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BRAIN TUMOUR DETECTION USING DEEP LEARNING BASED RESNET-152

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Abstract: *In the medical image study, the brain tumor classification using MRIs is difficult due to the brain's complicated structure and the high variance in tumor tissues' position. So, the requirement for useful and specific tumor identification methods is developing for medical recognition and regular medical applications. The conventional brain tumor identification performs anatomical knowledge of irregular tissues in the brain, helping the doctor design approach. The research proposes several techniques for brain tumor recognition. This work aims to present brain tumor identification methods based on evolutional intelligence and segmentation. Unusual areas in the brain are identified by using the Expectation-Maximization (EM) algorithm. In this paper, we are proposing methods for automating the detection process which can help the radiologist reaching at a faster conclusion in an efficient manner. We are proposing methods based on the pre-trained network models like ResNet and its variants for brain tumor detection. The obtained results shows that ResNet-152 is the most efficient one among them for brain tumor detection and we can automate the process more effectively.*

Keywords: *Brain tumor, Deep learning, ResNet-152, Expectation-Maximization, MRI.*

I. INTRODUCTION

A brain tumor is a mass of tissue such as a tumor or cancer depends on the slow addition of irregular and atypical cells and unusual tissue proliferation, causing damage to the vital system and increased pressure inside the skull. A brain tumor can be both benign (not cancerous) and malignant (cancerous). The most common brain tumors are glioma and low-stage meningioma, which is a type of malignancy. A homogeneous form of a benign brain tumor that no longer contains most of the cancer cells or has been removed entirely by surgery can be monitored radio logically. If a malignant mental tumor is present, it carries a cancerous cell phone treated with

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chemotherapy and radiotherapy. Magnetic resonance imaging (MRI) is primarily a clinical imaging method [1] that provides useful records of the analysis. It is mainly used by surgical radiologists who plan and visualize the frame's function and the frame's internal structure. Magnetic resonance imaging plays a vital role in detecting most cancers and tissue abnormalities with affected tissues' dimensions and area. Further evaluation is offered using MRI rather than CT images. It makes it especially useful in diseases of the cardiovascular system and the nervous system (mind).

The development of image processing into unique areas of interest has been connected with the latest clinical imaging techniques, as more acquisition models and larger images are being produced. It makes it insufficient to see the photos have received without image processing software. Thus, image processing packages have a important influence on the method of analysis by serving the physician investigate all volumetric information to make a treatment verdict and wait for disease consequences.

In just a few decades, there has been a variety of research involving the topic of segmentation of mental tumors because it is essential to understand the points obtained with MRI to predict and monitor treatment effectiveness [2].

The subdivision of mental tumors from the MRI shots presents a significant and difficult challenge in analysis and solution planning. Image segmentation is a living area in medical imaging, and it consists of extracting one or more areas of the image that constitute the site of interest. Several algorithms have been developed in the literature to detect mental tumors and methods that rely primarily on thresholds, strategies that depend mainly on regions, deformable strategies, separation techniques, and deep knowledge. Distorted models are the most popular of the various methods used to segment mental tumors using MRI. They are represented by (2D) curves or (3D) surfaces described in Figure [3] that rotate through the influence of two forces, internal or close forces defined within the curve to keep it calm at some point. From the deformation model, at the same time, external forces are calculated from photographic facts to pass the angle towards the boundary of the desired object. He distinguishes between two primary classes, parametric distorted or snake fashions and distorted geometric patterns in deformed techniques. The benefit of these patterns is their ability to topological seizures at some point in the curve diffusion.

