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Brain Tumor Detection and Classification using Deep Learning

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Abstract: *Machine Learning (ML) models are being built for the diagnosis of different medical conditions in people. A brain tumor is one of those medical conditions. Different ML models have been built and lots are being built with improved algorithms. The purpose of these models is to reduce the need for humans as identifiers of brain tumors. Lots of Magnetic Resonance Imaging (MRI) images are produced in medical organizations. These images are then observed by medical professionals. The proposed ML model will scan these images and will provide results in a very short amount of time. This reduces many human errors and reduces the required diagnosis time. Many different models are proposed for its diagnoses like Gray-Level Co-occurrence Matrix (GLCM), Bag-of-Words (BoW), Fisher Vector, basic Convolutional Neural Network (CNN) model, watershed & thresholding segmentation, and shape features extraction. CNN models with their deep convolutional layers can be used for feature extraction. However, CNN model requires a large dataset and time to give good accuracy. The use of transfer learning models like VGG-16 can overcome the shortcomings of the basic CNN models. The proposed system uses a fine-tuned VGG-16 model for feature extraction and a softmax layer for the classification of brain tumors.*

Keywords: Bag-of-Words (Bow), Back Propagation Neural Network (BPNN), Computer-Aided Diagrams (CAD), Convolutional Neural Network (CNN), Continuous Wavelet Transformation (CWT), Decentralized Application (DAPP), Deep Learning (DL), Decision Trees (DT), Discrete Wavelet Transformation (DWT), Gray-Level Co-occurrence Matrix (GLCM), Graphics Processing Unit (GPU), Kernels Extreme Learning Machines (KELM), Machine Learning (ML), Magnetic Resonance Imaging (MRI), Multilayer Perceptron (MLP), Probabilistic Neural Network (PNN), Radial Basis Function (RBF), Rectified Linear Unit (ReLU), Support Vector Machine (SVM), Visual Geometry Group (VGG)

I. Introduction

Early detection of brain tumors can play an indispensable role in improving the treatment possibilities, and a higher gain of survival possibility can be accomplished. But manual segmentation of tumors or lesions is a time-consuming, challenging and burdensome task as a large number of MRI images are generated in the medical routine. Medical image encompasses different image modalities and processes to image the human body for treatment and diagnostic purposes and hence plays a paramount and decisive role in taking actions for the betterment of the health of the people. MRI, also known as Magnetic Resonance Imaging is mostly used for a brain tumor or lesion detection. Brain tumor segmentation from MRI is one of the most crucial tasks in medical image processing as it generally involves a considerable amount of data. Computer-Aided Diagnostic (CAD), are systems that assist doctors in the interpretation of medical images. Due to the availability of data required for analysis and advancement in technology. It is possible to do this difficult task of Detection of brain tumors using Deep Learning Algorithms. In this paper, we proposed a fine-tuned VGG-16 model which detects and classify brain tumor into four classes. For the classification of brain tumors into four classes softmax is used and the four classes are Glioma, Meningioma, Pituitary, and healthy brain.

II. Literature Survey

'Gurbina, M., Lascu, M., & Lascu, D', proposed that the cerebrum tumor discovery and grouping framework be carried out utilizing CWT, DWT, and SVMs. The proposed technique utilizes various levels for wavelets, the high exactness part is obtained utilizing CWT. In practice, SVMs have significant computational advantages. A crossover approach is suggested in addressing appropriately the identification and grouping issues in brain tumors. [1].

'Jemimma, T. A., & Vetharaj, Y. J.', showed the significance of the watershed division calculation which separates the tumor districts in a powerful way for capable DAPP including extraction. The DAPP removes the surface highlights from the portioned tumor areas and histogram highlights are acquired. In future work, for the classification and segmentation of brain tumors, some other different features can be compared to get more accuracy. Algorithms for Brain Tumor Detection 13 [2]. Zaw, H. T., Maneerat, N., & Win, K. Y.', have detected brain tumors using Naïve Bayes classification with the help of a maximum entropy threshold. The REMBRANDT database is used in this study. The developed algorithm can accurately detect the tumor in all possible locations of the brain where the tumor can exist, including the temporal lobe (which aligns with the eye level). The algorithm yields an 81.25% detection rate on tumor images and a 100% detection rate on non-tumor images with an overall accuracy of 94% [3].

'Asodekar, B. H., Gore, S. A., & Thakare, A. D., have proposed the point of the study was to break down the viability of shape highlighting in order of mind tumor as a benevolent and dangerous tumor. The shape includes a vital part of brain tumor order. Utilizing distinctive shapes include extraction and characterization with support vector machines and random forest algorithms. Model accomplished 86.66% exactness with a random forest algorithm. Applications identified with this methodology resemble object recognition, clinical, order, security, and so forth [4].

