BRAIN NEOPLASM IDENTIFICATION USING DEEP LEARNING

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ABSTRACT:

This study offers a powerful brain tumor detection system that makes use of deep learning techniques, especially the VGG16 learning algorithm and Convolutional Neural Network techniques (CNN). The ultimate objective of the recommended strategy is to enhance the accuracy and efficiency of identifying tumors in magnetic resonance imaging (MRI) images.. Utilizing CNN allows the model to automatically extract intricate features from input images, while VGG16, renowned for its deep architecture, contributes to a more intricate understanding of complex patterns. The integration of these algorithms empowers the system to discern subtle nuances indicative of brain tumors, providing a reliable and swift diagnostic tool for medical practitioners. Experimental results demonstrate the system's effectiveness in achieving high accuracy rates, showcasing its potential as an invaluable asset in early tumor detection and subsequent medical intervention.

KEYWORDS: CNN, Brain tumor, Machine learning, Medical imaging

INTRODUCTION:

Brain tumors occur when unwanted tissues grow inside the skull. It comes into one of the two classifications. They were both normal and cancerous. Cancerous tumors proliferate and divide swiftly throughout the brain tissues that surround them. Tissue in the brain can also be affected by non-cancerous tumors. Normal tumors account for about 70% of all tumors. Thirty percent are cancerous. Brain tumors come in one hundred and twenty various varieties. Gliomas, pituitary, and meningiomas are the most common types of tumors. Certain brain cancers can be treated with surgery, radiation therapy, or chemotherapy. A doctor's guidance is necessary for a proper diagnosis and suggested course of therapy. Depending on the size and location of the tumor, signs of brain tumors can differ and may include symptoms such as headaches, seizures, vision impairment or struggle balancing. Early detection and treatment are crucial for improving outcomes and quality of life for patients with brain tumors. Glioma is the most dangerous brain tumor. Early detection of brain tumors can prevent deadly aspects.

The analysis indicates that each year, brain tumors afflict approximately 28 thousand people. In the United Kingdom, brain tumors are more prevalent than in other nations. Many methods, including tomographic imaging, radiation therapy, magnetic resonance imaging (MRI), and echocardiography, can be used to record medical imaging data. The most well-known of them is MRI since it produces radiation-free, higher-resolution images. A type of non-invasive test termed an MRI gives the radiologist the vital details about medical images in order to figure out abnormalities in the brain. Conversely, brain cancers can be identified early and without the need for human intervention thanks regarding the CAD (computer-aided diagnosis) technique. CAD systems have the ability to provide diagnostic reports and offer guidance to radiologists based on MRI images.

This paper proposes an algorithm for automatically categorizing tumors in the brain using two deep learning models: a single uses a 23-section CNN structure for multiple classes brain tumors, training with 3064 MRI images; a layer for dropping out and distinct kernel sizes are used to extract complex features; the initial model uses a fine-tuned model with a transfer learning-based the VGG16 model architecture for normal and abnormal brain images, applying four dense layers and a soft max activation function. The experimental results show models reach up to 97.8 percent and 100 percent prediction accuracy, surpassing previous studies.

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RELATED WORKS:

In order to differentiate brain cancers from vast amounts of medical MRI imaging data, machine learning algorithms are being developed. These techniques primarily focus on binary identification, but they also address dimension reduction, extraction of features, choice of features, and classification methods.

CNN does not require segmentation, hence it does not require labor-intensive hand-crafted feature extraction methods. Many CNN architectures have been proposed by researchers, the majority of them concentrate on multi-class brain tumor detection. On two datasets, a 16-layer CNN model produced prediction accuracy of 96.1 percent and 98.7 percent

In order to classify glioma tumors, ertosunetal. created a hybrid CNN model that achieved 96.0%, 71.0%, and 71.0% accuracy. Glioma tumors were detected by Anaraki et al. with 90.9% and 94.2% prediction accuracy, respectively.

The study utilized data augmentation to address the challenge of training a CNN model in the medical imaging field, which requires a large number of images. This technique helps introduce new variants during training.

Because transfer learning models require little computing power, they have been used to diagnose brain cancers. ResNet34, VGG19, AlexNet, and VGG19 are a few examples that have been optimized for various kinds of brain tumors. High prediction accuracy is achieved with large-scale data augmentation; prior research showed an accuracy of 87.4%.

