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Multiple Sclerosis Identification Based on Ensemble Machine Learning Technique

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ABSTRACT

The diagnosis of multiple sclerosis disease (MSD) is crucial because it is a neurological disease leading to communication failure between brain tissues and other parts of the body. Effective classification and segmentation of brain tissues are necessary for early detection of multiple sclerosis disease. In this proposed work, an ensemble learning-based classification technique is proposed to identify multiple sclerosis diseases from a database of healthy and unhealthy brain magnetic resonance (MR) images. Feature extraction from brain MR images is performed using an eighteen different Gray Level Co-occurrence Matrix (GLCoM) based features. Then, decision tree-based ensemble learning is accomplished on these features using three different boosting techniques for classification of healthy brain MR image from a weak brain MR image. Performance metrics like sensitivity (T_{PR}), specificity (T_{NR}), accuracy, precision (PPV), and F-score are utilized for MSD identification. It has been verified that the ensemble learning technique yielded higher accuracy of 94.91% from other states of the art techniques on the e-health dataset.

Keywords: Gray level co-occurrence matrix (GLCoM), Magnetic resonance imaging, Multiple Sclerosis disease (MSD), ensemble learning

I. INTRODUCTION

Multiple sclerosis is a demyelinating disorder in which the immune system of the body is severely affected. In this disease, the antibodies are directly attacked and cause communication breakdown between the brain and other parts of the body [17]. Gradually MSD emerges into lifelong damage to the veins. Early detection is essential to cease disease progression. Various researchers are working in the domain of MSD identification, and numerous Machine learning approaches have been proposed by various researchers for brain MR image segmentation [9] and classification [11] [29] for the identification of neurological diseases like a tumor, multiple sclerosis, Alzheimer's, etc.

In 2018, a GLCoM based classification of brain MR image using a feed-forward neural network on the e-health dataset [4] [10] has been proposed with ten folds cross-validation with an accuracy of 92.75%. [4] Haar wavelet transforms along with principal component analysis (PCA) has been proposed by [3] in 2017. Using Adaboost with random forest-based classification on different datasets has been suggested by [6] using two-dimensional wavelet transforms and probabilistic PCA (PPCA) dimensionality reduction. In [5] collection of a decision with a ensemble of support vector machine (SVM) on an MS dataset. Convolution neural network with a dropout approach was given by [1] in 2018. In this paper, a comparison of three different activation functions has been done to find the best accuracy. Feng *et al*. (2019) [26] gave a deep neural network-based multiple sclerosis segmentation frameworks [15] [16] with a new technique, i.e. random dropping of MRI sequences while forming the training inputs [7].

Jain *et al*. (2015) [27] gives a novel segmentation approach, i.e., MSmetrix. A three-stage process has been shown for segmentation using MSmetrix. Selvaganesan *et al*. (2019) [28] designed a classification model on brain MRI images [23] [25] using derivative-based features, it outperforms other segmentation strategies. Cetin *et al*. (2020) [29] presents a Euclidean distance-based clustering method of segmentation. Gessert *et al*. (2020) [30] presents a two-path architecture with attention-guided interactions that permit active information interchange between processing paths. Salem *et al*. (2020) [31] presents FCNN based segmentation of T2-weighted lesion identification in multiple sclerosis disease. Aslani *et al*. present a traditional

encoder-decoder network with a regularization network. Brosch *et al*. (2015) [32] explains a model based on a neural network with convolutional and deconvolutional layers that incorporate feature extraction and segmentation in a single model.
The above literature highlights the fact that different machine learning techniques have been utilized successfully for MSD identification on brain MR images. However, to compare and analyze the performance ensemble learning technique, it is used for the classification task. A reinvestigation has been carried out using distinct performance metrics on brain MR images. Eighteen Gray level co-occurrence matrix (GLCoM) based features are utilized for generating feature vector and fed to Ensemble learning-based classifier [12]. In this proposed work, the results of ensemble learning techniques on three different boosting algorithms and on different learning cycles have been analyzed for MSD identification. Observed results are examined and matched with state of the art techniques, as mentioned in section IV. The paper is resumed as follows. Section II gives a thorough explanation of the proposed approach. Section III gives the parameter selection, Section IV gives experimental results, and Section V presents the conclusion.

