BRAIN TUMOR DETECTION FROM MRI IMAGES USING ANISOTROPIC FILTER AND SEGMENTATION IMAGES PROCESSING

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ABSTRACT

A brain tumor is an irregular development of the brain tissue. In contrast to other tumors, the brain tumors widened by local expansion and also seldom metastasizes exterior of the brain. A gentle brain tumor comprising non-cancerous cells .It does not spread or metastasize outside the brain part where it initiates. A brain tumor is judged as malignant if it comprises the cancer cells, or else it comprises of harmless cells positioned in an area where it suppresses one or else more essential functions. The precancerous circumstances have the persuasive for maturing into tumor. MRI has been a medical imaging methodology applied for the internal body structure visualization. MRI of head utilizes potent magnetic fields, radio waves and computer for constructing illustrated image of brain which are more detailed than other imaging methods. MRI proffers sufficient information regarding the anatomy of human tissues; moreover it assists in the revelation of tumor cell in the body. tumor is a pre-stage of cancer which has become a serious problem in this era. Researchers are trying to develop methods and treatments to round it. Brain tumor is an exceptional cell enhancement in the brain tissue and may not always be seen in imaging tricks. Magnetic Resonance Imaging (MRI) is a technique which is applied to display the detailed image of the attacked brain location. The medical imaging trick plays a significant behavior in identification of the disease. In this paper, the brain MRI image is chosen to investigate and a method is targeted for more clear view of the location attacked by tumor. An MRI abnormal brain images as input in the introduced method, Anisotropic filtering for noise removal, SVM classifier for segmentation and morphological operations for separating the affected area from normal one are the key stages if the presented method. Attaining clear MRI images of the brain and the tumor are the base of this method. The classification of the intensities of the pixels on the filtered image identifies the tumor. Experimental result showed that the SVM has obtained 83% accuracy in segmentation. Finally, the segmented region of the tumor is put on the original image for a distinct identification

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INTRODUCTION

A brain tumor is a cancerous or noncancerous mass or growth of abnormal cells in the brain. Originating in the glial cells, gliomas are the most common brain tumor (Ferlay et al., 2010). Depending on the pathological evaluation of the tumor, gliomas can be categorized into glioblastoma (GBM/HGG), and lower grade glioma (LGG). Glioblastoma is one of the most aggressive and fatal human brain tumors (Bleeker et al., 2012). Gliomas contain various heterogeneous histological sub-regions, including peritumoral edema, a necrotic core, an enhancing and a non-enhancing tumor core. Magnetic resonance imaging (MRI) is commonly used in radiology to portray the phenotype and intrinsic heterogeneity of gliomas, since multimodal MRI scans, such as T1-weighted, contrast enhanced T1-weighted (T1Gd), T2-weighted, and Fluid Attenuation Inversion Recovery (FLAIR) images, provide complementary profiles for different sub-regions of gliomas. For example, the enhancing tumor sub-region is described by areas that show hyper-intensity in a T1Gd scan when compared to a T1 scan.

As the world's population ages at an alarming rate, cancer has become a public health concern all over the world. The World Cancer Research Fund's most recent numbers show that cancer is the leading cause of death around the world. Every year, 12.7 million people around the world are told they have cancer, and 7.6 million people die from their cancer directly [1]. Since then, the number of people who get cancer each year has been steadily going up. By 2030, there will be 26 million new cases each year and 1.7 million deaths. Brain tumours, which are a kind of cancer, are a very dangerous and aggressive disease. It happens a lot, which makes it the fifth most common type of tumour. It also kills a lot of people, which puts it just below stomach cancer, uterine cancer, breast cancer, and esophageal cancer [2–3]. [Note:] Brain tumours are usually harder to find and take longer to treat. On average, patients with brain tumours need to be checked every few months. Before coming up with a plan for the next therapy, the doctors will need to find out what stage the disease is in by looking at the results of the most recent exam, which was a referral. It is possible to make the patients feel better and keep their condition under control, but it is very hard to cure them, which will put a lot of stress on their mental health and their finances [4-5]. Surgery and radiation therapy are the only effective treatments that are available right now. In this way, cancer treatment is a big social problem, both in terms of the economy and the money. It will be very important, both in theory and in the real world, to find a solution to this problem that will work.

