An Effective Classification Methodology for Brain MRI Classification Based on Statistical Features, DWT and Blended ANN

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ABSTRACT. Brain MRI classification is one of the key areas of research. The classification of brain MRI can help radiologists in different brain disease diagnostics without invasive measures. Brain MRI classification is a difficult task due to the variance and complexity of brain diseases. We have proposed a novel and efficient binary classification model for brain MRI images. The proposed model includes discrete wavelet transform (DWT) used for features extraction, statistical features for diminishing the number of features, and a blended artificial neural network for brain MRI classification. Brain MRI classification with less features is a challenging task. In this paper, we have proposed a novel technique for statical features calculation of approximate RGB images obtained from DWT. We have also proposed a new blended artificial neural network to improve classification accuracy. The proposed technique is compared with other state-of-the-art techniques, and results show that the proposed technique gives better outcomes in terms of accuracy and simplicity.

INDEX TERMS Brain MRI, classification, artificial neural network, wavelet, statistical features.

I. INTRODUCTION

Distinct types of brain tumors can be categorized into malignant and benign. Malignant tumors are severe, deleterious and cancerous; they mostly cause deaths while benign tumors are mild, slow-growing, harmless and non-cancerous. The brain is composed of three parts. a) Gray matter- consists of neuron nucleus and dendrites and is responsible for nervous signal processing, it contributes 40 percent to brain volume, b) the white matter- made by the fiber-like cell structures; axons. This part makes 60 percent of the brain and c) cerebrospinal fluids- a colorless protective fluid around the brain tissue, it secretes various hormones. The tumors affect these three areas and cause abnormalities in the human body’s functions [1]. There are several types of brain disorders depending on which area/part is affected by the tumors. An important step towards brain tumor treatment is early brain tumor detection. It plays a significant role, improving the survival rates of the patients and helps us save more lives.

Medical image analysis has significant importance in clinical studies [2]. These techniques enable doctors and radiologists to process and analyze the disease and prescribe the diagnosis. Using image analysis, doctors can understand and visualize the internal body structures, find the abnormalities, and further study the disorder. So, the principal factor in the diagnosis of a brain tumor is the medical images - data obtained from different imaging techniques like mammograms, Computed Tomography (CT) scans, X-rays, and Magnetic Resonance Imaging (MRI). Each technique can be employed with its own benefits as well as side effects. One of the best techniques is MRI, and it is done via a scanning device that uses magnetic fields and computers to capture snapshots of the body parts [2]. It is safe as it does not use X-rays and has insignificant risk, while it offers significant help by providing the images of internal organs from different planes such that more accurate and reliable observation of the images can be done. MRI is the perfect suit for
extremely sensitive and complex clinical tasks, as it is painless and has less radiation exposure; either of which can greatly influence the detection and identification of brain tumors. MRI is mostly used because of its high-resolution images of the soft tissues and its non-invasiveness [3, 4].

Firstly, it is necessary to preprocess the images before further processing. During preprocessing, diverse types of noises are removed. Noises like Rician noise, salt and pepper noise corrupt the medical images, which makes it troublesome and impossible to further analyze the image. Effective observation of the image is only possible from a high-quality image, which is possible by enhancing the brightness, preserving the details of the edge and getting rid of noises. Using a median filter for noise reduction perfectly does the job [1].

After the preprocessing, the most important stage is feature extraction. By feature extraction, it is meant that the image/input data is transformed into a set of most useful features, which can be used for decision making. It is a kind of dimensionality reduction, using which a quantitative measure of the useful features from data is done. Feature extraction helps algorithms by extracting useful information from data and feeding it to the algorithm instead of the extremely large data the algorithm must process, which consumes more time as well as computational resources. Significance feature extraction is challenging too. Several studies [5, 6] have used different methods for feature extraction, e.g., Gabor feature, Discrete Wavelet Transform, Spectral Mixture Analysis, Texture Feature, Principal Component Analysis, Minimum Noise Fraction Transform. By dimensionality reduction, we can have our focus on only a few key features. Sometimes the features extracted in the feature extraction stage are greater in numbers and require further processing to reduce the dimensionality. Hence, in the feature reduction stage, the features extracted in the feature extraction stage are further reduced. The widely implemented algorithms for dimensionality reduction are independent component analysis, principal component analysis, linear discriminant analysis, genetic algorithms, statistical features, etc. [1].

