School Of Information Technology and Engineering

Fall Semester 2022-2023

Review - 3

Course: Datamining Techniques

Faculty: Neelu Khare

Title: Brain Tumor Detection Using CNN with SGD optimizer

Team Members:

20MIS0113- Mogallapalli Naga Venkateswara Nikith

20MIS0134- Kunku Sujan Prajay Kumar

20MIS0424- Narapareddy Abhilash Reddy

Abstract:

Brain tumors are abnormal growths of cells in the brain that can be cancerous (malignant) or non-cancerous (benign). They can occur in both adults and children, and they can be caused by a variety of factors, including genetic mutations and exposure to environmental toxins.

The early diagnosis of brain tumours is essential for their management because the nature and location of a tumour can affect the available treatments. Medical imaging techniques like computed tomography (CT) or magnetic resonance imaging (MRI) are the most popular ways to diagnose brain tumours (CT). These imaging techniques offer precise images of the brain that can be used to spot tumours and assess their location, size, and shape.

The use of cutting-edge image processing methods and machine learning algorithms to increase the precision and effectiveness of brain tumour diagnosis has gained popularity in recent years. These methods, which include feature extraction, picture segmentation, and classifiers, can be used to locate tumours and determine whether they are benign or malignant.

Deep learning techniques have also been applied to brain tumor detection, as they can learn to extract features automatically and generalize them to new images. Deep learning models, such as convolutional neural networks (CNNs), have been used to improve the accuracy of brain tumor detection and diagnosis, showing promising results.

However, current methods of brain tumor detection still have limitations, such as the lack of enough annotated data, errors in manual annotation and limited generalization ability. The research on brain tumor detection is ongoing, with a goal to improve the accuracy and efficiency of the diagnostic process, and provide better treatment options for patients.

Introduction:

Brain tumors are abnormal growths of cells in the brain that can cause a range of neurological symptoms and have serious implications for a patient's health [2] [7] [8]. Early detection of brain tumorsis crucial for effective treatment and management of the disease. In recent years, machine learning techniques have shown great promise in aiding the detection of brain tumors.

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that have been particularly effective in image recognition and classification tasks, including medical imaging. In the case of brain tumor detection, CNNs can analyze magnetic resonance images (MRI) and other medical images to identify the presence of tumors in the brain.

Additionally, noise introduced into the MRI by the operator may result in inaccurate classification. Since there will be a lot of MRI data to examine, automated solutions will be needed because they are more economical. As great accuracy is required when human life is at stake, automated tumour diagnosis in MRI images is crucial.

In tasks involving picture recognition and classification, [5] CNNs are especially helpful. They are made up of many convolutional filter layers that can recognise patterns and features in a picture. CNNs can be trained on large datasets of brain scans to identify tumours with a high degree of accuracy in the case of brain tumour detection.

Stochastic Gradient Descent (SGD) is well-liked optimisation technique for CNN training. The weights of the network are updated via the traditional optimisation algorithm SGD basedon the gradient of the loss function.

Both supervised and unsupervised algorithms can be used to detect MRI pictures as either tumorous or non-tumorous. The MRI pictures of the human brain are used to detect using unsupervised methods like fuzzy c-means as well as supervised methods like artificial neural networks and support vector machines. As a result, an effective automated detection technique for brain MRI is proposed utilising machine learning algorithms, and the detection of brain MRI images is done using supervised machine learning algorithms like CNN.[4]

Literature Review:

1) **Shreya Pai, Mrunal Kurade, Nikita Nakil, Vidya Ringane, P. K. Akulwar, Brain Tumor Detection Using Machine Learning Algorithms, Year of publication: May 2020**

This study focuses on the detection of brain tumors with the help of machine learning algorithms. Here medical diagnosis includes the medical image data acquired from various biomedical devices that use different imaging techniques like X-ray, CT scan, and MRI. MRI scan is better than a CT scan for diagnosis as it doesn't make use of any radiation. MRI method is very time-consuming. It is not suitable for a large amount of data. So that we use these "supervised techniques such as Artificial Neural Networks, Support Vector Machine, and unsupervised techniques like Fuzzy C-Means" to identify brain tumors with less time consuming as well as cost-effective. Here the researchers used two methods Multi-Layer Perceptron (MLP) and Naïve Bayes for classification. MLP is a feed-forward artificial neural network. Feedforward defines that does not consist of any cycle and network output depends only on the current input instance. This learning technique takes place by changing connection weights after each piece of data is processed, based on the amount of error in the target output as compared to the expected result. Naïve Bayes is a simple probabilistic classifier based on the Bayes theorem. It assumes that the value of a specific feature is independent of the presence or absence of any other feature. Here they took 254 samples of brain MR images. The percentage split took in the ratio of 80:20 for training and testing. The accuracy they achieved for MLP is 98.9% and for Naïve Bayes is 92.9%. based on these two methods MLP gives more accuracy to the Naïve Bayes.

