

Project Report

on

**Brain Tumor Classification using deep learning with
parametric optimization**

Submitted in partial fulfilment of the requirements for the award of the degree

of

Bachelor of Technology

in

Electronics and Communication Engineering

by

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INDIAN INSTITUTE OF INFORMATION TECHNOLOGY BHAGALPUR
An Institute of National Importance Under Act of Parliament

DECLARATION

We hereby declare that the work reported in this project on the topic “*Brain Tumor Classification Using Deep Learning With Parametric Optimization*” is original and has been carried out by us independently in the **Department of Electronics and Communication Engineering, IIIT Bhagalpur** under the supervision of **Dr. Prakash Ranjan**, Assistant professor, IIIT Bhagalpur. We also declare that this work has not formed the basis for the award of any other Degree, Diploma, or similar title of any university or institution.

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CERTIFICATE

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B. Tech. students of IIIT Bhagalpur, under my supervision and guidance. This project has been submitted in partial fulfillment for the award of “*Bachelor of Technology*” degree in *Electronics and Communication Engineering* at *Indian Institute of Information Technology Bhagalpur*.

No part of this project has been submitted for the award of any previous degree to the best of my knowledge.

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Abstract

A brain tumor is the growth of abnormal cells in the brain. There are many types of brain tumors, but this study will focus on meningioma, pituitary, and glioma tumor. Deep learning algorithms and Machine learning techniques have been playing a big role in early detection of brain tumors, many efforts have been created to make a highly accurate solution for the automatic classification and segmentation of brain tumors. To overcome these issues this study proposes the use of various pre-trained deep convolutional neural networks (CNNs) to extract features, classify and segment the tumors. EfficientNetB7 are popular pre-trained models that achieve good results in Image classification.

The Automatic Support Intelligent System is used to detect Brain Tumor through the combination of neural network and fuzzy logic system. It helps in the diagnostic and aid in the treatment of the brain tumor. The detection of the Brain Tumor is a challenging problem, due to the structure of the Tumor cells in the brain. This project presents an analytical method that enhances the detection of brain tumor cells in its early stages and to analyze anatomical structures by training and classification of the samples in neural network system and tumor cell segmentation of the sample using fuzzy clustering algorithm. The artificial neural network will be used to train and classify the stage of Brain Tumor that would be benign, malignant or normal.

The segmentation is performed by fuzzy logic system and its result would be used as a base for early detection of Brain Tumor which would improves the chances of survival for the patient. The performance of this automated intelligent system evaluates in terms of training performance and classification accuracies to provide the precise and accurate results. The simulated result enhances and shows that classifier and segmentation algorithm provides better accuracy than previous methodologies.

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Chapter 1: Introduction

1.1. Overview

Brain tumor classification is a critical task in medical image analysis. Early and accurate detection of brain tumors can significantly impact patient outcomes. This project focuses on leveraging deep learning techniques, specifically the EfficientNetB7 model, to classify brain tumor images into different categories.

Primary brain tumors are gliomas, meningiomas, and pituitary tumors. This study will focus on these 3 primary tumors. The term Gliomas is a general term for tumors that start from brain tissues other than nerve cells and blood vessel.

Meningiomas start from the membranes that surrounds the brain and surrounds the central nervous system while pituitary tumors are lumps that are inside the skull.

Brain tumor can cause brain damage and can also be fatal. Early detection plays a serious role as doctors can treat the tumor early. Brain tumor classification has a very important role in clinical diagnosis and effective treatment.

Manually evaluating Magnetic Resonance Imaging (MRI) images is time-consuming, and inclined to error due to the excess number of patients . And it is not good to only depend on the doctors for detection as they can miss-interpret and not detect it early.

This study proposes the implementation of EfficientNetB7 that has never been applied to brain tumor classification. Deep learning models require a large amount of data for training and that much data is not always available. To overcome this problem this study proposes the use of pretrained deep-learning models.

1.1. Literature Survey

Numerous techniques have been applied to brain tumor classification. One of those techniques is machine learning which was later on replaced by deep learning. Deep learning and artificial intelligence have made a big impact in the field of medical image analysis, more specifically in the field of disease diagnosis. This section focuses solely on the previous work done by other people and how they can be improved.

The major symptoms of brain tumours are strong headaches, blurred visibility, and loss of balance, mental confusion and seizures [1]. The treatments for human brain tumours include surgery, radiation therapy and chemotherapy. The human brain contains billions of active cells and is very complex to analyse. Today, one of the key reasons for increased mortality among children and adults is brain tumours. Primary brain tumours occur in roughly 250,000 individuals a year worldwide, and account for up to less than 2 percent of malignancies. This anomaly is usually indicative of a brain tumour. The position of such tumours is determined using MRI [2]. Some significant concern in the division of the pictures is the grouping of highlighted vectors that are comparable. Subsequently, the mining of adequate highlights is an essential prerequisite for effectively sectioning the pictures. The valuable component extraction of pictures is a troublesome errand because of the complexities in the designs of the different tissues in the cerebrum [3,4]. Nowadays, deep learning-based approaches are widely utilized for segmenting, classifying and optimizing medical images. The process of the segmentation of images involves classification on the basis of pixel-to-pixel techniques. The primary purpose may be fulfilled using a typical non-end-to-end convolutional neural network (CNN)-based classifier to predict the centre pixel of each patch of medical pictures. An important tool for image detection and prediction is the convolutional neural network (CNN). However, CNNs are mostly used for segmenting, classifying, and predicting patient recovery times for brain tumours [6–9]. Havaei et al. [10] developed a programmed technique for brain tumour segmentation based on flexible, high-capacity deep neural networks (DNNs). The challenges regarding the irregularity of the names of the tumour are disposed of by utilizing a preparation strategy that includes two stages. The division of the tumour district is a significant assignment for disease analysis, treatment and the assessment of treatment results. For tumour segmentation, a variety of semi-automatic and automatic methods and techniques are used [11].

