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# Medical Image segmentation using Image Mining concepts

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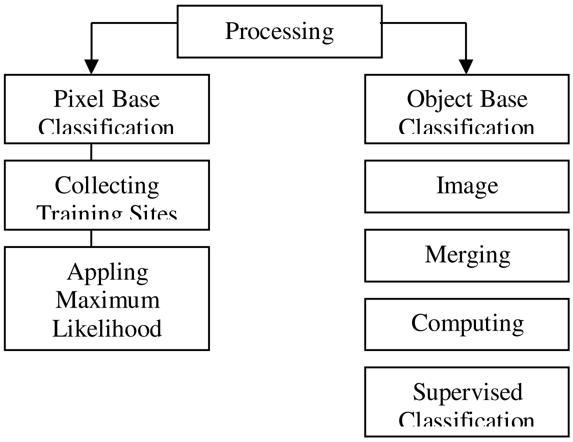
**Abstract**— Image differencing is usually done by subtracting the low-level skin texture like strength in images that are already associated. This paper extracts high-level skin texture in order to find out an efficient image differencing method for the analysis of Brain Tumor. On the other hand, this produces sets of skin texture that are both spatial. We demonstrate a technique that avoids arbitrary spatial constraints and is robust in the presence of sound, outliers, and imaging artifact, while outperforming even profitable products in the analysis of Brain Tumor images. First, the landmark are establish, and then the top entrant are sorted into a end set. Second, the top sets of the two descriptions are then differenced through a cluster judgment. The symmetry of the human body is utilized to increase the accuracy of the finding. We imitate this technique in an effort to understand and ultimately capture the judgment of the radiologist. The image differencing with clustered contrast process determines the being there of Brain Tumor. Using the most favorable features extracted from normal and tumor regions of MRI by using arithmetical features, classifiers are used to categorize and segment the tumor portion in irregular images. Both the difficult and preparation phase gives the proportion of accuracy on each parameter in neural networks, which gives the idea to decide the best one to be used in supplementary works. The results showed outperformance of algorithm when compared with classification accuracy which works as shows potential tool for classification and requires extension in brain tumor analysis.

***Keywords***— Images, MMR, MCR, Segmentation etc.

## I. INTRODUCTION

In this paper we discuss how to solve a medical image classification task, where depicted objects of the same kind have to be classified either normal or diseased, and there are only differences in local texture, often ill-defined, between objects from both classes. Previous pattern recognition approaches to this problem are based on pixel or region classification and subsequent fusion of local posterior probabilities to obtain an overall decision for the image under consideration. These approaches require pixel or region labels to train local classifiers. For example, to detect interstitial disease on chest radiographs pixel- and region-based classification approaches were applied in [1] and [2] respectively. In practice, a pixel or region ground truth is often unavailable, or is unreliable for ill-defined lesions. A ground truth on the image level, on the other hand, is almost always available during the collection of a data set, or is easier to obtain. Therefore we aim at a classification approach that allows us to classify an image as a whole from only overall image labels. Since the information that concerns the presence or absence of pathology is local, an image representation is introduced where global image features are derived from local per-pixel features. The starting point of the method is the extraction of local features from spatially corresponding pixels in all images under consideration. One way to obtain corresponding pixels across images is to warp a mean image to all images. We segment an image to get a number of fixed landmarks that can be used to establish a warping function. Next, a new set of image features is derived from local features of that image and local features of another image, which we call a reference image. Features are calculated as distances between two vectors whose elements are values of a certain per-pixel feature in all corresponding points from a given image and a reference image. In this feature space supervised classification of images can be performed using only global class labels of training images. With several reference images, different image representations can be constructed and a pool of classifiers can be trained. Then, for an unseen image, it is possible to combine multiple classification opinions in order to smooth over mistakes of individual classifiers. The experiments in this paper focus on a medical classification task, but the framework can be used for any image classification task where only overall image class labels are available. In other domains, such as object detection, this type of task is also recognized to be important (e.g. in [3]) and often referred to as weakly labeled image data. In the next Section, the method is described in detail. Section 3 presents experimental results. Finally, Section 4 provides a discussion and conclusions.