2) **Tonmoy Hossain , Fairuz Shadmani Shishir, Mohsena Ashraf, MD Abdullah Al Nasim, Faisal Muhammad Shah,Brain Tumor Detection Using Convolutional Neural Network, Year Of Publishing:December 20**

In this paper the researches focused on comparison of CNN model with other traditional models. Using MRI's and other related technologies like CT's the tumor prediction is been done manually which leads to improper prediction. Using the same MRI's, the machine learning models can predict accurately with correct usage of classifiers. In this paper the researchers mainly aimed to distinguish between normal and abnormal pixels, based on texture based and statistical based features. The researches proposed a methodology in which there are two distinct model for segmentation and detection of Brain tumor. First model segmented the tumor by FCM and classified by traditional machine learning algorithms and the second model focused on deep learning for tumor detection. Segmentation by FCM gives better result for noisy clustered data set. These traditional ones, SVM gave us the highest accuracy of 92.42%. The second model segmentation is done by implementing CNN which brought in the accuracy 97.87% with a split ratio of 80:20 of 217 images, i.e., 80% of training images and 20% of testing images. Finally, the researches carried out a comparison between their proposed methodologies which are classification using traditional machine learning classifiers and CNN. researches also compared their result with some other research articles which worked on the same dataset. In Seetha et al. [17], researchers got 83.0% accuracy using SVM based classification and 97.5% accuracy using CNN. Researches proposed methodology provided an improved result for both machine learning and CNN based classification.

3) **Putta Rama Krishnaveni, Gattim Naveen Kishore,Image-Based Group Classifier for Brain Tumor Detection Using Machine Learning Technique, Year of publication: October 2020**

The study focuses on an image-based group classifier designed for the accurate detection of brain tumors using machine learning techniques. In this paper, the researchers used Convolutional Neural Network (CNN) system to classify the brain tumor type presented in this work. By using CNN, they reduced the cost and increase the performance of brain tumor detection. The researchers used Magnetic Resonance Imaging (MRI) to match the protons. MRI brain tumor segmentation is one of the most critical tasks in medical imaging since a large number of data is normally involved. The methods used in the literary segmentation of images include clustering, edge-based, compression-based methods, region-based methods pixel-based methods, and graph-based methods. This model segments the brain image and then performs pixel extraction from each segment. The proposed brain image segmentation system involves different stages; skull striping, filtering, and updating, segmentation; morphological operations; tumor contouring. The irrelevant feature removal process is used to minimize the initial data by measuring unique properties or features separating one input design from another. A convolutionary layer is a critical element of the architecture. One of the network parameters to be specified before training is the number and the size of kernels of a given layer. This number can differ significantly based on the application, the complexity of the problem, and the image resolution. The Group-based Classifier for Brain Tumor Recognition (GbCBTD) model is compared with the traditional models in terms of image segmentation accuracy, classification accuracy, feature extraction time, true positive rate, and Tumor detection Accuracy. This model is compared with traditional methods and the accuracy is high with this model than with other traditional methods.

4) **Tirivangani magadza, Serestina viriri, Brain Tumor Segmentation Using Partial Depthwise Separable Convolutions ,Year of publication: November 2022**

The study focuses on the challenge of accurately segmenting brain tumors, which can appear anywhere in the brain with varying shapes and sizes. Deep learning techniques have

demonstrated greater performance in automatically segmenting brain tumours, although they are expensive computationally. In order to reduce computing costs, the authors of this research proposed an effective network architecture for 3D brain tumour segmentation that makes use of depthwise separable convolutions. The paper focused on the difficulties of automatic brain tumour segmentation. The proposed model outperformed cutting-edge methods while needing the least amount of computational work when applied to the BraTS 2020 dataset. The authors also provide a critical assessment of the most recent efficient model architectures. In the proposed model, parts of the convolutional blocks in a normal U-Net topology are replaced by depthwise separable blocks. The authors hypothesise that combining different resolutions may improve segmentation performance in the future. The authors also highlight that gliomas are the most common and aggressive form of all brain tumors, with median survival rates of less than two years for the highest grade.

