Novel Approach of Brain Tumor Segmentation Using Convolutional Neural Network Hybridized with Water Cycle Algorithm

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Abstract - *Brain tumors can become a deadly terminal disease in its advanced stages. Therefore, it is decisive to detect it in the early stages to nip it in the bud. However, brain structures and detection of the abnormalities remain an unsolved problem due to normal anatomical variations in brain morphology, variations in acquisition settings and MRI scanners, image acquisition imperfections, and variations in the appearance of pathology. An emerging machine learning technique referred to as deep learning can help avoid limitations of classical machine learning algorithms, and its self-learning of features may enable the identification of new useful imaging features for quantitative analysis of the brain. MRI based brain tumor segmentation studies are attracting more and more attention in recent years due to non-invasive imaging and good soft-tissue contrast of Magnetic Resonance Imaging (MRI) images. With the development of almost two decades, the innovative approaches applying computer-aided techniques for segmenting brain tumors are becoming more and more mature and coming closer to routine clinical applications. The purpose of this paper is to propose a novel approach of convolution-based water cycle optimization technique hybridized with the Random Forest Algorithm, to improve performances of Brain Tumor Segmentation. The experimental results of the proposed method show 96.50% Accuracy,96.60% Sensitivity,96.54%Specificity, and improved PSNR up to 29.20. Thereby, the proposed method shows better performance while comparing with the existing methods.*

Key Words: **Brain Tumor, Segmentation, Magnetic Resonance Imaging, Water Cycle optimization, Random Forest Algorithm.**

1. INTRODUCTION

The brain tumor is known to cause serious backdrop for the quick increment in the mortality among the youngsters, grown-up, and particularly in the old matured individuals. As per statistics, in India alone, the incidences of brain tumor ranges from 5-10% per 100,000 people and the rate is apparently increasing gradually. Although, early diagnosis and detection of tumors can lead to timely treatment. and thus, many lives are saved. Every tumor is not cancerous. Non-cancerous tumors are called benign tumors and are less harmful while cancerous tumors are called malignant tumors and are harmful that commonly spreads across the other tissues. Accordingly, every one of these situations leads us in building up the identification model for the brain tumor. It is essential to analyze the presence of tumor in the cerebrum as ahead of schedule as could reasonably be expected. Accurate diagnosis in the medical procedure has attained using different imaging modalities such as Magnetic Resonance (MR) imaging, Computed Tomography (CT), etc. These can provide a very detailed and informative anatomy of a subject. According to these developments, diagnosis imaging became an important tool in diagnosis and planning treatment [1]. MRI method is known for the clearness of pictures it can check. In MRI the presence of the tumor is extremely exact and high, for additional treatment and drugs the assistance of the doctors is likewise required. More often than not the clinical determination is finished utilizing the MRI checking as it delivers better outcomes. In this way, MRI is increasing a noteworthiness consideration and has immense future scope. With the advances of computational intelligence and machine learning techniques, the location of tumors in the beginning phase is conceivable with much more accuracy.

1.1 Brain Segmentation.

Brain region segmentation or skull stripping is an essential step in neuroimaging applications such as surgical, surface reconstruction, image registration, etc. The accuracy of all existing methods depends on registration and image geometry. When this fails, the probability of success is very less. To avoid this, Convolutional Neural Network (CNN) is used. For brain extraction which is free from geometry and registration. CNN learned the connectedness and shape of the brain. Brain region segmentation is an important first step in every neuroimaging application such as tissue segmentation and volume calculation. Automatic skull removal is an extremely difficult time-consuming process because of complex boundaries and low contrast. The research community develops many methods [2]. Deep learning, otherwise called as deep structured learning is one of the machine learning algorithms. It learns data from the input image using either supervised or unsupervised. There has been a significant effort in developing classical machine learning algorithms for the segmentation of normal (e.g., white matter and gray matter) and abnormal brain tissues (e.g. Brain tumors). However, the creation of the imaging features that enable such segmentation requires careful engineering and specific expertise. Furthermore, traditional machine learning algorithms do not generalize well [3]. Despite a significant effort from the medical imaging research community, automated segmentation of the brain structures and detection of the abnormalities remain an unsolved problem due to normal anatomical variations in brain morphology, variations in acquisition settings and MRI scanners, image acquisition imperfections, and variations in the appearance of pathology. Brain region segmentation is an essential task in many clinical applications because it influences the outcome of the entire analysis. This is because different processing steps rely on accurate segmentation of anatomical regions. For example, MRI segmentation is commonly used for measuring and visualizing different brain structures, for delineating lesions, for analyzing brain development, and for image-guided interventions and surgical planning [4]. This diversity of image processing applications has led to the development of various segmentation techniques of different accuracy and degree of complexity. Over the last few decades, the rapid development of non-invasive brain imaging technologies has opened new horizons in analyzing and studying the brain anatomy and function. Enormous progress in accessing brain injury and exploring brain anatomy has been made using magnetic resonance imaging (MRI). The advances in brain MR imaging have also provided a large amount of data with an increasingly high level of quality. The analysis of these large and complex MRI datasets has become a tedious and complex task for clinicians, who have to manually extract important information. This manual analysis is often time-consuming and prone to errors due to various inter- or intra operator variability studies. These difficulties in brain MRI data analysis required inventions in computerized methods to improve disease diagnosis and testing. Nowadays, computerized methods for MR image segmentation, registration, and visualization have been extensively used to assist doctors in qualitative diagnosis [5].

