International Journal of Basic and Applied Sciences, 14 (1) (2025) 52-58

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/4a7am078
Research paper

Multi-class brain tumor classification using deep learning and tumor segmentation using image processing techniques

R. Yamini Rani [1], Regidi Suneetha [2], A. V. V. Chakrapani [3], Gudepu Lavanya [4] *, Krishna Rupendra Singh [5], Nagamalli Arasavalli [6]

[1] *Department of Information Technology, Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India*
[2] *Department of Electronics and Communication Engineering, Sanketika Vidya Parishad Engineering College, Visakhapatnam, Andhra Pradesh, India*
[3] *Department of Computer Science and Engineering, Vignan's Institute of Information Technology (A), Visakhapatnam, Andhra Pradesh, India*
[4] *Department of Computer Science and Engineering, GMR Institute of Information Technology(A), Rajam, Andhra Pradesh, India*
[5] *Department of Computer Science and Engineering, Vignan's Institute of Engineering for Women(A), Visakhapatnam, Andhra Pradesh, India*
[6] *Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation, KL (Deemed to be University), Vaddeswaram, Guntur District, Andhra Pradesh, India*
**Corresponding author E-mail: lavanyagudepu46@gmail.com*

Received: March 16, 2025, Accepted: April 8, 2025, Published: April 14, 2025

Abstract

With the rising occurrence of brain cancers worldwide, accurate and timely tumor diagnosis is crucial. In this study, we provide a robust and efficient brain tumor classification and segmentation system that uses deep learning and digital image processing for tumor segmentation. We use convolutional neural networks to extract specific information from images. This will eventually eliminate the requirement for manual tumor extraction and detection. We employ a diverse collection of JPEG pictures of three types of tumors: glioma, pituitary, and meningioma-mas. Our CNN architecture is meant to record diverse patterns of the image, which assists our model in distinguishing between types of tumors and allows it to classify distinct types of tumors. In addition, we applied digital image processing for tumor segmentation, employing techniques such as contrast, erosion, dilatation, and many more. To improve the quality of our model, we applied several data augmentation approaches and dropouts in our CNN architecture to identify tumors more precisely and robustly. According to our findings, using deep learning technology for cancer categorization can improve the accuracy and speed with which brain tumors are detected. This can help to reduce the manual labor necessary to locate tumors.

Keywords: *VGG16; Mobile Net; Brain Tumor; Tumor Segmentation; Google Net.*

1. Introduction

Brain tumors, which are defined as rapid abnormal cell growth inside the brain, are one of the significant global health concerns. An accurate and timely tumor diagnosis is crucial for efficient treatment planning. Deep learning technologies, particularly Convolutional Neural Networks (CNNs), have achieved state-of-the-art image classification accuracy in recent years. Traditionally, brain tumor classification is done using manual work, which is both time-consuming and expensive. On the other hand, Deep learning uses neural networks in which each neuron is connected to other neurons, and it consists of multiple layers where data passes from one layer to another, which indeed helps to find some pattern in the image, which will help it to make some decision on that image. When used in image classification problems, CNNs have shown impressive results, especially in segmentation and classification. CNNs are good at identifying spatial hierarchies (detailed information – pixel level) in images. This makes them perfect for intricate patterns and structures in any image or medical scan.
With this study, we aim to use CNNs, a kind of deep learning, and their potential to classify brain tumors. Our model uses CNNs to eliminate the requirement for manual feature engineering, so by using this, we can save time and be cost-effective. For tumor segmentation, we will first use digital image processing techniques and increase the contrast so that there is a difference between the foreground and background. After that, we will try to identify the skull and remove it, then, followed by some other operations like erosion and dilation,

Copyright © R. Yamini Rani et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

and finally, segmenting the tumor. The findings could completely alter clinical procedures by giving medical professionals a more effective and dependable tool for accurate and early diagnosis of brain tumors, thus enhancing patient care and prognosis.