DATASET:

Two different kinds of datasets are employed in this study. The first dataset is accessible anywhere. The General Hospital, Nanfang Hospital, and Tianjin Medical University provided the data (China). There are 3064 MRI pictures in the collection. Meningiomas, gliomas, and pituitary tumors were among the 233 patients whose MRI pictures were recognized.
The Harvard repository provided the second dataset. There are 152 T1 and T2 weighted contrast MRI pictures in the dataset. Within this dataset, 81 abnormal photos with tumors are present, whereas the other 71 pictures are normal and devoid of cancers. Five different tumor forms can be seen in the aberrant images: meningioma, sarcoma, metastatic bronchogenic carcinoma, metastatic adenocarcinoma, and glioma.

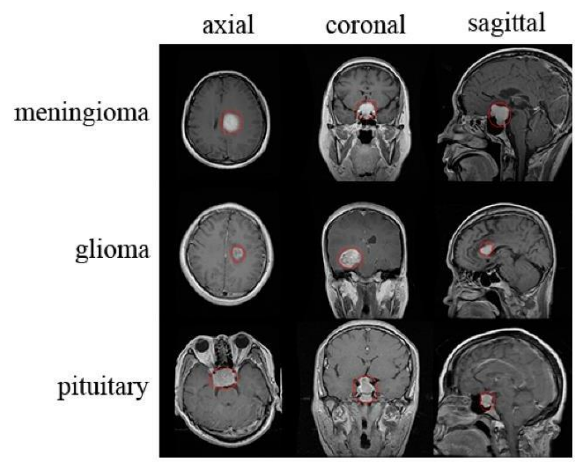
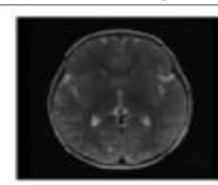
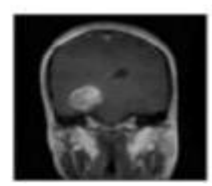
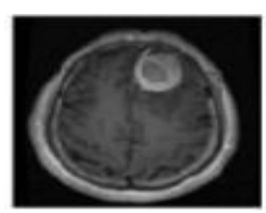
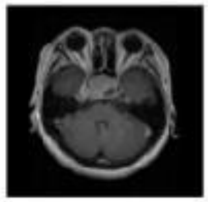


Fig 1: Description of normalized MRI pictures showing various tumor types in different planes

Table 1: Categorization of MRI brain pictures

	MRI Brain Images
No Tumor	
Glioma Tumor	
Meningioma Tumor	

Pituitary Tumor



CNN:

CNNs, inspired by the human visual cortex, are increasingly used for image classification tasks, learning hierarchical visual features from raw pixel data using convolutional, pooling, and fully linked layers.

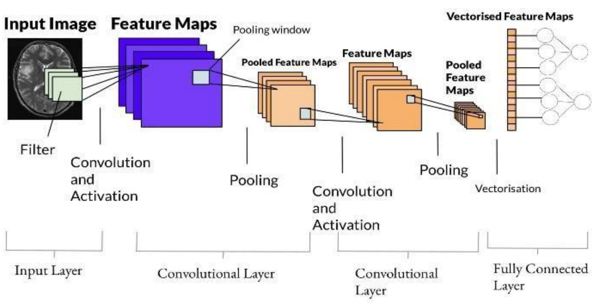


Fig 2:CNN algorithm

METHODOLOGY:

The architecture uses optimized VGG16 and proposed 23-layer CNN architectures on the used datasets for picture extraction, label loading, preprocessing, training, validation, and testing. Twenty-three convolutional layers with residual connections make up the CNN. The network receives as input the intracranial voltage measurement time series together with the patient's ID. VGG16 is a special 16-layer convolutional neural network model that is well-known for having good vision model architecture and minimal hyper-parameters.

Fig. 2 displays the developed block diagram for our suggested automated binary and multiclass brain tumor detection system. MRI pictures are considered input for the input layer of CNNs. By preprocessing, computing complexity is reduced. To train the dataset, the input images are transformed to 32 x 32 pixels from a variety of heights and widths. To reduce the complexity, input images are converted into grayscale. Then, using data augmentation, develop new images from old ones. For training purposes, the dataset is divided into training and validation. This structure is used to classify the MRI images, which include global, local, merging, and output routes. The Soft-max function is executed to carry out the brain tumor classification (tumor or non-tumor) process to get the result.

