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A hybrid image enhancement based brain MRI images classification technique

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ABSTRACT

The classification of brain magnetic resonance imaging (MRI) images into normal and abnormal classes, has great potential to reduce the radiologists workload. Statistical analysis based approaches has been widely employed for this purpose which are comprised of four stages such as pre-processing, feature extraction, feature reduction and classification. The outcome of such approaches are highly dependent upon the image quality: better the image, higher the outcome. In this paper, we present a hypothesis that the quality of the image, which is enhanced at the pre-processing stage, can play a significant role in enhancing the classification performance of any statistical approach. To strengthen our theory we first employed an improved image enhancement technique, which consists of three different sub-stages: noise removal using median filter, contrast enhancement using histogram equalization technique and image conversion from gray-scale to RGB. After image enhancement, we extract features from an enhanced MR brain image using a discrete wavelet transform and these feature are further reduced by color moments i.e mean, standard deviation, and skewness. Finally, we trained an advanced deep neural network (DNN) to categorize the human brain MRI images as normal or pathological. The approach obtained 95.8% which is significantly higher than the previous state-of-the-art techniques. The result evident that our hypothesis about the role of image enhancement process in medical image classification, is realistic and also have potential to improve the performance of other medical image analysis technique.

1. Introduction

Magnetic Resonance Imaging is a non-invasive medical imaging methodology [1]. MRI provides good quality images of the human body organs in 2D and 3D formats. MR imaging modality is nowadays considered to be one of the best accurate technique for MRI classification, due to its high-resolution images on the brain tissues [2], the modality is also utilized to diagnose various diseases due to its image quality [3,4].

The manual recognition of malignant and benignant images based on MRI images is a time consuming and challenging task. Manually classifying the brain MRI image is thoroughly depends on the radiologist experience which might lead us to a wrong decision. Several recent studies have demostrated that machine bases diagnosis not only expedite the process but also significantly reduce the risk of misdiagnosis as compare to human [5].

To overcome this issue, an automatic Computer Assisted Diagnosis (CAD) system is required to relieve workload of diagnosis and classification of brain MRI. Computer-assisted diagnosis is now a days an active research area in medical imaging, it has been applied to many other complex problem of computer vision domain such as abnormal heart-beat detection [6], emotion recognition [7,8], optical Pathology detection [9], for non-communicable diseases [10], for lung nodule quantification [11], and motion correction in MRI [12]. Especially for brain MRI classification computer technology is extensively utilized these days in medical decision support system, such as heart disease, brain tumors and cancer research. Fully automatic classification of brain MR brain image into benign or malignant is extremely important for clinical studies, research etc. Using machine learning techniques the brain MRI image classification is possible via supervised techniques (k-NN, SVM, and ANN) and unsupervised techniques such as fuzzy c-means and self-organizing maps. Generally, CAD system consists of four different phases, such as pre-processing, feature extraction, feature reduction and classification [13].

Preprocessing is an essential step for MR brain image dataset. The quality of the MR brain image is improved in this phase to make it suitable for further processing. The efficiency of an algorithm can be improved by performing image preprocessing. The brain MRI image is

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of low contrast and consist of various types of noise. Image enhancement and noise reduction can make the picture more attractive for viewing [14]. Image enhancement techniques enhance the visual quality of the picture and can extract the information easily. Image enhancement methodologies are: wiener filter, median filter, Gabor filter, low pass filter, and histogram equalization. Three steps have been performed in reference [15] during this stage, namely noise removal using Gaussian filter, contrast enhancement using histogram equalization and edge detection using laplacian edge enhancement.

In this stage, the relevant features are identified in the brain MRI image which leads to an easier, faster and better understanding of the image. The extracted features present the major information about the input image pattern. After feature extraction, the classifier will only receive essential features, which reduces the computational time and improve the accuracy. The author in [16] extracts the features from brain MRI images using level-5 two-dimensional wavelet decomposition. For image decomposition, the histogram has been used to form the feature set. A Haar wavelet level-3 2D discrete wavelet transform is employed in [17] for feature extraction from brain MRI.

The reduction of features is a fundamental requirement of any classifier. In this stage, the massive database gets reduced by measuring certain features or properties. Otherwise, the high amount of features maximize the storage memory and computation time. Therefore, the reduction of dimensionality is indispensable because excessive features create complexity for a classifier which is known as the curse of dimensionality. Reference [5] uses the concept of the associated likelihood function of PPCA for dimensionality reduction. The primary advantage of using PPCA is that the overfitting of data is averted during classification.

In this stage, the diminished features are presented to a classifier to determine normality and abnormality of the brain MRI image. El-Dahshan and Bassiouni [18] have employed two classifiers (such as k-NN which is based on Euclidean distance and ANN which is based on Levenberg–Marquardt) to classify the malignant and benign brain MRI and obtained high accuracy.