2. Literature survey

The problem of diagnosing brain tumors, which is typically laborious and dependent on radiologists, is addressed in the study [1]. The number of patients and data quantities has increased, making traditional procedures ineffective and expensive. Deep learning methods are being investigated for automated brain tumor identification and classification in order to improve efficiency and accuracy. Three computer vision models—AlexNet, VGG16, and ResNet-50 are evaluated in the study; VGG16 and ResNet-50 showed good performance. A hybrid VGG16–ResNet–50 model was created as a result, and it demonstrated remarkable accuracy, sensitivity, specificity, and an F1 score of 99.98%. The model's dependability in accurately and promptly identifying brain tumors is validated by comparative analysis.

According to the research study [2], brain cancers can be divided into three categories using deep learning, more precisely a Convolutional Neural Network (CNN): Glioma, Meningioma, and Pituitary Tumor. Appropriate therapy depends on accurate classification. After examining 3,064 MRI pictures, the researchers discovered that their CNN model worked incredibly well. Depending on whether the photos were segmented or cropped, it was able to detect cancers with up to 99% accuracy. This demonstrates that CNNs can be an effective technique for rapidly and precisely diagnosing brain cancers.

Improving brain tumor identification through the application of deep learning is the main emphasis of the study [3]. While earlier approaches relied on rudimentary machine learning and image processing, deep learning now provides far higher accuracy. Engineers built a more robust system by merging two models, a shallow convolutional neural network (SCNN) and VGG16. They were able to increase accuracy and decrease errors caused by unequal data distribution by combining features from the two models. They demonstrated that their model can successfully categorize various brain cancers with an accuracy of 97.77%.

By automating the process of diagnosing brain tumors, the study [4] aims to alleviate the time and money constraints associated with medical imaging. Two deep learning models, ResNext101_32×8d and VGG19, were employed by the researchers to categorize pituitary tumors and gliomas from 1,800 MRI scans. To improve model training, they used a super-resolution approach to boost picture attributes. Using PyTorch and TensorFlow, the models were able to attain nearly flawless accuracy, with ResNext101_32×8d reaching 100% and VGG19 reaching 99.98%. Metrics for performance proved their dependability, making them useful tools for assisting clinicians with brain tumor screening.

Brain tumors are a leading source of cancer-related mortality; the study [5] tackles the difficulty of making an accurate diagnosis of these tumors. Locating tumors with high precision is a challenge for traditional CNN algorithms. A new model was created by the researchers to enhance classification. It incorporates a multipath network and an attention mechanism. In order to improve feature extraction and simplify the process, the multipath network analyzes data over numerous channels, and the attention mechanism aids in focusing on crucial tumor locations. This model outperformed its predecessors and showed great promise as a tool for diagnosing brain tumors, with an accuracy of 98.61% when tested on a dataset of 3,064 MRI scans.

In order to diagnose brain tumors using MRI scans, the study [6] introduces a content-based image retrieval (CBIR) approach. The system finds comparable tumor photos in a database when a user outlines a tumor in a query image. Expanding the tumor region to improve context, splitting it into subregions to extract detailed characteristics, and using the Fisher kernel framework to generate a compact representation of the image are the three main phases that make up the suggested strategy to improve accuracy. Afterwards, an image matching method based on similarity measurements is applied. Undergoing testing on 3,604 MRI scans about meningioma, glioma, and pituitary tumors, the system demonstrated an exceptional level of accuracy of 94.68%, surpassing prior methods.

Enhancing deep learning's ability to classify brain tumors is the primary goal of the research [7]. Researchers suggest an automated solution using the DenseNet201 pre-trained model because traditional methods don't always succeed in achieving reasonable accuracy. They utilize deep transfer learning to adjust the model for unbalanced input and pull-out useful features from the average pool layer. To improve the accuracy of classification, two feature selection methods are presented: a modified genetic algorithm (MGA) and Entropy-Kurtosis-based High Feature Values (EKbHFV). The features that were chosen for classification are first improved and merged with a multiclass support vector machine cubic classifier. When put to the test on the BRATS2018 and BRATS2019 datasets, the suggested technique outperformed competing neural networks with an accuracy of more than 95%.

A technique for segmenting and classifying brain tumors using multi-modal MRI data is presented in the paper [8]. Data from the MICCAI BraTS 2013 challenge was utilized by the researchers, who applied preprocessing techniques such as skull-stripping and histogram matching. Extractions from the photos included wavelet texture, local neighborhood, intensity, and intensity differences. Next, five tumor-related regions—background, necrosis, edema, enhancing tumor, and non-enhancing tumor—were classified using a random forest classifier. Complete tumor, active tumor, and enhancing tumor were the three further categories into which these were placed. Dice overlap scores for entire tumors were 88%, core tumors were 75%, and enhancing tumors were 95%; these results were better than prior MICCAI BraTS challenge results.

