IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 11, Issue 06, June 2024 https://www.ijirae.com/archives

Brain Tumors Detection Using Deep Learning (SGO and SE Algorithm)

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Publication History
Manuscript Reference No: IJIRAE/RS/Vol.11/Issue06/JNAE10083
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.11/Issue06/JNAE10083
Received: 17, May 2024 | Revised: 27, May 2024 | Accepted: 05, June 2024 | Published Online: 29, June 2024
https://www.ijirae.com/volumes/Vol11/iss-06/04.JNAE10083.pdf
Article Citation: Ramachandran,Dr.Satish,Prof.Muhammadu(2024). Brain Tumors Detection Using Deep Learning (SGO and SE Algorithm). IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 11, Issue 06 of 2024 pages 705-712 **Doi:>**https://doi.org/10.26562/ijirae.2024.v1106.04
BibTeX Key Dr.Sathish@2024Brain

Abstract: Brain abnormality is the harsh illness among humans and is usually diagnosed with medical imaging procedures. Due to its importance, a significant quantity of image assessment and decision-making procedures exist in literature. This article proposes a two-stage image assessment tool to examine brain MR images acquired using the Flair and Diffusion-Weighted (DW) modalities. The combination of the Social- Group-Optimization (SGO) and Shannon's Entropy (SE) supported Multi-threshold is implemented to pre-processing the input images. The image post-processing includes several procedures, such as Active Contour (AC), Watershed and region-growing segmentation, to extract the tumor section. Finally, a classifier system is implemented using ANFIS to categorize the tumor under analysis into benign and malignant. Experimental investigation was executed using benchmark datasets, like ISLES2015 and BRATS (2013 and 2015), and also clinical MRI mages obtained with Flair/DW modality. The outcome of this study confirms that AC offers enhanced results compared with related segmentation trials employed. The performance of the ANFIS is validated with other classifiers, such as Decision-Tree, Random-Forest and KNN. The ANFIS classifier obtained an accuracy of 97.04% on the used DW modality and accuracy of 96.67% on the Flair MR images.
Keywords: Brain MRI, Tumor, Social group optimization, Shannon's entropy, ANFIS classifier, Clinical MRI dataset.

I.INTRODUCTION

Brain is responsible to supervise the complete function in human body by interpreting the information gathered from other body regions.

