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A Hybrid Model for Brain Tumor Segmentation using VGG16 and ResNet50

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Abstract:

Cancers of the brain are among the worst illnesses a person may get. The course of medical therapy is mostly determined by the tumor's location and kind. Neuro specialists and radiologists must carefully review Magnetic Resonance Imaging (MRI) pictures in order to arrive at a definitive diagnosis of a malignancy. Treatment option mapping, disease progression monitoring, and image-based tumor segmentation are of utmost importance in medical imaging because they provide information vital for cancer analysis and diagnosis. Some have speculated that deep learning might be the key to better brain cancer diagnosis and treatment. With its state-of-the-art segmentation and detection capabilities, the segmentation strategy has significantly improved the removal of abnormal tumor regions from the brain. In this study, we published a VGG16 and ResNet50 hybrid model for MRI brain tumor segmentation. With the use of the ResNet50 algorithm and the VGG16, a Transfer Learning method, brain tumors may be detected in segmented pictures. The findings show that our suggested approach is more accurate and performs better than other models when compared side by side.

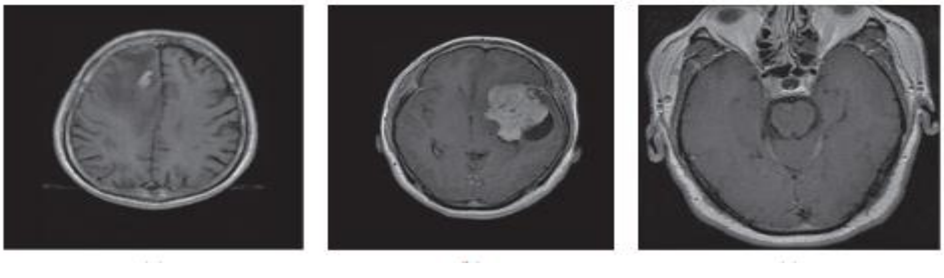
Keywords: Image Segmentation, CNN, Transfer Learning, VGG16, ResNet50

1. Introduction

Tumors in the brain develop when the brain's cell development is abnormal and uncontrolled. Since the human skull is inflexible and has limited space, any sudden alteration would have an effect on human function according to the region of the brain impacted, and the cancer might spread to other organs. As to the World Health Organization's World Cancer Report, fewer than 2% of all human malignant growths are cerebral illnesses. Whatever the case may be, it leads to major problems and harm. Worldwide, some 5,250 people lose their lives each year to malignancies of the brain, CNS, and other parts of the brain and spinal cord [1]. Cancer has risen sharply in recent years to become the leading global health concern. According to data collected from the country's population registry, cancer claims the lives of around 8 lacs people year, making it the second-leading chronic killer in India. The Indian Council of Medical Research (ICMR) estimated in 2016 that the Indian Territory had around 14 lacs recorded cases of cancer, however the true number of cases was probably far higher.

Additionally, a number of occurrences that were unrecorded by healthcare institutions were considered. Furthermore, the ICMR observed that the cancer diagnosis rate was at 25.8 per lac population up to 2019, and it is anticipated to reach 35 per year by 2029. The cancer diagnosis rate in India is third highest in the world, behind only China and the US. More than 2,000 cases of brain tumors are reported every day in three important Indian states: Kerala, Tamil Nadu, and Delhi. The survival rate is four to seventeen times lower since around 1200 of these individuals are in the advanced or late stages. Among female cancer patients, brain tumors rank second in incidence and second in fatality rates, behind only lung cancer. A recent study found that brain tumors were the cause of death for about 5 lacs of women in 2015. The World Health Organization estimates that 1.5 million more women will lose their lives to brain tumors in the next year. Even though it has one of the best healthcare systems in the world, the United States had about 2.5 million cases of brain tumors and 40,000 deaths from them in 2017 [2].