An assortment of picture-preparing procedures and strategies have been utilized for the determination and cure of a cerebrum tumour. Division is the major advance in picture handling methods and is utilized to separate the contaminated area of cerebrum tissue from MRIs [12]. Raja and Rani [13] studied brain tumour classifications by applying a hybrid deep learning encoder with a Bayesian fuzzy clustering-based segmentation technique to the BRATS 2015 database in a colab environment and found a classification accuracy of 98.5. Mustaqeem et al. [14] devised and published a useful algorithm for identifying brain tumours. Thresholding and watershed approaches were included in the established division strategy. The pictures of the human brains acquired from the MRI exam were utilized for the division interaction, yet this calculation cannot be utilized in the division of 3D pictures. Stacked de-noising auto-encoders [15] and convolutional restricted Boltzman machines [16] are two more deep learning-based methods for tumour segmentation, detection and prediction. Jia and Chen [17] presented a fully automatic heterogeneous segmentation using support vector machine (FAHS-SVM) technique for the identification and segmentation of MRI images of human brains and obtained a 98.51 percent accuracy in the detection of aberrant and normal tissue in their studies. Mahalakshmi and Velmurugan [18] built up a calculation to recognize cerebrum tumours utilizing molecule swarm advancement. CNNs outperform all other deep learning approaches and techniques in image segmentation, detection and prediction. Brain tumour segmentation, grouping and prediction methods were built using two-dimensional CNNs (2D-CNNs) [19–22] and three-dimensional CNNs [23,26]. The picture patch is divided into various groups by the segmentation processes, such as necrosis, stable tissues, edema, enhancing heart and non-enhancing core. Different characterization and division strategies that the PC helps with finding are the significant issues faced today in the MRI analysis of the human cerebrum, and this was studied by El-Dahshan et al. [27]. Dong et al. [28] established a completely automated system for segmenting brain tumours using deep convolutional networks based on U-Net. A technique was built by Padole and Chaudhari [29] for identifying the brain tumours in MRI pictures through part examination where normalized cut (Ncut) and mean shift algorithms were combined to identify the cerebrum tumour surface zone naturally. The dataset that is considered in this analysis has already undergone a pre-processing phase, with a total of 253 brain MRIs. Out of the 253 brain medical images, 98 images are in the form of a healthy condition and the rest of the 155 images are tumour-affected images [30].

1.2. Motivation

- Optimization techniques play a crucial role in the training process of deep learning models.
- By exploring and comparing the performance of popular optimization techniques such as Adam, Adagrad, Adadelata, SDA, and RMSprop, the project aims to identify the most effective approach for enhancing the convergence speed, stability, and overall performance of the brain tumor classification model.
- The model can accurately classify tumors across a wide range of scenarios, including different imaging modalities, tumor types, and patient demographics.

1.3. Objective

- Implement the EfficientNetB7 architecture for brain tumor classification.
- Explore and compare the performance of different optimization techniques: Adam, Adagrad, Adadelata, SDA, and RMSprop.
- Evaluate the model on a comprehensive dataset to ensure robustness and generalizability.

1.4. Proposed CNN Model in Brain Tumor Dataset

In this analysis, the python code is simulated on the Kaggle platform using TensorFlow, and the optimized “Adam” is chosen for classifying the brain tumors in the whole simulation. Similarly, other python libraries were utilized, such as “numpy”, “pandas”, “time”, “glob”, “matplotlib”, “os”, “cv2” and “shutil” libraries for building the python code and for classifying the considered dataset of brain tumours, where both the healthy and tumour-affected brain magnetic resonance images were presented. The dataset that is considered in this analysis has already undergone a pre-processing phase, with a total of 253 brain MRIs. Out of the 253 brain medical images, 98 images are in the form of a healthy condition and the rest of the 155 images are tumour-affected images [35]. The authors used 20% of the total dataset for testing purposes and the remaining 80% for training the model.

Chapter 2: Methodology

2.1 Data acquisition & pre-processing

2.1.1 Image Database

The dataset for this study was obtained from Kaggle and is therefore publicly available. Navoneel Chakrabarty and Swati Kanchan along with the team members Sartaj Bhuvaji, Ankita Kadam, Prajakta Bhumkar and Sameer Dedge(2020) collected the dataset. The dataset is called Brain Tumor Classification (MRI). The dataset consists of 2 227 training MRIs and 429 test MRIs. There are 826 glioma tumor, 247 meningioma tumor, 827 pituitary tumor and 327 no tumor MRIs in the train dataset. The test dataset consists of 98 pituitary, 100 glioma, 127 meningioma, and 104 no tumor MRIs.

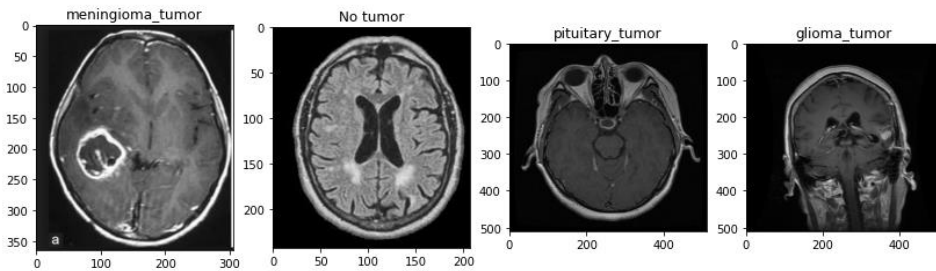


Figure.1 Examples of brain MRI for the 4 classes

2.1.2--- Image Pre-Processing

Image preprocessing is a crucial step in computer vision and image analysis pipelines. It involves a series of operations to enhance the quality of images, improve their suitability for a specific task, and facilitate better performance of machine learning models. The MRIs came in different sizes and were therefore resized to suit the different models presented in this study. The MRIs were also normalized. Normalization is very important because it ensures that each pixel has a similar data distribution to the other pixels. Normalization makes the network converge fast. The below figure shows a sample of a pre-processed image.

