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Brain Tumor Detection using CNN

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Abstract **-**Tumor is an abnormal growth of cell in human brain which is fatal if treatment is not provided at right time. Various imaging technique such as MRI, ultrasound are used to detect the tumor. Earlier, initial stage of tumor were detected manually through observation of image by doctors and the results obtained were sometimes inaccurate and process was time consuming due to large volume of data generated by MRI Scan. Automatic classifications methods are required for proper diagnosis of tumors which can be provided by image processing techniques. Image processing techniques involves four stages such as feature extraction, image segmentation, image pre-processing. In this paper a classifier based on a convolution neural network (CNN) is considered. Experimental result shows that CNN provides 97.33% accuracy.

***Index Terms* - Brain Tumor Detection, CNN, Image Preprocessing.**

I. INTRODUCTION

The management hub of the human body is the brain. It is in charge of carrying out all activities through a vast network of connections and neurons. One of the most dangerous conditions is a brain tumor, when brain cells grow abnormally and interfere with the nervous system's functions. Brain tumors occur in a variety of forms and can be either malignant or benign. Early tumor detection is dependent on the doctor's training and experience, giving the patient a chance to live and survive. The use of an automated approach for classifying brain tumors can help doctors choose a successful course of treatment. This technique makes use of pictures taken by brain radiologists' popular magnetic resonance (MR) imaging equipment.

The identification of a brain tumor correctly and other characteristics such as the type of tumor, its location, size, and stage of development will all affect how it is treated. Previously manually determining the tumor's stage with the aid of physicians' observation of the image, and sometimes it requires more time, and the results can be wrong. Only a qualified doctor is able to provide an accurate diagnosis for one of the many different types of brain tumors. A common tool added to computers today is utilized in the medical industry. These instruments have the quickness quality. And precise outcome. The most popular imaging method for examining a person's internal organs is magnetic resonance imaging (MRI). The key to successful treatment is accurate tumor detection. A precise Diagnosis tool is also necessary for effective treatment. Finding a tumor's Presence is the first step in detection. Four steps are

Required to identify a tumor using image processing methods. Image processing before segmenting and highlighting classification and extraction. Reprocessing's main goal is to raise the standard of the Magnetic Resonance (MR) images, which eliminate unnecessary noise, Keeping its boundaries while putting unwanted elements in the background. The pre-processed brain MR images are turned into binary pictures during segmentation. Feature extraction is the procedure for collecting more in-depth data from an image, colour, form, texture, and contrast are a few examples.

II. LITERATURE SURVEY

[1] A Hybrid Feature Extraction Method with Regularized Extreme Learning Machine for Brain Tumor Classification

The classification of the brain tumor is a crucial step that depends on the doctor's experience and knowledge. The brain tumors automated classification essential to aid radiologists and doctors in determining the tumor. Despite this, the current systems' accuracy needs to be enhanced for the treatment to be effective. The method that is suggested in this research includes feature extraction from the image, pre-processing of the brain image, and categorization of a brain tumor. The brain pictures are then subjected to feature extraction hybrid feature extraction, followed by computation of the features' covariance matrices after being extracted and projected employing a principle component, into a significant group of features analysis (PCA). Ultimately, a regularized extreme learning machine is used showed that the suggested strategy was successful and is more effective than the present methods. Also performance in terms of categorization accuracy improved for the experiment from 91.51% to 97.33%.

[2] Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines

In this paper the proposed approach includes (1) Pre-processing, (2) Training the SVM & (3) Submit training set to SVM and output the obtained predictions. At first stage denoising the medical images using different kind of wavelets while maintaining the important features. In segmentation for the extraction of the features, Otsu method was used for converting grey-level image to binary image. Finally, the data had two classes and SVM was applied for classification. The outcome shows that SVM with proper training dataset is able to differentiate between normal and abnormal tumor regions and categories as malignant tumor, benign tumor or a healthy brain.

