JOURNAL OF CRITICAL REVIEWS

ISSN- 2394-5125 VOL 7, ISSUE 15, 2020

Identifying Brain tumor presence using Support Vector Machine

Satyavati Jaga[1]

[1]Dept of ECECBIT, GandipetHyderabad, Telangana, India

[1]satyavati_ece@cbit.ac.in

Received: 01 May 2020 Revised: 23 June 2020 Accepted: 04 July 2020

ABSTRACT: The abnormal development of tissues within the brain that affects its activity is referred to as a brain tumor. The accurate detection of brain tumors is an important diagnosis function. The proposed work can classify the given MRI image into the presence of a tumor or the absence of a tumor. Initially, the given MRI image undergoes to prepossessing to remove noise using various filters, then segmentation using OTSU method, the features of segmented MRI image extracted using Discrete Wavelet Transform. The effective features from a bunch of features obtained by using Principle Component Analysis. These features are used to train Support Vector Machine with Radial Basis Function as well as test. The results of the proposed tumor detection method are efficient over literature.

KEYWORDS: Identifying Brain tumor presence using Support Vector Machine

I. INTRODUCTION

With the advancement of image processing technologies like image detection, interpretation and progress, the medical images are evolving rapidly. Medical imagery could be described as the production process for the scientific and medical study and treatment of visible photos of internal body structures and a visible insight into the function of the inner tissues. The whole approach aims at identifying and managing disorders. The quick advancements in biomedical imaging technology over the past two or three decades, with high-resolution, three-dimensional anatomical and physiological images, continue at an accelerating rate, enabling increasingly powerful diagnostic and intervention progress. "The National Cancer Institute defined tumor as an abnormal mass of tissue that results when cells divide more than they should or do not die when they should" [1]–[4]. There have been two different forms of brain cancers, malignant or benign. The malignant tumor is fast-growing throughout the brain cells that carry tissue. Unless this issue is not correctly and quickly observed, it will kill patients [5]. Brain MRI is a simple and safe procedure that uses radio signals as well as a magnetic field to obtain a complete brain imaging. Typically, the treatment of tumor sections in the picture is performed using MRI modalities. Thermal effects cause MR images to have little interference. Thus, it is important to eliminate interference before brain tumor segmentation[6].

The brain tumor detection uses MRS and MRI imaging. Venu, Natesan et al proposed deep learning algorithm for detection of brain tumor[7]. Rehman et al proposed machine learning based algorithm for detection and localization of brain tumor. The low-level features are obtained from segmented superpixels. These features are very helpful for prediction into tumor or non-tumor and further helpful for localization of tumor. Authors claiming this autonomous algorithm results good over literature [8]. Gokulalakshmi et al proposed a classifier to classify MRI images into tumor or non-tumor brain. GLCM features and Discrete Wavelet Transform features are extracted from MRI filtered image. Support Vector machine used to classify the given features in binary types such as tumor or non-tumor images. The outcomes of the simulation are fine, but it takes longer time [9]. The paper detailed as follows. Section 2 describes the proposed brain tumor methodology. The findings of the suggested brain tumor approach in section 3. Section 4 provides conclusions.

II. PROPOSED METHODOLOGY

In the proposed methodology first step, MRI image undergoes to prepossessing. Preprocessing consists of two steps, one is conversion of color image to gray scale image and second step is to remove noise using various filters such as Median, Adaptive Weiner, Gaussian filters. Segmentation involves partitioning the image into two major

ISSN- 2394-5125 VOL 7, ISSUE 15, 2020

classes namely, tumor and the part other than the tumor. The resemblance among the pixels is recognized and clustered into a segment. In proposed methodology, OTSU segmentation method is used. Feature extraction consists of converting the raw information into a group of most discriminating data. the features of segmented MRI image extracted using Discrete Wavelet Transform (DWT). The DWT converts given MRI image into four parts. In those, horizontal features, vertical features, diagonal features are three and remaining one is approximation image of the original MRI image. The operation of DWT presented in figure 1.