After the feature reduction stage, the classification stage is used to classify the brain MRI images. In the classification stage, the classifier takes selected features and classifies them into normal and abnormal images. Different classification algorithms, such as Artificial Neural Network (ANN) [3], k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), logistic regression, etc., have been used by different researchers for classification purposes.[7]

This paper proposes a novel model based on discrete wavelet transform, statistical features, and a blended artificial neural network model. The basic objective of the proposed model is to increase the accuracy of a classification and decrease the curse of dimensionality. In the proposed model, the statistical features have been calculated for each channel of approximate RGB images. Three artificial neural networks, namely, MLP-R, MLP-G, and MLP-B, have been applied with different specifications on the red channel features, green channels features, and blue channel feature, respectively, to classify the brain MRI images. In the end, a strategy based on majority voting is used to classify the brain MRI images into normal and abnormal. The majority voting strategy is applied to the outputs classification results of MLP-R, MLP-G, and MLP-R to classify the brain MRI images into normal and abnormal. The major contributions of this paper are as follows:

- We convert the brain MRI grayscale images to RGB images to obtain a different variety of pixels from each channel of RGB images.
- We apply the discrete wavelet transform to remove unnecessary information from converted RGB images and obtain small size approximation images with a lot of information in the feature extraction stage.
- We calculated the mean, variance, skewness, kurtosis, correlation, entropy, energy, contrast, and homogeneity statistical parameters of each channel (Red, green, blue) of approximate RGB images in the feature reduction stage.
- A novel classification technique, namely, blended artificial neural networks comprised of three artificial neural networks each for red, green, and blue channels, a majority voting strategy has been proposed in the classification stage.

The structure of the remaining paper is organized as below. Section II presents related work., the proposed methodology is discussed in detail in Section III. The implementation, experimental results, and discussion section are presented in Section IV. Section V presents the conclusions and future work.

II. RELATED WORKS

A great amount of research has been done recently to develop automated tools for medical image analysis. Automatic image analysis offers doctors and researchers the opportunity to view the internal working of tissues without any invasive surgery. Two commonly used, safe, and accepted technology for this purpose in hospitals and research facilities are Magnetic Resonance Imaging MRI and Computed tomography CT scans. The superiority of MRI is due to its high spatial resolution of brain/soft tissue anatomy, sharp contrast, non-invasive nature, and limited exposure to harmful radiations. These methods also provide valuable information about various tissue parameters like flow velocity, chemical shifts, spin-spin relaxation times, proton density, and spin-lattice, which leads to more accurate characterization of brain tissue [8].

Several methods have been introduced for MRI brain tumor classification. One of the major aspects of image processing that plays a significant role is image segmentation – it extracts the tumor location from the medical images. Zanaty and Aljahdali in 2011[9] produced automatic fuzzy algorithms which incorporated spatial constraints on the objective function/membership function and the validity of procedure for clustering. Using intra-cluster distance measure, they tested the working of the proposed method on synthetic images corrupted with
different levels of noise and MRI dataset, Somasundaram et al. [10] proposed two brain extraction algorithms, namely BEA for T2-weighted MRI scans. These methods were applied on both 3D and 2D information of slices, and the results were better than the brain extraction tool (BET) and brain surface extractor (BSF).

An improved version of the image segmentation method over Zanaty and Aljahdali’s method was proposed by Vasuda et al. [11]. They used Fuzzy C-Means (FCM) for fuzzy clustering to get an efficient image segmentation of MRI images. Another method for image segmentation is introduced by Logeswari et al. [12], where they used a two-phase method to classify the row of the image by row. In the first phase, the noise from the MRI image is removed. And in the second phase, vector quantization with Hierarchical Self Organizing Map (HSOM) is implemented to get a higher value of tumor pixels and computation speed. Joseph et al. [13] used a K-means clustering algorithm coupled with morphological filtering for the image segmentation and tumor location detection in brain MRI images. Morphological filtering helped in avoiding the misclassifying of regions after segmentation. It was an easy method to detect abnormal brain MRI images.

Rajini et al. [14] introduced a hybrid technique with two stages – feature extraction and classification – to classify MRI brain tumor images. DWT was used in the feature extraction stage, Principal component analysis (PCA) was used in the dimensionality reduction stage to focus on more essential features of MRI images. Then two classifiers, namely feed-forward back-propagation artificial neural network (FP-ANN) and K-NN, have applied for the classification of the subject MRI images into normal and abnormal images. The results for FP-ANN were 90% accurate, while K-NN the accuracy was calculated to 99%. An improved approach to Rajini et al. was adopted by Fayaz et al. [15] with three-stage methods - preprocessing stage, feature extraction stage, and finally classification stage. Using the median filter, the noise from MRI grayscale images was removed in preprocessing stage and converted into RGB colored images. During the feature extraction stage, the red, green, and blue channels were extracted from RGB images; for each channel the mean, variance and skewness are also calculated. Then using K-NN the final classification was carried out. An accuracy of 98% training and 95% testing data was obtained for normal images while 100% training, and 90% test accuracy for abnormal images were obtained. A similar three-stage method was also used by Nazir et al. [16]. In preprocessing, filters were used for noise removal, then during the features’ extraction phase, the color pigments were chosen as mean features for the third stage of classification using a feed-forward artificial neural network.

Furthermore, Wahid et al. [17] also suggested a three-stage classification method much like Fayaz et al. In the feature extraction stage, they focused on color moments and texture of the MRI images. Then a logistic function-based probabilistic classifier has given the images for classification. The classifier was also compared with different state-of-the-art existing SVM, Naïve Bayes, ANN, and normal densities based linear classifiers. 10-fold cross-validation was applied, which proved the results to be 90.66% accurate.