[3] Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images

Out of different types of brain tumors, malignant tumors are assertive and commonly occurring, decreasing the life expectancy. MRI is extensively used imaging method for assessing the tumors for resolving this, an automatic segmentation technique based on CNN is proposed, exploring small kernels. Employing small kernels allows designing a deeper architecture, alongside having an advantage against over fitting, given the small number of weights in the network. Use of intensity normalization in pre-processing with data augmentation has proven to be effectual for brain tumor segmentation in MRI images.

[4] Capsule Networks for Brain Tumor Classification Based On MRI Images and Course Tumor Boundaries.

As stated by the WHO, cancer is deemed to be second leading cause of human casualties. Out of different types of cancer, brain tumor is perceived as one of the fatal due to its vigorous nature, diverse characteristics and relatively low survival rate. Discovering the type of brain tumor has remarkable impact on the choice of therapy and patient's survival. Human based identification is usually inaccurate and unreliable leading in a recent sweep of interest to automize this process using convolutional neural network (CNN). As CNN fails to completely utilize spatial relations, which may lead to incorrect tumor classification the main offering is to provide Caps Net with access to tissues neighboring the tumor, without diverting it from the principal target. An improved Caps Net architecture is consequently proposed for the classification of brain tumor that takes the coarse boundaries of tumor as additional input within its pipeline for surging the focus of the Caps Net.

[5] Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI

Segmentation method is used for the purpose of analysis, and is done to distinguish the brain tumor tissue from other tissues such as fat, edema and normal tissue. The MRI image must be maintained at the edge of the first image with median filtering, followed by segmentation process that requires thresholding. Segmentation process is performed by giving a mark on the area of the brain and area outside the brain using watershed method then clearing the skull with cropping. 14 brain tumor images are used as an input in this study. The segmentation result compares brain tumor area with brain tissue area. The tumor was determined with average error rate of 10 percent.

3. PROPOSED SYSTEM

According to a literature review, automated brain tumor detection with high accuracy is essential when human lives are at risk. Automated tumor detection involves feature extraction and categorization in MR images. This paper outlines a machine learning system to automatically find tumors in MRI images. The proposed methodology is depicted in fig1.

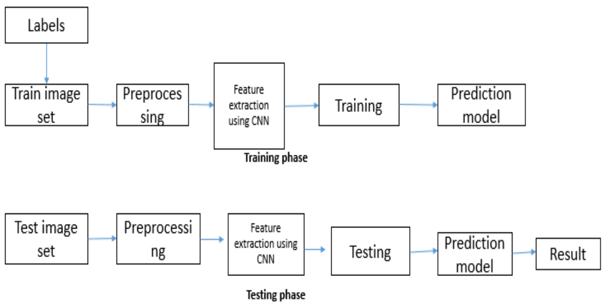


Fig.1: System Architecture

METHODOLOGY (CNN):

The procedure is divided into two phases, namely the training and testing phases. Training phase always takes place before testing phase. The feature extraction and classification is done by convolution neural network (CNN). Training image set are used to train the model and testing dataset are used to validate the model. Generally, labelled image set are used to train the model (Fig 1).

Convolutional neural network (CNN, or ConvNet) is a form deep learning and most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptron designed to require minimal pre-processing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared weights architecture and translation invariance characteristics. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand engineered. This independence from prior knowledge and human effort in feature design is a major advantage. They have applications in image and video recognition recommender systems, image classification, medical image analysis, and natural language processing. A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers.