II. PROPOSED APPROACH

This methodology comprises three phases, as shown in Fig-1. Firstly, the preprocessing of healthy and non-healthy (a person suffering from Multiple sclerosis disease) images has been performed on the e-health dataset to enhance an image's contrast. The dataset consists of 293 images in which 103 are healthy, and 190 are non-healthy. A random selection has been performed to extract 80% of the training dataset and 20% of the testing dataset. After this feature extraction has been performed, in which eighteen features are retrieved using a gray level co-occurrence matrix(GLCoM) as mentioned from Eq. (1-18). Next, the classification of unhealthy brain MR images is segregated from healthy brain MR images using ensemble learning techniques. Decision tree-based ensemble learning technique has been exploited along with AdaBoost, LogitBoost, and LPBoost algorithms. Various performance metrics have been utilized to analyze the accuracy, sensitivity, specificity, precision, and F-Score of the proposed approach. More than 90% of accuracy has been achieved using the proposed approach. It has been verified that the ensemble learning technique performs better than the neural network technique and wavelet transform [13].

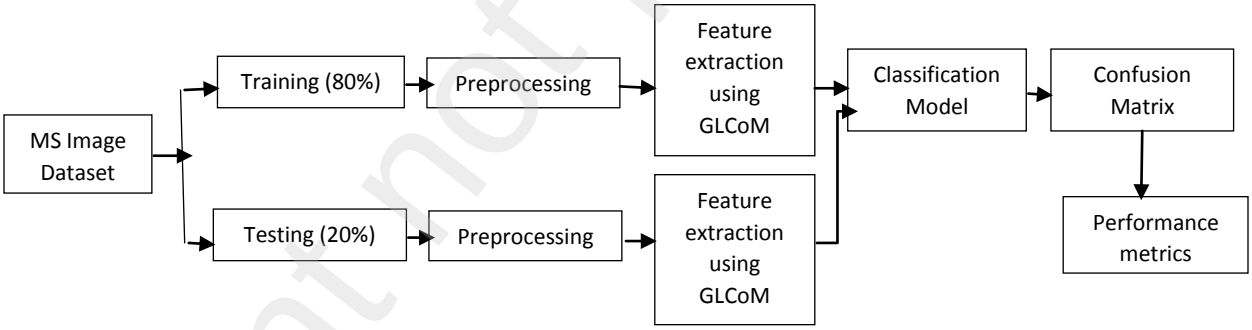

Fig-1 Block Diagram of Multiple Sclerosis Identification Based on the GLCoM Matrix Using Ensemble Machine Learning Techniques

A. Image preprocessing of healthy and Unhealthy brain MR image

1. Image resize- The first step of preprocessing is image resizing, the images in both training and the testing dataset are resized into 256×256 using bilinear interpolation. While resizing, resampling has also been performed using bilinear interpolation, i.e., output pixel is the weighted mean of pixels in the closest 2-by-2 locality. Bilinear interpolation is done first by interpolation in one direction and then again in another direction.
2. Grayscale conversion- Images in the dataset are colored image and thus every image in the training and testing dataset has been converted into grayscale.
3. Contrast limited adaptive histogram equalization (CLAHE) – Contrast limited adaptive histogram equalization technique strengthens the contrast of images obtained after grayscale conversion. CLAHE generates various

histograms for different parts of the image and uses them to readjust the lightness value of the image. Rayleigh distribution is used to remove the rician noise in the brain MR image.

B. Feature Extraction through Gray Level Cooccurrence Matrix(GLCoM)

A gray level level co-occurrence matrix computes second-order textural features of an image. First, the co-occurrence matrix is calculated from the input image matrix, and after normalization of the co-occurrence matrix, eighteen textural features are measured as mentioned in Eq. (1) to Eq. (18). $m(i, j)$ is the value of ith row and jth column is normalized co-occurrence matrix. μ is the mean and σ is the standard deviation measured from the normalized co-occurrence matrix.