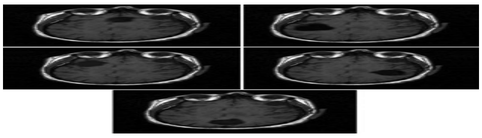

## II. METHOD

Further in this section we assume that the classification task relates to an area of interest within an image, and the word ”shape” is used to denote such an area. Shapes of the same kind are aimed to be classified, e.g. lung fields in chest radiographs. Image representation and pixel correspondence

For our method it is important to establish the correspondence between points within analogous shapes on two different images. Theoretically, various approaches to that might be considered. We describe here an approach that uses Active Shape Models (ASM) for segmentation (see [4]). After segmenting each shape X using ASM, positions of a number of corresponding landmark points on the outlines of images become available. From a large set of images, the mean position of these points can be computed. An image with these mean points is called a mean image. Next, a warping function is determined between an image I containing a shape X, and the mean image by demanding that the mean points are warped to the ASM landmark points in the image I. We use a warping algorithm that is described in [5]. A warping function finds for a point in the mean image a related point in the image I. We consider the following representation of X. Assume, that a number of features M are extracted per pixel i, i ∈ X. A pixel i is represented by a feature vector xi = (xi1, xi2. . . xiM). Thus we get a matrix representation of X:

## III. BRAIN TUMOR

For detecting brain tumor by Segmentation model, a similar method in feature extraction approach is used in both. [41,42] Fourier descriptors are used for precise extraction of boundary feature of the tumor region. But, these features introduce a large number of feature vectors that may cause the problem of over learning or misclassification. Accordingly, these works are followed by GA as a feature selection step. GA develops an efficient searching algorithm to combine these features to few significant ones that are capable of representing that particular class. In other kinds of features are applied for brain tumor detection. Six textural features based on GLCM have been used. GLCM {P (d, q) (i, j)} represents the probability of occurrence of a pair of gray-levels (i, j) separated by a given distance d at an angle q. The features such as contrast, inverse difference moment, correlation, variance, energy and entropy are used. In principle component analysis (PCA) is used as a feature extraction algorithm of brain tumor classification by use of Segmentation. PCA is one of the most successful techniques that have been used in image recognition and comparison. Image in this work is brain magnetic resonance image. Figure illustrates 5 division of brain tumor that are used.



**Five classes of brain tumor**

## IV. SEGMENTATION AND FEATURE EXTRACTION ALGORITHMS

Image segmentation plays a crucial role in many medical imaging applications, especially in medical image categorization. Because of this, correct features are extracting from a segmented representation. In addition, in some works after feature extraction, an extra step is necessary to select appropriate features among a large feature set. According to work in [4], feature selection is important for medical data mining to reduce processing time and to increase classification accuracy. According to the experiments in which the Segmentation model is used in the classification part, dissimilar diseases such as cancer, eye sickness, skin, brain tumor especially, breast cancer can be diagnosed.

In addition, the severity of diseases can be determined by the use of the image classifier. In this section, according to the type of diseases, the methods of segmentation and feature extraction are described.

Image segmentation and its performance evaluation are vital aspects in image dispensation because of the complexity of the medical images; segmentation of medical descriptions remains a challenging predicament. The Segmentation model can be used as an approach for segmentation of different diseases such as breast cancer renal calculi and, especially, brain tumor.

The layout of this paper is as follows: introduces the Segmentation structure and its learning algorithm.

## V. ECCENTRICITY CALCULATION EQUATION

Eccentricity (E) has been widely used as a shape feature. It illustrates the way in which the region points are scattered around the Centre of the image region. E is defined as the ratio of the major axis of the region to the minor axis. It is calculated using central moments.

$$E = \frac{\mu_{20} + \mu_{02} + \sqrt{\mu_{20}^2 + \mu_{02}^2 - 2\mu_{02}\mu_{20} + 4\mu_{11}^2}}{\mu_{20} + \mu_{02} - \sqrt{\mu_{20}^2 + \mu_{02}^2 - 2\mu_{02}\mu_{20} + 4\mu_{11}^2}}$$

## Segmentation

Image segmentation and its performance evaluation are vital aspects in image dispensation and, as the difficulty of the medical images; segmentation of medical imagery remains a challenging problem. The Segmentation model can be used as an approach for segmentation of different diseases such as breast cancer renal calculi and, especially, brain tumor.

