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Brain Tumor Classification using Transfer Learning

Vaibhav Narawade[1], Chaitali Shetty[2], Purva Kharsambale[3], Samruddhi Bhosale[4], Sushree Rout[5]

Department of Computer Engineering, Ramrao Adik Institute of Technology, D Y Patil Deemed to be University, Navi Mumbai, Nerul, India

Email: [1]vaibhav.narawade@rait.ac.in, [2]chaitalishetty261@gmail.com, [3]purvakharsambale2001@gmail.com, [4]samruddhi2001b@gmail.com, [5]alinaavipsarout@gmail.com

Abstract

Brain tumors are one of the more severe medical conditions that can affect both children and adults. Brain tumors make up between 85 and 90 percent of all primary Central Nervous System (CNS) malignancies. Each year, brain tumors are found in about 11,700 persons. The 5-year survival rate is around 34% for males and 36% for female patients with malignant brain or CNS tumors. Brain tumors can be classified as benign, malignant, pituitary, and other forms. Appropriate treatment, meticulous planning, and exact diagnostics must be used to prolong patient lives. The most reliable way for detecting brain cancer is Magnetic Resonance Imaging (MRI). The images are examined by the radiologist. As brain tumors are complex the MRI serve as guide to diagnose the seriousness of the disease. Since the placement and size of the brain tumor seems incredibly abnormal for persons affected by the disease it becomes difficult to properly comprehend the nature of the tumor. For MRI analysis, a qualified neurosurgeon is also necessary. Compiling the results of an MRI can be extremely difficult and time-consuming because there are typically not enough qualified medical professionals and individuals who are knowledgeable about malignancy in poor countries. Thus, this issue can be resolved by an automated cloud-based solution. In the proposed model, The Convolutional Neural Networks (CNN) is used for the classification of the brain tumor dataset with an accuracy of 99%.

Keywords: MRI (Magnetic Resonance Imaging), Brain tumor, Transfer Learning, Convolution Neural Network (CNN), Image Processing

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1. Introduction

The human body is composed of numerous other organs, in which the brain serves as the most crucial and important organ of all. The most frequent cause of brain impairment is neoplasm. A tumor is an uncontrolled accumulation of additional cells. When tumor cells expand so quickly that they finally eat up all the nutrients meant for healthy cells and tissues, causing brain failure . To identify the location and size of the tumor, doctors currently manually review the patient's MR scans of their brain. This results in an inaccurate tumor detection and is regarded as being extremely time-consuming. Brain cancer is a potentially fatal condition that claims many lives. Neoplasm organization and detection tools are available, which helps with early diagnosis. In Clinical diagnostics' most difficult assignment is classifying cancer. Since technology has advanced over the past few decades, more hospitals have employed the computer science techniques to aid in diagnosis, which encourages reform and the advancement of intelligent therapy at the same time. The central system nervosum of the brain, which is the most complex structure, regulates human higher neural activity like memory, intelligence, and awareness. Whether the tumor is benign or malignant, once it has spread to any area of the brain, it will harm the numerous functions of the form. The complex structure of the brain tissue over other body organs makes therapy and diagnosis challenging. Neoplasm is traditionally defined as the abnormal growth of tissues and unchecked cell proliferation, which results in the failure of the normal pattern of cell growth and death in addition to the analysis of a patient's symptoms. Two stages of a tumor exist: [8]

1. Primary Stage

2. Secondary Stage

Gliomas are a type of tumor and neoplasm, the two types of cell that grow slowly within the brain. Primary tumors are often less aggressive, but because of the pressure they put on the brain, the brain becomes dysfunctional. [2] Secondary tumors proliferate more quickly and are more aggressive. The majority of secondary brain tumors originate from other body locations. Neoplastic cells from these tumors move to the brain, lungs, and other organs of the body. The subsequent tumor poses a significant risk. Most of the emphasis for the explanation of secondary tumor causation belongs to cancers of the lungs, kidneys, bladder, and other organs.. MRI Images are widely used for top quality imaging mostly in brain scanning images because brain tumors are easily tracked by these images. MRI could be a useful method for identifying the tumor inside the form. [9]