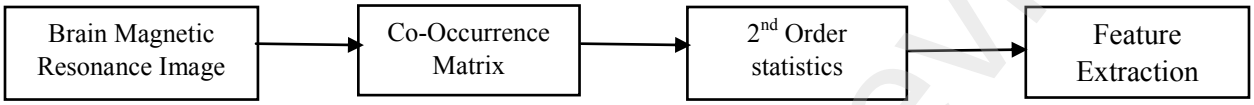

Fig-2 GLCoM based Feature Extraction Process for Images in the E-Health Dataset

Entropy (ENT) - Entropy is a mathematical measure of changeability that describes the texture of an image and denoted as:

$$\text{Entropy} = -\sum_{i,j} m(i, j) \log(m(i, j)) \quad (1)$$

Energy (ENE) - It's the rate of variation in the magnitude of the pixels over nearby areas and denoted as:

$$\text{Energy} = \sum m(i, j)^2 \quad (2)$$

Homogeneity (HOM) - It measured the proximity of the distribution of values in the GLCoM to the GLCoM diagonal and denoted as:

$$\text{Homogeneity} = \sum_{i,j} \frac{m(i, j)}{1 + (i - j)^2} \quad (3)$$

Contrast (CON) – It's a quantity of the gray level contrast between a pixel and its neighboring pixel over the entire image and denoted as:

$$\text{Contrast} = \sum_{i,j} |i - j|^2 m(i, j) \quad (4)$$

Correlation (CORR) – It is a quantity of how correlated a gray level value to its neighboring value over the entire image and denoted as:

$$\text{Correlation} = \frac{\sum_{i,j} (i - \mu i)(j - \mu j) m(i, j)}{\sigma_i \sigma_j} \quad (5)$$

Sum of Square Variance (SSQ) - It gives approximately high weights on the elements that vary from the average value and denoted as:

$$\text{Sum of the square: Variance} = \sum_{i,j} (i - \mu)^2 m(i, j) \quad (6)$$

Inverse Difference Moment (IDM) - It is a measure of local Homogeneity and denoted as:

$$\text{Inverse Difference Moment-} \sum_{i,j} \frac{m(i,j)}{1+(i-j)^2} \tag{7}$$

Angular second moment (ASM) - It is a measure of textural consistency of an image and denoted as:

$$\text{Angular second moment-} \sum_{i,j} \{m(i,j)\}^2 \tag{8}$$

Sum Average (SAVG)-It is a measure of the average sum of all the features in the GLCoM matrix and defined as:

$$\text{Sum average=} \sum_{i=2}^{2Ng} im_{x+y}(i) \tag{9}$$

Sum Variance (SVAR) - It is a measure of the sum of variances of all the features in the GLCoM matrix and defined as:

$$\text{Sum Variance} = \sum_{i=2}^{2Ng} (i - sumentropy)^2 m_{x+y}(i) \tag{10}$$

Sum Entropy (SENT) - It is a measure of the sum of entropies of all the features in the GLCoM matrix and defined as:

$$\text{Sum Entropy=} \sum_{i=2}^{2Ng} m_{x+y}(i) \log\{, m_{x+y}(i)\} \tag{11}$$

Cluster Shade (CS) - It is the lack of symmetry in the image and defined as:

$$\text{Cluster Shade=} \sum_{i,j} \{i+j-\mu_x-\mu_y\}^3 * m(i,j) \tag{12}$$

Difference Entropy (DENT) - It is a measure of the difference of entropies of all the features in the GLCoM matrix and denoted as:

$$\text{Difference Entropy=} \sum_{i=0}^{Ng} m_{x+y}(i) \log\{ m_{x+y}(i)\} \tag{13}$$

Cluster prominence (CP) - It is a measure of the skewness of the matrix and defined as:

$$\text{Cluster prominence=} \sum_{i,j} \{i+j-\mu_x-\mu_y\}^4 * m(i,j) \tag{14}$$

