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BRAIN TUMOR DETECTION IN MRI IMAGES USING OPTIMIZATION TECHNIQUES

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ABSTRACT

Imaging is one of the techniques used to visualize the internal structure of MRI Images, which is used to detect tumors. Classifying Tumor in MRI image data is challenging task. Features are extracted from MRI images by using wavelet decomposition method and feature reductions are obtained based on Singular Value Decomposition (SVD) techniques. For analytical data mining Boosting algorithm is used to produce a sequence of classifiers. The hybrid-learning techniques are used to boost the classification accuracy. The optimized Genetic Algorithm (GA) - Artificial Bee Colony (ABC) algorithm are proposed to increase the classification accuracy of tumor detection in MRI Images.

Keywords: MRI dataset, AdaBoost, pre-processing, median filter wavelet, singular value decomposition (SVD), genetic artificial bee colony (ABC), algorithm (GA).

1. INTRODUCTION

MRI is one of the reliable methods to detect tumors. There are different types of tissue observed based on absorption of radiation. An automated classification system based on machine learning techniques help the health provider to diagnose very faster. Machine learning technique involves two parts, extraction of features from the MRI image, reduction of features from the extracted features and also trains the classifier. Generally Texture features are used in the examination of MRI images. After that the features are selected, all the selected features are transformed and reduced or finest features preferred. A variety of numerical measures, like feature selection based on Correlation method along with Mutual Information (MI) are used with success.

There are different types of classifiers available, from this, Neural Network classifiers, Support Vector Machine and Ensemble classifiers similar to boosting algorithms are mostly used in the literature survey. The boosting algorithm used an ensemble of classifiers; it may be the weak learner. The boosting algorithms are used to grouping of the weak learners to produce a composite decision boundary. The iterations of boosting are gradient descent, ladder moves towards the interpreter of F(X), smallest amount risk for the loss L[Y, F(X)] =e^ (-Y F(X)). The various parameters are selected in boosting algorithms or choose the classifiers are NP rigid.

In this paper, we proposed hybrid optimization method to increase the classification accuracy of tumor detection in MRI images. The improved AdaBoost algorithms combined form of Genetic Algorithm and Artificial Bee Colony can be used to boost up the classification accuracy of tumor detection in MRI. In section 2, literature Survey and analysis is discussed. In the Section of 3, the proposed methodology are provided, which also includes MRI dataset, Artificial Bee Colony (ABC) algorithm, Wavelet Transform. The Sample MRI image are taken from data set and used to calculate the wavelet approximation, diagonal, vertical, horizontal based coefficients. The overall methodology explains in this paper. In 4th Section, the classification accuracy of tumor detection result is carried out based on MRI data sets. There are various parameters are measured such as Accuracy, Recall, RMSE, Precision and compared with optimization technique. The paper is concluded in last section.

2. RELATED WORKS

In [1], a classification model is implemented, which is used for tumor classification in MRI image. The classification outcome depicted how KNNs in addition to NN models alter the tumor classification in MRI images. The experiments results showed full-grown accuracies in ranking, using the KNN and 98.92% during Neural Networks. Similarly, in [2] this paper, illustrated a comparative study for diagnosing strokes on CT images and MRI images. In the proposed study predictable how to use MRI images as processing tools for categorizing hemorrhaging in the cranium. They were able to use Gabor filtering as seeded region growth algorithms to perform segmentations task. Finally, the product of this technique was implemented by using brain MRI images and CT scan images, screening various levels of the infarcts.

A novel approach was projected by Bhavani and Rajini in [3], who computerized the diagnosis system based on brain MRI image classification. In this proposed idea aggregating two different stages is divided based on the classification and feature extraction. The authors have procured the features related to brain MRI images in the early steps and using discrete wavelet transformation (DWT), they extracted features of brain MRI images had turn into diminished.

In this paper [4], suggested a new method to extract the cortex of inter brain subjects, based on co-segmentation process. In this method intends to split binary images together. The uses of Markov Random Field (MRF) as a formation for generate basic functions emphasized, by Jang. The utilizing optimal graph-cut algorithms for identifying indistinguishable voxel pairs, by using transformation matrix and computed during the matching of 3D SIFT attributes.