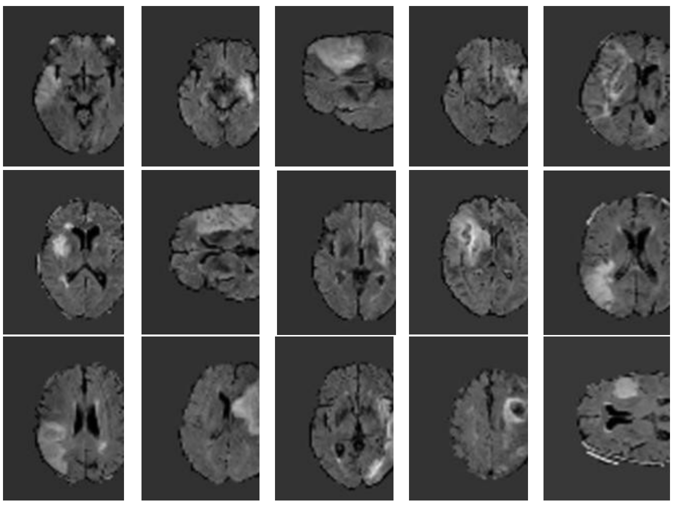


Figure1. Sample DW modality images of ISLES2015 dataset

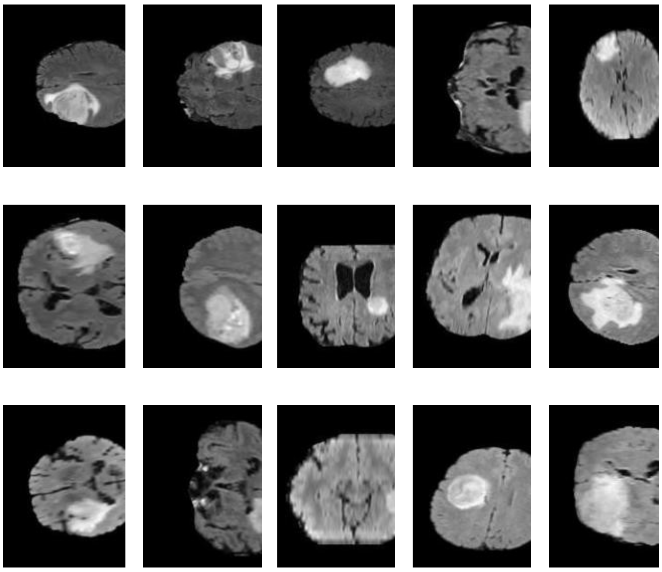


Figure2. Sample Flair modality images of BRATS 2013&2015

The foremost infirmity in brain, such as stroke and tumor, may cause moderate to harsh impact in patient's activity. A well planned medical examination and a competent diagnosis are necessary to recognize the position and harshness of brain abnormality to plan for an appropriate treatment procedure. Common healing approaches, such as chemotherapy and surgery, are widely adopted to treat the most common brain illness called tumor. Benign tumors are less hazardous and absolutely curable with precise surgery and chemotherapy. Malignant tumors are dangerous and require extraordinary consideration by the surgeon during the Examination as well as treatment planning.

Brain abnormality evaluation involves in the implementation of dedicated hardware systems to acquire essential brain information from brain-signals and brain-images in a controlled environment. Earlier research confirms that imaging based activities offer more apparent information on brain irregularity compared to the signal supported assessment [1-3].Mapping of brain signal along with the brain image is also a flourishing research field [4]. To have superior perceptive on brain irregularity, it is essential to consider imaging methods, like Magnetic- Resonance-Imaging (MRI), Computed Tomography (CT) and Positron- Emission- Tomography (PET), which are widely adopted in clinics [5-7]. PET is a nuclear imaging procedure normally used along with CT.

MRI is commonly used in medical domain to acquire images of internal body parts. The existing works on brain MRI confirms the availability of customary Machine-Learning (ML) and Deep-Learning (DL) based techniques implemented and evaluated on user defined and benchmark datasets [11,12]. The aim of this research was to realize a Computerized Disease inspection Tool (CDT) using a Hybrid Image Processing (HIP) practice recently discussed in the literature [1-3]. HIP was developed by integrating a pre- processing practice based on the Social- Group-Optimization (SGO) supported Shannon's threshold and a post-processing based on Active-Contour, Marker-Controlled- Watershed and Seed-Region-Growing procedures to segment the suspicious region.

The proposed CDT was initially tested on well- known benchmark MRI datasets, such as ISLES2015[13-15] and BRATS2013 & 2015[16,17], and then evaluated with real clinical brain MRI scans acquired with Flair and DW modalities. There are several modules used to get inner symmetry and patterns via magnetic and radio waves like X ray, Tumor is the synonym of neoplasm which is the division of cells in an uncontrolled and irregular fashion. Tumor creates an imbalance between grey matter, white matter and intra cerebral fluid due to intense pressure of excessive tissues. As brain is CPU and main power hub of entire body, any disorder leads to serious trauma and loss of co- ordination in body functions. Tumors can be either malignant (cancerous) or benign (noncancerous). Benign are non-invasive dormant type of effected cells as they do not attack on peripherals tissues. While malignant tissues make their concatenated colonies by invading adjacent tissues. I anchoring cells are affected through tumor then this type refers to GLIOMAS. If tumor cells are distributed in other parts via travelling through blood arteries then this condition refers to METASTSIS, A less fatal.

The main inspiration behind the proposed HIP was to build a soft-computing aided image examination system to inspect MR images with better accuracy. In real time scenario, it is compulsory to include an exclusive MRI diagnosing tool that can support doctors to inspect the brain pictures acquired with various modalities which high efficiency. This article also addresses common MRI issues, such as skull stripping, image re-scaling, choice of the segmentation method, and difficulties in classification. The proposed solution was implemented in Matlab software and the experimental findings confirm that it offers promising result on the considered benchmark datasets as well as real clinical brain images.

1.2 SURVEY

This study is purposed to detect brain tumor and classify them in two classes. Different algorithms are used to detect the brain tumor. First algorithm is pre-processing of MRI image and after that segmentation is applied on image, after segmentation morphological operations are performed. After detection process, particular image is classified with extraction of features from the image. Different algorithms are used for that purpose.

