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An Efficient Classification of MRI Brain Images

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ABSTRACT The unprecedented improvements in computing capabilities and the introduction of advanced techniques for the analysis, interpretation, processing, and visualization of images have greatly diversified the domain of medical sciences and resulted in the field of medical imaging. The Magnetic Resonance Imaging (MRI), an advanced imaging technique, is capable of producing high quality images of the human body including the brain for diagnosis purposes. This paper proposes a simple but efficient solution for the classification of MRI brain images into normal, and abnormal images containing disorders and injuries. It uses images with brain tumor, acute stroke and alzheimer, besides normal images, from the public dataset developed by harvard medical school, for evaluation purposes. The proposed model is a four step process, in which the steps are named: 1). Pre-processing, 2). Features Extraction, 3). Features Reduction, and 4). Classification. Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull, in the pre-processing step. During this stage, the images are converted from gray scale to colored images for further processing. In second step, it uses Discrete Wavelet Transform (DWT) technique to extract different features from the images. In third stage, Color Moments (CMs) are used to reduce the number of features and get an optimal set of characteristics. Images with the optimal set of features are passed to different classifiers for the classification of images. The Feed Forward - ANN (FF-ANN), an individual classifier, which was given a 65% to 35% split ratio for training and testing, and hybrid classifiers called: Random Subspace with Random Forest (RSwithRF) and Random Subspace with Bayesian Network (RSwithBN), which used 10-Fold cross validation technique, resulted in 95.83%, 97.14% and 95.71% accurate classification, in corresponding order. These promising results show that the proposed method is robust and efficient, in comparison with, existing classification methods in terms of accuracy with smaller number of optimal features.

INDEX TERMS Color moments (CMs), feed forward artificial neural network (FF-ANN), random subspace, random forest, bays.net, principle component analysis (PCA), discrete wavelet transforms (DWT).

I. INTRODUCTION

The robotized classification of images, obtained from Magnetic Resonance Imaging (MRI), is a critical procedure and for this reason, a number of classification strategies are developed in the most recent decades. It plays a vital role in analyzing and examining human mind. Brain MRI has significantly enhanced the findings and treatments of cerebrum pathology due to rich data, it produces, about the delicate tissue life structures. The non-obtrusive and torment free properties of cerebrum MRI get the consideration of scientists and clinicians.

Brain MRI provides better results, when it is contrasted with other imaging modalities such as Computed Tomography (CT), Positron Emanation Tomography (PET), where delicate tissue outline is important. Manual review of cerebrum MRI is a hectic job due to huge amount of information, it contains. To overcome this issue, automatic methods are introduced for the examination of brain MRI images [1]–[4].

The cerebrum MRI is an imperative route for recognizing sound brains, and brains having distinctive mind sicknesses such as cerebrum tumor, Alzheimer, and stroke. The standard classification model contains four phases which

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are: preprocessing, features extraction, features reduction and classification of brain MRI images [1], [5]. The preprocessing is the simplest phase among all phases of the classification model. In preprocessing stage, a noise removal algorithm is used for the removal of salt-and-pepper noise, and unwanted components such as scalp and skull from the images. Due to the removal of noise from images, their quality is improved. In this stage, the images are also converted from gray scale to color (RGB) images and, thus, the utilisation of rich information in colored images increase classification accuracy. For the removal of noise from images, a number of algorithms are used [6], in which the median filter has performed better for the removal of salt and pepper noise from images. It is also better because of not distressing the edges of images [7].

Feature extraction stage, which is followed by the preprocessing, is not only important but also a difficult task [8], [9], in which the format of an image is changed to a set of features. Images contain a lot of features but most of them are redundant, which are not useful for classification. The most monotonous task is the selection of an optimal set of features. A number of techniques are available to extract features from images, in which Discrete Wavelet Transform (DWT) [1], [10]–[12], Principle Component Analysis (PCA), Independent Component Analysis (ICA), gabor features, and minimum noise fraction transform [13]–[16] are the most widely used. When features are extracted, irrelevant features need to be reduced as they increase compilation time and memory usage. In this stage, those features are selected that are optimal and useful. Several algorithms such as Genetic Algorithm (GA) [17], PCA [1], [18], [19], ICA [20] and Linear Discriminant Analysis (LDA) [21] are used for dimensionality reduction. This reduced set of features is used in the last stage for classification. There are two broad categories for the classification of MRI Brain images called: supervised and unsupervised techniques. Supervised techniques include K Nearest Neighbors (KNN) and Support Vector Machine (SVM) [11], [18], [22], [23] while unsupervised techniques include Fuzzy C mean, and s-means [3], [23].

