AI Technique for Classification of Brain Tumor MRI Images for General Physicians

Arjun Thakur*[1], Rishab Khandelwal[2], Ganesh Bhutkar[3], Rajat Harne[4] and Sankalp Chordia[5]

*[1] Student, Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India

arjun.thakur20@vit.edu

[2] Student, Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India

rishab.khandelwal20@vit.edu

[3] Associate Professor, Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India

ganesh.bhutkar@vit.edu

[4] Student, Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India

rajat.harne20@vit.edu

[5] Student, Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, India

sankalp.chordia20@vit.edu

Abstract

Magnetic Resonance Imaging (MRI) is a standard medical image analysis technique that gives useful information for brain tumor diagnosis. One of the most influential and critical aspects of the brain tumor treatment procedure is determining the type of brain tumor. For successful treatment of brain tumors, accurate detection of tumors in earlier stages is essential which aids in saving a patient's life. The nature of tumor cells makes the task of classification of brain tumors quite challenging for radiologists. Deep learning models like Convolutional Neural Networks (CNN) have proven to be useful for the image-based classification of tumors. CNN is intended to extract features from the MRI scan image adaptively during the training process. A variety of layers that form the building blocks of a CNN architecture are utilized to fulfill the task of feature extraction and classification. These layers are convolutional layers, pooling layers, batch normalization layers, fully connected layers and dropout layers. This research emphasizes the CNN model's efficacy in classifying MRI images of primary brain tumors, specifically glioma, meningioma, and pituitary tumor.

Keywords: Brain Tumor, Convolutional Neural Networks (CNN), Deep Learning, Image Classification, Magnetic Resonance Imaging (MRI)

1. Introduction

Magnetic Resonance (MR) images are used in the early phases of medicine to diagnose the regions of the brain that are contaminated with tumor cells. A brain tumor is identified as an excessive growth of abnormal cells (mass) that forms inside the brain and is specifically impacted by the tissues underlying the skull or brain's supporting structures. A brain tumor can be either malignant or benign. These tumors press against the other brain cells and grow erratically [8]. This excessive pressure can result in numerous brain issues, which may trigger a seizure, a coma, or even death. The clinical identification of brain tumors and the formulation of treatment plans for patients both rely heavily on accurate brain tumor MR imaging. The accuracy of the classification of the various forms of brain tumors is completely

reliant on the radiologists' experience. It is an intricate and difficult task to manually classify brain tumors using MR images as they have quite identical structures; thus, it eventually depends on the radiologist's availability and level of expertise in correctly identifying and diagnosing brain tumors. This issue might be resolved by developing an efficient and reliable system, which would classify MR images of brain tumors with the least possible amount of human intervention.

The location of the brain tumor is one of the important factors for identifying the type of brain tumor [9]. This research is focused on the classification of primary brain tumors which include glioma, meningioma, and pituitary tumors. Gliomas are mostly located in the frontal and the temporal lobes specifically in the cerebrum or sometimes the cerebellum. Meningiomas are located near the interior surface of the skull or near the spinal cord (pons). Pituitary tumors are present in the pituitary gland which leads to an abnormal increase in the gland's size and causes an imbalance in hormone levels [9]. The Convolutional Neural Networks (CNN) model is trained with MRI images of these three types of brain tumors and accordingly can predict the class of tumor to which a particular image will belong.

