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MRI Brain Tumor Detection Using Deep Learning

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Abstract: ***A neoplasm could be a growth of abnormal cells within the brain. The anatomy of the brain is incredibly complex, with different parts accountable for different system functions. Brain tumors can develop in any a part of the brain or skull, including its protective lining, the underside of the brain (skull base), the brainstem, the sinuses and also the cavity, and plenty of other areas. There are over 120 differing types of tumors that may develop within the brain, counting on what tissue they arise from. a range of imaging techniques, including CT (or CAT) scan, MRI, occasionally an angiogram or X-rays may be wont to identify the tumor, pinpoint its location and/or assess the function of your brain. during this project we propose the Deep learning algorithms to beat the drawbacks of traditional classifiers where tumor is detected in brain MRI using deep learning algorithms. Deep learning and image classifier are often accustomed efficiently detect cancer cells in brain through MRI.***
Keywords: Brain Tumor, MRI Images, CNN, EfficientNet, deep learning

I. INTRODUCTION

Brain tumor is one in all the foremost rigorous diseases within the bioscience. an efficient and efficient analysis is often a key concern for the radiologist within the premature phase of tumor growth. Histological grading, supported a stereotactic biopsy test, is that the gold standard and also the convention for detecting the grade of a brain tumor. The biopsy procedure requires the neurosurgeon to drill a little hole into the skull from which the tissue is collected. There are so many risk factors involving the biopsy test, including bleeding from the tumor and brain causing infection, seizures, severe migraine, stroke, coma and even death. But the most concern with the stereotactic biopsy is that it's not 100% accurate which can lead to a significant diagnostic error followed by a wrong clinical management of the disease. Tumor biopsy being challenging for brain tumor patients, non-invasive imaging techniques like resonance Imaging (MRI) are extensively employed in diagnosing brain tumors. Therefore, development of systems for the detection and prediction of the grade of tumors supported MRI data has become necessary. But initially sight of the imaging modality like in resonance Imaging (MRI), the correct visualization of the tumor cells and its differentiation with its nearby soft tissues is somewhat difficult task which can flow from to the presence of low illumination in imaging modalities or its large presence of information or several complexity and variance of tumors-like unstructured shape, viable size and unpredictable locations of the tumor. Automated defect detection in medical imaging using machine learning has become the emergent field in several medical diagnostic applications. Its application within the detection of tumor in MRI is incredibly crucial because it provides information about abnormal tissues which is important for planning treatment. Studies within the recent literature have also reported that automatic computerized detection and diagnosis of the disease, supported medical image analysis, might be a decent alternative because it would save radiologist time and also obtain a tested accuracy. Furthermore, if computer algorithms can provide robust and quantitative measurements of tumor depiction, these automated measurements will greatly aid within the clinical management of brain tumors by freeing physicians from the burden of the manual depiction of tumors. The machine learning based approaches like Deep ConvNets in radiology and other life science fields plays a crucial role to diagnose the disease in much simpler way as never done before and hence providing a feasible alternative to surgical biopsy for brain tumors . during this project, we attempted at detecting and classifying the brain tumor and comparing the results of binary and multi class classification of brain tumor with and without Transfer Learning (use of pre-trained Keras models like VGG16, ResNet50 and Inception v3) using Convolutional Neural Network (CNN) architecture.

II. SYSTEM ANALYSIS

A. Existing System

The MRI image contains more detail than the CT or ultrasound picture on the given medical document. The MRI image contains basic details on brain structure and on the detection of defects of brain tissue. It is considered as the best ml technique for image classification due to high accuracy. Image pre-processing required is much less compared too the algorithms. It is used over feed forward neural networks as it can be trained better in case of complex images to have higher accuracies.

B. Proposed System

The proposed system mainly comprises four modules, namely pre-processing, segmentation using Contribution-based Clustering Algorithm, extraction of features, and classification of diseases. The first step that is pre-processing is the step in which the noisy images and also input defects are removed. The images are shapes and the edges are sharpened. It requires a large training data. It requires appropriate model. It is time consuming.

III.MODULE DESCRIPTION FOR TUMOR CELL DETECTION

All paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified

A. Dataset collection

Images may be within the type of .csv (comma separated values), .dat (data) files in grayscale, RGB, or HSV or just in .zip file as was within the case of our online Kaggle dataset. It contained 98 healthy MRI images and 155 tumor infected MRI images. The Multimodal tumor Segmentation (BRaTS) MICCAI has always been that specialize in the evaluation of state-of-the-art methods for the segmentation of brain tumors in resonance imaging (MRI) scans. The dataset contains 2 folders for the aim of coaching and testing. The 'train' folder contains 2 sub-folders of HGG and LGG cases- 220 patients of HGG and 27 patients of LGG. The 'test' folder contains brain images of 110 Patients with HGG and LGG cases combined.