The main problem while diagnosing and detecting the tumor is its accuracy that still pertains to many of the existing Machine Learning Methods. This can be solved by using an optimized technique using Water Cycle Algorithm (WCA) in collaboration with the Random Forest Algorithm. The greyscale pictures acquired from the database are pre-processed utilizing a non-local mean filter algorithm to expel the clamor and bends that are available in the information image. The CNN is then utilized for bunching and fragmenting the images lastly to recognize the tumor. The WCA streamlining calculation hybridized with the Random Forest Algorithm is thus applied for optimal grouping of the images.

2. Research Methodology.

The flow chart for the proposed Brain Tumor image segmentation utilizing Convolutional Neural Network (CNN) appears in Fig. 1. This proposed method is executed utilizing MATLAB software. The database contains grayscale images of the human cerebrum(brain). The images from the database are pre-processed utilizing a non-local mean filtering technique to expel the noise and diminish the distortions the mutilations. The following stage is the extraction of features. The extraction of features helps in deciding the parts of the cerebrum where the abnormal growth is seen. The filtered images where the tumors are available are recognized, classified, and clustered utilizing the CNN. K- means clustering techniques were utilized for the clustering of images whereas morphological segmentation for the purpose of segmentation. Water cycle optimization along with the Random forest algorithm is applied to figure out the weight and bias factor that has a noteworthy role in distinguishing and classifying the tumors. The components of weight and bias help in classifying the pictures with higher precision. In conclusion, the execution of this strategy is assessed for various parameters like specificity, accuracy, sensitivity, psnr, etc.

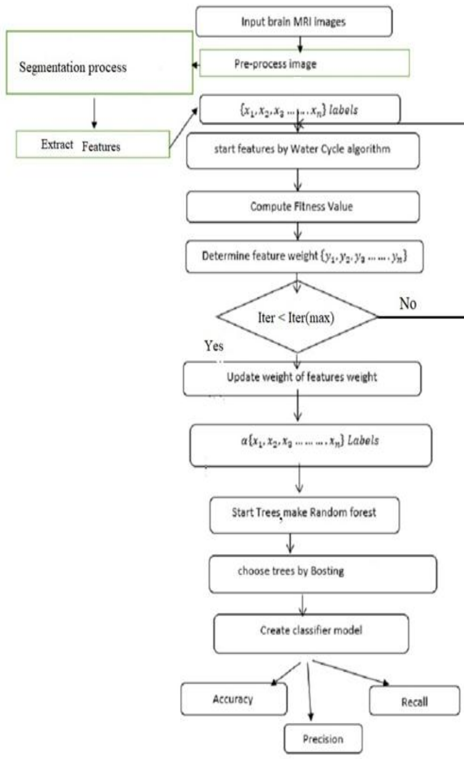

Fig -1: Proposed Flow Chart

A. Image Preprocessing

Pre-processing upgrades the nature of the images by removing noise and diminishing the distortions in the input image. The current strategy utilizes a non-local mean filtering procedure to pre-process the image. The methodology of the Non-Local Means filtering technique depends on evaluating every pixel intensity from the data given by the whole image and subsequently it exploits the repetition caused because of the presence of the similar patterns and features in the picture. In this technique, the re-established or restored gray value of every pixel is acquired by the weighted average of the gray values of all pixels in the image. The weight allocated is proportional to the similarity between the nearby neighborhoods of the pixel under consideration and the neighborhoods corresponding to other pixels in the image.

