



MACHINE LEARNING AND IMAGE PROCESSING TECHNIQUES FOR BRAIN TUMOR DETECTION

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Abstract:

In this article, classification of two types of brain tumors explained. In the method of the research, image filtering, segmentation, enhancement is used in image processing part and support vector machine is used in machine learning part. As a result of this research, test images are classified into two classes with minimum 62% accuracy rate.

Keywords— Brain tumor, GLCM, SVM, image processing, machine learning

INTRODUCTION

Brain tumors are one of the most dangerous illnesses that can be seen all people in every age. The reason brain tumors are highly dangerous is that they are located in the nervous system. Each year; approximately 12000 people are diagnosed by this disease. According to Davies [1], between the 20-44 age, while the rate of survival is 50%, after 65 years old the survival rate decreases to 5%. Because of the importance of brain tumors, diagnosing earlier will help to intervene rapidly. In addition, by using machine learning and image processing methods, the missed diagnoses cases can be detected truly. Brain tumor detection is possible by transferring MRI images to digital software. Transferred images can be classified according to tumor size and its location.

In this project; We will detect the brain images in our selected dataset using image processing and classify

the diagnosed tumors with machine learning techniques by using MATLAB. In literature review part; there are studies about brain tumor detection and classification methods which were useful for this project.

LITERATURE REVIEW

K-means clustering is one of the pixel-based segmentation methods that is introduced. This method is applied on two different data sets which taken from the gray feature vectors of the original MR brain images and the converted RGB features to detect the tumor objects in magnetic resonance (MR) images. Color translation, K-means clustering and histogram clustering are the applications that combined in this method. Because of the not causing extra overhead of the color space translation, this method is easy to apply and is efficient.

Gray level co-occurrence matrix (GLCM) was used to extract the second order statistical texture features for motion estimation of images which are introduced. In that project, Angular second moment, Correlation, Inverse difference moment and Entropy features are extracted by using Vivado FPGA. These features have high classification accuracy and require less extraction time that means they have some advantages. To conclude; GLCM is one of the most efficient feature extraction methods.

IBkLG classifier has been used to classification of normal, benign and malignant tumors in brain MRI images by

developing an automated method [4]. The IBkLG method is one of the successful methods that reach approximately 100% classification accuracy because of handling real valued features. In this proposed method; the system has ability to get rid of noisy images by using median filtering. For the preprocessing, the filtered image is converted gray to RGB and to l^*a^*b color space. After these steps; the image has transferred to color-based segmentation process that make the images ready to feature extraction. For the feature extraction, GLCM, Histogram of oriented gradients and canny edge detection has been used. The extracted features' mean, standard deviation, skewness, Root mean square value, and median absolute values are calculated. From this values a dataset table has been created to use in IBkLG classifier. IBkLG classifier has reached 86.6% classification accuracy.

DWT+PCA+SVM is a developed model to detect and classify the normal and abnormal MR images of brain. [5]. DWT stands for discrete wavelet transform that extract the information of the brain images without any loss. This method has advantages that can able to keep both frequency and location information. PCA stands for principal component analysis. PCA is used to reduce the dimensions of the images which will cause the worsened classification. For the SVM section, kernel SVMs types has been tried for classification. Among them, GRB SVM has reached the most accurate method for the classification. As a conclusion, DWT+PCA+SVM method's accuracy level is 99.38%.

Skull stripping is one of the preprocessing methods for the MRI brain images [6]. This method is the process of the brain tissue segmentation from surrounding region that are the skull and non brain area. Morphology based methods has been used to separate the brain area from skull. This method has 5 steps. These are, image thresholding, morphological operators that fill the gaps in extracted object, edge detection, creating a binary mask

and combining the binary mask. As a conclusion, this algorithm has provided more efficient MRI images that are not affected from surrounding region of the brain.

Dataset Definition

We took the dataset from Kaggle [7]. In this dataset; there are 3 different tumor types that are glioma, meningioma and pituitary and normal brain images. The description of the tumor types will be introduced in order and nonbrain area. Morphology based methods has been used to separate the brain area from skull.

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Figure 1

Gliomas are a general name used to describe a group of tumors that occur in the glial cells, the supporting tissue of the brain. Symptoms include headache, seizures, nausea, and vomiting.



