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Artificial Intelligence to Automate Brain Tumor Classification

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Abstract— The brain is our body's most delicate organ, which controls the centre capacities and attributes inside the body and is predictable to the National mind tumour Society. Inside the US, around 700,000 individuals acknowledge a cerebrum tumour, and in this manner, the figure will ascend to 887,000 by the highest point of 2021. Medical Imaging for Medical Diagnosis has benefited from ongoing advancements in the field of profound learning. CNN is the most commonly used AI calculation for visual learning and image recognition. The convolutional neural network (CNN) technique used in data augmentation and image processing is essentially proposed in our postulation to filter MRI images of the cerebral cortex into carcinogenic and non-harmful categories. This investigation introduces a programmed mind tumours arrangement utilising profound learning-based Visual Geometric Group (VGG) 16, which is applied to the data set followed by data collection, data augmentation, data preprocessing, and VGG 16 model. In the simulation, the overall accuracy of the model is 96%.

Keywords: *Brain Tumor; Deep Learning, TensorFlow, VGG-16, Transfer Learning, Computer Vision; Convolutional Neural Network*

I. INTRODUCTION

Using AI and Deep Learning, medical science has achieved significant advances in the last several years, such as the Medical Image Handling approach, which aids doctors in quickly and accurately diagnosing illness. So, to determine such sort of restrictions helped innovation is genuinely necessary since Medical Field needs effective and solid procedures to analyse hazardous infections like disease, which is the leading cause of death among patients worldwide. Using the information enlargement method and the convolutional neural organisation model, we were able to characterise brain tumours as hazardous or non-carcinogenic in our study using Brain MRI Images. Malignant and benign brain tumours are the two main forms. There are no malignant cells in benign brain tumours. Hence they develop very slowly. Unlike hazardous cerebrum tumours, which include malignant cells that rapidly grow and spread to other sections of the brain and spine, benign tumours do not spread and tend to remain in one area of the brain. A hazardous neoplasm is dangerous. As a result of the WHO's research, brain tumour associated with poor mental health are either labelled "generous tumours", which are low grade, or "dangerous tumours", which are high grade and are recognised as "dangerous tumours" [3]. Magnetic Resource Image (MRI) is the most commonly used treatment for assessing the tumour in the brain, but CT scans and EEGs are also used. X-rays use radio waves and magnetic fields to take images of the body's inside organs.

In this regard, an X-ray examination is more fundamental than a CT scan or an EEG since it offers more specific information about the inside organs. One method of solving a new problem is to apply previous training to the problem at hand. It is becoming increasingly popular in deep learning because it can train complex neural networks with minimal data, which is particularly beneficial in data science. After all, most real-world situations do not require millions of data points to train these sophisticated models. In this article, we'll examine the concept of transfer learning to understand more about how it works, its importance, and when it can be used. Many resources are accessible for models who have already been trained in learning transfers. For example, you can use the knowledge gained during training to recognise drinks if you train a basic classifier to predict whether a picture contains food.

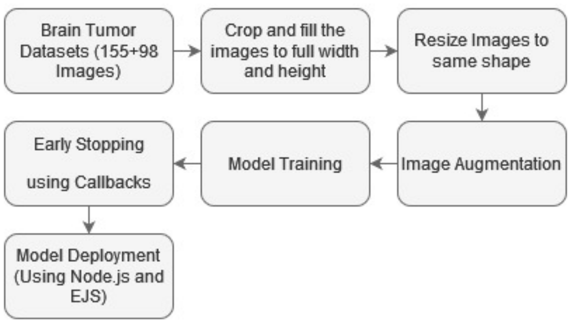

Fig1: Methodology of Brain Tumor Classification

II.DATASET

We used the dataset Brain MRI Images for Brain Tumor Classification, which is classified into two categories, i.e., Malignant and Benign. The data consists of 253 images, and we split the data into three parts 155 training images,50 validation images and up to 10 test images. All images are rescaled. The data consists of three main parts: training, validation, and testing. In order to improve the efficiency of our system, this work used several image preprocessing techniques. In order to speed up processing, this work resized all of our photographs to 240 x 240 x 3 to fit them into our model. Following that, this work used the image preprocessing techniques listed below. The Canny Edge Detection [15] approach was used to eliminate the black edges from the images and solely use the brain area from MRI data in this investigation. Detecting an object's edges with Canny Edge Detection is a multi-step process. A clever edge detection technique revealed the Real MRI brain's edges, clipping the brain region in the figure.