South East Asia is a significant region since it is home to more than a quarter of the world's population. Eleven middle-income countries make up the South East Asian Region (SEAR). According to the World Health Organization (WHO), it includes Bangladesh, Bhutan, North Korea, India, Indonesia, Maldives, Myanmar, Nepal, Sri Lanka, Thailand, and Timor-Leste. South East Asia's cultural traditions are diverse, with numerous languages spoken. South East Asia's neurologic illness pattern is mostly comparable to that of the West, with certain disease traits unique to this area. While Asia is home to more than half of the world's population, it only has 8.8 % of the world's neurologists [7]. This division is especially noticeable in the SEAR region, as seen in Fig. 1.
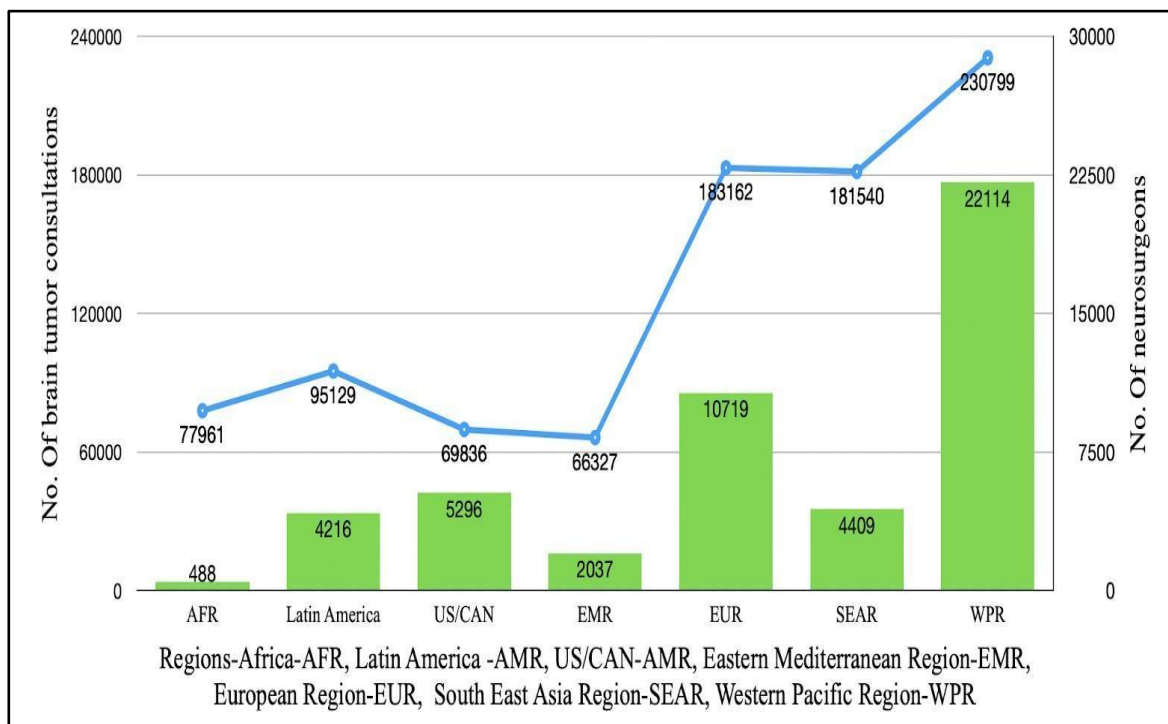

Fig. 1. Statistical graph for the number of brain tumor consultations and the number of neurosurgeons corresponding to different regions in the world as per WHO [7]

Table 1. Number of consultation cases and number of neurosurgeons corresponding to geographical region across the globe as per WHO [7]

Geographical Region	Number of Consultation Cases	Number of Neurosurgeons
Africa (AMR)	077961	00488
Latin America (AMR)	095129	04216
US / Can (AMR)	069836	05296
EMR	066327	02037
EUR	183162	10719
SEAR	181540	04409
WPR	230799	22114

Table 1 depicts the data of total brain tumor cases requiring neurosurgical consultations and a total number of neurosurgeons corresponding to WHO regions [7]. These statistics highlight the availability of a smaller number of neurosurgeons to treat a large scale of patients suffering from a brain tumor in the SEAR region. The proposed application of tumor classification can act as a recommendation or supportive tool that general physicians can use in local clinics. It can also help make the process of brain tumor treatment more efficient with the ability to successfully treat a maximum number of patients.

There are around 16,03,382 physicians, including only 4409 neurosurgeons in SEAR region including India [7] as seen in Table 1. Thus, due to the availability of more general physicians, patients usually consult with them regarding their illness, at first priority. However, general physicians may overlook significant instances and miss out on a critical case owing to a lack of information regarding brain tumor types and diagnostic techniques. The technique proposed in this paper will uplift the role of general practitioners, since this system will provide them with the capability of accurate brain tumor detection and patients could be referred quickly to neurosurgeons, reducing delay and complexities in the treatment. Hence, this system could be utilized efficiently by general physicians. The availability of neurologic treatment varies greatly depending on whether it is provided in an urban or rural setting, the level of economic development, and the healthcare financing structure in place [10]. When compared to manual traditional diagnostic procedures, computer-aided mechanisms with Artificial Intelligence (AI) capabilities produce better outcomes [11].