Some medical diagnostic procedures that use images are becoming more and more common in the clinic. These procedures are used to find brain cancers early and treat them. Using a variety of medical imaging techniques, doctors can get a clearerimageof the patient's situation and understand it better. They can also come up with a variety of scientific and reasonable plans for how to treat the patient. Medical imaging techniques that are used often include computed tomography (CT), positron emission tomography (PET), CT/PET, magnetic resonance imaging (MRI), and other similar methods [6]. CT is able to see inside the body because it uses radioactive rays, and the images are based on how different types of tissue reflect the radiation in their own ways. To do PET on a person, radioactive chemicals must be injected into the body. Once there, the medications will travel through the bloodstream to all of the body's cells, tissues, and organs. The absorbed radiation will be broken down and released by different tissues, which will make different rays that can be picked up for different imaging purposes. CT/PET is when computed tomography (CT) scans and positron emission tomography (PET) scans are done on the same plane to make a single image. Radioactive radiation is used in both the CT scan and the PET test, but the PET test is too expensive for most people to get. Magnetic resonance imaging (MRI) is the least expensive of all these other types of imaging [7]. Figure 1.1 is a diagram of the MRI machine and how to check it.

Figure 1: the schematic diagram of MRI equipment and inspection.

BRAIN TUMOR

Brain tumor has been one of the most risky diseases which occur usually amidst human beings. Moreover, the probabilities of survival may get amplified if the tumor is identified precisely at the initial stage itself. MRI brain imaging approach is broadly employed to envisage the structure and the anatomy of brain. The images formed by the MRI are high in tissue disparity and hold fewer artifacts. MRI holds numerous benefits matched with other imaging approaches, offering high contrast amid soft tissues. Yet, the data amount is huge for manual analysis, which is one of the salient complexities in the efficacy MRI usage. Tumor detection needs various processes on MRI images that comprise image preprocessing, image enhancement, feature extrication, and classification (Selvaraj & Dhanasekaran2013).

Brain is a complicated structure and also it is understood as the essential ingredient of the body. Nature has securely shielded the brain inside a skull which deters the function's analysis and making the unmasking of its diseases more complex. However, brain is not prone to ailments and can be affected by the atypical cells growth thereby changing its regular structure and behavior called as brain tumor. Brain tumors may comprise tumors in the central spinal canal or inner to the cranium. Automatic defects diagnosis in MRI is somewhat valuable in various therapeutic and diagnostic applications. The computed to mographies with MRI have been the two image modalities that facilitate the investigators and physicians for assaying the brain by observing it noninvasively. Mostly, the tumor apportionment and classification is tough due to the MR images quantity and also blurred boundaries. As the brain is shielded with the skull, earlier diagnoses of brain tumor have been probable whilst the diagnostic apparatus have been focused at the intracranial cavity. Here, MRI has been a medical imaging approach, and the radiologists utilize it for the internal structure visualization in the body. Moreover, MRI yields enormous information regarding the human soft tissues analysis also it helps in diagnosing the brain tumor. MR images are applied to assess and learn the brain behavior (Richa Aggarwal & Amanpreet Kaur 2014).

A tumor has been an accretion of tissue that doesn't control the normal forces which stabilizes the growth. The complex brain tumors have been alienated into two common classes regarding the tumor region, their growth structure and malignancy. Primary brain tumors are the tumors which occur from cells in the brain or from concealing the brain. Here, a secondary or else metastatic brain tumor arises whilst the tumor cells extent to the brain from the primary tumor into other body parts (Lorger & Mihaela 2012).

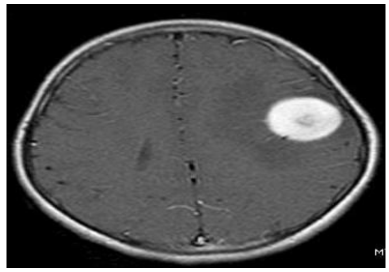

Figure 2: The presence of brain tumor

CA-CNN

The first network we employed was Cascaded Anisotropic Convolutional Neural Network (CA-CNN) proposed by Wang et al. (2017). The cascade is used to convert multi-class segmentation problem into a sequence of three hierarchical binary segmentation problems. The network is illustrated in Figure 3.