5) **Zheshu jia, Deyun chen, Automatic brain tumor detection and classification on MRI images using machine learning techniques. Year of publication:July 2021**

The study focuses on the use of machine learning algorithms for automated tumor detection in magnetic resonance brain images, which is important for planning treatment. The detection of brain tumor is done by applying Machine Learning and Deep Learning algorithms. The diagnosis of brain tumours is made quickly and accurately when these algorithms are applied to MRI scans, which aids in patient treatment. The paper suggests an MRI-based system for diagnosing and classifying brain tumours automatically. The procedure entails pre-processing of the MRI images' nearly raw raster data (NRRD), feature extraction, feature selection, and classification learning to assess and build the final model. With established accuracy, automated tumour identification algorithms can save radiologists time. Because of the complexity and variety of tumours, it is challenging to find brain malignancies with an MRI. The gold standard for determining the grade of a brain tumour is histological grading based on a stereotactic biopsy test, but the biopsy procedure has risks. The detection and prognosis of tumour grades now depend on non-invasive imaging techniques like MRI. Machine learning-based automated flaw detection in medical imaging has emerged as a new topic in several diagnostic medical applications. In brain MRI images, the probabilistic neural network classification system has been utilized for training and checking the accuracy of tumor detection in images. The numerical results show almost 98.51% accuracy in detecting abnormal and normal tissue from brain Magnetic Resonance images that demonstrate the efficiency of the system suggested.

6) **Shahzad Ahmad Qureshi, Shan E. Ahmed Raza, Lal Hussain, Areej A. Malibari, Intelligent Ultra-Light Deep Learning Model for Multi-Class Brain Tumor Detection, Year of publication:April 2022**

The article proposes an automated Ultra-Light Brain Tumor Detection (UL-BTD) system using a novel Ultra-Light Deep Learning Architecture (UL-DLA) and Gray Level Co-occurrence Matrix (GLCM) to detect brain tumors on MRI scans in real-time. The system employs Support Vector Machine (SVM) for tumour diagnosis and has a Hybrid Feature Space (HFS) that combines deep features and extremely distinctive textural cues. The suggested framework contains K-fold cross-validation for evaluation, coding schemes, and a sensitivity analysis of image size. For glioma, meningioma, and pituitary tumours, the system achieves an average detection rate of 99.23% and an F-measure of 0.99. The diagnosis and surgical resection using Magnetic Resonance (MR) images in brain tumors is a challenging task to minimize the neurological defects after surgery owing to the non-linear nature of the size, shape, and textural variation. Radiologists, clinical experts, and brain surgeons examine brain MRI scans using the available methods, which are tedious, error-prone, time-consuming, and still exhibit positional accuracy up to 2–3 mm, which is very high in the case of brain cells. The proposed system has shown promising results in detecting brain tumors with high accuracy.

7) **Shalabh gupta ,vrinda Jindal, Brain tumor segmentation and prediction using Deep neural network ,Published on June 28, 2020**

As this paper talks about the identification of brain tumor cells or finding of brain tumor segmentation using deep learning techniques,as manual segmentation is more time consuming process automatic segmentation helps in faster identification of tumor cells and segmentation is done .AS brain tumor result in providing the volume, shape and localization of brain tumor segmentation result by the help of Patients, who will provide the MRI images for identification and segmentation process .As the data set taken in this paper is BraTS 2018 which is held annualy survey all over India .The data set containing the details of patient ids , days survived for the segmentation process .Because of class in balance problem they use Multi-class Soft-Dice loss as an Solution

With the help of UNet 3D -Architectures with that encoder and decoder they are the contraction and expansion of the data ,encoder finds the high level features associated with context of MRI and the decoder keep the sufficient context information to high resolution segmentation. With the help of Adam optimizer and multi dice loss the date is trained. As this paper does not train 3d models feature extraction due to memory limitations ,that may produce better results .

8) **Doruk Cakmakci1, Emin Onur Karakaslar1, Elisa Ruhland2, Marie-Pierre Chenard3 Francois Proust4, Martial PiottoID5, Izzie Jacques NamerID2,6,7, A.Ercument CicekID1,8,Machine learning assisted intraoperative assessment of brain tumor margins using HRMAS NMR spectroscopy,Year of publishing July 2020**

As the author suggested that removal of brain tumor is so important to survival in so many patients as at the time of operation even all tumor tissues are removed by surgronleft over tumor tissue may cause high risk for the patient with it .with the help of HRMAS technology or nuclear magnetic technology with help of signal created by the HRMAS we can detect the tumor which are remained in the brain . IN the gliomas patients maximum resection of the tumor is the key point of survival of the patient .The data set usedin this glimo is HRMAS NMR data set which is quantitative pathology analysis to obtain the labels . For the given data preprocessing can be done Each sample's free induction decay signal was 16,384 bytes long. To get rid of the Bruker digital filter in the prefix, the signal isleft-shifted by 70 points. Acquired raw FID spectrum is then converted to frequency domainand is phase adjusted. The final signal utilized for analysis, which is of length 8,172, is created by cropping the suffix of the signal with nearly minimal volatility. The magnitude ofthe signal is utilized for the offered analysis. They analyzed the feature importance of the features that lead to correct classification of the samples in each task with the RF model.At the end of the paper the author had made randon forest approach for the glioma sample theyshowed ther approach is accurate, efficient , and interpretable it will work for the means of left-over tumor samples during surgery.