Some of the recent works have been using the three-stage approach. Ullah et al. [18] suggested that the implementation of efficient data mining techniques on medical data can dramatically improve the classification of various diseases. They examine the evaluation data mining on frequent local diseases like heart ailments, lung cancer and breast cancer. Ullah et al. [19] implemented the K-NN algorithm for MRI image classification and obtained 94.97% accurate results. Ullah et al. [1] implemented Forward Artificial Neural Network (FF-ANN) for the classification of MRI images, the accuracy of their proposed model on both testing and training images was 95.48%, while they got a good computation time for their three stages. 4.3216s for feature extraction, 4.5056s for feature reduction and 1.4797s for the classification.

Suhaimi et al. [20] came up with feature map size selection on functional MRI (fMRI) and MRI images dataset and concluded that feature map size selection is an integral part of designing CNN for fMRI classification. Moreover, a study by Saleh et al. [21] used agency system classification brain tumors. The preprocessing was done to remove salt and pepper noise, followed by detection of the tumor using multilevel threshold segmentation – to improve the results; opening and closing morphological operations were also implemented. The tumor segmentation was done using watershed transform and using the binary object feature method; the essential features were extracted. Then finally, the classification was done with 100% accuracy. Their system classified brain tumor images into Metastases and Gliomas, meningioma benign, meningioma tumor and normal tissue.

Another multilevel-stage approach was proposed by Keerthana et al. [22]; their system classified the tumor images along with providing health advice and disease description for the user. They used data mining techniques, pre-processing, segmentation, feature extraction and classification. SVM along with a genetic algorithm for enhancing the features and SVM parameters, were used to identify the type of brain tumor. Mathew et al. [23] also employed a similar four-stage method. Pre-processing was done using an anisotropic diffusion filter, DWT was implemented for feature extraction, and then SVM was applied on the final data for the classification. Korolev et al. [24] implemented the residual and plain 3D convolutional neural network architecture while skipping the feature extraction step to classify MRI images for Alzheimer’s.

III. PROPOSED METHODOLOGY

The proposed work consisted of four stages: preprocessing, feature extraction, feature reduction, and classification. The conceptual model of the proposed model is illustrated in FIGURE 1, and the detailed processing diagram of the proposed model is depicted in FIGURE 2. In the preprocessing stage, the median filter has been applied to the images to remove noise from the images, and the grayscale images are converted to RGB images for further processing in the next stage of the proposed model. The RGB images are then given as inputs to the discrete wavelet transformed
(DWT) to reduce the size of the images and remove unnecessary information in the feature’s extraction stage. In this stage, the red, green, and blue channels are extracted from the reduced images. The images achieve in the features stage are still exceptionally large, and we cannot directly feed these images to machine learning algorithms to process them because it requires a lot of computation power. Therefore we need to further process it and extract few features of interest from the images. In the feature reduction stage, the statistical features, namely, mean, variances, skewness, kurtosis, energy, entropy, correlation, contrast, and homogeneity have been extracted for red, green, and blue channels, respectively. Each module of the proposed model is further elaborated in the preprocessing, feature extraction, feature reduction, and classification stages.

**FIGURE 1. Proposed conceptual model**

**FIGURE 2. Detailed Schematic diagram of the proposed model**
A. PREPROCESSING

In the preprocessing stage, the noise that existed in the MRI images is removed. Different types of noises exist in different image modalities, such as speckle noise, Gaussian noise, salt-and-pepper noise, etc. To remove these noises from the images, different types of filters are used, such as wiener filter, mean filter, median filter, etc. The MRI images are normally affected by salt-and-pepper noise, and the most effective and commonly used filter for this type of noise is the median filter [32]. The median filter can sharpen the images without disturbing the edges of the images. In the proposed work, we have used the median filter with a window size $3 \times 3$ to remove salt-and-pepper noise from the images and smoothen the images. In this stage, the grayscale images are converted to RGB images, and these RGB will be used in further processing.

B. FEATURE EXTRACTION

In the feature extraction method, we have used discrete Haar wavelet transform (DWT). The purpose of using the discrete wavelet transform is to reduce the curse of dimensionality. The size of the original images is $512 \times 512$, which is a huge size and machine learning computation time will be very high if we give the whole number of features existing in the image to the machine learning algorithm. The DWT has also been used with the purpose to remove unnecessary information from images and extract an approximate image that contains only useful information.

The wavelet transform can be implemented in different ways, but the most powerful and effective implementation is discrete wavelet transform (DWT). The DWT uses the dyadic scales and position for wavelet implementation. The primary fundamental of DWT is introduced by using the following: Let $\chi(t)$ represents square-integrable function; then the definition of continues wavelet transform of $\chi(t)$ relative to a given wavelet $w(t)$ is given in Equations (1 and 2).

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} \chi(t) \psi_{a,b}(t) dt,$$

Where

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

Here, the wavelet $\psi_{a,b}(t)$ calculation has been carried from the mother wavelet $\psi(t)$ by using translation and dilation factors. $a$ and $b$ represent dilation and translation factors, respectively, and they are both positive real numbers. Wavelets have numerous different types, and these wavelets became famous throughout the development of wavelet analysis. Among these, the wavelet that has gained extensive popularity is the simplest wavelet – the Harr wavelet. It has been used extensively in a lot of applications [33]. The discretization of wavelet can be done by limiting $a$ and $b$ to a discrete matrix ($a = 2b$ & $a > 0$) to provide the discrete wavelet transform, represented in FIGURE 3.