The layout of this paper is as follows: introduces the Segmentation structure and its learning algorithm.

In segmentation and feature extraction algorithms section, the technique of segmentation and feature extraction in medical image applications in which the segmentation copy is applied as classifier are reviewed. Image classifier sector, presents a survey on works that used the segmentation model as classifier in medical image classification and a brief comparison with other classifiers is proposed. In order to clear the aim of this work, the outline of medical analysis by using the segmentation model is presented. The main purpose of this work can be followed by the solid line used in segmentation.

The approach is used in image segmentation. The first case is when ground truth is available and the other is when not available.

- When ground truth is available, segmentation can be evaluated in terms of accuracy and robustness. The accuracy reacts the precision of segmentation with respect to ground truth. The robustness is related to the accuracy degradation with respect to the degradation of the quality of test data. There are various evaluation schemes.

  a) Parameter based evaluation

  b) Boundary based evaluation

  c) Region based evaluation

- When ground truth is not available, evaluating segmentation results is similar to evaluating cluster validity. Evaluate segmentation in terms of the contrast between the heterogeneity among different regions versus the homogeneity within individual regions. Exact quantitative measure is difficult in this case.

**Parameter used for pixel**

**Mismatching Rate** -It denotes how many percentage of labels differ in two labeled matrices obtained by k Means classification technique

- **Misclassification Rate (MCR)** –The number of misclassified pixel divides by total number of pixels multiply with 100

- **MCR = (Number of misclassified pixel/ Total number of pixels)*100**

- **Computational Time:** Total time CPU taken by proposed method for computation

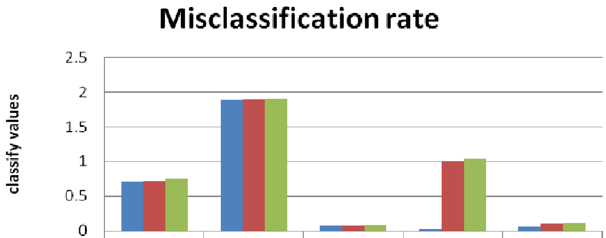
 

# VI. RESULTS

## 6.1 Misclassification Rate between Window Sizes:

| Image_name | MCR_2×2 | MCR_3×3 |
|---|---|---|
| Image 1 | 0.70 | 0.72 |
| Image2 | 1.89 | 1.90 |

TABLE 1 MCR between ground truth & segmented Image




| | Image 1 | Image2 | Image3 | Image4 | Image5 |
|---|---|---|---|---|---|
| MCR_2×2 | 0.7 | 1.89 | 0.076 | 0.0192 | 0.056 |
| MCR_3×3 | 0.72 | 1.9 | 0.077 | 1.001 | 0.099 |
| MCR_4×4 | 0.75 | 1.91 | 0.078 | 1.045 | 0.108 |

GRAPH1 Misclassification rate between Window Size

## 6.2 Mismatching Rate

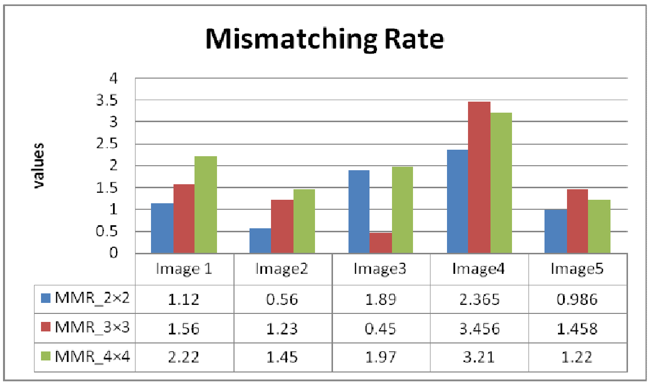
Table 2 contains the mismatching rate between segmented image and ground truth image.

| Image_name | MMR_2×2 | MMR_3×3 |
|---|---|---|
| Image 1 | 1.12 | 1.56 |
| Image2 | 0.56 | 1.23 |