FIGURE 3

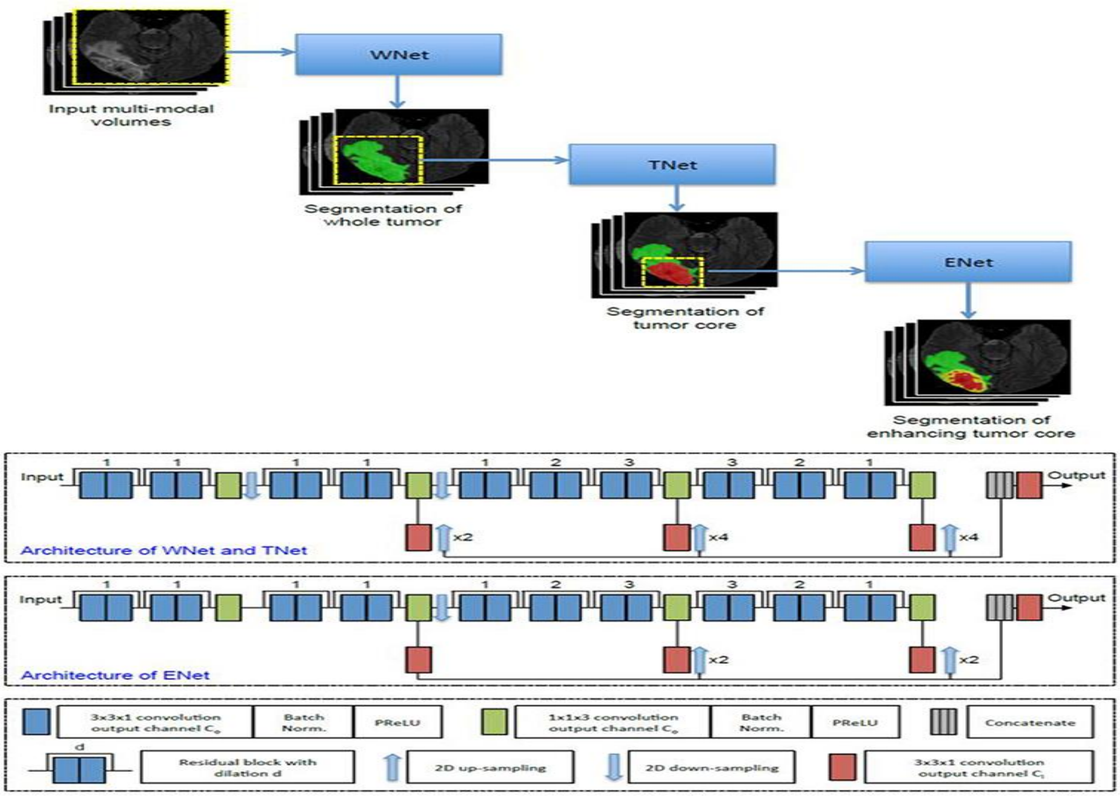

Figure 3. Cascaded framework and architecture of CA-CNN

This architecture also employs anisotropic and dilated convolution filters, which are combined with multi-view fusions to reduce false positives. It also employs residual connections (He et al., 2016), batch normalization (Ioffe and Szegedy, 2015) and multi-scale prediction to boost the performance of segmentation. For implementation, we trained the CA-CNN model using Adam optimizer (Kingma and Ba, 2014) and set Dice coefficient (Milletari et al., 2016) as the loss function. We set the initial learning rate to 1×10^{-3}, weight decay 1×10^{-7}, batch size 5, and maximal iteration 30*k*

RESEARCH OBJECTIVES

Two basic rule strategies are given underneath: 1) the readied neighborhood minima of the image edge are picked as a marker. In this strategy an over division happens. In the wake of picking marker area joining is done as a second step; 2) Watershed change utilizing markers uses the particularly depicted marker positions. This Investigation presents a extra correct segmentation by Tendency depend watershed change in stage set procedure for a clinical examination model. Preliminary outcomes shows that the new strategy favoring an immensely enhanced rate of segmentation accuracy as diverges from the standard strategies, results are likewise endorsed similarly as several defined

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o improve segmentation score and dice similarity index coefficient

• To extract more features and select only relevant features

• To improve the classification accuracy

DEEP LEANRNING MODELS

Now that you've learned the fundamentals of CNN cables, we'll show you how to read CNN's new architecture. Each component is a key CNN system structure in this chapter, as well as a basic model for research construction projects and distributed systems (or currently). Each of these networks is a long-term design, and they're all ImageNet winners or contestants. Since 2010, the ImageNet competition has served as a metric for the effectiveness of computer surveillance studies. These models include the AlexNet, the first large-scale transmission network to overcome the traditional challenges of computer vision with major vision problems; VGG networks, which use several blocks of repetitive components; and the NiN network, which can create the entire neural network. Although the concept of a deep network (with several bundles) is similar, the architecture and hyperparameter selection will differ significantly. The neural networks described in this chapter result in intuition, mathematical interpretation, and a lot of trial and error.