T1&T2 weighted, and FLAIR weighted MRI are only a few of the ones that can be used to map tumor-induced alteration. The most widely used T1 and T2 weighted MRI sequences. Only Bright FAT and Water are weighted in T1, whereas all other tissue types are weighted in T2. Compared to T2 weighted, repetition time (TR) is long in T1 weighted. The terms "TE" and "TR," which stand for repetition time and echo time, respectively, are used to describe the features of the heart beat sequence. The echo time is the separation between the RF pulse's center and the echo's center, and the TR is the interval between pulses and echoes in the TE's repeating series. The third most used sequence is the FLAIR. The T2-weighted image makes the Flair sequence basically identical. The TE and TR timings on an MRI are incredibly long, which is the only difference. Using scanned images, the brain tumor portions may be quickly recognized, found, and classified. In the modern era, manually sifting through the countless MRI images and pinpointing a tumor could be a very tedious task. Due to the substantial quantity of image datasets involved, it may be a time-consuming. It may also impact the patient's ability to receive the proper medical care. A very accurate automated tumor detection system is therefore necessary. As a result, it will greatly speed up therapy by assisting doctors in precisely detecting brain cancers in MRI images. [7]

2. Related Work

A hierarchical deep learning classifier for brain tumors is proposed in this study and is based on CNN. The model categorizes the input into the meningioma, pituitary, glioma, and no tumor groups. With a 92.13% accuracy rate, the proposed model outperformed current segmentation and diagnosis methods for brain tumors by a factor of 7.87%. The system for identifying cancers classifies them into many groups. Clinical help in the medical sector will be offered under the proposed model. [1]

According to this study, the best way to eliminate brain tumors from 2D MRI images is by first utilizing fuzzy C-Means clustering, then traditional classifiers, and finally CNN. For the experiment, a real-time dataset with different tumor sizes, forms, locations, and image intensities was utilized. (SVM), (KNN), (MLP), Logistic Regression, Naive Bayes, and

Random Forest are six types of classifiers used in the scikit-learn that implemented classical classifiers. Then CNN which was developed with Keras and Tensorflow is used since it outperforms the conventional ones. CNN has an impressive accuracy record of 97.87% during the investigation. The primary purpose of this research is to employ statistical and texture-based criteria to distinguish between excellent and poor pixels. [2]

Convolutional neural networks and data augmentation method were employed to classify brain tumors. a thorough examination of various CNN architectures together with information on how well they perform on smaller datasets is carried out to resolve the existing issue. By incorporating data augmentation, the performances on constrained brain tumor datasets can be enhanced. The results of the experiments indicated how highly motivating the model's propensity and competence is in classifying the images. Even with a tiny MRI dataset, data augmentation-based algorithms have demonstrated outstanding efficiency and accuracy [3]

If a brain tumor is not found in early stage, it might progress and result in serious, permanent consequences. The appropriate course of therapy must be initiated as soon as a brain tumor is discovered, which gradually lowers the patient survival rate. With 2D Magnetic Resonance (MR) Images, deep learning is a common technique used in finding brain tumors. A labeled dataset that includes images of the healthy and disordered brains is used to support the investigation's. Seven techniques are employed for transfer learning, including ResNet-50, InceptionResNetV2, InceptionV3, and DenseNet201, SVM, Random Forest, and Decision Tree and five conventional classifiers are used, that includes AdaBoost, Combining SVM with gradient boosting. The top model has an accuracy of 99.39% for 10-fold cross validation, according to the findings that were shown. It is expected that the outcomes of this study would be helpful in choosing the optimal techniques for deep transfer learning-based brain tumor diagnosis. [4]

Several aspects of human life are impacted by technological progress. Consider the significance of technology in medicine to human society. The major subject of this research is technical assistance for brain tumors estimations from websites in the US specializing in "brain tumors" around 700,000 people are thought to be affected by primary brain tumors, and 85,000 more people are diagnosed with brain tumors every year.

