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BRAIN TUMOR CLASSIFICATION USING XCEPTION AND MOBILENET

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Abstract: Brain tumor classification is a very important step after detection of the tumor to be able to attain an effective treatment plan. Hence, early detection helps to come up with better medications, it can also save a life in due time. We have used five Deep Learning (DL) models to classify brain tumors. The accuracy of the VGG19 had lowest with 50% and ResNet101 was 96.7% and Xception was 99.5% and ception +MobileNet was 99.9%. However, the MobileNet model performed the best, with an accuracy of 100%.

***Index Terms* – Xception, Mobilenet, Deep Learning, Brain Tumor**

I. INTRODUCTION

The advances in biomedical and human intelligence have overcome diverse diseases in the last few years but people are still, suffering from cancer due to its unpredictable nature. This disease is still a significant problem for humanity. Brain tumor cancer is one of the serious and utmost emergent ailments. In India, almost 43,000 patients were identified brain tumor cancer in 2021. The brain tumor analyzation, classification, and identification are critical issues for a neurologist who is using CAD (computer-aided diagnosis) as a supportive tool for a medical operation. There are three noticeable kinds of brain tumors: meningioma, pituitary, and glioma. The accuracy of prediction models and data analysis through DL techniques mainly rely on the data sample and its training as it needs more accurate data for better outcomes. To overcome shortcomings in training of data samples, transfer learning can be applied to secure better performance. Transfer learning is a DL technique in which trained features

of large data can be deployed to small data sets where the large data is called a source or base dataset and small data is named as target data set. The fine-tune MobileNet and freeze the layers of MobileNet are considered as two main scenarios of transfer learning where we can substitute and maintain the pre-trained ConvNet on a small dataset (target dataset) to continue the back-propagation. After this, the target dataset is classified by a fully connected layer. The motivation to use pre-trained deep learnings is time saving, because it does not need a large data set to obtain results. These models also extracted random features from images for classification. In the proposed model, we use Xception and MobileNet as the algorithms to classify the tumors into glioma tumor and pituatory tumor. There is a urgent need of making the classification simple so that it would be a time consuming process and the lifesaving one.

II. LITERATURE SURVEY

Machine learning approaches have been extensively employed in various domains including medical diagnostics and preventive medicine. A limited number of studies, however, have targeted diagnosis of brain tumor especially employing magnetic resonance imaging (MRI). Mostly ML methods train and test traditional ML algorithms on MRI data. Recently, some of the approaches have employed DL for the diagnosis of brain tumor.

Rehman et al. [5] proposed a framework that employed a setup called tri-architectural CNN (convolution neural network) for classification of tumors of different types (GoogLeNet, AlexNet and VGGNet). This classification involved pituitary gland tumors and glioma tumors, types. The above mention algorithm sliced the brain MRI to locate regions of interests. Fine tuning and freezing were also applied to the sets of data for further classification. The authors also considered data augmentationtechniques to obtain results' accuracy. This research attained an accuracy of 98.69% by employing VGG16 architecture for enhancing classification and detection.

Deepak et al., [6] also adopted the concept of deep transfer for classification of images and employed the same data source discussed in [5]. The features of images were extracted, and these features were also used in aggregation of testing and classification models. Employing a 5-fold model of classification at patients' level, the authors achieved an accuracy of 98%. The study concluded that a fully automated classification can help in regions classification, and performs better than manual regions classifications. Another study, based on CapsNets as a Capsule network model, by Afshar et al., [19] classified brain tumors. The study improved the level of accuracy by bringing a variation in the maps of CapsNet at some convolution layer. The study claimed a pronounced accuracy of 86.50% by using CapsNet in convolution layer. The setup was achieved by using 64 feature map to enhance the accuracy measures.

Another study by Abiwinanda et al. [20] adopted a deep learning model, that was based on CNN, applied to brain tumor images classification. Although the study adopted 5 classification models, it concluded model 2 as the best approximation for enhancement of images classification. The final architecture comprised of RELU layer and a maximum pool layer. This setup has 64 hidden neurons in the layered architecture. The study claimed to achieve an accuracy measure of 98.5% on training and 84.19% for validation. The authors in [21] employed a two-dimensional discrete transform based on wavelets and Gabor filters for extraction of features of brain MRI. The study achieved an accuracy measure of 91.9% by employing the aforementioned system setup with backpropagation NN.

Pashaei et al., [22] developed an architecture based on CNN for features extraction. They also designed a 5 layered architecture having all layers as learnable layers with customized 3×3 layered setup. The study claimed to achieve an accuracy of 81% that was further enhanced by another featured classification model of CNN based on ELM (extreme learning machine). The study noticed a limitation in the classifiers' discrimination capability by vetting classification differences in pituitary and meningioma images.

Sajjad et al. [7] proposed a system based on a neural network classification that further aided a clear provision of image segments (segmenting tumor region from dataset). In addition, the study employed various noise suppression techniques by using transformation and invariance concepts. The CNN setup could tune the prediction accuracy for the prediction of tumor grades. For the prediction accuracy, the data was passed to a fine-tuned CNN. Several experiments were performed on two different sets – Radiopaedia and brainctumor. This study employed both original and augmented datasets to determine systems accuracy i.e., 90.67%. Classification of tumor into different grades from image data can be very useful in clinical practice as it can also accelerate the treatment planning for a particular grade patient by overcoming the sampling error [23].