Most countries with bigger populations have created neurology training programs to assist alleviate the lack of neurologists. Even after such massive efforts taken by these countries the problem still would take a huge amount of time to be resolved. This is one of the reasons that our proposed system should be implemented in these SEAR countries.

2. Related Work

Most of the currently available methods are only capable of localizing the tumor and determining its size, however they cannot provide significant information regarding the nature of the tumor. Many cancer types cannot be diagnosed without removing a sample of suspect tissue and having it analyzed /

biopsied. However, the process of examining the susceptible tissue is a critical and challenging task. To tackle these issues, the technology described in the research work proposed by Choudhury et al., automates the classification and identification of diseased tissues. Choudhury et al. [1] have presented a CNN model for binary classification of MRI images as 'Tumor detected' and 'Tumor not detected'. The model provided mean accuracy of 96.08% and F1-score of 97.30%.

The training phase and the testing phase are the two stages of brain tumor categorization using Artificial Neural Network (ANN). During the training phase, the ANN is trained to recognize Astrocytomas – a type of brain cancer. The samples from the training set are first processed using a number of image processing techniques, which includes histogram equalization followed by thresholding along with application of a sharpening filter, before retrieving the textural properties using the Gray Level Co-occurrence Matrix. The knowledge base uses the collected characteristics to successfully classify unidentified photos [2]. To provide these characteristics as an input to ANN-based classifiers, they are normalized in the range of -1 to 1. Additionally, the use of image data from other medical scans (e.g., Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS)) helps broaden the system's coverage.

For accuracy levels with a reduced rate of error, CNN approaches work well. With this technique, the first level of the MRI scan image is used to extract areas of the brain, and each slice in that region is segmented to look for tumors. Segmented tumor regions are provided to the CNN architecture. The preparation and evaluation phases of CNN-based brain tumor classification are separate [3]. The images are divided into groups by naming the pictures with phrases such as tumor and non-tumor brain images. Preprocessing of the image samples, extraction of features from them, and classification are all employed in the training phase. The advantages of this approach are that it enhances performance in comparison to other systems by increasing the segmentation level and spatial localization of the picture.

The categorization of brain tumors is one of the most critical challenges in medicine. The accuracy of brain tumor classification with the Kernel Extreme Learning Machine (KELM) and CNN (KE-CNN) method gives an accuracy of 93.68% for the dataset [4]. The developed software effectively categorizes the input MRI scan of brain cancer patients into three different types namely, glioma, meningioma and pituitary tumor, which is the most important aspect of the research work. CNN acts as a feature extractor and KELM is used as a classifier [4]. KE-CNN method provides improved accuracy when compared with other classifiers like Support Vector Machine (SVM), etc. Compared to other networks with fewer parameters, it is quicker in computation and training.

Brain cancers can be diagnosed and located quickly using MRIs. Deep learning models automatically extract key attributes in a hierarchical learning technique, indicating that these models produce better results. Several strategies are made using image enrichment, segmentation, and separation techniques such that certain threshold values are taken into account during the segmentation process. The training images are examined using a back-propagation neural network technique to detect the existence of a tumor. Deep learning-based models capture simple structural feature information at early levels, such as edges and forms, whereas final layers encode or generate abstract interpretations for specific characteristics. A tumor has been detected using a CNN. The Radial Basis Function (RBF) Classifier and Softmax Fully Connected Platte used for classifying MRI images, have a classification accuracy of 98.67% [5].

Recent advances have replaced the labor-intensive and error-prone method of manual tumor identification with machine learning algorithms that process medical image data. Usually, to do this, features are extracted with a CNN, and then they are classified with a fully connected network. The research work presented in [6] uses a deep neural network approach and incorporates a CNN-based model to classify the MRI scan image as a tumor by determining whether it is a glioma, meningioma, or pituitary tumor, or to classify it as 'no tumor' if tumor is not present in the MRI image [6]. The accuracy of the model is 94.39%, and the average precision is 93.33%. Therefore, CNN Classifier will play a huge role in the medical industry and save precious lives.