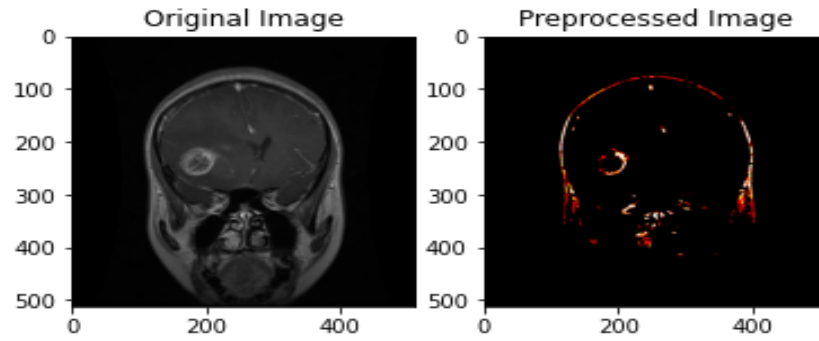


Figure.2: Image Pre-processing

2.2 Data training and fine tuning

In this section, the models used for the project were originally trained with the ImageNet dataset that is comprised of 1.2 million images that belong to 1000 categories. We used transfer learning which aims to transfer knowledge from one or more domains and apply the knowledge to another domain with a different target. The layers of the pretrained model EfficientNetB7 were all frozen, and 5 classification layers were added on top of the model layers. The following figure depicts the layers and the number of output nodes corresponding to the number of classes for the classification.

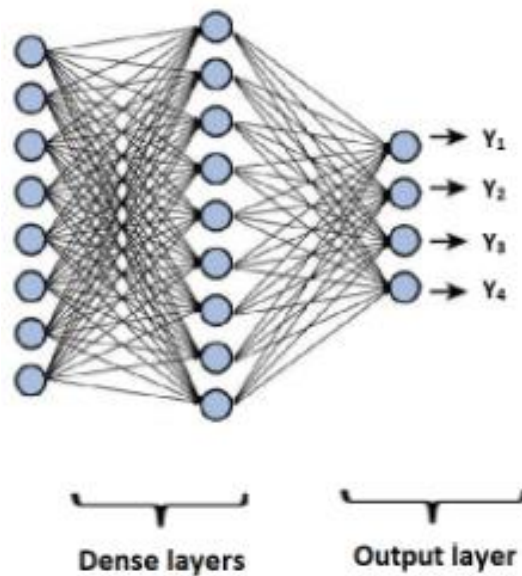


Figure 3: Structure of the out layer

2.2.1 Proposed Network

Tumor classification was done using transfer learning with EfficientNetB7. Transfer learning is a machine learning method that reuses a model trained on one task on another related task. Transfer learning can be described as a shortcut to saving time or getting best performance.

Deep learning models need abundant data for better performance. In the absence of such data transfer learning can be used to develop good performing models. Transfer learning transfers weights and biases from a pre-trained network which therefore provides a backbone that detects basic edges. Many pre-trained networks have been implemented to classify tumors. This study proposes a different approach by implementing EfficientNetB7 to classify brain tumors into 4 classes namely meningioma, malignant, pituitary and no tumor.

The EfficientNetB7 model, renowned for its outstanding performance in image classification tasks, was selected as the foundation for the brain tumor classification model. Leveraging transfer learning techniques, the model was initialized with pre-trained weights from the ImageNet dataset. This transfer learning approach enables the model to inherit knowledge from a broad range of visual features learned during its pre-training, contributing to its ability to discern relevant features in brain tumor images. Developers of EfficientNet put forward a method called compound scaling. Compound scaling suggests the use of a constant ratio to scale the network in all dimensions (width, resolution and depth). Compound scaling also solves the problem of the extent to which the network should be scaled therefore increasing accuracy of the network .

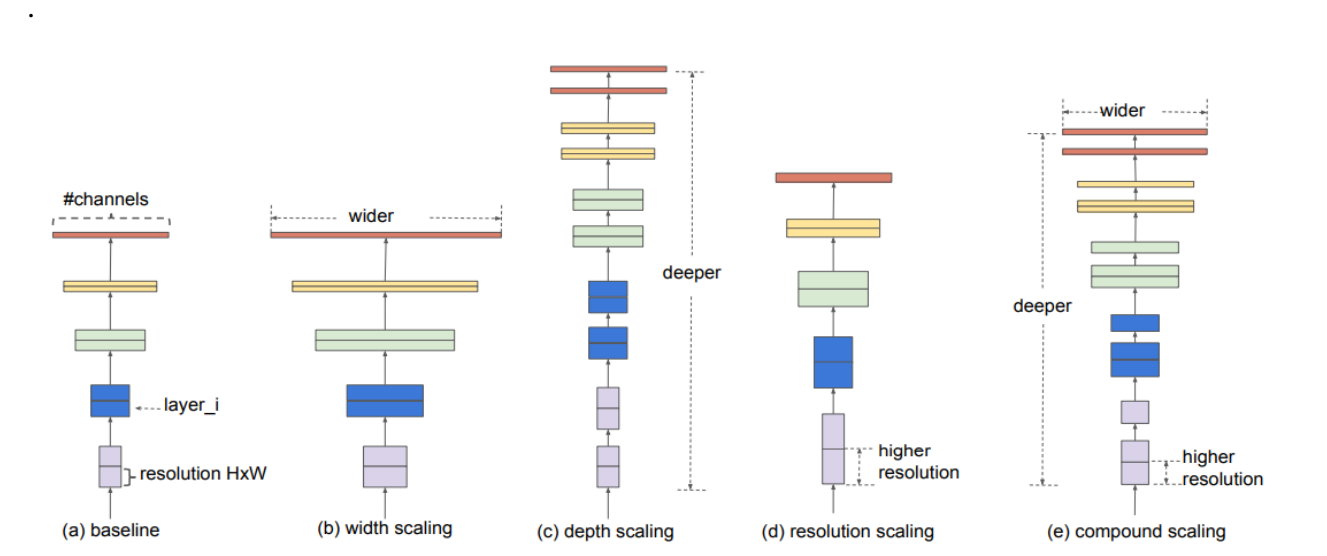


Figure.4: EfficientNet architecture

2.3 Fine Tunning

For this phase we tuned the following hyperparameters of the models, batch size, epochs, optimization method, and dropout values. For optimizers, we used only 5 optimizers to see which one works best, namely, SGD, RMSprop, Adam, Adagrad, and Adadelta. For number of epochs, we used only 4 epochs to choose the best performer from namely, 1, 2, 5, 10. With Batch size we used these batch sizes to choose the optimum batch size, namely, 8 and 16. For dropout value we used the following values to optimise the dropout of the model, values 0.5, 0.6, 0.7, 0.8, and 0.9.