There is a dramatic decrease in survival rate (4-17 times) as over 1200 of these patients are in advanced or later stages. In terms of cancer incidence and fatality rates in females, brain tumors rank second, after lung cancer. In 2015, brain tumors claimed the lives of about 5 lacs of women, as revealed by new study. Brain tumors may kill 1.5 million more women, says the World Health Organization (WHO). Despite being one of the most industrialized nations with the finest healthcare infrastructure, the United States reported about 2.5 lacs of brain tumor patients and forty thousand deaths in 2017 [2]. This remarkable soft tissue delineation becomes very important when attempting to distinguish between healthy tissues and infectious organisms [3]. Medical image analysis often use a number of techniques to generate pictures of the human body's soft tissues. Magnetic resonance imaging (MRI) is one of these tools that clinicians use often. In order to aid physicians in determining the patient's health, this approach correctly interprets imaging data of human brain tumors without invasive procedures. Thanks to its high-resolution pictures and tissue contrast normalization, it is a great tool. Imaging studies using magnetic resonance imaging (MRI) may provide light on the genetics, chemistry, physiology, and biology of brain problems. There are several types of tumors that are defined by their origin and cell type. It's important to remember that primary brain tumors originate in different human organs and spread to the brain, while vertebrate cerebrum malignancies often show up in the area of the brain's central hemispheres. Gliomas, meningiomas, and pituitary tumors are the three main forms of primary brain tumors, as seen in Figure1[4].



(a) (b) (c)

Figure 1: Typical brain tumor types.

The abnormal and uncontrolled growth of cells all across the body is what defines cancer. When these aberrant cell divisions proliferate in the brain at an abnormal rate, the result is a tumor. Despite their rarity, brain tumors are on the list of the most lethal malignancies. Although they originate from different places, the same kind of brain tumor is known as a primary brain tumor or a metastatic brain tumor. Although both primary and metastatic brain tumors originate in cells of brain tissue, the former originates in another part of the body and the latter spreads to it. Unregulated and abnormal cell growth throughout the body is a hallmark of cancer. The accumulation of these aberrant cell divisions in brain tissue is known as a brain tumor. Despite their rarity, brain tumors are among the most lethal forms of cancer. Metastatic brain tumors and primary brain tumors both refer to the same kind of tumor, although they originate from distinct places in the brain. While primary tumors begin in the cells of brain tissue, metastatic malignancies travel from another part of the body to the brain.

The future of image processing is highly dependent on image segmentation, a fundamental and important phase in the process. Brain tumor segmentation from MRI scans has been our primary emphasis here. It helps doctors get a precise location of the tumor in the brain. When we talk about "medical image processing," we're referring to the steps used to decipher and make sense of massive databases of three-dimensional (3D) medical pictures, often captured by MRI or CT scanners, for the benefit of research, diagnosis, or treatment planning. Medical professionals, engineers, and radiologists may learn a great deal about the anatomy of individuals and whole populations via medical image processing. Statistical analysis, measurement, and the development of simulation models that include actual anatomical geometries all provide the possibility of a more comprehensive knowledge of the interplay between medical equipment and human anatomy, for instance [6].

Incorrect results are produced by several ML algorithms when pixel classification occurs because these algorithms do not take into account the local dependencies of labels. In other words, segmentation labels are conditionally independent given the input picture. Conditional random fields (CRFs) and other computationally expensive inference methods with structured outputs may help with this. Another option is to utilize a cascaded architecture, which involves passing the pixel-wise probability estimates from one CNN into specified layers of another DNN, to explain label relationships. The effectiveness of convolutions suggests that this technique might be much faster than building a CRF [7].

Subfield of machine learning known as "deep learning" allows computers to learn data representations, which in turn allows them to draw inferences and make predictions based on data. These methods constitute a significant computational intelligence approach and find widespread use in medical imaging categorization. Deep learning has been very successful in many various domains and applications, but it is a data thirsty method that requires at least 10 times as many samples with degrees of freedom. If we use transfer learning to improve storing knowledge we've already learned on similar situations, we may potentially solve the difficulty of tiny training samples. In transfer learning, a large dataset (the base dataset) is used to train the network, and then its knowledge is applied to a smaller dataset (the target dataset) [8]. This is one way of deep learning.

In this study, we use Residual Networks (ResNets) to improve computation time and get around the problems with Convolutional Neural Networks (CNNs) and FCNs. The idea behind ResNets is to add the layer's output to its input. Since deep networks already include shortcut connections running parallel to their regular convolutional layers, this little tweak makes training them much easier. Training goes more quickly and accurately because to these live shortcuts, and gradients propagate readily across them, thanks to the much enhanced depth.One deep CNN architecture is VGGNet. In 2014, it came in second place in the ILSVRC competition [10]. Here, we provide a VGG16+ResNet50 hybrid model for MRI-based brain tumor segmentation.