I. Take MRI image as input
II. Removal of noise and converting into grey scale.
III. In order to enhance quality median filter is used.
IV. Segmentation
a. Threshold
b. Watershed
V. Morphological operation applied.
VI. Feature extraction by DWT And PCA
VII. Classification through SGO and SE
VIII. Results, Tumor Integration Testing Accuracy

II. PRE-PROCESSING

Image pre-processing involves in converting the input raw image into acceptable form by implementing procedures, such as de-noising, histogram equalization, adaptive threshold, and multi-threshold. In this work, the multi- threshold process with SGO+SE was implemented. Recent works in the literature confirm that heuristic algorithm supported tri- level threshold is executed to pre-process brain MRI [2,10]. The study by Rajinikanth et al. [22] confirms that SE offers enhanced image quality compared to other pre-processing schemes. Previous research by, Dey et al. [42] and Satapathy and Naik [43], confirms that SGO is very simple in implementation and presents improved optimization outcome compared with other heuristic techniques.

SOCIAL GROUP– OPTIMIZATION

SGO is proposed in 2016[43,44],which is built by replicating the information- sharing behavior in humans. SGO includes two core stages, explicitly: (i) advancing part to coordinate. The locations of individuals according to the cost value, and (ii) gaining part which authorize the individuals to decide the finest possible resolution for the selected task. The arithmetical structure of SGO is: G best j=max {f(Xi) for i=1,2,.. .N } Where Xi represents early information of individuals in group, i= 1, 2, 3,…, N Signifies total population of group, and fj Denotes fitness function. Xnewi,j☐Xoldi,j☐Ra*(Xi,j☐Xr,j)☐ Rb*(Gbestj☐Xi,j) Where Ra and Rb=arbitrary numbers [0,1] and Xr,j =arbitrarily chosen position of an individualin group. The primary algorithm constraints were defined as: N=30,c=0.2,iteration Value =1500 and stopping criterion = maximized Shannon's entropy.

SHANNON'S ENTROPHY

SE was formulated by Kannappan [45] and detailed in Paul and Bandyopadhyay's work [46]. Recently, SE based threshold was considered to pre-process medical images [2,22]. In order to explain SE, let us consider an image with dimension A*B. The gray-level pixel. Organizations of image(h,v) is expressed as G (h,v),for h☐{1,2,...,A}&v☐{1,2,...,B} .Let L be the number of gray levels of the test image and the set of all gray values {0,1,2,…,L-1} be symbolized as Z, in such a way that: G(h,v)☐Z☐(h,v)☐image Then, the normalized histogram will be: X={x0,x1,…,xL-1}. For tri-level threshold case, X(T)= x0(t1)+x1(t2)+x2(t3) f(T)☐max{X(T)} where, T={t1, t2,…, tL} is the threshold value, X ={x0, x1,…, xL-1} is standardized histogram, and f(T) is finest threshold. Other details on SE can be found in [2,22].

POST–PROCESSING

Post-processing scheme is implemented to mine the ROI from the pre- processed test image. Irrespective of MRI's modality, this scheme can segment the stroke or tumor section, i.e. the ROI, with greater accuracy. Based on the requirement, automated as well as semi- automated ROI mining procedures can be implemented. The earlier research works presents various segmentation procedures, tested and verified on the brain stroke MRI dataset called ISLES2015 and brain tumor dataset BRATS 2013 & 2015. In the proposed work, commonly used ROI mining procedures, such as AC [30], MCWS [47,48] and SRG[35] approaches were executed to mine the abnormal segment of chosen brain MRI. AC implements a bounding-box around the tumor segment to be extracted. It operates based on an adjustable snake, which continuously groups the related pixel values lies within the bounding box and converges towards the centre of the ROI based on the iteration value. More information on the AC implemented can be found in.

FUTURE EXTRACTION AND SELECTION

After detection process, next step is to extract features. There are two algorithms which are used to extract features from image. First one is DWT (Discrete Wavelet Transform) and second one is PCA (Principle component analysis). Both are used to extract features. DWT is used to extract coefficient of wavelets from brain MR images. According to classification, frequency information of signal function is important which is getting by wavelet localizes. CA is used to reduce the large dimensionality of the data.

