Segmentation of Brain Tumor using Glcm and Discrete Wavelet Transform

Alpana Jijja, Dinesh Rai

Abstract: To identify brain tumors at an early stage is a challenging task. The brain tumor is usually diagnosed with Magnetic Resonance Imaging (MRI). When MRI spectacles a tumor in the brain, the most common way of determining the type of brain tumor after a biopsy or surgery is to look at the results of a tissue sample. In this research to detect brain tumors faster and accurately the feature extraction techniques are used to segment the tumor affected area. One of such very effective technique of feature extraction measure is the Grayscale Co-occurrence Matrix (GLCM). This research focuses on the GLCM and Discrete Wavelet Transformation (DWT) technique to detect and label the tumor from an image based on the textures and categorizing it according to a tumor or non-tumor category. The convolutional neural network (CNN) uses these features to improve the accuracy to 91%.

Keywords: Convolutional Neural Network; Discrete Wavelet Transform; Feature Extraction; Grayscale Co-occurrence Method.

I. INTRODUCTION

The human body has a brain that is one of the most complex organs. The thought of being diagnosed with a brain tumor is one troubling and life-changing case. High-tech imaging has been used in the last few decades to see inside the body for better clarity and wider details. To detect and identify the wide range of brain disorders, MRIs, CT scans, ultrasounds, and PET scans are better technologies that greatly reduce the need for exploratory surgery to make a diagnosis. Various approaches have been used to enhance the identification of brain abnormalities in MRI images. In this research paper, the texture is one of an important feature used for evaluation and identification of the region of interest in an MRI image. Texture provides information in the spatial arrangements on color or intensities in an image. The texture is determined by the spatially distributed levels of intensity in the neighbourhood [1]. The textures may vary in randomness, regularity (or periodicity), directionality, and orientation despite their origin [2,3]. Therefore, if a pattern is quite random and natural it falls into the framework of texture. Texture analysis requires defining certain characteristics or properties that differentiate or define the textures. In the segmentation and classification of image recognition, texture analysis can be used to identify the texture borders, edge direction movement [4] and long linear patterns [5]. Several authors have applied image processing techniques in various medical diagnosis applications detecting brain tumors using MRI images [6], lung cancer [7] and mammogram[8], which are methods of texture classification and texture characterization [9-11]. The most important challenge of texture analysis is to deal with shape, classification and segmentation [12-14]. Texture analysis can be helpful if characteristics in an image are more differentiated by texture than their intensities and therefore traditional thresholding techniques cannot be efficiently utilized [15]. The texture is calculated statistically across the image using a moving window. The statistical method calculates the coarseness and directionality of the texture with respect to the averages in a window of an image. However, the syntactic approach defines the structure of the entities and their distribution [16]. The important features of the statistical method to achieve a better classification, involve precision, contrast, entropy, homogeneity, autocorrelation function, power spectrum, relevant gray level statistics and matrices with co-occurrence.

II. LITERATURE REVIEW

Haralick et al., first proposed the probability of co-occurrence using GLCM in their 1973 research paper. This method is used to identify image traits and is commonly used in the field of biomedicine. The GLCM is computed in the first step, while the functionalities based on the GLCM are decided in the second step. Various fourteen textural features that include image texture information, has features such as homogeneity, linear gray-tone dependencies, contrast, number and existence of boundaries present, and image complexity [17]. Rajesh et al., research focuses on classifying cancer using MRI brain images. The technique used in this research is the Rough Set Theory which derives the characteristics of the MRI brain image classification for cancer using Feed Forward Neural Networks. The features extracted thus produces a classification efficiency of 90% [18]. Saban and Byram in their research have extracted various features using GLCM, LBP, LBGLCM, GLRLM, and SFTA algorithms. Thus after comparing the results of these algorithms, they obtained an effective algorithm for classification [19].

A. Copeland et al., in their research illustrated a strong high degree of correlation between synthetically derived textures and how different textures are perceived by human observers[20]. Manjunath and Ma implemented Gabor wavelet-derived features. Results from this work have shown that Gabor filter retrieval performance is better than typical wavelet-based orthogonal features.

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The main drawback of the Gabor wavelet is durability and memory constraints [21]. He and Wang proposed in his research paper a novel statistical texture analysis technique, that decomposes a texture image into a set of texture units that are categorized by its texture spectrum [22].

III. METHODOLOGY

This research paper experiment is focused mainly to identify abnormal MRI brain images that determine tumors with the highest level of accuracy i.e. there should be less false positives.

The proposed solution classifies the brain tumor image based on shape and texture characteristics features. Fig.1 shows a block diagram with various steps involved in data processing operations for the extraction of the tumor. The initial datasets, consisting of MRI brain images, are collected from medical websites. The MATLAB ToolBox is used for processing and analysis of the images.