Fine-tuning is a critical phase in the development of a machine learning model where hyperparameters are adjusted to achieve optimal performance. In this phase, the project focused on tuning specific hyperparameters to enhance the efficiency and effectiveness of the brain tumor classification model. The hyperparameters targeted for fine-tuning included batch size, epochs, optimization method, and dropout values.

2.4 Hyperparameters Tunned

2.4.1 Batch Size:

Objective: Determine the optimal batch size for training the model.

Options Tested: Two batch sizes were considered, namely 8 and 16.

Rationale: Batch size influences the speed and stability of model training. By testing different batch sizes, the project aimed to identify the size that facilitates efficient convergence without sacrificing accuracy.

2.4.2 Number of Epochs:

Objective: Identify the best-performing number of training epochs.

Options Tested: The number of epochs considered were 1, 2, 5, and 10.

Rationale: The number of epochs defines how many times the entire dataset is processed during training. Testing a range of epoch values allowed the project to observe the trade-off between model convergence and potential overfitting.

2.4.3 Optimization Method:

Objective: Select the most effective optimization method.

Options Tested: Five optimizers were compared, including SGD, RMSprop, Adam, Adagrad, and Adadelata.

Rationale: Different optimizers have unique characteristics, and their performance can vary depending on the task. Evaluating multiple optimizers helps in choosing the one that performs best for brain tumor classification.

2.4.4 Dropout Value:

Objective: Optimize the dropout rate to prevent overfitting.

Options Tested: Dropout values of 0.5, 0.6, 0.7, 0.8, and 0.9 were considered.

Rationale: Dropout is a regularization technique that prevents overfitting by randomly setting a fraction of input units to zero during training. Tuning the dropout value helps strike a balance between model complexity and generalization.

The fine-tuning process allowed for the identification of the most effective hyperparameter configurations for the brain tumor classification task.

The best-performing combination of hyperparameters was selected based on comprehensive evaluation metrics.

The chosen hyperparameters contribute to a well-optimized model capable of accurately classifying brain tumors while minimizing the risk of overfitting.

This fine-tuning phase is crucial for extracting the maximum performance from the model, ensuring that it is tailored to the specific characteristics of the brain tumor dataset and the chosen EfficientNetB7 architecture.

Chapter 3: Optimization Techniques

Optimization techniques play a pivotal role in the training process, influencing the convergence and performance of the model. To explore and compare different optimization strategies, the project implemented the following techniques:

3.1. SGD

Stochastic Gradient Descent (SGD) is a widely used optimization algorithm in machine learning and deep learning. It is a variant of the traditional gradient descent algorithm and is particularly suited for large-scale datasets. The key idea behind SGD is to update model parameters based on the gradient of the loss function with respect to those parameters, but instead of computing the gradient using the entire dataset (as in batch gradient descent), it computes the gradient using a randomly chosen subset of the data at each iteration. This random subset is often referred to as a "mini-batch." Update the model parameters in the opposite direction of the gradient to minimize the loss function. The update rule for the parameters θ is given by:

$$\theta_{i+1} = \theta_i - \eta \cdot \nabla L(\theta_i)$$

where η is the learning rate, and $\nabla L(\theta_i)$ is the gradient of the loss function with respect to the parameters. SGD allows for parallel processing, making it suitable for distributed computing.