Artificial intelligence has assisted humans and medicine in devising a solution for it. MRI is the famous technique for finding brain malignancies (MRI). MRI is utilized in image processing and medical imaging to identify variations in various body sections. The domain's present problems that are identified, and suggests with the possible solutions . In medical image processing, CNN, performs well in processing of medical images, especially of the brain. The focus of this study, is to examine the MRI data using the CNN. [5]

CNN is combined with the local binary pattern and a multi-layered SVM to produce an autonomous brain tumor segmentation and identification model.

Brain tumours must be classified and diagnosed in order to support doctors, thus an effective method that uses more automated processes and requires less manual labour must be developed.

An RGB image is converted to a binary image using grayscale conversion and colormap processing, and the conversion is completed using local binary patterns (LBP). To highlight a feature and create something easily identifiable a multi-layer ML-SVM is used. There are several technical uses for the well-known deep learning algorithm CNN. Last but not least, the classification approach is used to determine whether a brain tumour is present or absent. Measures like the Dice Similarity and the Jaccard Similarity Index are also necessary. When compared to the overall effort recommended approach and the normal operating procedures utilizing the coefficients (DSC), (SE), ACC, SP, and PR. [6]

For the purpose of classifying brain cancer using MRI, CNNBCN is given in this paper. It is not intentionally constructed or optimized; rather, network structure is formed using random graph algorithms. Graphs that are produced randomly can be mapped into neural networks using the Network Generator. The improved CNN Model outperforms numerous other models in accuracy with a 95.49% accuracy rate. Comparing modified CNNBCN models to ResNet, DenseNet, and MobileNet models reveals less test loss of brain tumor classification.

Additionally, the process of constructing neural networks is enhanced, and it is quite good at classifying images of brain tumours. [7]

Deep CNN, a brain tumor segmentation and classification approach based on Dolphin-SCA, is recommended in this study to find tumors from MRI data. The MRI data are initially pre-processed in order to identify the regions of interest. The preprocessed images are then segmented using a fuzzy deformable fusion model that combines pixels of varying brightness. The best-possible segmentation constants of the Dolphin-SCA approach are multiplied by the output images of fuzzy and deformable algorithms. The Deep CNN suggested by Dolphin-SCA classifies the images as abnormal or normal depending on the characteristics obtained by varying the Deep CNN training technique. As compared to the performance of the proposed Dolphin-SCA-based Deep CNN, the accuracy rating of 0.963 demonstrates higher performance. [8]

Brain tumors have emerged as a leading cause of death in both children and adults in recent years. Since 2019, around 86,000 cases of brain tumors have been diagnosed, in accordance with WHO criteria. The average survival rate for brain tumors is just 35%, despite 16,830 fatalities from them from 2000 to 2019. Automated procedures are required to accurately assess brain cancers utilizing MRI data. For the classification of tumor types and the identification of tiny brain tumors. The first stage in the process is creating a 3D (CNN) architecture. Next, a pre-trained CNN model is fed with the brain tumor data to extract features. The selected attributes are validated with a feed-forward for the final classification, a neural network. Three BraTS datasets from 2015, 2017, and 2018 were used for validation and experiments, and they had accuracy of 98.32, 96.97, and 92.67%, respectively. The proposed design is equally accurate when compared to current approaches. [9]

Nuclear Magnetic Resonance (NMR) images of healthy subjects, meningioma, glioma, and individuals with pituitary gland tumors could all be classified with 100% accuracy at the training phase and 96% accuracy at evaluation phase using an algorithm using convolutional networks. Also, a distinct diagonal in the confusion matrix indicated that the expanded model performed as expected. Accuracy was further demonstrated by the performance graphs, demonstrating that overtraining was not the cause of that issue. [10]