The holistic rule-based method uses a set of optimization rules [4] To optimize the segmentation outcomes. Initially, brain tissue is improved by some methods; and an optimization algorithm is applied. The most commonly applied algorithms are nature-inspired or meta-heuristic techniques due to their simplicity and flexibility. Several sets of descriptive properties have been proposed for entirely rule-based segmentation techniques. In the hybrid strategies, additional tactics for the tumor area class of brain MRI are incorporated. This work presents a 3-D EM approach to SFLA potential dispersion (SFLA-SDS hybrid) that optimizes the 3D MRI category. The final part of the investigation is prepared in the following sections. The second section analyzes related works in the literature. Section 3 explains the different methods used in creation. Section IV analyzes the experimental results, and Section 5 concludes with panels.

II. LITERATURE SURVEY

The 3D brain tumor segmentation is a medical need for mental tumor analysis and radiotherapy planning. It is a difficult challenge because of the difference in genre. Several techniques, along with a set of Particle Clustering Optimization (PSO) rules, the size, location, and shape of the tumors have formed a topological association of slides that convert 2D images into 3D MRI images that no longer afford good results and depend on the number of segments introduced and the positions and shape of the MRI images. Gtifa et al. [5] proposed a practical approach to 3D mental tumor segmentation known as modified PSO. Moreover, the segmentation results are compared to the Darwinian PSO (DPSO) process and Fractional-Order DPSO (FODPSO).

Experimental effects showed that the technique achieved 97.6% 3D segmentation. When compared to DPSO and FODPSO techniques with 78.1% and 70.21% for the case of the T1 - C method, there is an additional accuracy rate Badura [6] presented new flexible swarm intelligence optimization method has been provided to different segment systems into 3D or 2D images. Merchants in a self-regulating colony discover their host, use stigma to communicate, and mark areas of interest that lead to element extraction. In this work, detailed specifications of a bacterial colony segmentation technique (BCS) in terms of individual and social behavior are defined. The approach has been demonstrated and evaluated through various experiments, including synthetic information, tomography, and ultrasound research. The results and observations obtained in terms of parameter settings and the approach's potential utility are discussed in the various segmentation tasks.

Mehmood et al., [7] developed intelligent computer-assisted diagnostic device specializing in magnetic resonance imaging of the human mind. These panels provided the ability to detect brain tumors, their fragmentation and the 3D display device, and offered good medical deals regardless of the geographical area and the degree of knowledge of scientific experts in this research. Malignant and benign based primarily on the BoW version of the Resistant Supporting Vector Machine (SVM). The BoW function extraction technology is further amplified by the powerful accelerated features (SURF) that incorporate a selection factor of interest factor. Finally, 3D visualization of the brain and tumor was implemented using a set of volume rules that are used to represent clinical events. The efficacy of the proposed system was constructed on a dataset collected from 30 patients and implemented with an accuracy of 99%. Sumathi et al., [8] a unique set of rules has been provided that has evolved and relied entirely on entropy-based morphological reconstructions and Kapoor's cuckoo search optimization filters. The former is used to locate and stage tumor boundaries, while the latter is used to eliminate unnecessary pixels within the cropped footage. The proposed method produces up to 97% accuracy in determining the tumor site's exact topographic region. It needs less computational time (about three milliseconds, on average) to process. Therefore, the proposed technique can help radiologists quickly find the exact topographic location of tumor areas, even if there are versions of excessive depth and harmful restrictions.

To arrive at and develop a unique dependency framework to prominently identify tumor regions and divide tissue systems, particularly in the human brain, Narayanan et al. proposed a unique combinatorial algorithm [9]. The algorithm is combined with two optimization technologies, namely PSO and Bacteria Foraging Optimization (BFO), whereby PSO allows for global bacteria's unique role for BFO. It supports Modified Fuzzy C-means (MFCM) algorithm by providing optimized block headers. Finally, the MFCM divides the tissue regions and identifies the tumor component, minimizing the reaction and difficulty encountered with a radiologist's help in the course of analyzing the affected person.