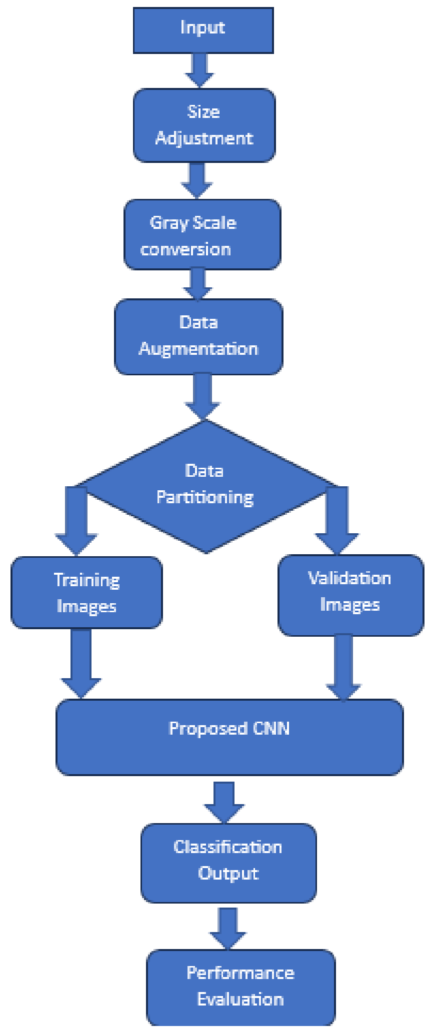


Fig 3: Framework of approach

METHODS AND MATERIALS:

This section describes our method for classifying brain cancers based on magnetic resonance imaging (MR). We use a schematic block design in Fig. 3 to visually represent the procedure. We start with brain tumor slice MR images and apply different preprocessing processes that are necessary for sample preparation prior to training. Given the difficulty of training deep convolutional neural network (CNN)

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architectures on small datasets, we use data augmentation approaches to enlarge the training set. This augmentation increases the diversity of the dataset by producing extra slices for every kind of tumor. Our approach is based on transfer learning, using Efficient-Nets and their variants that have already been trained. Focusing on MRI sequences from a CE-MRI brain tumor dataset, we specifically optimize five pre-trained Efficient-Net models (EfficientNetB0 to EfficientNetB4) for feature extraction and classification. We choose these models because they are very accurate on the Image-Net dataset when compared to other modern CNN designs, and they are computationally efficient, requiring a low number of floating-point operations per second (FLOPS) during inference. The next sections try to provide a thorough knowledge of the mechanics of our suggested technique by providing in-depth insights into each step.

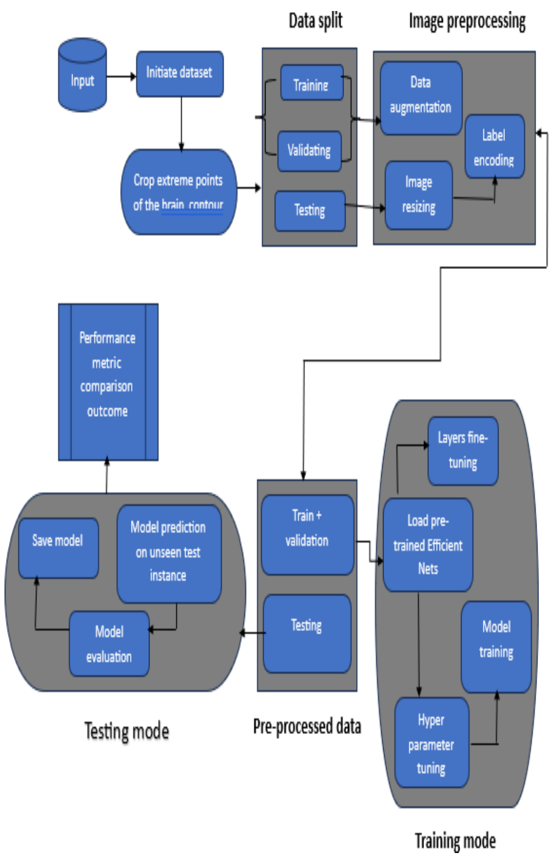

Fig 4: Proposed model block diagram

Pre-Processing:

In order to minimize computational strain during network training, the input images are down-sampled. Using image processing techniques to find outliers, the approach entails identifying and removing the outer margins of brain outlines. The random shuffle of data samples prevents attention from being drawn to a particular portion of the dataset. Following the process of cropping MRI scans of brain tumors, the samples are separated into training and test sets, with 70% going toward training and 30% toward testing. In both sets, the class labels for pituitary tumors, meningiomas, and gliomas are encoded as 0, 1, and 2.