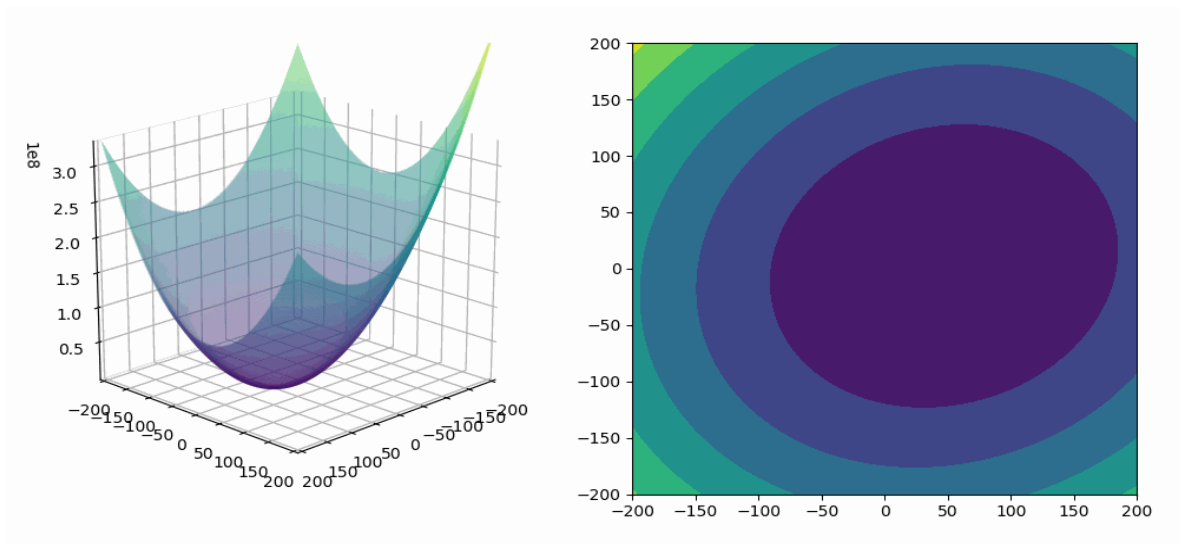


Figure.5: SDA

3.2. Adagrad

Adagrad, short for Adaptive Gradient Algorithm, is an optimization algorithm used in machine learning and deep learning. It is designed to adapt the learning rates of individual parameters based on their historical gradients during the training process. Adagrad is particularly useful when dealing with sparse data, where some features may have more frequent updates than others. Adagrad is an adaptive learning rate optimization algorithm that adjusts the learning rates for each parameter based on the historical squared gradients. While it can be effective, especially in scenarios with sparse data or varying feature importance, it is important to be mindful of its sensitivity to initialization and potential issues with accumulating squared gradients over time.

3.3. Adadelta

Adadelta is an optimization algorithm that is an extension of Adagrad. It addresses some of the limitations of Adagrad, particularly the issue of the learning rates diminishing too quickly for frequently updated parameters. Overall, Adadelta is an adaptive optimization algorithm that aims to overcome some of the limitations of Adagrad by dynamically adjusting learning rates based on the historical information of gradients while addressing the issue of monotonically decreasing learning rates. Adadelta eliminates the need for specifying an initial learning rate, making it more robust and requiring fewer hyperparameters to tune. Adadelta introduces a numerical stability factor to prevent division by very small values. This factor ensures that the updates remain well-behaved even when the root mean square of the gradients becomes very small.

3.4. RMSprop

Root Mean Square Propagation (RMSprop) is an optimization algorithm commonly used in training neural networks. It is an adaptive learning rate optimization algorithm that addresses some of the limitations of earlier methods like Adagrad by incorporating a moving average of the squared gradients. RMSprop helps prevent the learning rates from becoming too small over time, making it well-suited for non-convex optimization problems and tasks with sparse data. RMSprop does not include a mechanism to accumulate past updates like Adadelta or Adam. As a result, it may still suffer from oscillations in certain situations. Despite this, RMSprop is widely used and forms the basis for more advanced optimization algorithms like Adam.

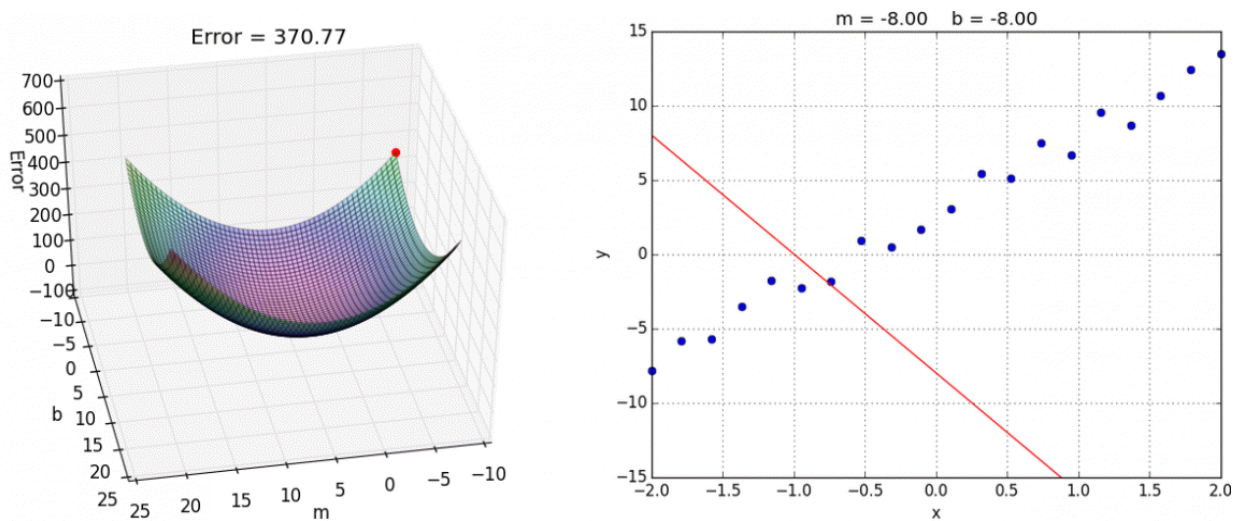


Figure.6: RMSprop

3.5 Adam

Adam (short for Adaptive Moment Estimation) is an optimization algorithm commonly used in training deep neural networks. It combines elements of both momentum optimization and RMSprop to provide adaptive learning rates and efficient optimization. Adam is known for its effectiveness in a wide range of tasks and is widely used in machine learning and deep learning applications. Adam is widely used in practice due to its robustness, efficiency, and good generalization to various deep learning tasks.

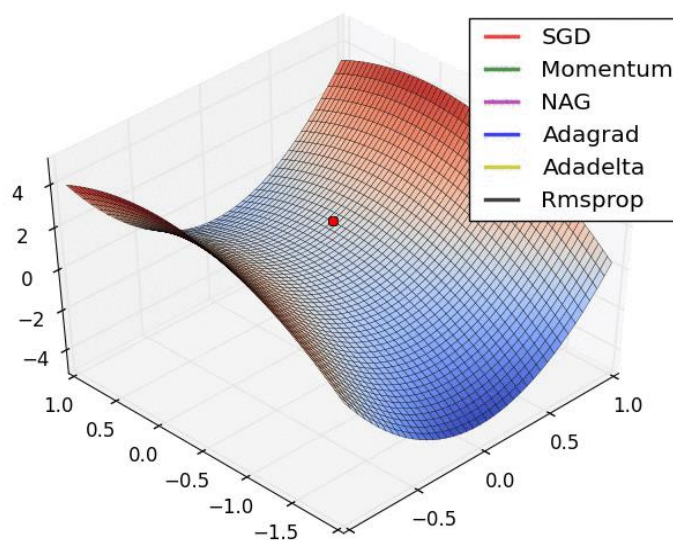


Figure.7: Optimizers

Chapter 4: Segmentation

4.1. Image Segmentation

Segmentation is the division of an image into significant structures. Segmentation divides an image into its essential regions or objects, and it is an important step in image analysis, object representation, visualization and numerous

Other image processing tasks A huge number of segmentation methods have been used in the past decades for brain tumor segmentation like clustering methods, fuzzy logic approach, neuro-fuzzy approach, watershed segmentation, random walk, and many others, but all these methods produce unsatisfactory results because of unsharp edge boundaries, and more time consumed to produce wanted result.