Figure 2

Meningiomas are slow-growing and mostly benign tumors that arise from the membranes surrounding the brain. Although they are not technically a brain tumor since they

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do not originate in the brain, they cause a number of symptoms by creating pressure on the brain with their growth. (Figure2)

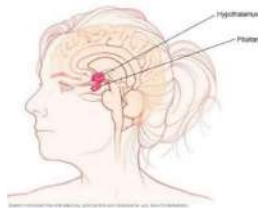


Figure3

Pituitary tumors are abnormal growths that develop in your pituitary gland. Some pituitary tumors result in too much of the hormones that regulate important functions of your body. Some pituitary tumors can cause your pituitary gland to produce lower levels of hormones. (Figure3).

Dataset has been separated by 2 files that are training images and test images. In training image file, there are 841 different images with different types. In testing image file, there are 156 different images. For our project we did not use all images. So, we took the MRI images that is taken by same shooting angle

METHODOLOGY

a. Image Processing(preprocessing)

Before starting classification, some methods have to be applied in Image Processing to make the image workable. Firstly, skull stripping method (Figure4) has been implemented to remove the surrounding area of brain. This method helps to focus on the brain tumor part. Secondly, median filtering (Figure5) has been applied to remove the noises from the brain MR images via built-in function in MATLAB. After the filtering is completed, normalization has been applied. Normalization has been used to change the range of pixel intensity values. Next methods after these steps are image enhancement and image segmentation. Image enhancement is used to adjust the digital images to make them more suitable for

displaying. For this implementation “imadjust” function has been used in MATLAB. Image segmentation’s goal is to change the representation of image to make easier to analyze and more meaningful. As a final step morphology operator has been applied to brain images. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. (Figure 6) [11]. After all steps completed, our MRI images are ready for GLCM that will extract the features of the images

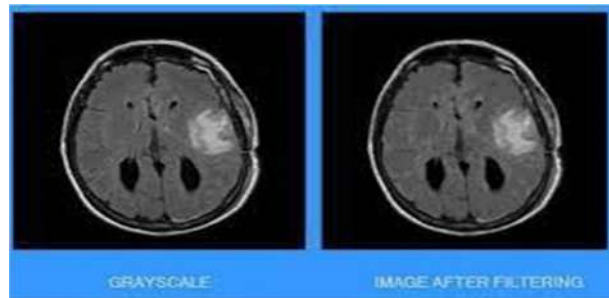


Figure 4

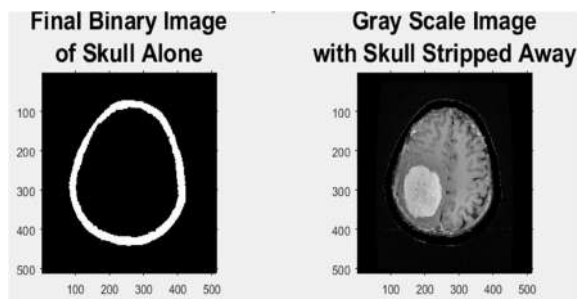
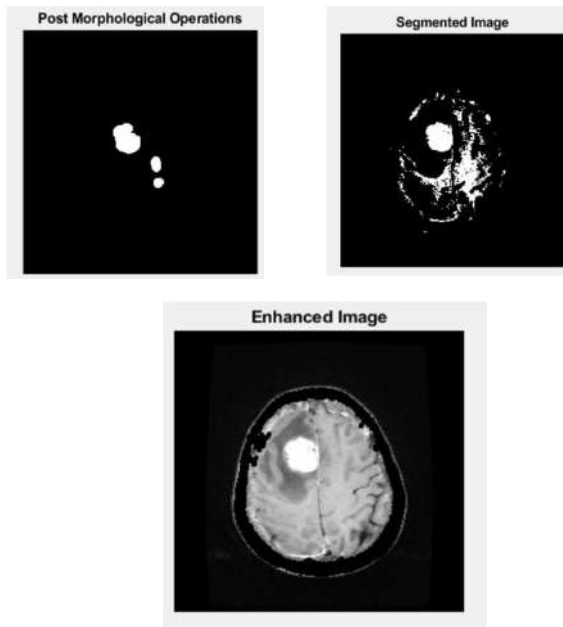
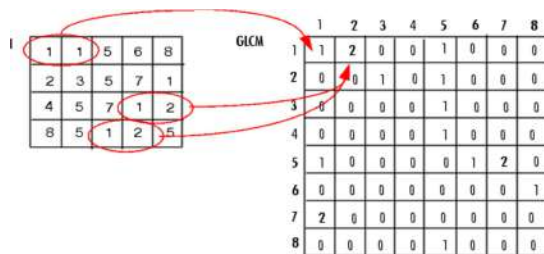