'Hussain, A., & Khunteta, A.', have completed the computation of GLCM features of images like contrast, correlation, energy, and homogeneity. At that point, the images will be grouped utilizing a support vector machine (SVM, for example, the picture with and without tumor) [5].

Ayyappa, Y., Bekkanti, A., Krishna, A., Neelakanteswara, P., & Basha, C. Z. in their paper Gaussian Filtering with MLP (Multi-Layer Perceptron)-Based BPNN (Back Propagation Neural Network) is proposed which produces better accurate results in detecting the brain tumor. They compared their proposed methodology with other Classifiers like PNN (Probabilistic Neural Network) and SVM (Support Vector machine) [6].

'Ali pashaei, Hedieh Sajedi, and Niloofar Jazayeri' in their paper have proposed two methods, first to use convolutional neural networks, consisting of 4 convolutional layers, 4 pooling layers, and 1 fully connected layer, some intermediate layers for normalizing data. The result of this method was 81.09 %. The second method used CNN for feature extraction and KELM for classifying these features [7].

Priyansh Saxena, Akshat Maheshwari, Saumil Maheshwari This paper presents a Convolutional Neural Network (CNN) based transfer learning approach to classify brain MRI scans into two classes using three pre-trained models. The performances of these models are compared with each other. Experimental results show that the Resnet-50 model achieves the highest accuracy and least false negative rates at 95% and zero respectively. It is followed by the VGG-16 and Inception-V3 models with an accuracy of 90% and 55% respectively [8].

Khan Swati, Zar Nawab; Zhao, Qinghua; Kabir, Muhammad; Ali, Farman; Ali, Zakir; Ahmed, Saeed; Lu, Jianfeng proposed a new approach for brain tumor image classification based on transfer learning and fine-tuning. The proposed strategy of transfer learning with blockwise fine-tuning suggests an alternative approach, which is different from using pre-trained CNN as an off-the-shelf feature extractor (without training) that train the separate method for classification (such as k-nearest-neighbors, Support Vector Machines, Boosted Trees, Decision Trees, and Random Forest).[9]

III. Proposed Definition

Brain Tumor is deadly cancer. More than half the patients suffering from brain tumors get treatment in the final stages when cancer spreads excessively due to late diagnosis and no treatment can slow or stop the growth of tumors. Most deaths among patients are due to late diagnosis. There are limits to the extent to which experts can recognize the patterns of the tumor to detect and classify the nature of the tumor. Computer-aided diagnosis using deep learning models can solve this problem and facilitate the detection and classification of brain tumors.Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

IV. Proposed Methodology

The proposed work will use a pre-trained fine-tuned VGG-16 model for brain tumor detection and classifying the tumor into four classes, which are Glioma, Meningioma, Pituitary, and healthy brain. The proposed model uses a fine-tuned VGG-

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16 model which gives significantly excellent accuracy and less loss compared to basic VGG-16 and CNN models.

4.1 Image Preprocessing

In image preprocessing of MRI images, first image normalization takes place and then the image is converted to grayscale. Extreme points around the skull are located which are then cropped to remove the unnecessary areas and it helps in avoiding unnecessary calculations. After converting the image into grayscale thresholding is performed to reduce the noises in the images. Dilation and erosion of images are performed using the OpenCV library. After contouring the images are of different dimensions. It is important to resize the image to the fixed dimension (224 * 224), as the VGG-16 model takes images of dimension (224 * 224) as input.

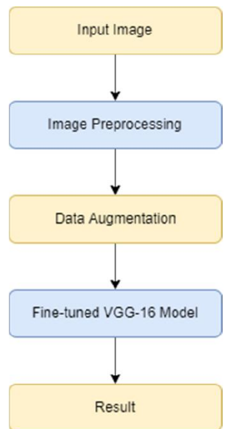

Figure 1: Flowchart of the proposed system

Then comes the data augmentation part where images are rotated or flipped to increase the size of the dataset. The dataset is available publicly which contains 3064 T1-weighted contrast-enhanced images of three kinds of brain tumors they are Glioma, Meningioma, and Pituitary tumor. These images are used for training the fine-tuned VGG-16 model. This input data is divided for testing and training. The dataset is divided into three sets they are training, validation, and testing in a 70:20:10 ratio respectively. For training fine-tuned VGG-16 model is used.

