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# A Robust Technique of Brain MRI Classification using Color Features and K-Nearest Neighbors Algorithm

Muhammad Fayaz[1], Abdul Salam Shah[2*], Fazli Wahid[3] and Asadullah Shah[4]

*[1]University of Malakand, KPK, Pakistan*
*[2,3]SZABIST, Islamabad, Pakistan*
*[4]International Islamic University Malaysia (IIUM), Kuala Lumpur, Malaysia*
*[1]hamaz_khan@yahoo.com, [2]shahsalamss@gmail.com,*
*[3]wahid_uomian@hotmail.com, [4]asadullah@iium.edu.my*

***Abstract***

*The analysis of MRI images is a manual process carried by experts which need to be automated to accurately classify the normal and abnormal images. We have proposed a reduced, three staged model having pre-processing, feature extraction and classification steps. In preprocessing the noise has been removed from grayscale images using a median filter, and then grayscale images have been converted to color (RGB) images. In feature extraction, red, green and blue channels from each channel of the RGB has been extracted because they are so much informative and easier to process. The first three color moments mean, variance, and skewness are calculated for each red, green and blue channel of images. The features extracted in the feature extraction stage are classified into normal and abnormal with K-Nearest Neighbors (k-NN). This method is applied to 100 images (70 normal, 30 abnormal). The proposed method gives 98.00% training and 95.00% test accuracy with datasets of normal images and 100% training and 90.00% test accuracy with abnormal images. The average computation time for each image was .06s.*

***Keywords:*** *Classification, Feature Extraction, K-Nearest Neighbor, Magnetic Resonance Imaging (MRI), Principle Component Analysis*

## 1. Introduction

The Magnetic Resonance Imaging (MRI) is the commonly preferred technique used for the diagnosis of brain related disorders and injuries. The MRI has the capability of spatial resolution to discriminate between soft tissues and the anatomical structure of the brain. Due to the non-invasive property of brain MRI, it is considered best as compared to other imaging modalities currently used for diagnosis of brain related disorders. The MRI provides detailed information about the soft tissues of the brain and has brought unparalleled improvement in the diagnosis of brain diseases [1].

Medical experts are trying to achieve a high degree of accuracy to investigate human brain tissues through different digital imaging methods. The brain is most commanding part of the human body and is responsible for controlling blood pressure, temperature, fluid balance, heartbeat, memory and emotions [2]. Mostly experts prefer MRI and Computed Tomography (CT) scan imaging techniques for detection of a tumor in the brain. Most of the techniques proposed by experts have generalized four stages for the classification normal and abnormal images; MRI Preprocessing, Feature Extraction, Dimension Reduction, and MRI classification [3].

The preprocessing is used for the improvement of the quality of images and to make them suitable for further processing as per requirement of the technique [4]. The brain MRI contains unwanted noises such as Gaussian, salt and pepper, speckle and Rician.

*Corresponding Author

The mean filter, median filter, and Weiner filter are common noise removal algorithms. The mean filter has a drawback of poor preservation of edges [5]. The median filter sharpens and preserves the edges of images and is the best choice for salt-and-pepper noise. The Weiner filter is useful for removing additive noise [6].

The feature extraction helps to extract only significant features instead of considering the whole image for processing. Researchers have used, Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT) [7], Fractal Dimension (FD) [8], and texture features, for the feature extraction. For feature reduction researchers have used Principal Component Analysis (PCA), Independent Component Analysis (ICA) [9], Linear Discriminate Analysis (LDA), and Genetic Algorithm (GA) [4].

For the classification, supervised algorithms such as k-Nearest Neighbor (k-NN) and Artificial Neural Network (ANN) and unsupervised algorithms such as Fuzzy-C-Means, Self-Organization Map (SOM) are used. Supervised algorithms have better classification accuracy as compared to unsupervised algorithms [10].

The manual inspection of brain MRI is an expensive and slow process and always exposed to errors, so it is necessary to analyze, classify and process the human brain images in an automatic way. In this paper, we have proposed an MRI classification technique based on color features and k-NN algorithm to improve the accuracy.