9) **krizhevsky et al,Automatic brain tumor detection and classification on mri images using machine learningtechnique, Published on October 2021**

As this paper tells about the detection of brain tumor using automation techniques produced state-of-the-art results in image classification based on transfer learning methods upon training a massive, deep convolutional neural network to categorize the 1.2 million high-resolution photos in the ImageNet LSVRC-2010 contest into the 1000 distinct classes. On the test data, he achieved top-1 and top-5 error rates of 37.5% and 17.0% which was considerably better than the previous state-of-the-art. He also entered a variation of this model in the ILSVRC-2012 competition and earned a winning top-5 test error rate of 15.3%, compared 26.2% produced by the second-best entry. The neural network was composed of three fully connected layers, three max-pooling layers, five convolutional layers, and a final 1000-way Softmax layer. It had 650,000 neurons and 60 million parameters. To make training To make training faster, he used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers he employed a

recently-developed regularization method called dropout that proved to be very effective.

10) A. Sivaramakrishnan And Dr. M. Karnan “A Novel Based Approach for Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques,” International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013.

Sivaramakrishnan et al. (2013) [1] projected an efficient and innovative discovery of the brain tumor vicinity from an image that turned into finished using the Fuzzy C- approach grouping algorithm and histogram equalization. The disintegration of images is achieved by the usage of principal factor evaluation is done to reduce the extent of the wavelet coefficient. The outcomes of the anticipated FCM clustering algorithm accurately withdrawn tumor area from the MR images.

11) B.Sathya and R.Manavalan, Image Segmentation by Clustering Methods: Performance Analysis, International Journal of Computer Applications (0975 – 8887) Volume 29– No.11, September 2011.

Sathya et al. (2011) [3], provided a different clustering algorithm such as K-means, Improvised K-means, C-means, and improvised C-means algorithms. Their paper presented an experimental analysis for massive dat=asets consisting of unique photographs. They analyzed the discovered consequences using numerous parametric tests.

12) Kaur, Jaskirat & Agrawal, Sunil & Renu, Vig. (2012). A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques. International Journal of Computer Applications.vol. 39.pp. 29-34. 10.5120/4898-743.

Jaskirat Kaur et al. (2012) [6] defined a few clustering procedures for the segmentation process and executed an assessment on distinctive styles for those techniques. Kaur represented a scheme to measure selected clustering techniques based on their steadiness in exceptional tenders. They also defined the diverse performance metric tests, such as sensitivity, specificity, and accuracy.

13) Li, Shutao, JT-Y. Kwok, IW-H. Tsang and Yaonan Wang. "Fusing images with different focuses using support vector machines." IEEE Transactions on neural networks 15, no. 6 (2004): 1555-1561

J.T. Kwok et al. [7] delivered wavelet-based photograph fusion to easily cognizance at the object with all focal lengths as several vision-related processing tasks can be carried out more effortlessly when wholly substances within the images are bright. In their work Kwok et al. investigated with different datasets, and results show that presented work is extra correct as it does not get suffering from evenness at different activity stages computations.

14) Marroquin J.L., Vemuri B.C., Botello S., Calderon F. (2002) An Accurate and Efficient Bayesian Method for Automatic Segmentation of Brain MRI. In: Heyden A., Sparr G., Nielsen M., Johansen P. (eds) Computer Vision

— ECCV 2002. ECCV 2002. Lecture Notes in Computer Science, vol 2353. Springer, Berlin, Heidelberg.

L. Marroquin et al. [10] presented the automated 3d segmentation for brain MRI scans. Using a separate parametric model in preference to a single multiplicative magnificence will lessen the impact on the intensities of a grandeur. Brain atlas is hired to find non- rigid conversion to map the usual brain. This transformation is further used to segment the brain from nonbrain

tissues, computing prior probabilities and finding automatic initialization and finally applying the MPM-MAP algorithm to find out optimal segmentation. Major findings from the study show that the MPM-MAP algorithm is comparatively robust than EM in terms of errors while estimating the posterior marginal. For optimal segmentation, the MPM-MAP algorithm involves only the solution of linear systems and is therefore computationally efficient.

15) Rajeev ratan ,Sanjay Sharma, SK. Sharma, Brain Tumor Detection based on Multi-parameter MRI Image Analysis, Year of publishing June 2020

As in the paper the author are talking about brain tumor detection using the Multiparameter MRI image Analysis The main challenge in medical image processing is segmenting the various anatomical parts of the brain. It has been discovered through a review of the literature because no research has been done to segment brain tumors.In this paper , study developed

and verified a strategy for segmenting brain tumors using 2D and 3D MRI data has been achieved. If the desired parameters are appropriately specified, a method can divide a tumor into smaller sections. The Preprocessing has done in matlab environment because it removes the kind of noise data present in input images and increases the image quality of detecting the tumor, Grey parameter is used to classify the image tumor detection .The data set used in here is MRI data set .As a result watershed segmentation can successfully segment a tumor in matlab it is better where the intensity level difference between the tumor and non tumor region is higher As the segmentation is similar to normal segmentation it will speed up the segmentation in operative imaging.