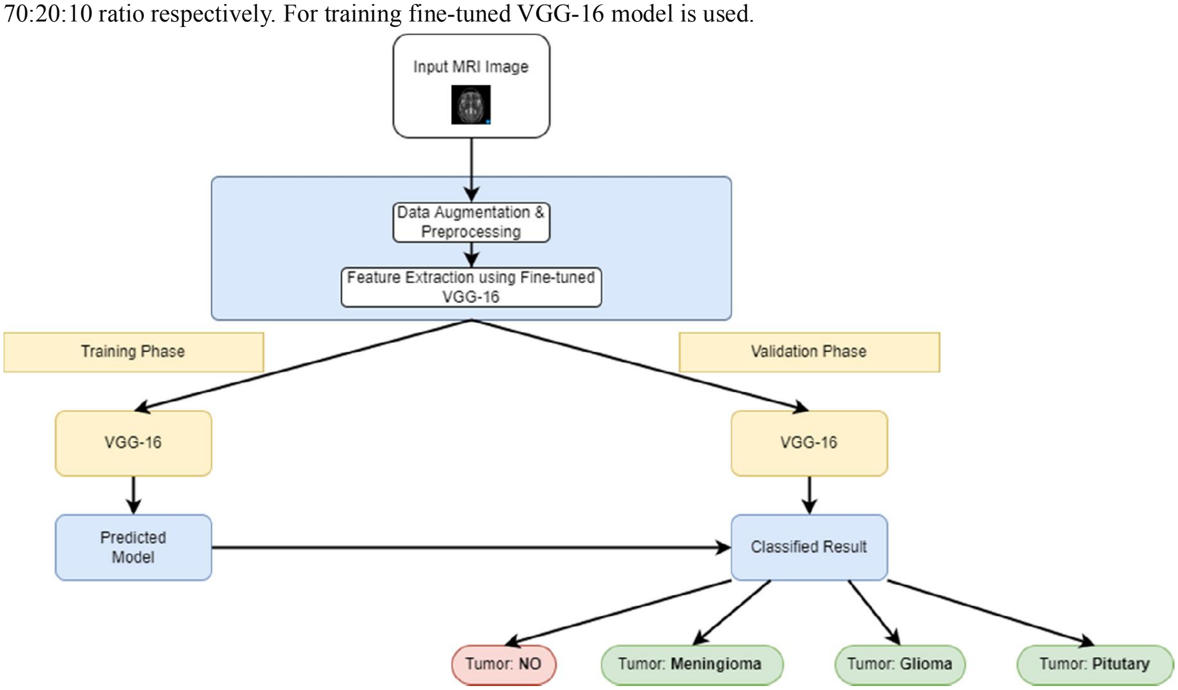

Figure 2: Proposed System

4.2 Fine-Tuning VGG-16

VGG-16 is trained on the ImageNet dataset which consists of 14 million images belonging to 1000 classes. These learned weights and filters give the network decisive feature extraction capabilities, which will help it perform better when it's trained to classify different classes. Deep layers of the VGG model can be very advantageous for feature extraction of brain tumors. VGG-16 model is pre-trained on the ImageNet dataset and it has pre-trained weights which can be very beneficial to extract generic features. In order to use this pre-trained model on the custom dataset, we have to fine-tune it so we can use the deep convolutional layers of VGG-16 very effectively.

In the fine-tuned VGG-16 model, the last convolutional block with 3 convolutional layers is re-trained with the MRI images from the dataset. The top four convolutional blocks are frozen i.e. the weights present earlier are used as they were. The reason for freezing the top three layers.

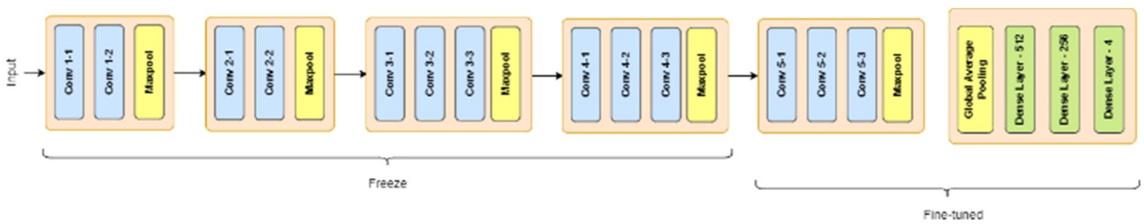

Figure 3: Fine-tuned VGG-16

In the fine-tuned VGG-16 model, the last convolutional block with 3 convolutional layers is re-trained with the MRI images from the dataset. The top four convolutional blocks are of the image into glioma, meningioma, no tumor, and pituitary. The last dense layer contains 4 neurons for the 4 classes with the softmax activation for classifying the images. A dropout of 50% is used in between each consecutive dense layer. Dropout operates by deactivating neurons and their associated connections at random. This keeps the network from depending too heavily on single neurons and drives all neurons to improve their generalization abilities. Dropout helps in countering the problem of overfitting.

