With regard to state-of-the art Scale-Invariant Feature Transform (SIFT) features in a Bag-of-Visual-Words approach, it proposed using the Laguerre Circular Harmonic Functions coefficients as feature vectors. An additional pre-classification step based on Alzheimer's disease early image abnormalities estimation was proposed to improve overall precision.

### 2.3 SURVEY ON FEATURE SELECTION FOR STROKE CLASSIFICATION

A new approach for feature selection based on K-Nearest Neighbors Rule (KNNR) proposed by Ferroudji et al (2011) proved effective for improved classification. Feature selection and extraction indicated ability to locate most relevant inputs resulting in higher classification accuracy and reducing feature vector size.

Existing literature about GA for feature selection was surveyed by Sindhiya & Gunasundari (2014) comprising a snapshot of GA from the author's perspective, including algorithm variations, and modifications /
refinements to prevent local convergence and GA hybridization with other heuristic algorithms.

A subset of features from real-time experimental data was chosen by Jung et al (2008) who built a classifier model to assess stroke patients upper limb functionality. The authors compared the model with combinations of different classifiers and ensemble schemes, proving that it outperformed its competitors. The authors proved that results from experimental data were consistent with clinical information, and captured changes of upper-limb functionality over time.

Multi-Cluster Feature Selection (MCFS) method to select efficient features from primary features for brain MRI classification was used by Kalbkhani et al (2015). Primary features were obtained from a 3-level two-dimensional discrete wavelet transform (2D DWT). Selected features were applied to K-nearest neighbor (KNN) classifier. The authors classified MRI as normal or as having one of seven different diseases. Results proved that the new method achieved higher accuracy than others in distinguishing different diseases.

Veeramuthu et al (2014) evaluated the efficiency/effectiveness of a feature selection algorithm. While efficiency concerns time needed to locate a features subset, effectiveness was related to the selected features proportion. Based on such criteria, it used Spatial Gray Level Difference Method (SGLDM) feature extraction algorithm and Correlation based Feature Selection (CFS). Projected Classification algorithm (PROCLASS) was used in brain image data. Experiments compared the algorithms with feature selection algorithm (FAST) and the Fast Correlation-Based Filter (FCBF) feature selection algorithm.
Decoding cognitive information from functional MR images using classification techniques was addressed by Michel et al (2008). The bottleneck in accurate prediction is selection of informative features (voxels). Authors developed a mutual information criterion based multivariate approach estimated by nearest neighbors. This handled many dimensions and detected non-linear correlations between features and label. Authors showed that using MI-based feature selection resulted in better performance with sparse feature selection, thus having a better understanding of information coding within the brain than the reference method which was a mass univariate selection Analysis of Variance (ANOVA).

2.4 SURVEY OF ARTIFICIAL NEURAL NETWORK FOR BRAIN IMAGE CLASSIFICATION

Othman & Basri (2011) employed and implemented the Probabilistic Neural Network (PNN) with image and data processing techniques for an automated brain tumor classification. MRIs containing noise caused by the operator leading to serious errors during the classification. The use of NN and fuzzy logic is observed to have great potential to improve the classification. The performance of the PNN classifier was evaluated in terms of training performance and classification accuracies. PNN gave fast and accurate classification and was a promising tool for classification of the tumors.

Sridhar & Murali Krishna (2013) proposed a novel technique for Brain Tumor Classification using PNN with DCT. The proposed framework extracted the features using DCT and applied dimensionality reduction techniques and then the classification was carried out using PNN. To evaluate the proposed technique, an image data base of 20 Brain Tumor images was used. The proposed method gave fast and better recognition rate when
compared with conventional classifiers. The main advantage of this method was its high speed processing capability and low computational requirements.

Larsen et al (2013) investigated about the perfusion measured with Dynamic Contrast-Enhanced Magnetic Resonance Imaging (DCE-MRI) for differentiating radiation necrosis from tumor recurrence in patients with high-grade glioma. The method was adept in classifying fourteen enhancing lesions as progressing or regressing. An empirical threshold of 2.0 ml/100 g for CBV allowed detection of regressing lesions with a sensitivity of 100 % and specificity of 100 %. Fluo Denoxy Glucose –PET (FDG-PET) and DCE-MRI agreed in classification of tumor status in 13 out of the 16 cases where an FDG-PET classification was obtained.

Saritha et al (2013) proposed a new approach by integrating wavelet entropy based spider web plots and PNN for the classification of MRI brain images. The spider web plot was a geometric construction drawn using the entropy of the wavelet approximation components and the areas calculated were used as feature set for classification. PNN provided a general solution to the pattern classification problems and the classification accuracy was found to be 100%.

Paul & Bandhyopadhyay (2012) showed that the success rate of the segmentation in images of brain MRI taken from all the three angles was quite high and satisfactory. The real time execution time in the test cases was less than 9 seconds in almost all the cases and thus could be said to be good as per the current industry standard and was also very less as compared with manual process. Similar results were also available in axial view MRI Images. Experiments conducted with nearly hundred MRI images demonstrated successful tumor detection in more than 96% cases.
Amin & Megeed (2012) analyzed different segmentation and feature extraction combinations with MLP classifier. The authors showed that the PCA / MLP had a peak recognition rate of 100% and average recognition rate of 78.2%. Segmentation / MLP results had a peak recognition rate of 96.7% and average recognition of 78%. Experimental results also showed that the time taken to classify the segmented images was much less than that was taken to classify the feature vector resulting from applying PCA network.