This research has led to the creation of a unique model that can discriminate between abnormal and regular images on brain MRI scans. The used data set consists of two classes. Image data that is normal and image data that is abnormal, both of which contain the mass, are divided into two groups. The Brain MRNet model's classification accuracy was better when compared to earlier experiments using the same dataset. [11]

The model focused on the important region of the MR images using attention modules. The feature maps that were extracted from the model at each level were transferred to the sequence structure in the final layer using the hyper column method. As a result, the classification process received the most useful data and all the pixel's features from input layer to output layer were preserved. Steps that have a detrimental impact on the depth of the model were minimized by using residual blocks. The classification success percentage for this study was 96.05%. [12]

3. Proposed Work

3.1 Architecture

EfficientNet, a family of convolutional neural network models optimized for accuracy and efficiency, is suitable for training on limited computational resources. To fine-tune the pre-trained EfficientNetB0 model, GlobalAveragePooling2D, Dropout, and Dense layers are added.

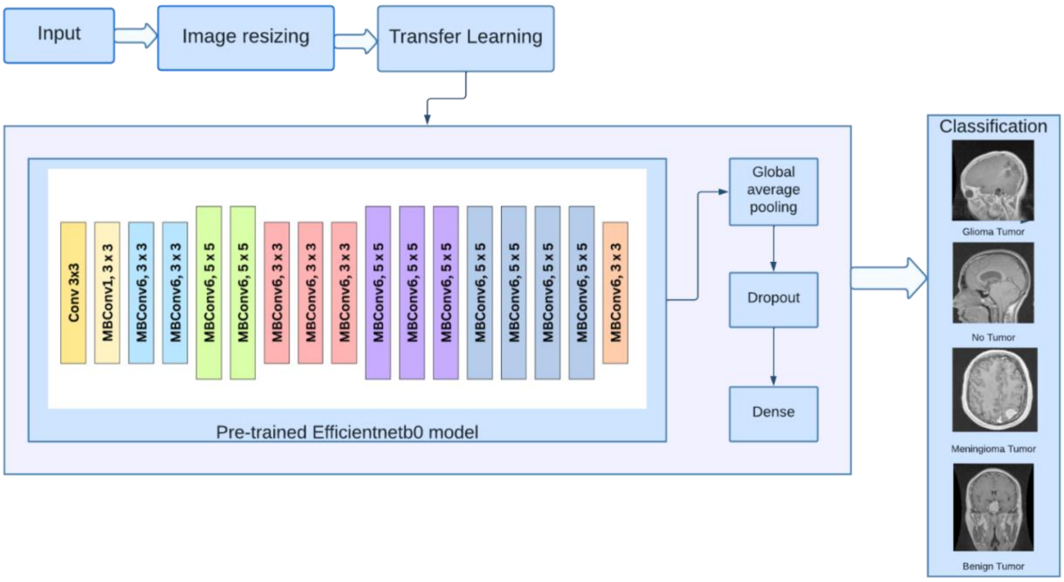

Figure 1. Architecture Diagram of Proposed Method

Import MR Images: MR images are imported from the database into the system. The imported image is an MRI scan from a section of the brain that has been processed to check for malignancies. The brain scan images are shown in the dataset [13].

1. Image resizing - The images were resized to 150 x150 pixels so that it could be manipulated and processed without losing information.

2. Transfer Learning using the EfficientNetB0 model - Transfer learning is a machine learning model developed for one task and used as the foundation for a model developed for another. It is a member of the EfficientNet family, which is made up of scalable and efficient models that provide cutting-edge performance on a number of image classification tasks. EfficientNetB0 takes brain images as input, which are typically in the form of three-dimensional MRI scans. These scans are passed through the initial layers of the network, which perform basic pre-processing operations such as resizing, normalization, and data augmentation to enhance the robustness and generalization of the model. These layers are responsible for extracting hierarchical features from the input images. Each layer performs a set of convolutional operations using learnable filters, which detect various patterns and features present in the images.

