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Detection and classification of tumor in brain using visual geometry group - 16 Architecture

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***Abstract*---**Now a day's brain tumor detection is an important matter in computer aided diagnosis for medical applications. The classification process is important and plays a vital role to diagnosis the brain tumors. The existing method concentrates on brain tumor detection, features extraction and classification. Though the traditional classification Algorithms is suffered from less accuracy and takes more time for execution. To enhance the premature stage brain tumor detection and classification, the main intension of this paper is to extract features, classification of brain tumor using VGG-16 Architecture. By using this method we achieved maximum accuracy of 99%, minimum loss, less time for execution,F1 score, sensitivity etc., as compare to CNN, for this method execution we collected the data from kaggle dataset, Brain MRI images of 2065 patients, out of which 1445 images are cancerous and 620 images are non cancerous.

Keywords---brain tumor classification, convolution neural network, VGG-16.

Introduction

In twenty-first century around 2k-3k adults are identified with brain tumor every-year in each state, and 40k-50k patients are diagnosed with brain tumor around the country out of this twenty percent are children suffering with brain tumor. The brain tumor detection and diagnose in early stage can increase the survival rate of the patient with better treatment choices. Brain tumor is uttermost serious illness. Brain is the most important organ of human body, which contains nerve cells and controls the activities of a human body such as vision, sensing etc.

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abnormalities in natural cell that leads to growth of mass of tissue in an around the brain causes brain tumor. Brain tumors are classified into cancerous and non-cancerous tumors such malignant and benign. Rapid growth of abnormal cells will affect other organs of the body called as malignant tumors. Benign tumors are non cancerous tumors which are diagnosable and we can predict it will not affect the other organs of the body. Tumor cannot be removed completely but we can predict to not growing of mass of tissue by proper treatment as per radiologist suggestion. Patients suffering from brain tumor having symptoms as headache, vision problem, vomiting, lack of vision etc. for neurologist identifying and classifying of brain tumor is difficult task and time consuming process by using traditional methods and hence automatic diagnosis methods are required for early identification of brain tumor in order to provide better treatment.

Different technologies are available in medical imaging such as MRI scan (magnetic resonance imaging), CT scan (computed tomography), PET scan (positron emission tomography) are used for early stage detection. An MRI scan gives clear information of soft tissues and tumor location in brain images. To detect a Brain Tumor, MRI scan is more effective compare to CT scan for evaluating digitally in order to have better accuracy and immediate treatment. These methods effectively classify brain tumors into benign and malignant. Frequently used traditional classifiers are Neural Networks, Random forest, Support vector machine, Genetic Algorithms. However, Deep learning technique i.e., Convolution Neural Network is commonly used method for classification but it suffers from computer vision. We proposed VGG-16 Architecture of CNN for feature extraction and classification of brain tumor. This approach can assist the radiologist to detect the brain tumor and offers better treatment to the patient at the right time to increase the survival rate of patient.

Literature review

[1] In 2020, Noreen et.al used two pre-trained models like Inception-V3 and DensNet-201 for extracting features and classification, after applying an input images Inception –V3 model the features were extracted, and once again input images are applied to Densenet-201 model for extracting different features and detection of tumor,The combined features are applied to softmax classifier for classification of tumor. Finally accuracy of the proposed model compared with traditional CNN (convolution neural network) and DL (deep learning) methods.[2] In 2014, Huang et al. used LIPC (local independent projection based classification) method for distributing each and every voxel into different diverse classes, then applied to softmax regression classification model in order to have better performance in terms of dice similarities, tumor detection compared with traditional methods unsupervised learning algorithms such as K-Means and Fuzzy clustering Algorithms are widely used for brain tumor segmentation and GBS segmentation provides an excellent performance for segmentation.[3]

In 2018, Ma et al proposed CCRF-MPAC (Connected and Concatenated Random Forest - Multiscale Patch driven Active Contour Model) for tumor segmentation, it offers high complexity while extracting features and provides better accuracy.[4] In 2019, Razzak et al. proposed 2PGCNN (2- pathway group convolution neural network) for brain tumor segmentation in order to extract local and global features of an input data parallely for reducing over-fitting complexities while sharing the parameters among them[5] and the output of convolution Neural Network considered as an another source while combining with final layer. This method is implemented on BRATS-2013 as well as BRATS-2015 in order to reduce the complexity problems and improves overall performance.[6]

In 2020,Zhan et.al proposed AGRU-NET(Attention Gate Residual U-Net) model implemented on BRATS-2017, BRATS-2018, BRATS-2019 for extracting features from noisy images.[7] In 2021, chen et al. proposed Extended Kalman Filter-Support Vector Machine, input images noise was removed by using local means filter (LMF), then applied to GLCM (Gray Level Co-occurrence Matrix) for extracting features, then applied to EKF-SVM (support vector machine) and finally iven to K-Means Clustering for tumor detection and classification, cross verifying its accuracy[8,9].[10] In 2020, salem et al. implemented CAD tool for classifying tumor from brain MRI, using chaos theory complex metrix are evaluated, then features are extracted using Discrete wavelet Transform (DWT) then applied to Gray level Co-occurrance matrix for classifying tumors into either benign or malignant.[11] these features are applied to different ML methods such as pattern Net, KNN and SVM for classification of tumor.[12] In 2019, serta et al. proposed Res-Net architecture for tumor segmentation,, then applied support vector machine and convolution neural network or features extraction and classification, results are evaluated in terms of accuracy.