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An MRI brain image segmentation method is presented by Adhikari *et al*., [5]. They have who consider utilizing the spatial knowledge and intensity of non-uniformity (INU), by the assist of a fuzzy C-mean clustering algorithm. The nonuniformity of MRI brain images are procured by MRI Scanner is repaired by using Gaussian plane fusion cells.

In [6] and [11], there are different types of optimization techniques such as "Particle Swarm Optimization algorithms (PSO), Genetic Algorithm (GA), Adaboost and Ant Colony Optimization (ACO) algorithms", which is used for Feature Selection (FS). Ant Colony Optimization has used as a search procedure for selecting various features. Genetic Algorithm is search methods, which take stimulation from natural selection. Feature Selection is one of the applications of Genetic Algorithm optimization techniques. The Feature Selection problems are solving by using Particle Swarm Optimization, which is gained more concentration. In this Paper [7], Proposed a New PSO (NPSO) with GA, which the features be classified through 3-layer Back Propagation Network hybridized using Particle Swarm Optimization algorithms.

In this paper [8], analyzes of Genetic Algorithms and Artificial Colony Optimization used for micro-calcification of mammogram images. Selected features were providing for a three-layer Back Propagation Network combined with ACO for classification. In [9], multilayer neural network with ACO and PSO algorithms are proposed for classification of digital mammograms images and the most favorable feature set were extracted by with multi-objective Genetic Algorithms. In [10], proposed segmentation methods by using Artificial Colony Optimization to map the edges in mammogram. A proposed new hybrid approach of ACO and cuckoo hunt named as "Ant-Cuckoo colony Optimization" method are used for selection of features in digital mammogram images [11]. A proposed technique shows the results better in a images. In [12], the author is proposed Swarm Optimization Neural Network for detection of micro-calcification in digital mammogram images by using texture features from the Region of Interest.

From the broad literature survey, it can be indentified that heuristic method based selection of feature has enhanced the classification accuracy of brain tumor detection in MRI image as normal or abnormal. Not a lot work has been done in classifier parameter optimization methods. Even if boosting techniques carry out in par with Support Vector Machine classifiers not a lot work has been done in that direction. This work addresses a number of the issues linked to Boosting classifiers.

3. METHODOLOGY

In this proposed method and construction of the brain tumor detection in MRI images and classification techniques is implemented. The following steps are involved.MRI dataset is used for valuation, features are extracted using discrete wavelets transform and feature reduction is obtained using singular value decomposition method. The feature obtained is classified by using Adaboost and Proposed method of Genetic Algorithm (GA) - Ant Colony Optimization (ACO) algorithms. The succeeding sections provided the detail of proposed framework.

A. Dataset

The MRI Brain image Datasets consists of 256 normal MRI images and 150 abnormal images, which is collected from medical hospitals. The ages of MRI images are between 18 and 96. The brain images were pre-processed to remove the skulls, retaining purely brain matter in the brain images. The brain image dataset has been mostly supporting research groups in understanding of tumor detection. Figure-1 shows a sample of Brain MRI image is used for investigation.

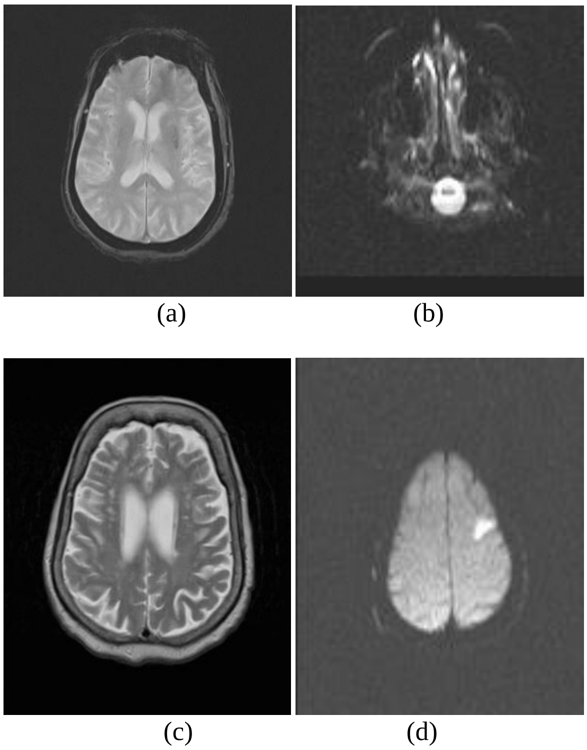

Figure-1. Sample Image, (a, c) Normal Image (b, d) Abnormal Image.