B. Data Augmentation

Data augmentation consists of Grey Scaling(RGB/Bw to ranges of grey), Reflection(vertical/horizontal flip),Gaussian Blur(reduces image noise),Histogram equalisation (increases global contrast),Rotation(may not preserve image size),Translation(moving the image along x or y axis), linear transformation such as random rotation(01-0degrees), horizontal and vertical shifts, and horizontal and vertical flips. Data augmentation is done to teach the network desired invariance and robustness properties, when only few training samples are available.

FOR EXAMPLE

```
datagen = ImageDataGenerator(
featurewise_center=False,
samplewise_center=False,
featurewise_std_normalization=False,
samplewise_std_normalization=False,
zca_whitening=False,
rotation_range=10,
zoom_range=0.2,
width_shift_range=0.2,
horizontal_flip=False,
vertical_flip=False
datagen.fit(X_train)
```

C. Image Pre-processing

Our pre-processing includes rescaling, noise removal to reinforce the image, applying Binary There is holding and morphological operations like erosion and dilation, contour forming (edge based methodology). Within the beginning of pre-processing, the memory space of the image is reduced by scaling the gray-level of the pixels within the range 0-255. We used Gaussian blur filter for noise removal because it is understood to administer better results than Median filter since the outline of brain isn't segmented as tumor here.

D. Segmentation

Brain tumor segmentation involves the process of separating the tumor tissues (Region of Interest – ROI) from normal brain tissues and solid brain tumor with the help of MRI images or other imaging modalities. Its mechanism is based on identifying similar type of subjects inside an image and forms a group of such by either finding the similarity measure between the objects and group the objects having most similarity or finding the dissimilarity measure among the objects and separate the most dissimilar objects in the space.

E. Feature Extraction

Feature Extraction is the mathematical statistical procedure that extracts the quantitative parameter of resolution changes/abnormalities that are not visible to the naked eye. Examples of such features are Entropy, RMS, Smoothness, Skewness, Symmetry, Kurtosis, Mean, Texture, Variance, Centroid, Central Tendency, IDM (Inverse Difference Moment), Correlation, Energy, Homogeneity, Dissimilarity, Contrast, Shade, Prominence, Eccentricity, Perimeter, Area and many more. Feature Extraction is identifying abnormalities.

