Analysis of Brain Tumor Using Convolutional Neural Networks and Deep Learning

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Abstract

Magnetic Resonance Imaging is commonly used to detect brain tumors as it is non-invasive, it does not use radiation and provides superior image quality. This paper proposes a Deep Learning model based on Convolutional Neural Network (CNN) to classify brain tumors into benign or malignant; and meningioma, pituitary tumor and glioma. High computational efficiency and faster learning enable accurate detection and classification. Survival period of patient is predicted. Accuracy of the proposed model is around 96.21%.

Keywords: *Brain Tumour, Deep Learning, Convolutional Neural Network*

1.0 Introduction

World cancer report of World Health Organization (WHO) reports that, brain cancer accounts for less than 2% of other cancer; but it results in morbidity and complications [1]. Cancer Research Corporation reports incidence of about 5,250 deaths per annum by the act of brain, other Central Nervous System (CNS) and intracranial tumors. Brain tumors can be classified as primary and secondary tumors. Among that primary accounts for 70% of all brain tumors[2, 3].

Most predominant type of brain tumors are Gliomas, that originate in the glial cells of the brain. 30% of all brain tumors include Gliomas and CNS, and 80% of all malignant brain tumors. Meningioma is a tumor that forms on the membrane that covers the brain and spinal cord inside the human skull and grows placidly [4]. However, pituitary tumor starts from the pituitary glands that control hormones and regulate functions in the body. Complications of pituitary tumors may cause permanent hormone deficiency and vision loss.

Detection and classification of brain tumor images is performed using Deep Neural Network: T1-weighted contrast enhanced brain tumor

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images are fed as input, where they are downsized to decrease dimensionality and augmented with salt noise. These augmented images are passed through the various layers of CNN-Convolutional layer where kernels are applied over input images, passed through ReLU layer to decrease model training time dramatically, and further normalized using cross channel normalization algorithm. Further processing is done in a pooling layer which reduces the number of computations in the deep neural network, and overfitting of the model is prevented by using a dropout layer [3].Other technique incorporates a two dimensional 2D denoising wavelet transform DWT to improve the accuracy of a prodiction model for overall remaining lifetime of brain tumor patients. Best accuracy is obtained with 10 folds cross validation with Support Vector Machine SVM which takes the patients age into consideration. This DWT removes the noise present in the raw MRI data which is seen using histogram features [4]. The histogram features are extracted from denoised MRI images and are then combined with the age information of patients. This information is used to train the model for overall survival time prediction.

Treatment methods can be chosen based on early detection and classification of brain tumors. Physicians and Radiologists has a vital role in the classification stage in the complicated cases. These complicated cases need experts to work on, localize the tumor, compare tumor tissues with adjacent regions, and apply filters on the image if necessary; to make it more clearly for human vision, and finally conclude; whether it is a tumor besides its type and grade if available. This task is time consuming and hence need computer aided diagnosis (CAD) [5].

This research combines the advantages of the multi-classification and the prediction of overall lifetime of malignant brain tumor. This is an added advantage as the system is faster and gives highly accurate results as it uses small kernels based deep neural CNN. The results show an accuracy of 96.21 with a low system complexity when compared to the previous works.

2.0 System Development

The proposed design addresses brain tumor analysis and classification into meningioma, pituitary tumor, and glioma and whether benign or malignant. Based on the analysis of CNN, the design also predicts the survival period of the patient. The results help decisions on treatment methods. A novel automatic brain tumor classification segmentation method based on Convolutional Neural Networks and Deep learning which gives accurate results is implemented. Algorithms such as canny edge detection, Gaussian filter, Gabor filter, Cross channel normalization are used.

2.1 Design Concept

Flow chart for implementing the proposed system is shown in Fig. 1, which depicts the steps involved in analyzing brain tumor:

1. Selecting the input brain tumor MRI image in .mat format.
2. Subjecting the selected image to preprocessing operations such as converting .mat to .jpeg format.
3. Extracting the region of interest along with the important features.
4. The features obtained in the previous step are important and act as an input for building and training the deep learning based CNN.
5. The Convolutional Neural network has several layers such as Cross Channel normalization layer, Rectified Linear layer, Dropout layer, Softmax layer, Convolutional layer, and classification layer.
6. Training the CNN requires several epochs or cycles of the input dataset. More the training, less is the error in analyzing the brain tumor.
7. The output of CNN gives the tumor level and the type of tumor in the selected input MRI image.
8. The proposed model also predicts an approximate remaining lifetime of the patient based on the average value of the image pixels obtained in the previous stages.

