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BRAIN TUMOR CLASSIFICATION USING CNN

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Abstract

Cancer is undesirable cell progress which increases intracranial pressure within the skull. For the most part, different image techniques, for example, CT scan, MRI and ultrasonography images are utilized to assess the tumor in a mind, lung, bosom, liver, prostate… and so on. The recognition of Mind tumor is generally done by Magnetic resonance imaging (MRI). The major drawback of this is to find the exact location/position. Hence it becomes important to find the means and methods to detect, identify and classify the disease based upon the image. Reliable and automatic classification system is important to avert human death rates. The automated classification of brain tumors is very difficult chore in broad spatial and structural heterogeneity of the surrounding brain tumor area. Automatic brain tumor finding is proposed in this work, by using the classification of CNN, where our primary objective is to build a deep learning model that can successfully recognize and categorize images into either a Brain Tumor (tumorous) or a Not a Brain Tumor(non-tumorous). In this paper, we present a CNN based transfer learning method to classify the brain MRI scans into 2 classes using VGG16 (pre-trained model). Experimental outcomes show that the CNN archives a 96.5% training accuracy and 90% testing accuracy with low complexity differentiate with all other approaches of the state of the art.

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I. Introduction

Brain cancer is an uncontrolled collection of tissue may be implanted in the sections of the mind that makes the responsive functioning of the body to be disabled. Tumor can be separated into 2 types: benign and malignant tumors.

Benign tumors are those that can grow and affect the rest of healthy brain tissue. Generally, malignant tumors grow outside the brain and are called brain cancer [1]. The image technique plays a key role in brain tumor diagnosis and treatment. Tumor imaging can be performed in many ways including CT scanning, MRI etc. MRI picture for a brain contains huge volume of spatial brain structure info and it can be used for medical diagnosis. Brain tumors are considered one of the most dangerous and complicated types of tumors to diagnose and treat [3]. With the progress of nearly two decades, the ground breaking approaches to the application of computer-aided techniques for the segmentation of brain tumor are gradually maturing and coming closer to standard clinical applications.

There are two phases in the brain tumor: -

(1) Primary stage

(2) Secondary stage

A primary brain tumor stage sets in motion in the brain. Many critical tumors of the mind are either pleasant, or dangerous. Amiable Malignancy does not degree from single body piece to next body piece. It may grow into brain cells, nerve cells, organs.

A secondary brain tumor stage, otherwise called a metastatic cerebrum cancer, arises subsequent to tumor cells degree to the tumor from elective body piece, for example, kidneys, lungs, skin or bosom. Auxiliary mind tumors are constantly threatening which can begin from the single piece of the body and increase into the other [1].

We used various methods such as SOM Clustering, Kmean clustering, Fuzzy C-mean technique, SVM, Deep Neural Network (DNN), and Convolutional Neural Network (CNN) to extract and segment the cancer. It can be seen that brain tumor identification from MRI images is achieved using different methods.

Brain MRI image is used mainly for tumor detection and tumor progress modeling process. Such knowledge is used specifically for the diagnosis and treatment of tumors. MRI image provide more data than the Computed Tomography or ultrasound picture on the given medical picture. MRI image provides detailed information about brain structure and anomaly detection in brain tissue.

Magnetic resonance imaging (MRI) is a radiology-based medical imaging technique used to create representations of the structure and physiological processes of the body health and disease. MRI scanners use strong magnetic fields, radio waves, and field gradients to generate images of the inside of the body.

MRI is founded upon the learning of nuclear magnetic resonance. Certain atomic nuclei, when placed in an outside magnetic field, can absorb and produce radiofrequency energy [5].

Hydrogen atoms are most often used in clinical and research MRIs to generate a detectable radiofrequency signal that antennas receive in close proximity to the anatomy being examined [7]. Hydrogen atoms naturally exist in abundance in humans and other biological organisms, especially in water and fat.