- Contrast
- Correlation
- Energy
- Homogeneity

- Kurtosis
- Mean(average)
- Standard Deviation
- Entropy
- Root Mean Square(RMS)
- Variance
- Inverse Difference Movement (IDM)
- Skewness
- Smoothness

The texture description of the ROI is extracted with the Haralick scheme that is extensively recognized as Gray Level Co-occurrence Matrix(GLCM)[51- 54]. The earlier research works with GLCM validate that; texture descriptions are usually adopted to collect essential details from the ROI. These details are then considered to train, test and validate the classifier units, which is created to categorize the brain tumor under analysis into benign and malignant, which may assist the doctor in taking the right decision and also to identify appropriate treatment method to cure or regulate the brain abnormality.

IV. LITERATURE SURVEY

4.1 BRAIN TUMOR DETECTION USING IMAGE SEGMENTATION AND CLASSIFICATION AUTHOR NAME: Rabia Ahmad , Asma Khalid , Hammeedur Rahman,[2020]

Image processing has an important factor called image Segmentation which is very important and initial step in medical image processing. In this process, image is partition according to distinct region. Processing of MRI scan image is the part of medical field. In this project, we use the patient's MRI scan image to detect the Brain tumor using GUI in MATLAB. Before detection, we remove noise by removal functions and apply some basic concept of image processing including segmentation and morphological operations.. This proposed method detects exact location of tumor from MRI image. This algorithm could be applied on different MRI scan images. In our purposed model, segmentation algorithm which detect the tumor region. After features are extracted through DWT followed by PCA for reducing features dimensions. Finally, SVM, CNN, Lazy IBK classifiers are applied on it to detect tumor type with high degree of accuracy.

4.2. REVIEW FOR BRAIN TUMOR SEGMENTATION, DETECTION AND CLASSIFICATION ALGORITHMS IN FMRI IMAGES. AUTHOR NAME : Tom Philip PRIES, Roshan Jahan, Preetam Suman [2018]

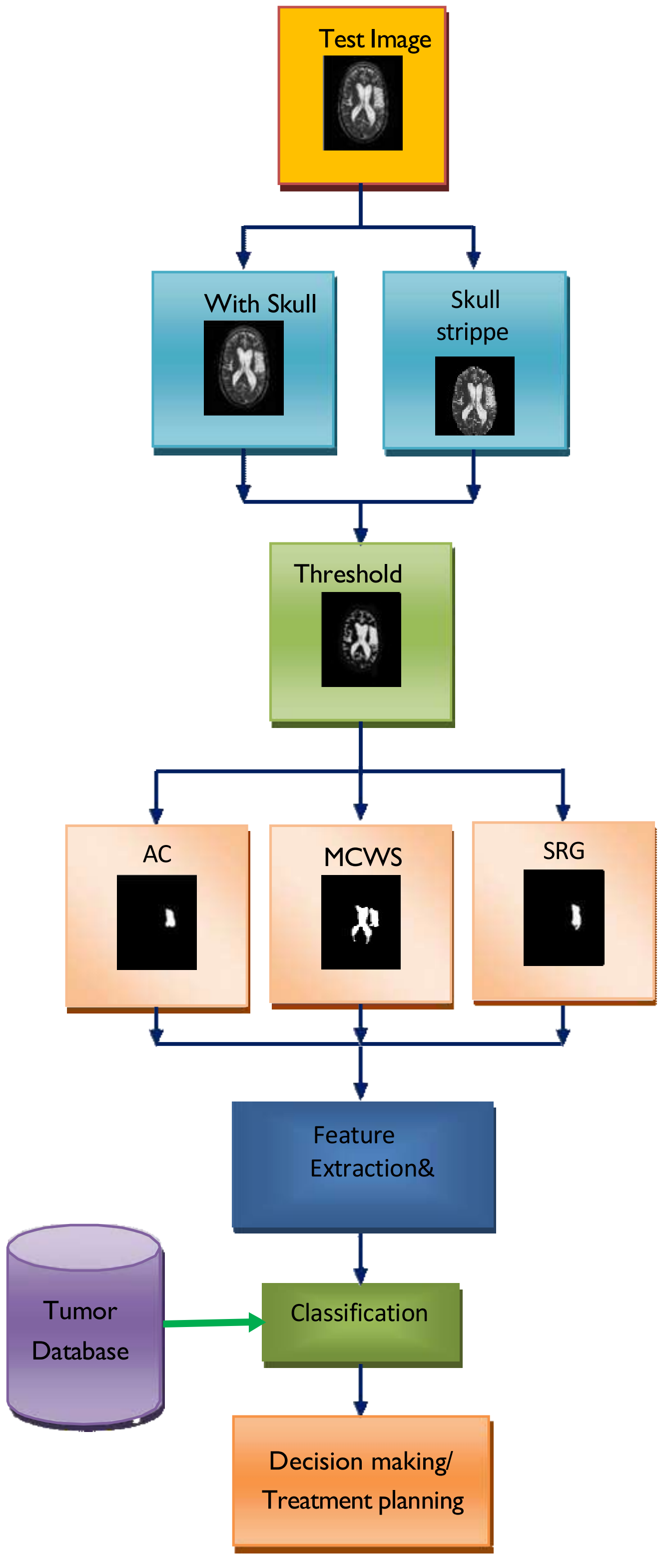
Nowadays Brain tumor detection in early stage is necessary because many people died due to unawareness of having a brain tumor. On the other side influence of machine learning becomes larger and larger in our life and our society, artificial intelligence might also start playing an important role in medical diagnosis and support of doctors and surgeons. This paper is focused on review of those papers which include segmentation, detection and classification of brain tumors. The common procedure for an algorithm which aims to classify brain tumors on MRI or MRI scans is: Preprocessing the image for example by removing noise, then segmenting the image, which yields the region which might be a brain tumor, and finally classifying features such as intensity, shape and texture of this region. Many machine learning approaches towards brain tumor detection have already been made. There for this research topic remains important and still requires attention.