Gupta *et al.* [24] suggested in their research work, a non-invasive system for the detection of brain glioma. The texture and morphological features with ensemble learning were used for detection purpose. Promising results were achieved which are 97.37% on JMCD and 98.38% on BraTS. Arasi *et al.* [25] proposed a clinical support system for improving the accuracy of detection and classification of brain tumor from the BraTS dataset using images. The GLCM extraction technique was used for collecting features of tumor region and LOBSVM was used for classification purpose. It achieved an average accuracy of 97.69%. Ullah *et al.* [26] proposed an enhanced technique for classification of brain MRI images into normal and abnormal images using color features and Artificial Neural Network (ANN). It achieved an accuracy of 100% and 90% during training and testing phases, correspondingly. Jeyong *et al.* [27] used machine learning method on DSC-MR images which are based on delta-radiomic features. The proposed algorithm was used for classification of HG and LG GBMs. The average accuracy achieved, for this work, was 90%. In short, the results produced using both techniques were good but in term of accuracy, the performance of supervised techniques was better than unsupervised techniques.

This research work proposes quite a useful technique to automate the time-consuming manual procedure of physicians, and provides a clear and effective methodology for the classification of MRI images into sound images and abnormal images containing disturbances and injuries. The proposed technique is using a four step process, in which, an image passes through four stages termed as: Preprocessing, Features Extraction, Features Reduction and Classification. Median filter is used in preprocessing stage for the removal of noise such as salt-and-pepper, and unwanted components such as scalp and skull. These images are, then, converted from gray scale to color (RGB) images for further processing. Discrete Wavelet Transform (DWT) is applied for features extraction in second stage. Color Moments (CMs) are used to reduce and select the optimal set of features. These optimal features are sent to FF-ANN using percentage split and hybrid classifiers named: Random Subspace with Random Forest (RSwithRF) and Random Subspace with Bayesian Network (RSwithBN) using 10-Fold cross validation for recognizing sound brains and brains with distinctive sicknesses.

The existing methods use a large set of parameters for classification purposes, which greatly increase their complexity in terms of space and time. The current studies, especially those using hybrid classifiers, are carried out using T1 weighted images. The basic aim of the this research is to develop a fast and efficient method that determines and uses a small set of optimal parameters. This work has used hybrid classifiers for an improved accuracy. Furthermore, this work is based on T2 weighted images. The main contribution of this work is as follows:

1) classification of images with an accuracy almost the same or even slightly better than other classifiers and that too with a set of only nine parameters.
2) reduction the complexity of the proposed method compared with other techniques as it processes each image against a limited set of features.

II. RELATED WORK

Zhang *et al.* in [1] proposed a new method for the classification of T2-weighted brain MRI images that consists of three stages. In the first stage (feature extraction), it extracts 1024 features from each image by using DWT. These features are reduced to 19 features, in stage 2 using PCA. The reduced set of 19 features is, then, feed to an ANN classifier in third stage, for the classification. It achieved good results in terms of accuracy. Rajini *et al.* in [23] proposed an automated approach to classify brain MRI images into normal and abnormal images, in a two stage process. The first stage extracts features using DWT, which are, then, reduced to an optimal features' set using PCA. The second stage performs classification using two classifiers with an accuracy of 94.5%.

Othman *et al.* [28] have used SVM to differentiate between the normal and abnormal MRI images. The technique, they presented, involves inputting brain MRI dataset, the implementation of wavelet-based feature extraction, and, then, classification using SVM. The images in the image set include T2 flair weighted images having a resolution of 256×256 pixels. This work considered a total of 32 images, in which 22 images were normal while 10 were abnormal. The images are passed to SVM classifier for classification after the successful extraction. Saritha *et al.* [29] proposed a new technique for the classification of MRI brain images, which used assimilating wavelet entropy-based spider web plots and probabilistic neural network (PNN). In the first step, wavelet entropy-based spider web plots is used for feature extraction while PNN is used for classification, in the second stage. For the evaluation purposes, they used 75 T2 weighted images, each having a resolution of 256×256 pixels. PNN is a good technique for the classification of patterns and, therefore, the proposed classifier response in terms of accuracy was good.

Lahmiri *et al.* [30] proposed an automated approach to classify healthy images and those which are affected by diseases such as Glioma, Tumor and Alzheimer. DWT is used to extract optimal features from sub-bands LH and HL. The brain MRI images are decomposed and features are extracted in both horizontal and vertical orders, respectively. Three classifiers PNN, KNN, Learning Vector Quantization (LVQ), combined in a single SVM, were used for the classification to improve the precision and effectiveness. They verified this technique on a dataset taken from Harvard medical college. This combined approach produced fruitful results.