B. Convolutional Neural Network

CNN is a feed forward neural network as represented in Fig. 2 and is most commonly utilized for image acknowledgment. This is comprised of neuron with learnable weights and biases. Every neuron gets a few data sources, takes a weighted sum over them, pass it through activation function and respond with the yield or output. CNN works over volumes like neural systems where the info is a vector but in the case of CNN the information is a multi-channeled image. CNN has beaten image segmentation challenges via automatically learning a hierarchy of increasingly complex features right away from the data. The CNN fundamentally is utilized in convolving the image with the kernels for the way toward acquiring the feature maps. The weights in the kernels help in associating every unit of the feature map to the previous layers. These weights of the kernel are used during training of the datasets for improving the attributes of the information input. The quantity of weights which must be trained in the convolutional layers is lesser when contrasted with the Fully connected (FC) layers on the grounds that the kernels are common to all the units of one specific feature map. A portion of the huge ideas as for CNN are mentioned below.

- Initialization is the most critical advance for achieving convergence. This procedure helps in keeping up the gradients at the necessary levels else there will be a chance of explosion of the gradients that are backpropagated.
- The activation function is responsible for the information change in a nonlinear way. There are different kinds of activation function of which the modified Rectifier is units (ReLU) is utilized. It is characterized as

$$f(x)=\max(0, x) + \alpha \min(0, x) \quad (1)$$

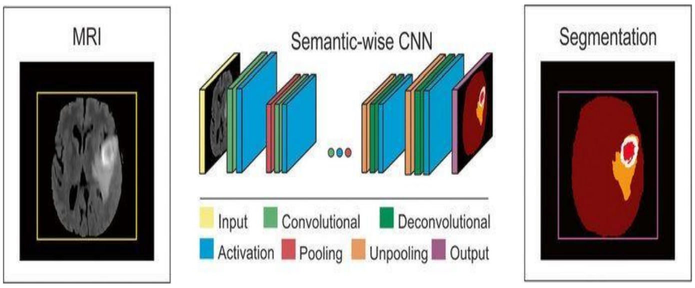

Fig- 2: CNN architecture for brain tumor segmentation Architecture of CNN.

- This type of architecture makes predictions for each pixel of the whole input image like semantic segmentation [6].Similar to auto encoders, they include encoder part that extracts features and decoder part that up samples or de-convolves the higher-level features from the encoder part and combines lower level features from the encoder part to classify pixels. The input image is mapped to the segmentation labels in a way that minimizes a loss function [4].
- In the feature maps, the process of pooling consolidates the features that is close by spatially. This sequence of redundant features helps in making the portrayal invariant on account of little changes and furthermore progressively compact. The computation load for the progressive stages is also decreased.
- The overfitting is diminished with the assistance of regularization. In each progressive step of training, it will wipe out the nodes of the network. Along these lines, all the nodes in the Fully Connected layer are compelled to learn better portrayals or representation and furthermore forestall the coadaptation of nodes.
- The quantity of parameters to train a Fully connected network is a lot more when contrasted with a CNN. In many images the nearby pixels are commonly related however a fully connected neural network doesn't consider while a CNN considers connection among space and pixel inside an image

C. Algorithm Used

Algorithms influenced by water flow have become more and more common for pursuing optimization problems. The one best known example is water cycle optimization (WCA). The WCA as name suggests is based on the ground water flow through rivers and streams to the sea as illustrated in Fig.3[7].

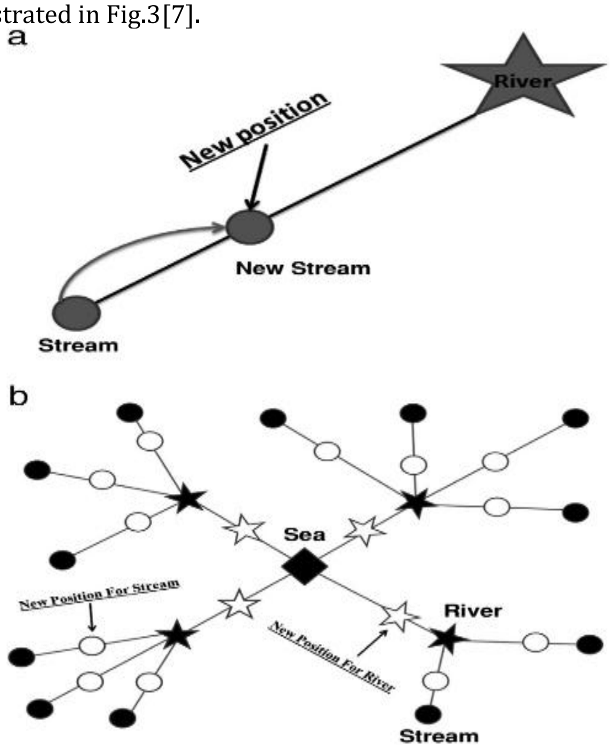

Fig-3: The WCA optimization process.