Krishna et al., [10] A version of the local radial linear function neural network (LLRBFNN) that relies primarily on PSO to classify and find mental tumors into malignant (precancerous) and benign (non-cancerous) tumors is provided. In these paints, the wavelets are reshaped to improve Magnetic resonance image segmentation and post-extraction performance. Machine learning techniques, the SVM device, and the least-squares mean (LMS) classifier were also examined to validate the proposed PSO-based LLRBFNN model. Whiteboards follow steps that involve extracting features that are viable functions for research work. In a second step, the characteristics are entered into the rating company's PSO-based LLRBFNN model. In a third step, the instrument was implemented to determine the LMS-based SVM and LLRBFNN approach to the category responsibilities and compare the results.

Sahu et al. [11] presented a hybrid version of LLRBFNN that mainly relies on ant-colony optimization - mimetic annealing (ACO-SA) to detect mental tumor tissue and its type of blurred images. Blurring the blurry images affected by the software becomes a complex and challenging task. The local ambiguous C (FLICM) segmentation algorithm was taken into account from the start. The algorithm's characteristic value was modified for a better final segmentation result to eliminate the MRI noise. The images are segmented using a modified FLICM algorithm. The functions are extracted using the Gray Level Matching Matrix Feature (GLCM) extraction method, fed as input to the proposed fully ACO-based LLRBFNN version for the cause of the class of malignant and benign neoplasms on MRI. The proposed model was compared with PSO-LLRBFNN and Adaptive Particle Swarm Optimization (APSO) - LLRBFNN, and the contrast results are provided. It has been observed that the proposed algorithm based entirely on ACO-SA LLRBFNN suggests better effects than conventional techniques.

III. PROPOSED METHODOLOGY

If we can develop automated systems for detecting the presence of brain tumor inside human brain, it will help the doctors as well as the radiologists to diagnose it more effectively and accurately. This paper deals with a comparative analysis of the possibility of the existing classifiers like ResNet-50, ResNet-101 and ResNet-152 for brain tumor detection via the method of classification. Here, we have used transfer learning for making the networks compatible for brain tumor detection detection. The block schematic of the proposed method is shown in fig. 1. Here, the first block indicates the images used for training the deep learning network. The dimension of the input images may not be equal to the size of the input layer of the existing network. Therefore, we need to resize the original images in accordance with the size of the input layer of the network. For example, if we are using ResNet architecture as the existing model then we need to resize the original images to a dimension equal to 224x224x3 in order to make it process by that network. The pre-processing block is doing this resizing. After this step, all the training images are given to the deep learning network for training the network. Here, we have used stochastic gradient descent momentum optimization function for training the network. After the training process, the trained network is tested by using the query images which should be of size 224x224x3. So the query should be preprocessed before giving as input to the network. As the last stage, we have used a segmentation process for segmenting out the tumor area using the algorithm mentioned in [14]. It is a simple global thresholding algorithm used for segmenting out the soft tissues.

IV. IMPLEMENTATION

Residual Network, or ResNet in short, is an efficient classifier which introduced the concept of skip connection. ResNet introduces a new structure called residual learning units which has different variants that differ in depths. Residual unit is having a feedforward network structure with skip connections which adds somewhat previous inputs into the network to generate new outputs. The main advantage or the fundamental breakthrough of this model was this allowed the user to train very deeper neural networks with more than 150 layers more efficiently. Different types of ResNet architectures are available in the literature. ResNet-18 is a Convolutional Neural Network (CNN) with 18 deep layers. Similarly ResNet-34, ResNet-50, Resnet-101 and ResNet-152 has 34, 50, 101 and 152 deep layers respectively. The number of layers is more when compared to other architectures like Alexnet, VGGnet, etc. but it is faster. The ResNet produces better classification accuracy without increasing the complexity of the network model. ResNet architectures are using batch normalization for increasing the performance of the network.