TABLE 2 MMR between ground truth & segmented Image

## 6.3 Mismatching Rate between Shape

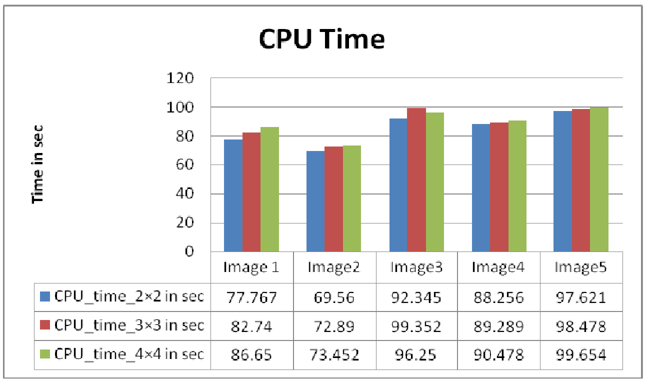



**Graph 2 Represent the Mismatching Rate between Shape:**

## 6.4 Time Comparison

| Image_name | CPU_time_2x2 in sec | CPU_time_3x3 in sec |
|---|---|---|
| **Image 1** | 77.767 | 82.74 |

**Table 3 contains the CPU time:**




**Graph 3 Represent Time Comparison**

## 6.5 APPLY NOISE:-

Image noise is the random variation of brightness or color information in images produced by sensors and circuitry of a scanner or digital camera [8] .The principal sources of noise in digital images arise during image acquisition (digitization) and/or transmission. There are different types of noise. The blast used here are:

Gaussian Noise arises in an image due to factors such as electronic circuit noise and sensor noise due to poor illumination.

- Salt and Pepper Noise is originate in location

### 6.5.1 Misclassification Rate between Window Sizes for Noisy image

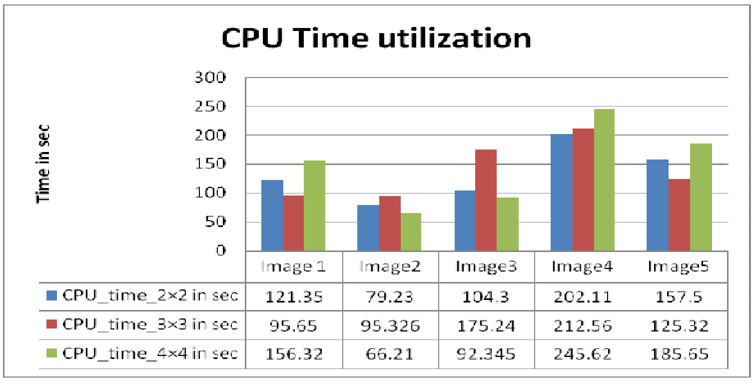
Table 1 contain the misclassification rate between segmented image and ground truth image.

| Image_name | MCR_2×2 | MCR_3×3 |
|---|---|---|
| **Image 1** | 2.16 | 2.99 |
| **Image2** | 1.11 | 1.67 |

### 6.5.2 CPU Time utilization after noice:

Table 3 contains the CPU time between segmented noisy image and ground truth image.

| Image_name | CPU_time_2×2 in sec | CPU_time_3×3 in sec |
|---|---|---|
| **Image 1** | 121.35 | 95.65 |
| **Image2** | 79.23 | 95.326 |




**Graph Represent the CPU time Utilization**

## VII. CONCLUSION & FUTURE WORK

In this work, we have tried to review the experiments in which Segmentation is applied as classifier in the field of medical image categorization. In addition, special methods are used for segmentation and feature mining steps in which applications that neural network is applied as classifier are described. Although this work emphasizes on neural network as classifier, in adding up, it can be used for other mission like denoising or segmentation. Neural network could be a good classifier for medical image classification and assist physicians for earlier diagnosis of dissimilar diseases. These classifiers conquer the disadvantage of fuzzy organization and neural networks by combining these two smart methods. On the other hand, like every process, it has some drawbacks. Large effort data could reduce the accuracy of its show. In addition, Neural Network performance decreases while input samples are not enough and, also, there are many nodes in Neural. In general, the performance of classifier depends on several factors such as size and quality of training position, the inflexibility of the training introduce and also parameters selected to feed to Neural net as inputs can be authority the classifier recital.

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