This Algorithm constructs a solution based on population of stream, where each stream is a candidate solution. Random solutions for the problem are being generated at first by distributing the streams into different positions as per the problem`s dimensions. The best stream is taken into account as sea and a specific number of streams are regarded as rivers. Then the streams are made to flow towards the position of the rivers and sea. The global-best solution is denoted by the position of the sea, whereas the local-best solution is denoted by those of the rivers. Each stream's movement is influenced by its local best-known position, but is also guided toward the best-known positions in the search-space, which are updated as better positions are found by other streams. This is expected to move the water cycle toward the best solution. The WCA in collaboration with Random forest algorithm plays an important role in Identifying, detecting and classifying the images with tumors. The flow chart for the WCA is given below in Fig.4.

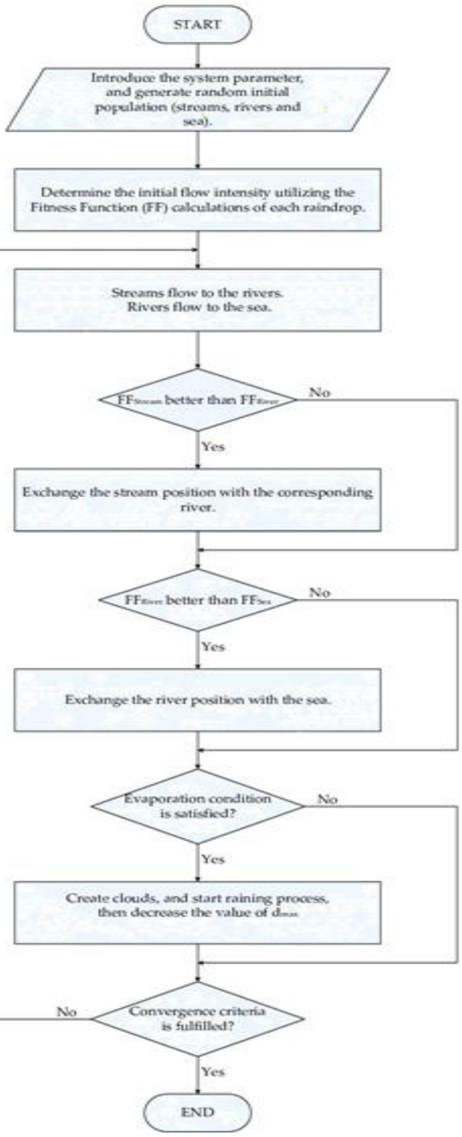

Fig-4: Flow Chart of WCA

3. Result and Analysis

The greyscale pictures acquired from the database related to brain tumors from the internet is the input to the proposed technique. The images from the database are split into two sets of training and testing images. These images are pre-processed utilizing a non-local mean filter algorithm to expel the clamor and bends that are available in the information image.Fig.5 illustrates the greyscale pre-processed image of the human brain obtained from the testing set of images.

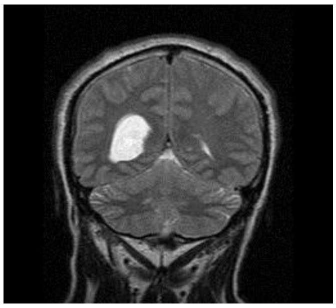

Fig-5: Greyscale brain image

Now the next step is the feature extraction from the image of the human brain. The last stage of post-processing incorporates segmenting, identifying and extricating the tumor from the image and will evacuate any of the associated parts anyway little the segments are. At this stage, the tumor is recognized alongside the territory that is covered by the disease. Fig. 6 shows the last yield of CNN.

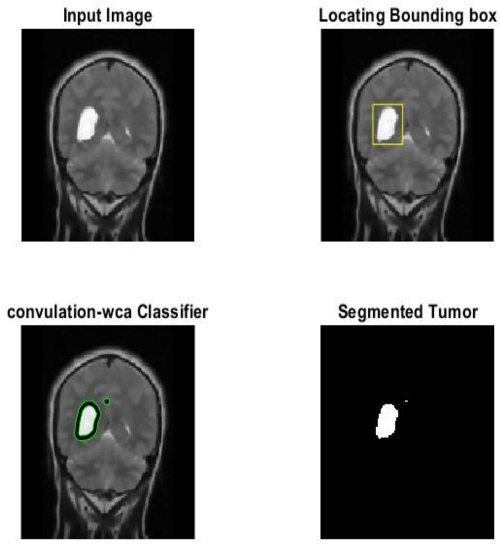

Fig-6: Different steps of tumor detection in proposed approach

A. Performance Evaluation

The performance of the proposed strategy is evaluated in terms of accuracy, sensitivity, specificity and PSNR; where TP =True Positive, FN=False negative.