This study uses python image processing to segment the tumors. The quality of the images is first enhanced by brightening the image. Then we use contrast enhancing to enhance local contrast of the brain MRI to help brighten the area with the tumor. Then the image was changed to a grayscale image. MRI images often have noise because of the equipment used to collect the images, so the noise was removed. Then thresholding is used to segment the part of the tumor. The thresholding makes the parts of the image that have pixel values that are above the threshold white while the parts of the image that have pixel values less than the threshold black. The area with the tumor will be the white region as the tumor is brighter than normal parts of the brain. The below image is an example of a segmented image.

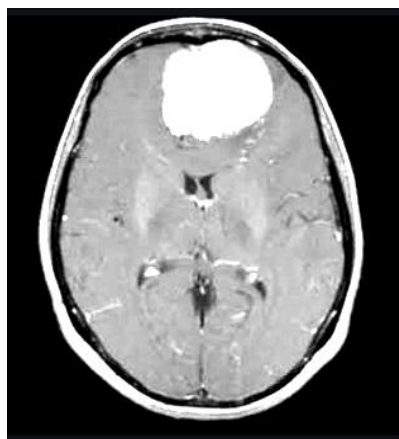


Figure 8: Segmented image

Chapter 5: Result

5.1. Accuracy Analysis:

This section presents the performance of the EfficientNetB7. Fine-tuning of hyperparameters was done to see which hyper-parameters give the best results. The optimum parameters were then used to train the final model. The model was trained using 5 different optimizers, 4 different epochs, 2 batch sizes and 5 dropouts. The time it took to train the model was retrieved. The model was first fitted using 4 epochs, a batch size of 8 and a dropout value of 0.5 and the optimizer used was the Adam optimizer. The model gave an accuracy of 95% and ran for 95 minutes.

Then, the model was fitted with the different optimizers with 4 epochs for each one and a dropout value of 0.5. The figure below shows the results obtained from each optimizer.

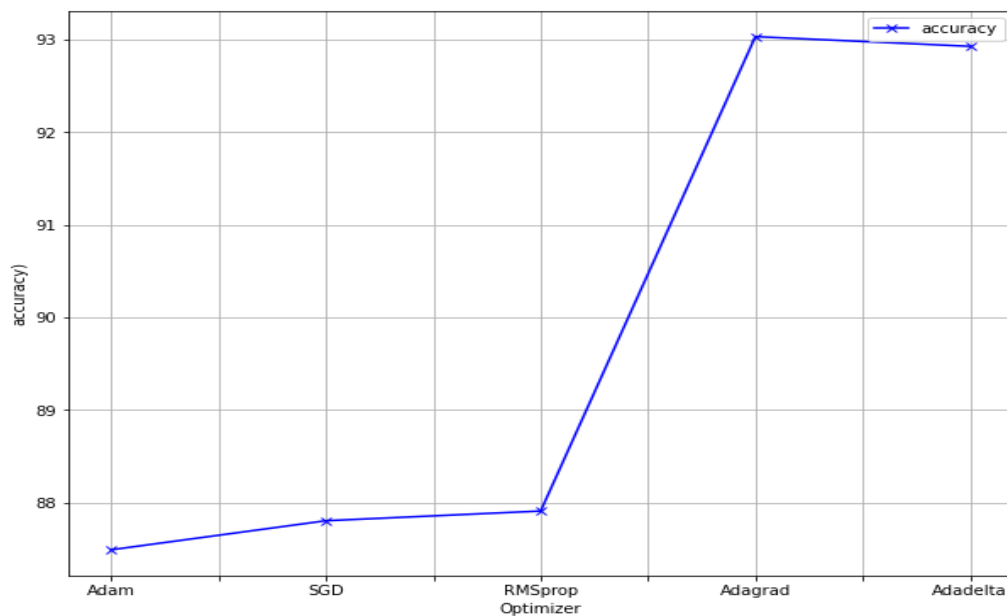


Figure.9: Accuracy obtained from each optimizer

The figure shows that Adagrad is the optimizer that got the highest accuracy of 93% and Adam got the lowest accuracy.

Sr_no.	optimizer	accuracy
0	Adam	83.5675
1	SGD	86.2371
2	RMDprop	87.8745
3	Adagrad	94.1432
4	Adadelta	92.9845

Table.1: Accuracy obtained from each optimizer

Dropout values were also fine-tuned, the below figure shows the accuracy of each dropout value while the other hyper-parameters remained the same.