The model proposed by Shabu et al. [12] uses 2-Level Gray Level Co-Occurrence Matrix (2-Level GLCM) features and scattered representation-based segmentation which gives 96.90% recall and 97.01% F1-score, respectively. This model provides representation of pattern-matching segmentation with the GLCM Classification System and 2-level Support Vector Machine (SVM) (S2LGSVM), which is a groundbreaking framework. In this case, The MRI data was pre-processed utilizing a bilateral framework improvement method and filtration [12]. It was aimed to create a free deep learning-based and web-based app that can be used to diagnose and detect brain tumors (glioma, meningioma, and pituitary) on T1-weighted MRI. The image blocks are classified into Region of Interest (ROI) and non-ROI regions using the least residue set of criteria, to represent the segmented data. This study can help in precise classification.

3. Research Methodology

This section discusses the complete process of development of the proposed Brain Tumor Classification System. The inferences drawn out from the study of related literature are used for the selection of dataset, data pre-processing, designing of the proposed CNN architecture and its training along with evaluation of its performance.

3.1 Dataset Selection

The brain tumor dataset is retrieved from Kaggle [13], and is a labeled dataset categorized based on tumor location and tumor type / category. It consists of about 7023 MRI images, which are then split into training and testing datasets. About 5712 images are considered for the training dataset and the remaining 1311 images are put into the testing dataset. The complete dataset with the number of images in each category is listed in Table 2 below.

Table 2. Dataset summary indicating the number of images in each category

	Tumor Type	Number of Images
Training Dataset	Meningioma	1339
	Glioma	1321
	Pituitary	1457
	No Tumor	1595
Testing Dataset	Meningioma	306
	Glioma	300
	Pituitary	300
	No Tumor	405

MRIs are preferred over Computed Tomography (CT) scans because they produce comparatively more detailed images and thus can be used to detect abnormal tissue growth in the brain. Four different

classes namely 'meningioma', 'glioma', 'pituitary tumor' and lastly 'no tumor' have been used within the dataset. The samples of each class are displayed in Fig. 2.
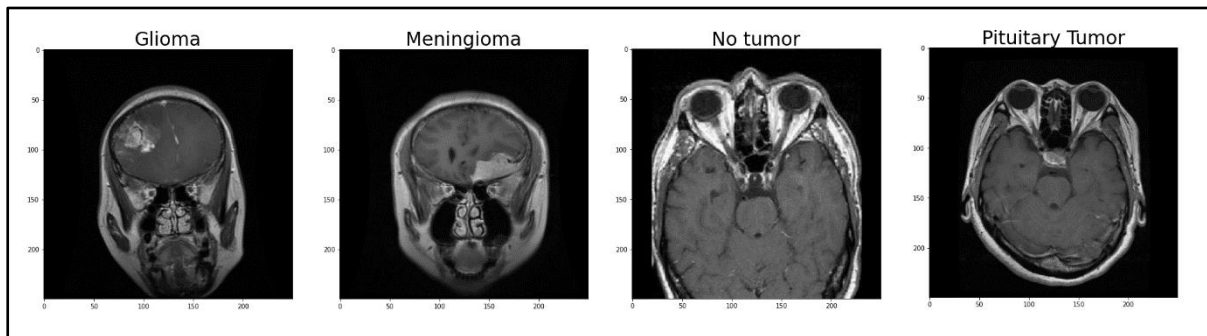

Fig. 2. Categorized dataset images

The dataset used in this research study comprises MR images with axial, coronal, and sagittal views of the brain, which helps in determining the location of the tumor and how it appears to be, when viewed from different directions.

3.2 Dataset Preprocessing

MRIs can sometimes have unnecessary noise present within them, which can influence the model prediction and hence, it becomes necessary to remove such noise from the image data for accurate prediction. Image pre-processing is the underlying advancement in image handling. Pre-processing includes forms such as transformation of image to grayscale, and picture reproduction.

The most well-known pre-preparation technique is to convert a color image to a grayscale image [15]. As a result, the MRI images used to train the proposed CNN model are first preprocessed and then enhanced with techniques such as grayscaling. Grayscaling of the image improves the image contrast which can help the model in understanding features in a better manner. Once the pre-processing is done on the MRIs, and the dataset is cleaned up, it can be used for further processes.