- The sensitivity is defined as the ability to determine the tumors correctly. It can be calculated using the following relation.

Sensitivity = TP / (TP+FN)

- The Specificity is defined as the ability for the correct determination of healthy cases. It can be calculated using the following relation.

Specificity = TN / (TN+FP)

- Accuracy is defined as the ability to differentiate healthy and unhealthy cases correctly can be calculated using the following relation.

Accuracy = (TN +TP) / (TN+TP+FN+FP)

- PSNR represents the ratio between the maximized possible signal power and the power of corrupting noise that disturbs the reliability of its depiction.

$$\text{PSNR} = \frac{\text{Max.possible signal power}}{\text{Power of corrupting noise}}$$

Table -1: The performance metrics calculated for the tested images

PARAMETERs	without optimization	ANN	Convolution-wca
Average PSNR	25.33333333	27.256	29.20222222
Average Sensitivity	91.01888889	92.61111111	96.60777778
Average Specificity	90.735	92.32722222	96.54611111
Average Accuracy	90.30398148	91.89972222	96.50592593

The performance metrics calculated for the tested images are tabulated in Table -1. and Chart-1 shows the plot for the parameters of sensitivity, specificity, accuracy, and PSNR of various existing methods in contrast with the proposed technique.

Thus, from Chart-1, it's clear that the overall performance of the parameters is improved which is what the proposed approach is supposed to be focused on as compared to the various existing automated segmentation approaches. It has been observed that the proposed WCA algorithm has performed and overcome image segmentation challenges by automatically learning a hierarchy of increasingly complex features directly from the data.

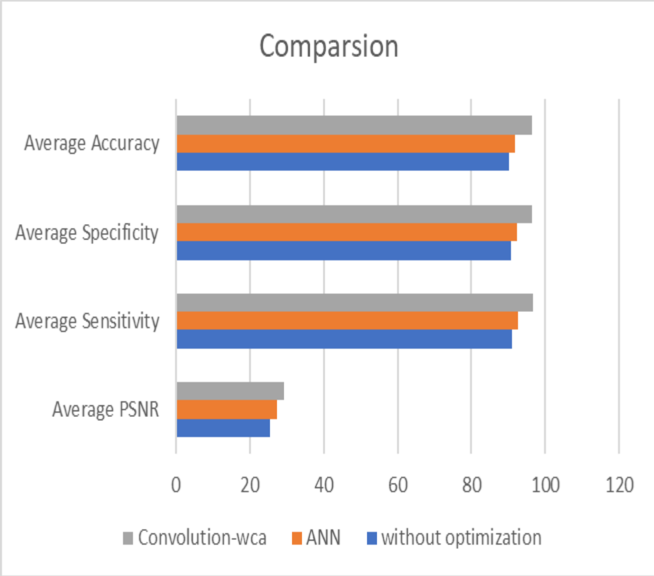

Chart -1: comparison of parameter performance between proposed and existing approaches

4. CONCLUSIONS

The present investigation built up an excellent automated strategy for the segmentation and location of a brain tumor. The greyscale pictures acquired from the database are pre-processed utilizing a non-local mean filter algorithm to expel the clamor and bends that are available in the information image. CNN is then utilized for bunching and segmenting the images lastly to recognize the tumor. The WCA optimization calculations hybridized with the Random Forest Algorithm is applied for optimal grouping of the images. The proposed automatic image segmentation and tumor detection method are found to have an accuracy of 96.50%, the sensitivity of 96.60%, the specificity of 96.54%, and an improved PSNR of 29.20. The correlation of the proposed strategy with existing strategies demonstrates that the method created in this paper has the most elevated exactness. The precision can be additionally improved utilizing enormous datasets, anyway when contrasted with their imaging territory, accessibility of dataset isn't effectively accessible. Along these lines sharing the information assets by various human services, specialist co-ops may assist with beating this issue.

5. FUTURE SCOPE

There are boundless chances to improve the human services framework by utilizing progressively refined channels on CNN. While the proposed model yields promising outcomes and rules out mistakes. In careful setting, it is basic to expel however much of tumor mass as could reasonably be expected without harming the encompassing solid tissue. In the future, enhance this work, by using the different forms of neural network. It would be curious to explore the behavior and output of the different forms of the neural network like ANN, PNN, DNN, and simple neural networks by using a smaller number of labeled images to perform well. There is a need to introduce an automated expert system which can identify the tumor at its earlier stage so that better planning could be organized for treatment

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