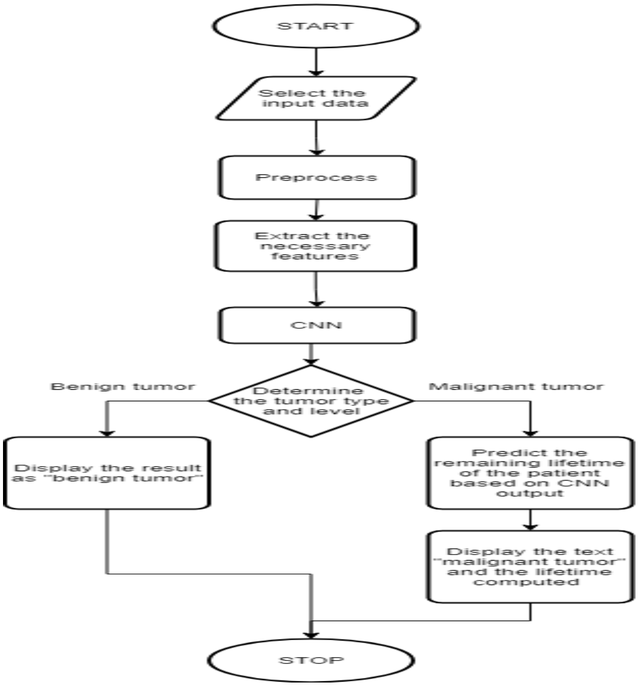

Fig. 1. Methodology for Brain Tumor Analysis

2.2 System Architecture

Fig. 2 presents the major components and sequence of the developed system. The basic components include the input dataset, preprocessing, partitioning the input dataset into training, validation, and test dataset, building the CNN architecture, training the CNN with the training set, fine tuning this architecture into the final CNN model, and finally computing the performance of the CNN model developed. This project implements a novel automatic segmentation method based on Convolutional Neural Networks and deep learning which gives accurate results. The data partition block shown in the diagram incorporates automatic feature selection algorithm which scans the input images for important features without any human supervision necessary. The CNN model here trains itself automatically at a fast rate and learns the underlying problem from input data, thus improving the model accuracy and the accuracy of results obtained.

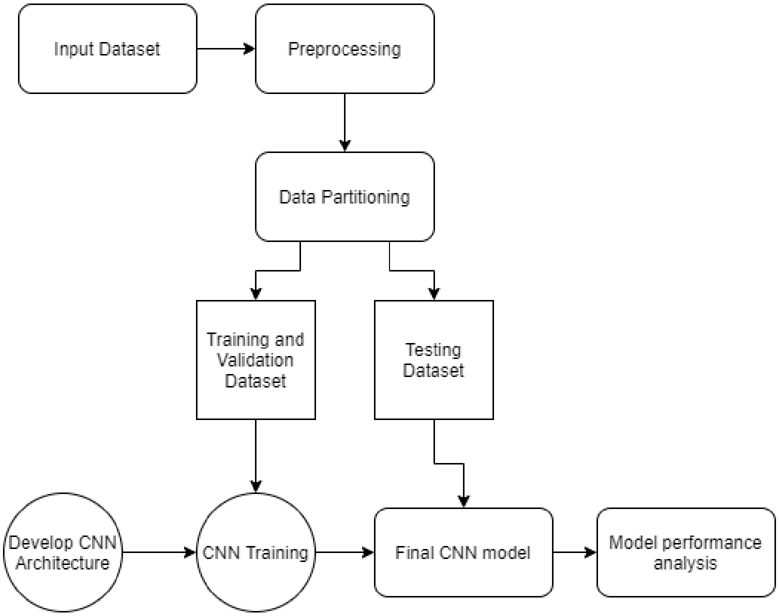

Fig. 2. Block diagram of Brain Analysis system

2.3 System Implementation

The primary components of the implemented system is as shown in Fig. 3. There are different stages: pre-processing, segmentation, feature extraction & classification using Convolutional neural network.