II.RELATED WORK

The visual characteristics of the tumor region significantly influence the accuracy of brain tumor identification and segmentation. It is possible for similar scans to show different tumor areas in terms of intensity, shape, location, and size. In this article, we review the research on methods for segmenting and detecting brain tumors in images.

With the addition of volumetric input patches, Jonas Wacker et al. [11] shown that AlbuNet3D outperforms AlbuNet2D even more. A more robust training method and better segmentation outcomes using U-Net based architectures for the problem of brain tumor segmentation are shown by using encoders pretrained on ImageNet. Regrettably, this is not applicable to their privately obtained clinical dataset, which necessitates further robustness via future study. Compared to the BraTS benchmark, the MRI data that is accessible in a real-world clinical setting is far more diverse.

In order to automatically detect brain cancers from MRI data, Ayesha Younis et al. [12] constructed a convolutional neural network (CNN). It would be easier and faster to train the network using a pre-trained VGG 16 model. When choosing a commercial model, it is vital to examine VGG 16, a CNN model with sixteen layers. Their paper's stated goal was to find a brain tumor using VGG 16, CNN model architecture, and weights to training data. The precision of the outcome was verified. They planned to use magnetic resonance imaging (MRI) scans of the brain to look for tumors. The findings showed that the proposed network design was both aesthetically pleasing and much more effective than conventional approaches in tumor identification. Several processing techniques were also carried out to enhance the model's performance even more.

Biomedical image segmentation is a common goal for both of the networks described by Mahnoor Ali et al. [13], which form an ensemble. When presented with the multimodal MRI images from the BraTS 2019 challenge, the ensemble is able to provide very accurate tumor segmentation, which compares well with predictions made by other state-of- art models. They blend the individual model outputs using a variable ensembling strategy to get the best ratings. To help with disease planning and patient care in the clinic, the suggested ensemble provides an objective and automated way to generate brain tumor segmentation.

In their study, YakubBhanothu et al. [14] discussed the use of a deep learning system for the automatic detection and categorization of brain cancers from MRI images. The Faster R-CNN approach was used to detect tumor areas and classify them as glioma, meningioma, or pituitary tumor. The Faster R-CNN approach was built on top of a VGG-16 deep convolutional network. The proposed approach employs RPN to ascertain the optimal bounding box for the successful localization of brain tumors. We enhanced the mAP for detecting brain tumors using the test dataset. They should broaden their research to find the tumor's percentage area in relation to the brain area as well. Their approach may also be useful for the categorization and segmentation of skin lesions, two additional medicinal applications.

Fahad Ahmed et al. [15] created a VGG16 model that trained with a precision of 99.88% and a testing accuracy of 97.33% using a dataset of brain pictures that included both normal and tumor images. The model successfully identified and predicted brain images. Applying Layer-wise Relevance Propagation (LRP) helped shed light on how the model arrived at its decisions. The combination of the VGG16 model with LRP offers a promising strategy for the identification and understanding of brain tumors.

Using multi-modal images, Sajid Iqbal et al. [16] demonstrated a similar network design for segmenting brain tumors. There were three models offered, each with an escalating performance level. The findings show that interpolation methods and intermediate Convolutional maps are viable options with good potential. The vast majority of the networks published so far are deep networks, which need extensive training before they can converge. Nevertheless, the suggested network architecture is compact, quick, and requires less memory. Their plans for the future include investigating SE blocks' potential application at various levels. Investigations into the relative merits of different weighting strategies and the potential benefits of various combinations thereof are equally intriguing.