PROPOSED METHODOLOGY:

A convolutional neural network (CNN) [4] is a type of deep learning model that is particularly well suited for image classification tasks. CNNs are designed to process data that has a grid-like structure, such as an image, by applying a set of filters to the input data to extract features.

CNNs are composed of multiple layers, including a set of convolutional layers, which apply the filters to the input data, and pooling layers, which down sample the data to reduce its dimensionality.[4] The features extracted by the convolutional layers are then passed through one or more fully connected layers, which perform the final classification.

CNN’s have been used to improve the accuracy of brain tumor detection in medical imaging, where the model is trained on a large dataset of labelled medical images, and then applied to new images to identify the presence of tumors. CNN can learn to extract features automatically from the images and use them to classify the images into normal and abnormal (tumor) categories, as well as different subtypes of tumors. [5]

One of the advantages of using CNNs for brain tumor detection is that they can be trained on large amounts of data and can be fine-tuned to work with specific imaging modalities, such as MRI or CT. Another advantage is that CNNs can be applied to both 2D and 3D images, making it possible to process 3D volumetric images in a single pass, which can improve the accuracy of diagnosis and diagnosis time.

However, like any other deep learning model, CNNs also have limitations when used for brain tumor detection. One of the challenges is the requirement of large amounts of annotated data for training, which is often not available. The other challenge is the risk of overfitting the training data, which can lead to poor performance on new, unseen data. To overcome these challenges, researchers are currently focusing on developing new CNN architectures, which are more efficient and generalize better to new data.