In Equations (3 and 4) the $c_{a,j,k}$ and $c_{d,j,k}$ represent the approximation components coefficient and detail coefficients, respectively. Accordingly, the low and high pass filters are represented by $g(n)$ and $h(n)$. For wavelet scale and translation parameters, $j$ and $k$ are used, respectively. The downsampling is represented by the DS operator.

$$c_{a,j,k}(n) = DS \left[ \sum_n \chi(n) g_i(2 - 2/k) \right],$$

$$c_{d,j,k}(n) = DS \left[ \sum_n \chi(n) h_i(n - 2/k) \right].$$

The given above decomposition operation can be repeatedly performed to divide the one signal into different levels of resolutions [33]. The complete process is named the decomposition tree, as illustrated in FIGURE 4.

In this paper, we are dealing with two-dimensional imaging; therefore, we need to apply DWT to each dimension separately. The structure diagram of the 2D discrete wavelet transform is given in FIGURE 5. As shown, there are four sub-bands, namely LL, LH, HH, HL images at each level.

FIGURE 4. A three levels decomposition tree.

FIGURE 3. Signal analysis development.
The LL subband is further divided into four mentioned bands. The LL indicates the image approximation component, and LH, HL, HH represent the detail components of the image.

As the number of levels increases, the image compaction is also increased, but coarser approximation components are achieved. In this study, a level-3 decomposition has been carried out using Harr wavelet for getting an approximate image of dense information. A three levels decomposition is shown in FIGURE 6 in tabulated form. In the first level of decomposition, the image is divided into four sub-bands, namely LL1, LH1, HH1, HL1, in which the LL represented an approximate image (LL1) which is of central interest and are further considered for processing. In the second level of decomposition, the LL1 is further decomposed into four sub-bands namely LL2, LH2, HH2, and HL2. The LL2 approximate image is further considered for processing. In the third level of decomposition, the LL2 is further decomposed in four sub bands named LL3, LH3, HH3, and HL3 [34].
C. FEATURE REDUCTION

The features (64 × 64 = 4,096) obtained in the feature extraction stage are still excessive numbers, and if these features feed to classification algorithms, it will tremendously increase the computation time. To handle this curse of dimensionality, it is obligatory to further reduce the number of features. In the feature reduction stage, the features obtained in the feature extraction are further reduced. The first four statistical moments, namely, mean, variance, skewness, and kurtosis, and co-occurrence matrix features, namely, entropy, energy, inverse difference, correlation, have been calculated of the approximate images obtained in the feature extraction stage [35]. In Equations (5-
8) mean, variance, skewness, and kurtosis have been represented, respectively. Mean is used to describe the bright and dark mean in an image. Variance is used to describe the contrast of the image. Skewness is a measure of symmetry, and kurtosis is used to measure the peak and flatness relative to a normal distribution.

\[
\text{Mean} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (5)
\]

\[
\text{Var}(X) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} \quad (6)
\]

\[
\text{Skew}(X) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{n} \quad (7)
\]

\[
\text{Kurtosis}(X) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{n} \quad (8)
\]

where \( n \) indicates the total number of pixels in the image, \( \bar{x} \) represents the mean of the image’s pixels values, \( x \) represents the image pixels values.

In Equations (9-13), energy, correlation, entropy, contrast, and homogeneity have been calculated accordingly. Energy is used for distribution between gray-level values, i.e.,

\[
\text{Energy} = \sum_i \sum_j (\lambda_{ij})^2 \quad (9)
\]

\[
\text{Correlation} = \frac{1}{\sigma_x \sigma_y} \sum_i \sum_j (x - \bar{x})_i (x - \bar{x})_j \lambda_{ij} \quad (10)
\]

\[
\text{Entropy} = -\sum_i \sum_j \lambda_{ij} \log \lambda_{ij} \quad (11)
\]

\[
\text{Contrast} = \sum_i \sum_j (\lambda_{ij})^2 (i - j)^2 \quad (12)
\]

\[
\text{Homogeneity} = \sum_i \sum_j \frac{\lambda_{ij}}{[i-j]} \quad (13)
\]

\( \lambda \). Correlation is used to describe the pixel similarity at a particular pixel distance. Entropy is used to measure the total content of the image. Contrast describes the difference between the highest and lowest intensity values of the image. Homogeneity describes how certain similar elements of the image are. The visualization of the features extraction and labeling is shown in FIGURE 7.