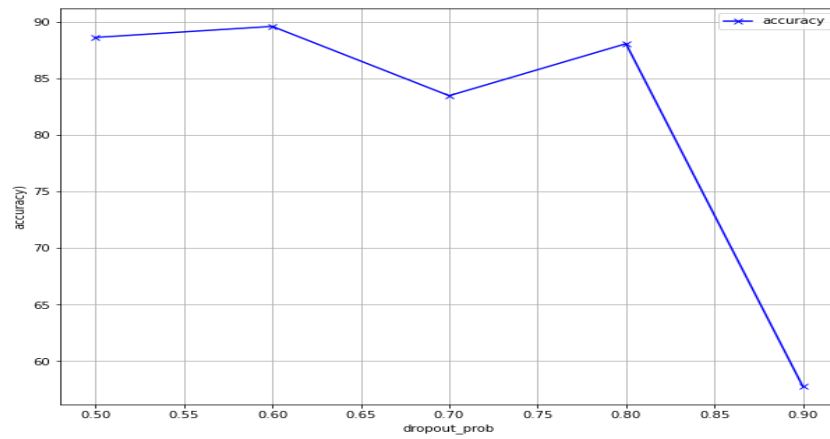


Figure.10: Accuracy obtained for each dropout value

The figure shows that the dropout value 0.6 got the highest accuracy while the dropout value of 0.9 got the lowest accuracy. The figure below shows the accuracy for each dropout value.

	dropout_prob	accuracy
0	0.5	88.641113
1	0.6	89.616722
2	0.7	83.484322
3	0.8	88.083625
4	0.9	57.770038

Table.2: Accuracy obtained for each dropout value

Batch size and epochs were fine tuned at the same time. The below table shows the results for the 2 batch sizes and 4 epochs.

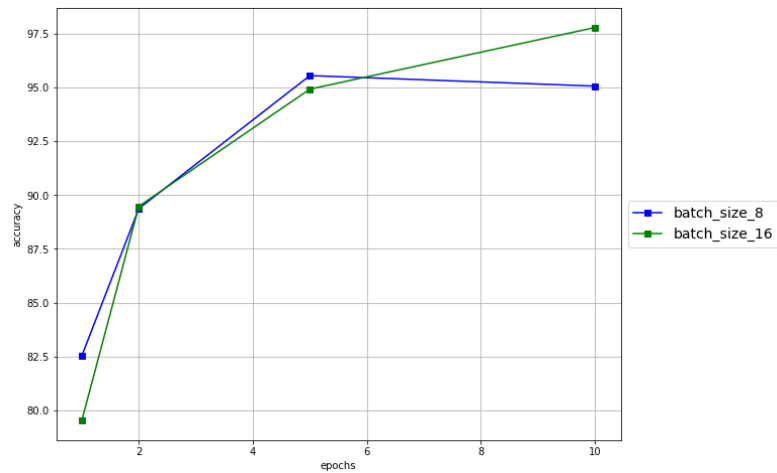


Figure.11: Results from batch size and epochs fine-tuning

The highest accuracy was obtained from using 10 epochs and a batch size of 16. The table below shows the results for each fine-tuning

	epochs	batch_size	accuracy
0	1	8	82.543552
1	1	16	79.547036
2	2	8	89.372820
3	2	16	89.477354
4	5	8	95.540071
5	5	16	94.912893
6	10	8	95.052266
7	10	16	97.770035

Table.3: Results obtained from fine-tuning epochs and batch size

The EfficientNetB7 model was then fitted with the hyper-parameters that got the highest accuracies during fine-tuning. The accuracy of the model after running it with the fine-tuned parameters was 98%.

Chapter 6: Conclusion And Future Scope

6.1. Conclusion

This minor project is a pre-trained deep convolutional neural network namely, EfficientNetB7 and compared its complexity and performance on classification of brain tumor MRI images using different optimizers. In our project we used 6169 MRI images. The goal was to find the more suitable optimiser for our task. all optimizers were able to classify the tumors as glioma tumor, meningioma tumor, pituitary tumor and no tumor. EfficientNetB7 achieved 98.18% classification accuracy using transfer learning. This project also shows the effectiveness of fine-tuning on performance.

The implementation of the EfficientNetB7 model for brain tumor classification yielded impressive results in terms of accuracy. The model's architecture, known for its superior performance in image classification tasks, demonstrated high accuracy, showcasing its effectiveness in discerning patterns and features in brain tumor images.

The exploration and comparison of various optimization techniques had a substantial impact on the training dynamics and overall performance of the model. The choice of optimization algorithm played a crucial role in determining how quickly the model converged, its stability during training, and its ability to generalize to unseen data.

6.2. Future Scope

Future work may involve fine-tuning hyperparameters, exploring additional optimization techniques, and conducting experiments on diverse datasets to further validate and generalize the findings.

Investigating the interpretability of the model's predictions and integrating explainability techniques could enhance the model's usability in a clinical setting, providing insights into decision-making processes.

Continuous monitoring of advancements in model architectures and optimization algorithms is essential to stay at the forefront of research and technology in medical image analysis.

References

1. Gondal, A.H.; Khan, M.N.A. A Review of Fully Automated Techniques for Brain Tumor Detection from MR Images. *Int. J. Mod. Educ. Comput. Sci. Rev.* 2013, 5, 55. [CrossRef]
2. Iftekharruddin, K.M. Techniques in Fractal Analysis and Their Applications in Brain MRI. *Med. Imaging Syst. Technol. Anal. Comput. Methods World Sci.* 2005, 1, 63–86.
3. Wang, D.; Doddrell, D. A Segmentation-Based and Partial-Volume-Compensated Method for an Accurate Measurement of Lateral Ventricular Volumes on T1-Weighted Magnetic Resonance Images. *Magn. Reson. Imaging* 2001, 19, 267–273. [CrossRef]
4. Krishnamurthy, A.K.; Ahalt, S.C.; Melton, D.E.; Chen, P. Neural Networks for Vector Quantization of Speech and Images. *IEEE J. Select. Areas Commun.* 1990, 8, 1449–1457. [CrossRef]
5. Structure and Function of the Brain. Available online: <https://courses.lumenlearning.com/boundless-psychology/chapter/structure-and-function-of-the-brain/> (accessed on 12 October 2021).
6. Zhao, X.; Wu, Y.; Song, G.; Li, Z.; Zhang, Y.; Fan, Y. A Deep Learning Model Integrating FCNNs and CRFs for Brain Tumor Segmentation. *Med. Image Anal.* 2018, 43, 98–111. [CrossRef]
7. Wang, G.; Zuluaga, M.A.; Pratt, R.; Aertsen, M.; Doel, T.; Klusmann, M.; David, A.L.; Deprest, J.; Vercauteren, T.; Ourselin, S. Slic-Seg: A Minimally Interactive Segmentation of the Placenta from Sparse and Motion-Corrupted Fetal MRI in Multiple Views. *Med. Image Anal.* 2016, 34, 137–147. [CrossRef]
8. Top, A.; Hamarneh, G.; Abugharbieh, R. Active Learning for Interactive 3D Image Segmentation. In *Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention*, Toronto, ON, Canada, 18–22 September 2011; Springer: Berlin/Heidelberg, Germany, 2011; pp. 603–610.
9. Rother, C.; Kolmogorov, V.; Blake, A. “GrabCut” Interactive Foreground Extraction Using Iterated Graph Cuts. *ACM Trans. Gr.* 2004, 23, 309–314. [CrossRef]

