

Detection of Frontotemporal Dementia using Artificial Intelligence Techniques



Sandhya. N. , Rama Prasath. A.

Abstract: Atrophy (degeneration) of frontal and temporal lobes in human brain causes a dysfunctionality in Language, Emotion, Executive abilities and these losses are irreversible. If Atrophy is detected at an early age it is beneficial for the patient. A detailed diagnosis of the patient in terms of physical, physiological, psychological and neuropsychological aspects are mandatory to trace the possibility. There is a continuous increase in population of the disease and limited number of specialists. Frontotemporal Dementia (FTD) happens due to the frontal and/or temporal lobe degeneration. The proposed system helps in the identification of the FTD in the brain using various Artificial Intelligence (AI) techniques. The study makes use of the MR brain images for the purpose of the detection of the FTD.

Keywords : Fronto Temporal Dementia (FTD), Back Propagation Network (BPN), Support Vector Machine (SVM), Naïve Bayes, Gray-Level Co-occurrence Matrix (GLCM).

I. INTRODUCTION

Frontal, temporal lobes of deteriorate over time and cause FTD. It affects language, personality, behavior, decision-making, emotion, suffer muscle and motor neurons dysfunctionality. The frontal lobes are placed above, behind forehead on both right, left sides of the brain control executive functioning, planning, sequencing, monitoring, prioritizing, multitasking, monitoring, corrections. Deterioration can start in the temporal lobe, in the frontal lobe or in both the lobes [1]. Some of the neuro psychological tests conducted for the detection of the FTD include Clock Drawing Test, Mini Mental State Examination, General Practitioner Assessment of Cognition, Memory and Verbal Tests, and Mathematical and visuospatial tests. With the advancement in medical imaging with the availability of imaging scanners like CT, PET, MR [2] and AI fields, it is possible to make use of it for the detection of the FTD. This paper focuses on the application of the various available AI techniques for the classification of the FTD using MR brain images. A system is proposed that makes use of the MR brain images and classifies the image.

II. PROPOSED SYSTEM ARCHITECTURE

The system architecture proposed is given below in fig. 1. The brain MR image is given as an input to the proposed system. The input image may be healthy or demented having degeneration in the frontal or temporal lobes or both. On the input brain MR image, various techniques as illustrated in the proposed system architecture is applied to finally classify the input brain MR image.

The channel with the maximum contrast is selected for the detection of demented region. Using Median filter the noise or unwanted distortion in the image is removed. Contrast normalization is done to enhance the input image contrast. CLAHE (Contrast Limited Adaptive Histogram Equalization) is used for preventing noise from being over amplified. Image Normalization is done to normalize the brain image.

Mathematical morphological operators Dilation and Erosion are used for the identification of the demented region of brain. These form the foundation for the operators open() and close(). Using the GLCM, texture descriptors like Homogeneity, Contrast, Energy, Entropy, and Correlation is extracted and are given as an input to the AI classifier, which then classifies the brain MR image.

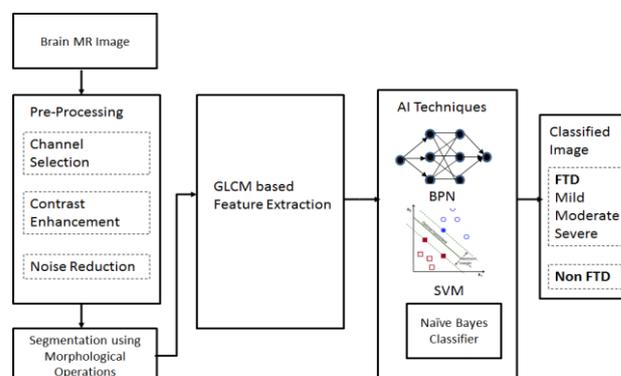


Fig. 1. Proposed System

III. IMAGE PRE-PROCESSING

The brain image which is in JPEG format is given as an input. The image is composed of three color channels. Red, Green and Blue and called as RGB image. For reducing the computing cost of data processing, the channel having maximum contrast was selected for processing. The demented region resides in high frequency component. Channel which provides maximum contrast is selected so as to aid in the process of finding out demented area.