Read image: The first step of the project is to read the input image which is MRI image from the input dataset.

Pre-processing: Pre-Processing strategies help in upgrading of the picture without changing the data content. Some of the flaws in the image are Low determination, Simulation, and Geometric Distortion. Pre-processing is a very important step in processing MRI images as it increases the accuracy of the result obtained.

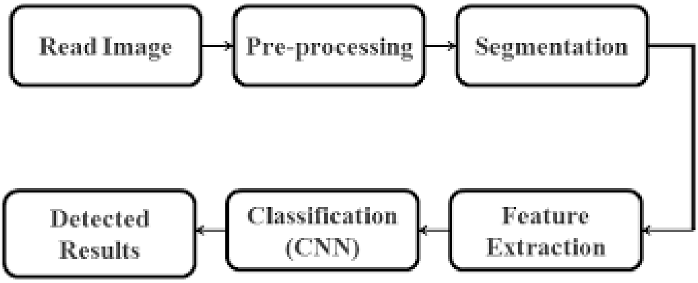

Fig. 3. Overall design of the CNN based brain tumor analysis system

Segmentation: This step deals with the image segmentation. It is the process of partitioning an image into multiple segments. Locating objects and boundaries in images are based on the Image segmentation. These methods are broadly classified into three categories: threshold, edge, and region-based methods, respectively. Histogram are used to detect single or multiple thresholds of the input image . Edges in an input image are detected through Edge-based image segmentation. Thus, segmentation is handled by determination of the region boundaries in the input image. Region-based image segmentation techniques initially search for some seed points in the input image and proper region growing approaches are employed to reach the boundaries of the objects.

Feature Extraction: The next step in the process is to extract features. Extraction of features which have data critical for further processing and characterization is done in this step. Features themselves can be classified as pixel intensity-based features, calculated pixel intensity-based features, and edge and texture-based features.

Convolutional Neural Network: Convolutional Neural Network (CNN) have been known to give breakthrough results when compared to other techniques. The application of Convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. To enhance certain characteristics of the input. The weights of the kernels are adapted during the training phase by back propagation. CNN are easier to train and less prone to overfitting.

Detected results: After performing all the previous steps, the results are obtained which clearly classify and determine the brain tumor levels in the input image. The implemented novel automatic segmentation method based on Convolutional Neural Networks and deep learning provides accurate results. An automatic feature selection algorithm scans the input MRI images for important features without any human supervision necessary. The deep learning algorithm used in the project trains itself automatically at a fast rate and learns the underlying problem from input data, thus improving the model accuracy and the accuracy of results obtained.

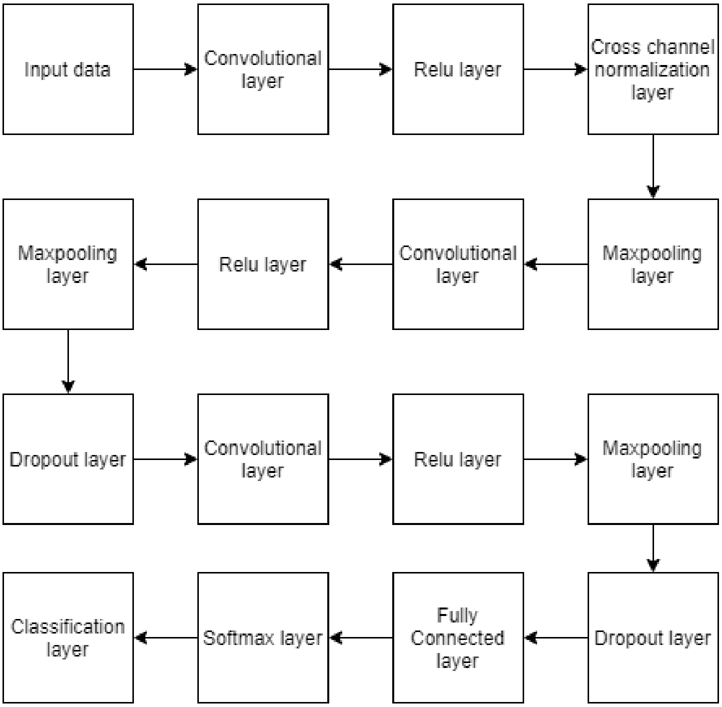

Fig. 4. Convolutional Neural Network built for brain tumor analysis

The Convolutional neural network proposed in this paper has 16 layers as shown in Fig. 4. Details of these layers:

Input layer: An image input layer inputs images to a network and applies data normalization.