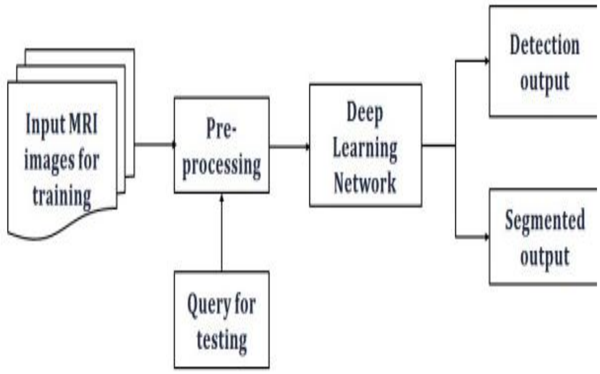

Fig.1 Proposed system architecture

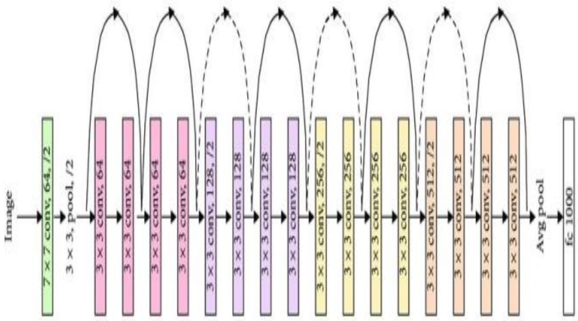

Fig.2 Basic architecture of ResNet-50

The basic architecture of ResNet-50 in [12] is shown in Fig. 2. This architecture consists of different stages. Each stage has a convolution block and an identity block. Each of these blocks has 3 convolution layers. This has a total of 50 layers and over 23 million trainable parameters. The convolutional layers are using filters of size 3x3 and 1x1. ResNet-101 is deeper than ResNet-50 with 101 layers. The basic architecture is shown in Fig. 3. The filter dimensions are same as that of ResNet-50, but the number of filters is more. Thus more amount of features will be extracted and accuracy will be more when compared to ResNet-50. ResNet-152 is deeper and more efficient than the previous ones with a total of 152 layers. Thus, it is eight times deeper than VGGnets. The basic architecture is shown in Fig. 4. This is also using the same size filters, but number of filters is more. Resnet architectures became the winner of the ILSVRC 2015.

Dataset Used

We used a dataset consists of 11722 MRI images downloaded from BRATS2017 challenge and Oasis Dataset. Different images are of different sizes. We have resized all images according to the size of the input layer of the corresponding network. Among these, 3250 are normal images and 8472 are tumor images. A total of 80% images are used for training, 10% for validation and remaining 10% for testing.

V. RESULTS AND DISCUSSIONS

A total of 1172 images are used for testing, 325 normal and 847 tumor images. The plot corresponding to the training process of ResNet-50, Resnet-101 and ResNet-152 obtained from the Deep Network Designer toolbox are shown in Fig. 5, 6 and 7 respectively. In all these figures, the first part is showing the accuracy of the training process (blue line) and validation (black dotted line) process respectively. The second part is showing the loss occurred during training process (red line) and validation process (black dotted line) respectively. From these, it is evident that training accuracy is starting from 30% and reaching to100% for ResNet-50. For Resnet-101, it is starting from 50% and reaching to 100%. For ResNet-152, it is starting from 60% and reaching to 100%. The corresponding losses are reaching to minimum.

Table.1 Performance of Proposed Detection Network

Parameters	ResNet-50	ResNet-101	ResNet-152
True Positive (TP)	786	805	812
True Negative (TN)	261	275	287
False Positive (FP)	64	50	38
False Negative (FN)	61	42	35
Precision, P = TP/(TP+FP) (in %)	92.5	94.2	95.5
Recall (Sensitivity), R = TP/(TP+FN) (in %)	92.8	95	95.9
Specificity = TN/(FP+TN) (in %)	80.3	84.6	88.3
F1 score = 2RP/(R+P)	0.93	0.95	0.96
Validation Accuracy (in %)	92.5	94.3	95.9
Error rate (testing) = False/Total (in %)	10.7	7.8	6.2
Testing Accuracy (in %)	**89.3**	**92.2**	**93.8**