Manuscript published on 30 September 2019

* Correspondence Author

Sandhya. N.*, Research Scholar, Department of Computer Applications, Hindustan Institute of Technology & Science, Padur, Tamil Nadu, India. (email: sandhya.n.deepak@gmail.com)

Rama Prasath. A., Asst. Professor, Department of Computer Applications, School of Computing Sciences, Hindustan Institute of Technology & Science, Padur, Tamil Nadu, India. (email: rprasath@hindustanuniv.ac.in)

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>

Contrast Enhancement methods of the image can be divided into two techniques: Direct method and Indirect method. Considering indirect methods, Histogram Equalization which is a simple and explicit approach is mostly used [3]. Contrast enhancement alters input image's pixel intensity to employ maximum bins or as many bins as possible.

A non-linear method called Median or Morphological filter is used to remove the noise present in the images. The filter preserves the edges and the sharpness of the image is not modified. The image moves in a manner of replacement of each pixel by value of media of adjacent pixel. Pixel is calculated by sorting the patterns of the neighbors in a numerical sequence, each pixel is replaced by median value.

IV. SEGMENTATION USING MORPHOLOGICAL OPERATORS

Morphological operators are used in our study for extracting the boundaries as morphology modifies the images based on shapes and maintains the structure. It uses a small template known as Structuring Element or Kernel. Dilation, Erosion, Open, and Close are the basic operators in morphology [4]. Mathematical morphological operators Dilation and Erosion are used for identifying the demented region of the brain.

V. GLCM BASED FEATURE EXTRACTION

Feature extraction is a procedure for reducing the data to find a subset of helpful variables based on the images. From each image, the Haralick texture descriptors – Homogeneity, Contrast, Correlation, Energy and Entropy are extracted [5]. The Co-Occurrence matrices are calculated for 45 degrees from the angles 0, 45, 90 and 135 degrees.

GLCM is a statistical method that tests the gray level transition between two pixels. It finds out how frequently pixel pairs with a particular value in a specific spatial association exist. It does it by constructing the GLCM image and by extraction of the statistical measures from matrix.

VI. AI TECHNIQUES

The performance of automatic FTD detection system can be enhanced by coupling them with Artificial Intelligence techniques. The three classifiers, namely, BPN (Back Propagation Network), SVM (Support Vector Machine) and Naïve Bayes classifiers are used, and performances are compared to suggest the one with best performance.

Back Propagation Network: A system having inputs and output modules and a weight associated with connection is called neural network. The input is fed to the input layer and information travels through the layers till the output phase is reached. At the output phase, Error is calculated as difference between expected and targeted. This error is propagated back through hidden layers and network works by changing weights. If the weights do not change at input layer, a state of stability is reached. This is a technique using gradient descent. It computes the gradient of loss of function at output and propagates back through the network layers. The error is propagated till a global minimum value is attained. It is considered as a supervised method. It is a way to train the system to attain the desired state [6].

SVM: It is discriminative by nature and a hyperplane that

separates defines this classifier. Such a classifier is called as Support Vector Machine. If a labeled training data is provided as in case of a supervised learning, SVM gives as an optimal hyperplane which segregates new instances. This hyperplane is nothing but a line which divides plane into two different sections and each class will lay on one side of line. SVM separates classes by finding a hyperplane. Gamma and Regularization parameter are the tuning parameters of SVM. Regularization parameter defines Optimization for SVM for avoiding misclassification of each training sample. The reach of influence of a training instance is described by the Gamma parameter. Points close to line means high Gamma and points away from plausible line means low Gamma. Margin means a line separating class points which are closer. Good margin means separation is greater for both the classes. Good margin permits all points to be in their corresponding classes without going to the other class [7].

Naïve Bayes: The Bayesian classification depicts a supervised learning approach. This approach is used for classification is statistical by nature. A probabilistic model is assumed capturing uncertainty in methodical method by deciding outcome's probabilities. For solving diagnostic, prediction problems, Naïve Bayes is used and was proposed by Thomas Bayes. It is preferred when inputs have a high dimensionality. For parameter estimation, method of maximum likelihood is used [8]. Even though assumptions are simplified, it performs well in complex situations. For the estimation of parameters, meager amounts of training data is sufficient. Class conditional independence naïve Bayes assumption is done for reduction of computational cost. Bayes' theorem and maximum posteriori hypotheses are bases for classifier [9].

VII. PERFORMANCE METRICS

Accuracy, Specificity and Sensitivity are the performance measures based on which the performances of the proposed classifiers are studied.