Data Augmentation:

In order to expand the dataset size for deep CNN architecture training, the research used data augmentation. To equalize instance distribution throughout each class, the researchers apply a variety of image alteration techniques, including rotation and scaling, to make the images of gliomas, meningiomas, and pituitary tumors taller. Images are distributed and compared both before and after data augmentation.

PROPOSED SYSTEM:

The suggested "23-layer CNN" layout is utilized for categorizing many tumor shapes, which include meningioma, pituitary, and glioma. In this instance, we utilize magnetic resonance imaging (MRI) findings as input, process them via a number of sections, and finally split the images from one another. In the above instance, the slice has been processed using 23 layers.

The layer of convolution is one of the key elements of the CNN model. To construct a transformed feature map, perform a dot product between two matrix. The original image's pixel intensity values are presented in one matrix, which is related to the kernel. The kernel is used to extract properties from the source image, such as corners, borders, and forms, by moving over it vertically and horizontally. The model finds more and better features as we proceed, including gradient direction, texturing, sharpening, and blurring. The four convolutional layers that have various kernel sizes that together make up a "23-layer CNN" layout are 22 × 22, 11 × 11, 7 × 7, and 3 × 3.

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We use stride two to move the filter over the input matrix two pixels at a time. In order to prevent losing image details, we apply zero padding to maintain the image's original size. The convolutional layer is represented by the following equation:

C (h,d) = (k×f) (h, d)=$\sum_i \sum_j k(h-i, d-j) f(i,j)$ (1)

Where K is the image with a size of (h, d), and (i, j) is the size of the kernel value that corresponds to the f-number of filters. The convolutional method used to create the feature map is shown in Fig 6.As a stimulating function, we utilize the Rectified Linear Unit (ReLU), which executes non-linear operations inside a convoluted layer. The gradient vanishing problem can be resolved with the help of the RelU function of activation and the back propagation approach. The RelU is defined as follows:

$f(z) = \max(0,z)$ (2)

The ReLU activation function is graphically displayed in Fig. 7. At the next stage, the pooling layers minimize the dimension of the changed feature map.

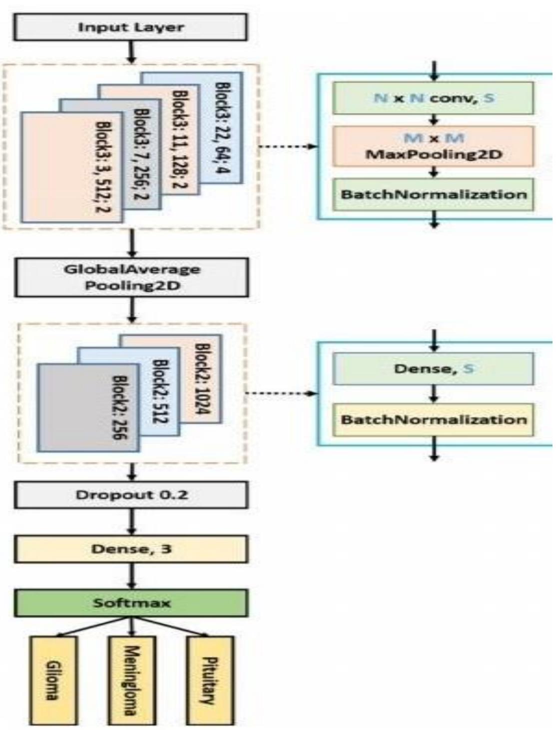

Fig 5:23 layer CNN architecture

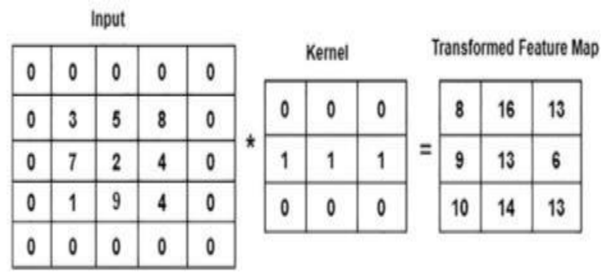

Fig 6: Convolutional operation on 5 × 5 image using 3 × 3 kernel.