Nandpuru *et al.* in [31] proposed a robotized technique to differentiate between effected and healthy MRI images. Median filter was used for the removal of salt-and-pepper noise, and unwanted components such as scalp and skull. The images quality was improved by reducing noise. It extracted four kind of features, which are: power law transformation, texture, symmetrical and gray scale features, respectively. PCA is used to reduce these features to an optimal set of features, which are, then, classified using SVM in the classification phase. For assessment purposes, they used Linear Kernels (LKs), Quadratic Kernels (QKs) and Polynomial Kernels (PKs), whose accuracy was 74%, 84%, and 76%, respectively.

Kalbkhani *et al.* [32] suggested a three stage technique to categorize normal and abnormal MRI brain images. 2-D discrete wavelet transform is used, in first stage, for features' extraction. To select optimal and efficient features, the multi-cluster feature selection method is used. It reduced the initial set of features to 41, which is forwarded to the next stage for classification. The researchers used multi-cluster features and KNN to classify healthy and those images that contain injuries and disorders. The classification accuracy was found good when compared with state of art techniques.

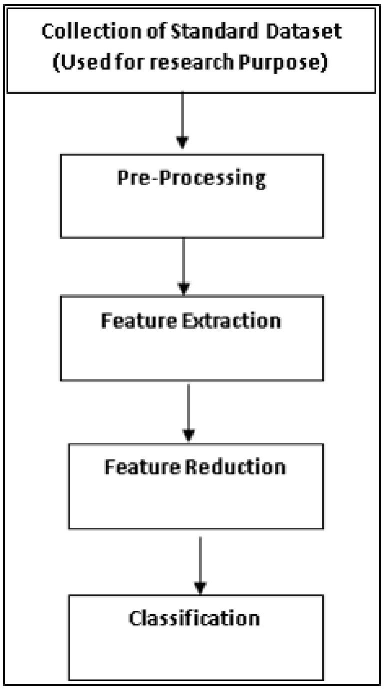


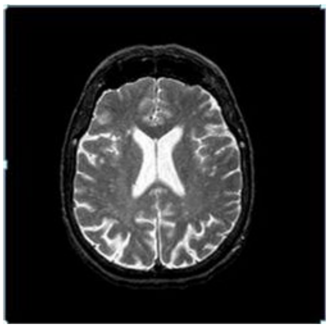
FIGURE 1. **The research model adopted for this work.**

Wahid *et al.* [33] also presented a three stage automated model for classification. In the first stage (pre-processing), noise is removed from the images. Two types of features: color moments and texture are extracted in the second stage, which are classified using probabilistic classifier. The classifiers used were based on logistic function, and a total of 150 images were taken into consideration, in which 66% were used to train the model and 34% were used to test the model. Overall accuracy achieved was 90.66%.

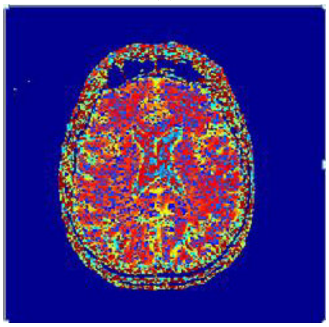
The rest of this paper is organised as follows. Section III describes the Materials and Methods. The proposed mechanism is presented in section IV. Section V provides the evaluation results. Conclusion is presented in section VI.

III. MATERIALS AND METHODS

One real world dataset is used in proposed work, which was taken from the Harvard Medical School [34]. The proposed model (presented in Figure. 1) used in the research have four (4) phases which are pre-processing, features extraction, features reduction and classification. Features are extracted in feature extraction stage from brain MRI images for their potential use in characterizing them, which are, then, used in our research work. Recent studies suggested that ANN and hybrid classification techniques are most suitable methods for classification due to their high accuracy rates. This article presents our investigations for the classification of MRI brain images on well-known classification techniques namely: the Feed Forward - ANN (FF-ANN), Random Subspace with Random Forest (RSwithRF) and Random Subspace with Bayesian Network (RSwithBN). To the best of our knowledge, no classification technique has been used with



(a)



(b)

FIGURE 2. Illustrating pre-processing of images. The image in: a). gray scale before processing, and b). Color (RBG) form after processing.

an optimal set of only nine features. For the classification of MRI brain images into normal and abnormal groups, the proposed model and the classification techniques that it uses, have proved best in terms of accuracy compared with similar techniques found in the Literature.