II. Related Works

In [1], goal is to provide a comprehensive overview of brain tumor and brain tumor imaging first. Then, they study the state of the art in correlated to cancercomportment brain pictures with an emphasis on gliomas in division, identification, and modelling. The segmentation objective is to outline the cancer with its sub-compartments and nearby tissues, while the main task in registration and modeling is the treatment tumorinduced morphological variations. The attributes of various methods are explored with an emphasis on methods which can be useful on standard protocols for medical imaging.

In [2], a fully automatic DNN-mind tumor segmentation method. The projected networks are tailored to the glioblastomas pictured in MR images (both low and high grade). CNN simultaneously exploits both local characteristics as well as more universal relative features. The networks also use a final layer, which is a convolutionary execution of a FC layer, that is dissimilar from most conventional usages of CNNs.

In [3], a review of methods for division of mind tumor based on MRI. Focus also on the recent trend in this field of deep-learning methods. First, there is an overview to mind cancers and approaches for segmentation of mind tumor. Then the state-of-the-art procedures are explored, with an emphasis on the current trend in deep learning methods.

In [4], the segmentation of Fuzzy C-Means (FCM) is applied to distinct the brain-tumour and non-tumour regions. Wavelet features is also extracted using multilevel DWT. Eventually, high precision DNN is implemented for the classification of brain tumors. This technique is compared with the classification method of KNN, Linear Discriminant Analysis (LDA) and Sequential Minimal Optimization (SMO). A 96.97% accuracy rate in the DNN based brain tumor classification analysis but the intricacy is very higher and performance is very lower.

In [5], a novel bio-physiomechanical tumor development demonstrating is introduced to break down the progression by steps tumor growth of patients. It will be applied for gliomas and strong tumor with singular edges to seizure the huge tumor mass impact. The discrete and consistent strategies are joined to make a tumor development displaying. The proposed plan gives the probability to implicitly fragment tumor-bearing cerebrum pictures dependent on map book-based enrollment. This procedure is essentially utilized for mind tissue segmentation. But the calculation time is high.

In [6], new multi-fractal (MultiFD) featureextraction and improved AdaBoost order plans are utilized to identify and fragment the mind tumor. The surface of cerebrum tumor tissue is extricated by utilizing MultiFD highlight extraction conspire. The improved AdaBoost arrangement strategies are utilized to locate the given mind tissue is tumor or non-tumor tissue. Intricacy is high.

In [7], nearby local independent projection-based characterization strategy is utilized to group the voxel of the cerebrum. Also, path feature is mined in this process. Thus, no compelling reason to perform unequivocal regularisation in LIPC. The precision is low-level.

In [8], a seeded tumor division strategy with new Cellular Automata (CA) system is displayed, which is contrasted and chart cut based division technique. The seed choice and Volume of Interest (VOI) is determined for productive mind tumor division. Additionally, tumor cut division is fused into this work. The intricacy is low. Yet, the precision is low.

In [9], new mind tumor division is presented, which is likewise called multimodal cerebrum tumor division conspire. Likewise brushing distinctive division calculation so as to accomplish elite than the current strategy. Be that as it may, the intricacy is high.

In [10], the study of mind tumor division is introduced. Talk about Various division techniques, for example, Region based division, limit-based division, fluffy *C* Means division, Atlas based division, geometric deformable model, Margo Random Field (MRF) division, deformable model the exactness, power, legitimacy is examined for all the strategies.

In [11], the fuzzy based control theory is utilized for mind tumor division and arrangement technique. The Fuzzy Interference System (FIS) is a one uncommon strategy, which is for the most part utilized for cerebrum division. Managed grouping is utilized to make an enrollment capacity of fluffy controller. The presentation is high and precision is low.

In [12], The pretrained CNNs, such as VGG-Net and AlexNet, are used to extract the features for an image search and classifications.

III. Proposed Methodology

The human brain is modeled on using neural network design and implementation. Neural networks are a set of algorithms that are loosely modelled after the human brain and intended to recognize patterns. The neural network is mainly used for vector quantization, estimation, data clustering, pattern matching, optimization functions and classification techniques.

Based on their interconnections the neural network is classified into three types:

1. Feedback Neural Network
2. Feed Forward Neural Network
3. Recurrent Neural Network

Image cannot be scalable within the usual neural network. Yet image can be scalable in CNN. CNN takes volume of 3D input to volume of output 3D (length, width, height).