The main contribution of this paper is the feature reduction using the first three-color moments as illustrated in Fig. 5. Using only 9 features, we have classified the benign and malignant images in the given dataset and achieved good accuracy. The main advantage of limited features is that it consumes less time as depicted in Fig. 9. We have also compared our results with other proposed similar studies.

This article is organized as follows: Relevant work is presented in Section 2 and proposed methodology for brain MRI classification is presented in Section 3. Database is presented in Section 4 and Section 5 describes experimental results and discussion. Finally, Section 6 presents conclusion and future work.

2. Relevant work

The number of patients are increasing tremendously with brain abnormalities day by day. Analyzing MR brain images manually is the most challenging task for radiologists. Therefore, an automated image analysis tool is highly required such as CAD system to overcome this problem [19]. This proposed work presents an automatic system for brain MRI classification using different techniques such as Median filter + Histogram equalization + DWT + Color moments + ANN.

Extensive work has been carried-out to classify the brain MRI without human interaction. Reference [20] used a convolution NN for feature extraction and Kernel Extreme Learning Machines (KELM) is used to classify the images and obtained an accuracy of 93.68%. Cheng et al. [21] employed gray level co-occurrence matrix, intensity histogram, and bag-of-words for feature extraction and evaluate a large dataset. Three classifiers have been used for classification purposes, K-NN, SVM, and sparse representation-based classification (SRC) and achieved 91.28%, 87.54%, and 89.72% respectively. Alam et al. [22] detect Alzheimer's disease using the dual-tree complex WT, PCA, and twin SVM and achieved reasonable accuracy. Nayak et al. [23] classify malignant and benign brain MRI using level-5 discrete curvelet transform and PPCA for feature extraction and feature reduction, respectively. The author in [24] extracts the features of an MR brain image using the Daubechies wavelet transform. Two classifiers have been used such a SOM and SVM to classify the malignant and benign MR images.

Jha et al. [17] proposed four stages algorithm for brain MRI classification where Wiener filter, DWT, and PPCA, is employed for noise reduction, feature extraction, and feature reduction, respectively. Random space ensemble classifier and KNN classifier has been used to classify the MRI image as normal or pathological. Lai et al. [25] proposed a novel algorithm for brain MRI segmentation using the Gaussian-Dirichlet mixture model and modified full CNN U-net. This proposed algorithm is also compared with other existing algorithms and the proposed algorithm was found superior. Abdullah et al. [26] find the normal and abnormal brain MRI using Learning Vector Quantization (LVQ). The main aim of their methodology is to improve the performance of LVQ. The round off function along with Euclidean distance function is employed to improve the performance. In reference [27], the feature extraction and classification tasks are performed by using Berkeley Wavelet Transform and SVM respectively and obtained reasonable accuracy. The results of normal and abnormal brain MRIs were evaluated and validated using accuracy, specificity, sensitivity, and dice similarity index coefficient.

In Ref. [28] median filter and ANN is employed for noise removal and MR brain image classification, respectively, and obtained 91.8% accuracy. In paper [24] DWT is used to get the approximation coefficients and SVM is employed for classification. Reference [29] employed stationary wavelet transform to replace the discrete wavelet transform. They combine artificial bee colony and particle swarm optimization to obtain high accuracy.

3. Proposed method

This proposed methodology comprised of 4-main phases, namely, preprocessing, feature extraction using 2D discrete Wavelet Transform,

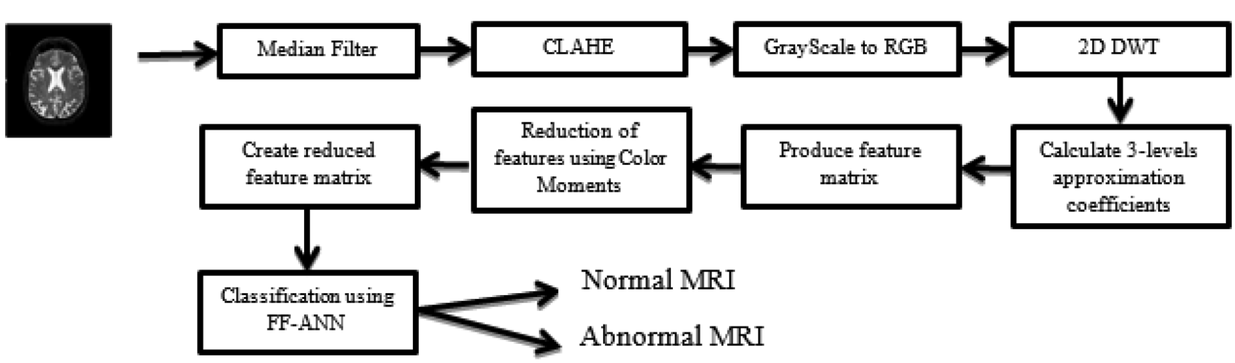

Fig. 1. Block diagram of proposed model for brain MRI.