A. PREPROCESSING

Though, MRI produces high quality images, however, the images include unwanted components such as scalp and skull and they might have noise due to the negligence of operators. To improve the accuracy of the proposed technique, it is necessary that the images should be not only sharp but free of unwanted components and noise. In the proposed work, median filter is used in the pre-processing stage for the removal of salt-pepper noise, and scalp and skull without affecting the edges of brain MRI images. In this stage, the given images are also converted from gray scale to colored (RGB) images that provide rich information. This work used a 3 × 3 mask for condensing computation time because of a small size window [17]. After successful execution of first phase, the images achieved are free of unwanted components and noise, which are converted to color (RGB) images. The reason behind this conversion is the fact that images in color (RGB) form contains rich information as compared to images in gray scale. Figure 2 illustrates the pre-processing stage of images. Figure 2 (a) presents the image in gray scale before processing while Figure 2 (b) is in converted color (RBG) form after processing.

B. FEATURES EXTRACTION

To achieve higher level of accuracy in the classification stage, it is essential to select an optimal set of features in the feature extraction stage. DWT is one the most powerful mathematical tool, which uses dyadic scales and positions, and it implements wavelet transform [22], [28]. To extract features from MRI brain images, DWT technique is used, in this work. DWT not only offers knowledge about time but also the frequency domain. Basic introduction of DWT is presented next.

Let suppose the square-integral function will be $x(t)$ the wavelet transform which is continuous of $x(t)$ relative to the given wavelet $\Psi_{c,d}$ (t) is defined in Equation. 1.

$$W\Psi_{(c,d)} = \int_{-\infty}^{\infty} x(t) \times \Psi_{c,d}(t)\, dx \tag{1}$$

where,

$$\Psi_{c,d}(t) = 1/\sqrt{c}\Psi(t - c/d) \tag{2}$$

Variables 'c' and 'd' are positive real numbers in Equation 2. Using translation and dilation, the wavelet $\Psi_{c,d}$(t) is computed from mother wavelet Ψ(t) where 'c' represent the dilation factor and 'd' represent the translation parameter. The simplest and mostly used wavelet for image processing is haar [35]. To decompose an image into sub-hands with their relative DWT co-efficient, the two cascading low and high pass filters of DWT technique, generally used to satisfy specific constraints, were used.

$$Ca_{j,k}(\text{n}) = \text{DS}[\textstyle\sum \text{x(n)g} \times j(\text{n-}2^j k)] \tag{3}$$

$$Cd_{j,k}\ (\text{n}) = \text{DS}[\textstyle\sum \text{x(n)h} \times j(\text{n-}2^j k)] \tag{4}$$

$Ca_{j,k}$ and $Cd_{j,k}$ in Equation 3 and 4 are approximation and detailed component coefficients while high and low pass filters are denoted by h(n) and g(n), correspondingly. The variables 'j' and 'k' denote wavelet scale and transition factor in these equations. The operator DS (↓) shows down sampling. The overall process is called wavelet decomposition tree, which is illustrated in Figure 3.

DWT is applied on every facet of the images separately. Figure 4 produces the results of four sub-bands (namely the HH, HL, LL, and LH) of images on each scale. The LL sub-band shows the approximation factor while the rest of the sub-bands indicate the detailed element of an MRI brain image. An MRI image can be decomposed up-to several levels to get more compact approximation factor. It should be kept in mind that, if, we intend to increase the influence of decomposition levels, we should increase the decomposition levels to an appropriate level.

The proposed work used haar wavelet to decompose the images up to three levels to extract features from the MRI images. Figure 5 illustrates the layout of the complete set of sub bands up-to three levels.

The left hand side of Figure 6 shows a color (RGB) image, which is converted from a gray scale image. The size of this colored (RGB) image is 256 × 256×3 which is too

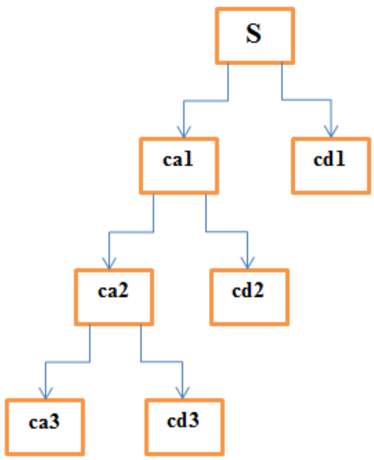


FIGURE 3. A 3-Level decomposition tree. S represents the root image while ca and cd having 1, 2, and 3 represents the approximation and detailed component coefficients at level 1, 2, and 3.

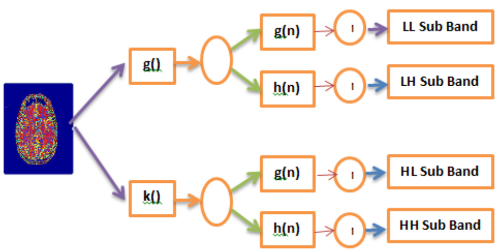


FIGURE 4. Diagram of DWT in 2D.

