BRAIN TUMOR DETECTION USING MRI IMAGES

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Abstract - Clinical pictures assume a vital part in making the right determination for the specialist and in the patient's treatment interaction. Utilizing clever calculations makes it conceivable to rapidly recognize the injuries of clinical pictures, and it is particularly essential to separate elements from pictures. Many examinations have coordinated different calculations into clinical pictures. For clinical picture include extraction, a lot of information is investigated to acquire handling results, assisting specialists with presenting more exact defense analysis. In view of this, this paper takes cancer pictures as the exploration article, and first performs nearby double example highlight extraction of the cancer picture by revolution invariance. As the picture shifts and the turn changes, the picture is fixed comparative with the direction framework. The strategy can precisely portray the surface highlights of the shallow layer of the growth picture, consequently upgrading the vigor of the picture area portrayal. Zeroing in on picture include extraction dependent on convolutional neural organization (CNN), the fundamental system of CNN is assembled. To break the impediments of machine vision and human vision, the examination is reached out to multi-channel input CNN for picture include extraction. Two convolution models of Xception and Dense Net are worked to work on the exactness of the CNN calculation. It tends to be seen from the exploratory outcomes that the CNN calculation shows high precision in cancer picture include extraction. In this paper, the CNN calculation is contrasted and a few traditional calculations in the nearby paired mode.

***Key Words*:** CNN, FCM, Medical Image, segmentation, SVM

INTRODUCTION

Medical imaging techniques are used to image the inner portions of a human body for medical diagnosis. And medical image classification is one of the most challenging & affluent topics in the field of Image Processing. Medical image classification problems, tumor detection or detection of Cancer is the most prominent one. The statistics about the death rate from brain tumor suggest that it is one of the most alarming and critical cancer types in the Human body. As per the International Agency of Research on Cancer (IARC), more than 1,000,000 people are diagnosed with brain tumor per year around the world, with ever increasing fatality rate. It is the second most fatal cause of death related to Cancer in children and adults younger than 34 years [1]. In recent times, the physicians are following the advanced methods to identify the tumor which is more painful for the patients. To analyse the abnormalities in different parts of the body, CT (Computed Tomography) scan and MRI (Medical Reasoning Imaging) are two convenient methods. MRI-based medical image analysis for brain tumor studies has been gaining attention in recent times due to an increased need for efficient and objective evaluation of large amounts of medical data.

The medical imaging processing refers to handling images by using the computer. This processing includes many types of techniques and operations such as image gaining, storage, presentation, and communication. This process pursues the disorder identification and management. This process creates a data bank of the regular structure and function of the organs to make it easy to recognize the anomalies. This process includes both organic and radiological imaging which used electromagnetic energies (X-rays and gamma), sonography, magnetic, scopes, and thermal and isotope imaging. There are many other technologies used to record information about the location and function of the body. Those techniques have many limitations compared to those modulates which produce images.

LITURATURE SURVEY

Ming Li, Lishan Kuang, Shuhua Xu, Zhanguo Sha etal., In this paper, in medical, magnetic resonance-imaging is a tough field in image processing because accuracy percentage must be very high so doctors could get proper idea about diseases to save patient's life. Some MRI images have been taken as inputs data. The brain tumor segmentation process is performed for separating brain-tumor tissues from brain MRI images, The MRI images should be filtering such as with the median filtering technique and skull stripping should be done in pre-processing, the thresholding process is being done on the given MRI images with using the watershed 4 Tumor Recognition utilizing X-ray pictures segmentation method. Then at last the segmented tumor region is obtained. And then in other phase features extracted by GLCM methods using MATLAB software. Then, the some images have been classified using support vector machine (SVM), this system obtained with the average accuracy of 93.05. Which is quite better than other conventional models [1].

Chirodip Lodh Choudhury, Chandrakanta Mahanty, Raghvendra Kumar, Brojo Kishore Mishra etal., In this research paper, the authors have proposed a new system based on SVM, which discriminates between the Brain MRI images to mark them as tumorous or not. The model achieved an accuracy of 96.08%, with an f-score of 97.3. The model is having SVM with 3 layers and requires very few steps of pre-processing to produce the results in 35 epochs. The purpose of the research is to highlight the importance of diagnostic machine learning applications and predictive treatment.[2].

Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf, MD Abdullah Al Nasim , Faisal Muhammad Shah etal., The paper focuses on detecting brain tumors using machine learning. The authors of this paper had compared the SVM Classification Technique and SVM Classification Technique. So, as per the paper first model is segmented by Fuzzy C Means Algorithm (FCM) and then classified by a traditional machine learning algorithm. The second model focused on deep learning for tumor detection. FCM gives better results for noisy clustered data set. SVM Classification Technique gives 92.42% of accuracy. And 5-layer SVM Classification Technique gives 97.87% of accuracy. [3].

