TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

ENHANCING BRAIN TUMOR DIAGNOSIS WITH HYBRID TRANSFER LEARNING: A HIGH-PRECISION MRI-BASED SEGMENTATION MODEL USING MASK R-CNN

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Abstract

Effective patient evaluation and therapy depend on an understanding of brain tumors, especially their categorization. Although a variety of imaging methods are used to diagnose brain tumors, magnetic resonance imaging (MRI) is the most popular because it produces images with higher quality, less ionizing radiation, and more accuracy and precision. The usefulness of hybrid transfer learning models for identifying and categorizing brain cancers is investigated in this work. We introduce a novel hybrid transfer learning-based model with good sensitivity and accuracy for segmentation using Mask R-CNN (region-based convolutional neural network). Several metrics, such as F1 score, recall, specificity, sensitivity, precision, and overall accuracy, are used to thoroughly assess the model's performance. In our experiments, the proposed model was tested on three different architectures: VGG16, Inception V3, and ResNet-50. Remarkably, it achieved precision and sensitivity rates of over 99%, significantly outperforming the performance of current methodologies. The model was trained using Efficient-ResNet hybrid transfer learning architectures, which further contributed to its robustness and reliability. By integrating these advanced techniques, our approach not only improves tumor detection capabilities but also supports more accurate treatment planning for patients. The results show that hybrid transfer learning has the potential to revolutionize medical imaging, opening the door to better patient outcomes and more accurate diagnosis in the treatment of brain tumors. This work lays the groundwork for future research aimed at refining these models and exploring their applications in other areas of medical imaging.

Keywords: Brain Tumors (BT), Laplacian of Gaussian, RCNN, EfficientNet B4, Inception-ResNet50.

1. INTRODUCTION

Brain tumor problems, which are quite harmful and seriously affect people, appear to have gained a lot of attention in recent years. Brain cancer ranks as the tenth most common cause of death for both men and women. The International Agency for Research on Cancer reports that each year, brain tumors result in over 126,000 new cases and 97,000 fatalities globally. The survival rate for individuals with malignant brain tumors, however, varies greatly and is influenced by a number of variables, with the patient's age and the type of brain tumor [1].

Integrating deep learning with computer vision has greatly improved the effectiveness of illness identification and treatment in the healthcare industry. According to studies, the only cause of cancer patients' mortality in nearly 90% of cases is a delayed tumor diagnosis. People postpone frequent check-ups at the hospital due to careless conduct, which causes serious problems. Intelligent healthcare systems work well in these situations because individuals can readily and routinely check their health with little determination. Medical image diagnostics is the newest and most auspicious tumor recognition method [2].

The development of aberrant tissues inside the human skull causes brain tumors. They could be malignant or benign. They can also be categorized as secondary malignancies originating from other organs or primary tumors inside the brain. Several medical imaging modalities such as computed tomography (CT) and MRI can be used to visualize the brain. The tumors seen on these images vary widely in size and shape. How tumor sites differ from other tissue sites depends on tumor type and size. Automated tumor identification functions require intelligent algorithms based on image processing technology to differentiate tumor and normal regions in brain images captured using different modalities [3].

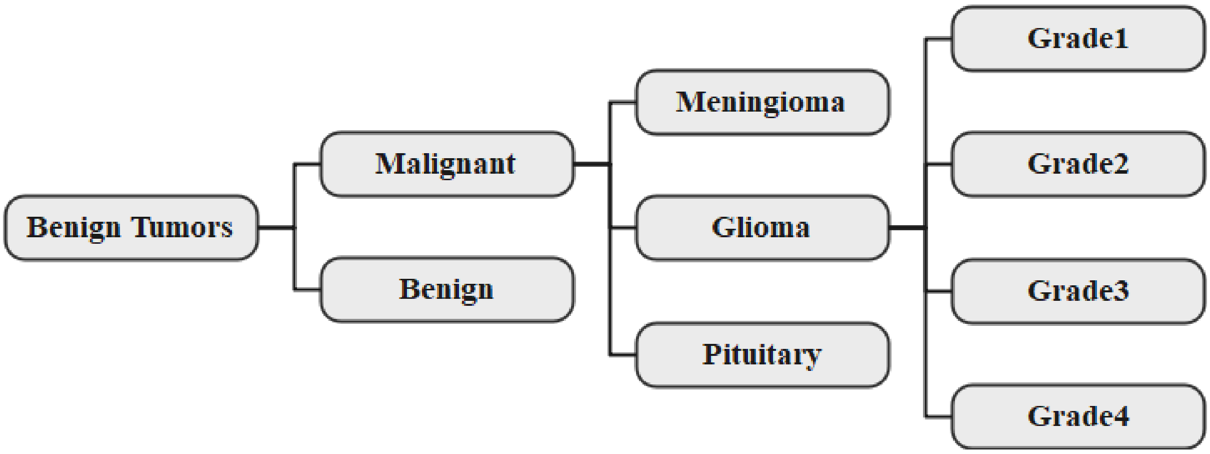


Figure 1. Types of brain tumor

Brain tumors come in two varieties: benign and malignant. Malignant tumors can also include pituitary tumors, gliomas, and meningiomas. As seen in Figure 1, which depicts a variety of brain tumor types, gliomas can be divided into four categories. Using EfficientNet and ResNet50, this study presents a hybrid transfer learning model for automated brain tumor identification. Several learning methods, such as ResNet and Inception v3, are being studied for the early detection of brain cancers.