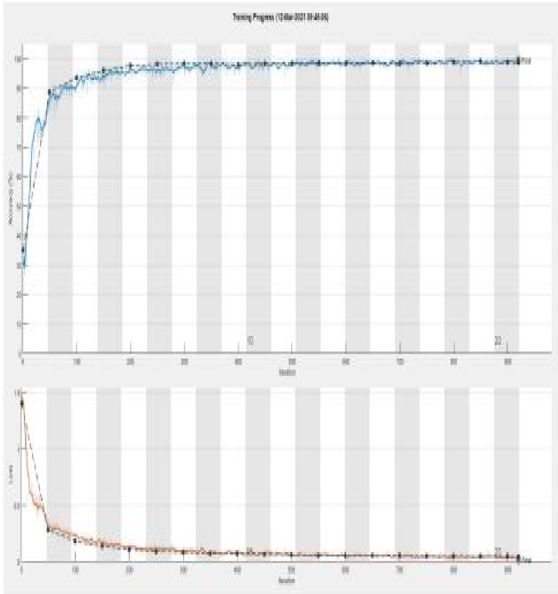

Fig.3 Training accuracy and loss curves of ResNet-50

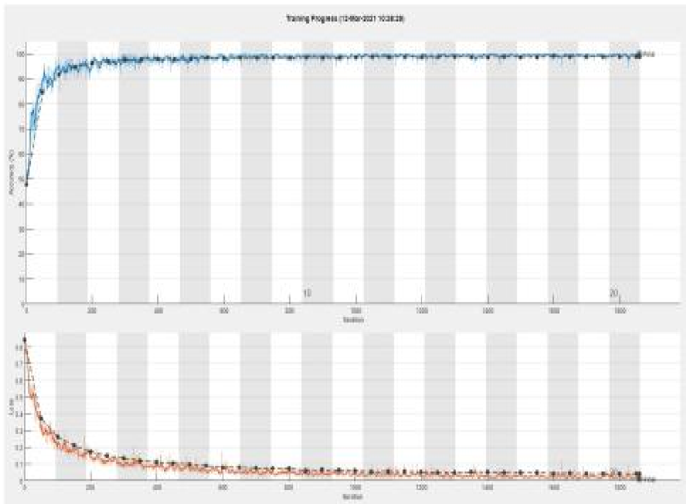

Fig.4 Training accuracy and loss curves of ResNet-101

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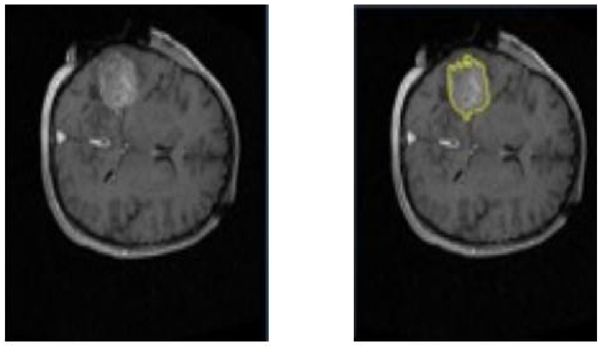

(a) (b)

Fig.5 a) Input tumor image and b) segmented output image

VI. CONCLUSION

In this paper, we proposed a comparative analysis of different variations of ResNet, such as ResNet-50, ResNet-101, and ResNet-152. All networks are modified by the knowledge change approach with the help of changing the last three layers of existing models. They are then retrained to test whether they suit brain tumor detection. From the results, we will conclude that the retrained model of ResNet-152 performs better than the rest. This network can be used to automate the process of detecting mental tumors. As a target paper, we will evaluate other green classifiers with them and use these networks to classify other diseases. In addition, we will see if they can be used simultaneously to analyze the data in real-time. These networks can be used as a basis for developing new green networks for brain tumor detection and classification.

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