IV. DATA FLOW DIAGRAM

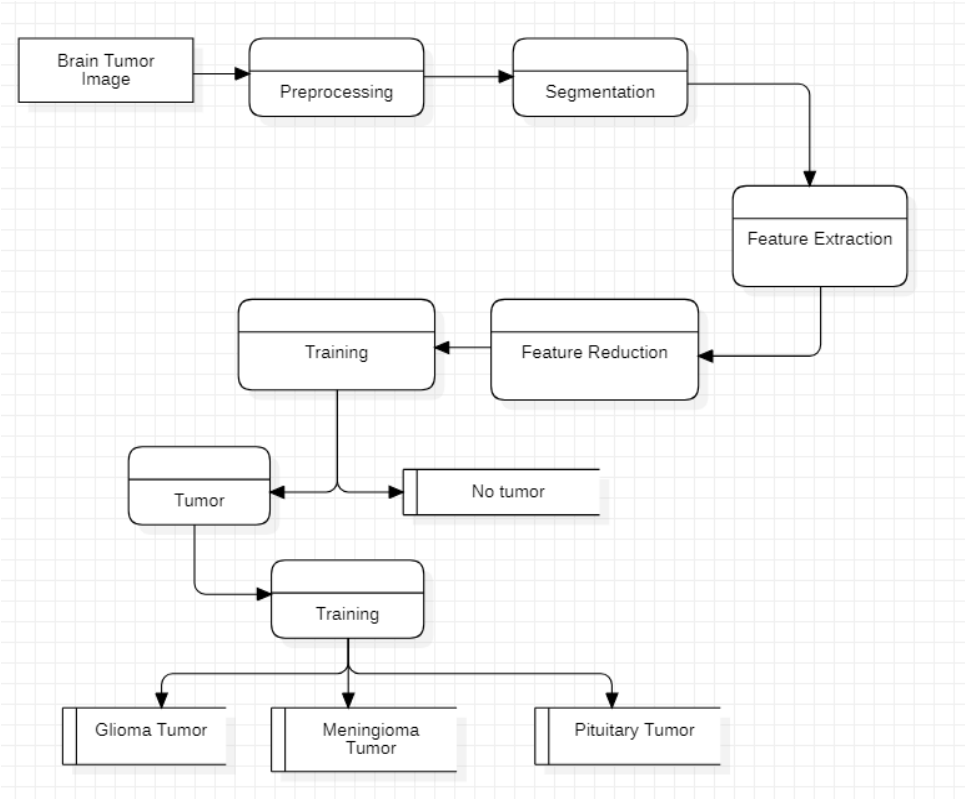

Fig. 1 Data flow of the tumor detection

Figure 1 represents the data flow of the tumor detection. It analysis begins with the dataset being pre-processed. It shows the Pre-processing of images and segmentations. And it extract the image to know the cells condition either it is tumor cell or not.

V. RESULT ANALYSIS

Figure 2 represents the sample images of MRI scan reports with tumor cells. It classifies the types of tumor.

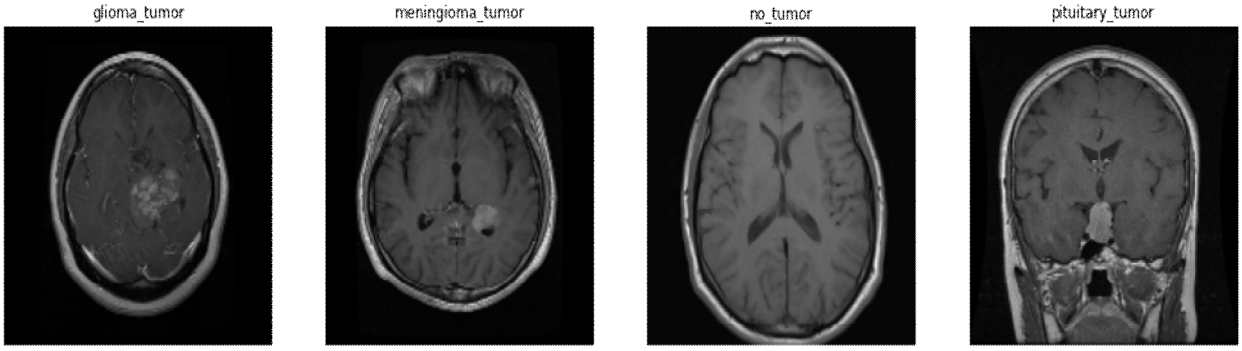

Fig. 2 Sample images of MRI scan reports with tumor cell

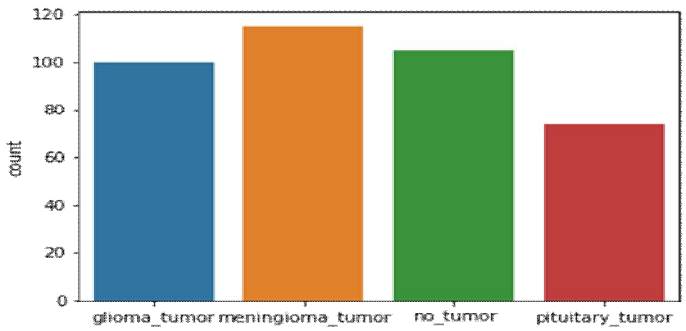

Fig. 3 TESTING DATA

Figure 3 represents the Testing data of Tumor images is in correct category.

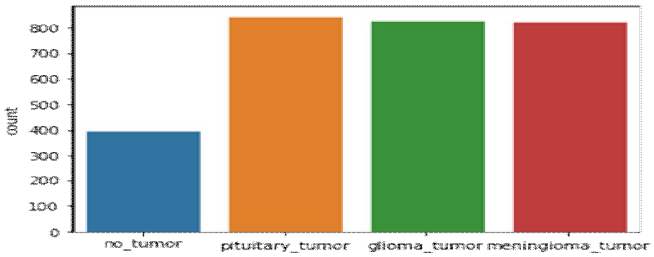

Fig. 4 TRAINING DATA

Figure 4 represents the Training data of Tumor. It shows the Tumor cells in Category

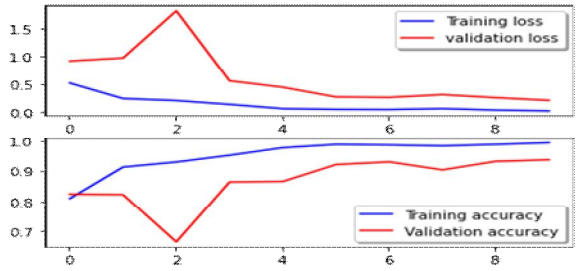

Fig. 5 Plot the Loss and Accuracy curves for training and validation

Figure 5 represents the Loss and Accuracy curves for Training and Validation.

