Detection of Brain Injury Using Different Soft Computing Techniques: A Survey

Swapnil Sinha
M. Tech. Scholar (Digital Electronics)
Department of Electronics & Telecommunication Engg.
Rungta College of Engg. & Tech., Bhilai (C.G.), India
E-mail: swapniletc1@gmail.com

Sunil Kumar Kushwaha
M. Tech. Scholar (Digital Electronics)
Department of Electronics & Telecommunication Engg.
Rungta College of Engg. & Tech., Bhilai (C.G.), India
E-mail: sunilkumarkushwaha.117@gmail.com

Prof. Shrikant B. Burje
Associate Professor
Department of Electronics and Telecommunication Engg.
Rungta College of Engg. & Tech. Bhilai (C.G.), India
E-mail:sbburje@gmail.com

Shawetangi Kala Jain
Assistant Professor
Department of Electronics & Telecommunication Engg.
Rungta College of Engg. & Tech., Bhilai (C.G.), India
E-mail:shawetangikala@gmail.com

Akshay Singh
Assistant Professor
Department of Electronics & Telecommunication Engg.
Rungta College of Engg. & Tech., Bhilai (C.G.), India
E-mail:akshayjk.1990@gmail.com

Abstract— The detection of brain injury is one of the important and difficult task in the field of medicine. If the brain injuries are not detected in time, then it can cause serious problems in patients and sometimes can even lead to death. Traumatic brain injury (TBI) is one of the major causes of mortality and poor quality of life among the survivors. Various imaging techniques are available for taking the images of the brain so that the injuries can be detected. Magnetic resonance imaging (MRI) is one of the common medical imaging technique used for the delineation of soft tissues such as that of the brain. This paper analyses few of the methods and their performances that have been proposed for the detection of the brain injury. In these methods different soft computing techniques such as artificial neural networks (ANN), k nearest neighbor (k-NN), support vector machine (SVM), Parzan window, etc. were used for the classification of abnormal and normal brain images. Before classification feature extraction and reduction were done using the methods such as DWT, GLCM, PCA, etc.

Keywords- Soft Computing, MRI, DWT, PCA, ANN, SVM.

*****

INTRODUCTION

Brain injuries affect millions of people worldwide. Brain injuries can be broadly classified into two types: 1) Non-Traumatic Brain Injury and 2) Traumatic Brain Injury (TBI). A non-traumatic brain injury are the injuries that doesn't occur as a result of trauma. This includes tumors, stroke, infectious diseases, toxicity, lack of oxygen, etc. These are also known as acquired brain injury (ABI). A TBI occurs when an outside physical force is applied to the head. The external force consists of a blow to the head (such as an assault, a fall, or when an individual strikes his/her head during a motor vehicle accident) or from a rapid acceleration-deceleration event (like a motor vehicle accident) [1].

Among various injuries, traumatic brain injuries (TBIs) are a leading cause of morbidity, mortality, disability, socioeconomic losses and poor quality of life among survivors. It is estimated that nearly 1 million persons are injured with TBI, 200,000 people die and nearly 1 million require rehabilitation services every year in India [2]. India has the highest rate of brain injury in the world. In India, 1 out of 6 trauma victims die, whereas in the USA this figure is 1 out of 200. Half of those who die from TBI do so within the first two hours of injury [3]. Thus early and appropriate management of brain injury is critical for the survival of these patients.

Depending on what caused it, brain injury may be classified as:

1. severe brain injury,
2. moderate brain injury and,
3. mild brain injury.

The symptoms of severe brain injuries are bleeding, loss of consciousness, abnormal eye movements, inability to focus the eyes, loss of muscle control, seizures, vomiting, etc. The symptoms of mild brain injury include inability to stand, confusion, small cuts or bumps, headaches, nausea, temporary memory loss, ringing in the ear, etc. [4].

Clinical evaluation of brain injury is based on the Glasgow Coma Scale (GCS). GCS evaluates a patient’s consciousness level through his/her ability to respond to motor, verbal and visual stimuli. For the mild brain injury the GCS score is 13-15, for moderate brain injury the GCS score is 8-12 and for severe brain injury GCS score is below 8 [5]. Depending on the clinical response of the patient, a radiologic evaluation for the detection of brain injury is performed. The radiological evaluation includes X-rays, computed tomography (CT) and magnetic resonance imaging (MRI). Unlike CT scans and X-rays, no radiations are involved in MRI, hence MRIs are more suitable for soft tissues such as that of the brain. Figure 1 shows an example of the normal and abnormal MR images of the brain.