The Convolution Neural Network (CNN) consists:

1. Input layer
2. Convolution layer
3. Rectified Linear Unit (ReLU)
4. Pooling layer
5. Fully Connected layer (Dense layer)

A general architecture of CNN is shown in figure below:

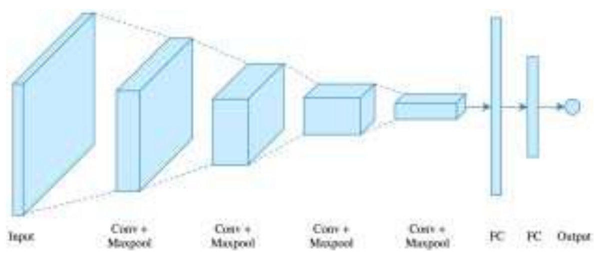

Figure 1. General architecture of CNN [16].

The first layer in CNN is convolutional layer. CNN's use filters to extract input image features. A filter is a matrix of predefined weights that are used to detect specific features. The provided input image is divided into specific, small regions in the convolutional layer. Convolution layer simply helps us filter out specific features from the input image resulting in a stack of filtered images. where the relu function then applied to account for non-linearity. After applying relu function the filtered images can now be processed in the pooling layer. Pooling's function is to reduce the number of parameters and computation in the network. Pooling layer operates on each feature map independently. It helps in reduce overfitting by reducing dimensionality of the filtered image which we get after applying relu function.

The CNN procedure initiates with convolution and pooling, the image is broken down into features and analyzed independently. The product of this procedure feeds into a fully connected neural network structure which drives the final decision on the classification.

The classification of brain tumor based on CNN is divided into 2 phases, such as training and test phases. The quantity of images is separated into different categories by using name labels such as tumor and non-tumor brain image.

The methodology proposed is prepared in 3 distinct steps. In the first step, data pre-processing for the tumor detection dataset on the brain MRI images is done to run and test the model developed. Data incrementation or augmentation is done in second step.

Finally, in the third step, VGG16 a pre-trained CNN model is trained and uses transfer learning to categorize a given tumor as malignant or benign. VGG16 is a 16-layer architecture.

Pre-processing, augmentation, feature exaction and loss function classification are performed in training step to create a predictive model. Primarily, label the training picture set. Resizing of the image is applied in the preprocessing to adjust the image according to vgg16 architecture i.e. 224* 224.

The CNN is used for automated detection of the brain tumors. I am using Transfer Learning with VGG-16 architecture and weights as a base model. Eliminate the last fully connected layer i.e. output layer, run the pretrained model as a fixed feature extractor, and then use the outcome features to train a new classifier. Actually, VGG16 architecture is an image-classification model and also Pretrained on the ImageNet Dataset. If you want to train from the start layer, we need to train the whole layer i.e. to the end layer. So, it is very high time consumption. It will affect the model performance. We'll only train last layer in the proposed CNN. We don‟t have to train all the layer.

VGG16 network architecture is shown in the figure below:

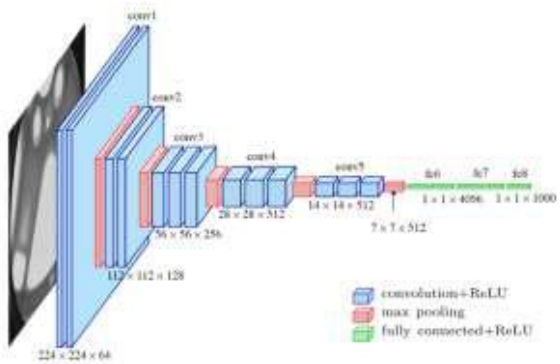

Figure 2. General architecture of CNN [17].

Meanwhile the efficiency is high, computation time is low. To improve the accuracy the estimation of the loss function is very important. If the loss function is high, then the precision is low. Similarly, when loss function is low the accuracy is high.

