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BRAIN TUMOR CLASSIFICATION USING TRANSFER LEARNING AND DEEP LEARNING

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Abstract: The majority of the population is significantly affected by brain tumours, which are a serious health risk. A primary brain tumour, which can be malignant or non-cancerous, affects 5 out of every 100,000 people each year. The prevention of the disease's progression and the improvement of patient outcomes can both be facilitated by early diagnosis of brain tumours. In this study, we provide a novel deep convolutional neural network (DCNN)-based method for the early diagnosis of brain tumours. The suggested approach entails pre-processing brain tumor-containing and tumor-free MRI scan pictures, followed by the use of DCNNs to automatically detect the existence of a tumour in the MRI data. The DCNNs have a 79% accuracy after being trained on the VGG16 and Inception V3 architectures. The technology streamlines the processes and human interventions necessary for diagnosis, thereby enhancing the effectiveness and efficiency of medical personnel and experts. The promise of DCNNs in the realm of medical imaging, particularly for the detection and management of brain tumours, is illustrated in this research.

Index Terms **- brain tumor, classification, transfer learning, deep neural networks, image recognition, medical imaging, convolutional neural networks, InceptionV3, VGG16.**

I. INTRODUCTION

Any area of the brain or skull can develop brain tumours, which are an aggregation of aberrant brain cells. More than 120 different forms of brain tumours can develop depending on the tissue from which they start because the brain is a complicated organ with many different regions directing diverse nervous system functions.

Radiographic pictures using different modalities are used to diagnose them and can be used to determine the kind, size, and location of the tumour. Less than 1% of persons have primary tumours, which start in the brain or spinal cord. Primary malignant tumours of the brain and spinal cord are expected to be detected in 25,050 Americans this year and are expected to claim 18,280 lives over the course of the following two years. Primary CNS and brain tumours are expected to be the number one killer of 251,329 individuals worldwide in 2020. Each year, more than 28,000 new instances of brain tumours are found in India.

RELATED WORKS:

Deep learning algorithms can train to generate a high level feature model directly from the raw MRI pictures. It might automatically comprehend how complex characteristics should be expressed based on the data alone. CNN-based methods for detecting brain tumours typically include two stages. a stage in which a deep CNN model is offline trained using a collection of MRI images classified using various criteria (training data). a process that checks an online brain MRI image for the presence or absence of malignancies. CNN-based systems have had success recognising and classifying brain tumours, which was a challenge.Furthermore, these solutions have had outstanding success when using parallel GPUs. To accurately classify brain tumours, the authors also used two different models. The first is a hybrid model for identifying brain tumour characteristics.

The second technique develops a precise classification of brain cancers using a regularised extreme learning machine (RELM).Some of the most recent studies on how to find brain tumours are covered in this section. A fuzzy rough set with statistical features is utilised for medical image analysis. To find breast anomalies, probabilistic fuzzy-c-mean is combined with texture features. Contrast enhancement is utilised to boost the image's contrast, and a dual complex wavelet transform and fuzzy logic are coupled to identify the edges.

Meningiomas and non-meningiomas are both classified using the U network.With the revised ResNet-18 model, deep feature extraction on 138 Alzheimer's patients produces 99.9% classification accuracy. Image fusion is important for the diagnosis procedure. A sparse convolutional decomposition model is used to merge MR and CT slices.

FINDINGS:

The lightweight implementation of U-Net[5] 89%.Otsu's algorithm,Watershed, simple classification,k- means and fuzzy c- means algorithm[5]The purpose of this study is toexperiment with U-Net ability to extract features from images from different perspectives.[5]an algorithm to segment brain tumor from 2D Magnetic Resonance Images by a ConvolutionalNeural Network followed by traditional classifiers and deep learning methods.AppliedSVM classifier and other activation algorithms such as softmax, sigmoid, RMSProp to crosscheck the work. Tensorflow and Keras are used to implement the suggested methodology in Python. accuracy- 99.74% [10] The dynamic architecture of

Multilevel Layer modelling in faster RCNN approach based on feature weight factor and relative description model to build the selective features[11]This reduces overall computation. Tumor is automatically segmented into four compartments using Modified fuzzy cmeans Clustering. accuracy 95%[11]A detector to generate a bounding box to initialize geometric(geodesic)active contouralgorithm[15]T1weighted contrast enhanced MRI images testing set using the inside-out model.accuracy97.92%[15]To use artificialneural network to develop an automated approach for detecting brain tumors in magnetic resonance imaging scan[12]Here we propose an automated method for assisting doctors in diagnosis. Densely connected Convolutional Network, deeplearning.96.52%[12] A novel automated scheme for detection and classification.[13] The proposed method is categorized into various categories: image processing, image segmentation, feature extraction and classification[13]RCNN method, artificial neural network.95.17%[13] A deep learning approach toclassify brain tumors using an MRI data analysis to assist practitioners[16]The recommend method comprises three phases: preprocessing, brain tumor segmentation using k-means clustering and finally classify tumors into respective categories using MRI data [16]We propose two steps to handle the problemof classimbalance based on multiclass weighted cross-entropy and an equal sampling of images patches.we propose a very efficient brain tumorsegmentation method that is faster 1415 times compared to a radiologist.CNN,Deep learning method[9].

