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MULTI-VIEW CLASSIFICATION OF BRAIN TUMOR

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Abstract:

One of the most common and serious conditions that affect the central nervous system is brain tumours. Early diagnosis is essential for patients to obtain the best care. Radiologists need an automated method to accurately identify brain tumour images. The identification process can be laborious and error-prone. The subject of completely automated brain tumour classification using magnetic resonance imaging is considered in this paper, taking into account meningioma, glioma, pituitary, and no tumour categories of brain tumours. Convolutional neural networks (CNN) are suggested for classification in this study.

Keywords — Brain tumors, classification, convolutional neural networks.

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I. INTRODUCTION

Machine learning (ML) is a part of Artificial intelligence (AL) which is used to build the models based on the sample data. Without being expressly taught to do so, machine learning algorithms create a model using sample data, sometimes referred to as training data, in order to make judgments. Machine learning algorithms are utilised in a broad range of applications, including speech recognition, email filtering, computer vision, and medicine, when it is challenging or impractical to create traditional algorithms to carry out the required functions. Computers use available data to learn in order to do certain tasks. Traditional classifications of machine learning methods fall into three basic groups.1.Supervised learning: Mathematical model which is a collection of data that includes the inputs and desired outputs is created using supervised learning techniques. 2. Unsupervised learning algorithms analyse a collection of input-only data to identify patterns, such as clustering of data points. Therefore, test data that hasn't been labelled, classed, or categorised is used to train the algorithms. 3. Reinforcement learning: A computer code must accomplish a certain task while interacting with a dynamic environment. When abnormal cells develop within the brain, a tumor is created. Malignant tumors and benign (non-cancerous) tumors are the two primary categories of tumors. These can also be divided into two categories: primary tumors, which originate inside the brain, and secondary tumors, or brain metastasis tumors, which often have spread from cancers outside the brain. Further the primary tumors are classified into four types they are: 1.Glioma is a particular kind of tumor that develops from glial cells in the brain or spine. Of all brain and CNS (central nervous system) tumors, gliomas make up roughly 30%, and they account for 80% of all malignant brain tumors.2. Meningioma, commonly referred to as a meningeal tumour, is frequently a slowly growing tumour that develops from the meninges, the membrane coverings that surround the brain and spinal cord.3. Pituitary adenomas tumor is a tumor that occurs in pituitary gland.

Anatomical and physiological images of the body are created using the medical imaging technology known as magnetic resonance imaging (MRI). To produce images of the body organs, MRI scanners employ powerful magnetic fields, magnetic field variations, and radio waves. The difference between MRI and CT and PET scans is that MRI does not employ X-rays or ionising radiation. There are three different views of MRI headscan i.e., Axial, Coronal, Sagittal. Axial headscan orientation is from top to down. Coronal headscan orientation is from front to back and sagittal headscan orientation is from side to side. Different views of MRI images considered for brain tumor classification are depicted in the below figure 1, 2, 3 respectively.

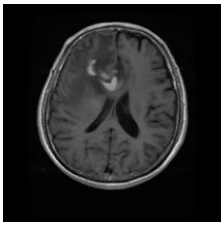

Fig1: Axial view

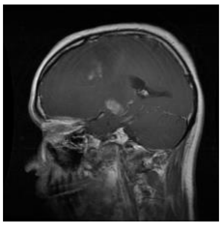

Fig 2: Sagittal view

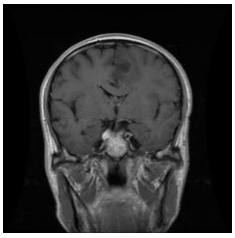

Fig 3: Coronal view

II Related Work

Kenya Kusunose et al., [1] developed clinical practical and precise view categorization of ECG data using deep convolutional neural network. In a learning database with incorrectly classified images that were not evaluated by observers, the aim of this paper is to assess the accuracy of 2 different classification input methodologies and the prediction model for EF. To train a neural network to classify views combining 5 standard perspectives and 10 images in a cycle, they enrolled 340 patients. All DICOM images were precisely registered and rescaled to create a reference image that matched the size of cardiac images. Five different conventional echocardiographic images were used to train and generate convolutional neural network models. The convolutional neural network technique was employed. The error rate is 1.9 percent, and the accuracy reached up to 98.1 percent. Well-classified instances and incorrectly-classified cases were distinguished in this study. Even for seasoned observers, determining an accurate picture in misclassified situations was challenging. This work's advantages include accuracy and clinical viability.

K S Shriram et al., [2] proposed a paper in which automated view categorization of echocardiograms was achieved using histograms of directed gradients. In this study, a method for automated detection and categorization of conventional views of different types was used. Gross structures can be encoded by the differentiating feature, and relevant heart images can be visually categorised. Ultrasound imaging presents a challenge for the features that demand precise image correspondences due to its high degree of appearance fluctuation. In this situation, a Histogram of Oriented Gradients offers a compromise between preserving local structure and avoiding the need for exact correspondences across images. Support vector machine classification was the method utilised, and it achieved a 98 % accuracy rate.