3. GlobalAveragePoolingPooling2D - In EfficientNetB0, a Global Average Pooling layer is applied to the output of the last convolutional layer. This layer acts similarly to the Max Pooling layer in CNNs, with the distinction that it pools using average values rather than max values. Downsampling is performed using a 2-D global average pooling layer by finding the mean of the input's height and breadth dimensions.

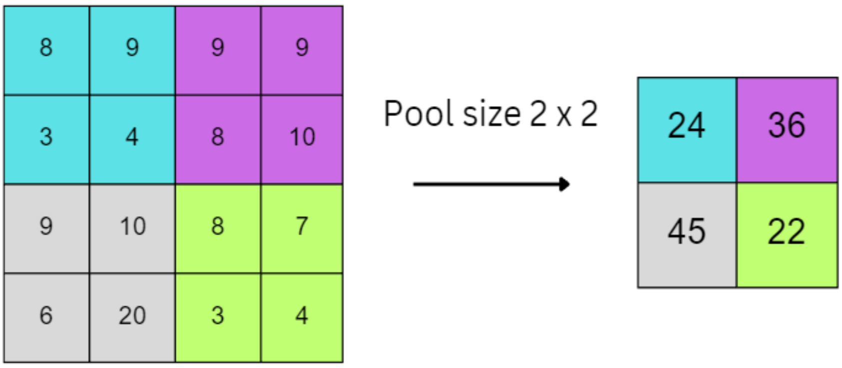

Figure 2. Overview of Global Average Pooling 2D

4. Dropout - In order to increase the neurons' independence from their nearby neighbours, this layer removes a portion of each neuron at each phase. By doing this, overfitting is

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prevented. The neurons to be excluded are chosen at random. The learning rate probability is that neuron's activity will be set to 0 before the drop out.

5. Dense - this is the output layer. The given image is classified into one of the four potential classes. It uses the softmax function, a sigmoid function generalization. Each potential class's probability is calculated using the Softmax function. A vector having probability for every possibility is the result of a Softmax. This layer divides the image into the three categories of tumor.

$$Softmax(z_j)=\frac{exp(z_j)}{\Sigma_j\, exp(z_j)}$$

3.2 Evaluation

True positives, false positive rate, true negative rate, and false negatives rate are four important outcomes used to assess the effectiveness of the proposed deep transfer learning framework.

Accuracy can be defined as the ability to successfully identify a brain tumor from a target image. The percentage of true positives and negatives cases under consideration is called accuracy.

Accuracy - $\frac{TP+TN}{TP+FP+FN+TN}$

Precision is a TP measure that is

Precision - $\frac{TP}{TP+FP}$

Recall (Sensitivity) is used to assesses the system's ability to accurately classify brain tumors, and it is the percentage of true positives.

Recall - $\frac{TP}{TP+FN}$

The F1-score is a single statistic that is calculated by averaging the precision and recall of a classifier. The general form of the F1-score is

F1-score - $2.\frac{precision.recall}{precision + recall}$

0 - Glioma Tumor

1 - No Tumor

2 - Meningioma Tumor

3 - Pituitary Tumor

	precision	recall	f1-score	support
0	0.98	0.99	0.98	93
1	1.00	1.00	1.00	51
2	0.99	0.98	0.98	96
3	1.00	1.00	1.00	87
accuracy			0.99	327
macro avg	0.99	0.99	0.99	327
weighted avg	0.99	0.99	0.99	327

Figure 3. Classification Report

3.3 Dataset

MRI dataset from Kaggle and offline dataset from private hospital is used for analysing and evaluating the proposed method. The dataset used during this research work consists of 2870 NMR brain images of different dimensions, in which 2475 images were identified as resonances with the presence of tumors, specifically: 826 of glioma, 822 of meningioma and 827 of pituitary gland and 395 images are considered to be with no tumor. JPG images in grayscale. Eventually, an augmentation approach is used to enhance the dataset size. Jupyter Notebook was used to implement the model.