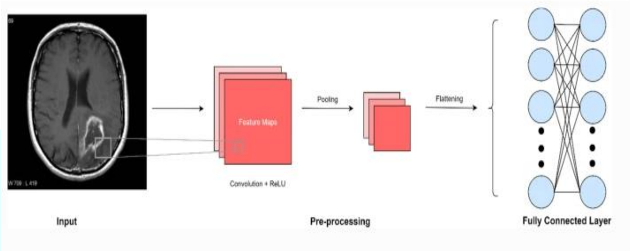
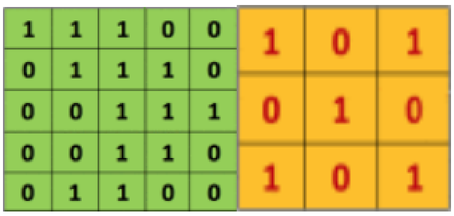


Fig2. Simple Convent

The input images are divided into 6 classes namely Benign, no tumor, glioma, pituitary, malignant, meningioma.
Benign tumor is a mass of cells that grows relatively slowly in the brain.
Glioma and malignant both are same but glioma don’t usually spread outside spine but malignant spread.
Pituitary tumor that forms in the pituitary gland near the brain that can cause changes in the hormone levels in the body.
Meningioma tumor that arises from the meninges the membranes that surround the brain and spinal cord.
A number of the ConvNet in the above figure has four major operations:

1. Convolution
2. Non-Linearity (ReLU)
3. Pooling or Sub Sampling
4. Classification (Fully Connected Layer)

The Convolution Step:
The "convolution" operator is where the name "ConvNets" comes from. In the case of a ConvNet, the main goal of convolution is to extract features from the input image. Convolution keeps the pixels' spatial connection by learning employing tiny squares of input data to create image characteristics. Every image is thought of as a matrix of pixels as stated above. Consider a 5 × 5 image. Pixels can only have values of 0 and 1.



Also, consider another 3 x 3 matrix as shown. Then, the Convolution of the 5 x 5 image and the 3 x 3 matrix can be computed as shown in the Fig3:

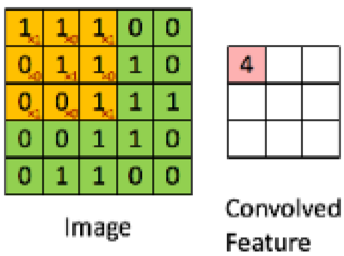


Fig3: The Convolution operation

Slide the orange matrix over our original image (green) by 1 pixel (also called 'stride') and for every position, compute element wise multiplication (between the two matrices) and add the multiplication outputs to get the final integer which forms a single element of the output matrix (pink). Note that the 3×3 matrix "sees" only a part of the input image in each stride. In CNN terminology, the 3×3 matrix is called a 'filter' or 'kernel' or 'feature detector' and the matrix formed by sliding the filter over the image and computing the dot product is called the 'Convolved Feature' or 'Activation Map' or the 'Feature Map'. It is important to note that filters act as feature detectors from the original input image.

Introducing Non-Linearity (ReLU):

An additional operation called ReLU has been used after every Convolution operation in Figure. ReLU stands for Rectified Linear Unit and is a non-linear operation. Its output is given by:

Fig4: ReLu function

ReLU is an element wise operation (applied per pixel) and replaces all negative pixel values in the feature map by zero. The reason ReLU is used in a Convolutional Neural Network is because most real-world data is nonlinear. This introduces a nonlinear function into the network, which helps to account for the complexity of the data.

The Pooling Step:

Each feature map's dimensionality is decreased but the most crucial data is retained by spatial pooling, also known as subsampling or down sampling. Spatial Pooling may be useful for several categories, including Max, Average, Sum, etc. In the Max Pooling scenario, specify a spatial neighborhood (for instance, a 2 by 2 window) and select the largest element from the rectified feature map inside that window. The total of all the items in that window is the average of all of them. It has found that Max Pooling works better with practice. Fig5 Demonstrates a Max Pooling operation on a Rectified object.

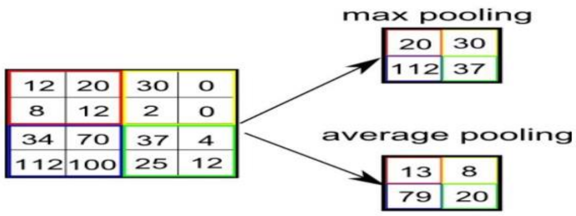


Fig5: Pooling

As shown in Fig5, this reduces the dimensionality of our feature map.