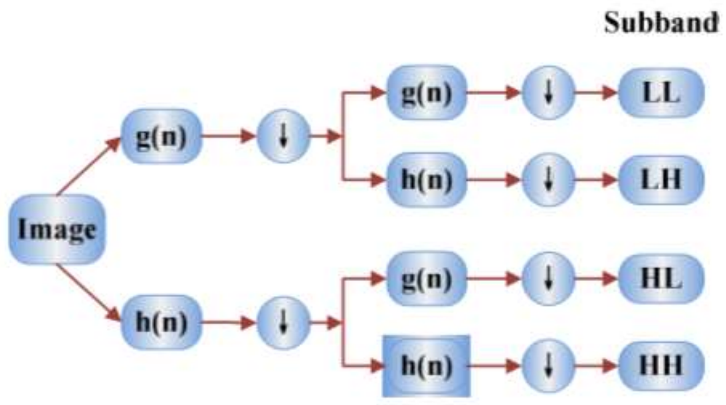

Figure 1. DWT Decomposition

The main features can be retained and the redundant can be discarded in order to save time and space in the computer. The effective features from a bunch of features obtained by using Principle Component Analysis[10].

These effective features are used to train Support Vector Machine with Radial Basis Function later to classify MRI image of tumor presence[11]. Various kernels are available to SVM those are polynomial kernel, Gaussian kernel, Hyperbolic tangent kernel, Radial Basis function kernels, among all RBF providing better results over remaining kernels[12][13]. The flow diagram of proposed brain tumor presence detection using Support Vector Machine is described in figure 1.

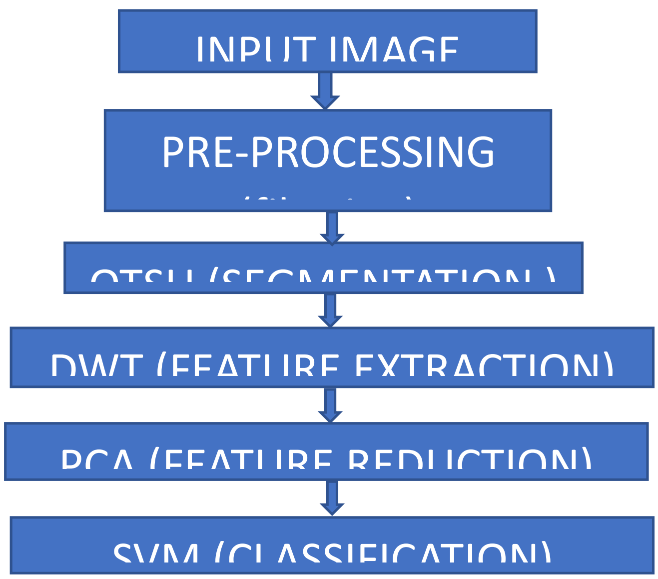

Figure 2. Proposed Method

III. RESULTS AND DISCUSSIONS

The input image is converted to gray scale to change 3 channels to one channel for easy image analysis. This is the first step of image preprocessing. The grayscale converted image is then sent through noise filters to remove

ISSN- 2394-5125 VOL 7, ISSUE 15, 2020

unwanted elements. This step is known as filtering. As mentioned above, there are different types of filters for different type of noises. The MRI images after filtering can be seen in figure 3.

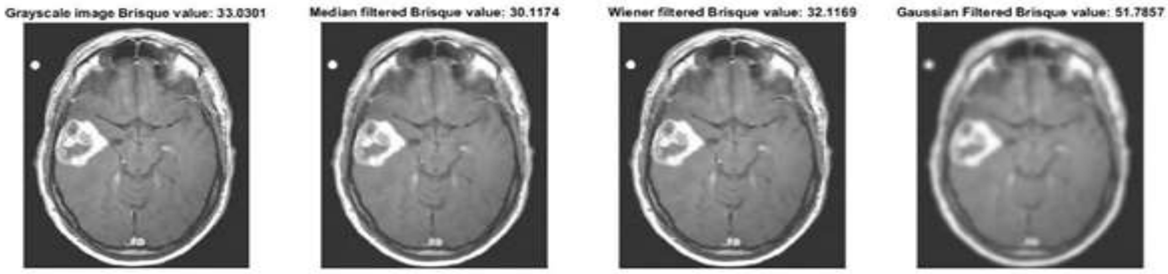

Figure.3: Pre-processing output using Median, Weiner and Gaussian Filters

The performance of all three filters has been evaluated using the performance metrics MSE, BRISQUE and PSNR. Figure 3 shows the results after the above filters were applied to the grayscale image. The values obtained for the performance metrics MSE and PSNR have been tabulated in the table 1 while table 2 shows the obtained BRISQUE values for Median, Adaptive Wiener and Gaussian Filters.