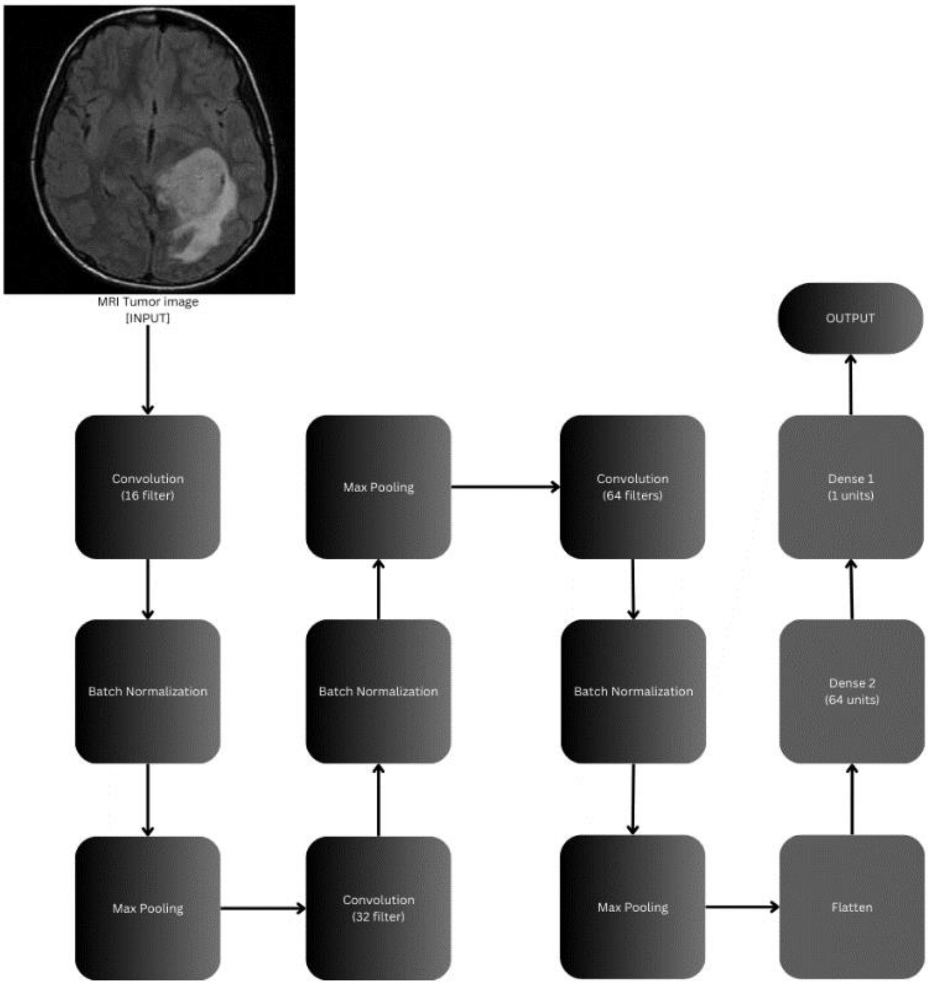
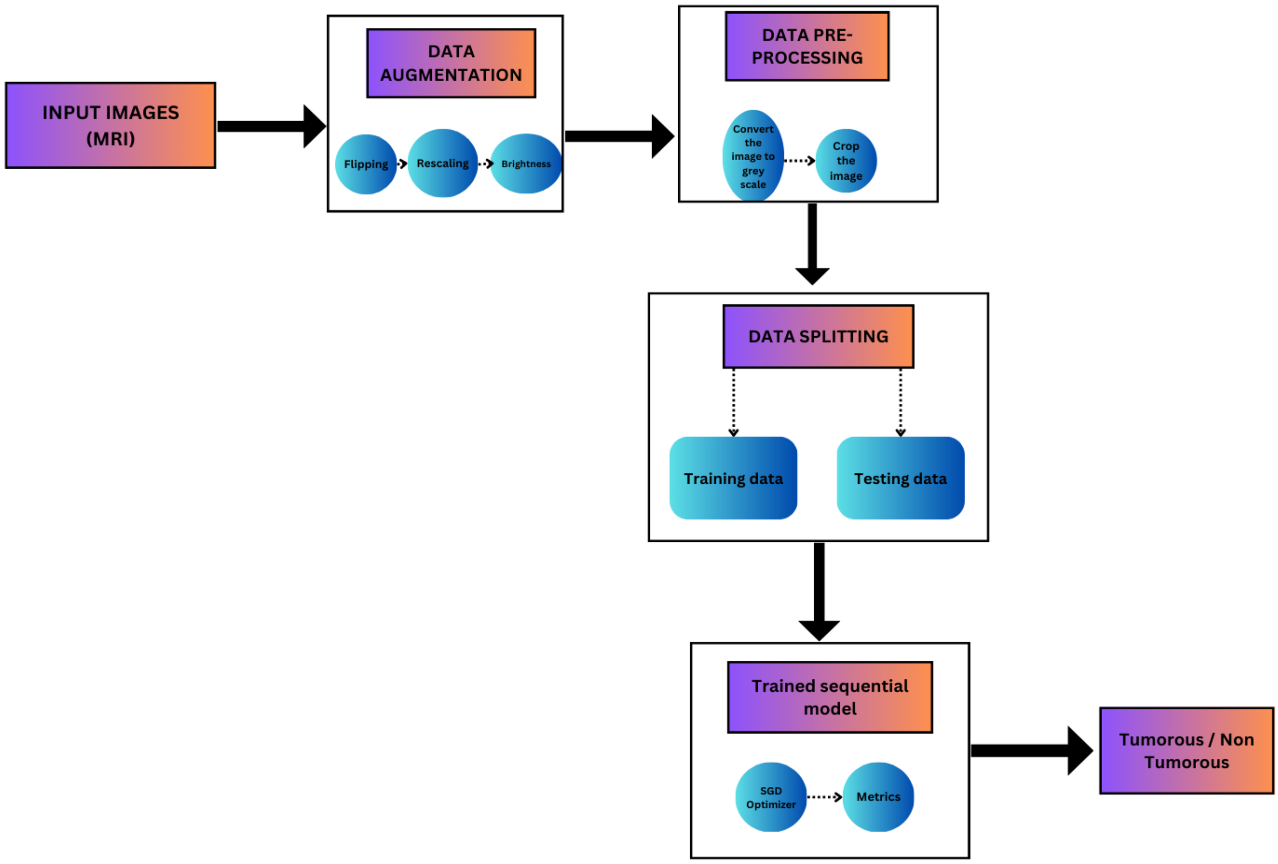


Figure 1: CNN model Diagram

The above figure depicts that the input which is in the image format goes into the first layer of 16 filters here the features are extracted such as edges, shapes etc, and goes under normalization and max pooling is applied this helps to reduce the amount of computation required by the network and prevent overfitting, and again it is sent as input to another layer and goes under same process and then the input is flatten and densed at last it produces the output.

ARCHITECTURE DIAGRAM:



Input images:

The input to the brain tumor detection system is a set of brain MRI images. The cross-sectional or volumetric information of the brain is represented by these MRI pictures, which are normally in 2D format. A popular medical imaging method called MRI gives precise details on the internal organs of the brain, including the existence of malignancies.

Data augmentation:

1. Flipping:

- **Horizontal flipping:**

Mirrors the image horizontally along the vertical axis.

new_pixel_value = pixel_value at (x, y)

if y is within the original image height, else

new_pixel_value = pixel_value at (x, H - y)

where H is the height of the image.