B. Pre-Processing of MRI Images

The pre-processing techniques are very important for medical images to remove unwanted noise in the images. The pre-processing is used to improve the image quality to make it ready to use further processing. This is used to removing the unrelated portions of the brain MRI images. Hence pre-processing is crucial to get better quality of the images. There are various filter such as median filter, wiener filter, Mean filter and Adaptive median filter. From this filter, Adaptive median filter provides better results while compare with other filters [13].

C. Adaptive Median Filter

Adaptive median filter works based on a rectangular region Rxy. It is changes the size of Rxy for

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the period of the filtering operation depending on convinced conditions as listed is given below. The every output pixel contains the median value in the form of 3-by-3 region around the equivalent pixel in the brain input images. Zeros however, restore the edges of the images [14]. The filter output is a single value, which swap current pixel value at (x, y), the point on which R is centered at the time. The following notation is usedin the filtering operations:

Emin = Minimum Pixel Value in Rxy
Emax = Maximum Pixel Value in Rxy
Emed = Median Pixel Value in Rxy
Exy= Pixel value at coordinates (x, y)
Smax = Maximum allowed size of Rxy

The Adaptive Median filtering is used to soft the non-repulsive noise from the two-dimensional signals with no blurring edges and conserved images. It is particularly suitable for enhancing MRI images. The preprocessing techniques used in MRI images, orientation, label, artifact removal, improvement and segmentations. The pre-processing techniques involved in creating masks for pixels with maximum intensity value, to reduce resolutions and to segment the MRI brain images [15].

D. Feature Extraction Using Wavelet

Signal multi-resolution representation provided by wavelet functions and each frequency component is analysed with an unrelated resolution and scale. Wavelet Transform is used to differentiate the discontinuities in a signal with "short" functions and at the same time highlight low frequency components with using "wide" functions [16].

To decompose a signal, wavelet transform is used to convert signal f into a set of *scaling functions* with help of wavelet functions, the wavelet function basis as follows:

$$\left(W_a f\right)(b) = \int f(x)\psi^*_{a,b}(x)\,dx$$

The function $\psi(x)$ can be represented by using mother wavelet

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right)$$

such that

$$\int \psi(x)\,dx = 0$$

The Discrete wavelet is receiving by setting value

$$a = 2^n$$
$$b \in \mathbb{Z}$$

The selected attributes and coefficients are exposed in surface plot of the pixel values in Figures 2 (a)-(d). In Figure-2a, the energy coefficients peak values can be seen, which are distinctive in the center of the different classes of images and grave for the learning algorithm.

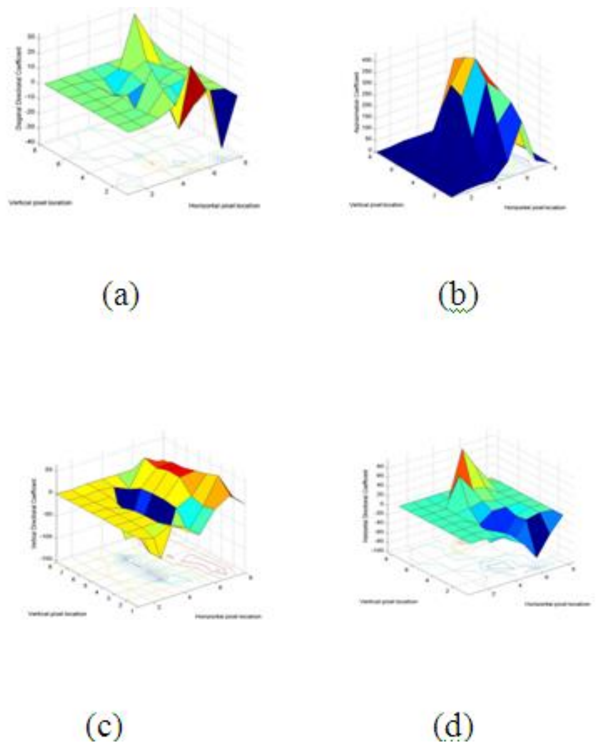

Figure-2. Discrete Wavelet Coefficient function images, (b) Diagonal Coefficient for image1 (a) Approximation for image1 (c) Coefficient for Vertical sample image1 (d) Coefficient for Horizontal sample image1.