Dataset and proposed methodology

Dataset

The data set has been collected from kaggle brain MRI images for detection of brain tumor. It consists of total 2065 patients data, out of which 620 are normal brain images file and 1445 are abnormal brain images file respectively. These brain MRI images are pre-processed using Gaussian filter, and augmented using shifting, rotating, resizing, thresholding and normalizing by using this techniques data size is increased. Then these augmented data is subdivided training data set and testing data set of 70% and 30% then this processed data implemented on VGG-16 Architecture in order to evaluate performance metrics of proposed system.

Block Diagram

The proposed diagram of brain tumor detection system can be shown in Figure 1. Initially Brain MRI images are taken as input for analysis.

- These input images are resized to [224,224] as required by Visual Geometry Group-16 Architecture.
- Pre-processing is performed to remove noise present in input images.
- Data augmentation is performed for processed input images in order to increase training dataset size by shifting, thresholding, rotating, resizing etc.
- The augmented images are taken as input by the Visual Geometry Group-16 Architecture for brain tumor detection and classification

- The training data is followed by testing and validation data which analyze the performance metrics of the proposed system.

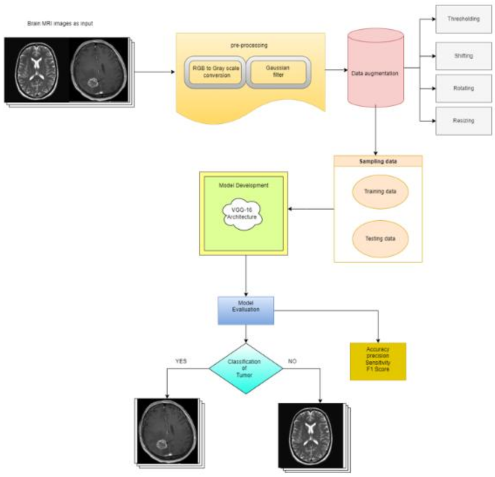

Figure 1. Block diagram of Brain Tumor detection using VGG-16

Convolution Neural Network

In deep learning (DL), a Convolution Neural Network (CNN or ConvNet) is a branch of deep learning, usually applied to image processing.VGG-16 has a 16 layers in its architecture, it is a Neural network based on CNN for object localization and classification, It is proposed by Karen Simonyan and Andrew Zisseman of the VGG Lab of oxford University in 2014. It is an outstanding model till date because of its convolution layers is having a 3x3 filter size with a stride of 1 and always used same padding, and maxpooling layers of size 2x2 with a stride 2. A Combination of convolution layers and maxpooling layers together are used to extract the features and then applied to Fully connected layer for classification, followed by a softmax output.

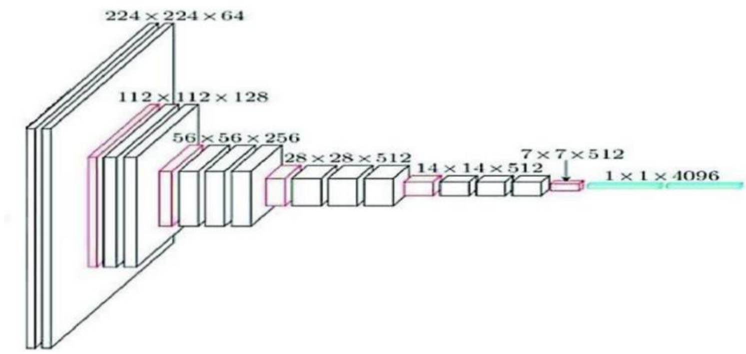

Figure 2. VGG-16 Architecture

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_2 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 112, 112, 64)	0
conv2d_3 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_4 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_5 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_7 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_3 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_8 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_10 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_13 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_5 (MaxPooling2	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 4096)	102764544
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 2)	8194

```
Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0
```