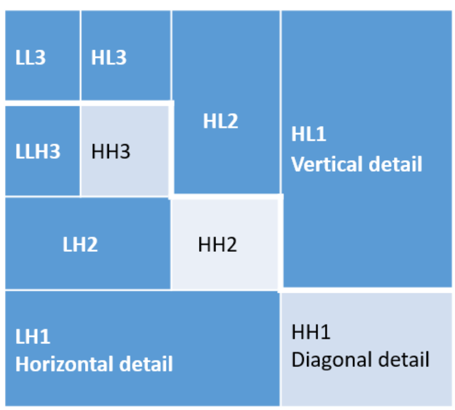


FIGURE 5. Layout of the wavelet sub-bands.

huge for computation, so it should be reduced and compressed without loss of optimal information. The proposed method decomposed this image up-to 3 levels, as we used wavelet decomposition, which reduces and trims the size of an image using 3 level decomposition. The right hand side of Figure 6 shows this decomposed image. The approximate coefficient (LL3) is our interesting part and its size is 32×32 × 3.3072, which is still very large as an input for classifiers, in terms of computation. Therefore, it should be optimised to reduce computation overhead. For this reason, Color Moments (CMs) are applied to an approximate coefficient at level 3.

C. FEATURES REDUCTION

The proposed model, at this stage, proposed using quite a useful technique for features reduction. Since, 3072 features extracted in features extraction stage were quite large and intense for computation and classification, we used CMs to greatly reduce the features set without the information. This reduction was important as a set of large number of features not only increases computation overhead but also memory usage. The proposed method extracted Red, Blue and Green channels from the converted color (RGB) images. For each channel, the values for Mean, Skewness and Standard deviation (variance) are calculated, which are very useful in classification. An optimal set of only nine features is obtained, in this stage, which represents a complete image used for an increased classification accuracy while reducing computation overhead and complexity [33]. The equations, given below, mathematically illustrate the Mean, Variance, and Skewness for the Red, Green and Blue channels, respectively. Equation 5, 6, and 7 represent the Mean, Variance and Skewness for the Red, Equation 8, 9, and 10 for the Green, while Equation 11, 12, and 13 represent them for the Blue channel.

$$M_{1,1} = 1/N \sum_{j=1}^{N} I_j \tag{5}$$
$$M_{1,2} = 2\sqrt{\sum_{j=1}^{N} (t_j - M_{1,1})^2} \tag{6}$$
$$M_{1,3} = 1/N \sum_{j=1}^{N} (I_j - M_{1,1})^3 \tag{7}$$
$$M_{2,1} = 1/N \sum_{j=1}^{N} I_j \tag{8}$$
$$M_{2,2} = 2\sqrt{\sum_{j=1}^{N} (t_j - M_{2,1})^2} \tag{9}$$
$$M_{2,3} = 1/N \sum_{j=1}^{N} (I_j - M_{2,1})^3 \tag{10}$$
$$M_{3,1} = 1/N \sum_{j=1}^{N} I_j \tag{11}$$
$$M_{3,2} = 2\sqrt{\sum_{j=1}^{N} (t_j - M_{3,1})^2} \tag{12}$$
$$M_{3,3} = 1/N \sum_{j=1}^{N} (I_j - M_{3,1})^3 \tag{13}$$

The variables 'I' and 'N', in the above equations, denote the intensity and total number of pixels, respectively. These equations compute three color channels (Red, Green and Blue) from the color (RGB) images at level 3 using approximate coefficients presented in Figure 6. The Mean, Variance and Skewness are, then, calculated for the three channels. The ultimate set of these nine features is stored in a one dimensional array, which are used by the classifiers such as FF-ANN and hybrid classifiers RSwithRF and RSwithBN, for classification purposes.

D. CLASSIFICATIONS

The proposed technique used an individual classifier called: Feed Forward - ANN (FF-ANN), and two hybrid classifiers namely: Random Subspace with Random Forest (RSwithRF) and Random Subspace with Bayesian Network (RSwithBN) for classification purposes, in the last