Table 1: Performance Metrics MSE and PSNR Outputs for Median, Adaptive Wiener and Gaussian Filters

	MSE			PSNR		
Image	**Median**	**Adaptive Wiener**	**Gaussian**	**Median**	**Adaptive Wiener**	**Gaussian**
1	0.0428302	0.0190258	0.264706	31.8133	35.32671	23.90867
2	0.0453991	0.0164322	0.228848	31.56033	35.91843	24.59193
3	0.0424617	0.0236616	0.264053	31.85082	34.42638	23.91389
4	0.1182725	0.0529375	0.6729797	27.40197	30.92973	19.85078
5	0.0617819	0.0512961	0.3984042	30.22219	31.01867	22.12757
6	0.0649641	0.0393913	0.4386329	30.0557	32.20469	21.70979
7	0.1097161	0.0379302	0.4366374	27.7281	32.3913	21.72959
8	0.0248236	0.0113244	0.1593963	34.18214	37.51159	26.10602
9	0.1668295	0.0476224	0.4527642	25.90808	31.36732	21.57208
10	0.6929491	0.0312277	0.3879701	29.72379	33.0898	22.24282
11	0.3774369	0.0230992	0.2439242	32.36236	34.49483	24.25825
12	0.6456994	0.2909166	0.2973721	30.0305	33.49312	23.3978

Table 2: BRISQUE metric outputs for Median, Adaptive Wiener and Gaussian Filters

	BRISQUE			
Image	**Grayscale**	**Median**	**Adaptive Wiener**	**Gaussian**
1	0.2976654	0.248903	0.290699	0.5818034
2	0.334155	0.3674808	0.3803661	0.5577838
3	0.3303006	0.3011742	0.3211686	0.5178572

ISSN- 2394-5125 VOL 7, ISSUE 15, 2020

4	0.3264018	0.3185032	0.2745447	0.5978557
5	0.3269516	0.4325867	0.4233188	0.516256
6	0.3747391	0.3964636	0.3851871	0.5515654
7	0.4217699	0.4072121	0.4195929	0.564071
8	0.3161564	0.3452099	0.3404899	0.4630666
9	0.3023391	0.3065298	0.2715795	0.5511022
10	0.3955594	0.374501	0.4137814	0.5647691
11	0.4139435	0.4100598	0.435094	0.4978967
12	0.4951446	0.4923476	0.512577	0.5580911

It is observed that median filter has given the best results with least BRISQUE value. Lower values of score reflect better perceptual quality of image. The least BRISQUE value of 24.8903 is acquired for Median filter.

The first block on the GUI is to upload the input MRI image. The second GUI block is to trace the boundaries of the tumor. The third GUI block resembles to the segmentation of the tumor from the rest of the brain image. OTSU algorithm threshold limit can segment the image to two clusters; the tumor part which is foreground and the rest of the brain as background. The fourth block on the GUI shows the features that are extracted from DWT using db4 wavelet[11], [14]. Finally classified the given MRI image into the labels BENIGN/ MALIGNANT using SVM Classifier with four different kernels linear, quadratic, polynomial and RBF are used to train the model.