Convolutional layer: This layer performs a convolution between the input image and the image kernel selected.

Relu layer: The Rectified Linear Unit is an integral component of the convolutional neural networks' process. The use of a rectifier function is to increase the percentage of non-linearity in the input MRI images. This operation is performed because images are non-linear in nature. It has several transitions between pixels, several colors, and abrupt borders. The Relu layer breaks the linearity even further in order to compensate for the linearity that is imposed on the input image when it is subjected through the convolution operation.

Cross channel normalization layer: The cross-channel normalization layers are used to prevent sudden variations in gradients such as vanishing or exploding gradients, to stabilize the CNN training, and to support learning which has higher rates and faster convergence. Using the elements from a certain number of neighboring channels, normalization layer replaces each element with a normalized value it obtains.

Maxpooling layer: The purpose of a maxpooling layer is to reduce the number of connections to the further layers by performing down-sampling. The down-sampling is done by dividing the input into rectangular pixel regions and computing the maximum of each region.

Dropout layer: The dropout layer helps prevents the overfitting of the Convolutional Neural Network by setting the input elements to zero with a given probability. Dropout mask random (size(X)) < Probability, sets input elements to zero, where X is the layer input and then scales the remaining elements by 1/(1-Probability).

Fully-connected layer: The fully connected layer identifies patterns by combining all the features which are learned in the previous layers of CNN. A bias vector is added to the weight matrix which is multiplied by the input. It also combines the features to classify the images based on tumor types and levels.

Softmax layer: The softmax layer applies a softmax function to the input which is as shown in Fig. 5. Softmax is used in neural networks to map the non-normalized output of a CNN to a probability distribution over predicted output classes.

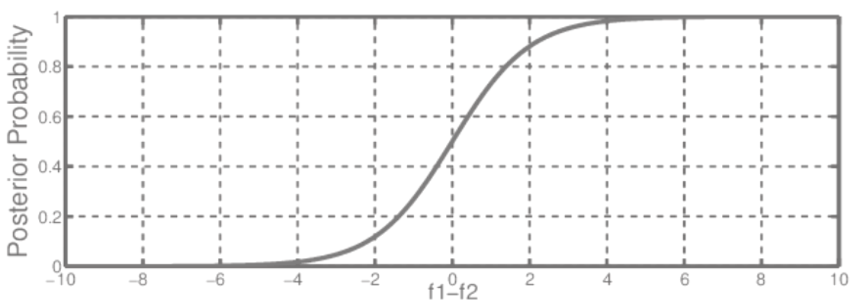

Fig. 5. *Softmax layer characteristic function*

Classification layer: The classification layer computes the cross-entropy loss for multi-class classification problems with mutually exclusive classes. Cross-entropy is a measure of the difference between two probability distributions for a given random variable or set of events.

The CNN based brain tumor analysis is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumor and non-tumor brain image etc. Prediction model is made in the training phase, preprocessing, feature exaction and classification with Loss function.

Initially, label the training image set. In the preprocessing image resizing is applied to change size of the image. Finally, the convolution neural network is used for automatic brain tumor classification and remaining lifetime prediction of the brain tumor patient.

3.0 Results and Discussion

The developed brain tumor analysis system is given an input dataset, Fig. 6.

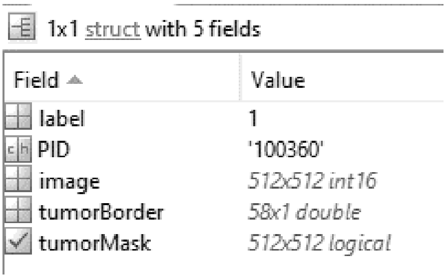

Fig. 6. Input image in .mat format

The Graphical User Interface is shown in Fig. 7.