Difference Variance (DVAR) - It is a measure of the difference of variances of all the features in the GLCoM matrix and defined as:

$$\text{Difference variance=} \sum_{i=0}^{Ng} (i - sumentropy)^2 m_{x+y}(i) \tag{15}$$

Maximum probability (MAXPRO) - It shows the appearance of the gray-level value a_i adjacent to the gray-level value a_j more supreme in the image and defined as:

$$\text{Maximum probability} = \max\ m(i,j) \tag{16}$$

Autocorrelation (AUTOCORR) - It is defined as a closeness measure between dataset and shifted copy of dataset and mentioned as:

$$\text{Autocorrelation=} \sum_{i} \{\sum_{j} i.j.m(i,j)\} \tag{17}$$

Dissimilarity (DISS) - It is the variation of gray level pairs mentioned as:

$$\text{Dissimilarity=} \sum_{i} \{\sum_{j} |i.-j|.m(i,j)\} \tag{18}$$

C. Classification

Classification of unhealthy brain MR image from a healthy brain MR image ensemble learning technique has been implemented on the e-health dataset.[10] Ensemble Learning is the technique that combines different classification models with some error rate to get the resultant approach in which the error rate is low. The ensemble works on various base learners created sequentially so that the model's final performance is enhanced. A class label is predicted using the mode of member predictions. The class probability is calculated and then summed up the probabilities for each class label. The class label which receives maximum probability is chosen as the predicted class label. In ensemble learning, equal weights are assigned to different models regardless of their performance. On the other hand, boosting algorithms are applied to reduce the bias by training weak learners sequentially in which each weak learner is trying to correct its predecessor.

In this proposed work decision tree with three different boosting algorithms (AdaboostM1, LPBoost, logitboost) has been implemented to do the binary classification task that separates the healthy brain MR image from the multiple sclerosis brain MR image. In the decision tree, many trees are built, and each tree selects a class where the class that receives the most votes by a simple majority designated as the predicted class. It gives a signal to the learning algorithm "n" the number of times in eachiterations, a training weight is allocated to every training sample. At the start of the algorithm, all the weights for each training example were the same and in the subsequent rounds, the weight of incorrectly classified objects has been enhanced to target challenging objects in the training set. Lastly, a robust approach is constructed. The decision tree with LPboost gives the highest accuracy rate of 94.91% based on ensemble learning classifier as mentioned in Section-III

3.1 AdaboostM1- It is a meta-algorithm which is used in association of other technique to give improved results. A boost is a classifier of the form as mentioned in Eq. (19)

$$Y(x) = \sum_{t=1}^{T} y_t(x) \tag{19}$$

Where every y_t is weak learners which takes an entity as input and gives a value that depicts the class of the object. Y(x) is the robust learner constructed from weak learners.

3.2 Linear programming (LPBoost)- It is a training model which escalates a margin between training pattern of different classes label and hence belongs to the class of maximizing-margin classification algorithms.

3.3 Logit Boost- Logitboost works on the minimization of the logistic loss function to classify the data objects to one of the classes for the binary classification task [2].

III. EXPERIMENTAL RESULTS

In this section, the system's performance is examined and the experiments have been done on an e-health dataset, consisting of 103 healthy control brain MRI images from Kaggle [24] [25] [8] and 190 unhealthy brain MRI images from e-health [10], i.e., images of a person suffering from multiple sclerosis disease for a total of 293 images.

The size of each image has a dimension of 512×512 with a resolution of 57 dpi. The experiments are carried out in MATLAB R2020a. Proposed work was performed on a computer with Intel Core i5, 2.5-GHz CPU, and a RAM of 4GB. The investigation is performed and performance comparison ensemble classifier on different learning cycles with different boosting methods. Random selection of images (80%) from the dataset has been used for training purposes, i.e., 82 healthy images and 152 unhealthy images.

The different performance metrics mentioned in Eq. (20-25) are identified through four different parameters as illustrated below:

True Positive (T_P) = No. of healthy brain image accurately predicted as healthy.