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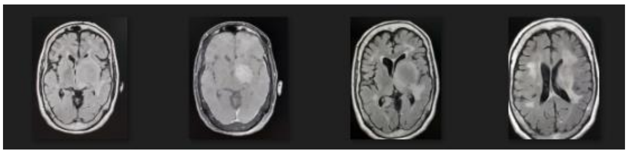

Figure 4. Brain MRI without Tumor

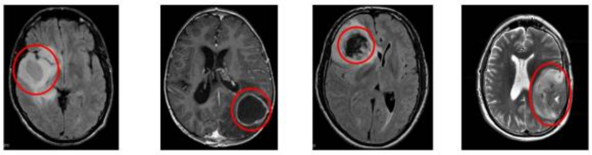

Figure 4. Brain MRI with Tumor

4. Results and Discussion

The system receives two-dimensional MRI images as input from Kaggle that have been uniformly scaled to 255x255. The objective standard of CNN is modified by suggested approach to include a mean field term. Throughout training, the model's accuracy was 99%. The evaluation's results are also heavily loaded on the diagonal, as seen on the confusion matrix. An accuracy of 99% was found during the examination.

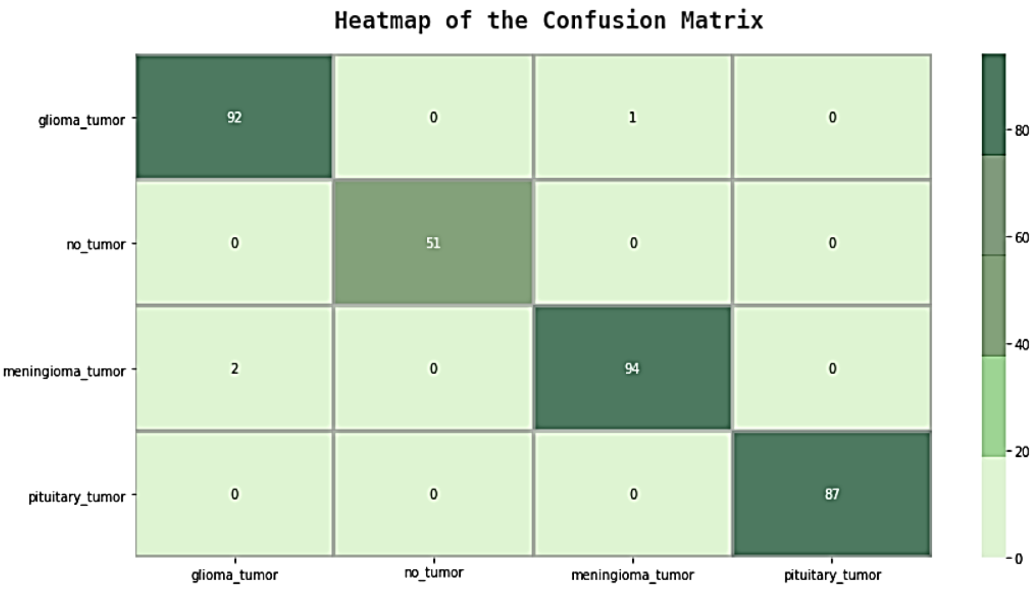

Figure 5. Heatmap of the Confusion Matrix

In this figure, Heatmap represents each data point by colored rectangle or square, and color represents the value of the data point. In confusion matrix 1 indicates perfect positive correlation and 0 indicates no correlation. In the heatmap of confusion matrix in the figure 4 classes of tumor are represented as glioma tumor, no tumor, meningioma tumor, and pituitary tumor. Color ranges from low to high. Here the scale ranges from 0 to 80 representing cool color at 0 which is light shade of green and shade goes on becoming dark and ends at 80 which is dark green. Data Points are plotted as 92, 51, 94, and 87.