Ahmed I. Shahin et al., [3] presented a deep learning system that classifies various echocardiography images and determines their physiological position. The system is accurate and quick and is dependent on fusing deep features and

LSTM. Using the feature concatenation approach, the spatial neural feature as well as CNN features collected from echo-motion is combined. In this study, different network optimizers were used to first analyse the training and testing accuracy curves and the training and testing loss curves. The best optimizer is selected based on lowest epoch number and highest accuracy score. The second step is to determine whether pre-trained networks activation is the best feature extractor. They make use of eight different network configurations for the classification task. Finally, they discuss the metrics for assessing the suggested system. In the final section, the results of the confusion matrix for heart rate and cardiolocations are given. The acquired accurate result was 96.3 %, while the obtained sensitivity was around 95.75 %.

D. M. Bowers., [4] offered echocardiography view-classification utilising low-level characteristics in their article. The support vector machine algorithm was employed in this study. The programme categorises images taken at any point in the heartbeat cycle. This method uses kernel-based approaches for both training and testing and is based on low-level picture characteristics. The 2700 frames used in the training and testing are from the whole set of echocardiograms. Given a single-image SVM that has been trained, the classification method operates as follows. Computed and evaluated against the learned multiclass SVM is the new image features transform. Using the probability estimate provided by the classifier, the classification confidence is determined. If the class probability exceeds a certain threshold, the classification is returned. If not, the subsequent image is obtained, processed, as well as a new feature is created as the convex total of the kernels. This new feature is then assessed even against multi-class SVM that use the previous image. This process is carried out again until the max video window is reached or a categorization is provided. The overall accuracy of the method was 98.51 percent, with 100% accuracy on two visually comparable images (A4C and A2C). For an 8-way classification, 98.15 % accuracy was attained.

Seeland M et al. [5] suggested Multiview categorization with CNN layers; a categorization approach based merging visual input obtained images depicting the same item from several views. They provide strategies for integrating this knowledge by extracting and encoding visual characteristics from various perspectives using convolutional neural networks. In this article, the author looked into three different approaches: fusing convolutional feature maps at different network layers, fusing bottleneck latent representations before classification, and fusing score data. Early fusion is another name for the merging of fully convolutional mappings at various network layers. In the first fusion, all feature mappings from several CNN branches are overlaid and then processed jointly component per component. Late fusion is another name for the merger the bottleneck latent representations that occurs before categorization. In this study, they examine the use of multi-view categorization as a machine learning technique to improve classification performance. This means that the term "view" is to be used literally, i.e., that each view is a new image showing the same objects instance or aspect of it. Images of same subject captured from multiple angles can constitute a photo collection. PlantCLEF, compcars, and antweb datasets all have accuracy rates of 83.9 %, 76.7 percent, and 83% respectively.

Anuja Arora et al., [6] in this paper the rich information about brain tumor architecture provided by MRI scans makes it a crucial tool for accurate treatment. A brain tumor segmentation and identification method is presented to address this issue, and tests are conducted. For each patient in this data, four separate MRI modalities T1, T2, T1Gd, and FLAIR are included. As a result, a segmentation image and the ground truth for tumor segmentation, or class label, are supplied. The tumor location was localised using the U-Net deep learning model; the contracting section of U-Net effectively captures the information from the compressed feature extraction and expansion route localization. Asymmetric parameter tuning of the contracting and expanding route layers was used to obtain great accuracy.

Dinthisrang Daimary et al., [7] in this paper, a mixture of the new architectures SegNet and UNet is the planned USeg-Net and SegU-Net. By comparing the suggested hybrid architecture with the widely used CNN models for segmentation, U-Net, SegNet3, SegNet5, and, it is possible to examine the segmentation capabilities in terms of accuracy. The enhancing tumor, necrotic & non-enhancing tumor, peritumoral edoema, and anything else are each represented by the colours green, red, yellow, and grey, respectively. Each model passes 172,800 neurons through the various hidden layers after accepting them as input in the input layers. In the output layer, these neurons are divided into four types. Five metrics are taken into account to assess how effectively the model executes segmentation tasks: global correctness, mean correctness, mean Intersection Over Union, weighting IOU, and mean BF-scores. The mean accuracy for the U-SegNet, Seg-Unet and Res-SegNet, and was 91.6 percent, 93.1 percent, and 93.3 percent, respectively.

Momina Masood et al., [8] in this paper, they suggest an automated technique using the Mask RCNN framework to improve the stability of brain tumor detection and segmentation. Tumor segmentation and localization with pixel-to-pixel accuracy utilizing the region proposal network. To demonstrate the effectiveness of our strategy, a thorough quantitative and qualitative analysis of the recently developed methodologies was conducted on two internet datasets. The suggested method is resilient to MRI aberrations such noisy, bias field effects, and varied acquisition angles as well as differences in tumor size, size, location, and overlap with normal brain tissues. Researchers used learning to perfect the model using MRI data for segmentation after initializing it with pre-trained weights of the COCO data. For the experiment, they employed a 70:30 split, with training sets making up 70% and test sets making up 30%.