4.3. BRAIN TUMOR DETECTION BASEDON SEGMENTATION USING MATLAB AUTHOR NAME: AnimeshHazra, Ankit Dey, Sujit Kumar Gupta [2017]

An unusual mass of tissue in which some cells multiplies and grows uncontrollably is called brain tumor. It starts growing inside the skull and interposes with the regular functioning of the brain. It needs to be detected at an early stage using MRI or CT scanned images when it is as small as possible because the tumor can possibly result to cancer. This paper, mainly focuses on detecting and localizing the tumor region existing in the brain by proposed methodology using patient's MRI images. Pre-processing stage involves converting original image into a grayscale image and removes noise if present or crept in. This is followed by edge detection using Sobel, Prewitt and Canny algorithms with image enhancement techniques. Next, segmentation is applied to clearly display the tumor affected region in the MRI images.

V. BLOCK DIAGRAM

This section presents a summary regarding the procedures considered to develop a CDT for brain MRI analysis. Then, the database considered, the initial task in brain image assessment, pre- processing, post-processing, segmentation, tumor feature extraction and classification are discussed in detail. Figure 1 presents the various phases available in the developed CDT. Firstly, a2D MRI slice is used for the assessment. In the literature, much effort is taken to strip the skull section from the brain MRI [33]. The skull can be retained or eliminated based on the procedure considered to develop the CDT. Initial enrichment of the raw MRI is to be carried with a suitable image pre- processing procedure and a chosen post-processing practice is to be considered to mine the tumor/stroke segment from the brain picture. Feature mining schemes are then employed to extort the noteworthy information from the The details of the steps considered in this CDT are presented below.



Region of Interest (ROI)

The key features are then selected from the extracted features to train and test the classifier scheme. The classifier compares the available feature with respect to an existing tum or feature set and provides a result for the considered 2D test image. This result is then evaluated by a doctor, who takes the decision about the further treatment procedure to be considered to regulate or completely cure the brain abnormality.

VI. CLASSIFICATION

Classification is a technique to categorize data into some specific domains or category. Mostly domains are in the form of classes. Classification problem is related to identify unlabelled data in some domain/category according to available information. An algorithm that try to fall incoming data in specific domain. SVM (support vector machine), Lazy IBK and CNN (Convolutional Neural Networks) are different algorithms for classifications.