Milica M. Badˇza and Marko C. Barjaktarovi´c etal., The paper discusses the detection of brain tumors for three types- meningioma, glioma, pituitary tumor. So, they had taken images from three different planes- sagittal plane, axial plane, coronal plane. Then, with all the images Data Augmentation process is performed. Then it goes through a 5-layer SVM classification technique. Further, the output came from the SVM process is been trained by use of Confusion Matrices Algorithm. So, the best result for 10-fold cross-validation was achieved for the record-wise method and, for the augmented dataset, and the accuracy was 96.56%.[4].

P.Muthu Krishnammal ,S. Selvakumar Raja etal., In this paper, a convolutional neural network (SVM) is designed for classifying the tumor. For extracting quantitative information from an image discrete wavelet transform was used for extracting wavelet coefficients and gray-level co-occurrence matrix (GCLM) for statistical feature extraction. Uses a K -means segmentation algorithm for localizing and segmentation of tumor part once the classification of tumor image was done This study used a dataset of 100 images for training the model

AIM & OBJECTIVES

- The main objective of this project is to build a model that can predict whether the medical images contain a tumor or not and find its properties.
- To build a model that can predict whether the medical images contain a tumor or not. Some useful information that also be extracted from this algorithm in simpler form in front of the users, for treating the patient.
- To develop an algorithm that will able to provide information like size, dimension and position of the tumor, which will provide the base for the medical staff for further treatment.

MOTIVATION

- Observing the recent statistics of death rate caused by brain tumors, the automatic brain tumor detection and classification needs to be studied.
- Tumor detection in medical images is time consuming as it depends on human judgment.
- The experts in this field, such as radiologists, specialized doctors examine CT scan, MRI, PET scan images and give decisions upon which the treatment depends.
- This whole process is time consuming. Automated medical image analysis can help to reduce the time and effort taken here and the workload of a human as it will be done by machines.

PROPOSED SYSTEM

The proposed method consists of several steps. At first, the MRI of the brain images is taken as the input image. Next, data normalization is conducted where image resizing and dilations have been applied dispense with noise. The assembled database of MRI images of the brain is processed. After that the images were resized for the model's input and a pre-trained CNN, CNN is employed to classify the images into two classes of YES and NO. A Convolutional Neural Network (CNN) is a type of artificial neural network used in image recognition and processing that is specifically designed to process pixel data. The database used in this study is composed of images of brain MRI scans. There are a total of 3000 raw images of varying dimensions. The images are collected from Kaggle datasets of Brain MRI Images. They are in JPG format. The dataset is labeled into two classes of YES and NO based on the presence of tumors. Overall, there are 1500 images with brain tumors and the remaining 1500 images are of without tumors brains

SYSTEM ARCHITECTURE

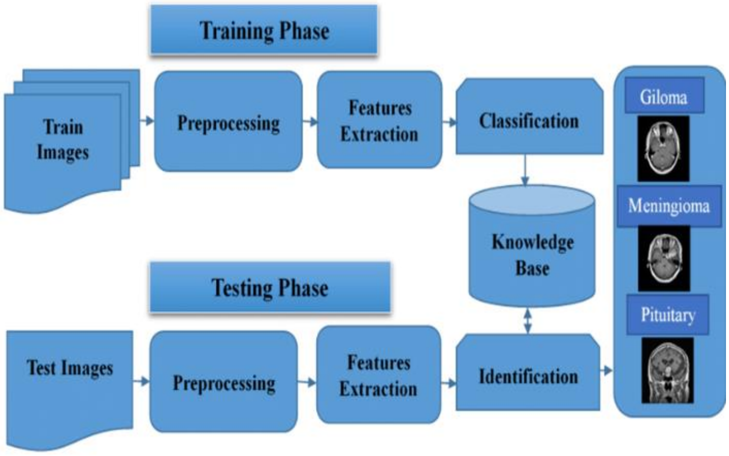

Fig -1: System Architecture Diagram

DETAILS OF MODULE

1. **Data Collection:** Gather a dataset of MRI brain images that are labeled with tumor and non-tumor classes. The dataset should include a sufficient number of examples for each class to ensure balanced training.

2. **Data Preprocessing:** Perform preprocessing steps on the MRI images to make them suitable for input to the CNN. This may include resizing the images to a consistent resolution, normalizing pixel values, and applying any necessary augmentation techniques such as rotation, flipping, or cropping to increase the variability of the training data.

3. **Dataset Split:** Divide the dataset into training, validation, and testing sets. The training set is

used to train the CNN, the validation set is used to tune hyperparameters and monitor the model's performance during training, and the testing set is used to evaluate the final performance of the trained model.