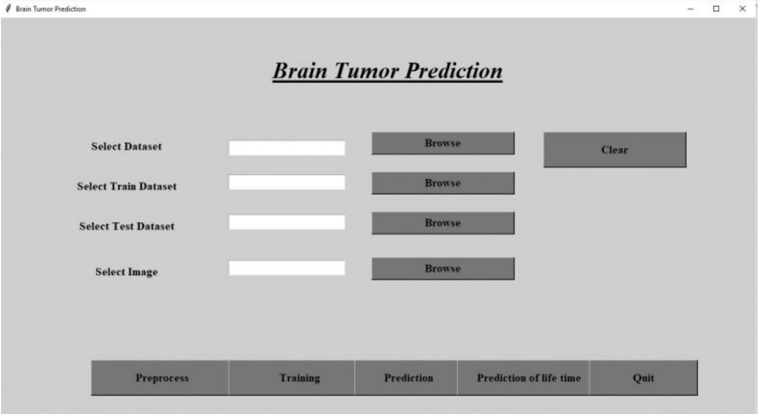

Fig. 7. GUI developed for Brain tumor prediction and analysis

User can use the GUI to select the input dataset, performing the training of the CNN, test the model developed for testing images, determine the level of tumor and also predict the remaining life time of the patient. In the preprocessing step, the input .mat image is converted into jpeg format which is as is shown in Fig. 8.

Fig. 8. Input MRI image in jpeg format

This input MRI image is subjected to feature extraction which gathers the various features embed in the image. The output of feature extraction is as shown in the Fig. 9 where the red spots indicate the important features scanned by the feature selection algorithm implemented in the project.

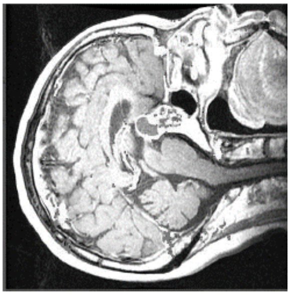

Fig. 9. Feature extracted image

The input image is also subjected gray blur whose output is shown in Fig. 10. This is done to average out the sudden changes in pixel intensity. It removes the odd pixels that cause noise in the image.

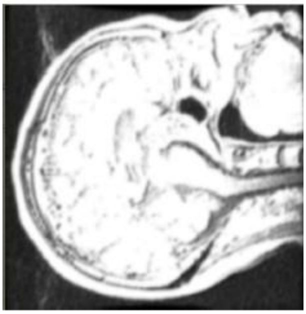

Fig. 10. Input image subjected to Gray blur

Image thresholding is performed to create a binary image from input grayscale image. The result is as shown in Fig. 11. This is often done to separate operate/foreground pixels from background pixels which helps in accurate image processing.

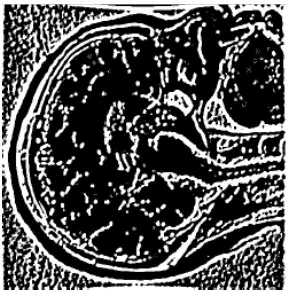

Fig. 11. Output of thresholding operation

Image segmentation is one of the crucial image processing operations done. The output of this step is as shown in Fig. 12.

Fig. 12. Segmentation of input image

Image segmentation is the process of assigning a label to every pixel in the image so that pixels with the same label share particular characteristics. Fig. 13 depicts the final result with the tumor location marked in a red circle

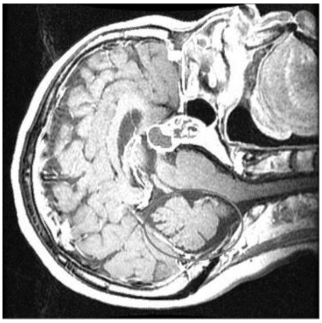

Fig. 13. Final result image with tumor location

The tumor level and class of the selected input MRI image is as shown in Fig. 14. The class of tumor is Meningioma and it is benign in nature.