True Negative (T_N) = No. of unhealthy brain images accurately predicted as non- healthy

False Negative (F_N) = No. of unhealthy brain images inappropriately predicted as healthy

False Positive (F_P) = No. of healthy brain images inappropriately predicted as non-healthy

$$(T_P + T_N) = diagonal \quad (confusionm \quad atrix) \tag{20}$$

$$Sensitivit \quad y(T_{PR}) = \frac{T_P}{(T_P + F_N)} \tag{21}$$

$$Specificit \quad y(T_{NR}) = \frac{T_N}{(F_P + T_N)} \tag{22}$$

$$Accuracy \quad = \frac{(T_p + T_N) * 100}{(T_P + T_N + F_P + F_N)} \tag{23}$$

$$F - score \quad = \frac{T_p}{T_P + (F_p + F_N)/2} \tag{24}$$

$$Positivepr \quad edictedval \quad ue(PPV) = \frac{T_p}{T_p + F_p} \tag{25}$$

TABLE-1 BRAIN MAGNETIC RESONANCE IMAGES FROM E-HEALTH AND KAGGLE DATASET

Training Images (80%)		Testing Images (20%)		
Healthy(Kaggle)	Unhealthy(e-health)	Healthy(Kaggle)	Unhealthy(e-health)	Total
82	152	21	38	293

A. Selection Of Boosting Method And Learning Cycles in Decision Tree Classifier (Ensemble Learning)

The true positive rate (sensitivity) achieves the highest value of 98.42% in the Adaboost algorithm with 100 learning cycles, as mentioned in Table-4 and figure-3. In contrast, the true negative rate reaches the most elevated of 93.33 % with the LPboost with 100 learning cycles, as mentioned in table-4 and figure-4, respectively. The positive predictive rate (PPV) precision is the number of correctly identified healthy brain MR images divided by the true positives and true negatives rates. PPV achieves a 96.37% result in linear programming boost with 100 learning cycles, as illustrated in table-4. F-score is the harmonic mean (HM) of positive predicted value and true positive rate. F-score is 96.17% in Logitboost with 200 learning cycles. The highest accuracy of 94.91% was achieved in LPBoost with 100 learning cycles and Logitboost with 200 learning cycles, as mentioned in figure-7 and table-4, table-6, respectively.

TABLE- 2 PERFORMANCE METRICS FOR ENSEMBLE LEARNING WITH 50 LEARNING CYCLES

Classification Model	Sensitivity(TPR)	Specificity(TNR)	Precision(PPV)	F-Score	Accuracy
ENSMBL_AdaBoosM1_50	97.63	70.47	85.74	91.29	87.96
ENSMBL_LPBoost_50	92.63	88.57	93.71	93.10	91.18
ENSMBL_LogitBoost_50	95.26	81.42	90.49	92.71	90.33

TABLE- 3 PERFORMANCE METRICS FOR ENSEMBLE LEARNING WITH 75 LEARNING CYCLES

Classification Model	Sensitivity(TPR)	Specificity(TNR)	Precision(PPV)	F-Score	Accuracy
ENSMBL_AdaBoosM1_75	97.37	76.66	88.56	92.68	89.99
ENSMBL_LPBoost_75	90.79	83.33	90.94	90.78	88.13
ENSMBL_LogitBoost_75	97.37	84.28	91.97	94.54	92.70

TABLE- 4 PERFORMANCE METRICS FOR ENSEMBLE LEARNING WITH 100 LEARNING CYCLES

Classification Model	Sensitivity(TPR)	Specificity(TNR)	Precision(PPV)	F-Score	Accuracy
ENSMBL_AdaBoostM1_100	98.42	83.33	91.61	94.85	93.04
ENSMBL_LPBoost_100	95.79	93.33	96.37	96.05	94.91
ENSMBL_LogitBoost_100	96.78	83.33	91.57	93.87	91.86

TABLE- 5 PERFORMANCE METRICS FOR ENSEMBLE LEARNING WITH 125 LEARNING CYCLES

Classification Model	Sensitivity(TPR)	Specificity(TNR)	Precision(PPV)	F-Score	Accuracy
ENSMBL_AdaBoosM1_125	96.58	85.23	92.36	94.37	92.54
ENSMBL_LPBoost_125	94.73	85.23	93.24	93.41	91.30
ENSMBL_LogitBoost_125	95.79	87.61	93.49	94.57	92.87