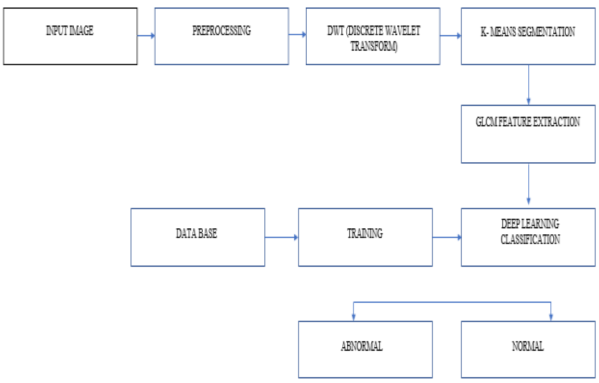

Fig. 1. Block diagram of proposed MRI brain image segmentation using deep learning techniques.

After the collection of data and storing it, various classification techniques are performed to get the desired results:

Step 1: While pre-processing the image Median filtering is applied to eliminate outlier's i.e salt and pepper noise.

Step 2: DWT method is applied to decompose the image to the third level.

Step 3: At the third stage of this process of segmentation, K-means clustering is implemented.

Step 4: GLCM is a feature extraction technique used to find various statistical features.

Step 5: These selected features are finally used as CNN classifiers for the categorization of the brain condition.

Step 6: test images are evaluated using Performance evaluation criteria, to detect normal (no tumor) or abnormal(tumor) images.

Firstly, an image is selected as an input from the database using imread( ). Image is resized to 256X256 using imsize( ). Further RGB is converted into grayscale using rgb2gray ( ). Generally, the data points are split in two compartments, one is for training the dataset and another is for testing dataset. Fig. 2 is a test image of brain MRI which is selected from the testing folder, preprocessing technique i.e. image resizing, color conversion and reshaping is performed.

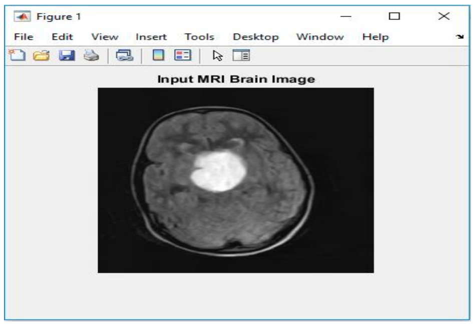

Fig. 2. Input brain MRI image

IV. RESULTS AND DISCUSSIONS

A. Preprocessing and Filtering

In this step, the selected input test image is first reshaped and resized. The image quality is improved using a filtering technique. Filters are primarily applied to enhance the quality of the pixels and eliminate the noise, thereby reducing the distortion of the given input MRI image. The median filter, which is a nonlinear technique, is used in digital filtering. This technique improves an image or a signal by eliminating noise. This noise filter is a typical pre-processing step for improving later and improving edges in the image. The proposed technique uses the median filter using medfilt2 ( ), apart from removing noise that exists in the image, it preserves edges within the image as well. The median filter, one of the most popular filters, operates by moving pixel by pixel throughout the image pixels and replacing each value of the pixel with the neighboring median value pixel. This filter, which is a pattern of neighbors, is known as the "window". This window slides pixel by pixel over the entire image, this movement is called "stride". The median of the window is calculated by first sorting all the pixel values into ascending or descending order, and then the pixel being considered is replaced with the middle (median) pixel value. Fig.3 shows the output of the median filter applied to the test image of brain MRI.

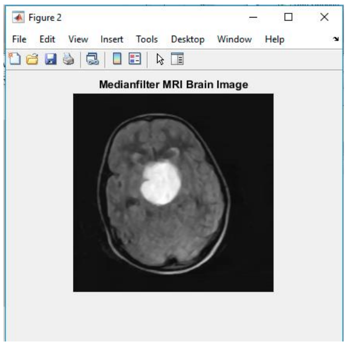

Fig. 3. Median filter

B. Feature extraction

Feature extraction happens to be the most critical task to compute the textual characteristics of a digital image. The extraction of a feature is the first step towards the image texture analysis.

This activity will help in determining the texture classification and shape determination. The GLCM is the most popular method of texture analysis of second-order statistics. Each image consists of pixels of a specific intensity level.

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The GLCM is popularly known as co-occurrence distribution, it tabulates, how often in an image or image segment with different combinations of gray levels co-occur. A gray-level co-occurrence matrix may demonstrate several characteristics of the spatial grey level spread. For classification, the displacement of pixels is small for fine textures and large for coarse textures. This displacement value is represented by "d". The four co-occurrence submatrix can be measured in four scanning directions (0^o, 45^o, 90^o, 135^o), to obtain information about the spatial distribution and its orientation.