The structure of the remaining paper is organized as; the objective of study is presented in section 2, the related work is presented in section 3, the proposed model is discussed in section 4, the section 5 is about Implementation and experimental results, discussion is carried out in section 6, and finally the conclusion and future work is provided.

## 2. Objective

The brain tumor is the topic of research since last decay, for the detection of the tumor CT scan and MRI images are used. Currently, experts analyze MRI images manually on the basis of their experience which is a time-consuming process and also prone to errors. The decision also depends on upon the experience of experts. The classification and analysis of images can be automated with digital image processing techniques and suitable classifier. The automated technique may also reduce the computation time and also less error prone as expert systems have proved more accuracy than humans. The objective of this paper is to propose an automated model using color features and k-Nearest Neighbor (k-NN) and to improve the classification accuracy of normal and abnormal MRI images.

## 3. Related Work

Lahmiri *et. al.,* in [11], proposed a method for discrimination of normal brain Magnetic Resonance Imaging (MRI) from Pathological MRI. Pathological images including the image of brain suffering from Metastatic Bronchogenic Carcinoma, Glioma, and Alzheimer's disease. First order statistics were used to extract efficient features from LH and HL sub-bands of the discrete wavelet transformed and decomposed brain MRI image. The features were extracted from the horizontal (LH) and vertical (HL) directions. A Probabilistic Neural Network (PNN), k-Nearest Neighbors (k-NN) and Learning Vector Quantization (LVQ) were used for classification. The decisions of three classifiers were aggregated into the Support Vector Machine (SVM) to improve classification accuracy and efficiency. The developed system was tested with the database of Harvard Medical College, the ensemble approach has obtained higher accuracy of classification.

Nandpuru *et. al.,* in [12], used Support Vector Machine (SVM) to discriminate between normal and abnormal MRIs. The authors have applied a median filter for removal of noise from brain MRI and for skull removal, morphological operations, dilation, and erosion have been used. Image enrichment has been carried out with Power Law Transformation. Texture features, symmetrical features, and grayscale features have been extracted.

Principal Component Analysis (PCA) has been used for dimension reduction, and classification has been carried out with the Support Vector Machine (SVM). In order to evaluate the performance of classification, Linear, Quadratic and Polynomial Kernels have been used and they have proved an accuracy of 74%, 84%, and 76% respectively.

Kalbkhani *et. al.,* in [13], used multi-cluster features and K-Nearest Neighbors for the classification of brain MRI. For the feature, extraction they have used two-dimensional Discrete Wavelet Transform 2-D (DWT). The multi-cluster feature selection method has been used to select efficient features from primary features. Selected features were classified into normal or seven other diseases using k-Nearest Neighbor (k-NN) and achieved 98.75% accuracy with 41 features.

Mohammad-Jafarzadeh *et. al.*, in [14], presented three stages model for MRI classification. To extract the valuable features from the MRI, the images have been transformed to two-dimensional wavelet of three levels. For the dimension reduction of feature vectors, Spectral Regression Discriminant Analysis (SRDA) method has been proposed by the authors. The reduced features obtained from the SRDA are fed to support vector machine for classification. The normal images and image of nine diseases have been considered. They have considered 9 features of each image for classification and achieved average PCC of 97.98% with 100 images and 100% with 80 images.

## 4. Proposed Model

The proposed model for the brain MRI classification consists of three stages as elaborated in Figure 1.