The literature review does cover major deep learning advances; however, it doesn't go into detail on the latest developments in multimodal deep learning or transformer-based models. Those from studies using MICCAI BraTS 2020 and BraTS 2021 outperformed those from studies using older datasets. Furthermore, CNNs have not been successful in all classifications of brain tumor tasks. Vision Transformers (ViTs) and Swin Transformers, on the other hand, are better at capturing contextual linkages and long-range dependencies. These models have a lot of promise for enhancing brain tumor identification and classification, so researchers should look into them in the future.

3. Methodology

Proposed System We seek to develop a reliable brain tumor classification model using an 8,000-image (JPEG), which has been taken from a slice of an MRI obtained from Kaggle [9]. The primary goal is to correctly detect tumors in these medical images as early as possible so that diagnosis and treatment can be planned quickly. For tumor classification, we use a CNN architecture. This architecture can classify three types of tumors: pituitary, glioma, and meningioma. After classification, we do the tumor segmentation on the input image, which is done using digital image processing, which follows some steps like contrast, erosion, dilation, removal of skull, or extra noise. The proposed system will analyze images using some methodologies and has a sequential model design.

The dataset will be preprocessed with scaling, normalization, horizontal flip, normalization, zoom range, and generalization of an image. Augmenting the data will help to eliminate overfitting issues and make the model more robust. The system's custom sequential neural network architecture consists of a fully connected layer for classification and multiple layers of convolutional neural networks (CNNs) for feature extraction. Using this, our CNN model will be able to store essential features of an image, allowing it to identify significant patterns and textures connected to brain tumors. The proposed system will undergo rigorous testing and training to ensure that it can consistently and accurately classify brain tumors. Then, the image will undergo a series of steps for tumor segmentation. It can help medical professionals diagnose patients quickly and accurately by classifying new MRI images as either tumor-present and classifying different types of tumors or tumor-absent once it has been trained. As new data becomes available, the model may undergo regular updates and revisions to improve its performance and Accuracy in classification and segmentation.

Aside from that, we have used different architectures like VGG16 [9], Mobile Net, and Google Net for tumor classification for comparison purposes and to check how our model is performing.

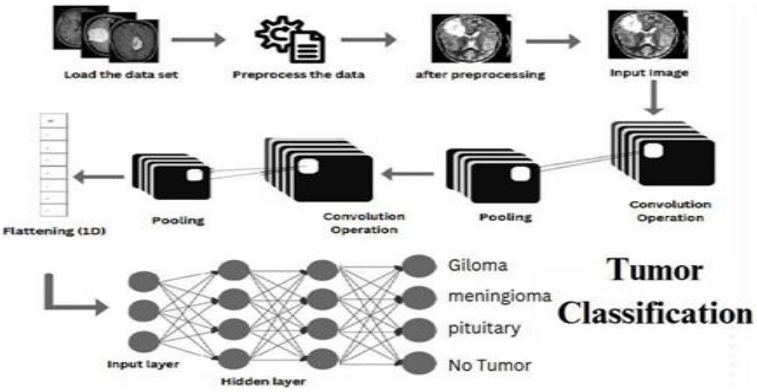

Fig. 1: CNN Architecture for Tumor Classification.

In the above Fig.1, we first load the dataset and perform some tasks. Data preprocessing includes scaling, zooming, normalization, horizontal shift, etc. After that, we pass the image to our CNN model, which consists of convolutional, pooling, and fully connected layers. Convolutional layers extract features from input images using convolution processes, whereas pooling layers downsample features.

Maps to reduce computational complexity. Fully connected layers are often used in the network's later stages to perform classification based on previously learned features. In the output layer, our model uses the SoftMax function to classify three different types of tumors, calculates the loss function, and then again backpropagates to reduce the loss function and improve the accuracy of our model. In our model, we use dropout so that our model doesn't overfit the data, and after performing some iterations, our model is ready for classification. This will be discussed in more detail in the algorithm section.