Figure 5

Autocorrelation, Contrast, Correlation, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Entropy, Homogeneity, Homogeneity, Maximum probability, Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation1, Information measure



When the image processing part is completed, to extract the features from the images GLCM Texture has been used. Gray level cooccurrence matrix is a statistical method that examines the texture by considering the spatial relationship of pixels.[6] The



GLCMs are stored in a three-dimensional matrix that (i x j x n). n represents the number of GLCM's calculated where n is the number of GLCMs calculated.

By implementing GLCM, some characteristic features are extracted. Contrast, Correlation, Energy, Homogeneity are the most important features among them. Contrast calculates the local variations of the GLCM matrix. Correlation calculates the joint probability of occurrence of the pairs. Energy shows the sum of squared elements in GLCM. Homogeneity calculates the closeness of the distribution of elements in GLCM [8],[9].

Table 1 GLCM Features Values

There are many options for classification in Machine learning. To select the best option for this project, we used classification learner app in MATLAB. We trained our dataset via this application. The highest accuracy has reached with Kernel SVM. To train and cross validate fitsvm function has been used. The common syntax is;

```
SVMModel=fitsvm(X,Y,'KernelFunction','rbf',
...'Standardize',true,'ClassNames',{'negClas
```

Sample	tumour	autocl	contr	corrtn	corrpl	cprom	chad	disi	energ	entro	homom	homop
1	0	1.0057485	0.0002216	0.9433374	0.9433374	0.0294651	0.0148711	0.0002216	0.9558797	0.0156812	0.9958891	0.9958891
2	0	1.2535489	0.0048260	0.9716224	0.9716224	0.9131436	0.3064934	0.0048260	0.8396211	0.3172226	0.9977809	0.9977809
3	0	1.0723460	0.0017964	0.9622397	0.9622397	0.3418847	0.1758909	0.0017964	0.9506325	0.1250545	0.9910175	0.9910175
4	0	1.1743444	0.0045636	0.9567791	0.9567791	0.7127295	0.3786761	0.0045636	0.8847448	0.2493678	0.9977181	0.9977181
5	0	1.0040400	0.0001758	0.9360230	0.9360230	0.0206897	0.0104364	0.0001758	0.9970760	0.0116764	0.9991205	0.9991205
6	0	1.0162824	0.0005045	0.9539765	0.9539765	0.0827915	0.0418691	0.0005045	0.9885314	0.0375267	0.9997477	0.9997477
7	0	1.4170910	0.0058020	0.9768203	0.9768203	1.2274268	0.4952403	0.0058020	0.7439242	0.4505174	0.9970989	0.9970989
8	1	0.9979360	0.5671828	0.0039062	0.9612254	0.0155275	0.0002216	0.0039062	0.8906444	0.1570844	0.9992612	0.9992612
9	1	0.9123336	0.7756333	0.1705066	0.7535571	0.3141547	0.0042600	0.0284066	0.9114431	0.6415931	0.9985246	0.9985246
10	1	0.9747202	0.6234339	0.0487611	0.7964817	0.1244113	0.0017964	0.0131516	0.9018385	0.4326190	0.9994011	0.9994011
11	1	0.9389027	0.7095359	0.1179308	0.7190979	0.2462043	0.0045036	0.0291490	0.8832353	0.5718008	0.9984787	0.9984787
12	1	0.9685361	0.6459399	0.0027514	0.9701874	0.0155445	0.0001758	0.0016809	0.8816526	0.1350624	0.9999412	0.9999412
13	1	0.9942361	0.5762788	0.1102111	0.9134887	0.0371769	0.0005045	0.0043343	0.9014897	0.2444052	0.9983118	0.9983118
14	1	0.8504349	0.9291600	0.2933280	0.9056022	0.4464957	0.0058020	0.0354630	0.9193078	0.7318786	0.9980696	0.9980696

```
s','posClass'});
```