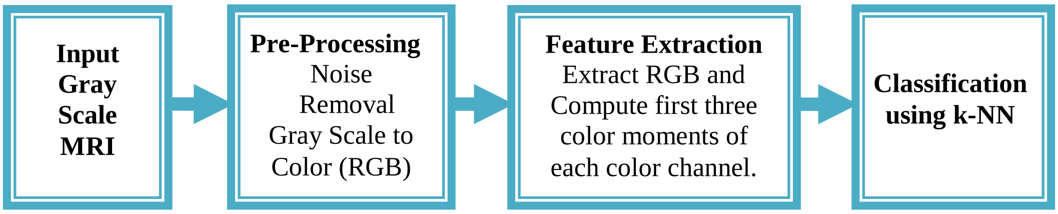
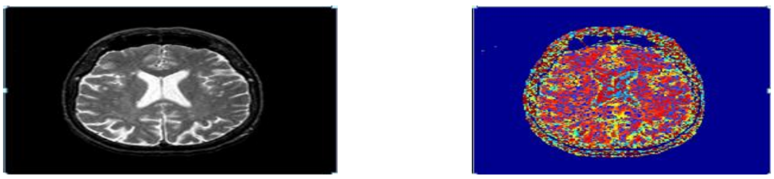



**Figure 1. Proposed Model for Brain MRI Classification**

### 4.1. Preprocessing

The grayscale images had salt and pepper noise so a median filter of 3*3 size has been applied for the removal of noise. The small size of the mask has reduced the computation time and also the median filter has preserved the edges of the image. First three color moments of a grayscale image are very informative, so the grayscale image has been converted to the color image (Red, Green and Blue (RGB)) [15]. The conversion of the grayscale image to color (RGB) images has been carried out using Matlab {rgb Image = gray Image / max(max(gray Image));}. The image after conversion can be seen in Figure 2. The first three channels of the RGB image has been calculated using {color Moments = [mean R std R mean G std G mean B std B];}.



(a) Grayscale Image (b) Color RGB image

**Figure. 2. Grayscale Image Converted to Color RGB Image [14]**

### 4.2. Feature Extraction

In feature extraction three channels, red, green and blue were computed from the images. After that first three color moments; mean, variance and skewness were calculated for red, green and blue channels [16]. In the proposed approach only nine features were extracted that represents a complete image. The reduced number of feature reduced the complexity of calculation for classifier. The detailed description of the features used is given bellow:

**1) Mean:** It represents the average of intensities of pixels of red, green and blue channels that can be calculated by (1).

$$E_{r,i} = \frac{1}{N}\sum_{j=1}^{N} I\ i,j \tag{1}$$

**2) Variance:** It represents the variations in the intensities of pixel values of each color channel. The standard deviation is used here, which is the square root of the variance and can be computed by (2).

$$R_{r,i} = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}\left(I_{i,j} - E_{r,i}\right)^2} \tag{2}$$

**3) Skewness:** It represents the distribution of intensities of pixel values of each color (RGB) channel and can be calculated by (3).

$$S_{r,i} = \frac{1}{N}\sum_{1}^{N}\left(I_{i,j} - E_{r,i}\right)^3 \tag{3}$$

The total number of pixels of image are denoted by 'N', and the intensity of each pixel is denoted by 'I', in equations (1), (2), and (3).

### 4.3. Classification

For classification we have used k-Nearest Neighbors (k-NN). In k-NN, the observation having the shortest distance has the chance to belong the same class. The probability of a point 'x' belongs to a class can be estimated by the proportion of training points in a specified neighborhood of 'x' that belongs to that class. The points can be classified by majority vote and similarity degree sum method [17]. In the majority, voting method, those points which belong to each class in the neighborhood are counted and the class to which the highest proportion of points belongs is the likely classification of 'x'. In similarity degree, sum method, similarity scores are calculated for each class, based on the k-Nearest Neighbors and classification of 'x' is decided on the basis of class which has the highest similarity score [17]. The majority voting method is frequently used as compared to the similarity degree sum method due to its lower sensitivity to outliers. In k-NN we have used Euclidean Distance. The Euclidean distance between each test point ft and training set point fs, each with n attributes, is calculated by (4).

$$d = \left[(f_{t1} - f_{s1})^2 + (f_{t2} - f_{s2})^2 + \cdots + (f_{tn} - f_{sn})^{\frac{1}{2}}\right] \tag{4}$$

The steps of k-NN are summarized as:

a) The selection of 'k'.

b) Calculation of distance.

c) Sorting of distance in ascending order.

d) Finding 'k' class value.