SVM takes the set of feature vectors as input, generates a training model after scaling, selecting and validating, and generates a training model as the output. This training model is then used to classify the image as either benign or malignant based on the features generated from the feature extraction step. Features are extracted from image by DWT&PCA. CNN does not use the features from the feature extraction step to classify the tumor. It uses a neural network generated from the segmented images of training data to classify the tumor. CNN is multilayer perceptron's which is designs to identify two-dimensional image information. Classifiers are employed to segregate the available data into various classes based on requirement. In the literature, a substantial number of classifiers are available [55,56]. During the brain tumor assessment task, it is essential to take complete care while choosing the slice's ROI features to train and test the classifier. Usually, the MRI exam is available as a 3D image, however, during the evaluation process, various 2D slices are extracted to minimize the complexity in examination. In this process, one can note that, while converting the 3D image into 2D slices, the tumor section will not be same in the every slice. Some slice may contain the information of edema and some other may show the tumor core. If entire slice of the 2D MRI of a single patient is considered through the training and testing stage of the classifier, the final classification result will be wrong and that will affect the decision making or treatment planning process. Training is recognized with forward and reverse trails. Initially, the computed GLCM features (S) are separated into two sets: $S\square S_1\square S_2$ where S=whole constraints, S1=principle values, S2 = consequent values, and the symbol denotes the direct sum.

VII. RESULT

This division offers the results achieved with the proposed CDT. The literature confirms the availability of a significant number of image processing procedures for MRI examination. The proposed effort executes a two-stage procedure to inspect the bench mark brain MRI and the MRI images obtained from the clinic. This work considers the assistance of the modern heuristic procedure called the SGO along with the SE. A detailed assessment among the existing segmentation procedures, such as AC, MCWS and SRG, was also conducted. Finally, a tumor classification system was implemented based on the ANFIS, and trained and tested using the well-known texture features called GLCM. The advantage of ANFIS is evaluated and authenticated against DT, RF and KNN approaches. The Developed CDT was executed in a workstation with an AMD C70 Dual Core 1 GHz CPU with 4GB of RAM and implemented in Matlab.

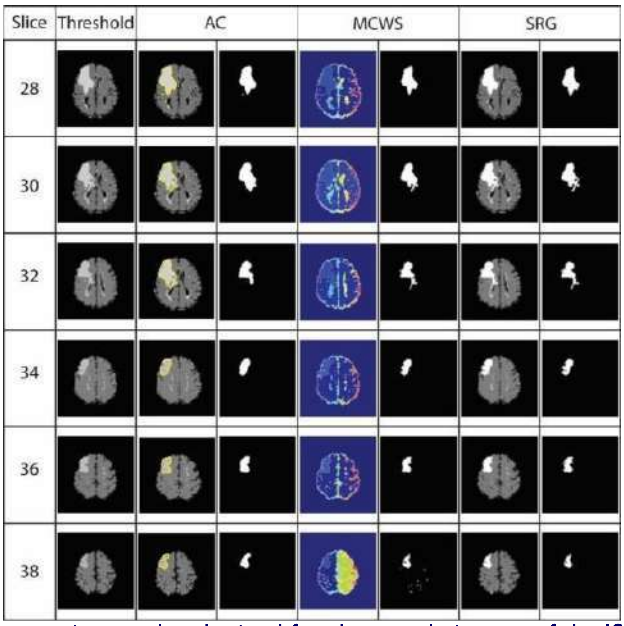


Figure3 Pre-processing and Post-processing results obtained for the sample images of the ISLES dataset (Flair modality).

Initially, the original images were down scaled to 256x256 pixels and then the proposed CDT was used to extract and examine the tumor section from the 2D brain slices. Figure 6 presents the 2D slices of the DW modality MRI with the slices number from SDW27 to SDW36

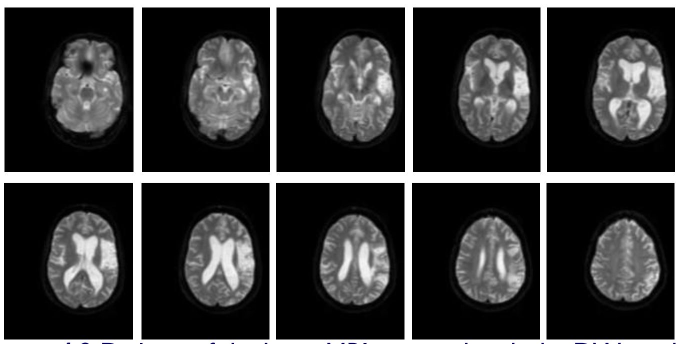


Figure 4.2 D slices of the brain MRI acquired with the DW modality.