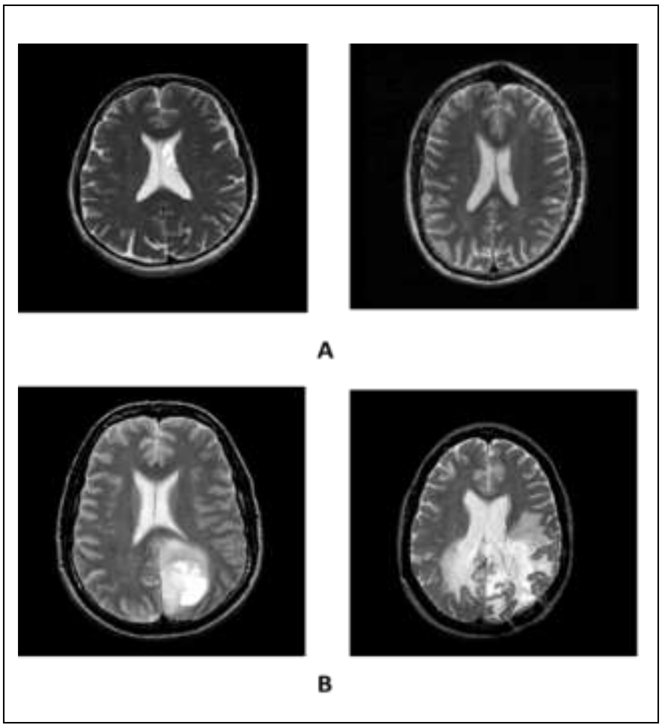

Figure 1. Examples of A) normal and B) Abnormal MR brain images.

The manual detection of brain injuries is a time consuming and challenging task. The manual detection process identifies the location and size of a lesion from MRI with correlative histology and assessment of long term neurological effects. The manual detection of lesions brain often requires 1) hours per scan for manual region-of-interest analysis, 2) a trained operator to improve inter- and intra-rater reliability, and 3) large data sets, for statistically sound analysis, but this is not feasible as it becomes resource intensive [6]. Hence a methodology for the automatic detection of the brain injury is highly desirable. For the automatic detection of injury the soft computing techniques are integrated with the biomedical imaging techniques such as MRI. Soft Computing techniques are the methods which were designed for modeling and computing the solutions for the problems of the real world such as detection of brain injury, which are difficult to model by conventional (hard computing) mathematical models [7]. Soft Computing techniques are basically an optimizing techniques for finding the solutions to the problem that are very hard to answer. The principal constituents of soft computing techniques are artificial neural networks (ANN), fuzzy logic, evolutionary computing, genetic algorithms (GA), chaotic systems and probabilistic reasoning [8].

I. Related Works and Contributions

N. Hema Rajini et. al. [9] proposed a methodology for the automated classification of MR brain images based on feature extraction and classification. The features related to MRI were obtained using Discrete Wavelet transform (DWT). The discrete wavelet used was the Haar wavelet. Haar wavelet is basically a square wave of one period. The extracted features were then reduced using Principle Component Analysis (PCA). In PCA the input feature space was reduced to a lower dimensional feature space using the largest eigenvector of the correlation matrix. The feature vector was reduced from 1024 to 7. These features were then used for training classifiers which automatically detects whether the brain is a normal one or having some lesion. The classification stage consisted of two classifiers. First was based on Artificial Neural Network (ANN) and the second was based on k-nearest neighbor (k-NN). The k-NN classifier based on distance function and voting function in k nearest neighbors, used the Euclidean distance as a metric. The ANN used was the feed forward back propagation neural network consisting of three layers. The first layer consisted of 7 elements for 7 input feature vector. The hidden layer consisted of four neurons. The output layer had a single neuron for classifying normal and abnormal human brain. The Levenberg-Marquardt learning rule was used for the ANN based classifier. N. Hema Rajini et. al. evaluated the performance of the methodology in terms of sensitivity, specificity, and accuracy. Sensitivity or true positive fraction is the probability that a diagnostic test is positive, given that the person has the disease and is given by eq. (1). Specificity or true negative fraction is the probability that a diagnostic test is negative, given that the person does not have the disease and is given by eq. (2). Accuracy is the probability that a diagnostic test is correctly performed and is given by eq. (3).