Table-I: Performance Metrics Formula

Indices	Accuracy	Specificity	Sensitivity
Formula	$\frac{(tp + tn)}{(tp + tn + fp + fn)}$	$\frac{tn}{(tn + fp)}$	$\frac{tp}{(tp + fn)}$

where:

tp (true positives) indicate that subject has FTD and it is correctly classified as being with FTD,

tn (true negative) indicate that subject has FTD, but it is being classified as healthy,

fp (false positives) indicate that subject is healthy but being classified as demented,

fn (false negative) indicate that subject is healthy and being classified as healthy.

Sensitivity measures the true positive rate that the test is optimistic when the subject has FTD.

Specificity measure the true negative rate, that the test is pessimistic, given that the subject is not having FTD.

Accuracy measures the prospect that a diagnostic test is properly achieved.

VIII. RESULTS AND DISCUSSION

The proposed system is implemented using Matlab. By plotting the histogram of the RGB channel, the channel with highest contrast is selected. Green channel had the highest contrast and is used for further processing after being enhanced using CLAHE. Morphological operators is used to localize the demented region. Dilation operation helped in clear marking of boundaries by adding pixels. Erosion operation helped in restoring boundaries to their initial position.

The five texture features - Homogeneity, Contrast, Correlation, Energy, and Entropy are extracted using GLCM and these features are fed as an input to the three classifiers – SVM, Naïve Bayes and ANN. Sensitivity and Specificity is used as measures for evaluating the accuracy of the system.

A. BPN Classifier Performance

During training the network architecture showed good performance with steady error reduction. Because of large number of input patterns, the time of computation for training network was very high. The size of weight matrices was also large.

The method was validated with a dataset of brain images. The proposed system could classify exactly in 96% of the input images but with some low contrast images there was some misclassification. The subjectivity of the user and differences in contrast were main reasons for this deviation. There was some misclassification where some background region shared same textural features as FTD region and background as the segmentation was very meager. For certain images the results were not satisfactory, when the captured image had a blur, unexpected patient motion, distortions and those images which had lesions, tumors, infraction, hematoma, edema and other types of dementia like Cortical Atrophy were excluded from the study.

Around 30 samples were taken for training the network. With the first set of data sample, In the normal class of first data set, 100 percent accuracy was obtained as all 27 images were rightly classified as normal. For the mild class 22 were rightly classified as mild correctly thus giving 91.7% accuracy. 1 mild image was wrongly classified normal giving misclassification instance 4.2% and 1 image was wrongly classified as moderate giving 4.2% mis-classification instance. 100% of all moderate images were classified as moderate and all 8 images in set were correctly classified and for severe set all 2 images in the set were correctly classified. Thus giving 100 %. This result is for one set of data. Such process was repeated for the remaining 3 sets of data having total of 200 images and ANN could classify the input images with 96.72% accuracy. Wrongly classified instances were 3.27%. It yielded sensitivity of 96.32%, specificity of 98.71%.

B. Naïve Bayes Classifier Performance

Navies Bayes classifier yielded an accuracy of 63.93%. 25 images in the normal class were correctly classified as normal and 61% classification accuracy was obtained. 10 images were misclassified as mild with 24.4 % misclassification instance and 5 images were wrongly classified as moderate with 12.2% misclassification instances 1 image was wrongly classified as severe with 2.4 % misclassification instances.

In the images having mild FTD, 12 images were correctly classified as mild thus giving 66.7% accuracy.3 images were wrongly classified as normal giving 16.7% wrongly classified

instance. 3 images were classified as moderate and gave 16.7% wrongly classified instance. Moderate class, could classify single image as moderate and gave 100 %. Severe class also could classify single image as severe and gave 100 %.

Classification for a total of 200 images were performed and Naive Bayes classifier provided a classification accuracy of 63.93 %, error 36.07 %. Sensitivity was 51.23%. Specificity was 84.03 %.

C. SVM Classifier Performance

SVM classifier yielded an accuracy of 85.25%. SVM is a statistical classifier for correct classification of data. It works by building a single or a set of hyperplanes. It employed feature selection method. Features selected from GLCM were input to the classifier. In the normal class of first data set, all were correctly classified gave 100 % accuracy classifying all 28 images as normal.

In mild class, 21 images were correctly classified as mild giving 72.4 % accuracy. 8 images were wrongly classified as moderate giving misclassified percentage as 27.6%. In the moderate class, 50 % instances were correctly classified as moderate inclusive on single image and remaining 50% of images were wrongly mild including single image case. In severe class, 100% classification accuracy was obtained as both images were correctly classified as severe.

Classification for a total of 200 images were performed and SVM classifier provided a classification accuracy of 85.25%. Sensitivity was 76.64%. Specificity was 94.39%.