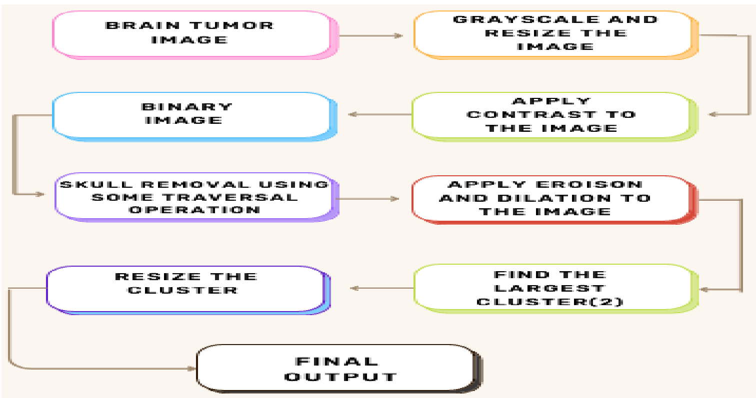

Fig. 2: Tumor Segmentation.

In the digital image processing method, we do segmentation of the tumor first, after classification of cancer using CNN; if our model predicts that the cancer is present, then we do the segmentation, and if our model predicts that there is no tumor, then we don't do the tumor segmentation, if there is tumor than we do the following steps to detect cancer, first we take the image and grayscale the image, and after that, we resize the image into 224*224 pixels then we increase the contrast in the image so that we can have a difference in the foreground and background image and post that we convert the image into a binary image using some threshold value such that is the pixel value is less than a particular value then we make it black otherwise we make the pixel as white, then we have our binary image then we perform some vertical operation.

A horizontal traversal operation removes noise and unwanted parts, like the skull, from the image. Then, we do the erosion and dilation to the image so that extra noise is removed using erosion, and dilation is used to enhance the pixels. After that, we find the most significant cluster using the BFS (Breadth First Search) or connected component algorithm (at maximum 2 clusters and minimum 1 cluster). BFS is used as a cluster detection algorithm to identify and extract the most significant region (tumor) from the processed MRI image. It helps traverse connected pixels in a binary or segmented image to find distinct clusters of tumor regions. After doing that, scale our predicted tumor pixel to match the original tumor size in the image. We have one condition: we didn't find any pixels after dilation, so we took the picture after the horizontal and vertical operations image and saw the cluster. The largest cluster is our final output shown in Fig.2.

Dataset: This brain tumor dataset consists of 8000 images in jpeg format, that is, 2D images. These images are taken from a slice of an MRI image, and the dataset has been taken from Kaggle [10]; this dataset is particularly helpful for categorizing brain tumors, and the photos are classified into four groups that are Glioma tumor, Meningioma tumor, Pituitary tumor, and no tumor. Because each category provides a complete representation of all forms of brain tumors, the dataset is a versatile tool for training and testing deep learning models for brain tumor classification. Adding the No Tumor category helps create models that recognize standard brain images. This dataset can potentially increase the efficiency of brain tumor early detection and prognosis.

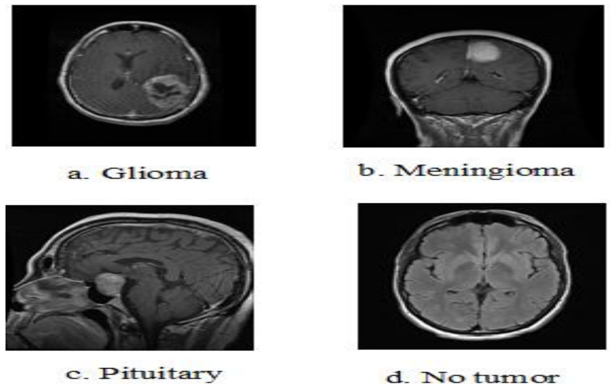

Fig. 3: Sample MRI Images.

As shown in the Fig.3, we have four images: the first image is of a glioma, the second image is of a meningioma tumor, the third is for a pituitary tumor, and the fourth is a no-tumor. These are examples from our dataset and comprise four groups.