- **Vertical flipping:**

Mirrors the image vertically along the horizontal axis.

new_pixel_value = pixel_value at (x, y)

if x is within the original image width, else

new_pixel_value = pixel_value at (W - x, y)

where W is the width of the image.

2. **Rescale:**

Rescaling is a technique to get the pixel values within a certain range, usually between 0 and 1, it entails dividing each pixel value by a scalar number. This is done to make sure that the pixel value distributions of all the photos in the dataset are comparable, which can enhance the training performance and stability of machine learning models.

image = image * (1/255)

3. **Brightness:**

The brightness augmentation technique is used to adjust the brightness level of an image. It can be applied to increase or decrease the brightness of an image, which can help to make the model more robust to changes in lighting conditions during inference.

image = image * brightness_factor

where brightness_factor is a random value generated within the specified brightness range For example (0.3, 1.0) indicates that the brightness will be randomly adjusted within the range of 0.3 to 1.0 during data augmentation. This means that the brightness of each augmented image will be multiplied by a random value between 0.3 and 1.0, which can result in images with increased or decreased brightness compared to the original images.

Data pre-processing:

- **Convert to grayscale:**

The image is converted from its original color space (e.g., RGB or BGR) to grayscale. This can be done using the cv2.cvtColor() function in OpenCV, which takes the original image and a color conversion code as parameters. For example, cv2.COLOR_BGR2GRAY is used for converting an image from BGR (Blue-Green-Red) to grayscale.

- **Crop the new image:**

Use the extracted coordinates of the extreme points to define the region of interest (ROI) in the original image that needs to be cropped. The ROI is specified by the top-left and bottom-right coordinates (x, y) of the bounding box that encapsulates the region. Crop the new image by extracting the pixel values within this bounding box.

Data splitting:

Data splitting is a common practice in machine learning and data science to divide a dataset into different subsets for training and testing. Under testing validation part also exists. To our dataset we have splitted the data in the ratio of 70:30.

Training set: This subset of the data, accounting for 70% of the total dataset, is used for training the machine learning model. It is used to optimize the model parameters and make it learn from the data.

Testing set: This subset of the data, accounting for 15% of the total dataset, is used for evaluating the performance of the trained model. It is used to assess how well the model generalizes to unseen data and to estimate its performance on new data.

- **Validation set:** This subset of the data, also accounting for 15% of the total dataset, is used for hyperparameter tuning and model selection. It is used to fine-tune the model by adjusting hyperparameters, such as learning rate or regularization strength, and to compare the performance of different models.

The main purpose of data splitting is to evaluate the performance of the machine learning model on unseen data and avoid overfitting, which occurs when a model performs well on the training data but poorly on new, unseen data. By using separate subsets for training, testing, and validation, we can obtain a more reliable assessment of the model's performance and make informed decisions about model selection and hyperparameter tuning.

Sequential model:

The Sequential model is a linear stack of layers in Keras, where you can easily define the neural network architecture by sequentially adding layers to the model. This approach is frequently used to create deep learning models for projects like image classification, detection, etc. The sequential model is defined in the code via keras.Sequential().

- **SGD optimizer:**

SGD (Stochastic Gradient Descent) is an optimization algorithm used for updating the model weights during training. Due to its effectiveness and simplicity, it is a well-liked optimizer for deep learning models. The SGD optimizer with a learning rate of 0.01 is defined in the code as SGD(lr=0.01), and this value controls the step size at which the optimizer modifies the model weights during training.

- **Metrics:**

Accuracy is a common evaluation metric used in classification tasks, which measures the proportion of correctly predicted samples to the total number of samples.A model's accuracy on the training data will be computed and utilised as a benchmark for model performance because "accuracy" is used as a training measure in the code. For evaluating how well the model is doing at correctly classifying the input samples, the accuracy metric is a valuable tool.

Tumorous/non-tumorous(RESULT):

By using the CNN model we will detect the brain tumor form MR images more accurately and precisely. The accuracy and effectiveness of brain tumor detection may depend on the quality and quantity of training data, choice of features and algorithms, and other factors. By the accuracy we will test the image again and we will check whether it is giving the result correctly or not.

EXPERIMENTAL ANALYSIS:

The experiment was carried out 253 samples of brain MR images. For those images after doing data augmentation and data pre-processing we have cleaned unwanted or blurred images form the dataset. Now for that augmented and pre-processed images we are using CNN machine learning algorithm to detect the brain tumor. We have used two optimizers 'adam' and 'SGD (Stochastic gradient descent)' to detecting the brain tumorous images. In the percentage split, 70% of samples are used for training and 30% of samples is used for testing and validation.