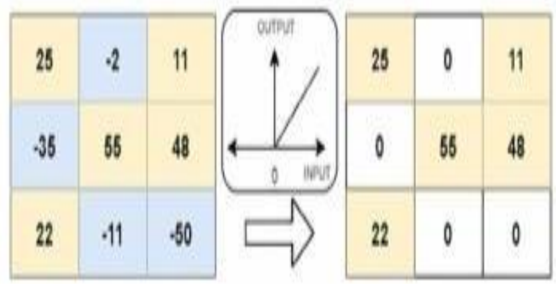

Fig 7 :ReLU operation

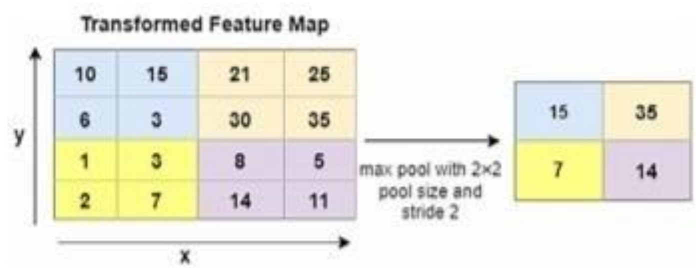

Fig 8:Drop out layer

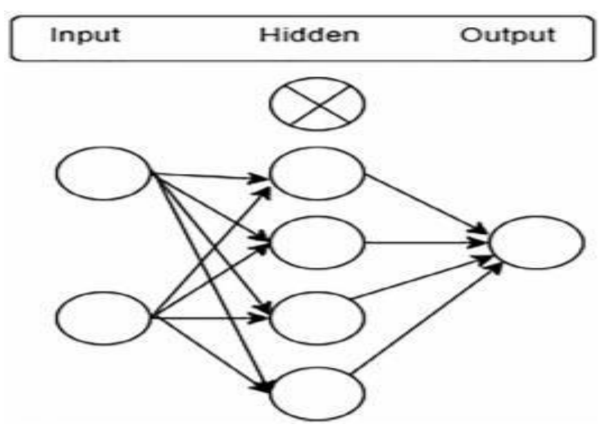

Fig 10: Max pooling procedure

FUTURE SCOPE:

Integrating 3D data into brain tumor detection systems enhances diagnostic accuracy and treatment planning through deep learning. Unlike 2D imaging, 3D approaches like volumetric MRI provide a comprehensive spatial view, allowing DL models to better understand tumor morphology and spatial relationships. These models excel in tumor segmentation by analyzing complete volumes, accurately delineating boundaries crucial for treatment planning. They seamlessly integrate data from modalities like MRI, CT, and PET scans, elevating diagnostic accuracy. Real-time visualization of 3D data enables clinicians to interactively explore images, aiding diagnosis and treatment decision-making with intuitive representations. Additionally, 3D DL models facilitate longitudinal analysis of tumor progression and treatment response, tracking changes over time to optimize treatment plans. Despite computational challenges, advances in hardware and algorithms make the integration of 3D DL models into clinical practice increasingly feasible, promising significant improvements in brain tumor diagnosis and treatment.

RESULT:

This proposed system produce classification of brain tumor including glioma tumor, meningioma tumor and pituitary tumor. And also show high accuracy using CNN and VGG16 architecture. Fig 11 describe the result of proposed system.

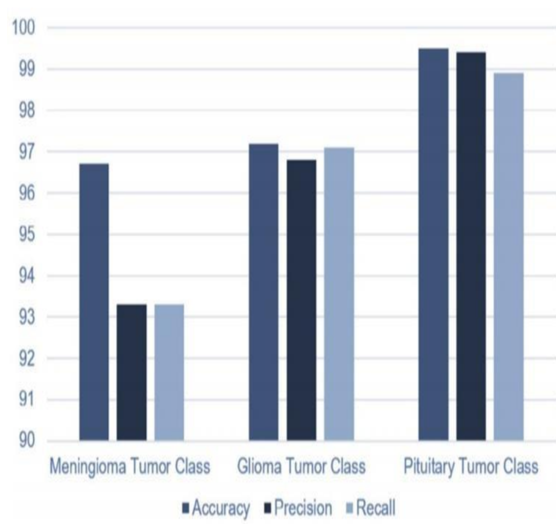

Fig 11: Performance of the proposed method

CONCLUSION:

Two deep learning models for recognizing anomalies in the brain and grading tumors are presented in this research. The fine-tuned CNN with VGG16 is ideal for limited data, whereas the 23-layer CNN architecture is meant for massive image data. With prediction accuracy of 97.8% and 100%, respectively, these models show promise in the identification of brain tumors.

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