3.3 Proposed Model

The classification model proposed in this research study will help the general physicians to analyze MRI images and also help in detection of tumors in early stages.

3.3.1 System Architecture

This study suggests a CNN model based on deep learning for the precise classification of MRI images of brain tumors. The dataset's MRI scans of brain tumors are used to train the algorithm. The key steps involved in the entire process of classification are image preprocessing, followed by enhancement, and providing the image to the CNN model as an input. Furthermore, the model will perform feature extraction along with classification of the images using the fully connected layer of the neural network architecture.

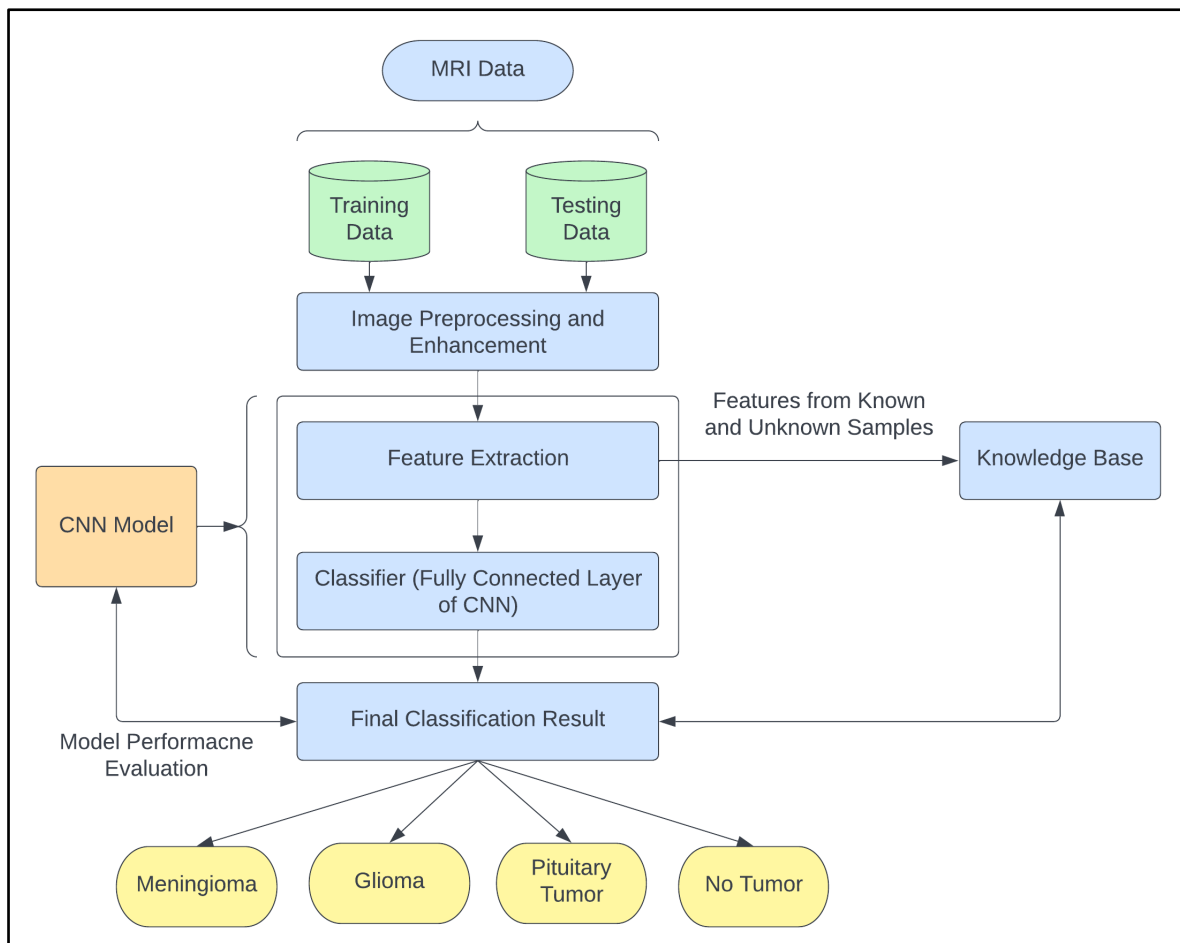The complete methodology of classifying MRI images of brain tumors is shown in the block diagram in Fig. 3.