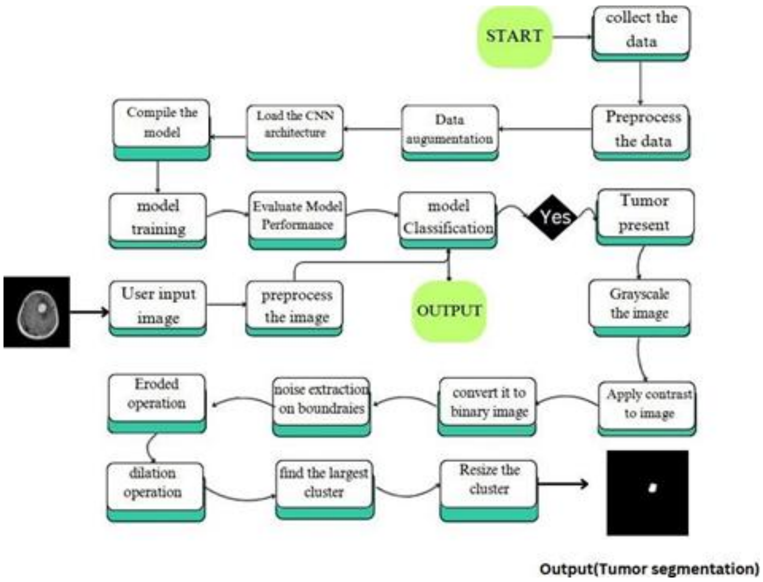

Fig. 4: Proposed Model.

So, the Fig.4 shows our paper's workflow, whereas Figures 1 and 2 demonstrate our CNN architecture and tumor segmentation, respectively. In our work, we have used CNN for classification and digital image processing for segmentation. Data-loading and preprocessing: Now, let's look at our CNN architecture in which we first gather the data and load it, then we carry out the preprocessing on the image, then after we apply data augmentation on the photos that includes scaling, horizontal flipping, zooming in by some percentage, shifting width and height by 20%. The key benefit of these data augmentation strategies is that our dataset will have an
The formula for the same padding is

$$\text{Padding} = (\text{Kernel Size} - 1)/2 \tag{1}$$

The total output image size with padding is (n +2p).
Activation Function- After applying an activation function to our model, we have used RELU as the activation function. The main motive for using the RELU activation function is that it introduces non-linearity, which helps the network learn complex patterns in data. Mathematically, RELU is straightforward to compute, and its gradient is well-defined. And RELU helps mitigate the vanishing gradient problem.
The formula of RELU is-

$$F(x)=\max(0, x) \text{ where } x \text{ is the input} \tag{2}$$

RELU returns the input value if it's positive and zero otherwise.
Max pooling: After applying max pooling to our image, we apply max pooling so that it retains all the essential features while reducing its size, which also helps reduce the computational complexity of the model. By downsampling the feature maps, we decrease the parameters and operations required in subsequent layers, leading to faster training. By doing this, we will also enhance the features.
Flatten and fully connected layer: After performing all these three convolution operations, we flatten it into a 1D array and then pass it to the fully connected layer, where we have used the activation function as RELU and for output for last layer, we have used SoftMax because we want to classify Three different types of tumors and one no-tumor type, The three different types of tumors are Glioma, Pituitary tumor and meningioma tumor.
In addition, we have dropped out of 0.3, which helps to reduce the overfitting and makes our model more robust. After that, we backpropagate to reduce the loss function and change the weights. This process is repeated until our loss function is less than 0.2, and then, after, we evaluate our model. After this, our model will be ready for classification. So, by using this architecture, we have achieved 96% accuracy on the training data and 93% accuracy on the test data.

Tumor Segmentation: Now, after classification, we do the tumor segmentation if our model tells us there is a tumor. If no cancer is predicted, then this step is skipped, so when the tumor is predicted, we follow specific steps to segment the cancer. The first step involves converting the image into grayscale, resizing the image to 224*224 pixels, and then increasing the contrast in the image so that there is a difference between the foreground and background images.