VI. CONCLUSION

Without pre-trained Keras model, the train accuracy is 97.5% and validation accuracy is90.0%.The validation result had a best figure of 91.09% as accuracy. It is observed that without using pre-trained Keras model, although the training accuracy is >90%, the overall accuracy is low unlike where pre-trained model is used. Also, when we trained our dataset without Transfer learning, the computation time was40 min whereas when we used Transfer Learning, the computation time was 20min. Hence, training and computation time with pre-trained Keras model was 50%lesser than without. Chances over over-fitting the dataset is higher when training the model from scratch rather than using pre-trained Keras.

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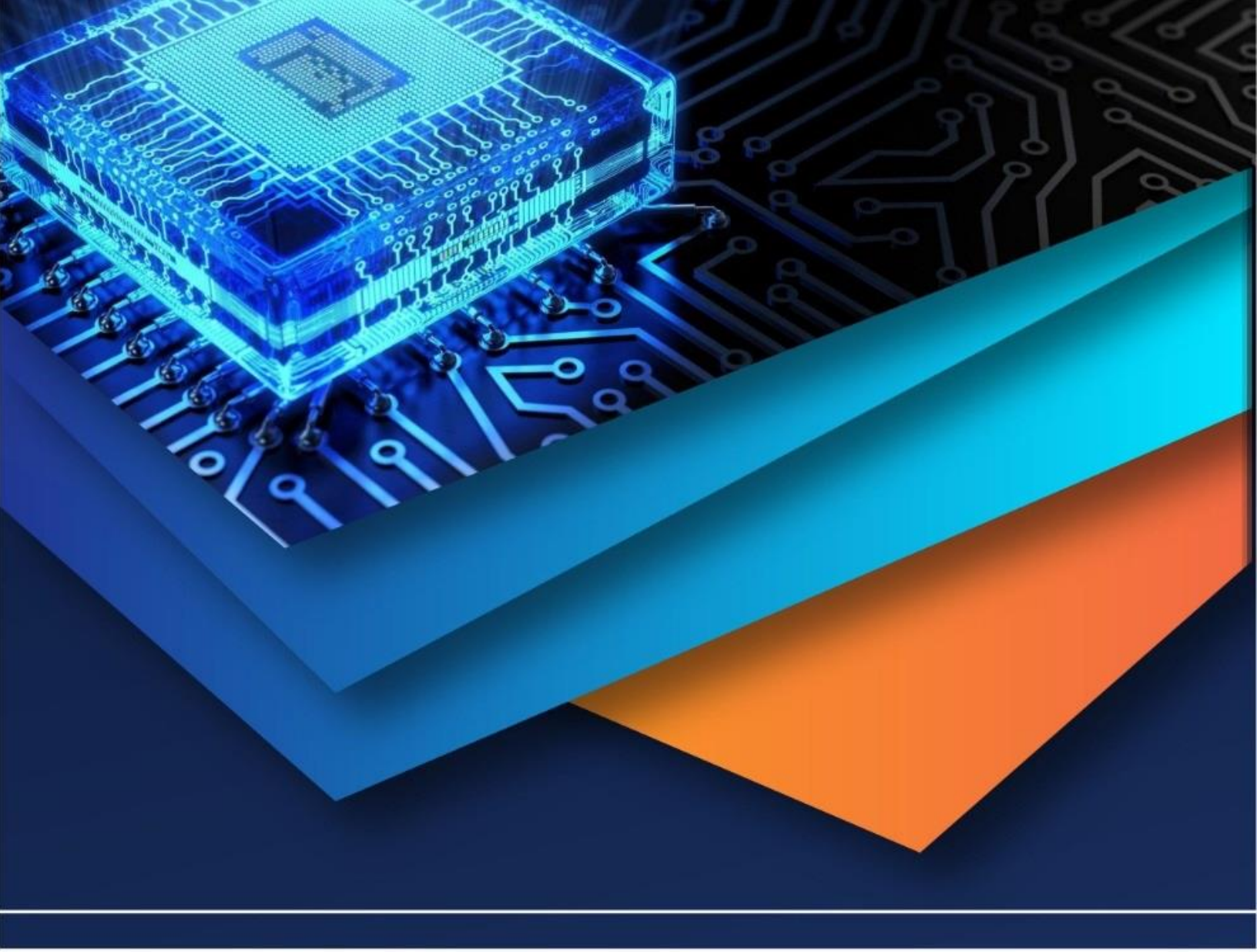

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