D. CLASSIFICATION

In the proposed work, we have used a blended artificial neural network classifier. The artificial neural network performs well as compared to other machine learning algorithms for noisy, big, and complex data [36]. In this work, we have used three artificial neural networks of MLP type consisted of an input layer, a hidden layer, and an output layer [37, 38]. The summation of the production of weights and bias is carried out by using the summation function (\( \varphi \)) given in Equation (14) on the hidden layer’s nodes of each MLP.

\[
\varphi_q = \sum_{p=1}^{k} \lambda_{pq} t_n + \psi_q \quad (14)
\]

Where \( k \) represents the number of inputs, \( l_n \) indicates input variable \( z \), \( \psi_q \) denotes the bias term, and \( \chi_{pq} \) represents weight. There are many activation functions; the selection of activation function for hidden layer’s nodes is a trial-and-error type of practice. The sigmoid, hyperbolic sigmoid, and ReLU activation functions are represented in Equations (15-17), respectively.

\[
\psi_q (x) = \frac{1}{1 + e^{-\psi_q}} \quad (15)
\]

\[
\psi_q (x) = \frac{e^{\psi_q} - e^{-\psi_q}}{e^{\psi_q} + e^{-\psi_q}} \quad (16)
\]

\[
\psi_q (x) = \max(0, \varphi_q) \quad (17)
\]

The mean, variance, skewness, kurtosis, entropy, correlation, energy, contrast, and homogeneity features calculated in the feature reduction stage are feed to MLP-R, MLP-G, MLP-B, respectively. By applied an activation function on \( \psi \), the output of a partial neuron can be obtained as given in Equation (18).

\[
\theta_q = \psi_q \left[ \sum_{p=1}^{k} \chi_{pq} t_n + \psi_q \right] \quad (18)
\]

In the proposed work, we have calculated nine features, namely, mean, variance, skewness, kurtosis, entropy, correlation, entropy, energy, contrast, and homogeneity features calculated in the feature reduction stage are feed to MLP-R, MLP-G, MLP-B. The nine features of the red channels are feed to MLP-R, the green channels features are given as inputs to MLP-G, and the blue channel features are inputs to MLP-B. As for each channel for the RGB image, we have calculated nine features; hence nine inputs neurons are specified in each MLP. The specification of neurons in the hidden layer is a trial and error type of practice; hence we have tried a different number of neurons in the hidden layer and saved the best combination. We want to classify the brain MRI images into two classes, namely, normal and abnormal; hence one neuron is specified in the output layer. Similarly, selection for hidden layer nodes is also a trial-and-error type of practice. In the proposed work, we have applied different activation functions, such as sigmoid, ReLU, and hyperbolic sigmoid, etc. to get the best results. As we need binary classification, hence sigmoid function is applied on the output layer’s node. Features of each channel are then fed to each neuron, and each neuron, based on the nine fed features, provides the output in binary form. In the end, we have applied a majority voting strategy where the maximum occurring class is selected as a final resulted class. The proposed blended artificial neural network is illustrated in FIGURE 8.
IV. IMPLEMENTATION, EXPERIMENTAL RESULTS, AND DISCUSSION

A. IMPLEMENTATION SETUP

In this section, we have briefly discussed the implementation details. The entire implementation of the proposed work is done in MATLAB version R2019a installed on Intel(R) Core(TM) i7-7500U having NVIDIA GeForce 940MX GPU, 15 GB DDR2 RAM.

The images that are considered in the proposed work are of T2-weighted MRI of 512 × 512 sizes. The dataset is achieved from [39]. We have selected 500 images for experiments, the selection of the images is made randomly. In the selected images, 255 are normal and 245 are abnormal.

The following diseases have existed in the abnormal images, namely, glioma, meningioma, Alzheimer’s, Alzheimer’s plus visual agnosia pic’s disease, sarcoma, and Huntington’s. A sample image from each disease is illustrated in FIGURE 9, along with a normal brain MR image. In the preprocessing step, we have applied a median filter of (3 × 3) size, the median has been used with the purpose to remove the abnormalities from the images. In the preprocessing, we have also converted the grayscale images to RGB images as illustrated in FIGURE 10.

![FIGURE 8. Classification based on artificial neural network and majority voting strategy.](image)

![FIGURE 9. (a) normal brain MRI, (b) glioma, (c) meningioma, (d) Alzheimer, (e) Alzheimer plus (f) visual agnosia pic’s disease, (g) sarcoma, and (h) Huntington’s](image)

![FIGURE 10. a) original image, b) RGB image](image)
wavelet on the RGB images to further reduce the size of the images. The original sizes of the images are 512 × 512, in the first level of decomposition, the images’ sizes are reduced to 256 × 256, in the second level size of the images are reduced to 128 × 128, and in the third level, we obtained 64 × 64. These 64 × 64 are approximate images that are used for further processing. The schematic diagram of three levels decomposition method of discrete Haar’s wavelet is illustrated in FIGURE 11. Further, the red, green, and blue channels are extracted from approximate RGB images as illustrated in FIGURE 12 obtained in the feature extraction stage, and calculate statistical features, namely mean, variance, skewness, kurtosis, entropy, correlation, energy, contrast, and homogeneity of each channel. We have made three files and saved the resulted features for each channel in each file. We have applied the three classifiers MLP-R, MLP-G, and MLP-B on each red, green, and blue channels’ feature, respectively, with different specifications listed in TABLE 1.