After that, we convert our grayscale contrasted image into a binary image to contain only white and black pixels. We do this by using some thresholding, and if the pixel value is less than that threshold value, then we make that pixel black; if it is more than that threshold value, then we make that pixel white. After that, we try to remove some noise from the image and remove the skull from the boundaries. For this, we do some horizontal and vertical traversal operations. After that, we perform erosion and dilation operations; erosion is used to remove some noise from the image, and dilation is used to increase the size of the pixels. Then, after, we may have one or more clusters in which we find the largest cluster (at maximum two and minimum 1 cluster) by using the BFS algorithm or connected component algorithm, and then try to scale that cluster to match the tumor size. Below are some examples of it (Tumor segmentation) shown in Fig.5.

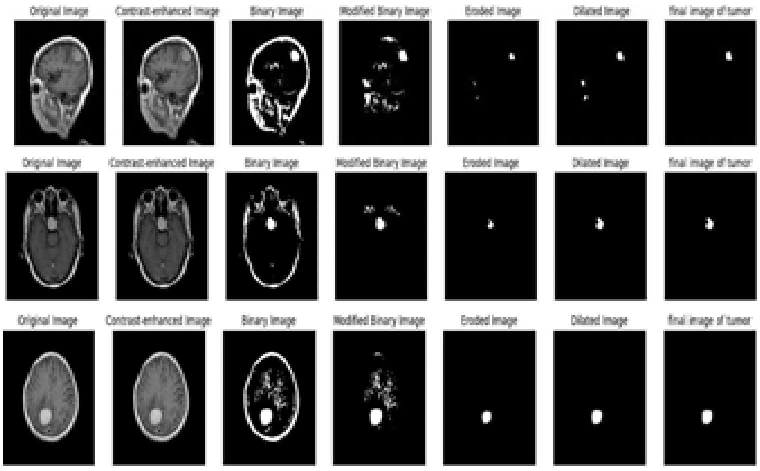

Fig. 5: Sample Images Tumor Segmentation.

Detailed steps involved in Tumor segmentation.

i) Resize the image

First, we have an image size of 512*512 and then scale the image to 224*224. We are using bilinear interpolation to resize the image.

$$(x,y)=(1 - dx) * (1 - dy) * A + dx * (1 - dy) * B + (1 - dx) * dy * C + dx * dy * D \tag{3}$$

Where (x,y) are the targeted pixel values and dx and dy are Distances from the targeted pixel to the original pixel. A, B, C, and D are the values at an original pixel. We take an average weighted sum of four neighboring pixels in bilinear interpolation.

ii) Increase the contrast of the image

We increase the contrast in the image such that there can be a difference between foreground and background pixels; by enhancing the contrast, the lighter value becomes lighter, and the darker value gets darker.

To increase the contrast of an image, we follow the steps below:

- First, normalize the value so dividing each pixel by 255. So that all the values are between 0 and 1.
- Then multiply each pixel value by the contrast factor.
- We clip the values greater than 1 to ensure they remain within the valid range of 0 to 1
- Scale the adjusted values back to the range of 0 to 255 by multiplying by 255.

iii) Convert the image into a binary image

In this step, we convert the contrast-enhanced image into a binary image using a threshold value. We convert it into a binary image by traversing the image matrix. If a pixel value is less than the threshold value, then we make that pixel value 0(Black), and if the pixel value is greater than the threshold value, then we make that pixel value 255(White). Calculation of threshold value: To calculate the threshold value, we take the average weighted sum of the pixels where the pixel value is greater than 20.

To calculate the average weighted sum of the image, we have taken a pixel value greater than 20 because, in the brain tumor image, we do have a black pixel in the boundaries of the image, which is of no use; if we take that pixel value, then our average value will be decreased so to avoid that we are only taking pixel whose value is greater than 20.

iv) Remove the skull near boundaries and noise

After converting the image into a binary image, we also have a skull and some extra noise. To remove that noise, we use horizontal and vertical traversal operations and try to remove the skull and other noises near it.

v) Erosion and dilation

After that, we apply erosion and dilation to the image; erosion helps shrink the picture, so it helps remove the noise in the image. This is the opposite of erosion, which helps expand the image.

vi) Find the largest Cluster

After performing erosion and dilation operations, we may have two or more clusters, so we must find the largest cluster for tumor segmentation. For this, we use the BFS algorithm.

vii) Resize the Cluster

After getting the most significant cluster from our image, we try to scale it to its original size using the BFS algorithm. Here, we take any pixel value from the most significant cluster and then find that pixel value in the binary image and find its neighbor pixel, whose value is 255. By doing this, we can scale the tumor to its original size.