In this regard, Pereira et al. proposed a 3D CNN that automatically grades glioma from conventional multi-sequence MRI by defining a region of interest automatically. The anticipated grading system has dual functions: extraction of regions of interests and prediction of glioma grade. The proposed system was assessed on the publicly available dataset, called BRATS 2017 Training
set in which subjects are classified as per images datasets. The accuracy of system was 89.5 %, in addition to the accuracy of predicting tumor that was achieved at 92.98% based on regions of interests.

Anaraki et al. [24] proposed a strategy based on CNN and GA (genetic algorithm) to classify various types of Glioma images using MRI data. The proposed system used GA for an automatic selection of CNN structure. They obtained 90.9% accuracy predicting Glioma images of three types. Besides, the study brought an accuracy of 94.2 % in the classification of Glioma, Meningioma, and Pituitary.

Zhou et al. [25] purposed a method to use the 3D holistic image directly. First of all, 3D holistic image is converted into the 2D slices in the sequence, and then they applied DenseNet for the extraction of the features from each 2D slice. After that, Recurrent Neural Network was applied on each 2D slice which used the Long Short-Term Memory for the purpose of the classification. They performed experiments on public and proprietary datasets. They also applied pure convolutional neural network in the DenseNet as a convolutional auto encoder for the sequence representation learning. So, they used the DenseNet long Short-Term Memory and DenseNet Convolutional Neural Network to perform tumor screening and tumor type classification. Their system achieved an accuracy of 92.13% with DenseNet-LSTM.

Muneer et al. [26] used the real dataset from clinics of the United States. They used a customized classification algorithm based on Wndchrm. The tool has the concepts of neighborhood distance measure employing morphology and deep learning for CNN. The authors with this proposed setup achieved an accuracy of 92.86% in addition to 98.25% that was achieved through Wndchrm classification.

Banerjee et al. [27] discussed the convolutional neural network to enhance MRI images classification by employing a sequence of multiple MRI images. They proposed ConvNet models, that were customized to be developed from ab initio, based on concepts of slicing and patching of MRI images. The study aggregated the existing models i.e. ConvNets and VGGNet that were developed for processing of different MRI imaging. The study evaluated the performance of proposed models and claimed to achieve an accuracy measure of 97% tested on various datasets of MRI images.

III. DATASET

The brain dataset investigated in this study is comprised of 3064 T1-weighted contrast MR images of 233 [5]. Three different types of tumors such as , glioma, and pituitary are existing in this dataset. The image resolution 512 × 512 with voxel spacing size of 0.49 ×0.49 mm2 consisted of axial (transverse plane), coronal(frontal plane), or sagittal (lateral plane) planes has been used in this dataset. The axial plane distribution based on number of classes consisted of 708, 1426, 930 sample instances of glioma, meningioma, and pituitary tumors respectively.A min-max normalization method was used within pixel intensity value ranging between 0 to 1.

IV.PROPOSED MODEL

The proposed model has the following algorithms :

Xception: Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals .

MobileNet: MobileNet is a computer vision model open-sourced by Google and designed for training classifiers. It uses depthwise convolutions to significantly reduce the number of parameters compared to other networks, resulting in a lightweight deep neural network.

Xception with MobileNet: MobileNets and Xception have the same ideas but dif- ferent pursuits. Xception pursues high precision, but Mo- bileNets is a lightweight model, pursuing a balance between model compression and accuracy.

The Xception and MobileNet algorithms are used on pre-trained models for classifying the glioma and pituatory tumor. Using the SQLite to store the database are used.

V. IMPLEMENTATION

1. Importing the packages
2. Exploring the dataset - Brain Tumor Data
3. Single Image Super Resolution using Pretrained GAN Pytorch
    - Define Layer of blocks
    - Class Function for Residual Block
    - Class Residual Dense Block
    - Loading the pre-trained model
    - Appending CPU as device for modelling
    - Appending the model
    - Reading the image
4. Exploring the saved dataset of HR images
5. Image processing - using Image Data Generator
    - Zooming the Image
    - Horizontal Flip
    - Reshaping the Image
6. Building the model
7. Training the model
8. Dumping the model

9. Flask Framework with Sqlite for signup and signin
10. User Upload an image for analysis
11. The given input is preprocessed
12. The trained model is used for predicting the result
13. Final Outcome is display

VI. RESULTS AND DISCUSSION

OUTPUT WITH COMPARISON

Sl no	ML Model	F1-score	Recall	Precision
0	VGG19	0.500	0.500	0.500
1	ResNet101	0.967	0.967	0.967
2	MobileNet	1.000	1.000	1.000
3	Xception	0.995	0.995	0.995
4	Xception + MobileNet	0.999	0.999	0.999

Table 4.1: Descriptive Statics

VII. CONCLUSION AND FUTURE SCOPE

In this paper we have discussed the application of deep learning models for Identification of Brain tumor. In paper, two different scenarios are assessed. Firstly, pre-trained MobileNet deep learning model was used, and the feature were extracted from various blocks. Then, these features were concatenated and passed to classifier for classifing the brain tumor. Secondly, the features from different Xception modules were extracted from pre-trained Xception model and concatenated and then, passed to the flask for the classification of brain tumors. Both scenarios were evaluated with the publicly available three-class brain tumor dataset. Consequently, the ensemble method based on concatenation of dense block by using MobileNet pre-trained model outperformed as compared to the current research methods for brain tumor classification problem. The proposed method produced 100% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor.

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