The following points might be used to sum up this study's contribution:

1. It presents a hybrid transfer learning model that can identify brain tumors early on to speed up therapy and stop the spread of cancerous tissues.
2. This dataset was pre-processed using an edge-decision-based Laplacian of Gaussian approach to assess how well deep learning models identified and categorized brain cancers. When R-CNN masks are used for brain tumor segmentation,
3. The hybrid transfer learning classification, which blends EfficientNet with ResNet, yields better results and is more accurate than conventional techniques.

Section 2 highlights relevant research on brain tumor detection, emphasizing significant developments and approaches from earlier investigations. The methodology is described in Section 3, which also includes the designated algorithms and the suggested approach for brain tumor detection. The effectiveness of the proposed strategy in comparison to current procedures is discussed in Section 4, which also provides an explanation of the outcomes of our studies. Lastly, a summary of the results pertaining to the detection of brain tumors is given in Section 5.

2. LITERATURE SURVEY

The author [1] created reliable and widely used methods to detect brain tumors, assess their properties, and categorize gliomas using MRI images. Histogram equalization (HE) is employed in the suggested technique to increase the contrast of the original photographs. Features are extracted from the preprocessed images using a gray level co-occurrence matrix (GLCM). These retrieved features are then used to train a probabilistic neural network (PNN) classifier, and the accuracy of the classifier in detecting brain tumors in MRI images is assessed.

To assist medical experts, the author [2] developed a new method to recognize and classify brain tumors. It was characterized by classifying brain neoplasms into three groups (pituitary, meningioma, and glioma) using a hierarchical deep learning technique. Convolutional neural networks (CNNs) in clinical image processing are making remarkable progress in the areas of tumor classification and diagnosis, which are critical for complete and rapid recovery. After training the data, the CNN separates the image slices into multiple tumor classifications. A CNN is used in a proposed hierarchical DL-based BT classification system (HDL2BT) to perceive and classify BT.

Since MRI scans provide information on the blood supply inside the brain, we have included them in our suggested model. The author used Several filters [3] to pre-process the images. A picture is separated into many areas in our subsequent phase, image segmentation. We have used various segmentation methods, such as region-derived triple thresholding, fuzzy C means, and active contour snakes. In addition, we have employed computer-aided detection methods and two hybrid segmentation models. Watershed filtration, extraction, and artificial bee colony optimization are used to post-process the data. Next, we use the VGG-16 CNN model to categorize two pictures into tumor and non-tumor categories.

This study [5] used CNN-based magnetic resonance imaging to classify three distinct forms of brain tumors: pituitary gland, meningioma, and glioma. The dataset included in this study consists of 3,064 contrast-enhanced T1 scans from 233 patients. This paper presents a comparison of models to show how much better our model is than others. In addition, the results of pre-processing and amplification of pre- and post-data were compared.

A CNN network is used to classify the image once the brain has been extracted from the skull by a preprocessing unit. The network extracts important components from the images to create feature maps. After that, the network's second section identifies the secondary features extracted from the feature maps. The datasets utilized in this work are the BRATS2017 dataset for glioma tumor pictures and the IXI dataset for normal brain images [6].

This research describes a DL approach for BT diagnosis that includes several crucial components. Initially, information was collected from the multi-slice MRIs of 130 participants in the REMBRANDT dataset. Preprocessing techniques used included histogram equalization, skull removal, and grayscale image conversion. Then, the segmentation process was carried out using a genetic algorithm. After extracting features using discrete wavelet transform (DWT), the most relevant features were selected using a particle swarm optimization technique. For categorization, the U-Net architecture was employed. Based on experimental evaluations, the proposed GA-UNET model performed better than state-of-the-art models, achieving impressive results with an accuracy of 0.97, a sensitivity of 0.98, and a specificity of 0.98.

This study proposes a revolutionary four-step pipeline [8]: CNN for feature extraction, multilayer perceptrons for classification, enhanced fuzzy C-means for tumor segmentation, and image down-enhancement and enhancement preprocessing. 40,300 MRI images from the BRATS-2015 dataset across four modalities were used to evaluate the system, focusing on 65 cases. There were 26 cases of low-grade glioma (LGG) tumors and 39 cases of high-grade glioma (HGG) tumors in this dataset. With an astonishing average accuracy of 98.77%, the suggested CNN feature-based classification method outperformed previous methods and greatly improved the segmentation results.