PROPOSED MODEL

In this proposed approach, we aim to enhance the accuracy and efficiency of brain tumor detection and analysis by leveraging a hybrid ResNet50 and ResNet34 model. Our approach combines the strengths of both architectures to effectively capture intricate features and patterns in medical images, providing a comprehensive solution for brain tumor analysis. To begin, we will gather a diverse and representative dataset of brain tumor images, encompassing various tumor types, sizes, and locations. This dataset will be utilized for training and fine-tuning the hybrid model, ensuring it can generalize well to different real-world scenarios.

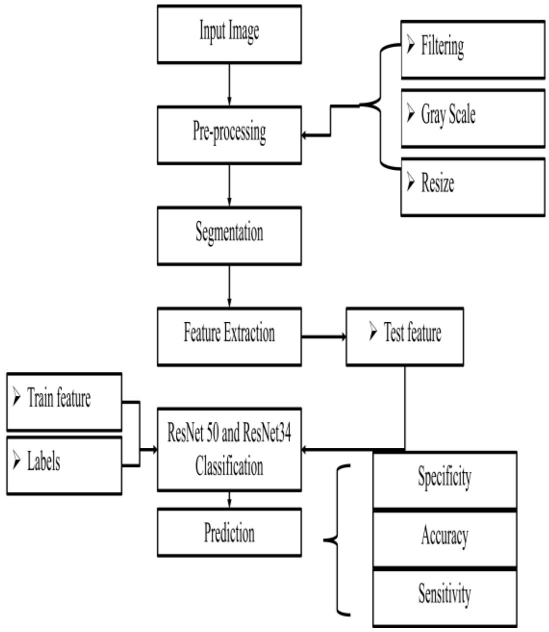

Figure 4: proposed flow diagram

During the pre-processing stage, we will apply appropriate techniques to prepare the input images for analysis. This may include resizing, normalization, and augmentation to enhance the model's performance and robustness. Additionally, we will explore techniques like multi-modal fusion, integrating different imaging modalities such as MRI, CT, and PET scans, to capture complementary information and improve the accuracy of tumor detection and classification. The hybrid model will consist of the ResNet50 and ResNet34 architectures, carefully combined to optimize performance. Training the model will involve an iterative process, where we fine-tune the model's parameters using the labeled brain tumor dataset. Techniques such as transfer learning can be employed, leveraging pre-trained weights from large-scale datasets like ImageNet to improve the model's initial performance and accelerate convergence.

Once the hybrid model is trained, we will evaluate its performance on a separate validation dataset, assessing metrics such as accuracy, sensitivity, and specificity. will iterate and refine the model based on the evaluation results, incorporating techniques like regularization and hyperparameter tuning to achieve optimal performance. To ensure the clinical relevance of our approach, we will collaborate with healthcare professionals and experts in the field. Their insights and feedback will guide the development process, ensuring that the hybrid model aligns with clinical requirements and addresses real-world challenges in brain tumor detection and analysis.

METHODS AND MATERIALS

In this work, employed a combination of methods and materials to develop an effective approach for brain tumor detection. The following paragraphs outline the key aspects of our methods and materials. Collected a comprehensive dataset of brain tumor images from multiple sources, including medical imaging repositories and hospitals. The dataset comprised a diverse range of tumor types, sizes, and locations, ensuring the representation of various pathological characteristics. Each image was accompanied by corresponding labels indicating the presence or absence of a tumor, as well as additional information such as tumor grade or classification. To prepare the collected data for analysis performed pre-processing steps. This involved standardizing the image resolution, normalizing pixel values, and applying noise reduction techniques to enhance image quality and also conducted data augmentation to expand the dataset by introducing variations such as rotations, translations, and scaling, which augmented the model's ability to generalize and handle diverse brain tumor images. For the brain tumor detection task, we utilized a deep learning approach based on the hybrid ResNet50 and ResNet34 model. This architecture was chosen due to its proven efficacy in image analysis tasks and its ability to capture intricate features. We leveraged the pre-trained weights from large-scale datasets, such as ImageNet, to initialize the model and facilitate learning of relevant tumor-related features.