Algorithm for CNN based Classification

1. Import libraries

2. Image pre-processing steps

3. Import "ImageDataGenerator" for Data

Augmentation

4. 'train_datagen.flow_from_directory()' by using this generate the data

5. Apply Transfer Learning and download the weights of VGG16 model

6. Add dense layers with Sigmoid Activation function

7. Compile the model (optimizer, loss, metrics as a parameters)

8. Run the model by using 'model.fit_generator()'

IV. Result and Discussion

Our data set includes MRI pictures for tumor and nontumor and collected from various online resources like: ImageNet, BRATS. Radiopaedia contains real cases of patients.

In proposed method, we use Transfer Learning with VGG16 Model Architecture for Brain Tumor Classification model. The feature extraction output is required in the SVM-based Brain Tumor Classification Model (traditional methods) and the classification output is created using those feature values and the accuracy is calculated. High calculation time and low accuracy.

In Proposed CNN based classification model does not require Feature Extraction step separately because Convolutional Base has provided Feature Maps and the feature value is taken from CNN itself.

In figure 3 and figure 4 shows the Model Accuracy and Model Loss of Proposed Model. The time of computation and complexity is low, and an accuracy is high.

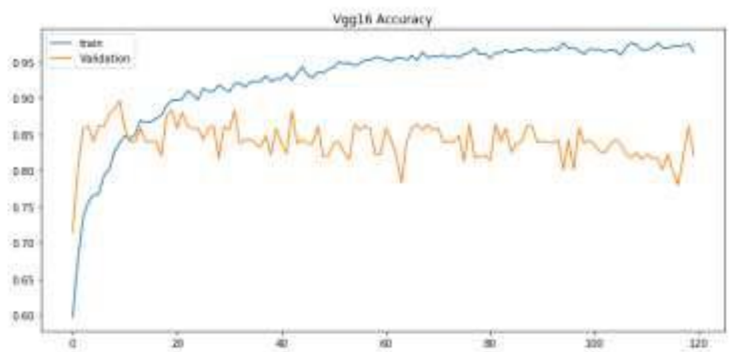

Figure 3. Model Accuracy.

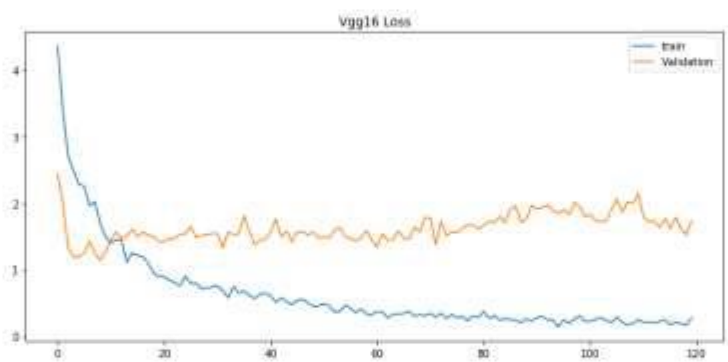

Figure 4. Model Loss.

The performance for the proposed methodology was measured in terms of Cohen's kappa(κ), F1-score, area under the ROC curve (AUC-ROC), training accuracy (96.5%) and test accuracy.

Table 1 shows the performance analysis of proposed methodology:

Table 1. Model performance.

Model	Cohens kappa (k)	F1-score	AUCROC	Training time (sec)	Accuracy
VGG16	0.80	0.90	0.90	3086.63	90%

V. Conclusion

The fundamental target of this examination work is to make productive automatic brain tumor classification with high precision, performance and low intricacy. In the conventional cerebrum tumor classification is achieved by utilizing FCM based division, texture and outline feature extraction and SVM and DNN based arrangement are bring out. The intricacy is lower. But the calculation period is higher meantime precision is low. Afore to enhance the accuracy and to decrease the calculation time, a CNN-based classification is introduced in the proposed scheme. Model Accuracy and Model Loss are given in Figure 3 and figure 4. Training accuracy is 96.5% and Testing accuracy is 90% which is pretty good as comparison to SVM, FCM based classification. So also, the validation precision is high and validation loss is exceptionally low.

In future, we can increase accuracy by using transfer learning on large datasets. And we can use a better preprocessing technique to enhance the performance of model.

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