In this study [9], we present a strategy for glioma cell segmentation in MRI images that combines edge detection methods in image processing algorithms with Faster RCNN. This study used a tumor mask to localize the tumor and more accurately identify the region of interest, or glioma cells, in the MRI image.

This study [10] develops a hybrid model based on CNN to classify normal brain magnetic resonance images, pituitary tumors, meningiomas, and gliomas. The suggested hybrid model gathers features using pre-trained Shufflenet and Efficientnet architectures. Additionally, the current dataset's photos have been enhanced by adding color and serve as a backup database.

The brain tumor and pancreatic tumor datasets were pre-processed to evaluate how successfully deep learning models recognized and classified brain tumors [11]. Low-grade gliomas, classified as grades I and II, can frequently be treated with total surgical excision. On the other hand, high-grade III and IV-grade I gliomas typically require further radiation therapy. With a 96% accuracy rate, the suggested model's accuracy produces incredibly useful outcomes.

The BRATS 2013 challenge dataset was used to evaluate the CNN and ML algorithms; CNN's accuracy of 95% was the highest [12]. to provide a free online deep learning tool for detecting and diagnosing brain cancers using T1-weighted MRI data [13]. Transfer learning was found to significantly enhance the advanced YOLOv7 model's capacity to identify pituitary tumors, meningiomas, and gliomas. Our proposed strategy achieved an astounding accuracy rate of 99.5%, outperforming current approaches [14].

In this study, the visually accessible Rembrandt image collection was employed to preprocess a deep neural network (DNN) classification model using the synthetic minority oversampling technique [15]. The suggested approach has a 95.0% accuracy rate and includes 1,319 trainable criteria for classifying brain tumors. The F1-measure, precision, and recall findings are 94.9%, 95.4%, and 95.0%, respectively.

Table 1. Brain Tumor detection deep learning algorithm with dataset and performance metrics

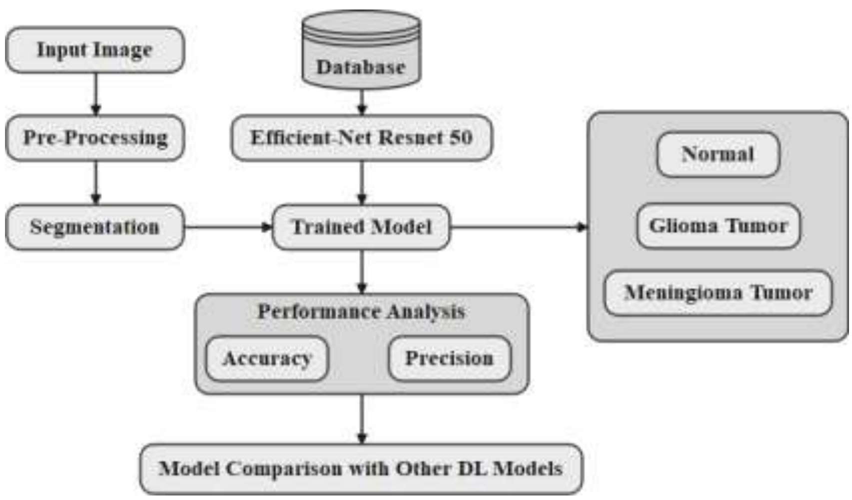
Reference	Algorithm used	Dataset used	Performance achieved
[16]	Gaussian convolutional neural network	Tianjin Medical University, China, 2005-2010, Cancer Imaging Archive (TCIA)	Accuracy rate: 97.14%, 99.8%
[17]	deep learning network (VGG19)	OASIS and BRATS2018 challenge	Accuracy: 95.78
[18]	squeeze-and-excitation block DenseNet with weighted cross-entropy	Central Nervous System Diseases Biobank	Accuracy: 86.5 % (Patch level from histological patch image)
[19]	Support Vector Machine	T1-weighted CE-MRI dataset	Accuracy:99.23 %
[20]	inceptionresnetv2, inceptionv3, transfer learning and BRAIN-TUMOR-net	MRI brain tumors.	100% f1 score, recall, accuracy, and precision.

The literature review includes the various deep learning algorithms used to predict brain tumors. Regarding the brain tumor dataset, the different datasets and the effectiveness of the deep learning model are discussed. In addition, the performance of the model including its f1-score, recall, accuracy, and precision values are evaluated.

3. PROPOSED METHODOLOGY

In this work, we suggest a hybrid model that combines the EfficientNet and ResNet architectures for the detection of brain tumors. The tumor segmentation is done using Mask R-CNN (Region-Based Convolutional Neural Network). Three essential steps make up our methodology: preprocessing, segmentation, and classification. To guarantee ideal data appropriateness, we improve the quality of MRI images during preprocessing by normalizing and augmenting them. Mask R-CNN is used in the segmentation step to precisely identify and define tumors, utilizing the advantages of ResNet's skip connections and EfficientNet's efficiency to enhance feature extraction and classification accuracy. Lastly, the segmented tumors' properties are utilized to identify their types, such as high-grade or low-grade gliomas, during the categorization stage. With accuracy and sensitivity rates above 99%, our model performs exceptionally well, improving tumor detection skills and opening the door for more precise diagnosis and efficient treatment planning for patients with brain tumors. The overall architecture shown in figure 2.