An MRI model for brain cancers was proposed by Abdullah A. Asiri et al. [17] using a convolutional neural network (CNN) that incorporates fine-tuned ResNet50 and U-net. Their approach is superior in both tasks because it combines the greatest aspects of two different designs. The Fine-Tuned ResNet50 configuration is used for brain tumor detection, which comprises detecting tumors in MRIs. The U-net design may be used to the task of brain tumor segmentation, which comprises the exact separation of the tumor from the surrounding healthy tissue. The study compared CNN with fine-tuned ResNet50, two models developed for use in MRI image classification and tumor detection. Statistically speaking, for both the non-tumor and tumor classifications, the CNN model outperforms the fine-tuned ResNet50 model. The refined ResNet50 model obtained an accuracy rate of 0.94, a recall of 0.95, an F1 score of 0.93, and a precision of 0.98 in the non-tumor class. The model's preciseness was 0.87, recall was 0.92, F1 score was 0.88, and accuracy was 0.96 in the tumor class.

Two pipelines were developed by Mostefa Ben naceur et al. [18] to segment GBM brain tumors using learnt feature maps and deep convolutional neural networks (DCNNs). To optimize the model's feature representation, the first pipeline employs up-sampling filters and skip connections. The second pipeline improves tumor area localization by combining low-level and high-level features via lengthy skip links that promote feature reuse. The scientists trained two more machine learning algorithms—logistic regression and random forest—and extracted the feature maps to solve the issue of false positive and false negative areas.

A technique for classifying data and detecting tumor locations using Deep Residual Networks (ResNet) was suggested in a publication by Madona B. Sahaai et al. [19]. In the field of restorative dentistry, their model is useful for more accurate, detailed, precise, and analytical prediction of a patient's Brian tumor. Across several types of brain tumor datasets, their model achieves a validation accuracy of 95.3%. In their study, they compared the results of multi-class brain tumor classification using Transfer Learning with a pre-trained ResNet50 model that used CNN architecture. In the absence of the pre-trained PyTorch model, the training accuracy stands at 93.5% and the validation accuracy at 90%.

Mostefa Ben naceur et al. [18] used trained feature maps and deep convolutional neural networks (DCNNs) to build two pipelines for GBM brain tumor segmentation. To make the most of the features represented in the model, the first pipeline employs up-sampling filters and skip connections. To improve tumor area localization, the second pipeline employs lengthy skip connections to promote feature reuse, which aids the model in integrating low- and high-level information. After obtaining the feature maps, the writers trained two further ML algorithms—logistic regression and random forest—to deal with the issue of false positive and false negative areas.

Summary:

- A brain tumor develops when an aberrant cluster of cells grows in the human brain. Brain and spinal cord tumors are known as gliomas, whereas meningiomas are tumors that form in the meninges. When cells inside the pituitary gland multiply abnormally, a tumor forms.
- When diagnosing brain tumors, radiologists often employ magnetic resonance imaging (MRI).
- A branch of ML known as deep learning (DL) has shown impressive results in several fields, including image analysis and recognition. Its revolutionary capacity to automate complicated operations and drastically cut human effort has led to its widespread adoption and changed many industries, including healthcare. Deep learning algorithms have shown impressive accuracy in MRI-based brain tumor identification, which may aid doctors in making well-informed judgments.

III.PROPOSED MODEL

When it comes to global mortality tolls, cancer is second only to cardiovascular diseases. Brain tumors are very dangerous forms of cancer due to their aggressiveness, diversity, and poor prognosis. Some of the distinguishing features that cause a brain tumor to be named include its location, texture, shape, and aggressiveness [2]. Among brain malignancies, glioma is the most common. The location and subtype of a patient's glioma determine their symptoms and prognosis [21]. Several approaches to brain tumor segmentation make use of the underlying data to construct a probabilistic model, either parametric or non-parametric. A previous model and a probability function that match the data are common components of such models. Because they are aberrant, tumors may be segregated as distinct from normal tissue and subjected to constraints on form and connection [22].When it comes to segmenting brain tumors in MRI images, we provide a hybrid model that combines VGG16 with ResNet50 in this study. In addition, we segmented brain tumors by using data preprocessing and data augmentation.