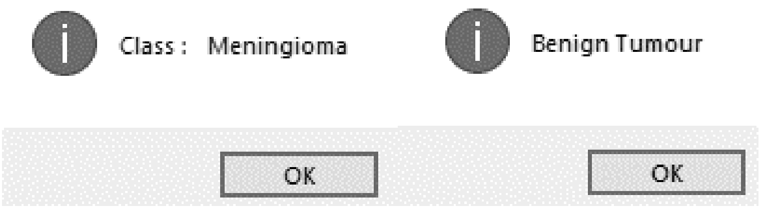

Fig. 14. Result depicting the tumor level and class

The model developed also gives the approximate remaining lifetime of the patient based in the average value of pixels obtained in the CNN output. This is as shown in the Fig. 15.

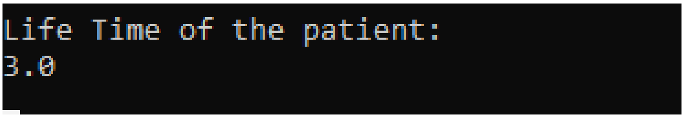

Fig. 15. Result depicting the approximate remaining lifetime of the brain tumor patient

In this case, the average value of the pixel lies between 0.6 and 0.7 and hence the approximate remaining lifetime of the patient is predicted to be 3 years.

Training and validation accuracy of the proposed model is shown in Fig. 16 and calculated by using keras callbacks function. The training and validation accuracy is observed while operating with the different number of epochs. Maximum accuracy of 96.13% is obtained after 5epochs in the developed model .

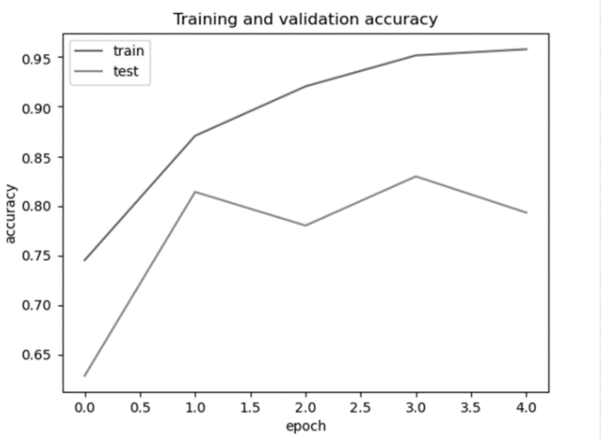

Fig. 16. Accuracy of the proposed CNN model

Table I depicts the performance comparison between the Zacharaki et al model and the model proposed in this system.

The proposed model achieved an accuracy of 96.21% that is 2945 images are correctly predicted and classified out of 3061 images. Three parameters are returned for every input MRI image: (i) class of the detected tumor, (ii) probability of the tumor being in that class and (iii) tumor location.

This procedure uses the deep learning Tensorflow library. In this library, the minimum softmax probability value feature is set to 0.8 for assigning a class label to a detected tumor by default. This means that a tumor whose probability value lies below 0.8 goes unclassified. By modifying this probability threshold the variation in number of misclassified and unclassified images is observed.

In this research MRI brain images are fed as the input for detection and classification of tumor using the automatic method based on CNN and Deep Learning. This CNN model is trained using images containing three types of tumor. Based on the classification and detection accuracy of 96.21% is obtained as shown in Table 1, it can be concluded that the model developed is suitable for this problem which is better than similar work.

The major advantage of Deep Learning is that the classification accuracy increases with the increase in number of training image samples. The CNN model used in the paper shows the location of tumor and has a high classification accuracy as mentioned above.

Table 1. Performance Comparison

Methodology	**Accuracy %**
Zacharaki et al	85
Proposed Deep learning based CNN model	96.21

4.0 Conclusions

This paper introduced deep learning based CNN to automatically analyze and classify three types of brain tumor Glioma, Meningioma, and Pituitary and two levels-benign and malignant. The implemented model achieved an accuracy of 96.21% that is 2945 images are correctly predicted and classified out of 3061 images. It also predicted the remaining lifetime of brain tumor patients in years. This analysis can be used by doctors to diagnose patients better.

Limitation of the method is that Input MRI images which are misclassified/unclassified are output as not containing any tumors even though they have a tumor in its initial stage. This can be overcome by adding healthy brain MRI images to the model training dataset. Additional algorithms such as histogram equalization can be incorporated in the image pre-processing step to supplement missing of crucial features in such images.

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