Figure 2. Overall flow diagram of proposed brain tumor detection



a. Preprocessing

The Laplacian of Gaussian (LoG) filter is a well-liked edge detection method for biomedical image preprocessing. The Laplacian is used to identify edges, while Gaussian smoothing minimizes noise. Because biological samples and medical equipment can produce noise, a Gaussian filter smoothes the brain tumor image and lowers noise. This is crucial in biological imaging. The Gaussian-filtered input image is subjected to the Laplacian transformation in this procedure. The image's second-order derivatives are computed using this method. Since the Laplacian is calculated on a Gaussian smoothed image, double edges are found. To find edges, look for zero crossings among double edges. Gx and Gy provide the horizontal and vertical kernels for the LoG edge detector [22].

$$G(x,y)=\frac{1}{2\pi\sigma^2}exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (1)$$

$\sigma - controls\ the\ degree\ smoothing$

Larger σ values achieve more smoothing, but fine features may be blurred, which might impact biomedical pictures with weak or tiny edges.

The Laplacian operator is a second-order derivative that measures the rate of intensity changes in the picture. It highlights regions, often the edges, where the intensity fluctuates rapidly. In mathematics, the Laplacian may be obtained by:

$$\nabla^2 I=\frac{\partial^2 I}{\partial x^2}+\frac{\partial^2 I}{\partial y^2} \qquad (2)$$

$I - image\ in\ density$

Convolution is frequently used to approximate the LoG filter using a single kernel that integrates the two processes, resulting in computational efficiency:

$$LoG(x,y)=-\frac{1}{2\sigma^2}\left(1-\frac{x^2+y^2}{2\sigma^2}\right)exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (3)$$

b. Segmentation: RCNN (region-based convolution neural network)

Tumor localization and segmentation are done using R-CNN. Our method just segments using the meningioma dataset. Nonetheless, this model can retain its generality when incorporating the glioma dataset. From the meningioma dataset, 110 verification photographs and nine training photos were selected. In the last CNN layer, a 3x3 sliding window descends to a lower dimension by moving inward across the feature map. Finding each site on the most recent feature map is the main goal. It's intriguing how region-centric search boxes of various sizes are used. The core of RCNN is the recurrent convolutional layer (RCL). The component elements of the RCL units change across the discrete time step.

Over the discrete time step, RCL units vary. The net input Zlmn(t) for a unit in (l, m) in feature map n of an RCL at time step t is provided by

,

$$\left(w_n^f\right)\left(w_n^f\right)\left(w_n^f\right)^T u^{(l,m)}(t)+w_n^r)^T x^{l,m}(t-1)+b_n \qquad (4)$$

$u^{(l,m)} - feed - forward$

$x^{l,m}(t-1) - recurrent\ input\ at\ l,m$

$w_n^f - weights\ of\ feedforward$

$w_n^r - recurrent\ weights$

$b_n - bias$

This unit's state is determined by its net input, which is represented by the equation,

$$x_{lmn}(t)=g(f(x_{lmn}(t))) \qquad (5)$$

Here,

$f - corrected\ linear\ activation\ function$

$g - local\ response\ normalization$

Below the equation, the linear activation function and local response normalization (LRN) are illustrated,

$$f\left(z_{lmn}(t)\right)=\frac{f_{lmn}(t)}{((f_{lmn'})(f_{lmn'})(f_{lmn'})^2)^\beta} \qquad (6)$$

Pseudo code for RCNN-based brain tumor segmentation

Algorithm steps: *Step 1: Take a brain MRI as an image* *Step 2: Convert it to grayscale image if it is not grayscale* *Step 3: Then we apply noise removal on grayscale image* *Step 4: Sharpen the image* *Step 5: Pass the resulting image through adaptive filter to improve image quality* *Step 6: Calculate k-means segmentation* *Step 7: Calculate thresholding segmentation* *Step 8: Finally, the output will be a tumor region*

EfficientNet B0-ResNet 18 architecture for classification

In this study, the ResNet architecture is coupled to a modified EfficientNet-b0. EfficientNet-B0 was chosen for this work because of its state-of-the-art performance, transfer learning capability, and parameter efficiency. However, because of its effectiveness across various datasets, interpretability, usability, and quicker training time, ResNet-18 emerged as the winner. The final three EfficientNet-bo layers classification, softmax, and fully connected are eliminated. A flattened layer is put after the global average pool layer. The ResNet Layers are then expanded to include 1280 hidden units, with tanh serving as the state activation function and log-sigmoid as the gate activation function. Finally, the FC layer, softmax, and classification are attached and optimized by deep transfer learning. ResNet-18 is an 18-layer convolutional neural network.