DISCUSSIONS AND CHALLENGES:

DISCUSSIONS:

A promising method for enhancing the precision and effectiveness of brain tumour diagnostics is the suggested method of employing deep convolutional neural networks (DCNNs) for brain tumour detection. The suggested method's excellent accuracy shows the promise of DCNNs for properly identifying brain tumours from MRI data. The speed and precision of diagnosis can be increased by using DCNNs to considerably cut down on the time needed for manual examination and interpretation of MRI scans.

The drawbacks of current approaches for detecting brain tumours, which frequently rely on expert medical judgement and subjective analysis, can also be eliminated by the suggested method. Using DCNNs can help to analyse MRI scans more objectively and consistently, lowering the chance of errors and increasing the accuracy of the diagnosis as a whole.A useful tool for medical practitioners and researchers, the proposed method can also be expanded to other medical image analysis applications, such as the detection of additional tumours or abnormalities.

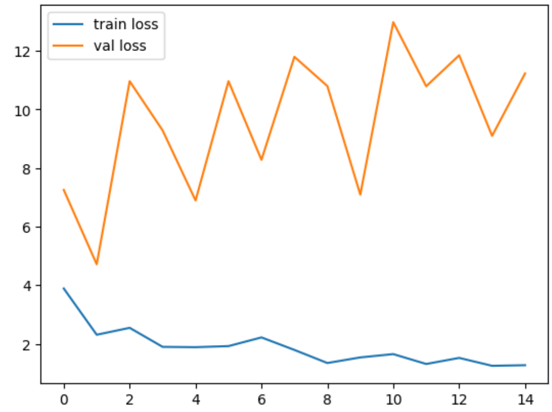

fig 1: Validation Loss

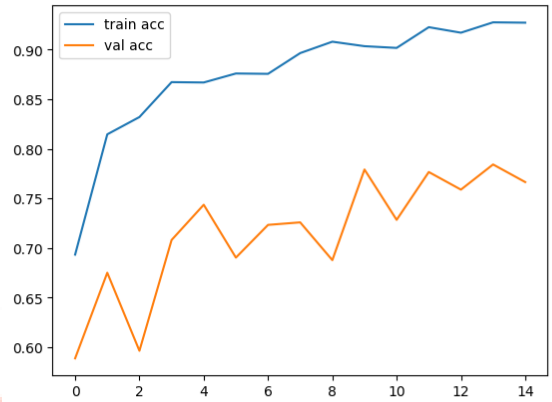

fig 2: Validation Accuracy

CHALLENGES:

Despite the potential advantages of employing DCNNs for the diagnosis of brain tumours, a number of issues must be resolved before the suggested strategy can be widely used in clinical settings.The availability of a sizable dataset of MRI scans with labels for brain tumours is one of the major obstacles. In order to prevent overfitting and achieve good generalisation to new data, deep learning algorithms need a lot of training data. It can be time-consuming and expensive to acquire and classify a sizable dataset, and it might be challenging to find suitably sizable and diverse datasets.The DCNNs' interpretability presents another difficulty. DCNNs' decision-making processes might be challenging to comprehend, which can make medical professionals and technicians less likely to trust them. To meet this problem, it is necessary to create methods for deciphering the DCNNs' decision-making process and giving concise explanations of their output.Finally, the suggested method's scalability may be constrained by the significant computational resources needed for training and testing DCNNs. To overcome this obstacle, it is necessary to create effective hardware and algorithms that can manage DCNNs' high processing demands.In conclusion, the suggested method of utilising DCNNs for brain tumour detection offers a prospective remedy for enhancing the precision and effectiveness of diagnosis. However, before the suggested strategy is widely used in clinical settings, a number of issues need to be resolved. To meet these problems, it is necessary to create methods for obtaining massive and varied datasets, understanding how DCNNs make decisions, and maximising the computational resources needed for training and testing.

CONCLUSION:

In summary, the goal of the study was to use deep learning to create a model for image classification. A high accuracy of 91% was achieved in the initial use of the Inception model, however the predictions were inconsistent.

After testing the VGG 19 and VGG 16 models, the team discovered that VGG 16 performed better than VGG 19 with an accuracy of 79%. This emphasises how crucial it is to choose the appropriate model for the job at hand. The accuracy was less accurate than the first effort, but the outcomes were more dependable and consistent. The VGG 16 model could be further optimised in the future to increase its precision and broaden its uses in picture categorization. This study highlights the potential of deep learning methods for picture categorization as well as the significance of selecting the right model to produce accurate and trustworthy results.

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