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{-- (1)}$$

$$Specificity = \frac{TP}{TP+FN} \quad \text{-- (2)}$$

$$Accuracy = \frac{TP+TN}{TP+FN+FP+FN} \quad \text{-- (3)}$$

Where,

TP (true positive) - correctly classified positive cases,
TN (true negative) - correctly classified negative cases,
FP (false positive) - incorrectly classified negative cases,
FN (false negative) - incorrectly classified positive cases.

According to [9] classification accuracy was 90% when FP-ANN was used and accuracy of 99% when k-NN was used.

Shahla Najafi et. al. [10] proposed an automated method for the diagnosis of normal and abnormal MR images of the human brain. The proposed method consisted of four stages, pre-processing of MR images using histogram equalization of image, DWT based feature extraction, feature reduction based on PCA and classification. For classification three methods were used: k-NN, ANN, and parzen window. Preprocessing was done using histogram equalization for correcting the intensity non-uniformity due to data acquisition scanner problem. The discrete wavelet used for extracting the initial features was the Haar wavelet which is basically a square wave of one period. The three scale Haar (H2) basis function given by (4) was employed for DWT feature extraction. For the image of size 256×256 approximation coefficient of third level was used as feature, i.e. this stage used 1024 numbers of features. The extracted features were then reduced using PCA by minimizing the dimensionality of the pattern representation.

$$H_2 = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \text{-- (4)}$$

According to [10] the number of features that achieved the maximum accuracy after feature extraction and reduction using PCA was 6 for k-NN, 5 for parzen window and 7 for ANN classifier. The correct classification ratio achieved by [10] is 98.2% with ANN classifier, 99.2% with parzen window and 99.2% with k-NN.

A hybrid technique based on two classifiers was proposed by El-Sayed et. al. [11] for the classification of the MRI images of the human brain. The hybrid technique proposed consisted of three stages: feature extraction, feature reduction, and classification of MR images. The features related to MRI images were extracted using DWT. Then the features of MRI were reduced using PCA to the more essential features. The last stage is the classification stage, which consisted of two classifiers based on supervised machine learning. The first classifier was based on feed forward back-propagation artificial neural network (FP-ANN) and the second classifier was based on k-nearest neighbor (k-NN). The method proposed gives success of 95.6% and 98.6% using classifiers based on FP-ANN and k-NN respectively.

A methodology for the multiclass classification of brain tumors using MR images was proposed by Vinod Kumar et. al. [12]. This system was used for classifying primary tumors such as Astrocytoma (AS), Glioblastoma Multiforme (GBM), child tumor-Medulloblastoma (MED) and Meningioma (MEN), and secondary tumor-Metastatic (MET). The methodology consisted of four stages: marking of the region of interests (ROIs), feature extraction from ROIs, feature reduction and classification. Gradient vector flow (GVF) was used for extracting tumor boundary. 6 types of intensity and texture features were extracted. They are:

1. Gray level covariance matrix in which four different features named contrast, homogeneity, correlation, and energy were calculated for four different offset. Thus contributed 16 features.
2. Laplacian of Gaussian (LoG): four statistical parameters (mean, standard deviation, kurtosis and skewness) were retrieved for the LoG filter output in ROI. The different Gaussian widths used were 0.25, 0.50, 1 and 2, thus contributing 16 features.
3. Directional Gabor texture features: λ (in pixels) and θ (in degrees) were varied for five different values ($2\sqrt{2}$, 4, $4\sqrt{2}$, 8, $8\sqrt{2}$) and (0°, 22.5°, 45°, 67.5°, 90°) respectively to get 25 features. Four statistical features (mean, standard deviation, skewness and kurtosis) were extracted for each filter output so that to get total 100 features.
4. Rotation Invariant Circular Gabor Features: For five different values of λ ($2\sqrt{2}$, 4, $4\sqrt{2}$, 8, $8\sqrt{2}$) and two values of □ (0°, 90°), 10□rotation invariant circular Gabor features were extracted. Four statistical parameters for each filter output were retrieved so that to get 40 features.
5. Rotation invariant Local Binary Patterns: This system used range filter, standard deviation filter and average filter, with neighborhood of 7×7 on three LBP images of radii -1, 2 and 4 pixels to get 9 filtered images. Four statistical features were obtained from these images so that total 36 images were obtained.
6. Intensity based features: Four intensity-statistical features were retrieved from the histogram of the image. From these four features, mean entropy of the ROIs was also calculated, so that 10 more features were obtained.