The selection of hidden layer neurons is a trial-and-error type of practice. In the proposed method, we specified a different number of neurons in the hidden layer, recorded the results, and saved results with the best combination. After several iterations, we specified 10 neurons in the hidden layer of MLP-R, 12 neurons in the hidden layer of MLP-G, and 15 neurons in the hidden layer of MLP-B. The neural networks views of different numbers of neurons in the hidden layer are exhibited in FIGURE 13.

B. RESULTS AND DISCUSSION

To get the results, we used the blended neural network based on the majority strategy for brain MRI images classification. We have obtained three files of features from the feature reduction stage, each for each channel. In the proposed work, we have used three neural networking with different specifications, namely, MLP-R, MLP-G, and MLP-B.

In the preprocessing, we obtained the RGB images. In the feature extraction stage, we apply the discrete Haar’s

![FIGURE 11. Process of obtaining an approximate image from an original image by using three levels discrete Haar’s wavelet.](image1)

![FIGURE 12. Red, green, and blue Channels extraction from an RGB image.](image2)

| TABLE 1. Implemented multilayer perceptron (MLP) classifier constrains values. |
|-----------------|---------------------|------------------|
| MLP             | Parameter           | Value            |
| MLP-R           | Input Layer Neurons | 9                |
| MLP-R           | Hidden Layer Neurons| 10               |
| MLP-R           | Output Layer Neurons| 1                |
| MLP-R           | Learning Rate       | 0.5              |
| MLP-R           | Activation Function on Hidden Layer | Sigmoid |
| MLP-R           | Activation Function on Output Layer | Sigmoid |
| MLP-R           | Momentum Rate       | 0.4              |
| MLP-R           | Number of Epochs    | 500              |
| MLP-G           | Input Layer Neurons | 9                |
| MLP-G           | Hidden Layer Neurons| 10               |
| MLP-G           | Output Layer Neurons| 1                |
| MLP-G           | Learning Rate       | 0.5              |
| MLP-G           | Activation Function on Hidden Layer | Sigmoid |
| MLP-G           | Activation Function on Output Layer | Sigmoid |
| MLP-G           | Momentum Rate       | 0.4              |
The MLP-R is applied on the features pool extracted from the red channel to classify the brain MRI images into normal and abnormal. The MLP-B has been applied on the features set obtained from the green channel for the classification of brain MRI images into normal and abnormal. Similarly, the MLP-B has been applied on the features' file obtained from the blue channel in the feature reduction stage. We have used a majority voting strategy to classify the original brain MRI images into normal and abnormal.

For performance measurements, we have used different performance evaluators to measure the performance of the proposed approach, such as precision, recall, and F1-Schore. The confusion matrix is illustrated in Error! Reference source not found. In the dataset, we have 245 abnormal images, which are labeled as 0’s, and 255 are abnormal images which are labeled as 1’s.

First, we applied the MLP-R, MLP-G, MLP-B on the features obtained in the features reduction stage for red, green, and blue channels, respectively. The MLP-R algorithm is used to classify the brain MRI images based on red channel’ features. The MLP-G, and ANN-B classify the images green channel and blue channel features, respectively. In the end, the majority strategy is used to classify the brain MRI images. The majority voting strategy is very simple; first, an image is selected if MLP-R classifies the images as normal (1), and MLP-G and MLP-B classify the same image as abnormal (0), then according to the majority, strategy the image is classified as abnormal. Similarly, when all the ANNs classify an image as normal, the image is classified as normal according to the majority strategy.

1. The confusion matrix for classification results obtained through MLP-R is illustrated in FIGURE 14. As the confusion matrix shows that the out of 245 abnormal images, the MLP-R accuracy classified 233 images and inaccurately classified 12 images. Similarly, out of 255 normal images, the MLP-R classified 246 images are classified correctly. The precision, recall, and F1-score are calculated for MLP-R classification results and are listed in TABLE 2.

![FIGURE 14. Confusion Matrix for MLP-R Classifier](image)

| TABLE 2. The overall performance results of MLP-R classifier |
|-------------------------------------------------------------|
| Precision | Recall | F1-score |
|-----------|--------|----------|
| 0         | 0.95   | 0.95     | 0.95     |
| 1         | 0.95   | 0.96     | 0.96     |
| Overall   | 0.95   | 0.95     | 0.95     |

The confusion matrix for classification results obtained through MLP-G is illustrated in FIGURE 15. As the confusion matrix shows that out of 245 abnormal images, the MLP-R accuracy classified 231 images and inaccurately classified 14 images. Similarly, out of 255 normal images, the MLP-R classified 246 images correctly
and inaccurately classified 9 images. The precision, recall, and F1-score are calculated for MLP-R classification results and are listed in TABLE 4.

![Confusion Matrix for MLP-G Classifier](image1)

**TABLE 3.** The overall performance results of MLP-G classifier.

|        | Precision | Recall | F1-score |
|--------|-----------|--------|----------|
| 0      | 0.96      | 0.94   | 0.95     |
| 1      | 0.95      | 0.96   | 0.95     |
| Overall| 0.95      | 0.95   | 0.95     |

The confusion matrix for classification results obtained through MLP-B is shown in FIGURE 16.