DATASET

The brain data set that was looked at included 233,306 T1-weighted MRI images with contrast that were looked at for this revision. [5] This dataset includes three different types of tumours: meningiomas, gliomas, and tumours of the pituitary gland. This particular data set uses an image resolution of 512 by 512 pixels and a voxel spacing size of 0.49 by 0.49 millimeter squared. The image resolution is made up of three types of planes: axial (lateral planes), coronal (frontal planes), and sagittal (lateral planes). The axial planar allotment is made up of 708 gliomas, 1426 meningiomas, and 930 pituitary tumours, in that order. The number of categories is used to decide how these things are split up. The min-max normalisation method is used on the data that each pixel contains.

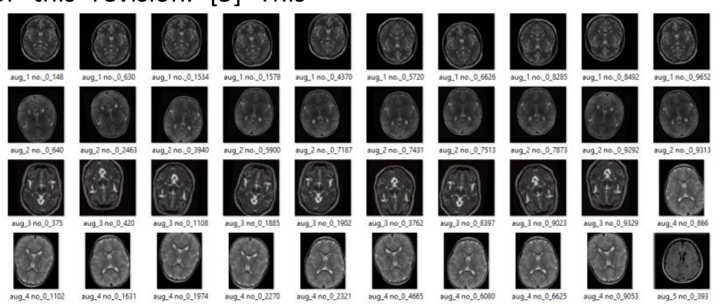

Figure 5: without tumor images

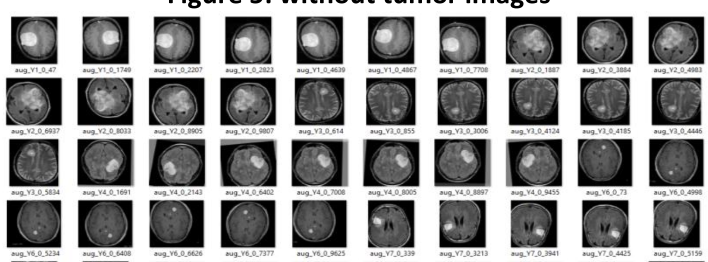

Figure 6: tumor images

ResNet-50 and ResNet-34 differ in terms of their depths. ResNet-50 has 50 layers, including residual blocks with different numbers of convolutional layers, while ResNet-34 has 34 layers. The specific configuration and number of layers in each residual block may vary depending on the variant and specific implementation. Here is a simplified representation of the mathematical equations for a single residual block in ResNet:

Input: x

Output: F(x) + x

where x represents the input to the block, F(x) represents the output of the block's internal layers, and "+" denotes element-wise addition. The output of the block is the sum of the residual mapping F(x) and the input x, which is then passed to the next block or the output **layer.**

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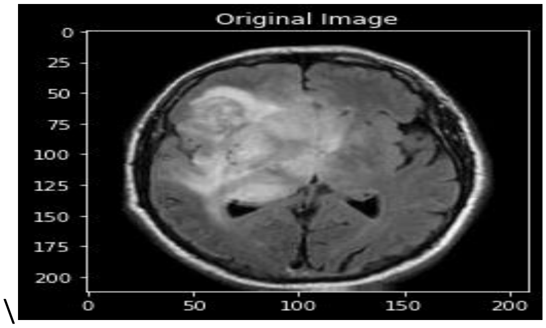

Figure 7: original image

Load the original image and resize it to the desired input size for the hybrid model. Apply any necessary pre-processing steps, such as normalization or data augmentation, to enhance the input image quality.