The network has so amassed rich visual data for a variety of pictures. Images having a resolution of 224 by 224 are accepted by the network. For the classification challenge, we suggested a modified version of the ResNet-18 with EfficientNet in this study. The multi-head self-attention mechanism in ResNet-18 is added to the model. After the flattening Layer, a multi-headed self-attention with six heads and 384 keys is added. With this update, the model investigates the relationships between every point in the input feature maps to get comprehensive contextual information. Because of its flexibility, the model may be used for jobs with unpredictable patterns. This change allows the model to extract hierarchical characteristics from pictures and encode successive relationships, creating a comprehensive and perceptive representation of the input pictures. The deep feature representation specifically improved the work efficiency. The offered improved EfficientNet-ResNet architecture is shown in Figure 3.

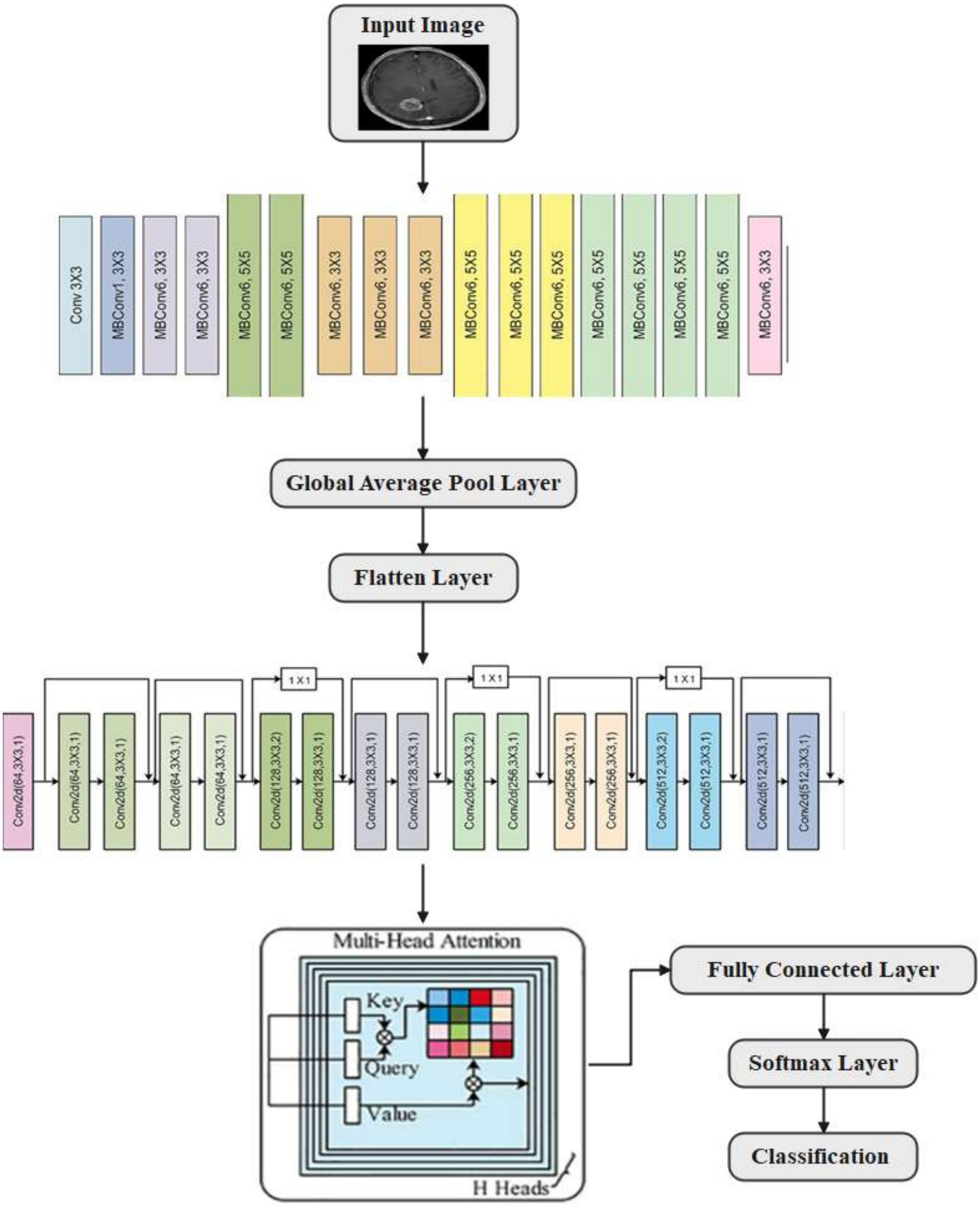


Figure 3. Hybrid Efficient Net and Resnet architecture

4. Result and discussion

4.1 Dataset details

The suggested transfer learning architecture is tested using MRI brain tumor data. This collection of MRI brain tumors includes 826 glioma MRI images, 822 glioma MRI photographs, 827 pituitary tumor MRI images, and 835 MRI images from healthy individuals. Several examples of the dataset used to test the model for pituitary tumors, meningiomas, gliomas, and healthy subjects are shown in Figure 4.