4. Results and discussion

Our CNN architecture has achieved 96.2% accuracy on the training data and 93.2% on the test data. The model consists of three Convolution layers that perform convolution and max pooling before flattening and passing to fully connected layers. Then, our model goes through 25 iterations of training, goes both forward and backward in each iteration to update the weights and bias, and tries to reduce the loss value, improving our model accuracy and performance. For the loss function, we used categorical cross-entropy, so on the first iteration, our model accuracy was 58%, but gradually got better with each iteration, and upon completion, our model achieved an accuracy of 93.2% on test data and 96% accuracy on train data. So, it can classify the tumor into four categories: pituitary, glioma, meningioma, and no-tumor. Then, if our model predicts that a tumor is there, we segment the tumor using image processing methods like dilation, erosion, contrast, and thresholding. Apart from our model to classify different brain tumors, we have used other architectures (VGG16, Mobile Net, Google Net) to compare with our model and how our model is performing. Fig.6 gives the training and validation loss of our model.

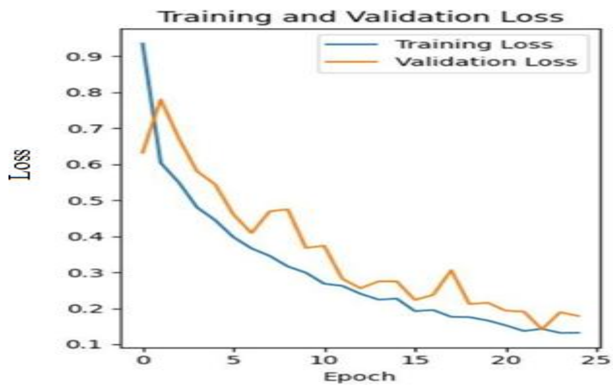

Fig. 6: Training and Validation Loss.

On using VGG16, we obtained 86.04% accuracy; on using Google Net, we obtained 88.4%; and on mobile Net, we achieved 96.88% accuracy shown in Table 1.

Table 1: Accuracy of Proposed Models

Model	Accuracy
CNN	96.88%
VGG16	86.04%
Google Net	88.4%
Mobile Net	94%

Confusion matrix: We achieved an accuracy of 96.88% for our CNN model. Fig.7 gives the confusion matrix with performance metrics of our proposed model.

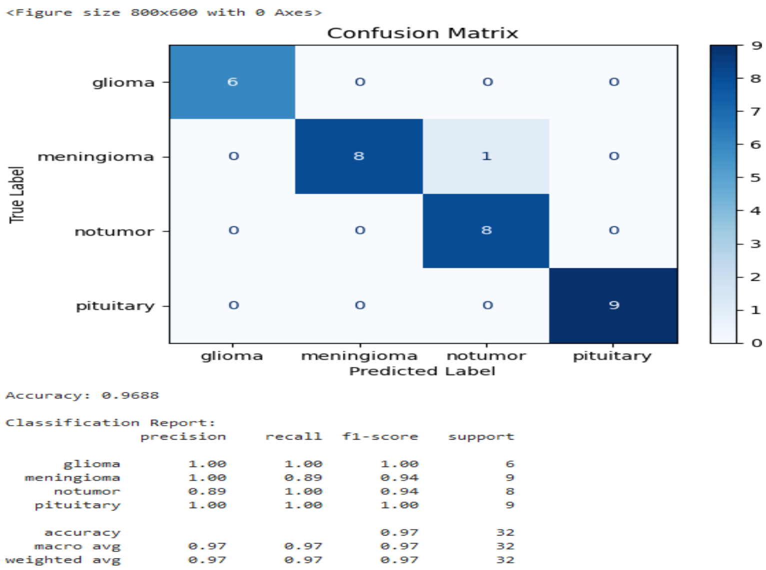

Fig. 7: Confusion Matrix.