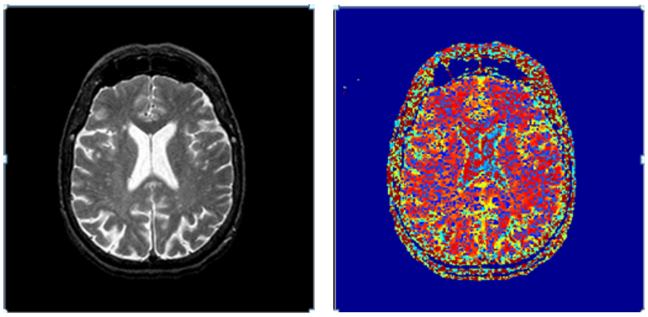

Fig. 2. Preprocessing, enhanced grayscale image and conversion to RGB image.

feature reduction using color moments, and classification using feed-forward neural network as illustrated in Fig. 1. In order to improve the MRI image quality, pre-processing techniques are grouped into three main categories: noise reduction using median filter, contrast enhancement using histogram equalization technique and image conversion from gray-scale to RGB, as the color of the image will be utilized as main features for classification. The preprocessing stage is followed by the feature extraction from MR images using level-3 2D-DWT approximation coefficients. Then, the first three-color moments are utilized to select the optimum features. Finally, the reduced features were classified using Feed-Forward Artificial Neural Network (FF-NN). The proposed block

The brief description of all stages is illustrated below:

3.1. Preprocessing using median filter and Contrast Limited Adaptive Histogram Equalization (CLAHE)

The brain MRI images were individually downloaded from the website of Harvard Medical School [30]. The given dataset is comprised of seventy-one images out of forty-six normal and twenty-five are abnormal MR brain images. The dataset needs to be preprocessed to improve the image quality and hence acquired optimal features. We have used a median filter for noise removal while CLAHE is employed for image enhancement.

The median filter is nonlinear filter and the fundamental idea of this filter is to calculate the median of a number of elements at its input. The median value of the neighborhood (mask) replaced the noisy value of the image. The window size is 'W' in the standard median filtering, where W is odd. This window is convolved along values of the image. The size of the window is constant and the filter mask must be odd such as 7 × 7, 5 × 5, or 3 × 3. The shape of the mask may be square, circular, linear, and etc. The brain MRI image is mostly comprised of salt and pepper noise and the median filter is the best choice to remove this type of noise. We have utilized a 3x3 size window because the large size window needs higher computation time and it affects the edges as well. The main objective of using this filter is to remove the noise and preserve the edges of the image.

Afterward, CLAHE is applied to this noise-free image for further enhancement. CLAHE overcome the over-amplification issue of histogram equalization by diminishing noise-like artifacts in homogenous regions. The image is equally partitioned into rectangular blocks and in each block HE is performed. Many studies have been done on CLAHE for image contrast enhancement [31–33]. The function of CLAHE is different from traditional HE. CLAHE utilized a clip point to limit the contrast of the image generated by traditional HE. CLAHE split the image into tiles of height and width pixels. Also, the input image in CLAHE is splitted into various non-overlap sub-blocks [34].

In this work, we have set the clip limit to 0.02. CLAHE is used to control the noise problem which is existed in traditional HE. In the MRI image, CLAHE works on the small regions which are known as tiles and it also calculates different histograms, and then compares each histogram to a specific part of the image and furthermore, it is utilized to reorganize the contrast estimation or brightness of the image. CLAHE provides more details as compare to standard HE as CLAHE improves the contrast of the image effectively but CLAHE still has the inclination to amplify unwanted pixels that have to be improved in the future work. The CLAHE clip limit is a pre-defined value as illustrated below:

$$clip = \frac{M_b}{L} + \alpha(M_b) - \frac{M_b}{L} \tag{1}$$

Where α denotes the clip factor having range [0,1]. While M_b represents the pixels strength in each sub-block. The range of clip limit is $\frac{M_b}{L, M_b}$based on the above Eq. 1. When $\frac{M_b}{L}$ is equal to clip limit, then the input image range from [0, L-1] to output image range from [0, R-1] will be linearly mapped.

Finally, in the preprocessing step, the enhanced grayscale image is converted to Red, Green, and Blue image components because of its easiness in further processing as shown in Fig. 2. Also, the RGB image offers more information than the grayscale image.

3.2. 2D-DWT

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3.3. Wavelet Transform

Analysis of signals via FT has been the most commonly used tool. FT converts the signal from a time domain to a frequency domain. However, it removes time information from the signal domain. Therefore, the reader cannot determine when a specific event took place which is a serious shortcoming of this technique. With the loss of time information, the classification accuracy will be decreased.

The FT is modified by Gabor to study a minor part of the signal which is known as short-time FT (STFT) or window [35]. STFT is like a compromise between frequency information and time information. Whereas, accuracy of information depends on window size. The next logical step is established by a wavelet transform (WT). The WT utilizes windows technique with variable size, and in Fig. 3, the signal analysis progress has been illustrated. The WT selects a "scale" instead of traditional "frequency" which is the main advantage of this technique. For instance, it generates a time-scale view instead of the time–frequency view. Likewise, the time-scale view is the most commonly used and effective methodology.

3.4. DWT

DWT utilizes the dyadic scales and positions and it is an effective implementation of the WT [24]. The basics of DWT has been depicted below. Let suppose x(t) is a square integral function. The continuous wavelet transform of the signal x(t) to a real-valued wavelet $\Psi(t)$ and is given as follows:

$$W(a, \tau) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \Psi^* \left(\frac{t-\tau}{a}\right) dt \tag{2}$$

where $w(a, \tau)$ is the wavelet transform, τ illustrates the function over x (t). The asterisk (*) denotes the complex conjugate while 'a' represents the dilation factor (both positive and real values).

The approximation of Eq. 2 is possible by restraining τ and 'a' to a discrete matrix $(a = 2^j and \tau = 2^j k)$ to deliver the discrete wavelet transform, which is as follows:

$$cA_{j,k}(n) = DS\left[\sum_n x(n) I_j^*(n - 2^j k)\right]$$

$$cD_{j,k}(n) = DS\left[\sum_n x(n) h_j^*(n - 2^j k)\right] \tag{3}$$

In the above equations, $cD_{j,k}$ and $cA_{j,k}$ illustrates the coefficients of

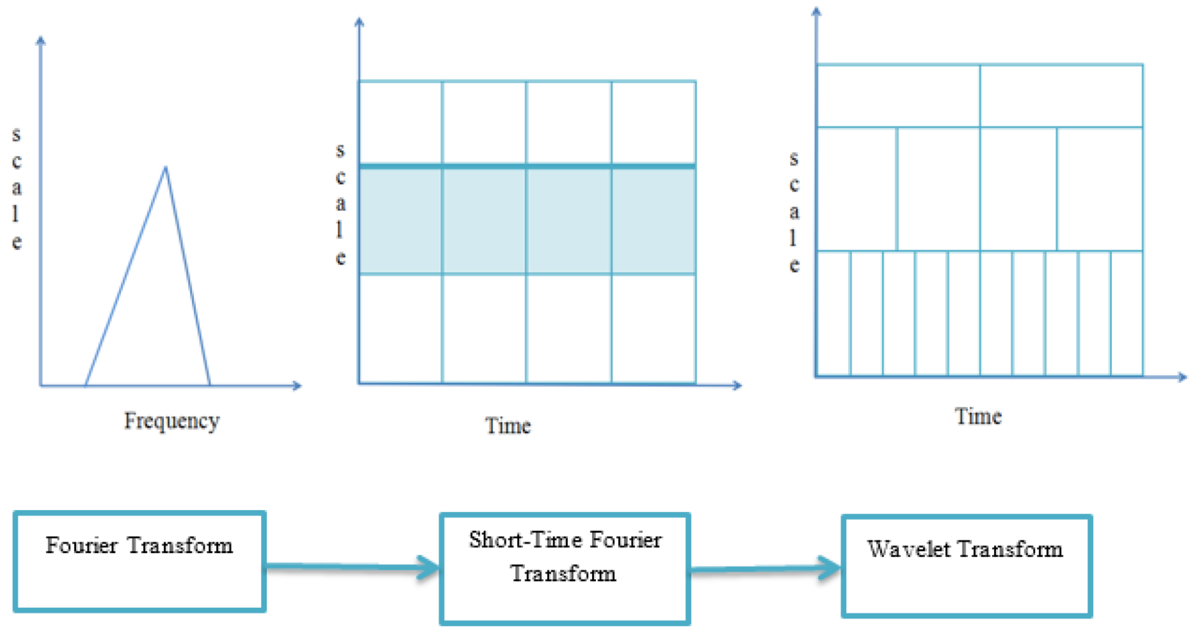

Fig. 3. Signal analysis progress.

detailed components and the approximation components, respectively. h(n) Denotes the high-pass filter (HPF) and l(n) denotes the low-pass filter (LPF). 'k' and 'j' represent the translation factor and wavelet scale, respectively. The DS is an operator and it represents down sampling. The detailed components have high-frequency, whereas the approximation component contains low-frequency.

3.5. 2-Dimensional DWT

Computing DWT for a 2-dimensional image, the original image is convolved in both x and y directions by HPF and LPF as illustrated in Fig. 4. The acquired images are down sampled by columns specified by 2 ↓. The columns down sampled means that simply even indexed columns are selected [36] [37]. With the help of HPF and LPF, the resultant images are then convolved again. Now, these images are further downsampled by rows which are denoted by 1 ↓ and eventually produce 4-subbands which is half the size of the original image. The obtained 4-subband images are LL_1, LH_1, $HL_1 and HH_1$. LH_1 provide horizontal information, HL_1 provide vertical information and HH_1 contains diagonal information of the image. The LL_1 subband represents the approximation coefficient and maximum information of the image lies in this subband. For further decomposition, LL_1 is selected same like the selection of original image. Likewise, we have decomposed the image up to 3-levels by utilizing 2D wavelet decomposition. The acquired approximation coefficients are LL_1, $LL_2 and LL_3$ as shown in Fig. 5.

There are different types of wavelets such as symlets 1, Daubechies, biorthogonal, and coiflets wavelets. With each type of wavelet, we have tested our result as depicted in Table 1. In this experiment, the approximation coefficients of 3-level wavelet decomposition along with Haar wavelet produce good outcomes related to the rest of the wavelets. Haar wavelet is the most significant and simplest wavelet as compared to other wavelets. We have done three-level wavelet decomposition via Haar wavelet for feature extraction, as the image lost most of its details at the fourth level. Eventually, the features for all the images have been extracted and generate a feature matrix.

3.6. Feature reduction using color moments

To classify MR brain images accurately, excessive features need to be reduced. Because the huge number of features increases the complexity of the classifier, which is known as curse-of-dimensionality. Also, the redundant features increase the storage memory and computation time. Therefore, the feature reduction is necessitated.

The DWT also minimizes the features in the feature extraction phase from 256 × 256 to 232 × 232, after decomposing the image up to 3-levels. However, this dimension is still large enough, and for classification purpose, all the features are not relevant. Therefore, further dimensionality reduction is required.

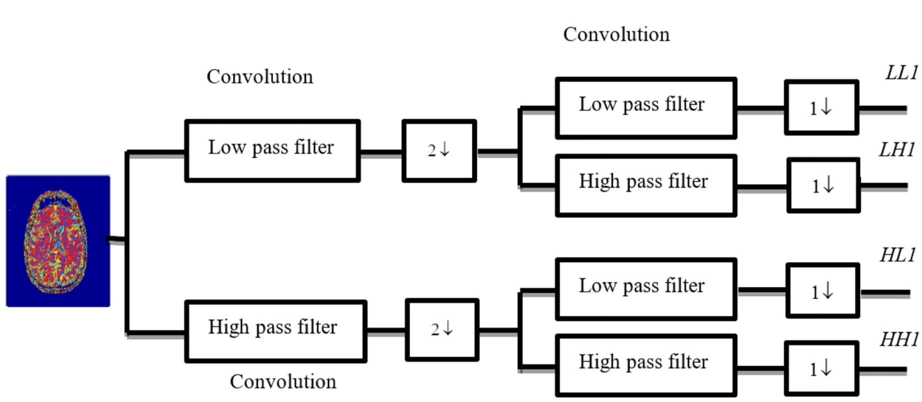

Fig. 4. Extraction of 2D Discrete Wavelet Transform components.

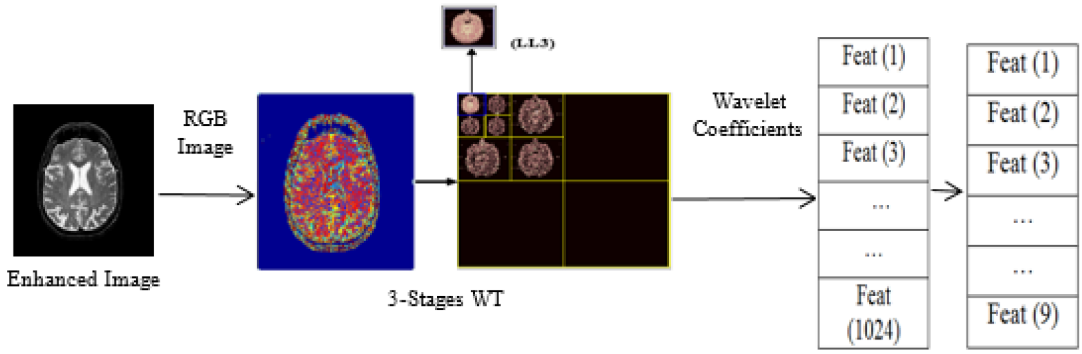

Fig. 5. Schematic diagram for feature extraction and reduction scheme.

Table 1
Comparisons of different wavelets.

Wavelet Family	Classification accuracy
Coiflets 1	93.5%
Daubechies 2	94.4%
Symlets 1	94.6%
Biorthogonal 1.1	93.8%
Haar	**95.8%**

In our proposed work, we have considered the first three-color moments for feature reduction such as mean, standard deviation, and skewness for each of the RGB color channels. These color moments are briefly explained below:

3.7. Mean

Mean is the first color moment and in an RGB image it represents the average of Red, Green, and Blue channel.

3.8. Standard deviation

SD is the second color moment and in an RGB image it represents the variance of the distribution of colors in Red, Green, and Blue channel.

3.9. Skewness

is the third color moment and it illustrates asymmetry of color distribution of colorful image. The following equations represent each of the three color moments:

$$A_{c,i} = \frac{1}{N}\sum_{j=1}^{N} I_{ij}, \tag{4}$$

$$V_{c,i} = \sqrt{\frac{1}{N}\sum_{j=1}^{N} (I_{i,j} - A_{c,i})^2} \tag{5}$$

$$S_{c,t} = \sqrt{\frac{1}{N}\sum_{j=1}^{N} (I_{i,j} - A_{c,t})^3} \tag{6}$$

Where ‘A’ depicts the mean of a color channel. The value of ‘i = 1–3’ depicting the RGB channels. ‘N’ depicts the total pixels and ‘I’ illustrates the intensity of each RGB component value. ‘V’ illustrates the standard deviation of the RGB channel in an image. ‘S’ denotes skewness of each RGB channel in an image.

The summary of the above computations are as follows:

Initially, in the feature reduction stage, we have extracted three different color channels from the color image. Then we calculated the mean, standard deviation, and skewness of each single color channel. Therefore, we obtained 3-color moments for each single color channel, so the total features are 9 per image such as 3 features for Red (mean, standard deviation, and skewness), 3 features for Green (mean, standard deviation, and skewness) and similarly 3-features for Blue channel. Finally, all these 9-features have been stored in a 1-dimensional array and were presented to a classifier to determine the normal and pathological brain MRI image.

3.10. Classification of brain MRI images

The obtained set of features is then presented to a classifier. We have used an artificial neural network to categorize benign and malignant images due to its simplicity and for its good classification performance.

3.11. Feed-forward neural network

To classify the brain MRI images into benign and malignant, a feed-forward NN is employed. It consists of hidden layer and an output layer. The hidden layer having 10-neurons whereas the output layer having single-neuron that classify MRI image into either normal or abnormal. The output layer uses a linear transformation function while the hidden layer uses the sigmoid transformation function.

The reduced 9-features are presented to the hidden layers. The hidden layers calculate these features and then send them to the output layer for a final decision. Where the value 1 is assigned to normal MRI image and 0 is assigned to pathological MRI image as shown in Fig. 6.

3.12. Advantages of proposed model image enhancement and feature reduction

The MRI image is low contrast image and further processing in the up-coming stages creates complexities. Therefore, we have employed

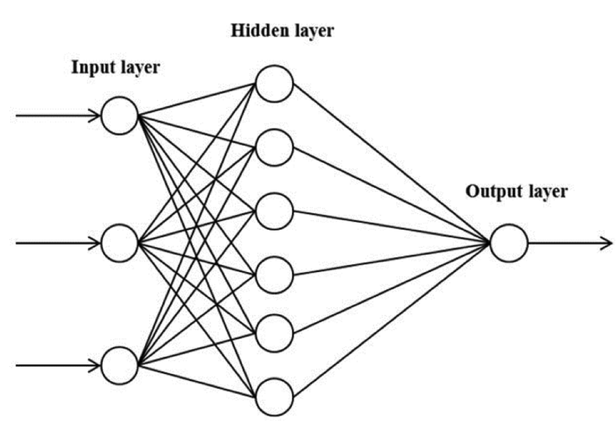

Fig. 6. FF-ANN Architecture used for MRI classication.

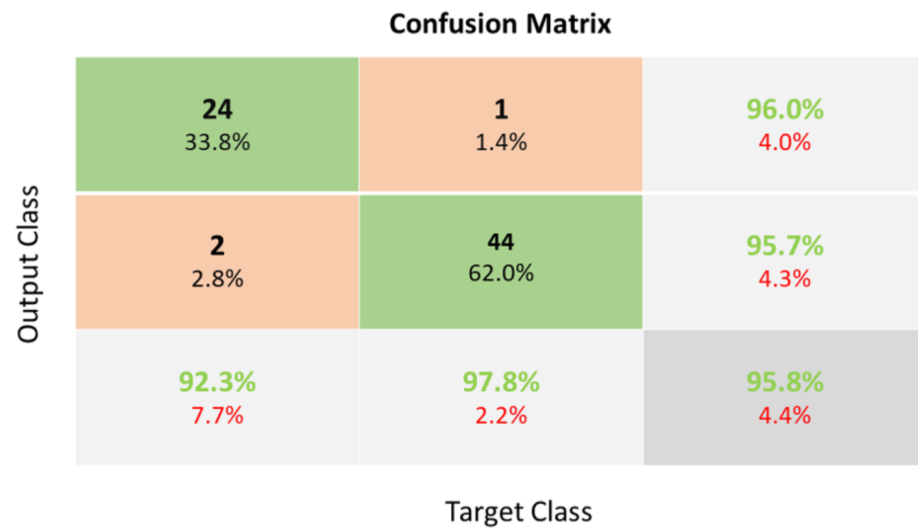

Fig. 7. Confusion matrix of Image-level classification results.

CLAHE to enhance the contrast and make it suitable for further processing. Furthermore, the three-color moments have been calculated of level-3 image i.e 32 × 32 to reduced the size of features to only 9 vital features for classification.

4. Database

The proposed hybrid techniques have been implemented on the human brain MRI dataset. We have downloaded this dataset from Harvard Medical School website (http://med.harvard.edu/AANLIB). Total 71 T2-weighted, 256 x 256 pixels brain MRI images were selected randomly, with 25 abnormal and 46 normal. The following diseases are involved in the dataset: acute stroke, Alzheimer's disease, and MRI, and tumor disease. We have developed this algorithm using MATLAB R2018a using a combination of Wavelet Toolbox (The MathWorks) and Image Processing Toolbox. The computation of Median filter + CLAHE + DWT + CM + FF-ANN classification has been performed on a personal Core i5-4200U CPU having a 2.3 GHz processor and 8192 MB of memory, running under a windows-10 operating system. This program can be run or tested on any machine where MATLAB tool is available.

5. Results and discussions

In this section, we have evaluated the proposed approach using performance evaluation methods. The performance of the proposed method has been evaluated using confusion matrix, sensitivity, and specificity and is defined as follows:

5.1. Confusion matrix

This matrix illustrates the summary of predictions made by the model in which each column depicts predicted class and each row depicts actual class [38]. The confusion matrix depicts the correct and incorrect results of classification as shown in Fig. 7.

Furthermore, the performance of the proposed methodology has also been evaluated on the basis of sensitivity, specificity, and accuracy [39] as shown in Table 3.

5.2. Sensitivity (True Positive (TP) Rate):

This is the probability that a diagnostic test is positive, given that the patient has the disease.

```
Input: T2-W 256 × 256 brain MRI
Parameter: N is the total number of images
i = 1: N
    Read the images
    Implement the median filter and CLAHE
    Apply 2D-DWT for the 3rd level to extract the wavelet coefficients.
    All the wavelet coefficients are stored in matrix X[MxN].
    Implement the first three Color Moments on the acquired wavelet coefficients.
    Put the new dataset in a matrix Y.
    Generate the NN design with a feed-forward algorithm.
    Generate a target vector
    Train the network with the given dataset and the desired target.
    Input the test image features. Trained the NN.
    Classify test image into benign and malignant.
end for
```

Compute average specificity, sensitivity, and accuracy.

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

Specificity (True Negative (TN) rate): This is the probability that a diagnostic test is negative, given that the patient does not have the disease.

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

Accuracy: measured how many diagnostic tests are performed correctly:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

TP illustrates – Correctly classified positive instances,
TN illustrates – Correctly classified negative instances,
FP illustrates – Incorrectly classified negative cases, and.
FN illustrates – Incorrectly classified positive instances.

In this experiment, a supervised machine learning classifier is employed for brain MRI image categorization. Our proposed methodology comprised of four important phases. The first phase utilizes the median filter and CLAHE for noise removal and image enhancement respectively. The second phase uses DWT, where we calculated the 3-levels coefficients of decomposition of MRI images using Haar wavelet for feature extraction. The third phase uses Color Moments (CM) for feature reduction and Neural Network is used in the last phase for brain MRI classification.

The complexity of the system is reduced using a feature reduction phase, Color Moments are used for feature selection as described in section 3.3. We have reduced the dimension of the feature vector from

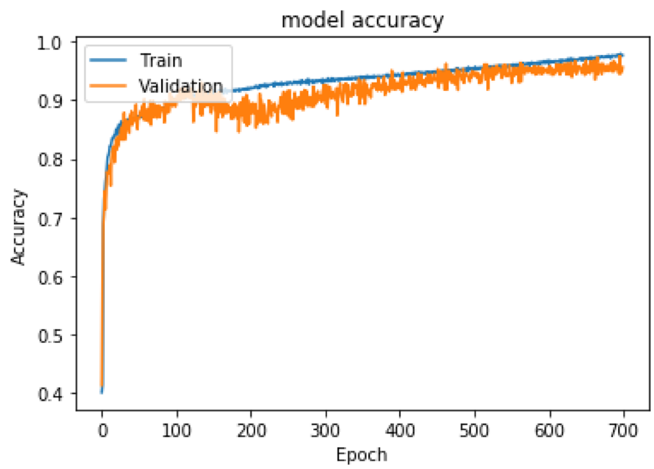

Fig. 8. Model performance using cross-entropy.

Table 2
Classification accuracy based comparisons with existing techniques for the same brain MRI images datasets.

Existing Techniques	Classification accuracy (%)
DWT + PCA + ANN	95.7%
DWT + SOM	94.3%
DWT + PCA + KSVM (LIN)	95.2%
Quadratic Kernel + PCA + SVM	84.7%
Proposed Technique	
Median filter + CLAHE + DWT + CM + FF ANN	95.8%

1024 to 9 only using Color Moments. Hence, the selection of essential features curb time complexity and increase accuracy rates. Figs. 8. depicts the system performance.

Finally, we have compared our results with the previous proposed results to evaluate the efficiency of our methodology as illustrated in Table 2. It is observed from the comparison that our methodology outperformed the existing methodologies in terms of classification accuracy and computation time. This is due to image enhancement and feature reduction which is based on CLAHE and Color Moments respectively.

5.3. Time analysis

Measuring the computation time is also an essential factor to assess the classifier. We sent all the 71 images to a classifier and recorded the computation time.The average computation time consumed by our proposed system in feature extraction, feature reduction and NN classification is about 0.022, 0.0185, 0.0030 s, respectively also depicted in Fig. 9.

The average time taken by each image is about 0.05 s, which is quite fast for real time diagnosis.

6. Conclusion and future work

This paper proposed a medical decision support system using malignant and benignant classes. This system is designed by median filter, CLAHE, wavelet transform, color moments and feed-forward NN. The proposed system provide astounding results in categorizing the malignant and benignant MRI images. Considering this methodology, the physician can make the final decision without any hesitation which is the main advantage of this system.

The experimental results illustrates that this method is effective for classification of benignant and malignant brain MRI. The sensitivity rate and specificity rate of the proposed system is 96.0% and 95.65% respectively. SVM and SOM [40,24] provides the same results. We have also compared our results with the recently reported results based on the same MRI T2-W images. This methodology can be applied on T1-W, T2-W and proton density MRI images and can provide accurate classification.

In future work, we will emphasize on these aspects. First, the proposed methodology should be used with larger datasets having numerous diseases. Second, Image enhancement play a vital role in obtaining high accuracy. Therefore, we intend to consider super resolution for brain MRI image enhancement. Third, the computation time can be improved by employing advanced WT for instance lift-up wavelet for feature extraction.The major shortcoming of this work is that whenever there is an increase in image database then it requires fresh training each time.

Table 3
Classification rate for the classifier.

Technique	TP	TN	FP	FN	Sensiti-vity(%)	Specif-icity(%)	Accur-acy(%)
Median + CLAHE + DWT + CM + ANN	24	44	2	1	96.0	95.65	95.8

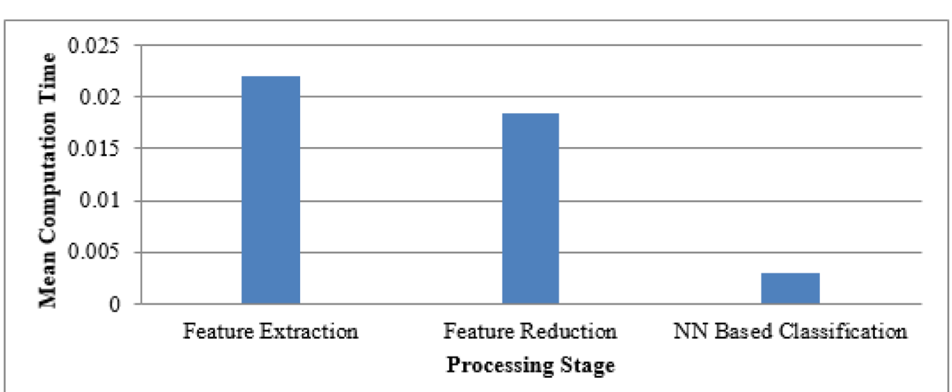

Fig. 9. Stage-wise time analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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