Figure 3. Layers used in VGG-16 Architecture for Brain Tumor detection

Results and Discussion

Brain tumor detection and classification plays a vital role to medical application. Early stage detection and diagnose can offer better treatment choices to patient which increase survival rate of patient. In this paper total 2065 patients brain MRI images are considered out of which 70% of images are given to training and 30% of images are given to testing, then applied to 5 convolution layers, 5 maxpooling layers with 3 dense layers and 10 epochs to train data where 1 epoch is equal to 10 steps. The results of the proposed method can be evaluated in terms of performance metrics such accuracy, loss, F1 score etc., as the epochs rises, the loss falls down. Finally, we would be able to see the output in terms of training and validation datasets. The proposed method estimate Brain tumor detection with 97.68 % Accuracy and 0.26 % Loss. The Accuracy of the proposed system can be improved further by using different datasets, and increasing epochs. The output specifies tumor whether present in human brain or not with better accuracy.

```
Epoch 1/10
130/130 [==============================] - 871s 7s/step - loss: 1.3406 - accuracy: 0.8552 - val_loss: 0.8603 - val_accuracy: 0.8877
Epoch 2/10
130/130 [==============================] - 532s 4s/step - loss: 0.8517 - accuracy: 0.9051 - val_loss: 1.6790 - val_accuracy: 0.8518
Epoch 3/10
130/130 [==============================] - 532s 4s/step - loss: 0.8478 - accuracy: 0.9240 - val_loss: 0.8406 - val_accuracy: 0.9109
Epoch 4/10
130/130 [==============================] - 533s 4s/step - loss: 0.6523 - accuracy: 0.9433 - val_loss: 0.5306 - val_accuracy: 0.9443
Epoch 5/10
130/130 [==============================] - 533s 4s/step - loss: 0.5332 - accuracy: 0.9506 - val_loss: 0.2454 - val_accuracy: 0.9700
Epoch 6/10
130/130 [==============================] - 532s 4s/step - loss: 0.4033 - accuracy: 0.9584 - val_loss: 0.1457 - val_accuracy: 0.9816
Epoch 7/10
130/130 [==============================] - 532s 4s/step - loss: 0.3726 - accuracy: 0.9671 - val_loss: 0.1351 - val_accuracy: 0.9821
Epoch 8/10
130/130 [==============================] - 531s 4s/step - loss: 0.4562 - accuracy: 0.9622 - val_loss: 0.2298 - val_accuracy: 0.9768
Epoch 9/10
130/130 [==============================] - 536s 4s/step - loss: 0.2632 - accuracy: 0.9768 - val_loss: 0.1737 - val_accuracy: 0.9821
Epoch 10/10
130/130 [==============================] - 535s 4s/step - loss: 0.3777 - accuracy: 0.9724 - val_loss: 0.0982 - val_accuracy: 0.9864
```

Figure 4. Training Dataset for Brain Tumor Detection model using VGG-16

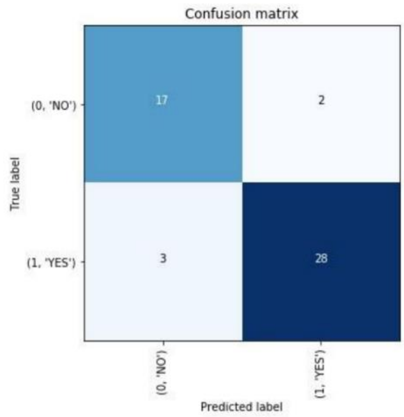

Figure 5. Confusion matrix for Brain tumor detection model using VGG-16

- True Positive (TP) - 17, Brain MRI images with tumor were correctly identified with tumor.
- False Negative (FN) – 2, Brain MRI images with tumor were identified without tumor.
- True Negative (TN) – 28, Brain MRI images without tumor were correctly identified without tumor.
- False Positive (FP) - 3, Brain MRI images without tumor were identified with tumor.

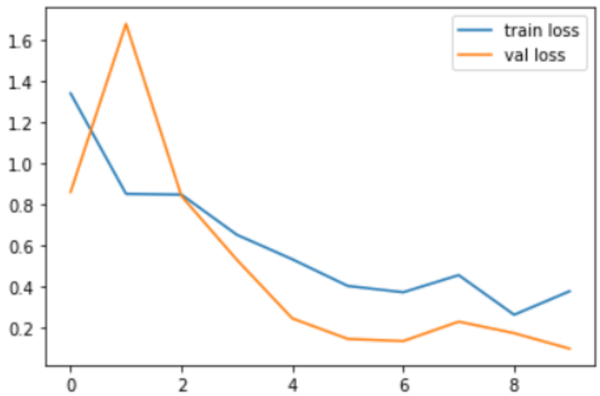

Figure 6. Training and validation loss for Brain tumor detection model using VGG-16

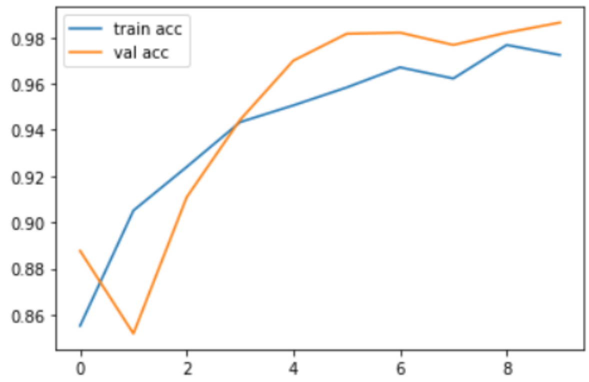

Figure 7. Training and validation Accuracy for Brain tumor detection model using VGG-16

The proposed method mainly focused on brain tumor detection accurately and in less time span for physician's, it takes brain MRI images taken as input and produces result specifies whether the tumor is present or not in the brain. This method produces results with better accuracy. In future we are able to get better results by using different dataset, other DL Algorithms. Finally brain tumor detection and classification at correct time offers better treatment possibilities which will increase survival rate of the patient.

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