III.EXPERIMENT

This section focuses on the construction process of Brain Tumor Classification. The construction process of the model is done using the Transfer Learning VGG-16 model.

3.1. Data Collection

The dataset Brain MRI Images for Brain Tumor Classification is classified into Malignant and Benign. The data consists of 253 images, and we split the data into three parts 155 training images,50 validation images and up to 10 test images. All images are rescaled. The data consists of three main parts: training, validation, and testing

3.2. Data Preprocessing

In order to improve the efficiency of our system, this work used several image preprocessing techniques. In order to speed up processing, this work resized all of our photographs to 240 x 240 x 3 in order to fit them into our model. Following that, this work used the image preprocessing techniques listed below.

3.3. Data Augmentation

Data augmentation [16] is a technique for artificially enhancing the volume and complexity of current data. Findings from this study reveal the need for a vast amount of data while fine-tuning deep neural networks. We had to use the data augmentation technique [17] to increase the size of our training dataset by rearranging and brightening our photos due to their modest size. Our model will treat each little alteration as a new image, helping it learn faster and perform better on unknown data. It will expand our training data. It results in many augmented images being presented on top of one another.

3.4.VGG-16 Model

ImageNet (ILSVR) competition winner VGG16 used a convolutional neural net (CNN) design in 2014. If you've seen a vision model, you've seen this one. In step 1, VGG16 uses 3x3 channel convolution layers and the same cushioning and max pool layer as in step 2, which is a significant departure from previous VGG iterations. Throughout the game, it relies on its convolution and max pool layer strategies. The full picture of Two FC (completely associated layers) and a SoftMax (yielding layer) round up the final steps. Levels with loads are represented by the number 16 in VGG16. This organisation spans a large geographic area, with over 138 million (approximate) borders. K. Simonyan and A. Zisserman of the University of Oxford suggested VGG16 as a convolutional neural organisation model in their study "Exceptionally Deep Convolutional Networks for Large-Scale Image Recognition." In ImageNet, a dataset of over 14 million images divided into 1000 categories, the model obtains a top-5 test precision of 92,7 per cent. 2014 ILSVRC-2014 was one of the most popular models. With its unique 33-bit estimated channels, it outperforms Alex Net regularly (11 and 5 in the first and second convolutional layers, respectively). In the end, VGG16 was powered by NVIDIA Titan Black GPUs after a lengthy development period.