NA

NA

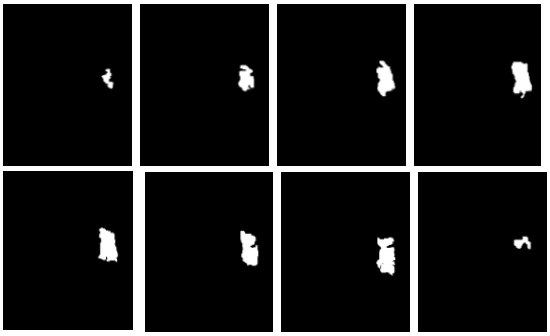


Figure 5. Outcome of the proposed CDT with AC for the chosen slices of the DW MRI modality.

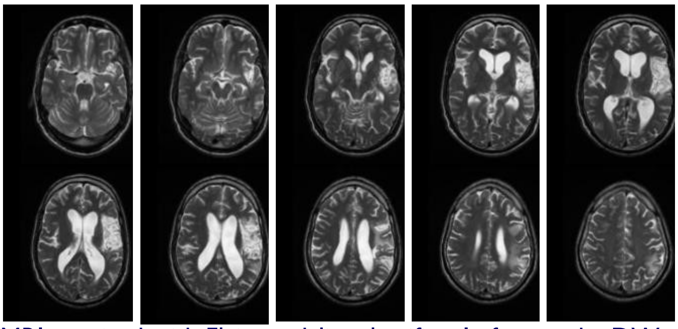


Figure 6.2D slices of the brain MRI acquired with Flair modality classifier. In future, the DW and Flair modality

NA

NA

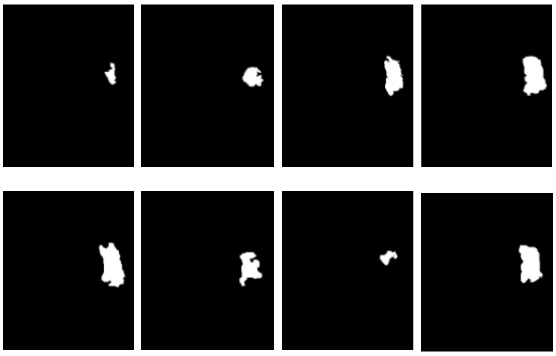


Figure 9. Results of proposed CDT with AC for chosen slices of Flair MRI modality

The CDT's performance is then validated with the state-of-the-art techniques and the related results are depicted in Table11. In the literature, there exists minimal number of Works for the ISLES2015 data base and the Images can be examined with a chosen deep- learning procedures.

VII. CONCLUSION

This article proposed a Computerized Disease inspection Tool (CDT) using a Hybrid Image Processing (HIP) procedure. The implemented HIP technique implements the combination of the SGO assisted Shannon's threshold and segmentation based on AC/MCWS/SRG procedures. During the experimental evaluation, the benchmark ISLES2015 and BRATS 2013&2015 datasets were considered for the initial assessment. Later, the proposed CDT was tested on real time tumor MRI of Flair and DW modalities obtained from a medical center. Finally, the GLCM features for the tumor section were extracted, and an ANFIS classifier was developed based on the available GLCM features. The experimental outcome confirms that, ANFIS classifiers offers better performance compared to the DT, RF and KNN classifiers. The relative evaluation of the proposed technique with other existing techniques, confirms that, the ANFIS classifiers provides a better result compared to other existing classifiers in the literature and satisfactory result compared to the SVM existing results are very less compared to the work of Praveen et al.[66]. Hence the outcome received with the AC+ANFIS is compared and validated with the results of Praveen et al. [66] and this comparison reveals that, the DC, PRE, and SEN obtained with the proposed technique is approximately similar to the earlier work. For the BRATS database, there exist a considerable number of ML and DL methods and few recent works are considered to validate the proposed AC+ANFIS technique. This comparison confirms that, the DC offered by the DCNN of Amin et al.[72] is better compared to the DC of AC+ANFIS. But, the other performance measures, such as ACC, PRE, SEN and SPE attained by the CDT are superior compared with the considered ML and DL approaches.

This work considered only the GLCM features to classify the ISLES and BRATS database. The attained performance measures are <97%. Hence, in future, along with the GLCM; other features discussed in earlier techniques [67- 69] can be considered to increase the classifier outcome. From the literature, it can also be illustrious that, the classification accuracy attained by the SVM classifier is better compared to other techniques. Hence, in future, the Flar / DW modality datasets can be classified using the Support-Vector-Machine (SVM) classifier. Further, a chosen DL technique can also be implemented to classify the ISLES and BRATS datasets in to benign and malignant class.

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