4. RESULTS

Dataset contains tumor and nontumor MRI images and collected from different online resources. In this work, efficient automatic brain tumor detection is performed by using convolution neural network. Simulation is performed by using python language. The accuracy is calculated and compared with the all other state of arts methods. The Support Vector Machine based classification is performed for brain tumor detection. It needs feature extraction output. Based on feature value, In the proposed CNN based classification doesn't require feature extraction steps separately. The feature value is taken from CNN itself. The accuracy is obtained by using CNN is 97.33%.

In training phase and testing phase

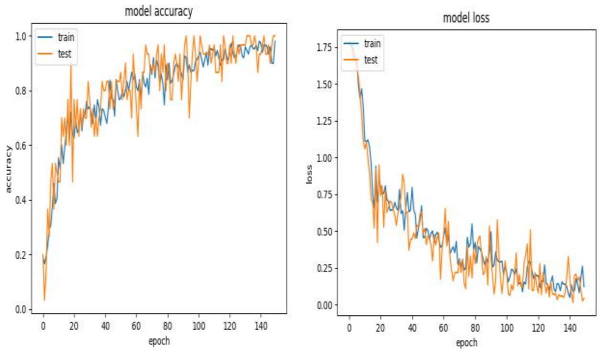


Fig 6: Accuracy of brain tumor classification

In the Fig 6 it shows that the percentage of model accuracy and model loss. Here 150 epochs are considered and got 97.33% model accuracy.

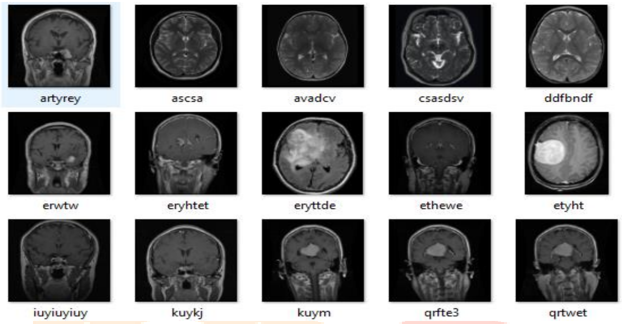


Fig7: Input images for tumor classes

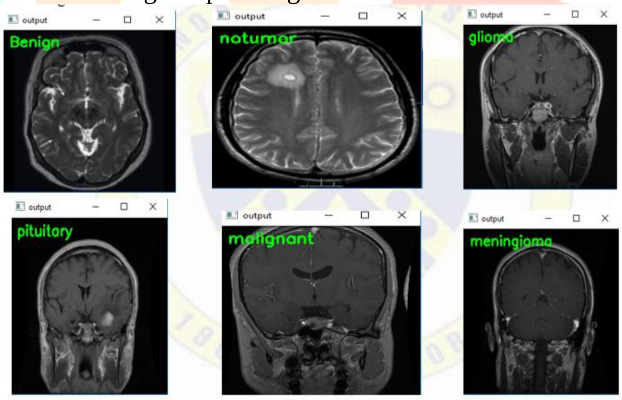


Fig8: output of tumor classes prediction

In the Fig8 shows that output of classes prediction, it shows output of 6 classes of tumor namely, Benign, no tumor, glioma, pituitary, malignant, meningioma. If random brain tumor images are given it will predict these 6 classes.

5. CONCLUSION

CNN is considered as one of the best technique in analyzing the image dataset. The CNN makes the Prediction by reducing the size the image without losing the information needed for making predictions. The model developed here is generated based on the trial and error method. In future optimization techniques can be applied so as to decide the number of layers and filters that can use in a model. As of now for the given dataset the CNN proves to be the better technique in predicting the presence of brain tumor.

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