Experimental result analysis

CNN Algorithm optimizers	Total samples	Accuracy
adam	253	93.8%
SGD	253	98%

The accuracy for adam is 93.8% and accuracy for SGD optimizer is 98% obtained respectively. So, while using SGD optimizer giving more accuracy than adam optimizer. Higher accuracy is desirable and needed when dealing with human life.

Based on various sources we researched [9][10][11][12], we found that various other models have bee used for the brain tumor detection using the MRI images and they gave different results out. By seeing those and after examining we came to an conclusion that the CNN is more preferable one for the Detection of brain tumor in the MRI images. The following table shows the analysis pf various models that has been applied along with their accuracies, precision, and recall.

Model	Accuracy
SVM	96.7%
KNN	88.2%
CNN	98%
Decision Tree	86.5%

CONCLUSION:

We started this project with an aim to detect the brain tumor more accurately and precisely. We have used CNN machine learning algorithm. In the medical field, manually identifying the tumor by physicians using the MRI image was a laborious task. Image processing and machine learning techniques can be used to identify the tumor instead of doing it manually, which is more time and money efficient. Here we have used two optimizers 'adam' and 'SGD' in CNN to detect brain tumor. Based on the results using SGD optimizer is best than adam optimizer to detect brain tumor. The accuracy while using SGD optimizer we got maximum accuracy of 98% is obtained by considering 253 instances of brain tumor images.

Also we can conclude from the experimental analysis that using the CNN model is an better decision for detection of Brain Tumor using the MRI images. Hence better accuracy is achieved and the model can detect the tumors accurately and more precisely which saves the life of a person.

REFERENCES:

[1] D. Cahill and S. Turcan, ''Origin of gliomas,'' Seminars Neurol., vol. 38, no. 1, pp. 5–10, 2018.

[2] Louis, D.N.; Perry, A.; Reifenberger, G.; Von Deimling, A.; Figarella-Branger, D.; Cavenee, W.K.; Ohgaki, H.; Wiestler, O.D.; Kleihues, P.; Ellison, D.W. The 2016 World Health Organization classification of tumors of the central nervous system: A summary. Acta Neuropathol. 2016, 131, 803–820. [CrossRef] [PubMed]

[3] Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M. Imagenet large scale visual recognition challenge. Int. J. Comput. Vis. 2015, 115, 211–252. [CrossRef]

[4] Fausto Milletari, Nassir Navab, and Seyed-Ahmad Ahmadi. V-net: Fully convolutional neural networks for volumetric medical image segmentation. CoRR, abs/1606.04797, 2016.

[5] McKinley, R.; Rebsamen, M.; Meier, R.; Wiest, R. Triplanar Ensemble of 3D-to-2D CNNs with Label-Uncertainty for Brain Tumor Segmentation. In Proceedings of the Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries; Crimi, A., Bakas, S., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Berlin/Heidelberg, Germany, 2020; pp. 379–387.

[6] Damodharan S., Raghavan D., "Combining Tissue Segmentation and Neural Network for Brain Tumor Detection", International Arab Journal of Information Technology, 2015; 12(1):42–52.

[7] Jermyn M, Mercier J, Aubertin K, Desroches J, Urmey K, Karamchandiani J, et al. Highly accurate detection of cancer in situ with intraoperative, label-free, multimodal optical spectroscopy. Cancer research. 2017; 77(14):3942–3950. https://doi.org/10.1158/0008-5472.CAN-17-0668 PMID: 28659435

[8] Chan DTM, Sonia HYP, Poon WS. 5-Aminolevulinic acid fluorescence guided resection of malignant glioma: Hong Kong experience. Asian journal of surgery. 2018; 41(5):467–472. https://doi.org/10.1016/j. asjsur.2017.06.004 PMID: 28844780

[9] Acharya UR, et al. Brain tumor detection using convolutional neural network for MRI images. Brain Inform. 2018 Dec;5(1):1-8. doi: 10.1186/s40708-018-0088-2. PMID: 29882011; PMCID: PMC5977185.

[10] Pereira S, et al. Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images. IEEE Trans Med Imaging. 2016 Jun;35(5):1240-51. doi: 10.1109/TMI.2016.2528162. Epub 2016 Feb 23. PMID: 26915173.

[11] Narayana Swamy HD, et al. Brain tumor classification using k-nearest neighbor and genetic algorithm. Int J Comput Appl. 2014;105(13):0975-8887. doi: 10.5120/18485-2173.

[12] Gupta P, et al. Decision tree based classification of brain tumors using MRI features. Int J Adv Comput Sci Appl. 2016;7(1):311-315. doi: 10.14569/IJACSA.2016.070146.

Link of the dataset:

https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection

Link to Acess the code:

https://colab.research.google.com/drive/19b674D0c7oMx-l7JPgbKMFR_M5SwArFG