![Confusion Matrix for MLP-B Classifier](image2)

**TABLE 4.** The overall performance results of MLP-R classifier.

|        | Precision | Recall | F1-score |
|--------|-----------|--------|----------|
| 0      | 0.96      | 0.95   | 0.96     |
| 1      | 0.95      | 0.96   | 0.96     |
| Overall| 0.96      | 0.96   | 0.95     |

The precision, recall, and F1-score are calculated for MV classification results and listed in TABLE 5.

![Confusion Matrix for MV](image3)

**TABLE 5.** The overall performance results of MLP-R classifier.

|        | Precision | Recall | F1-score |
|--------|-----------|--------|----------|
| 0      | 0.99      | 0.98   | 0.98     |
| 1      | 0.98      | 0.99   | 0.98     |
| Overall| 0.98      | 0.98   | 0.98     |

The overall accuracy of MLP-R, MLP-G, MLP-B, and MV is illustrated in FIGURE 18. As it is clearly depicted that the performance of the majority voting method is better as compared to MLP-R, MLP-G, and MLP-B.

In our work, we have done a comparison in several ways to evaluate the performance of the proposed model in a better way. As in the proposed model consisted of four stage, we have introduced a novelty to covert the grayscale images to color RGB images, feed the RGB images to discrete Haar’s wavelet to achieve informative approximate images, extract red, green, and blue channels of each approximate image and calculate statistical features namely mean, variance, skewness, kurtosis, entropy, energy, correlation, and homogeneity. Hence for the comparison, we have ignored the conversion of grayscale images to color RGB images and discrete wavelet transforms and directly calculated these features for grayscale images after preprocessing stage.

![Overall Accuracy of MV, MLP-B, MLP-G, and MLP-R](image4)

**FIGURE 18.** Overall accuracy of MLP, MLP-G, MLP-B and MV strategy.
The confusion matrix and the corresponding performance matrix for features of grayscale images and simple artificial neural networks are illustrated in FIGURE 19 and TABLE 6. The graphical comparison of the proposed majority voting strategy with color features and artificial neural network with grayscale features is depicted in FIGURE 20.

![Confusion Matrix for MV](image)

**TABLE 6.** Overall performance results of MLP classifier for features of grayscale images.

| S.No. | Methodology     | Accuracy |
|-------|-----------------|----------|
| 0     | CM + ANN [16]   | 92%      |
| 1     | DWT + ANN [14]  | 90%      |
| 2     | Zahid et al. [1] | 95%      |
| 3     | Fayaz et al. [15]| 96%      |
| 4     | Proposed Methodology | 98%      |

The proposed method has outperformed the counterpart algorithm in terms of accuracy. The accuracy of the proposed method, along with other methods, is illustrated in TABLE 7. The proposed method is also very simple, and a smaller number of features are used as compared to another state-of-the-art algorithm. The criteria for the selection of counterpart algorithms are based on simplicity, computation complexity, and accuracy.

![Overall Accuracy of MV and MLP-GF](image)

**V. CONCLUSIONS AND FUTURE WORK**

In this paper, a novel and efficient binary classification model for brain MRI images is proposed. The purpose of the proposed model is dimensionality reduction and accuracy enhancement. Different methods have been proposed for this purpose, but all of them have limitations in one way or the other. Some methods provide good results, but the computation complexity is very high, some techniques are very fast, but their accuracy is very low. Hence, in the proposed work, we have proposed a two folds model based on discrete Haar wavelet, statistical features, and blended artificial network to increase the accuracy and reduce the dimensionality. The proposed model consisted of four stages: preprocessing, in which the median filter has been applied to remove noise from the images. In the preprocessing stage, the grayscale images are converted to color RGB images. In the second features extraction stage, the discrete Haar wavelet has been used for reducing the size of the RGB images and remove unnecessary information. The three channels, namely red, green and blue, have been extracted from the color-reduced images in the feature extraction stage. The statistical features, namely mean, variance, skewness, kurtosis, entropy, energy, correlation, contrast, and homogeneity, have been calculated for each channel of RGB images, stored and labeled in the third features reduction stage of the proposed model. In the fourth stage, the MLP-R is applied on the red channel’s data, MLP-G is applied on the green channel’s features, and similarly, MLP-B is applied on the blue channel’s features. The output classification results of the MLP-R, MLP-G and MLP-B are then fed to the majority voting module in which the class which is in the majority is selected as a final class for the corresponding images in the blended neural network. Different performance measures such as accuracy, recall, precision, and F1-score have been used to evaluate the performance of the proposed model. The comparison of the results of the proposed model is done in different ways to measure the proposed model efficiently and robustly. The results indicate that the performance of the proposed model is far better as compared to counterpart algorithms.

**REFERENCES**

[1] Z. Ullah, S.-H. Lee, M. J. I. J. o. A. Fayaz, and A. Sciences, “Enhanced feature extraction technique for brain MRI classification based on Haar wavelet and statistical moments,” vol. 6, no. 7, pp. 89-98, 2019.
[2] M. F. B. Othman, N. B. Abdullah, and N. F. B. Kamal, "MRI brain classification using support vector machine," in 2011 Fourth International Conference on Modeling, Simulation and Applied Optimization, 2011, pp. 1-4: IEEE.