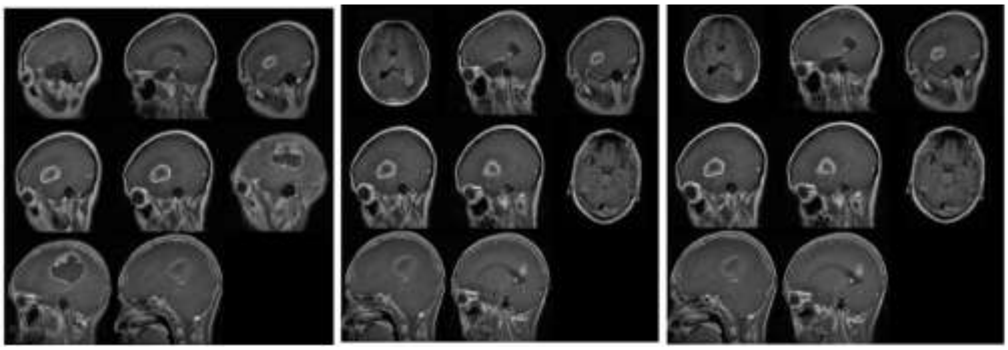


Figure 4. Different MRI samples of brain tumor images such as gliomas, meningiomas, and pituitary and normal brain image

4.2 Performance Metrics

A. Confusion Matrix

A confusion matrix can ascertain any classifier's confusion. This matrix comprises false positives (Fp), false negatives (Fn), negative trues (Tn), and true positives (Tp).

To find the performance metrics help of confusion matrix as demonstrate below,

B. Accuracy- It illustrates how frequently the classifier is accurate.

$$A = \frac{TP + TN}{(TP + TN) + (FP + FN)} \; x \; 100$$

C. Precision - How frequently is it accurate when it predicts yes.

$$P = \frac{TP}{FP + TP}$$

D. MCC

In 1975, Brian Matthews created the MCC, a model evaluation technique. It is comparable to the chi-square statistic for a 2x2 contingency table and compares actual and expected values.

$$MCC = \frac{TN \; X \; TP - FN \; X \; FP}{\sqrt{(TP + FP)(TP \; + FN)(TN + FP)(TN + FN)}}$$

E. F1-score

Harmonic mean of precision and recall is called F1 score.

$$F1 \; score = \; 2 * \frac{Precision * Recall}{Precision + Recall}$$

F. Kappa

The Kappa(k) statistic is used to evaluate the system accuracy and random system accuracy. The estimated Kappaise was as follows:

$$K = \frac{P_0 + P_e}{1 - \; P_e}$$

Here,

$P_0 - overall\ accuracy\ of\ the\ model,\ P_e\ agreement\ between\ model\ prediction\ and\ actual\ values$

4.3 Tumor image preprocessing using Laplacian Gaussian Filter

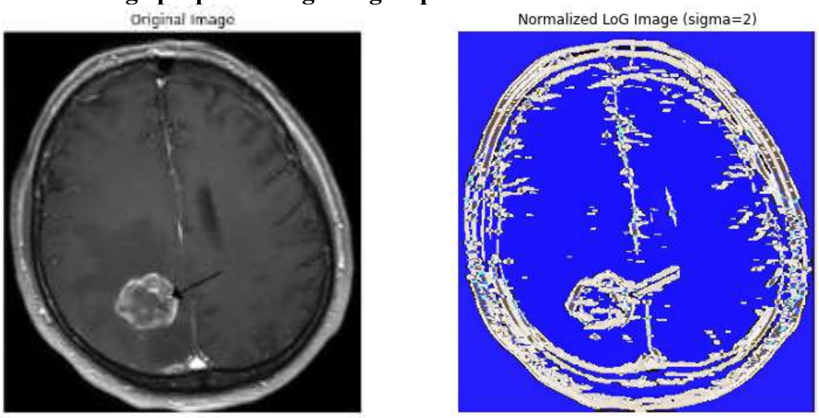


Figure 5. preprocessing (a) Original Image (b) Normalized LoG image (Sigma = 2)

Figure 5 shows the (a) original MRI scan image of the brain and Normalized Laplacian of the Gaussian image. In Laplacian of Gaussian, the sigma value controls the smoothing effect. A greater sigma may be needed for larger tumors or characteristics, whereas a lower sigma is needed for smaller ones.

4.4 Brain Tumor Segmentation using RCNN

A RCNN is used to segment the tumor area from the preprocessed image. Figure 6 shows the segmentation of brain tumors using RCNN. First, the program detects whether the input image is a tumor or a normal image. The application stops and displays a warning if the image belongs to the standard class. On the other hand, if the image is part of a tumor class, the algorithm employs the segmentation procedure to obtain these segmented images in stages.