The selected feature is unique from the distinctness and each class of image as exposed in Figure-2 (a) - (d). The distinct features are created, which is used to train a classification algorithms.

E. Adaptive Boosting Classifier (AdaBoost)

High level features are selected Based on Singular Value Decomposition algorithm and also trained [17] by binary classifier AdaBoost. The AdaBoost Classifier can be defined by as follows:

$$H(z) = \operatorname{sgn}\left(\sum_{t=1}^{L}\gamma_t c_t(z)\right)$$

where L is the number of weak learners

c_t is the learner

γ_t is the weight

At every iteration process, a new hypothesis c_t is selected by the classifier to decrease the error encountered in earlier rounds. The Weak learner c is dependent on the performance of the Ada Boost. Even though, good selection of weak learners can be improved by the performance of last classifier H. If the feature space is very high for similar classifiers to Support vector machine or ANN cannot be used. We are selecting h is NP hard. In this work, the weak learner selection of AdaBoost overcome by using modified Genetic Algorithms and - Artificial Bee Colony metaheuristic.

F. Artificial Bee Colony Optimization

The Artificial Bee Colony (ABC) algorithm replica the behaviors of the actual bees finding food source from various location and shares the food source information to other bees in the nest [18]. The real type of bees can be categorized into three types and each bee performs a specific job in Artificial Bee Colony algorithms and explained as follows:

a) The initially employed bee will find the new food source for nest.
b) Onlooker bees will collecting information from the employed bees about the food sources and prefer any one of the food source from collecting information to collect the nectar.
c) The scout is also answerable for discovery the new food sources for the nest.

To find good food sources, the sequence is iterated till best possible solutions or termination criteria are reached [19].

G. Genetic Algorithms (GA)

Genetic Algorithms (GA) are used to reproduce the natural evolutionary process, which is used to achieve optimal solutions. The randomly generated initial population of solutions and prearranged as binary strings known as chromosomes. The Fitness value function evaluates the truthfulness of the solutions. New populations are generated by Genetic algorithms operator's selection; crossover and mutation are applied to earlier existing population. Two units are selected in a probabilistic approach as parents proportional to finesses in the process of selection and the parents are crossed over to reproduce fresh two individuals known as offspring, during an exchange of parts of chromosome. The mutation that refers to incremental changes to each unit in the population with small probability to explore novel attributes which strength not be in the population up till now. The fitness is calculated for the every new populations and the process is iterated for stable number of iteration or till termination criteria is achieved.

H. Proposed Hybrid Learning Genetic Algorithm-Artificial Bee Colony (GA-ABC)-AdaBoost

The Artificial Bee Colony metaheuristic impersonates the performance of real bees seen in natural searching for nectar and process of food source sharing to other bees [18]. Artificial Bee Colony algorithms, it has three main steps such as the employed bee, onlooker bee and the scout bee. The Onlooker bee collecting all the information from employed bees for food source anywhere as the scout bee also involves searching a fresh food sources (solutions). The Artificial Bee Colony algorithms convergence speed is little. To improve the optimization competence, Genetic Algorithm is integrated within Artificial Bee Colony algorithms. In the proposed method, hybrid learning of Genetic Algorithm and Artificial Bee Colony with AdaBoost, evolves, select features. The selected features based on AdaBoost bases its classifiers. The crossover operator is used in Genetic Algorithm to get better food source of Artificial Bee Colony. The application of Genetic Algorithm, the present set of food source restored with offspring of new high fitness. The benefit of the proposed method, computational cost of AdaBoost is lowered significantly. The various steps of the proposed algorithm are as follows:

"1. Take Training set
$(x_1, y_1)\ldots(x_n, y_n); x_i \in \{-1, +1\}$
2. Initialize weights randomly of each learner
3. For $k = 1, \ldots K$
4. Train weak learner using training set
5. **Initialization of Artificial Bee Colony to optimize weak classifier**
Initialize the initial population of weak learners and Evaluate fitness;
 iteration← 0;
do while (iteration < NumOfIte)
 for i = 1 : EmployeedBee
 Select a random solution (an AdaBoost solution) and evaluate;
 Sort the solutions in ascending order based on the fitness
 Determine the probability for each solution, based on the following formula :
$$p_i = \frac{\sum(1/fit_i)^{-1}}{fit_i}$$
 end for
for i = 1 : OnlookerBee
 Select the solution based on probability;
 perform local search
 if (current_solution better tha Prev_solution)
 interchange food source
 end if
end for
Genetic Algorithm for i=1: food source
 Select parents randomly
 Crossover - produce new food source
 Greedy selection of food source
end for
 Scoutbee replaces abandonded food source with fresh source
 increment
end do
Terminate when objectives met or termination criteria reached"

4. RESULTS AND DISCUSSIONS

The proposed technique is used for evaluating MRI brain image datasets. The discrete wavelets transform were used for Features extraction and features selected

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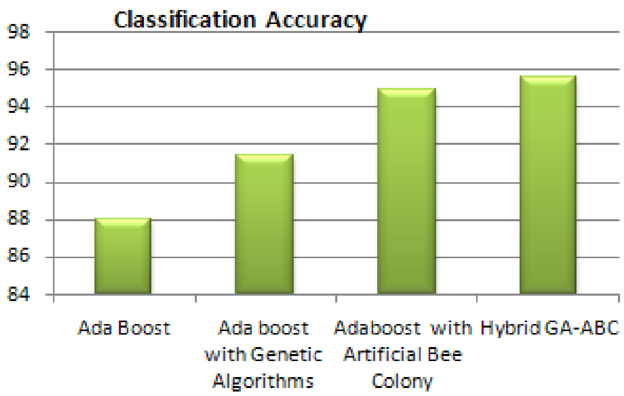
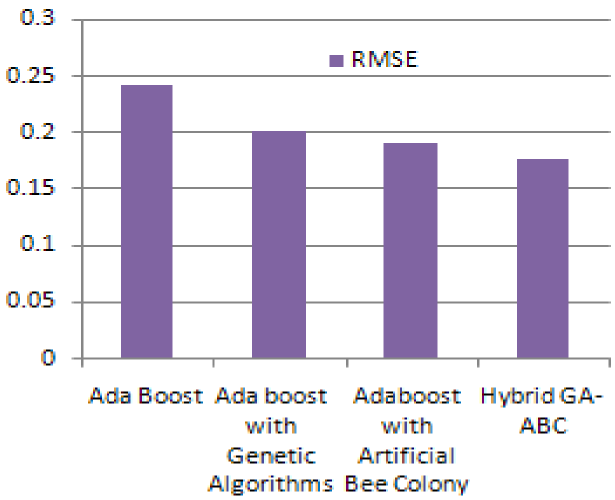
from SVD techniques. The selected features are classified by use of AdaBoost and proposed method. Table-1 shows, the Classification Accuracy of the brain tumor detection in MRI and Root Mean Square Error for AdaBoost optimization with Hybrid GA-ABC methods.

Table-1. Classification accuracy and RMSE.

Techniques	Classification Accuracy	RMSE
Ada Boost	87.05	0.2414
Ada boost with Genetic Algorithms	91.41	0.2004
ADA boost with Artificial Bee Colony	94.95	0.1894
ADA boost with Hybrid GA-ABC	95.61	0.1758



(a)



(b)

Figure-3. a) Classification Accuracy, b) Recall obtained.

The observed experimental result from the table 1, it shows that proposed hybrid-optimization method achieves an enhanced classification performance of 8.56 % while compared of AdaBoost technique. Similarly, when compared to Genetic Algorithms and ABC algorithms, the proposed hybrid GA-ABC technique improved the accuracy of classification by 4.2% and 0.66% respectively. The Root Mean Square Error is considerably decreased with the proposed optimization technique. Figure-4 (a) and (b) shows, the recall and precision carried out based on two techniques.