Figure 4. GUI Layout

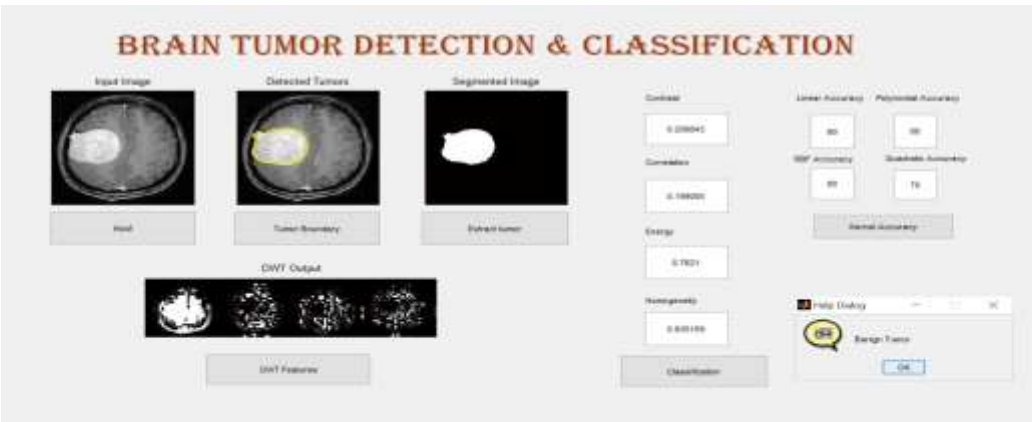

Figure 5. GUI output for Benign Tumor

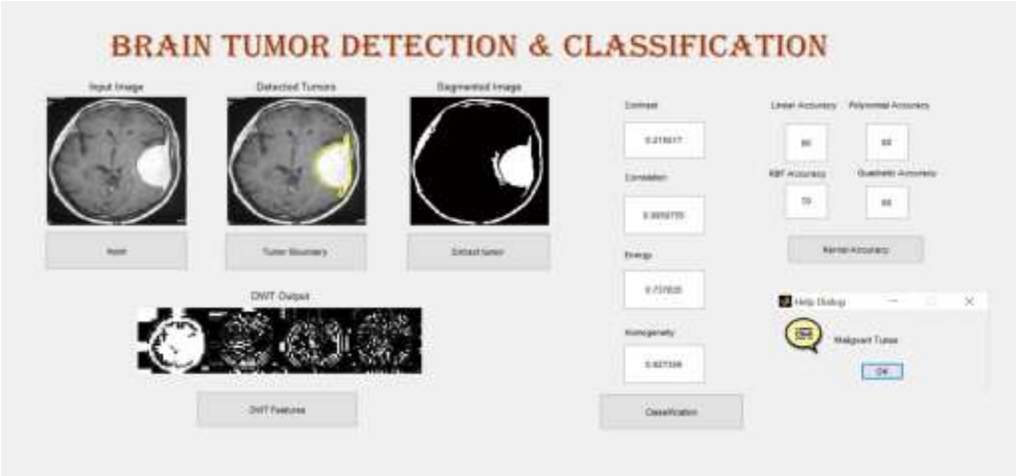

Figure 6. GUI Output for Malignant Tumor

IV. CONCLUSIONS

The proposed work able to classify efficiently the given MRI image into the presence of a tumor or the absence of a tumor. The input MRI image undergoes to prepossessing to remove noise present in it, then segmentation using OTSU method, the features of segmented MRI image extracted using Discrete Wavelet Transform. The effective features from a bunch of features obtained by using Principle Component Analysis. These features are used to train Support Vector Machine with Radial Basis Function as well as test. The Preprocessing results were analyzed using quality metrics MSE, PSNR and BRISQUE. Median Filter gave the best results of the chosen filters. Each block in the GUI has shown the significant steps involved in detecting, segmenting and classifying tumor. The resulting accuracies have been compared for different kernels used in classifying tumor. RBF kernal was found to give the best accuracy at 98%. The results of the proposed tumor detection method are efficient over literature.

V. REFERENCES

[1] A. Padma Nanthagopal and R. Sukanesh Rajamony, “Classification of benign and malignant brain tumor CT images using wavelet texture parameters and neural network classifier,” Journal of Visualization, vol. 16, no. 1, pp. 19–28, Feb. 2013, doi: 10.1007/s12650-012-0153-y.