III Methodology

A. Data Acquisition

In this step, the data is collected and it spliced into training dataset and testing dataset. In our model the dataset is spilt into 80:20 ratios which consist of 2870 images and 394 images respectively. The dataset consists of three views namely Axial, Coronal and sagittal shown in the figure 1, 2, 3 respectively. Dataset also consists of types of tumor which consists of four types of tumor namely meningioma, glioma, pituitary and no tumor.

B. Data Preprocessing

Pre-processing will be essential since the images will come from various sources and have varying sizes, among other factors. When data is acquired from many sources, it is usually done so in a raw format that makes analysis impossible. The images undergo the pre-processing step where resize of the images takes place since the images vary in size and will be not compatible with the proposed model. Resize of the images takes place with respect to height, width, length of the images. Preprocessing also includes the reduction of noise of the images.

Using Preprocessing data makes it simpler to understand and apply. This procedure removes data inconsistencies or duplication, which may otherwise have a detrimental impact on a model's accuracy. Preprocessing the data makes sure there aren't any inaccurate or missing numbers caused by bugs or human mistake. The image will be resized using the openCV library. By specifying an integer number in the rotation range parameter, the ImageDataGenerator class enables to freely rotate pictures across any angle between 0 and 360 degrees.

C. Classification Using CNN Model

In the proposed model the CNN model is used to classify the type of brain tumor. This model will use tensorflow, keras library which will help to classify the types of brain tumor. EfficientNetB3 model is used in CNN model the intuition behind using this is that it performs all scaling operations which will leads to the increase in the accuracy rate. Baseline network developed by Neural Architecture search (NAS) then scaled up the baseline network generate a series of models they are called EfficientNets B1 to B7. EfficientNetB3 is a CNN design and scaling technique that uses a compound coefficient to consistently scale all depth, breadth, and resolution parameters. Using a fixed resource constraint, the applied grid search technique was used to determine the connection between the various scaling parameters of the baseline network. By employing this method, we will able to determine the necessary scaling coefficients for all of the dimensions that needed to be increased. This baseline network will be scaled to the required size using these factors. A CNN has three scaling dimensions: resolution, depth, and width. Depth simply refers to the network's layer count, or how deep it is. Width merely refers to the network's size. Compared to other model EfficientNetB3 is light-weighted and also it uses less parameter and yields with higher accuracy.

D. Evaluation

Model assessment is the practise of applying several evaluation measures to comprehend model's performance as well as its strengths and flaws. With the early stages of research, it is crucial to evaluate a model's effectiveness. Model evaluation also aids in model monitoring.

IV. CONCLUSIONS

The results of the suggested classification (Fig 4, 5, 6, 7) approach for brain tumors are presented in this section. Many images were used to validate the suggested technique, which was developed using the tensorflow and keras packages in Python. The outcomes are examined in terms of the classification data's accuracy. With the aim of optimizing the proposed methodology to be able to categorise the tumors with the maximum performance for all kind of imaging modality was employed in the work presented. Additionally, all axial plane slices are used in this experiment since these are having a greater resolution and less noise than coronal and sagittal plane planes.

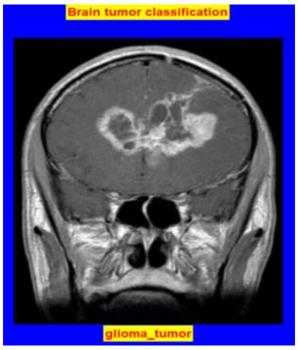

Fig 4: Classification of glioma tumor

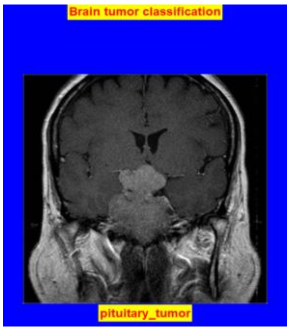

Fig 5: Classification of pituitary tumor

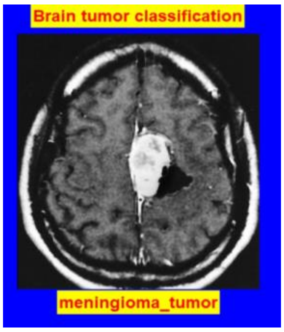

Fig 6: Classification of meningioma tumor

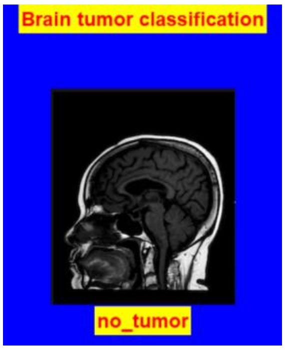

Fig 7: Classification of no tumor

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