TABLE- 6 PERFORMANCE METRICS FOR ENSEMBLE LEARNING WITH 200 LEARNING CYCLES

Classification Model	Sensitivity(TPR)	Specificity(TNR)	Precision(PPV)	F-Score	Accuracy
ENSMBL_AdaBoosM1_200	95.69	86.19	92.90	94.23	92.37
ENSMBL_LPBoost_200	95.26	81.42	90.60	92.76	90.33
ENSMBL_LogitBoost_200	98.15	89.04	94.33	96.17	94.91

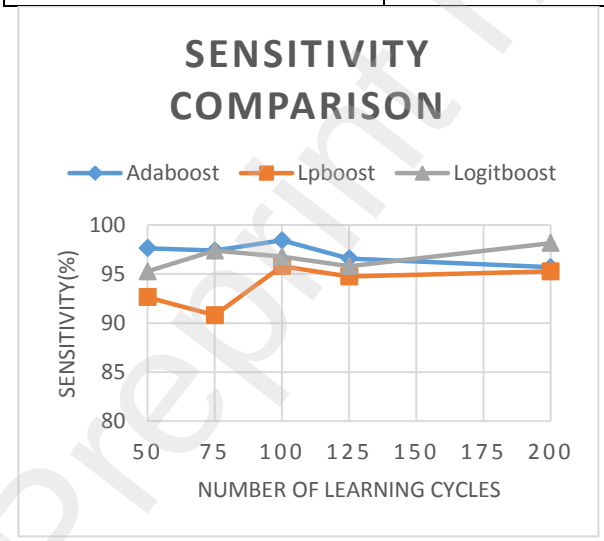

Fig-3

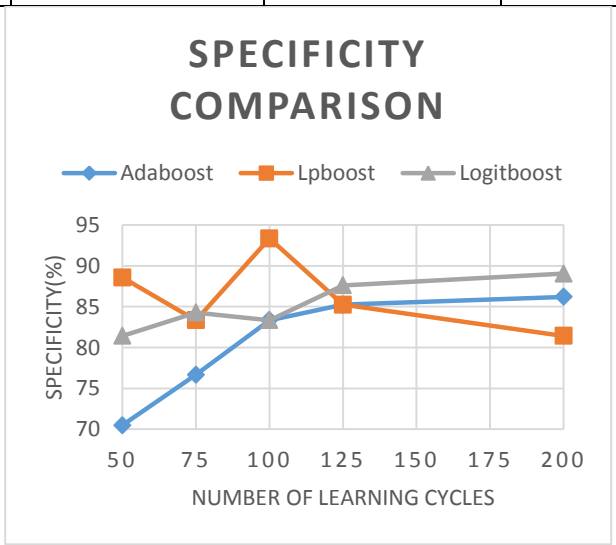

Fig-4

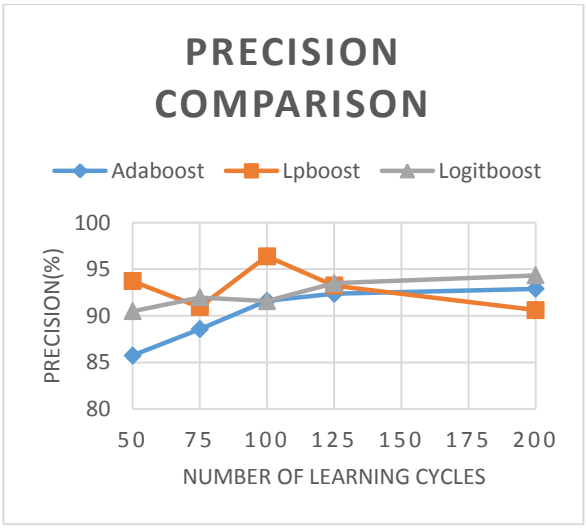

Fig- 5

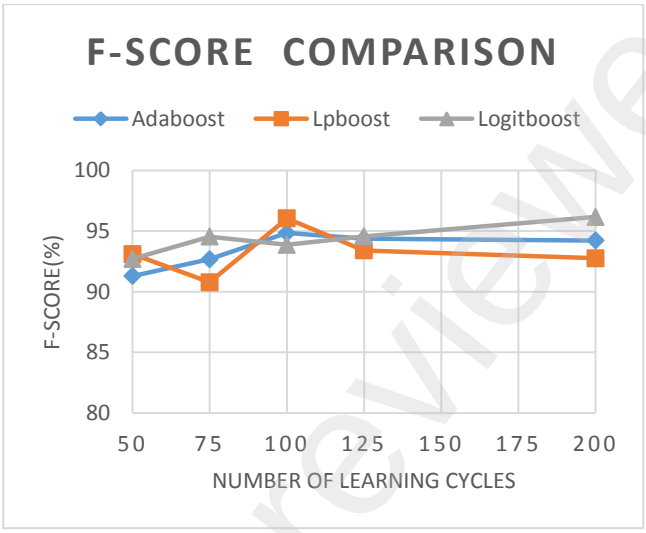

Fig-6

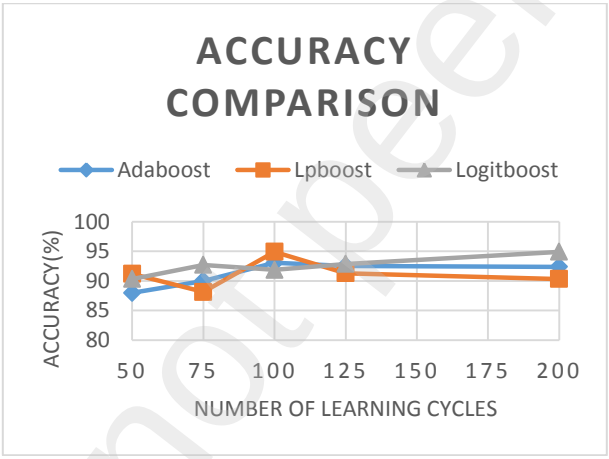

Fig-7

B. Comparison of the Proposed Technique with Earlier Studies

A comparison of the different classifiers on the e-health dataset is as shown in Table-7. Our proposed work gets an accuracy of 94.91 % using the ensemble learning technique on the e-health dataset (unhealthy) [10] and Kaggle dataset (healthy) [25]. The state of art techniques works on MSD identification based on the e-health dataset for unhealthy brain MR images and healthy images from other sources.

TABLE-7 PERFORMANCE ANALYSIS WITH OTHER STATE OF THE ART TECHNIQUES

Reference	Approach	Sensitivity	Specificity	Accuracy
-	proposed(GLCoM+ensemble+LogitBoost)	95.792	93.334	94.91%
-	proposed(GLCoM+ensemble+AdaBoost)	98.42	83.33	93.04%
-	proposed(GLCoM+ensemble+LPBoost)	96.78	83.33	91.86%
4	GLCM+FFNN	92.75	92.76	92.75
3	Haar wavelet+ PCA+LR	-	-	89.72

IV. CONCLUSION AND FUTURE SCOPE

In this article, the classification of unhealthy brain MR images (MS) from healthy brain MR images has been done on eighteen gray level cooccurrence matrix based features. The experiments are carried out on data consisting of 103 healthy brain MRI images from the Kaggle dataset and 190 unhealthy (Multiple sclerosis) brain MRI images from the e-health dataset. The classification has been performed using ensemble Machine Learning techniques along with three different (AdaBoost, Linear programming boost, and LogitBoost) boosting algorithms. Performance has been analyzed using five different (sensitivity, specificity, precision, F-score, accuracy) performance metrics and it has been verified that ensemble machine learning outperforms neural networks and wavelet-based classification with an accuracy of 94.91% in ensemble classifier with LPboost in 100 learning cycles and ensemble classifier with LogitBoost in 200 learning cycles. In future work, the GLCoM is analyzed based on convolution neural network to identify multiple sclerosis diseases.

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