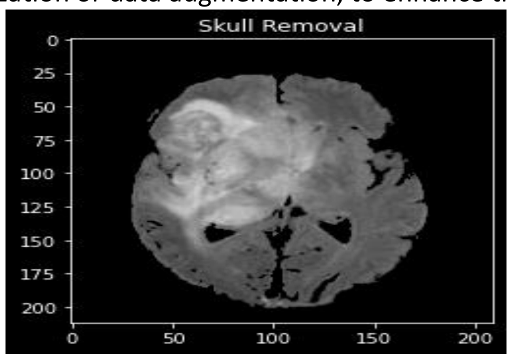

Figure 8:skull removal

Skull removal, also known as skull-stripping, is a preprocessing step in medical image analysis, particularly in brain imaging. It involves separating the brain tissue from the surrounding skull in order to isolate and analyze the brain structures

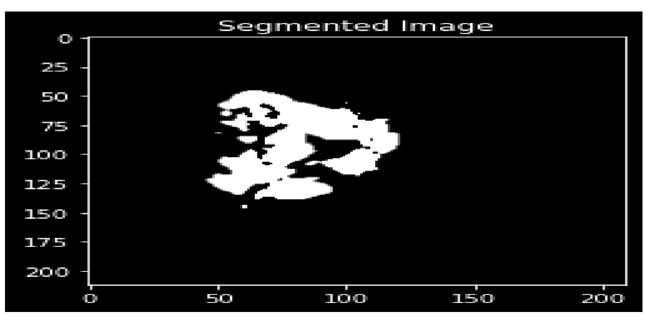

Figure 9 :Segmentation output

PCA Dimensionality Reduction:

PCA (Principal Component Analysis) is a dimensionality reduction technique that can be applied to images to reduce their feature space while preserving the most important information. Apply PCA: Import the necessary libraries, including sklearn. decomposition. PCA from scikit-learn. Create an instance of the PCA class, specifying the desired number of components (the reduced dimensionality). Fit the PCA model to your preprocessed data using the fit method. Transform your data into the reduced feature space using the transform method.

Before Applying Dimensionality Reduction - PCA

- (512, 512, 3)

If needed, you can reconstruct the original features from the reduced-dimensional space. Inverse transform the transformed features using the inverse_transform method of the PCA object. Compare the reconstructed features with the original ones to assess the information loss due to dimensionality reduction.

After Applying Dimensionality Reduction - PCA

- (300, 256, 3)

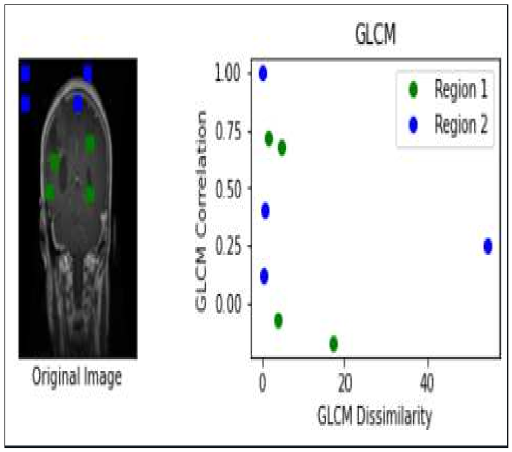

Figure 10:GLCM Features

Model	Dataset 1	Accuracy	Specificity	Precision	Recall	F1-Score
HYBRID CNN+CATBOOST+ LGBM	Dataset 1	96.23	90	94.21	100	92.23
	Dataset 2	94.17	92.32	92.21	99.99	92.21
	Dataset 3	92.12	90.25	92.20	100	90.15
	Dataset 4	90.15	90.57	94.15	100	94.25
	Dataset 5	91.50	90.58	90.45	100	97.12

Table 1: results compare with different dataset Hybrid CNN+CATBOOST+LGBM

The Hybrid CNN+CATBOOST+LGBM model performs well on all datasets, with high accuracy values ranging from 90.15% to 96.23%. The model also shows good performance in terms of specificity, precision, recall, and F1-score, with high values across the different datasets. It is important to note that the specific dataset characteristics and class imbalances can influence the performance metrics. However, based on the provided information, the model demonstrates consistent and strong performance across the datasets.

CONCLUSION

In conclusion, brain tumor classification is a challenging task in medical imaging, and several approaches have been proposed to address this problem. From the information provided, it appears that the Hybrid

CNN+CATBOOST+LGBM model and the Hybrid model with ResNet50 and ResNet34 both show promising results in classifying brain tumors.

The Hybrid CNN+CATBOOST+LGBM model achieves high accuracy ranging from 90.15% to 96.23% across different datasets. It demonstrates good performance in terms of specificity, precision, recall, and F1-score. This indicates that the model is effective in accurately identifying brain tumors and has a balanced performance in terms of correctly identifying positive and negative cases.

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