D. Performance Comparison of ANN, Naïve Bayes and SVM Classifiers

Listed below is the performance comparison of the three classifiers – BPN, Naïve Bayes and SVM. Accuracy, Sensitivity and Specificity of the three classifiers are listed below.

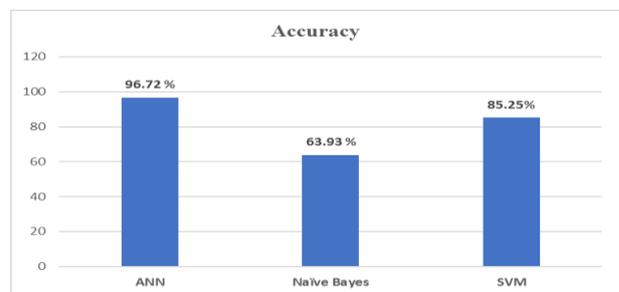


Fig. 2. Accuracy Comparison of Classifiers

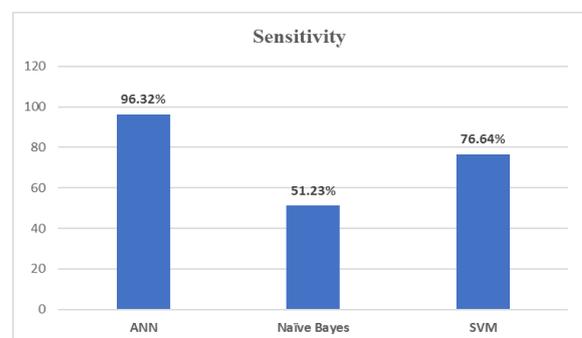


Fig. 3. Sensitivity Comparison of Classifiers



Fig. 4. Specificity Comparison of Classifiers

IX. CONCLUSION AND FUTURE DIRECTIONS

This study performed the identification of FTD in the brain MR images using Artificial Intelligence techniques BPN, SVM and Naïve Bayes and compared the performance of the classifiers. BPN had the highest accuracy in identification of FTD in the brain MR images.

The system is accurate in the detection of demented region and its extraction, a vast amount of scope is still there for development of automatic dementia detection system. Images the segmented region can be used for a number of purposes like detection of other memory disorders and probability of other diseases. The study can be extended for the detection of other forms of memory disorders like Vascular Dementia, Alzheimer's disease etc., and the region wise extract and classify like normal, mildly demented, moderately demented, severely demented also can be applied for other types of dementia like Vascular Dementia, Dementia with Lewy bodies.

REFERENCES

1. Hornberger, M., Piguet, O., Kipps, C. and Hodges, J.R. (2008). Executive function in progressive and non-progressive behavioral variant frontotemporal dementia. *Neurology.*, 71 (19): 1481-1488
2. Gonzalez, R. C. and Woods, R.E., (2008). *Digital Image Processing*. Pearson Prentice Hall India Edition, Chap. 6, pp. 402-405. ISBN: 978-81-317-2695-2.
3. Akhila, J.A., Markose, C. and Aneesh, R.P. (2017). Feature Extraction and Classification of Dementia using Neural Network. *Proc. International Conference on Intelligent Computing, Instrumentation and Control Technologies.*, 1446-1450.
4. Prasath, A.R. and Ramya, M.M. (2015). Detection of Macular Drusen Based on Texture Descriptors., *Research Journal of Information Technology*, 7(1): 70-79.
5. Haralick, R.M. (1979). Statistical and Structural Approaches to texture. *IEEE.*, 67 (5): 786-804, <https://doi.org/10.1109/PROC.1979.11328>.
6. Rathamani, K., Saravanan, P., Manickam, T., Anubharathi, P. and Gowtham, N. (2017). Automatic Classification of MR Brain Images using Artificial Neural Network. *SSRG International Journal of Electronics and Communication Engineering.*, 2348-8549.
7. Kang, W., Yang, Q., & Liang, R. (2009, 7-8 March 2009). The Comparative Research on Image Segmentation Algorithms. Paper presented at the 2009 First International Workshop on Education Technology and Computer Science.
8. Leung, K. M. (2007). Naive bayesian classifier. Polytechnic University Department of Computer Science/Finance and Risk Engineering.
9. Shivanandam, S.N. and Deepa, S.N., (1993). *Principles of Soft Computing*. Wiley India Edition., Chap. 3, pp. 74-83. ISBN: 9788126527410.