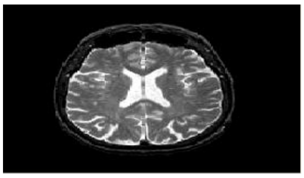
e) Finding the dominant class.

The selection of optimal 'k' value is a challenging task, the small value of 'k' will not be appropriate to estimate the population proportions accurately around the test point. The selection of larger value of 'k' create more biased and less variance in probability estimates in the result. Therefore ‘k’ should be selected as larger to minimize the probability of a non-biased decision, and should be as small so that included points can give accurate estimate of class. In this paper the value of ‘k’ has been selected as 3.

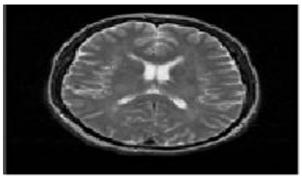
## 5. Implementation and Experimental Results

### 5.1. Database

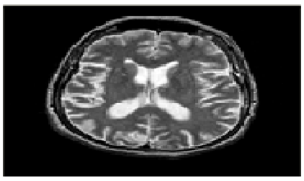
MR images have been taken from www.med.harvard.edu/AANLIB [18]. Total hundred (100) standards T-2 weighted, 256*256 brain MR images were selected for experimentation, out of them seventy (70) normal and thirty (30) abnormal. The abnormal images consist of Alzheimer, stroke, brain tumor diseases as shown in Figure 3.



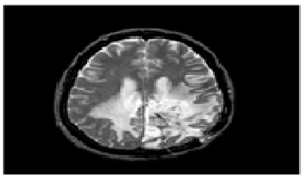
(a) Normal Brain



(b) Brain Tumor



(c) Stroke



(d) Alzheimer

**Figure 3. Sample of Brain MRIs**

### 5.2. Experimentation Environment

The experiments were carried out with the following software, hardware specification and other additional resources. The pre-processing and feature extraction has been carried out with Matlab and Weka has been used for the classification.

| | |
|---|---|
| **Processor:** | i3-2310M CPU @ 2.10 Ghz |
| **RAM:** | 8.00 GB |
| **System Type:** | 64bit |
| **Operating System:** | Windows 10 Professional |
| **Development Environment:** | Matlab 7.6.0 (R2008a) |
| **Classification Tool:** | Weka 3.7.10 |

### 5.3. Ratio of Training and Test Images

The dataset has been divided into two sub-datasets with the ratio of 70% training and 30% testing. The available dataset has a total hundred (100) images; seventy (70) for training and thirty (30) testing as illustrated in the Table 1.

**Table 1. Ratio of Training and Test Images**

| Total Images | | Training Images | | Test Images | |
|---|---|---|---|---|---|
| 100 | | 70 | | 30 | |
| **Normal** | **Abnormal** | **Normal** | **Abnormal** | **Normal** | **Abnormal** |
| 70 | 30 | 50 | 20 | 20 | 10 |

### 5.4. Performance Evaluation

Different statistical measures have been used to analyze the quantitative evaluation of the proposed method and its performance comparison with other proposed techniques in literature. The most of the authors have used accuracy to measure the performance of their proposed methods. In the proposed method, we have used sensitivity, specificity, and accuracy. The sensitivity and specificity are also called true positive rate and false positive respectively, and the percentage of correctly classified samples known as accuracy of the classifier. We have also calculated the true negative and false negative. The mathematical representation of performance measure is provided in (5), (6), (7), (8), and (9).

$$True\ Positive\ (TP)rate = \frac{TP}{(TP+FN)} * 100\% \tag{5}$$

$$True\ Negative\ (TN)rate = \frac{TN}{(TN+FP)} * 100\% \tag{6}$$

$$False\ Positive\ (FP)rate = \frac{TP}{(TP+FP)} * 100\% \tag{7}$$

$$False\ Negative\ (FN)rate = \frac{TN}{(TN+FN)} * 100\% \tag{8}$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} * 100\% \tag{9}$$

TP, represents correctly classified positive instances, TN correctly classified negative instances, FP incorrectly classified negative instances, and FN incorrectly classified negative instances [12]. The detailed calculations and results are represented in the Table 2-7.