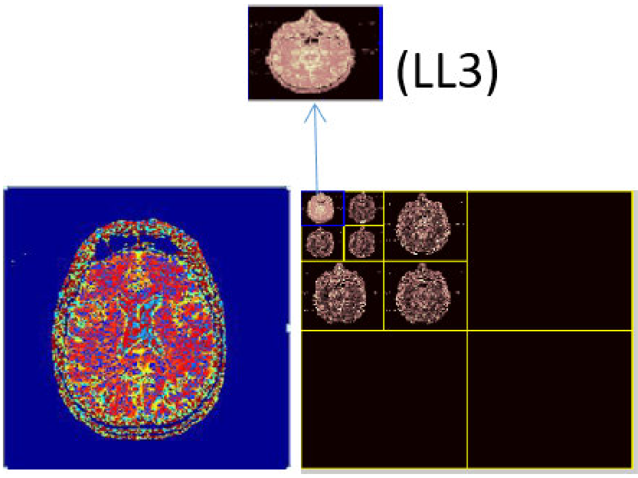


FIGURE 6. blue image, on the left, is an original colored (RGB) image, and the right side black color image shows the decomposition of an color (RGB) image up to level 3, where LL3 is an approximate coefficient at level 3.

stage of the model. These classifiers are discussed in this section.

1) CLASSIFICATION USING FEED FORWARD-ANN

This work used the FF-ANN classifier for the classification of MRI brain images into normal and abnormal classes. The main reason behind using a neural network is, its most extensive and prevalent use, for the classification of patterns, because an ANN not only requires information about probability distribution but also priori probabilities. The structure and working of Artificial Neural Networks (ANNs) are like human brain as they perform storage, interpretation and cognitive activities in a similar fashion to human brain. The training of a neural network for a particular activity takes a huge amount of computation time, however, once it is trained, then, it identifies the unknown objects in excellent manner. The mathematical model of an ANN comprises of artificial and non linear neurons, which run in parallel. An ANN could have a single layered or multilayered architecture. Generally, a three layered architecture use an input, a hidden and an output layer. The hidden layer behaves like an interface between the input and output layers. The intermediate layer implements the main function. There are many types of ANNs, in which, the FF-ANN is the most common and simplest among all. In the proposed model, an FF-ANN with two layered architecture is used. The two layers are hidden layer and output layer. The hidden and output layers, used in the proposed methodology, have ten (10) and one (1) neurons, as illustrated in Figure 7. Sigmoid function is used in the hidden layer while linear function is used in the output layer. The optimal set of nine features, obtained in last stage, are sent to hidden layer for execution while the output layer classifies an image as a normal or abnormal image. A normal image is represented by a 1 while an abnormal by a 0. The FF-ANN was trained using BP- Algorithm [36] of Leven berg-Marquardt, which automatically adjust the weights until it reaches its objective.

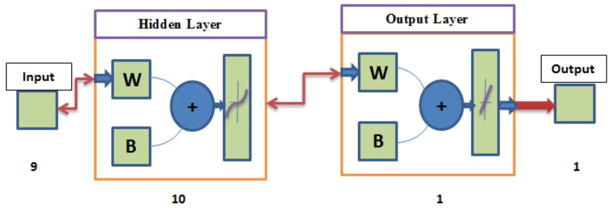


FIGURE 7. The ANN used in the proposed model.

2) CLASSIFICATION USING HYBRID CLASSIFIERS

The proposed work also utilized hybrid techniques to classify MRI brain images into normal and abnormal images. While studying the Literature, it was found that the performance of hybrid classifiers is better than individual classifiers. The main reason is that these ensembled techniques balance the performance of individual classifiers before the ultimate decision is taken. They support individual classifiers against failure and, thus, enable them to perform better [37].

In the proposed technique, we hired Random Subspace (RS) classifier that is used in combination with base learner classifiers such as Random Forest (RF) and Bayesian Network (BN) in ensemble fashion. These are selected because they give promising results when combined with weak classifiers. The results showed that it is a good approach for classification of healthy images which are free from diseases and abnormal images that contain injuries and diseases. The detailed explanations of these classifiers are given below:

1) Random Subspace (RS): The best thing about RS is that it attempts to increase and preserve its accuracy, whenever, it becomes more complex. The RS consists of several classifiers. It modifies the features space without modifying example space in training set.
2) Random Forest (RF): can be used not only for regression but it can also be used for classification. It contains a number of decision trees just like classifiers. Each decision tree gives vote to a class and votes of every tree in the forest are counted. The tree or class with maximum votes in the forest is selected [38].
3) Bayesian Network (BN): A BN is a network structure that is shortly called Bays Net or Bays model. It belongs to the probabilistic graphical models, and it is represented as a DAG (directed acyclic graph) defined mathematically in terms of a set of variables ($U = \{X_1, \ldots, X_n\}$ where n $\geq$ 1) and probability tables (B_p = {p(u | pr(u)), where u $\in$ U}). The pr(u) represents u's parent set in the BN. The conditional probability distribution of BN is calculated as P(U) = $\prod_{u \in U}$ p(u | pr(u)).