[3] R. Mishra, "MRI based brain tumor detection using wavelet packet feature and artificial neural networks," in Proceedings of the International Conference and Workshop on Emerging Trends in Technology, 2010, pp. 656-659.

[4] J. H. Kazmi, K. Qureshi, and H. J. M. J. o. C. S. Rashid, "Enhanced MRA Images Quality Using Structure Adaptive Noise Filter And Edge Sharpening Methods," vol. 20, no. 2, pp. 99-114, 2007.

[5] S. Chaplot, L. M. Patmaik, N. J. B. p. Jagannathan, and control, "Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network," vol. 1, no. 1, pp. 86-92, 2006.

[6] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," in Fundamental Papers in Wavelet Theory: Princeton University Press, 2009, pp. 494-513.

[7] M. Ahmad, M. Hassan, I. Shafi, and A. J. I. J. o. C. E. Osman, "Classification of tumors in human brain MRI using wavelet and support vector machine," vol. 8, no. 2, pp. 25-31, 2012.

[8] P. Georgiadis et al., "Improving brain tumor characterization on MRI by probabilistic neural networks and non-linear transformation of textural features," vol. 89, no. 1, pp. 24-32, 2008.

[9] E. Zanaty and S. Aljahdali, "Improving fuzzy algorithms for automatic image segmentation," in 2011 International Conference on Multimedia Computing and Systems, 2011, pp. 1-6: IEEE.

[10] K. Somasundaram, T. J. C. i. b. Kalaiselvi, and medicine, "Fully automatic extraction algorithm for axial T2-weighted magnetic resonance images," vol. 40, no. 10, pp. 811-822, 2010.

[11] P. Vasuda, S. J. I. J. o. C. S. Satheesh, and Engineering, "Improved fuzzy C-means algorithm for MR brain image segmentation," vol. 2, no. 5, p. 2010, 2013.

[12] T. Logeswari, M. J. I. J. o. C. T. Karnan, and Engineering, "An improved implementation of brain tumor detection using segmentation based on hierarchical self organizing map," vol. 2, no. 4, p. 591, 2010.

[13] R. P. Joseph, C. S. Singh, M. J. I. J. o. R. i. E. Manikandan, and Technology, "Brain tumor MRI image segmentation and detection in image processing," vol. 3, no. 1, pp. 1-5, 2014.

[14] N. H. Rajini and R. Bhavani, "Classification of MRI brain images using k-nearest neighbor and artificial neural network," in 2011 International Conference on Recent Trends in Information Technology (ICRITT), 2011, pp. 563-568: IEEE.

[15] M. Fayaz, A. S. Shah, F. Wahid, A. J. I. J. o. S. P. Shah, Image Processing, and P. Recognition, "A robust technique of brain MRI classification using color features and K-nearest neighbors algorithm," vol. 9, no. 10, pp. 11-20, 2016.

[16] M. Nazir, F. Wahid, S. J. I. J. o. I. Ali Khan, and F. Systems, "A simple and intelligent approach for brain MRI classification," vol. 28, no. 3, pp. 1127-1135, 2015.

[17] F. Wahid, R. Ghazali, M. Fayaz, A. S. J. I. J. o. B. S. Shah, and Bio-Technology, "Using Probabilistic Classification Technique and Statistical Features for Brain Magnetic Resonance Imaging (MRI) Classification: An Application of AI Technique in Bio-Science," vol. 8, no. 6, pp. 93-106, 2016.

[18] Z. Ullah, M. Fayaz, A. J. I. J. o. M. E. Iqbal, and C. Science, "Critical analysis of data mining techniques on medical data," vol. 8, no. 2, pp. 42, 2016.

[19] Z. Ullah, S. H. Lee, M. N. A. Khan, M. Fayaz, and M. M. J. T. Iqbal, "Features Reductions Using Color Moments and Classification of Brain MRI Using K-NN," vol. 23, no. 4, pp. 77-83, 2018.

[20] F. Suhaimi, Z. Z. J. I. J. o. A. Hikke, and A. Sciences, "Feature map size selection for fMRI classification on end-to-end deep convolutional neural networks," vol. 5, no. 8, pp. 95-103, 2018.

[21] S. R. Saleh and A. M. Al-Bakry, "MRI images classification based on software agent," in 2017 Annual Conference on New Trends in Information & Communications Technology Applications (NTICT), 2017, pp. 225-229: IEEE.

[22] T. Keerthana and S. Xavier, "An intelligent system for early assessment and classification of brain tumor," in 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), 2018, pp. 1265-1268: IEEE.

[23] A. R. Mathew and P. B. Anto, "Tumor detection and classification of MRI brain image using wavelet transform and SVM," in 2017 International Conference on Signal Processing and Communication (ICSPC), 2017, pp. 75-78: IEEE.

[24] S. Korolev, A. Safiullina, M. Belyaev, and Y. Dodonova, "Residual and plain convolutional neural networks for 3D brain MRI classification," in 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017), 2017, pp. 835-838: IEEE.

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