There are two types of co-occurrence matrix – symmetric in which pairs segregated are counted in a given direction θ, and another non-symmetric in which only pairs segregated by distance are counted. GLCM matrix is symmetrical around the diagonal, if each pair of pixels are counted twice, once forward and once backward, the symmetry will be achieved [1].

C. Decomposition of an Image with DWT

DWT decomposes the enhanced MRI brain image to obtain the decomposed coefficients. The decomposed coefficients are combined in the wavelet domain based on the fusion rule. The fused image is achieved by taking the inverse DWT on fused coefficients thus reducing the noise to improve efficiency. Fig. 4 is a DWT image of the third level of the test image.

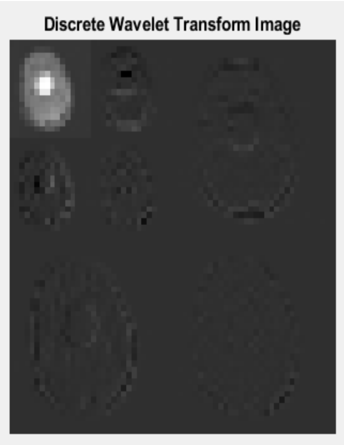

Fig. 4. Discrete Wavelet Transform image

Fig. 5. 3 level 2-Dimensional DWT brain image.

The image in Fig.5 is divided into four regions, a region with high details. Using separate and distinct wavelet features, a one Dimension wavelet transform can be expanded to a two-dimensional (2-D)transformation. The 2D transformation implements separable 1D filters transforming throughout the input rows and then reappearing as a 2D image[2]. Subsequently, in one level of transformation, the image is decomposed subsequently to the 2-Dsub-band decomposition to low level (LL) sub-band. Such iteration method results in certain transformation levels like wavelet decompositions, in which a pair of wavelet filters are used to measure wavelet coefficients, using low pass filters and high pass filters. The

LL image conducts decomposition that uses the same filters, which often have the lowest frequency component positioned in the image's upper left corner. Every stage produces the next 4 sub-images for analysis, the size of which is scaled down twice over the previous scale. Better results of segmentation of the texture can be obtained in the scale of 2 to 4 wavelet decomposition.

D. K-Means Clustering and Segmentation

K-means clustering is a very common and popular clustering and segmentation algorithm, which treats each pixel with RGB values in an image as a feature pointing to a location in space. The K- means algorithm randomly locates the number of cluster centers in multidimensional measuring space. The pixel that has a mean vector closest is assigned to the cluster. The process persists until there is no substantial change amongst subsequent iterations of the algorithms in the direction of class mean vectors. After denoising the MRI test image, it is fed to the K-means clustering technique. In this proposed algorithm, the number of clusters taken is k=4 and the maximum iteration taken is 100. The output is shown in Fig.6 is an image of 4 clusters using morphological operations to extract the boundary pixels using dilation. Dilation is the area closing applied to pixels of higher value image while erosion technique is area closing applied to pixels with lower value image for detection of the tumor. Imerode ( ) is used with a structuring element on the binary image to remove the unwanted area, the fourth cluster image shows the extraction of the tumor. Tumor area is counted using (sqrt (Pcount))* 0.264. Fig.7 shows a clear image of the extracted tumor area from the image.

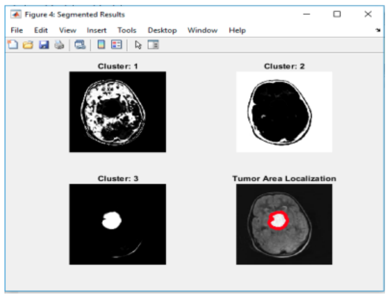

Fig. 6. Clustered images.

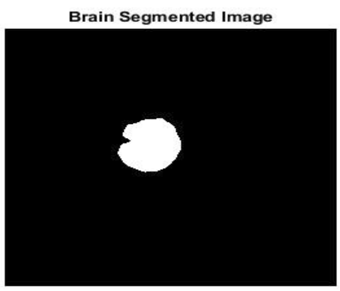

Fig. 7. Segmented image of the brain.

E. Convolutional Neural Network for Classification

The convolutional neural network has emerged as a powerful technique when the training set is very large. Several studies have shown that this deep learning model is used on images to give better results. The proposed model uses CNN on MRI of brain images. Fig.8 comprises a diagram of the classification of brain tumors focused on the convolution neural network. A CNN-based classification model is partitioned into two phases. The number of filters in the test phase is 10, the filter dimension is 8x8 and the dimension of the pooling region is 3x3.

The images are further divided into various categories by using label names such as normal and abnormal brain images. Later, CNN is used for the automated detection of brain tumors. The time taken by the model to compute is low. At the same time, the performance is high in the proposed automatic classification scheme.

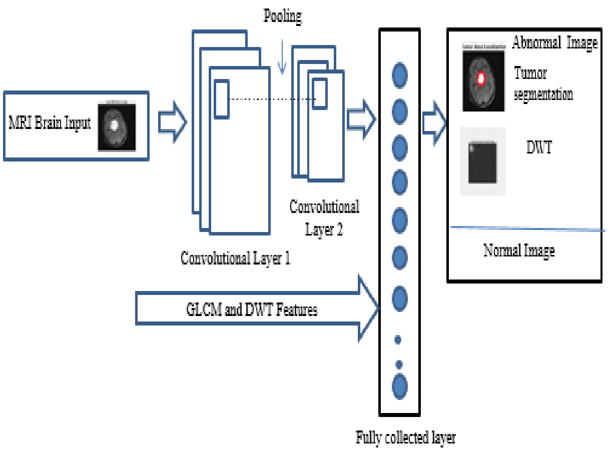

Fig. 8. Convolution neural network model for ascertaining brain abnormalities in MRI images.

The two sets of Haralick statistical features (Energy, contrast, correlation, Homogeneity, and Entropy) for HL3 are extracted using graycoprops(GLCM) and passed through convolutional layers 1 and convolutional layer 2. Table1. shows two sets of GLCM statistical features.

Table I: Two sets of statistical features

Features	*Set1*	*Set2*
Energy	.0002	.0001
Contrast	3.1251	7.5633
Coorelation	.0007	.0002
Homogeneity	.0006	.0005
Entropy	.00045	.0049

```
0.0002
3.1251
0.0007
0.0006
0.0045
0.0001
7.5633
0.0002
0.0005
0.0049

convolution code passed the training.
pooling code passed the training.
No of Defect Cells from Benign:
     1966

Tumor Area Localization
Sensitivity:
   88.2353

Specificity:
   93.8776

Accuracy:
    91
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Fig.9. Statistical features of CNN.

Fig. 9 shows the features obtained, after applying these features in the convolutionl filter, ReLu activation function helps in smoothing the filters. Further sensitivity, specificity, and accuracy of the MRI images are calculated.

F. Performance Evaluation

The results of brain tumor image classification obtained during training using CNNs is shown in Fig.10.

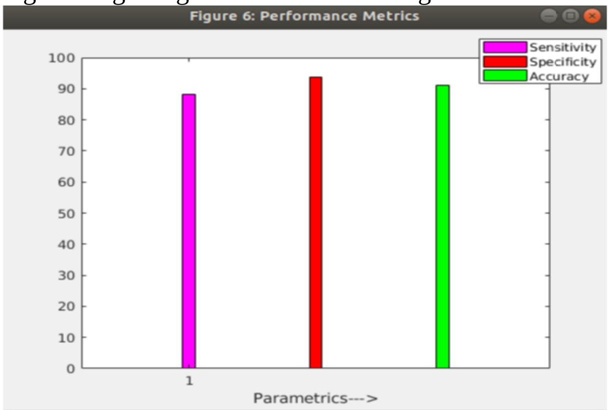

Fig. 10. Performance matrix.

This research work proposes the efficient brain tumor detection performed using deep learning techniques of convolutional neural networks. MATLAB toolbox is an image processing software that helps simulate results. The research suggests that the classification is based on CNN, the feature extraction steps are not extracted separately but this model uses GLCM extraction features for better specificity. Fig.10 displays the results or performance matrix of classification and segmentation of test MRI images. The classification results- accuracy, sensitivity, and specificity are calculated and are found very high. Henceforth complexity and calculation time are now reduced, and precision is improved. Finally, in the classification results, the affected area of the tumor in the brain is detected.

V. CONCLUSION

The main aim of the research is to develop an accessible and successful automatic brain abnormality classification with high accuracy and high performance. The analysis of the proposed system consists of specific preprocessing measures, which involve separation, feature isolation and categorization. In the preprocessing, the median filter is applied for noise removal. DWT and GLCM techniques are applied for feature extraction for texture analysis on MRI brain images. DWT extraction involved in decomposing the signal to get detailed coefficients and approximation at the third level with the help of segmentation and decimation techniques. GLCM uses the spatial relationship of pixels and examines the texture using the geometric method. Haralick features for level 3 are used to calculate the statistical features e.g. Entropy, energy, homogeneity, and contrast for texture analysis. For segmentation, K- means techniques are used to create four clusters of MRI images representing various segmented features of the image. In the last stage of training, DWT and GLCM features are applied to CNN to achieve an accuracy of 91%, sensitivity of 88.23% and specificity of 93.87%.

The findings achieved in the experiment are high accuracy in the classification of normal and abnormal tissue textures from brain MR images showing the efficiency of the proposed technique.

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