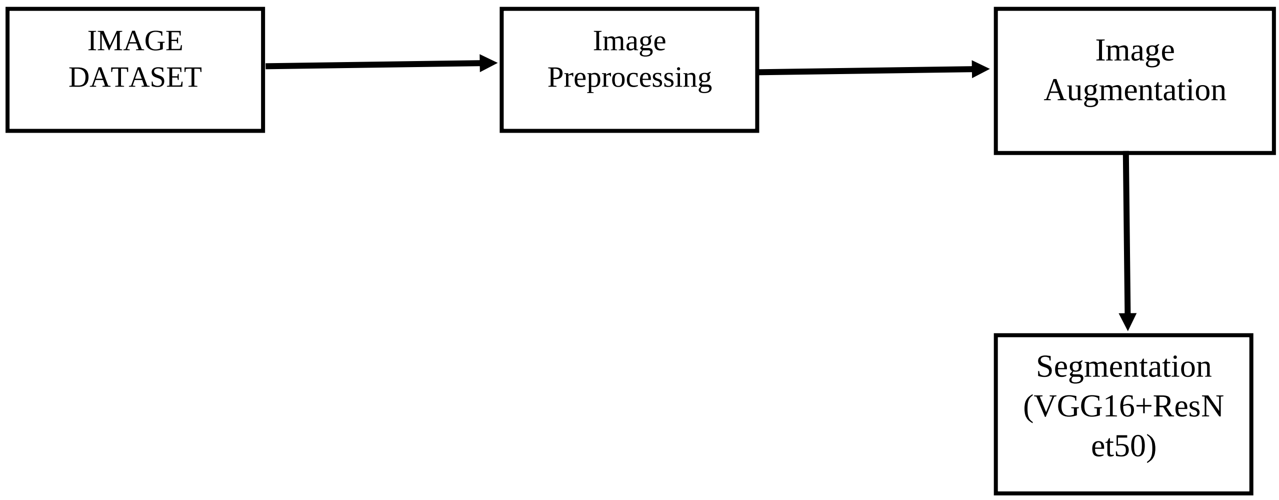


Figure1. Block Diagram of VGG16+ResNet50 model

i. Dataset Description.

We have limited our use to MRI pictures that have been identified using the recommended approach in this work. The Kaggle dataset has 253 images from different imaging modalities.

ii. Image Preprocessing

Preprocessing is necessary for the dataset's pictures because to the large variation in intensities, which exceed the standard industry threshold of 255. The smooth and quantitative training of the network depends on completing a certain set of preprocessing processes. There is some evidence that preprocessing may improve segmentation accuracy [16].

The process of histogram equalization, which involves mapping new pixel values to the histogram, enhances the contrast of a grayscale image. Image histogram dynamic range expansion is the goal of this method. Histogram balancing increases image separation and ensures a uniform distribution of forces in the output image by assigning force estimates to pixels in the input image.

$$(a,b) = \begin{cases} 1 & f(a,b) \geq T \\ 0 & f(a,b) \leq T \end{cases} \quad (1)$$

In this case, a and b are two spatial coordinates, and T is the image's gray level count. The imagegraphs have too much noise for ResNets to make a difference. The noise in images will be reduced via binarization. The RGB (red, green, and blue) channels of a color image may take on values between zero and two hundred and fifty. The transformation of grayscale images into monochrome (0 to 1) images is a crucial part of binarization. The contours of different objects in the image are simplified and smoothed down via binarization. The model's learning is facilitated by this function extraction.

iii. Data Augmentation:

When applied to larger training sets, it helps to decrease overfitting. The data augmentation was limited to rotational operations as the patch's class is retrieved by the center voxel. Image translations are also considered by some writers, although they may assign the incorrect class to the patch when used for segmentation. As a result, we rotated an existing patch to create new ones during training, which enriched our data set. Even though we used angles that are multiples of 90 degrees in our suggestion, we will be contemplating an alternative option [22].

With data augmentation, we may make inputs that aren't always accurate. Cropping, zooming, and rotating MRI images is as easy as using image editing software. By excluding morphological arrangements that are not meaningful across images, the neural network is able to avoid overfitting and avoid recognizing particular patterns in the input dataset. To introduce uncertainty into the dataset, dropout briefly removes nodes from the convolutional neural network. One way to lower the weighting strength of biased nodes is to use batch normalization. Since these heavy weights could be linked to particular, accurate traits in the training set, they do provide generalizability to other datasets [20].

iv.Proposed VGG 16+ ResNet50 segmentation model:

An efficient DL technique, transfer learning (TL) allows for the reuse of trained models and the approximations they acquired for new uses. Because it increases performance, speeds up training, and makes better generalization, it is useful in many applications where data is few and computer resources are constrained. Another benefit of TL is that it allows data training with lower model design expenses [20]. Specifically, this piece makes use of a VGG 16+ ResNet50 hybrid model [15].