4.3 Training and Optimization

The dataset used for developing the system contains a total of 3459 MRI scans. The number of MRI scans of Meningioma, Glioma, Pituitary, and no tumor is 708, 1426, 930, and 395 respectively. The dataset is split into three sections: training, validation, and testing, with a 70:20:10, split respectively for each type of tumor. The optimization used in this work is Adaptive Moment Estimation (Adam optimizer) and the loss function used is the Sparse categorical cross-entropy function. The use of sparse categorical cross-entropy saves time in both memory and computation since each class is represented by a single integer rather than an entire vector. The models can be improved by reducing the learning rate by a factor of 2 to 10 once learning stagnates. The use of ReduceLROnPlateau(), a frozen i.e. the weights present earlier are used as they were. The reason for freezing the initial layers of a VGG-16 model is because it is used to pick up small, general patterns and the later layers are used for more complex features which are very critical for brain tumor detection and classification. Three dense layers are used with 512 neurons, 256 neurons, and 4 neurons respectively in a dense block which is used for the classification callback function from Keras, can monitor a quantity and if there is no improvement seen for a 'patience' number of epochs, the learning rate is reduced.

V. Evaluation

5.1 Performance Management

Key terms regarding performance management are as follows,

A. True Positive

1. The predicted value is the same as the actual value
2. The actual value was positive and the model predicted a positive value

B. True Negative

1. The predicted value is the same as the actual value
2. The actual value was negative and the model predicted a negative value

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C. False Positive – Type 1 Error

1. The predicted value was faulty
2. The actual value was negative and the model predicted a positive value
3. That is what so-called a type 1 error

D. False Negative – Type 2 Error

1. The predicted value was faulty
2. The actual value was positive and the model predicted a negative value
3. That is what so-called a type 2 error

E. Model accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

F. Model precision is calculated as:

$$Recall = \frac{TP}{TP + FN}$$

G. Model F1-Score is calculated as

$$F1 - score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

VI. Results

In the fine-tuned VGG-16 model, the last convolutional block with 3 convolutional layers is re-trained with the MRI images from the dataset. The top four convolutional blocks are frozen. used. Three dense layers are used with 512 neurons, 256 neurons, and 4 neurons respectively. The last dense layer contains 4 neurons for the 4 classes with the softmax activation for classifying the images. A dropout of 50% is used in between each consecutive dense layer.

Table 1: Classification using standard vgg-16 vs fine-tuned vgg-16

Image Type	Standard VGG-16 (F1-Score)	Fine-Tuned VGG-16 (F1-Score)
Glioma	93	97
Meningioma	76	92
No Tumor	96	100
Pituitary	91	98

The standard VGG-16 model provides F1-scores of 93 for Glioma, 76 for Meningioma, 96 for no tumor and 91 for Pituitary and the fined-tuned VGG-16 provides F1-scores of 97 for Glioma, 92 for Meningioma, 100 No Tumor and 98 for Pituitary. The fine-tuned VGG-16 model provides a significant increase in accuracy for detection and classification of brain tumors of 97 % over a standard VGG-16 model which provided the accuracy of 90%.