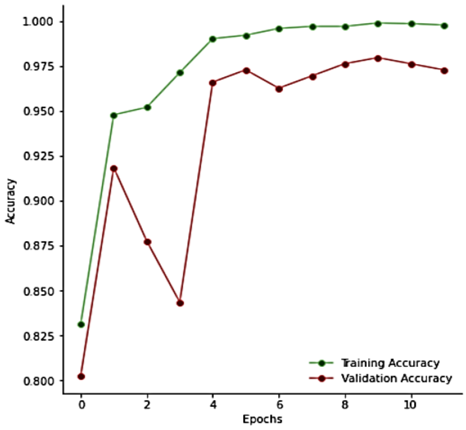

Figure 6. Epochs vs Accuracy

This figure indicates a graph of Accuracy vs Epochs. Training Accuracy is shown by green color and Validation Accuracy is shown by Red color. Epochs are the number of passes in training data. Data Points are plotted in the graph and connected with lines.

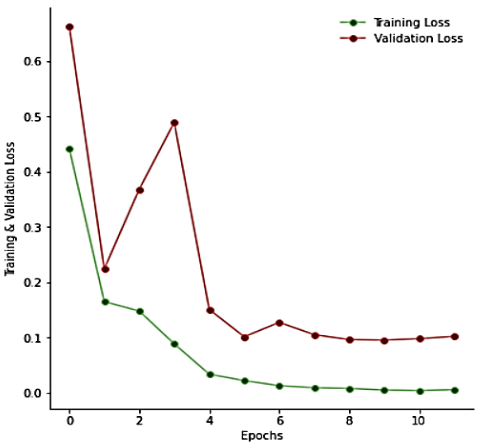

Figure 7. Epochs vs Training and Validation Loss

This figure indicates a graph of Training & Validation Loss vs Epochs. Training Loss is shown by green color and Validation Loss is shown by Red color. Epochs are the number of passes in training data. Loss is calculated to see whether model fits into the training data or not. Data Points are plotted in the graph and connected with lines.

5. Conclusion

Because of the wide variety of medical images, image segmentation is crucial in the processing of these images. MRI and CT scan images were used to segment brain tumors. For segmenting and classifying the brain tumors, MRI is most frequently used. The functionality of the brain may be impacted by an aberrant multiplication of brain cells. Early diagnosis of a brain tumor can lead to a quicker response to treatment, improving survival chances. MRI brain scans are frequently used to find brain cancers. With the advancement of AI techniques, CNN can be used to classify MRI images in order to identify tumors. In this study, CNN EfficientNet model B0 has been used to do automatic brain tumor identification.

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Author's biography

Dr. Vaibhav Narawade is a professor in D Y Patil Deemed to be University, Ramrao Adik Institute of Technology at Nerul where he has been a faculty member since 2019. Professor Narawade's area of expertise includes Wireless Sensor Network, Image Processing, and Data Science. He has more than 19+ years of teaching and administrative Experience. He has served University of Mumbai as member of senate (2008-2010) and currently also served as member of Management Council and Member of Senate, University of Mumbai (2017-2022).

In Academis, he is a board of studies member in Computer Science and Engineering, Information Technology Fraternity in University of Mumbai, and Faulty member in DBATU, Lonere Dr. Narawade has author / co-authored in various international conference/journal publications and book chapter. He has also published two books. He acts as Session Chair in International conferences and also reviews papers for the same. He is also an editorial member for American Journal of Agricultural Science, Engineering, and Technology (AJASET). He also act as a Judge for Avishkar Research Convention, Mumbai University. He is a fellow of ISTE an ACM.