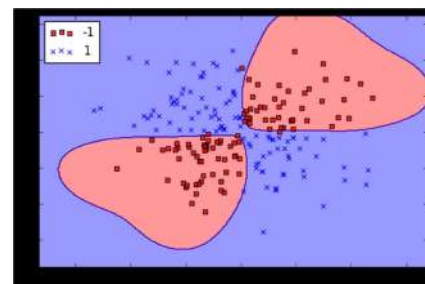


Figure 10 RBF Kernel

In our SVM model Gaussian RBF (Radial Basis Function) is used. RBF is stands for Radial Based Function. RBF kernel is a function whose value depends on the distance from the origin or from some point.[10]

RESULTS AND DISCUSSION

The methods in Methodology section were applied to the two different data which contain Glioma and Meningioma tumor MRI images. According to results of the algorithm, the accuracy rate shows that the algorithm classifies the tumor type. However, the rate is less than the expected value. One of the possible reasons of this issue is number of low-quality images in the dataset. Moreover, because of the MRI nature, all of the images have different perspective even though some are similar to each other. Another possible reason of the low accuracy is image processing part. Skull stripping algorithm remove some important part of minority of the total images and if a K-means algorithm for segmentation due to the gray scale of the image is used successfully, the results can be more trustable. Even though we used first K-means algorithm to detect tumor and working on just tumor instead of rest of the brain, there are some disadvantages have occurred and it didn't work every MRI images. That's why, it was eliminated from the algorithm.

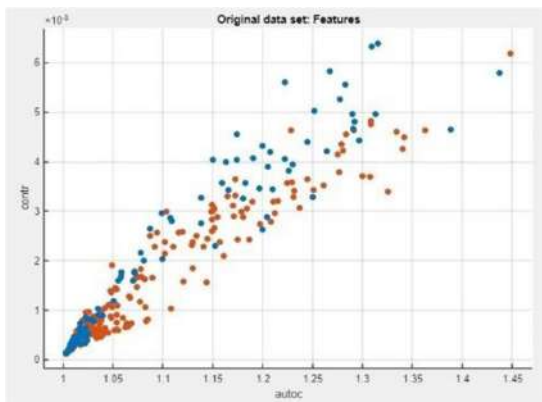


Figure 11 Spreading of Autocorrelation vs Contrast

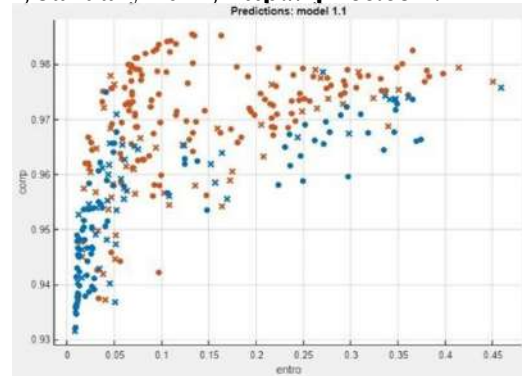


Figure 12 Spreading of Entropy vs Correlation

In order to increase the accuracy rate, MATLAB's own algorithm that generated from 'Classification Learner' can be used. Even though the accuracy rate of Support Vector Machine algorithm is more and more high, the results of our SVM algorithm gave less accuracy rate. Further, the number of GLCM texture features can be rearranged to obtain more accurate results

CONCLUSION:

As a conclusion; different types of brain tumor images have been detected and classified successfully by using image processing and machine learning techniques. Firstly, image processing techniques has been applied to make the image suitable for the classification. Secondly, GLCM Texture Features method has been used to extract the characteristic features of the brain images. Finally, RBF Kernel SVM provides us to classify the brain images. To testing the machine learning algorithm, 200 training examples of each two group were used and algorithm was trained. The accuracy rate obtained as minimum 62%.

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