IV. THE PROPOSED MECHANISM

The algorithm used in the proposed model (presented in algorithm 1) takes MRI brain images as input, which are passed through the four step process, for their classification as normal or abnormal images. This algorithm uses certain terminologies such as assignment operator and functions such as Median_Filter (K) and RGB(), where the former apply median filter on images while the latter convert an MRI brain image from gray scale to a colored (RGB) image. The procedures Decomposed_3L () and Approx_3L() use haar wavelet for the decomposition and approximation of images to three (3) levels, respectively. Channel (1), Channel (2), Channel (3) subroutines are used to extract the Red, Green, Blue channels of the converted color (RGB) images. The procedures named: Mean_Image (), Stand_Dev_Image (), and Skewness_Image () are used to compute the Mean, Standard Deviation and Skewness of the colored images.

Algorithm 1 The Proposed Classification Algorithm

```
Require: MRI Brain images, Number of Images;
  //Initialisations
  int n = Number of Iages;
  float FeaturesDate [n,9] = 0;
  MRI_Image = Nil;
  for(int i = 1; i <= n; i++)
      M_Image = Get the ith image;
      //The following are Phase 1 (pre-processing stage) steps
      Median_Filter (M_Image);
      L = RGB (M_Image);
      //The following are Phase 2 (feature extraction stage) steps
      N = Decomposed_3L(L);
      C = Approx_3L (N);
      //The following are Phase 3 (feature reduction stage) steps
      Red = Channel (1);
      Green = Channel (2);
      Blue = Channel (3);
      //Get the nine features for each image and store them in array
      FeaturesDate[i,1] = Mean(Red);
      FeaturesDate[i,2] = Standard_Deviation(Red);
      FeaturesDate[i,3] = Skewness(Red);
      FeaturesDate[i,4] = Mean(Green);
      FeaturesDate[i,5] = Standard_Deviation(Green);
      FeaturesDate[i,6] = Skewness(Green);
      FeaturesDate[i,7] = Mean(Blue);
      FeaturesDate[i,8] = Standard_Deviation(Blue);
      FeaturesDate[i,9] = Skewness(Blue);
  end for //The following are Phase 4 (classification stage) steps
  Apply various classifiers with different arrangements on array FeaturesDate[,];
  Record the accuracy of each classifier against the given settings;
```

V. EVALUATION AND RESULTS

To implement and evaluate the proposed algorithm, this work used a Core i5 system having 2.4GHz processor and 3GB RAM. The system was running 64-bit window 8 operating system. The tools used for experiments were Matlab R2010a and Weka having version 7.10.0 and 3.6, respectively. A standard dataset containing 70 T2 weighted images was used to evaluate the proposed methodology. The images in this database had 256 × 256 resolution and this was adopted from [34] like other researchers. Among the total 70 images considered in this work, 45 images were abnormal and they were effected by three different kind of diseases namely: brain tumor, acute stroke, and alzheimer. From every disease, only 15 images were considered for experimental purpose. The remaining 25 images were normal and they were not affected by any kind of injuries. Figure 8 illustrates normal and abnormal images. This work used a percentage split of 65% and 35% for training and testing purpose, when FF-ANN classifier was used. However, to test hybrid classifiers, it used 10 Fold cross validation technique.

TABLE 1. Details of MRI images.

Groups of Images (in Num)		
Normal	Abnormal	Total
45	25	70

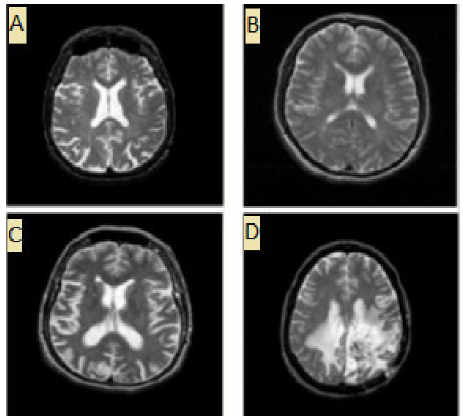


FIGURE 8. MRI sample images A. Normal MRI B. MRI with acute stroke C. MRI with Alzheimer disease D. MRI with Tumor.

A. ALGORITHM ACCURACY

This work examined the proposed technique using different statistical techniques and results are compared with the existing work. From the Literature, it was learnt that most of the researchers used accuracy to measure the performance. Table 2 and 3 present the performance and accuracy achieved by the proposed algorithm for hybrid classifiers and FF-ANN, respectively. The accuracy recorded for the RSwithRF and RSwithBN classifiers was 97.14% and 95.71%, respectively. The classification accuracy of the proposed model for the FF-ANN was 100% during the training while it was 91.66% during the testing stage. Overall, 95.83% accuracy, on average, was observed based on both training and testing.