4. **Network Architecture Design:** Define the architecture of the CNN. Typically, a CNN consists of a stack of convolutional layers, followed by pooling layers to down sample the features, and finally, fully connected layers for classification. You can experiment with different architectures to find the one that works best for your task.

5. **Model Compilation:** Compile the CNN model by specifying the loss function, optimizer, and evaluation metrics. For binary classification (tumor vs. non-tumor), the binary cross-entropy loss function is commonly used.

6. **Model Training:** Train the CNN using the labeled MRI images. During training, the model learns to extract relevant features from the images and classify them into tumor or non-tumor classes. The weights of the network are updated iteratively based on the computed loss and the chosen optimization algorithm.

7. **Model Evaluation:** Evaluate the trained model using the validation set to assess its performance. Calculate metrics such as accuracy, precision, recall, and F1 score to measure the model's ability to correctly classify tumor and non-tumor images. Adjust hyperparameters or network architecture, if necessary, based on the evaluation results.

8. **Testing and Deployment:** Once you are satisfied with the model's performance, evaluate it on the independent testing set to obtain a final evaluation. Use the trained model to make predictions on new, unseen MRI images for real-world tumor detection applications.

CONVOLUTION NEURAL NETWORK CLASSIFIER

1. **Convolution:** In CNNs, convolutional layers are used to extract features from the input images. Convolution involves sliding a small filter (also known as a kernel) over the image and computing element-wise multiplications between the filter and the corresponding pixels in the image. These multiplications are then summed to produce a single value in the output feature map. This process is repeated for all positions of the filter across the image. The convolution operation can be expressed as:

$$(I * K)(i, j) = \Sigma\Sigma\, I(m, n) * K(i-m, j-n) \quad \ldots\ldots\ldots(1)$$

Here,
I : input image,
K : filter
(i, j) : the position in the output feature map.

2. **Activation Function:** After each convolutional layer, an activation function is typically applied element-wise to introduce non-linearity into the network. Common activation functions include Rectified Linear Unit (ReLU), sigmoid, or hyperbolic tangent. The equation (2) shown the Rectified Linear Unit (ReLU) activation function which has input x as an input value. If the input value is less than 0, in this time the output is 0. If the input value is greater than 0, in this time the output is not changed the same equal to the input.

$$ReLU(x) = \begin{cases} 0 \ if\ x < 0 \\ x \ if\ x \geq 0 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

3. **Pooling:** Pooling layers are used to downsample the feature maps, reducing their spatial dimensions while preserving the most important information. Pooling helps reduce the computational complexity of the network and makes it more robust to small translations and distortions in the input images.

4. **Fully Connected Layers:** The fully connected layers in a CNN are responsible for performing the final classification. These layers connect every neuron in one layer to every neuron in the next layer, similar to a traditional neural network. Each neuron in the fully connected layer computes a weighted sum of the outputs from the previous layer, followed by an activation function. The output of the final fully connected layer represents the predicted probabilities of each class (tumor or non-tumor) through a softmax or sigmoid activation function.

5. **Loss Function:** The loss function measures the difference between the predicted output and the true labels in the training data. The goal of the network training is to minimize this loss function, adjusting the weights and biases of the network through optimization algorithms.

6. **Optimization Algorithms:** The optimization algorithms, such as Stochastic Gradient Descent (SGD), Adam, or RMSprop, are used to update the weights and biases of the network during training. These algorithms use the gradients of the loss function with respect to the model parameters to iteratively adjust the weights, aiming to find the optimal values that minimize the loss.

7. **Backpropagation:** Backpropagation is a fundamental algorithm used to calculate the gradients of the loss function with respect to the weights and biases in the network. It uses the chain rule of calculus to efficiently compute these gradients layer by layer, starting from the output layer and propagating the gradients backward through the network. These gradients are then used by the optimization algorithm to update the parameters during training.

8. **Evaluation Metrics:** Once the model is trained, evaluation metrics such as accuracy, precision, recall, and F1 score can be computed to assess the performance of the model on the validation or testing dataset. These metrics provide insights into the model's ability to correctly classify tumor and non-tumor images, and they are derived based on the true positive, true negative, false positive, and false negative predictions.

PERFORMANCE MEASURES

To evaluate the proposed model’s efficiency, for comparison, we relied on eight models of machine learning methods, between the classical and the modern ones. The comparison between the proposed differential deep-CNN model and the other models was based on the following values. The proposed algorithm has been assessed through various performance evaluation metrics that include True Positive, True Negative the former one that designates how many times does the proposed algorithm is able to correctly recognize the damaged region as damaged region and the later one designates how many times does the proposed algorithm correctly identified non-damaged region as non-damaged region. And the False Positive (FN) and False Negative (FN) the former one designates how many times does the proposed algorithm fails to recognize the damaged region correctly, and the later represents how many times does the proposed algorithm fails to identify the non-tumors region as non-tumors regions. Basing on values of TP, TN, FP, and FN, the values of Accuracy, Specificity and sensitivity are calculated of the proposed algorithm.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots\ldots (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad \ldots\ldots (4)$$

$$Sensitivity = \frac{TN}{TP+FN} \quad \ldots\ldots (5)$$

TABLE 1 Represents the true positive, true negative, false positive and false negative values of the proposed approach for different set of images.