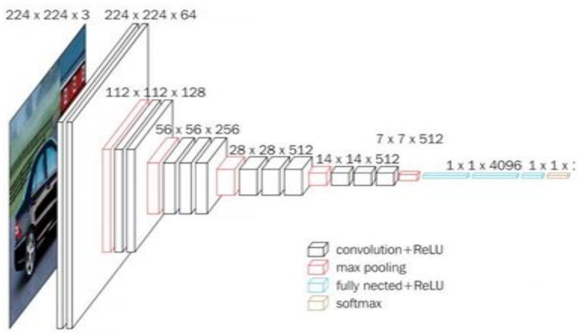

Fig2: VGG-16 Architecture

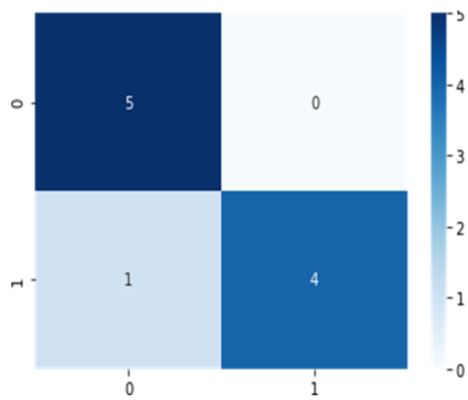

Fig3: Confusion Matrix

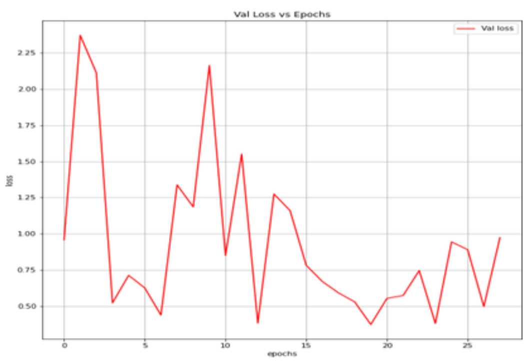

Fig:4 Val Loss

To use the cov1 layer, you must provide an RGB image with an exact dimension of 224 by 224 pixels. There are 33 convolutional (Conv.) layers applied, and the channels are adjusted to that size so that the concepts of left/right, up/down, and focus may be captured. It also uses 11 convolution channels in one of the setups, which can be viewed as a direct shift in the information channels (trailed by non-linearity). In order to maintain the spatial aim after convolution, the convolution step is fixed at 1 pixel, and the spatial cushioning of Convolutionlayer input is 1 pixel for three ConvolutionLayers Five max-pooling layers follow a segment of the Convolutionlayers to achieve spatial pooling (not all the Convolutionlayers are trailed by max-pooling). A 22-pixel window is used for max-pooling in the second step. Two 4096-channel FC models are used first, followed by three 1000-way ILSVRC-grouping FC models, each with 4096 channels. After the stack of convolutional layers, three Fully-Connected (FC) models are added (one for each class). The final layer is the max layer, which is extremely sensitive. Taking everything into account, the architecture of all of the levels is quite similar.

IV.RESULT

When comparing training and test photos, the model's overall accuracy (defined as the percentage of images correctly identified out of all images) was 96% and 90%, respectively. The confusion matrix for the model is shown in figure3.

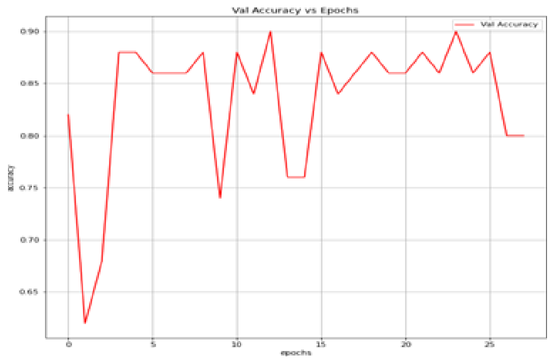

Fig:5 Val Accuracy

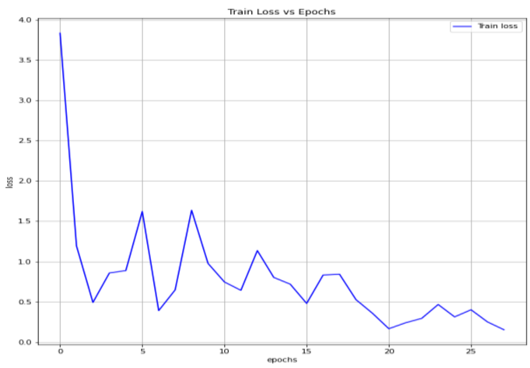

Fig:6 Train Loss

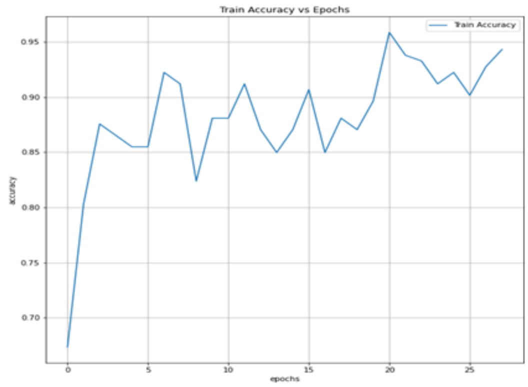

Fig:7 Train Accuracy

V.CONCLUSION

Another strategy for arranging cerebrum tumours was introduced in this paper using the image edge location approach to find the region of interest in MRI images and clip them. After that, this work used the information expansion method to increase the quantity of our prepared data. Second, we give a productive philosophy to cerebrum tumour order by proposing a Transfer learning model VGG-16. For refined and exact outcomes, the neural organisation requires a lot of information to prepare. However, our trial results show that we can obtain 100% exactness and a good precision rate even with a small dataset. Our suggested framework can potentially aid in detecting malignancies in patients with cerebrum tumours. Extensive hyper-boundary adjustment and a superior preprocessing approach can be considered to improve the model's efficacy further

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