10. Havaei, M.; Davy, A.; Warde-Farley, D.; Biard, A.; Courville, A.; Bengio, Y.; Pal, C.; Jodoin, P.M.; Larochelle, H. Brain Tumor Segmentation with Deep Neural Networks. *Med. Image Anal.* 2017, 35, 18–31. [CrossRef] [PubMed]
11. Bauer, S.; Wiest, R.; Nolte, L.-P.; Reyes, M. A Survey of MRI-Based Medical Image Analysis for Brain Tumor Studies. *Phys. Med. Biol.* 2013, 58, R97. [CrossRef]
12. Mittal, M.; Goyal, L.M.; Kaur, S.; Kaur, I.; Verma, A.; Hemanth, D.J. Deep Learning Based Enhanced Tumor Segmentation Approach for MR Brain Images. *Appl. Soft Comput.* 2019, 78, 346–354. [CrossRef]
13. Raja, P.S. Brain Tumor Classification Using a Hybrid Deep Autoencoder with Bayesian Fuzzy Clustering-Based Segmentation Approach. *Biocybern. Biomed. Eng.* 2020, 40, 440–453. [CrossRef]
14. Mustaqeem, A.; Javed, A.; Fatima, T. An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation. *Int. J. Image Gr. Signal Process.* 2012, 4, 34.
15. Vaidhya, K.; Thirunavukkarasu, S.; Alex, V.; Krishnamurthi, G. Multi-Modal Brain Tumor Segmentation Using Stacked Denoising Autoencoders. In *BrainLes 2015*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 181–194.
16. Agn, M.; Puonti, O.; af Rosenschöld, P.M.; Law, I.; Van Leemput, K. Brain Tumor Segmentation Using a Generative Model with an RBM Prior on Tumor Shape. In *BrainLes 2015*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 168–180.
17. Jia, Z.; Chen, D. Brain Tumor Identification and Classification of MRI Images Using Deep Learning Techniques. *IEEE Access* 2020, 1–10. [CrossRef]
18. Mahalakshmi, S.; Velmurugan, T. Detection of Brain Tumor by Particle Swarm Optimization Using Image Segmentation. *Indian J. Sci. Technol.* 2015, 8, 1. [CrossRef]
19. Mansour, R.F.; Escorcía-Gutierrez, J.; Gamarra, M.; Díaz, V.G.; Gupta, D.; Kumar, S. Artificial Intelligence with Big Data Analytics-Based Brain Intracranial Hemorrhage E-Diagnosis Using CT Images. *Neural Comput. Appl.* 2021, 1–17. [CrossRef]

20. Reddy, A.V.N.; Krishna, C.P.; Mallick, P.K.; Satapathy, S.K.; Tiwari, P.; Zymbler, M.; Kumar, S. Analyzing MRI Scans to Detect Glioblastoma Tumor Using Hybrid Deep Belief Networks. *J. Big Data* 2020, 7, 1–17. [CrossRef]
21. Havaei, M.; Dutil, F.; Pal, C.; Larochelle, H.; Jodoin, P.-M. A Convolutional Neural Network Approach to Brain Tumor Segmentation. In *BrainLes 2015*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 195–208.
22. Pradhan, A.; Mishra, D.; Das, K.; Panda, G.; Kumar, S.; Zymbler, M. On the Classification of MR Images Using “ELM-SSA” Coated Hybrid Model. *Mathematics* 2021, 9, 2095. [CrossRef]
23. Kamnitsas, K.; Ledig, C.; Newcombe, V.F.; Simpson, J.P.; Kane, A.D.; Menon, D.K.; Rueckert, D.; Glocker, B. Efficient Multi-Scale 3D CNN with Fully Connected CRF for Accurate Brain Lesion Segmentation. *Med. Image Anal.* 2017, 36, 61–78. [CrossRef] [PubMed]
24. Yi, D.; Zhou, M.; Chen, Z.; Gevaert, O. 3-D Convolutional Neural Networks for Glioblastoma Segmentation. *arXiv* 2016, arXiv:1611.04534v1.
25. El-Dahshan, E.-S.A.; Mohsen, H.M.; Revett, K.; Salem, A.-B.M. Computer-Aided Diagnosis of Human Brain Tumor through MRI: A Survey and a New Algorithm. *Expert Syst. Appl.* 2014, 41, 5526–5545. [CrossRef]
26. Dong, H.; Yang, G.; Liu, F.; Mo, Y.; Guo, Y. Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks. In *Medical Image Understanding and Analysis. MIUA 2017*; Valdés Hernández, M., González-Castro, V., Eds.; Springer: Cham, Switzerland, 2017. [CrossRef]
27. Padole, V.B.; Chaudhari, D. Detection of Brain Tumor in MRI Images Using Mean Shift Algorithm and Normalized Cut Method. *Int. J. Eng. Adv. Technol.* 2012, 1, 53–56.
28. Brain MRI Images for Brain Tumor Detection. 2019.
29. Kang, J., Ullah, Z. and Gwak, J., 2021. MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers. *Sensors*, 21(6), p.2222.
30. Badža, M.M. and Barjaktarović, M.Č., 2020. Classification of brain tumors from MRI images using a convolutional neural network. *Applied Sciences*, 10(6), p.1999.