Different set of Images	True Positive (%)	True Negative (%)	False Positive (%)	False Negative (%)
128 * 128 Images	83.7	84.5	16.3	15.5
256 * 256 Images	82.4	84.1	17.6	15.9
512 * 512 Images	82.1	83.7	17.9	16.3

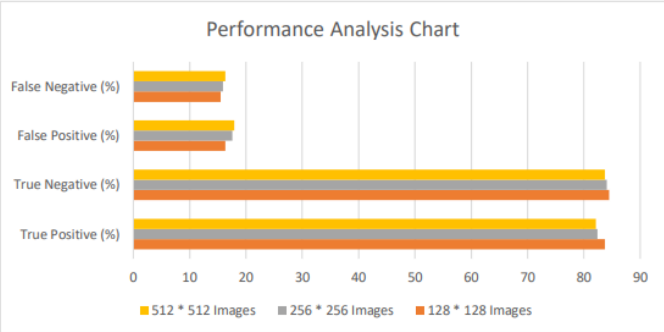

Fig -2: Represents the performance analysis of CNN

It is observed from table 2 upon performing proposed segmentation technique for different set of images that have the ability to recognize the isolated region from the MR images that are used to analyze the shape and size of the image. We have used Convolutional Neural Network (CNN) for segmentation, and the output of our proposed work is pleased with better accuracy, sensitivity, and computational time.

TABLE 2 Represents Test results of system with steps.

Task	Description	Action	Result
001	application accessible to the user	User should open web application from mobile or PC	PASS
002	Login page	The login page is displayed on application	PASS
003	New Registration	new user register with name, email ID and password	PASS
004	user Login	user should log in first by entering a username and password	PASS
005	Authentication	if username and password are valid then only system will display the page of Brain Tumor identification system	PASS
006	Patient Details	User first enter patient details and upload the x-ray file on page.	PASS
007	Processing	System compares that X-ray image with database image.	PASS
008	Output	System will notify user after detecting the tumor and also system will display the tumor detection image Prediction.	PASS

RESULTS

Fig -3: Sign in Page

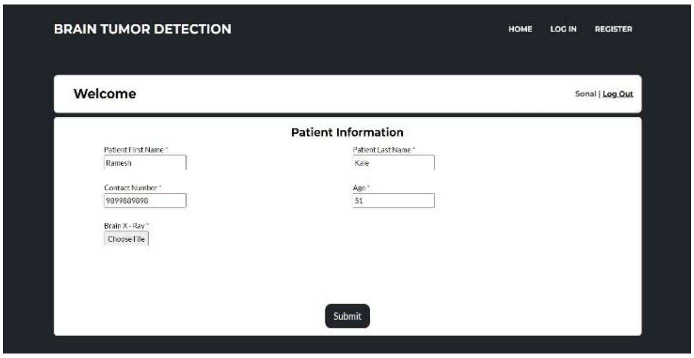

Fig -4: Patient details with MRI File upload

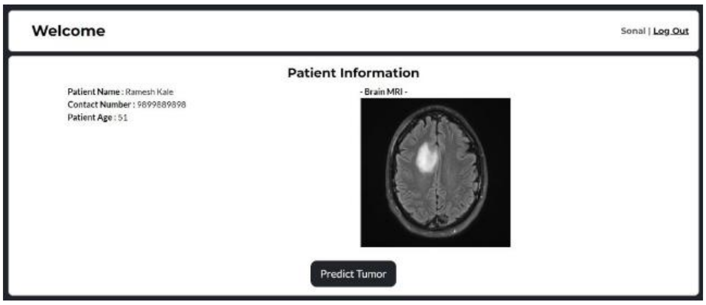

Fig -5: Brain tumor detection with Patient Details Page

CONCLUSION

We proposed a computerized method for the segmentation and identification of a brain tumor using the Convolution Neural Network. The input MR images are read from the local device using the file path and converted into grayscale images. These images are pre-processed using an adaptive bilateral filtering technique for the elimination of noises that are present inside the original image. The binary thresholding is applied to the denoised image, and Convolution Neural Network segmentation is applied, which helps in figuring out the tumor region in the MR images. The proposed model had obtained an accuracy of 84% and yields promising results without any errors and much less computational time.

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