Thus, total 218 texture and intensity features were extracted. This methodology used PCA for the feature reduction to obtain optimal subsets of features. 49 eigen features were selected. Multi-layer perceptron based on supervised learning algorithm was used for classification. For estimating weights, momentum weights and bias based learning, gradient descent back propagation with momentum algorithm was used. According to [12] the overall accuracy achieved using PCA-ANN was 91.97%. The individual accuracy obtained for each class was: AS-90.74%, GBM-88.46%, MED-85.00%, MEN-90.70%, MET-96.67% and NR-93.78%.

A methodology was proposed by Mehdi Jafari et. al. [13] for the detection of brain tumor tissue in the MR images of the human brain based on support vector machine (SVM) and genetic algorithm (GA). Three texture and intensity feature set were used as input. The first set consisted features such as mean, energy, momentum, entropy, kurtosis, skewness, correlation, etc. The second and third feature sets were derived from wavelet and frequency transformation respectively. Then the genetic algorithm (GA) was used for selecting the most informative input features. And finally SVM was used for classifying brain tissue as normal and abnormal tissue. The accuracy up to 83.22% was achieved by this method.

Akhanda Nand Pathak et. al. [14] proposed a methodology for the diagnosis of brain tumor based on four staged classifier. In this methodology after pre-processing of MR images in the first stage, the feature extraction was done using DWT and in the third stage feature reduction was done using PCA. In this 256×256 MR images were decomposed into 64×64 image of lower resolution having 4096 pixels, by using two level wavelet decomposition. PCA was then used to reduce the extracted feature into seven different eigen vector. After getting the input feature vector, support vector machine (SVM) was used as a classifier. Like any other machine learning techniques SVM also involved two basic steps, training and testing. In training phase the known data were fed to form a finite training set. In the testing phase the test data were compared with the training set to detect the tumor. The accuracy of 99% was achieved with this methodology.

A methodology for the detection of Mild Traumatic Brain injury was proposed by Anthony Bianchi et. al. [15]. The proposed methodology used the low level static and dynamic context features integrated into a discriminating voxel level classifier for the improvement of the detection of mTBI. Context is the information related to object detection, categorization and classification task, but not directly due to physical appearance of the object as perceived by the image acquisition system. This method used a cascade of classifiers that detect the lesion at each time point, where the information at each time point were propagated to the next stage. The first classifier estimated the lesion using only the visual features. Then the second classifier formed the context feature from the posterior probability map. This contextual features propagates spatial information for the improved classification. And finally the dynamic contextual features were calculated from the final classifier at a single time point. Four types of texture features were used in this methodology. They are uniform local binary pattern (ULBP) local histograms in the coronal plane (59 features), local statistics (mean, variance, skewness and kurtosis) of a Gabor filter bank with 8 orientations and 4 scales in the coronal plane (128 features), basic histogram of oriented gradients in the coronal plane (9 features) and local neighborhood statistical feature (mean, variance, skewness, kurtosis, range, entropy, gradient magnitude xyz) (9 features). Thus a total of 205 features was used.