5. Conclusion

In the first step of our work on Brain Tumor Classification using deep learning methodologies (CNN), we focused on selecting suitable algorithms and building the workflow for our model. Our main goal is to develop a robust system that can accurately recognize brain images and differentiate them based on training data, providing us with precise results. By utilizing advanced deep learning and computer learning techniques, we are able to verify and differentiate brain tumors, which is of utmost importance. It might improve how doctors diagnose by collecting information related to this tumor classification. While there are many things to be figured out, like we must make sure that the patient's data is correct and that they follow all the rules, it could also be an enormous help for patients with medication. We should keep researching and using this technology thoughtfully because healthcare must evolve as the technologies get more advanced to get the best results and progress in understanding brain tumors. This technology also significantly aids patients in their medication regimen. We should keep researching and using this technology thoughtfully because healthcare must evolve as the technologies get more advanced to get the best results and progress in understanding brain tumors.

6. Future scope

Cross-Platform Integration: Deep learning models for brain tumor classification could be integrated seamlessly with various medical imaging platforms, such as MRI, CT scans, and PET scans. This would allow for consistent and standardized analysis across different imaging modalities, improving diagnostic accuracy.
Multi-Modal Fusion: Combining information from multiple imaging modalities (e.g., MRI, functional MRI, diffusion tensor imaging) using deep learning can provide a more comprehensive understanding of the tumor's characteristics, aiding in precise diagnosis and treatment planning.
Enhanced Accuracy: Continued research and development will likely lead to higher accuracy rates in classifying brain tumors. Training deep learning models is possible. They are refining their ability to distinguish subtle tumor characteristics on more extensive and diverse datasets.

Acknowledgement

I would like to thank my colleagues for their support in this research work.

Conflict of interest

The authors declare that there is no conflict of Interest.

References

[1] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain Tumor Detection and Classification Using Transfer Learning Models," *Engineering Proceedings*, vol. 62, no. 1, p. 1, Feb. 2024, https://doi.org/10.3390/engproc2024062001.
[2] A. M. Alqudah, "Brain Tumor Classification Using Deep Learning Technique - A Comparison between Cropped, Uncropped, and Segmented Lesion Images with Different Sizes," International Journal of Advanced Trends in Computer Science and Engineering, vol. 8, no. 6, pp. 3684–3691, Dec. 2019, https://doi.org/10.30534/ijatcse/2019/155862019.
[3] S. Patil and D. Kirange, "Ensemble of deep learning models for brain tumor detection," Procedia Computer Science, vol. 218, pp. 2468–2479, Jan. 2023, https://doi.org/10.1016/j.procs.2023.01.222.
[4] S. Mohsen, A. M. Ali, E. -S. M. El-Rabaie, A. ElKaseer, S. G. Scholz and A. M. A. Hassan, "Brain Tumor Classification Using Hybrid Single Image Super-Resolution Technique with ResNext101_32× 8d and VGG19 Pre-Trained Models," *IEEE Access*, vol. 11, pp. 55582-55595, 2023, https://doi.org/10.1109/ACCESS.2023.3281529.
[5] W. Jun and Z. Liyuan, "Brain tumor classification based on attention guided Deep learning model," International Journal of Computational Intelligence Systems, vol. 15, no. 1, May 2022, https://doi.org/10.1007/s44196-022-00090-9.
[6] J. Cheng et al., "Retrieval of brain tumors by adaptive spatial pooling and fisher vector representation," PLoS ONE, vol. 11, no. 6, p. e0157112, Jun. 2016, https://doi.org/10.1371/journal.pone.0157112.
[7] M. I. Sharif, M. A. Khan, M. Alhussein, K. Aurangzeb, and M. Raza, "A decision support system for multimodal brain tumor classification using deep learning," Complex & Intelligent Systems, vol. 8, no. 4, pp. 3007–3020, Mar. 2021, https://doi.org/10.1007/s40747-021-00321-0.
[8] K. Usman and K. Rajpoot, "Brain tumor classification from multi-modality MRI using wavelets and machine learning," Pattern Analysis and Applications, vol. 20, no. 3, pp. 871–881, Feb. 2017, https://doi.org/10.1007/s10044-017-0597-8.
[9] Rao, Marada S., S. Praveen Kumar, and Konda S. Rao. "A Methodology for Identification of Ayurvedic Plant Based on Machine Learning Algorithms." International Journal of Computing and Digital Systems. Vol. 14. no.1, pp.10233-10241, 2023. https://doi.org/10.12785/ijcds/140196.
[10] https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset.