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Brain Tumor Detection Using Texture Characterisation and Classification Based on the Grey-Level Co-Occurrence Matrix

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ABSTRACT

Detection of brain tumour is very important current scenario of the health care society. Image processing techniques are used to extract the abnormal tumour portion and other features in the brain. Brain tumor is an abnormal mass of lesson in which cells grow up and multiply uncontrollably, apparently unregulated by the mechanisms that control cells. Several techniques like Segmentation, morphological have been developed for detection of tumor in the brain. Texture is a critical feature of several image types and textural features have a lot of application in image processing, content-based image retrieval and so on. There are several ways of extracting these features and the most common way is by using a gray-level co-occurrence matrix (GLCM). In our proposed work Texture characterisation has been made to obtain the Haralick features and SVM classifier is used in the Texture classification algorithm which used in detecting the brain tumor. This technique has been tested for 45 images, true positives are 33, True negative is 1, false positive is 1, and True negatives are 10. Sensitivity 97.0%, Specificity 90.9%, Precision or Positive Predictive Value (PPV) 97.0%,Negative Predictive Value (NPV)90.9%, Accuracy 95.0%.

Key words: Brain tumor, Texture characterisation, Texture classification.

1. INTRODUCTION

Brain tumor is a aggregation of abnormal cells that develops inside the head or around the brain (Selvanayaki & Karnan, 2010, 1). Brain lesson is one of the general common main causes for the increase in Mortality among children and adults in the world.

Brain Tumor can basically be defined as Solid Intracranial Neoplasm. Treatments of Brain Tumor are determined by different factors which include volume of the Tumor, Type of Tumor, locality of the tumor, health record and Age of Patient. Brain tumor characterization and categorization is a procedure leads to the right choice and facilitates provision of high-quality and suitable treatment [2]. Since the brain tumor detection and localization becomes automatic many researchers developed different algorithms to enhance the same. All the algorithms are either supervised or unsupervised. Clustering techniques [2,3,4,5] are exploratory type techniques, hence these segmentation methods take much more time when the expected results to be better.

Supervised algorithms need training before they integrate into the application. More the number of samples added in the training phase more efficient the algorithm. A comparison study made on the supervised and unsupervised algorithms to conclude which is better category and the discussion in [5] came to end by deciding supervised algorithms.

The current study is implemented depending on image texture features as they reflect regular changes of gray values in images and such changes are correlated spatially statistically [6]. Appearance and surface characteristics of an object given by the size, shape, density, arrangement, proportion of its elementary parts are generally represented by texture. This information, texture feature extraction is a key function in content based image retrieval. Texture features can be extracted in several methods, but this study uses statistical information, in which using the Gray Level Co-occurrence Matrix (GLCM) is most common as it contains the second-order statistical information of spatial relationship of pixels of an image. The co-occurrence features were found to be the best by [7] as the study compared texture feature extraction schemes based on the Fourier power spectrum, second order gray level statistics, the co-occurrence statistics.

The thirteen Haralick measures were used to extract useful texture information from the co-occurrence matrix, they are energy, contrast, entropy, variance, correlation, IDM, Sum Average, Sum Variance, sum Entropy, Difference variance, difference entropy, information measures of correlation1, measures of correlation. Every haralick feature provides different useful information. Classifier is trained to detect and localize the tumor part in the brain. Depending on the settings configured to obtain these features. Classifier is is trained to detect and localize the tumor part in the brain. The texture classifier is a SVM classifier which is a supervised algorithm. In the paper statistical parameters are also calculated and presented and the results for some of the important haralick features along with the classifier output for the tumor detection of brain tumor images are also presented.

2. METHODOLOGY

The complete paper has two main steps which are pre-processing the image to make it suitable for the further processing and the texture training interface to detect and enhance the tumor for better diagnosis analysis.

2.1 Image Pre-processing

Even though the article uses texture analysis there by texture classifier, the Image Pre-processing is necessary before proceeding. In the current study pre-processing of the image involves four steps namely

1. Resampling
2. Color Plane Modifications
3. Spatial Domain Transformations
4. Morphological Operations

Initial step is to acquire the image which has tumor defect. Resampling ensures that every image with equal width and height there by each image will have same size. Resampling does not concerns with any intensity modifications it only deals with size of the Image. Luminance plane is extracted to reduce the over brightness of the image through Color plane extraction. Applying square transformation will improve every pixel intensity value by its square, this makes the image more analysable and enhances the region of interest as tumor detection is the main objective.
This procedure makes the image more suitable for the algorithm to be applied. Skull will be there in every MRI scanned brain image, skull should be removed in order to produce robust algorithm. Many skull stripping algorithms [8,9,10] had been developing for the past years but in the current study simple morphological operations are used to remove boundaries of the image, erosion works well in this kind of scenario.

2.2 Tumor Detection by Supervised Texture Algorithm

Supervised algorithms require training unlike unsupervised algorithms. In the texture analysis classifiers textural defects will be detected but before training the texture classifier textural defect characterizations need to be adjusted because the texture classifier algorithm uses defect characterization settings to extract texture features in order to distinguish textural defects. Therefore, The Texture Training Interface consists of the Defect Characterization and Texture Classifier processes.

In the paper haar wavelet transform is selected for defect characterization as it gives more precise haralick features of the image. To show the different haralick features of the image the classifier moves a window across the haar wavelet subband images and generates a grey-level co-occurrence matrix for each window position.

Haralick [11] introduced the co-occurrence matrix and texture features. Haralick proposed two steps for texture feature extraction. The first is computing the co-occurrence matrix and the second step is calculating texture feature based on the co-occurrence matrix. The GLCM is a tabulation of how often different combinations of pixel gray levels could occur in an image[12].

Based on the grey-level co-occurrence matrix, the classifier calculates the Haralick features. Finding the haralick features is a must for the texture classifier as it will not detect a texture defect if it is not visible in the Haralick feature space. To calculate co-occurrence matrix specifying a co-occurrence level and a window size that matches the smallest texture defect that is going to be detect is necessary. More processing time requires when co-occurrence level is high, but the classifier may distinguish texture defects more easily and a larger window size results in a coarser level of texture defect detection but decreases the time required to process the image. Along with the co-occurrence level and X by Y window size, a displacement vector is necessary to produce a co-occurrence matrix. A displacement vector that describes the relationship between pixel intensities which characterize the texture. A non-zero step size captures texture information more robustly, but increases the time required to process the image. Smaller values indicate greater overlap between windows. The settings saved in the texture classifier are used to detect texture defects in testing images by using them while training the texture classifier, a one-class SVM classifier.

The next step in the texture training interface is texture classifier, before taking the samples to train the classifier several important settings are to be adjust for better execution results. Tolerance, the maximum gradient of the quadratic function which compute support vectors as texture classifier is State vector machine classifier, its default value is 0.001. If the texture classifier does not yield result as expected because the trained texture samples do not represent every possible variation of the texture, try increasing the default value. The mask or window that the algorithm uses to determine if a sample is a texture or contains a texture defect. Radial Basis Function is the default, which is a real valued function, depends on the

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Euclidian distance between origin and the some other point.

Cross-Validation score indicates the accuracy and standardness of the classifier and its values range from 0 to 1000. Higher values indicate greater robustness. The cross-validation value may change everytime when adding samples. Minor variations indicate a stable texture algorithm and large variations indicate an unstable texture classifier. Another setting is Min Score indicates the minimum texture defect classification score required for a sample to be classified as a texture defect. The initial value is based on the Suggested Score.

After adjusting all the settings training the algorithm is the task. While training the algorithm consider different images and pre-process them. Draw the region of interest and add the sample, after adding the sample train the algorithm. The process repeated for almost 20 images and 200 samples were collected and trained the algorithm.

3. RESULTS AND DISCUSSION

Energy, entropy, contrast, homogeneity and correlation features are often used Haralick texture features among the 13 to reveal few important properties about the spatial distribution of the texture image in the tumor detection algorithm. The Homogeneity measures the similarity of pixels and entropy measures the randomness of the intensity of image and the both them gives the indication on the dominancy values. The energy supplies the information on the randomness of the spatial distribution. Contrast represents the quantity of local changes in an image. It reflects the sensitivity of the textures in relation to changes in the intensity. How correlated a pixel is to its neighbourhood is given by Correlation feature.

Ten brain tumor images and approximately 200 samples were collected from the tumor images to train the texture classifier algorithm. The result obtained by the texture classifier along with the haralick features of the particular image are presented below.

In the above result three images along with their output is presented. First two images are tumor images whereas third image is of no tumor image. The proposed algorithm is succeeded in not showing anything in the result of no tumor image but it detects accurately when tumor image is passed to it. Statistical parameters plays major role in deciding whether designed algorithm is robust, sensitive to the desired output while being unsensitive to the noise.

Statistical Parameters:

Total images= 45

True Positives(TP)-33; True negative (TN)-01; False positive (FP):01; False negative (FN)-10

Sensitivity or true positive rate (TPR)

$$TPR = \frac{TP}{FN + TP} = 97.0\%$$

Specificity (SPC) or True Negative Rate

$$SPC = \frac{TN}{TN + FP} = 90.9\%$$

Precision or Positive Predictive Value (PPV)

$$PRV = \frac{TP}{FP + TP} = 97.0\%$$

Negative Predictive Value (NPV)

$$NPV = \frac{TN}{FN + TN} = 90.9\%$$

Accuracy

$$ACC = \frac{TP}{FP + FN + TP + TN} = 95.0\%$$

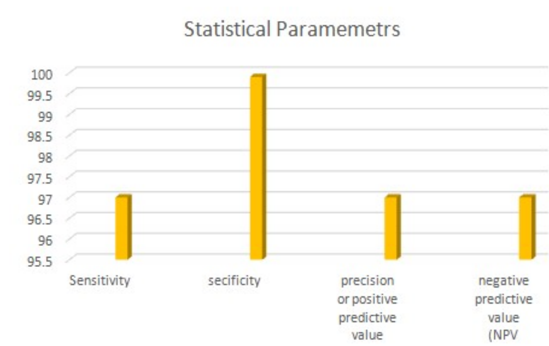

Figure1 Graph of the statistical parameters which reveal the standardness of the algorithm

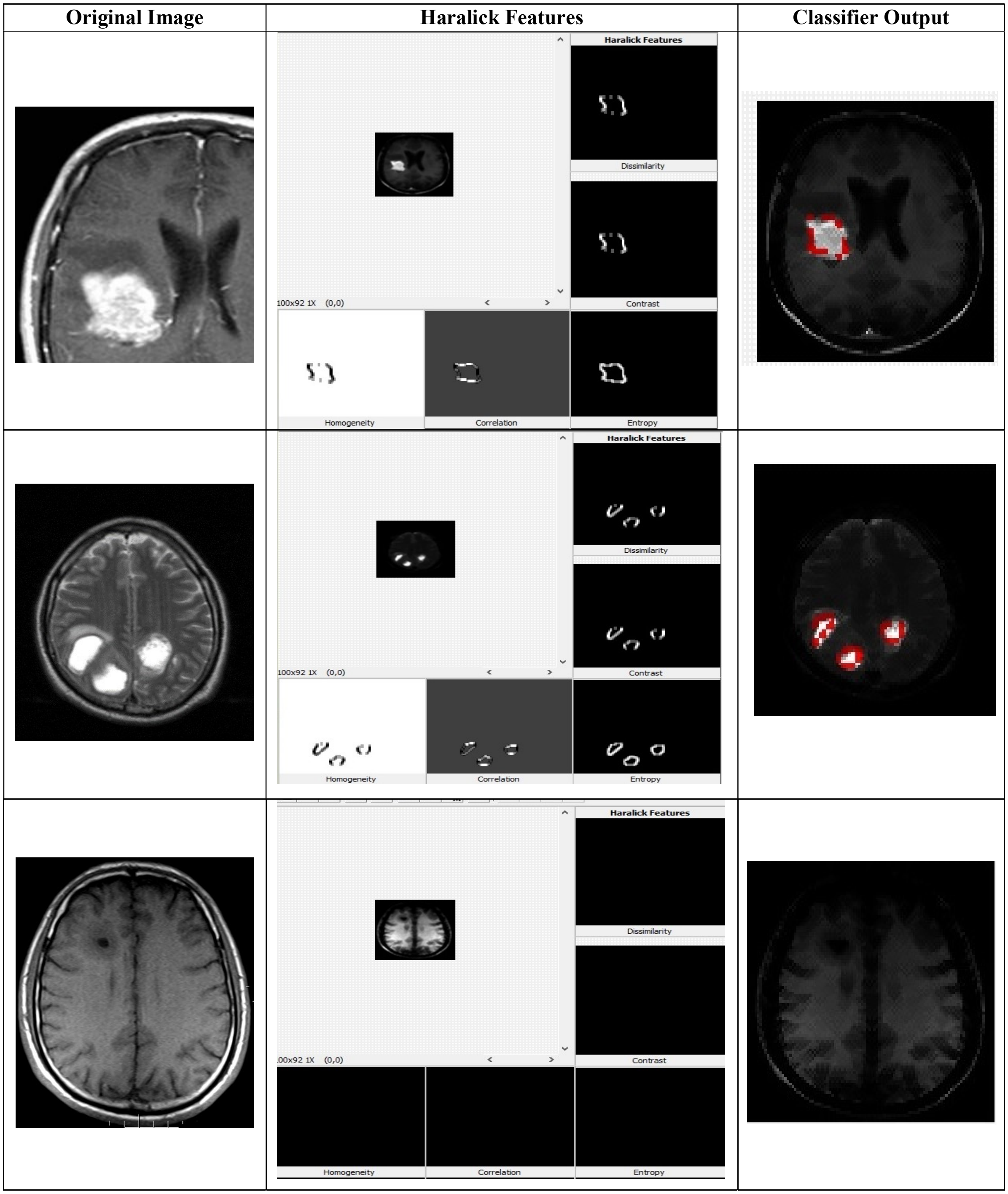

Figure 2 Result along with the haralick features of the images.

5. CONCLUSION

The objective of Automatic characterisation and classification of Brain Tumors through the developed methodology is achieved. Finally, the segmentation implemented by our method yielded highly promising results on simulated data and a great concordance between the true segmentation and the proposed system. Characterisation and classification of medical images will lead towards improving the accuracy, exactness and computational/processing speed of segmentation approach and also minimizes the manual interaction/intervention. Real time processing applications are crucial and are effective.

This paper presents a new approach for automatic Textural defects of Brain tumors .Results indicates that this technique has great possible for resolving the difficult problem of segmenting, localizing. This technique has been tested for 45 images, true positives are 33,True negative is 1,False positive is 1, True negatives are 10. Sensitivity 97.0%, Specificity 90.9%, Precision or Positive Predictive Value (PPV) 97.0%,Negative Predictive Value (NPV)90.9%, Accuracy 95.0%.

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