Dahab et al (2012) presented a modified version of the conventional PNN method that could successfully handle the process of MRI image classification with 100% accuracy when the spread value was equal to 1. It was also concluded that the proposed Learning Vector Quantization (LVQ)-based PNN system decreased the processing time to approximately 79% compared with the conventional PNN and despite considerable progress in PNN, there had been a room for improvement as far as network structure determination was concerned.

Kumari & Mehra (2014) presented the classification accuracy of DWT+PCA+ANN method was improved by 95.7% when compared with DWT+Self Organizing Map (SOM) classifier, HAAR+PSO+SVM, and KNN classifier methods.

John (2012) evaluated the percentage of accuracy of classification using PNN and it was found to be nearly 100%, when the spread value was set to 1. Based on this result PNN was considered to have major advantages over conventional NN, due to the fact that PNN learns from the training data instantaneously. This speed of learning made the PNN to of adapt in real time learning. This method of automatic early detection and classification of MRI brain into normal, benign and malignant, based on their statistical texture features, not only replaces conventional invasive techniques, but also helps in reducing the fatality rate.
2.5 SURVEY ON OPTIMIZED CLASSIFICATION FOR BRAIN STROKE MRI IMAGE

Using a classifiers ensemble to decode visual stimuli from functional Magnetic Resonance Imaging (fMRI) data was proposed by Cabral et al (2011). Each classifier in ensemble specialized in a stimulus using an optimized feature set for that specific stimulus. Output for every individual stimulus was got from corresponding classifier and final classification achieved by choosing the best score. The new method was applied to two empirical fMRI datasets from multiple subjects performing visual tasks with 4 classes of stimuli. Results showed that a classifiers ensemble must provide an advantageous alternative to single classifiers when decoding stimuli linked to specific brain areas.

Neonatal brain segmentation algorithms in literature focused on by Devi et al (2015) ensured an overview of clinical MRI of a new born brain and challenges in neonatal brain MRI automated tissue classification. It presented a complete survey of current segmentation methods and their salient features. Different approaches were categorized into intracranial and brain tissue segmentation algorithms based on their tissue classification level. Also, brain tissue segmentation techniques based on their atlas usage were grouped into atlas-based, augmented atlas-based and atlas-free methods. Additionally, research gaps and lacunae in literature were also identified.

Kharat et al (2012) presented two NN techniques for the classification of the human brain MRIs. The proposed NN technique consisted of three stages, namely feature extraction, dimensionality reduction, and classification. ANNs were developed for a wide range of applications such as function approximation, feature extraction, optimization, and classification. In particular, they were developed for image enhancement,
segmentation, registration, feature extraction, and object recognition and classification. Among these, object recognition and image classification was more important as it was a critical step for high-level processing such as brain tumor classification. Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Hopfield, Cellular, and Pulse-Coupled neural networks were used for image segmentation. These networks could be categorized into feed-forward (associative) and feedback (auto-associative) networks.

Selvanayaki (2013) presented the intelligent system that showed that the Particle Swarm Optimization (PSO) was an extremely simple and accurate algorithm for brain tumor detection. PSO gives 99.28% of accurate detection than Ant Colony Optimization (ACO) and GA. So it seems to be effective for optimizing a wide range of functions. In past several years, PSO was successfully applied in many research and application areas. Another reason that PSO was attractive is that there are few parameters to adjust.

2.6 SURVEY ON HYBRID OPTIMIZATION FOR BRAIN IMAGE CLASSIFICATION

A novel hybrid machine learning system based on GA and SVM for brain tumor classification was proposed by Sachdeva et al (2011). Input was tumors texture/intensity features. GA selected a set of most informative input features. The study was performed on 55 patients real 428 post contrast T1-weighted MR images. Results showed that GA optimization technique enhanced overall SVM accuracy from 56.3 % to 91.7%. It also revealed that GA-SVM ensured more accurate results than earlier methods and was tested on diversified datasets.
An intelligent classification technique to identify normal/demented patients using Least Square Support Vector Machine (LSSVM) was proposed by Sivapriya & Thavavel (2012). Manual interpretation of huge brain MRI volumes may result in incomplete diagnosis. Hence, LSSVM was used with multiple biomarkers to facilitate accurate classification, a current requirement. SVM-PSO, LS-SVM-PSO classifiers are compared to LS-SVM trained by Chaotic PSO. LS-SVM-Chaotic PSO yielded 100% results outperforming other classifiers regarding sensitivity, specificity and accuracy in the analysis.

An Ant Colony Optimization (ACO) hybrid with Fuzzy segmentation proposed by Karnan & Logheshwari (2010) segmented a MRI brain image through ACO Hybrid with Fuzzy method to extract the suspicious region. The next step dealt with similarity between new segmented algorithms and Radiologist report. Tumor position and pixel similarity of ACO Hybrid with Fuzz techniques were measured with a Radiologist’s report.

Zhang et al (2011) developed a novel hybrid classifier to distinguish normal and abnormal brain MRIs. The method obtained 100% classification accuracy on both training and test images of the selected datasets, and the computation time for each image was only 0.0451 s.

Bauer et al (2011) presented the computation time for the segmentation algorithm (excluding preprocessing) which was between 20 and 120 seconds on a single CPU running at 2.33 GHz. Computation time mainly depended on the size of the image dataset and on the complexity of the SVM optimization. Hybrid algorithms were found to be more efficient.
2.7 SUMMARY

In this chapter various techniques cited in the literature for feature extraction, feature selection and classification algorithms were investigated. Not much work in the literature dealt with investigation of multiple features due to the large feature space it generates. However feature selection could be effectively used for reducing the feature space. Similarly though Artificial Neural Network (ANN) was extensively cited in literature, the parameters used for ANN learning has been selected heuristically leading to further investigations in this area.