**Table 2. Training and Testing Accuracy of Normal Images**

| Total Images | Correctly Classified | Incorrectly Classified | Accuracy |
|---|---|---|---|
| Training Accuracy of Normal Images | | | |
| 50 | 49 | 1 | 98.00% |
| Testing Accuracy of Normal Images | | | |
| 20 | 19 | 1 | 95.00% |

**Table 3. Training and Testing Accuracy of Abnormal Images**

| Total Images | Correctly Classified | Incorrectly Classified | Accuracy |
|---|---|---|---|
| Training Accuracy of Abnormal Images | | | |
| 20 | 20 | 0 | 100% |
| Testing Accuracy of Abnormal Images | | | |
| 10 | 9 | 1 | 90.00% |

**Table 4. Training and Testing Confusion Matrix**

| TP | TN | FP | FN |
|---|---|---|---|
| Training | | | |
| 98 | 2 | 100 | 0 |
| Testing | | | |
| 95 | 5 | 90 | 10 |

**Table 5. Detailed Accuracy by Class**

| Accuracy of Class | TP Rate | FN Rate |
|---|---|---|
| Normal Class | 97.14 | 2.86 |
| Abnormal Class | 96.67 | 3.33 |

**Table 6. Classification Accuracy Comparison**

| Reference No | Technique | Accuracy Rate |
|---|---|---|
| [12] | Linear Kernel + PCA + SVM | 74.00% |
| | Quadratic Kernel + PCA + SVM | 84.00% |
| | Polynomial Kernel + PCA + SVM | 76.00% |
| [13] | 2-D (DWT) + K-NN | 98.75% |
| [14] | SRDA + SVM | 97.98% |
| [15] | IF + TF + ANFIS | 98.25% |
| [19] | DWT + PCA + FP-ANN | 97.00% |
| | DWT + PCA + k-NN | 98.00% |
| [20] | Encoded Information + PCA + KNN | 96.33% |
| [21] | MsFCM | 96.77% |
| | FFCM | 99.30% |
| | FCM | 97.62% |
| [22] | DWT + PCA + FP-ANN | 90.00% |
| | DWT + PCA + k-NN | 99.00% |
| Proposed Technique (with Normal Images) | Color Features + K-NN (Training) | 98.00% |
| | Color Features + K-NN (Testing) | 95.00% |
| Proposed Technique (with Abnormal Images) | Color Features + K-NN (Training) | 100.00% |
| | Color Features + K-NN (Testing) | 90.00% |

**Table 7. Feature Based Comparison**

| Reference No | Technique | Number of Features |
|---|---|---|
| [1] | DWT + SOM | 4761 |
| | DWT + SVM with Linear Kernel | |
| | DWT + SVM with Polynomial Kernel | |
| | DWT + SVM with radial basis function based Kernel | |
| [3] | SCG + DWT + PCA + NN | 19 |
| [13] | 2-D (DWT) + K-NN | 41 |
| Proposed Technique | CM + KNN | 9 |

### 5.5. Time Complexity

The evaluation of classification method can be carried out with computation time. We calculated the computation time for all 100 with k-NN classifier. The average computation time for each image is represented in Figure 4. The computation time taken by each image during feature extraction is 0.05718, feature reduction has no time complexity because we have not used any feature reduction algorithm due to less number of features extracted in the feature extraction stage. The computation time of classification is 0.0058 seconds. The total time taken by each image is 0.06 seconds.