The comparative analysis of hybrid and individual classifiers revealed that hybrid classifiers are more beneficial and sophisticated than individual classifiers. Hybrid classifiers

TABLE 2. Evaluation results of hybrid classifiers (in terms of accuracy).

	Classification of Images and their accuracy											
	Normal				Abnormal				Overall			
Classifier	Total (Num)	Correct (Num)	Incorrect (Num)	Accuracy (%)	Total (Num)	Correct (Num)	Incorrect (Num)	Accuracy (%)	Total (Num)	Correct (Num)	Incorrect (Num)	Accuracy (%)
RSwithRF	25	24	1	96	45	44	1	97.77	70	68	2	97.14
RSwithBN	25	24	1	96	45	43	2	95.55	70	67	3	95.71

TABLE 3. Evaluation results of individual classifiers (in terms of accuracy).

	Classification of Images and their accuracy										
	Normal				Abnormal				Overall Accuracy		
Classifier	Total (Num)	Correct (Num)	Incorrect (Num)	Accuracy (%age)	Total (Num)	Correct (Num)	Incorrect (Num)	Accuracy (%)	Training (%)	Testing (%)	Average (%)
FF-ANN	9	8	1	88.88	15	14	1	93.33	100	91.66	95.83

TABLE 4. Comparative analysis based on classification accuracy.

Method	Technique	Overall Accuracy (%)
Nandpuru et al. [31]	LK + PCA + SVM	74
	QK + PCA + SVM	84
	PK + PCA + SVM	76
El-Dahshan et al. [19]	DWT + Feed Forward Back Propagation- ANN (FP-ANN)	92
El-Dahshan et al. [19]	DWT + PCA + FP-ANN	97
Ibrahim et al. [22]	Encoded Information + PCA + KNN	96.33
Nandpuru et al. [31]	MsFCM	96.77
Rajini et al. [23]	DWT + PCA + FP-ANN	90
Wang and Fei [39]	PCA + SVM	85
	Pearson Correlation Co-efficient (PCC) + SVM	79
	ICA + SVM	82
Proposed Method	DWT + RSwithRF	97.14
	DWT + RSwithBN	95.71
	DWT + CMs + FF-ANN	95.83

TABLE 5. Features based comparative analysis.

Method	Technique	Features (Num)
Chaplot et al. [11]	DWT + Self Organizing Map (SOM)	44761
	DWT + SVM with LK	
	DWT + SVM with PK	
	DWT + SVM with QK	
Kalbkhani et al. [32]	2-D (DWT) + KNN	41
Zhang et al. [1]	DWT + PCA + ANN	19
Proposed Method	DWT + RSwithRF	9
	DWT + RSwithBN	
	DWT + CMs + FF-ANN	

perform beter than individual classifiers. Detailed comparative analysis of proposed method with existing models in terms of accuracy and the number of features being used for classification purposes are presented in Table 4 and 5, respectively.

B. LIMITATIONS OF CURRENT STUDY

Though, the proposed mechanism suggested improvements over the existing methods, however the current study has a number of limitations. It tested the proposed mechanism against only a single individual and two hybrid classifiers. Similarly, it is tested against 70 images of only one dataset. Furthermore, this work considered only three (3) statistical features. Moreover, this work is not compared with the most recent studies based on deep learning.

VI. CONCLUSION

This paper suggested a new mechanism to differentiate MRI brain images into normal and abnormal using individual and hybrid classifiers. The suggested method used median filter in the pre-processing stage. Discrete Wavelet Transform was used to extract the features and Color Moments were introduced to reduce the features to an optimal set of nine features and, thus, minimise the complexity and memory usage. These nine features were extracted from all 70 images considered in this work, in which 25 were normal and the remaining 45 were abnormal images, which were affected by three kind of diseases. These feature sets for all images were passed to supervised classifiers, in which Feed Forward - ANN, and hybrid classifiers: Random Subspace with Random Forest and Random Subspace with Bayesian Network had a promising response in terms of classification accuracy, in differentiating normal and abnormal images. The accuracy for the above mentioned individual and hybrid classifiers was 95.83%, 97.14% and 95.71% respectively. Experimental results further proved that the proposed mechanism is far better than different existing techniques in terms of accuracy and features being used.

In future, we intend to extend the proposed model to investigate more individual and hybrid classifiers. This research would also be extended to evaluate the proposed model with more parameters. This work could be also extended to use different features reduction methodologies while keeping the execution time at minimum. It would be interesting to compare the results of the proposed technique with the methods based on deep learning. It would be further interesting to check the impact of statistical features other than those used in this work.

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