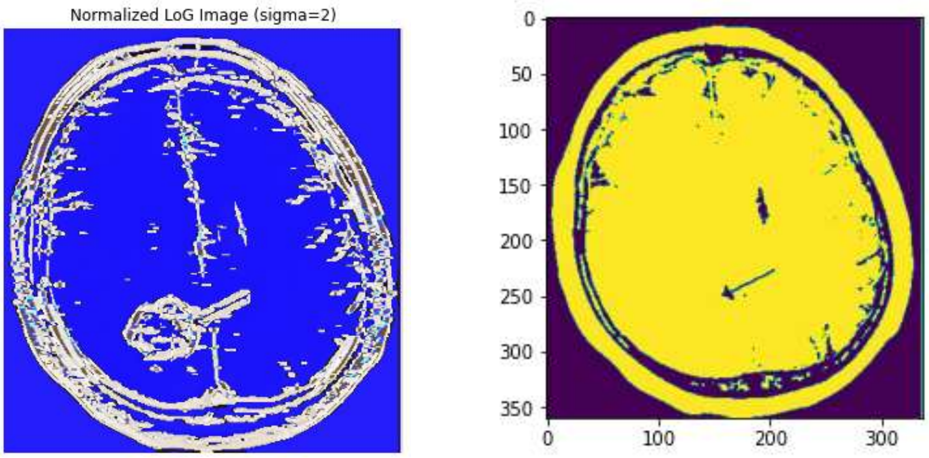


Figure 6. (a) Preprocessed image (b) segmented image

4.5 Performance comparison of the Transfer learning model

Our model's performance was thoroughly evaluated, and the results are shown by looking at several performance indicators. The confusion matrix related to the EfficientNet-ResNet model is specifically shown in Figure 7. This matrix has integer identifiers 0 through 3, each of which denotes a different form of tumor: 0 : pituitary, 1 : normal, 2 :meningioma, and 3: glioma. The systematic numbering of the model allows the classification results to be readily displayed. A thorough confusion matrix analysis demonstrates how well the EfficientNet-ResNet model worked. Specifically, the model accurately recognized 24 images as "pituitary," 32 as "glioma," 43 as "meningioma," and 24 as "no tumor.".

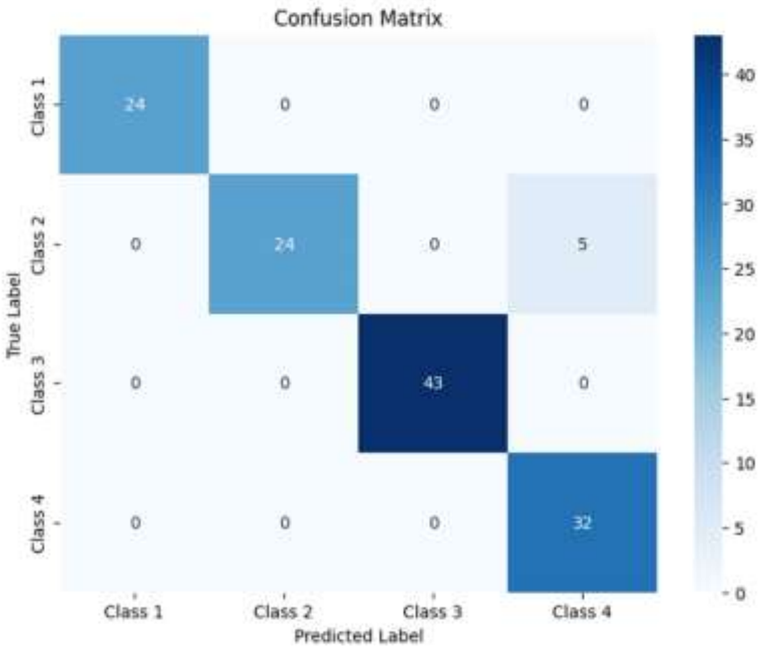


Figure 7. Confusion Matrix of Proposed Model

The assessment includes important performance criteria: recall, f1-score, accuracy, and precision. With an accuracy of 98.5%, ResNet 50 remarkably outperforms all other models in the research, making it the undisputed leader among the models. Furthermore, with an accuracy of 99.75%, EfficientNet-ResNet exhibits remarkable efficacy, demonstrating its strong performance in categorizing brain tumors. Figure 8 shows the performance in accuracy comparison of some deep learning models with a proposed transfer learning model.