Table-2. Precision and recall of proposed method.

Techniques	Precision	Recall
Ada Boost	0.87	0.86
Ada boost with Genetic Algorithms	0.91	0.89
adaboost with Artificial Bee Colony	0.93	0.90
ADA boost with Hybrid GA-ABC	0.95	0.92

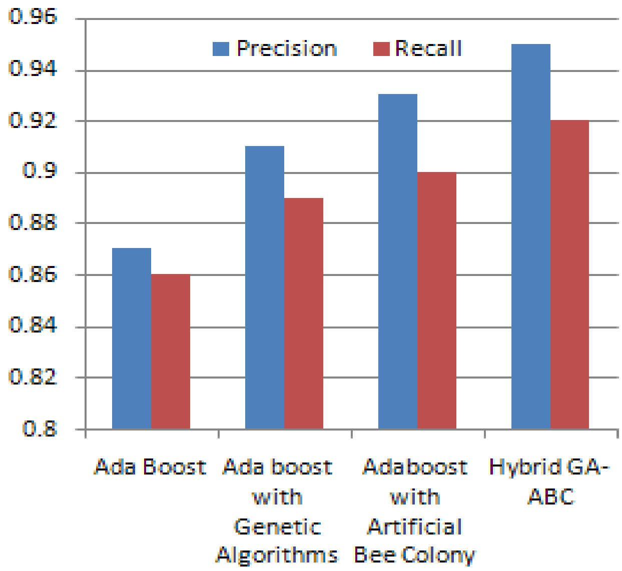


Figure-4. Precision and recall obtained.

The proposed hybrid optimization technique observed a better precision in the range of 2 % to 8% while compare with other methods. The optimized weights are applied to every weak learner and given best feature. The hybrid optimization technique achieves improved recall by 6%, 3%, 2% when compared to AdaBoost technique, GA and ABC respectively. In Figure-5 shows the convergence characteristics of the hybrid optimization technique.

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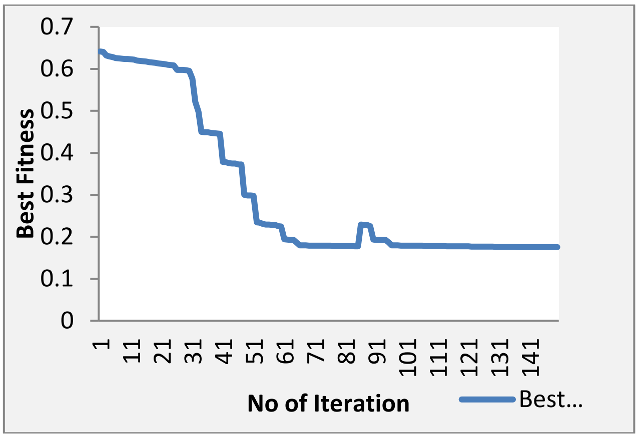

Figure-5. Performance of hybrid Optimization Techniques algorithm

Which is very fast during the iteration 88-91 and the converge rate at the 137th iteration in the implemented hybrid optimization techniques. It can also be seen that the local minima problem and was able to come out of the same.

5. CONCLUSIONS

The MRI Imaging technique is evolving as a very popular method for the finding of tumors and visualization of internal structure of the MRI. The Discrete Wavelet Transform used for feature extraction for the MRI images and Singular Value Decomposition also used for feature reduction. The Adaboost classifier algorithms are used to optimize for improving the classification accuracy of the MRI images. The optimized Genetic Algorithm - ABC algorithms are used to identify the tumor in MRI Images. A hybrid-learning method Genetic Algorithm - Artificial Bee Colony Optimization (ABC) with AdaBoost technique is projected to increase the classification accuracy of tumor detection in MRI images. The Experimental results obtained based on the MRI datasets with help of matlap software and compared with existing algorithms. The classification accuracy of tumor detection is increased by 7.89% while compared to adaboost algorithms.

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