Two new static features were also proposed by [15], one that incorporated a sense of the surrounding without a known direction while the other gave a general sense of direction. The first feature gave the average posterior probability at various distances around the observed voxel. The distance function used was the Manhattan distance that allowed a cuboidal region. The second feature describes the posterior probability in various directions from the observed voxel. From the observed voxel the rays were sampled at various distance ranges and angles. The proposed posterior marginal edge distance (PMED) feature is the distance of a voxel from the perimeter of objects of a class found by the maximum posterior marginal (MPM) estimate. MPM was obtained from the output of the classifier. The distance transform was applied to the image and the inverse image so that the feature is given by:

$$PMED = d(MPM) - d(\sim MPM) \quad \text{-- (5)}$$

$$MPM = argmax\ p(\omega = c|F) \quad \text{-- (6)}$$

Where $d(*)$ is the Euclidian distance transform, ω is the estimated class, c is the specific class and F is the feature set at a given voxel.

The primary classifier used by [15] was adaboost where a small decision tree was used as a base classifier, allowing for the inherent feature selection i.e. the features having errors were rejected. Also, it is insensitive towards feature normalization. During the training process a cost matrix given in eq. (7) was used, in which the first row represented the cost of normal appearing brain matter (NAMB) and the second row represented the cost of lesion voxels.

$$Cost\ matrix = \begin{bmatrix} 0 & 1 \\ \frac{\sum NABM\ voxels}{\sum Lesion\ Voxels} & 0 \end{bmatrix} \quad \text{-- (7)}$$

The segmentation results of the approach proposed by [15] were evaluated using dice coefficient, which is the ratio of the intersection between the detected object and the target object and is given by eq. (8).

$$Dice = \frac{2TP}{(TP+FP)+(TP+FN)} \quad \text{-- (8)}$$

Results of [15] show that the dynamic approach is better than the static approach and the auto context approach. The proposed approach can also be applied to other brain lesion problems because of the generality and flexibility of the approach.

II. CONCLUSION

We have studied a few of the papers in the field of detection of brain injury in the MR brain images. The early detection of brain injury is very essential for saving lots of precious life. For correct and efficient detection of TBI and to reduce the load on the human observer and medical practitioners, an automatic method for detection of brain injuries is highly desirable.

In this paper various automated brain injury detection methods through MRI has been surveyed. After surveying we can conclude that the automatic detection method for the brain injury in the MRI can be broadly classified into following sequence of methods: pre-processing, feature extraction, feature reduction, and classification. Various algorithms have been proposed in the literature for each image processing stage. For example, for feature extraction DWT and GLCM are used. DWT extracts spatial features whereas GLCM is used to extract texture features. Feature reduction is done either using PCA or by using linear discriminant analysis (LDA). For classification the soft computing techniques such as artificial neural network (ANN), fuzzy logic, GA, support vector machine (SVM), etc. were employed. The advantage of ANN is that it does not require the prior knowledge of the system under consideration and are very well suited for modelling the dynamic systems on a real-time basis. Fuzzy logic fills the gap between human reasoning and computational logic. K-nearest neighbor (k-NN) decision rule is a universal classification method with good scalability. GAs is more suited to search and optimization problems due to their robust ability of exploiting the information which is accumulated about an initially unknown search space. The results of methods proposed by different people in medical image processing are used to focus on the various combinations of techniques and their performances. The results of various algorithms are discussed.

III. Future Scope

The detection of the brain injury in the MRI scan is a difficult task. After studying the previous research papers in the field of detection of brain injury, it is found that a lot of work has been done in the field of detection of non-traumatic brain injury especially in the field of tumor. But very little research work has been done in the field of traumatic brain injury specifically for the detection of mild traumatic brain injury. Further, the development of automated analyses of mTBI has been hindered by the subtle nature of mTBI abnormalities which appear as a low contrast MR region. Hence there a very large scope of research in this field exist.

Acknowledgment

We are thankful to Rungta College of Engineering and Technology, Bhilai, C.G., India, for providing the laboratory facilities. We also take this opportunity to express a deep sense of gratitude to Prof. Lalit Kumar Bhaiya, The Head of Department of Electronics and Telecommunication Engineering, Rungta College of Engineering and Technology, Bhilai, India for his support, valuable information and guidance. We are also thankful for the guidance and support received from the members of the Department of Electronics and Telecommunication Engineering and especially to M.Tech. coordinator Mr. A. Prabhakar Rao, Associate Professor, Rungta College of Engineering and Technology, Bhilai, C.G., India.