[2] M. Sharif, U. Tanvir, E. U. Munir, M. A. Khan, and M. Yasmin, “Brain tumor segmentation and classification by improved binomial thresholding and multi-features selection,” Journal of Ambient Intelligence and Humanized Computing, pp. 1–20, Oct. 2018, doi: 10.1007/s12652-018-1075-x.

[3] M. H. O. Rashid, M. A. Mamun, M. A. Hossain, and M. P. Uddin, “Brain Tumor Detection Using Anisotropic Filtering, SVM Classifier and Morphological Operation from MR Images,” in International Conference on Computer, Communication, Chemical, Material and Electronic Engineering, IC4ME2 2018, Sep. 2018, doi: 10.1109/IC4ME2.2018.8465613.

[4] S. Giraddi and S. v. Vaishnavi, “Detection of Brain Tumor using Image Classification,” in International Conference on Current Trends in Computer, Electrical, Electronics and Communication, CTCEEC 2017, Sep. 2018, pp. 640–644, doi: 10.1109/CTCEEC.2017.8454968.

[5] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, “A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned,” Magnetic Resonance Imaging, vol. 61. Elsevier Inc., pp. 300–318, Sep. 01, 2019, doi: 10.1016/j.mri.2019.05.028.

[6] K. Kaplan, Y. Kaya, M. Kuncan, and H. M. Ertunç, “Brain tumor classification using modified local binary patterns (LBP) feature extraction methods,” Medical Hypotheses, vol. 139, p. 109696, Jun. 2020, doi: 10.1016/j.mehy.2020.109696.

K. Venu, P. Natesan, N. Sasipriyaa, and S. Poorani, “Review on Brain Tumor Segmentation Methods usinConvolution Neural Network for MRI Images,” in 2018 International Conference on Intelligent Computing and Communication for Smart World (I2C2SW), Dec. 2018, pp. 291–295, doi: 10.1109/I2C2SW45816.2018.8997387.

[8] Z. U. Rehman, M. S. Zia, G. R. Bojja, M. Yaqub, F. Jinchao, and K. Arshid, “Texture based localization of a brain tumor from MR-images by using a machine learning approach,” Medical Hypotheses, vol. 141, p. 109705, Aug. 2020, doi: 10.1016/j.mehy.2020.109705.

[9] A. Gokulalakshmi, S. Karthik, N. Karthikeyan, and M. S. Kavitha, “ICM-BTD: improved classification model for brain tumor diagnosis using discrete wavelet transform-based feature extraction and SVM classifier,” Soft Computing, pp. 1–11, Jun. 2020, doi: 10.1007/s00500-020-05096-z.

[10] S. B. G. Tilak Babu, V. Satyanarayana, and C. Srinivasarao, “SHIFT INVARIENT AND EIGEN FEATURE BASED IMAGE FUSION,” International Journal on Cybernetics & Informatics (IJCI), vol. 5, no. 4, 2016, doi: 10.5121/ijci.2016.5418.

[11] R. Mehrotra, M. A. Ansari, and R. Agrawal, “A Novel Scheme for Detection Feature Extraction of Brain Tumor by Magnetic Resonance Modality Using DWT SVM,” in 2020 International Conference on Contemporary Computing and Applications, IC3A 2020, Feb. 2020, pp. 225–230, doi: 10.1109/IC3A48958.2020.233302.

[12] S. B. G. T. Babu and Ch. S. Rao, “Texture and steerability based image authentication,” in 2016 11th International Conference on Industrial and Information Systems (ICIIS), Dec. 2016, vol. 2018-Janua, pp. 154–159, doi: 10.1109/ICIINFS.2016.8262925.

[13] S. C. Kumar and H. D. Phaneendra, “Categorization of Brain Tumors using SVM with Hybridized Local-Global Features,” in Proceedings of the 4th International Conference on Computing Methodologies and Communication, ICCMC 2020, Mar. 2020, pp. 311–314, doi: 10.1109/ICCMC48092.2020.ICCMC-00058.

[14] C. Srinivasa Rao and S. B. G. Tilak Babu, “Image Authentication Using Local Binary Pattern on the Low Frequency Components,” in Lecture Notes in Electrical Engineering, vol. 372, Springer Verlag, 2016, pp. 529–537