A combination of ResNet50 and VGG16 for MRI-based tumor detection and segmentation via a hybrid technique. Using the enormous ImageNet dataset, ResNet50 is a convolutional neural network (CNN) model trained for object recognition tasks. Completely linked, pooling, and convolutional layers are among its many components. This model's feature extraction capabilities could be useful for solving the brain tumor detection problem. Using public picture features as a basis, the ResNet50 model's bottom layers learn to detect brain cancers. To detect and separate brain tumors, a new set of fully connected layers takes the place of the ResNet50 model's last few levels [17].

A CNN architecture was presented in 2014 by the Visual Geometry Group (VGG) at Oxford University. A number of computer vision applications heavily use its deep architecture, including image segmentation, object detection, and classification [15]. We name a CNN model with sixteen layers VGG 16. One of the most well-known and effective models still in use today is this one. Having a large number of parameters is not as important as using ConvNet layers with a 3 × 3 kernel size in the VGG 16 model architecture. What makes this model unique is that its values are freely available online and may be integrated into many systems and applications. When compared to other well-established comprehensives, it stands out for being very straightforward to comprehend. This model is capable of handling input images as tiny as 224 × 224 pixels with three channels. Optimization methods compute the weighted sum of the input to ascertain whether a neuron is necessary for a neural network to be active. Kernel function is necessary since it induces non-linearity into the output neuron. The training procedure, bias, and weight all function together in a neural network. Inaccurate output causes changes to the neuronal connection weights. With the use of activation functions and input layers that give non-linear input, a neural network may learn and do complex tasks [12]. Figure 3 shows a typical architecture of a VGG 16 network.

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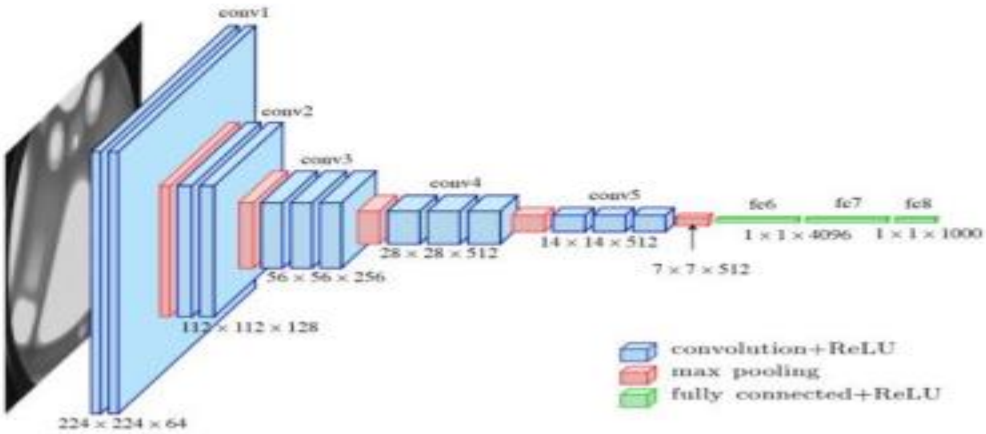

Figure 3. A Standard VGG 16 Network Architecture

DCNN models include ResNet, also known as Residual Network. It improves performance in a number of areas by employing transfer learning, which leads to high classification results. In 2015, ResNet won first place in the Common Objects in Context (COCO) and ImageNet Large Scale Visual Recognition Challenge (ILSVRC). When a deep network's layer count increases, a degradation issue arises. It is not possible to properly update the layer's weights to the following layer. Using short connections in parallel with the standard convolutional layers, ResNet eliminates this degradation issue. In Figure 4, we can see the lone remaining construction component that has a short link. The equation H(X) that defines the residual block's output is as follows:

$$H(x) = F(x) + x \qquad (2)$$

The stocked non- linear weight layer F(x) is given as:

$$F(x) = H(x) - x \qquad (3)$$

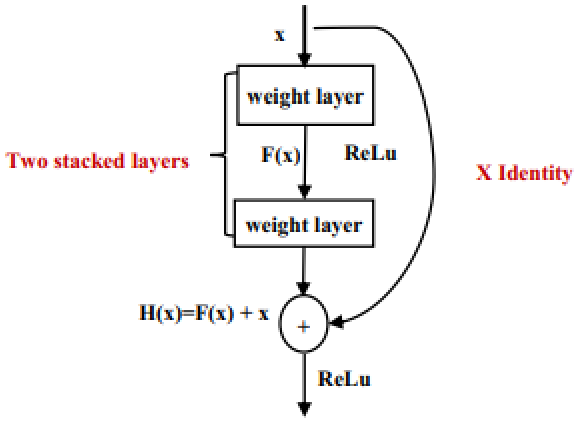

Figure4. Residual Network: a building block.

The categorization of brain tumors is carried out in this study using the ResNet50 model. A 7×7 convolution layer, a 3×3 max-pooling layer, 16 residual building blocks, a 7×7 average pooling layer, a new fully-connected layer, and segmentation at the final layer make up the modified ResNet50 that utilizes transfer learning, as shown in Figure 5. For this network, 224 X 224 X 3 is the input image size.

Figure 5. ResNet50 architecture

There were few blocks cut out of the current VGG-16 model at the encoder area. The pre-trained model's first layers were removed. Basic characteristics, such as horizontal and vertical edges, are detected by the earliest layers of the model. The further you go into the network, the more complicated the model becomes, which makes feature extraction much easier. For layers that are not sequential, concatenation skip connections are used. Dense blocks provide an extra benefit: access to a massive quantity of feature channels in the network's final layers, which allows for more compact models and drastically increased feature re-usability. To predict what will be in the output region, the model looks at the segmentation map of the output [23]. The goal is to train a ResNet50 model using VGG16 to differentiate between normal and abnormal brain MRI images. The pre-trained ResNet50 model provides a solid foundation for brain tumor diagnosis, and it may be fine-tuned using a new dataset of MRI images to make it suit the task at hand. This approach has effectively used magnetic resonance imaging (MRIs) to accurately detect and separate BTs.

Algorithm1. VGG16+ResNet50 algorithm

1. Starts
2. Loading the dataset of brain image
3. pre-processing Histogram equalization
4. I = imread("GFG.jfif");
5. figure
6. subplot(1,3,1)
7. imshow(I)
8. subplot(1,3,2:3)
9. imhist(I)
10. Data Augmentaion using CNN model
11. Transfer Learning_model T = [a1,a2, . . . ak]
12. For j = 1 to M do
13. Predict, Q = generate(O)
14. Z = add (Q, along c axis)
15. Ic = index_max (Z, along d axis)
16. print(Accuracy(i),segmentation_report);
17. End

v.Results

The capacity to accurately distinguish between the various forms of brain tumors is dependent on accuracy. The following relations are used to determine the fraction of analyzed examples with true positives and true negatives, which allows us to quantify the test's accuracy:

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \qquad (3)$$

$$Recall\ =\ TP/TP + FN \qquad (4)$$

The capacity of the model to correctly identify the specific kind of brain tumor is called specificity, and it is calculated as:

$$Specificity\ =\ TN/TN + FP \qquad (5)$$

It is possible to calculate precision, the genuine positive measure, using the following relation:

$$Precision = \frac{\mathrm{T\,P}}{\mathrm{T\,P + FP}} \qquad (6)$$

V.CONCLUSION

A brain tumor is the growth of abnormal brain cells in a person. Researchers still don't fully understand what causes brain tumors, but they have identified several risk indicators that may be used to track the progression of a tumor. A glioma is a tumor that develops in the brain or spinal cord; a meningioma is a tumor that develops in the meninges. Pituitary tumors are the result of an aberrant proliferation of cells inside the pituitary gland. When it comes to segmenting brain tumors in MRI images, we provide a hybrid model that combines VGG16 with ResNet50 in this study. Compared to other models already available, our proposed technique outperforms them in terms of accuracy and performance. Eventually, we'll be able to use more advanced transfer learning algorithms for more precise brain image segmentation.

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