References

[1] Brain Injury Alliance of Utah, available online at: http://biau.org/types-and-levels-of-brain-injury/

[2] G. Gururaj, S. V. R. Kolluri, B. A. Chandramouli, D. K. Subbakrishna and J. F. Kraus, "Traumatic Brain Injury", National Institute of Mental Health & Neuro Sciences, Publication no. 61, Bangalore-560029, India, 2005.

[3] Indian head injury foundation, available online at: http://indianheadinjuryfoundation.org/traumatic-brain-injury/

[4] Brindles Lee Macon and Elizabeth Boskey, PhD. Medically Reviewed by George Krucik, MD., available online at: http://www.healthline.com/health/head-injury#Description1

[5] T. Morris, “Traumatic brain injury,” in Handbook of Medical Neuropsychology, C. L. Armstrong and L. Morrow, Eds. New York: Springer, 2010, Ch. 2, pp. 17–32.

[6] Anthony Bianchi, Bir Bhanu, Virginia Donovan, Andre Obenaus, “Visual and contextual modeling for detection of repeated mild traumatic brain injury”, IEEE transaction on medical imaging, vol. 33, No. 1, January, 2014.

[7] Lukesh M. Barapatre, Anand Sharma, “Soft Computing: A survey”, International Journal of Modern Trends in Engineering and Research, Volume 02, Issue 01, January 2015, pp 232-238.

[8] Rahul Malhotra, Narinder Singh, Yaduvir Singh, “Soft Computing Techniques for Process Control Applications”, International Journal on Soft Computing, Vol.2, No.3, August 2011, pp 32-44.

[9] N. Hema Rajini, R. Bhavani, “Classification of MRI Brain Images using k-Nearest Neighbor and Artificial Neural Network”, IEEE-International Conference on Recent Trends in Information Technology, ICRTIT 2011 IEEE MIT, Anna University, Chennai, 3-5 June 2011, pp 863-868.

[10] Shahla Najafi, Mehdi Chelel Amirani, and Zahra Sedghi, “A New Approach to MRI Brain Images Classification”, ICEE conference 2011, pp. 1-5.

[11] El-sayed A. El-dahshan, Abdel-badeeh and Tamer H. Younis. “A Hybrid Technique for Automatic MRI brain Images Classification”, Studia Univ. Babes_Bolyai, Informatica, Vol. LIV, No. 1, pp. 55-66.

[12] Vinod Kumar, Jainy Sachdeva Indra Gupta, Niranjan Khandelwal, Chirag Kamal Ahuja, “Classification of brain tumors using PCA-ANN”, In Proceedings WICT, Mumbai, India, pp. 1079-1083, 2011. DOI: 10.1109/WICT.2011.6141398.

[13] Mehdi Jafari, Reza Shafaghi, “A hybrid approach for automatic tumor detection of brain MRI using support vector machine and genetic algorithm”, Global Journal of science, engineering and technology, issue 3, 2012, pp 1-8.

[14] Akhanda Nand Pathak and Ramesh Kumar Sunkaria, “Multiclass Brain Tumor Classification using SVM”, International Journal of Computer Applications, Volume 97 – No.23, July 2014.

[15] Anthony Bianchi, Bir Bhanu and Andre Obenaus, ”Dynamic Low-Level Context for the Detection of Mild Traumatic brain Injury”, accepted on June 25, 2014 for publication in a future issue of IEEE journal.

[16] Anthony Bianchi, Bir Bhanu, Virginia Donovan and Andre Obenaus, “Detecting mild traumatic brain injury using dynamic low level context”, IEEE international conference on image processing, Melbourne, Australia, Sept. 15-18, 2013.

[17] M. B. Vijayalaxmi, B. V. Dhandra, “Script Recognition using GLCM and DWT Features”, International Journal of Advanced

ISSN: 2321-8169
934 - 939

Research in Computer and Communication Engineering Vol. 4, Issue 1, January 2015, pp 256-260.

[18] Simon Haykin, “Neural Networks – A Comprehensive Foundation”, Prentice Hall International Inc., second edition, 1999.

[19] Rafael C. Gonzalez, Richard E. Woods, “Digital Image Processing” Prentice Hall, second edition.

[20] Brain Injury Association of USA. http://www.biausa.org/about-brain-injury.htm