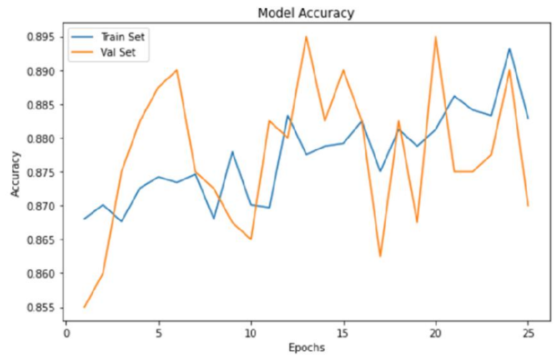

Figure 4: Accuracy vs Epoch Graph for standard VGG-16 model

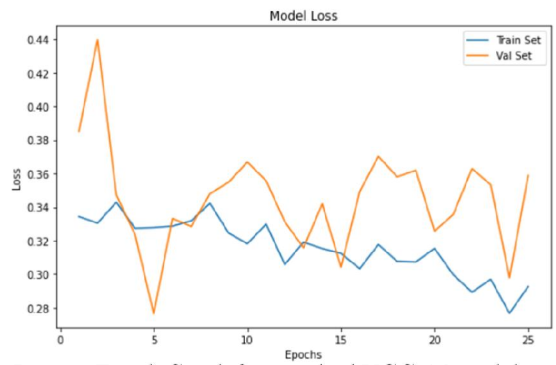

Figure 5: Loss vs Epoch Graph for standard VGG-16 model

The above curve shows the accuracy and loss of the model till 25 epochs. These results are obtained in the traditional VGG-16 model. In graph (Fig. 4.) X-axis represents epochs and Y-axis represents accuracy, in graph (Fig. 5.) X-axis represents epochs and Y-axis represents a model loss. The blue line is for the training dataset and the orange line is for the validation dataset. The graph shows how accuracy is hit by the model at each epoch

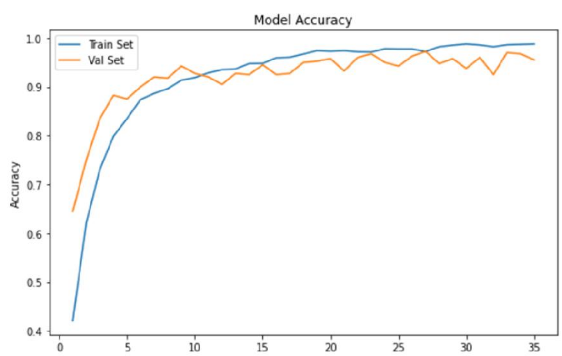

Figure 6: Accuracy vs Epoch Graph for fine-tuned VGG-16 model

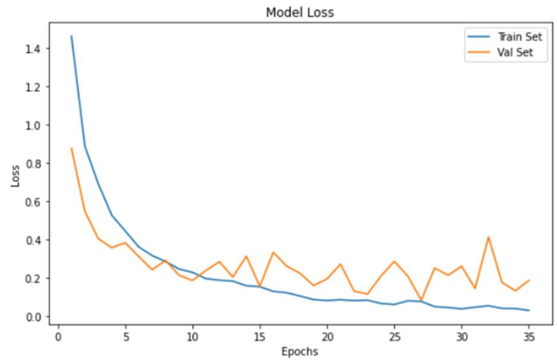

Figure 7: Loss vs Epoch Graph for fine-tuned VGG-16 model

VGG-16 is trained on the ImageNet dataset which consists of 14 million images belonging to 1000 classes. These learned weights and filters give the network decisive feature extraction capabilities, which will help it perform better when it's trained to classify different classes. Deep layers of the VGG model can be very advantageous for feature extraction of brain tumors. The above curve shows the accuracy and loss of the model till 35 epochs. These results are found in fine-tuned VGG-16 model. In graph (Fig. 6.) X-axis represents epochs and Y-axis represents accuracy, in graph (Fig. 7.) X-axis represents epochs and Y-axis represents a model loss. The blue line is for the training dataset and the orange line is for the validation dataset. The graph shows how accuracy is hit by the model at each epoch.

From these graphs, it is clearly visible that the loss is high in the traditional VGG-16 model and the curve is irregular. In fine-tuned VGG-16 model dropout of 0.5 is used and as a result, a smoother curve can be seen in the figure.

VII. Conclusion

The presented work is a study in the domain of brain tumor detection and classification using transfer learning and fine-tuned VGG16 architecture. We applied transfer learning techniques using natural images of the ImageNet dataset and classified the brain tumor type from glioma, meningioma, pituitary, and no tumor. After the training phase, we found that the fine-tuned VGG16 model provides almost 97% accuracy in detecting and classifying the brain MR image. The precision values in each category of classification, glioma, meningioma, no tumor, and pituitary, are 0.97, 0.95, 1.00, and 0.96 respectively.

The classification is performed in the following way, image pre-processing which includes converting the image to grayscale, cropping an image to get the required part only using image contouring, then converting the image to fixed dimensions, dataset Augmentation, and at last fined-tuned VGG16 CNN architecture. By combining deep learning models with data augmentation approaches, we were able to improve the accuracy of tumor categorization. We can incorporate this research into the Computer-Aided Verdict program. Non-radiologist clinicians/discussing doctors can utilize it to detect tumors. In the future, using different deep learning models we can outspread our work for spotting the actual shape and size of the tumor, the location of the tumor, and how quickly it is growing. This will help in the early detection of the presence of a tumor and will help in the early and proper treatment of patients.

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