**Figure 4. Execution Time of Proposed Technique**

## 6. Discussion

The implementation of the proposed model is much easier. Three channels red, green and blue were extracted from the color MR images and for each color channel, only three color moments, mean, standard deviation and skewness have been computed. A total of nine features were extracted from each brain MR image. This whole operation for obtaining a total of nine features is computationally very simple and easy. The reduction algorithm has not been used, due to less number of features extracted in the feature extraction stage. This reduces the computation complexity of the proposed approach.

In the proposed method only hundred images have been used, the increase in number of images will reduce the classification rate as the k-NN has a disadvantage that its performance reduces on larger datasets [17].

## 7. Conclusion and Future Work

In this paper, a modified method for brain MRI classification using color features and the k-NN algorithm has been proposed which has achieved 98.00% and 95.00% accuracy with normal images during training and test datasets subsequently. The accuracy with abnormal images is 100% and 90.00% during training and testing subsequently. A total of nine features extracted from red, green and blue channels have been used and feature reduction algorithm has not been used that reduced the computation time of brain MRI classification. The value of ‘k’ has been selected as 3. The average computation time taken by each image was 0.06s.

In future work, we will consider MRI images having different contrast for the deployment of proposed technique and increase the number of MRI images for both training and testing. We will also test the same model with other classifiers and focus on computation time with the consideration of less number of features using dimension reduction techniques.

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## Authors

**Muhammad Fayaz,** is currently perusing Ph.D. in Computer Science. He received MS in Computer Science from SZABIST, Islamabad, Pakistan in 2014. He did MSC from the University of Malakand, KPK, Pakistan in 2011. His areas of interest are NP problems, Approximation Algorithms, Image Processing, and Pattern Recognition.

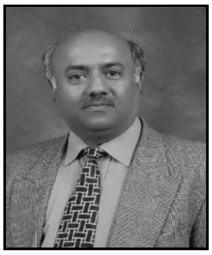
**Abdul Salam Shah**, is currently doing specialization in Management Information System (MIS) from Virtual University of Pakistan. He has completed MS degree in Computer Science from SZABIST, Islamabad, Pakistan in 2016. He did his BS degree in Computer Science from Isra University Hyderabad, Sindh Pakistan in 2012. In addition to his degree, he has completed short courses and diploma certificates in Databases, Machine Learning, Artificial Intelligence, Cybercrime, Cybersecurity, Networking, and Software Engineering. He has published articles in various journals of high repute. He is a young professional and he started his career in the Ministry of Planning, Development and Reforms, Islamabad Pakistan. His research area includes Machine Learning, Artificial Intelligence, Digital Image Processing and Data Mining.

Mr. Shah has contributed in a book titled "Research Methodologies; an Islamic perspectives," International Islamic University Malaysia, November, 2015.

**Fazli Wahid**, received BS in Computer Science from University of Malakand, Pakistan in 2006, and MS in Computer Science from SZABIST, Islamabad, Pakistan in 2015.

His area of interest are energy consumption prediction, optimization, and management using multilayer perceptron, Artificial Bee Colony, Ant Colony and other Machine Learning Techniques.



**Dr. Asadullah Shah**, is working as Professor and Head of department of Information Systems (HOD) at the Kulliyyah of ICT, International Islamic University Malaysia (IIUM) before joining IIUM, he worked as Head of Telecommunication Engineering & Management department, IoBM Karachi Sindh, Dean Faculty of Computer and Management Sciences, Isra University Hyderabad Sindh and Head of Telecommunication Engineering and IT, Sukkur IBA, Sindh-Pakistan.

He did his Ph.D. from the university of Surrey UK, in 1998, with the specialization in Multimedia Communication. He started his academic carrier from University of Sindh Jamshoro, Pakistan in 1986 as a lecturer.

He has published 200 research articles in highly reputable international and national journal in the field of computers, communication and IT. Also, he has published 12 books in his 30 years of the academic carrier. Currently he is supervising great number of postgraduate students, working in multiple disciplines, specially, animation, social media and image processing in the Department of Information Systems, Kulliyyah of Information and Communication Technology, International Islamic University Malaysia.