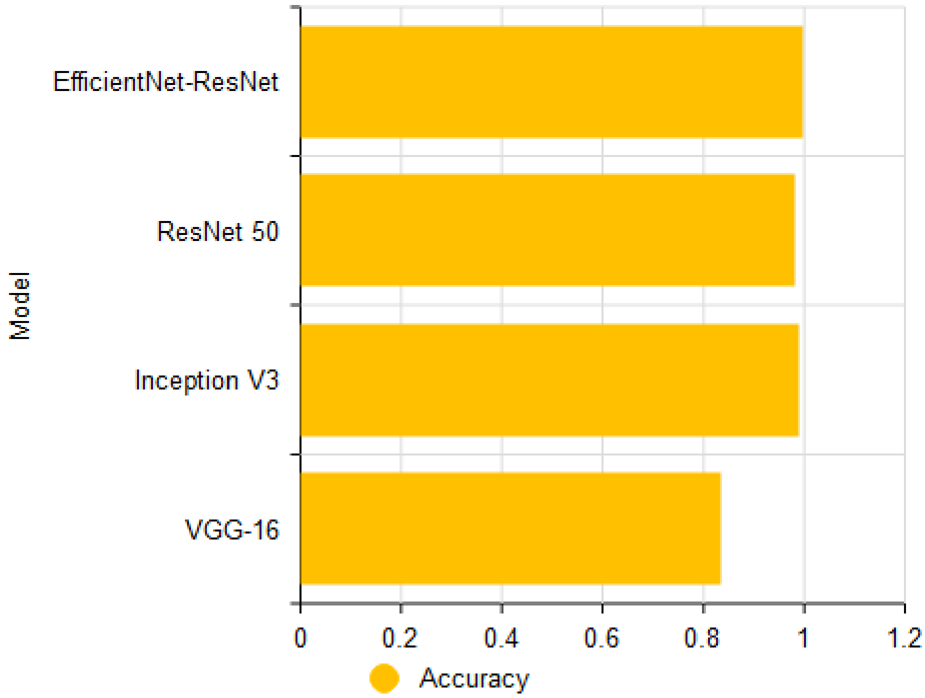


Figure 8. Accuracy comparison proposed transfer learning model with deep learning model

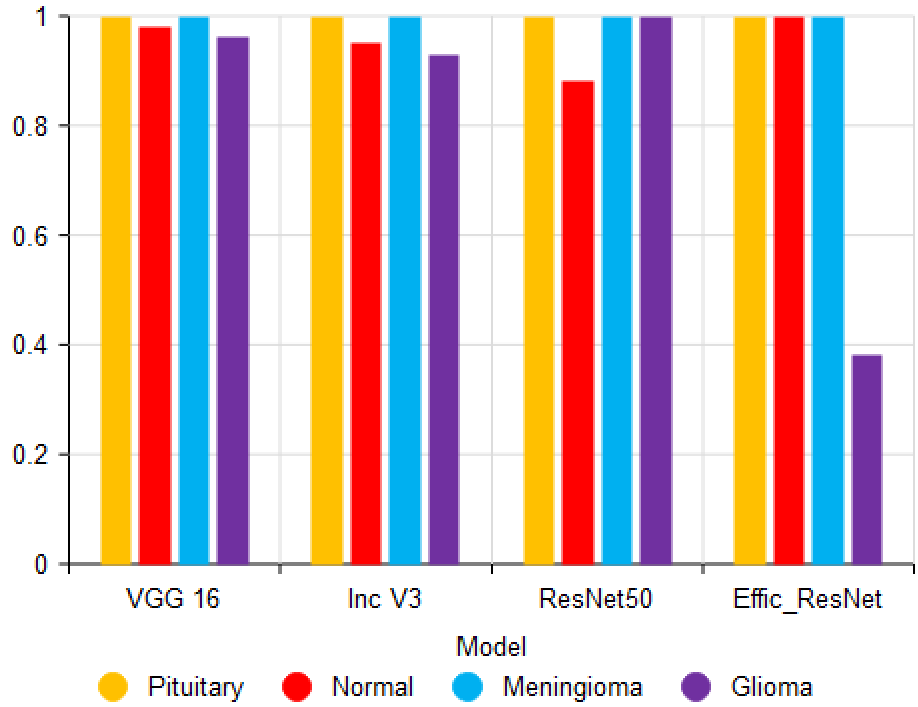


Figure 9. Precision Performance comparison of Transfer learning model with VGG16, Inception v3, and ResNet50.

Figure 9 compares the suggested model's precision performance with other deep-learning models for several brain tumor classes, including pituitary, normal, meningioma, and glioma. Except for categorizing glioma tumors, the suggested model performs better across all classes in the dataset.

5. CONCLUSION

The categorization of brain tumors and their segmentation using MRI images were described in this research. This work uses a Laplacian of Gaussian filter for the first preprocessing. The tumor component of the categorized tumor picture is segmented using the RCNN, and an EfficientNet-ResNet network based on transfer learning is produced.95 photos are selected for the training dataset from the gathered dataset, and the remaining images are tested based on the training network's output. The method is more efficient than existing algorithms, with an accuracy of around 99.75%. Research on more precise brain tumor detection can be done in the future utilizing actual patient data from various image collection scanners. To enhance the categorization outcomes, hand-crafted and deep characteristics might be combined. Likewise, low-tech techniques like quantum machine learning can be very helpful in enhancing precision and effectiveness to save radiologists' time and raise patient survival rates.

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