Fig. 3. Block diagram illustrating how to classify brain tumor MRI images

3.3.2 Model Description

The proposed CNN architecture consists of convolutional layers, batch normalization layers, pooling layers, flatten layer, dense layers and dropout layers. The MRI image is provided as an input to the 2D convolutional layer, which performs convolution operation using a filter or a kernel that slides over the input image and performs element wise multiplication of pixel values in an image patch and the values in the filter matrix, the obtained results will be summed into a single output pixel. The kernel does the same procedure for each patch as it slides over the image. Hence, a 2D matrix is obtained, which consists of different features. It is also called a convolved feature matrix, which is then passed to the further layer. Rectified Linear Unit (ReLU) function is employed as an activation function for convolution layers, adding nonlinearity to the network.

The next layer introduced in the network is the batch normalization layer, which standardizes the inputs and stabilizes the training process. The max pooling layer conducts down sampling of features detected in the feature maps using the features collected by the batch normalization layer as its input. This layer provides a feature matrix as an output, considering the maximum value from each patch of the input feature map.

A second set of convolutional layers followed by batch normalization layer and max pooling layer is added to the architecture, followed by a flatten layer. The flatten layer transforms a 2D matrix into a 1D array which is then passed to a dense layer with the ReLU activation function. A dropout layer is introduced after the dense layer to prevent overfitting. A set of 2 dense and 2 dropout layers are used

before the final dense layer, which is responsible for final classification using the Softmax activation function. Adam Optimizer is used for optimizing the model parameters while training and the best value of model parameters are considered for final classification. The layers of the CNN model are displayed below Fig. 4.
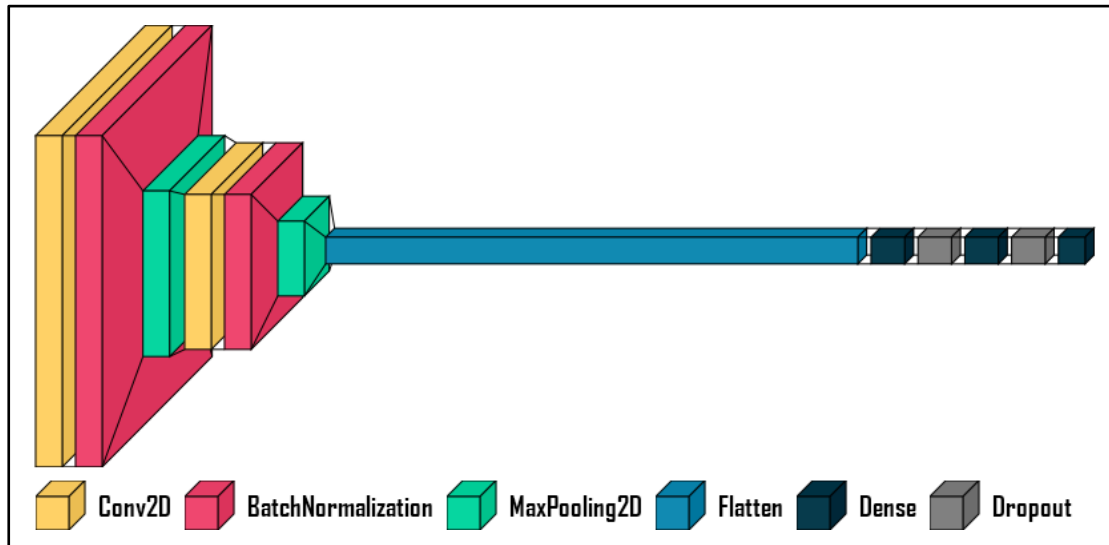

Fig. 4. Layers of CNN architecture

A flow of the model creation is provided below in Fig. 5. The proposed model is first used to unzip the dataset that has been imported, as seen in Fig. 3. After unzipping, the images are loaded using OpenCV, which is a library used for resizing the images. These images are then converted into NumPy arrays for creating feature vectors out of them. The model is then trained along with which hyper parameter tuning is performed. The criteria used to assess the model's performance are accuracy, confusion matrix, F1-score, precision, and recall.
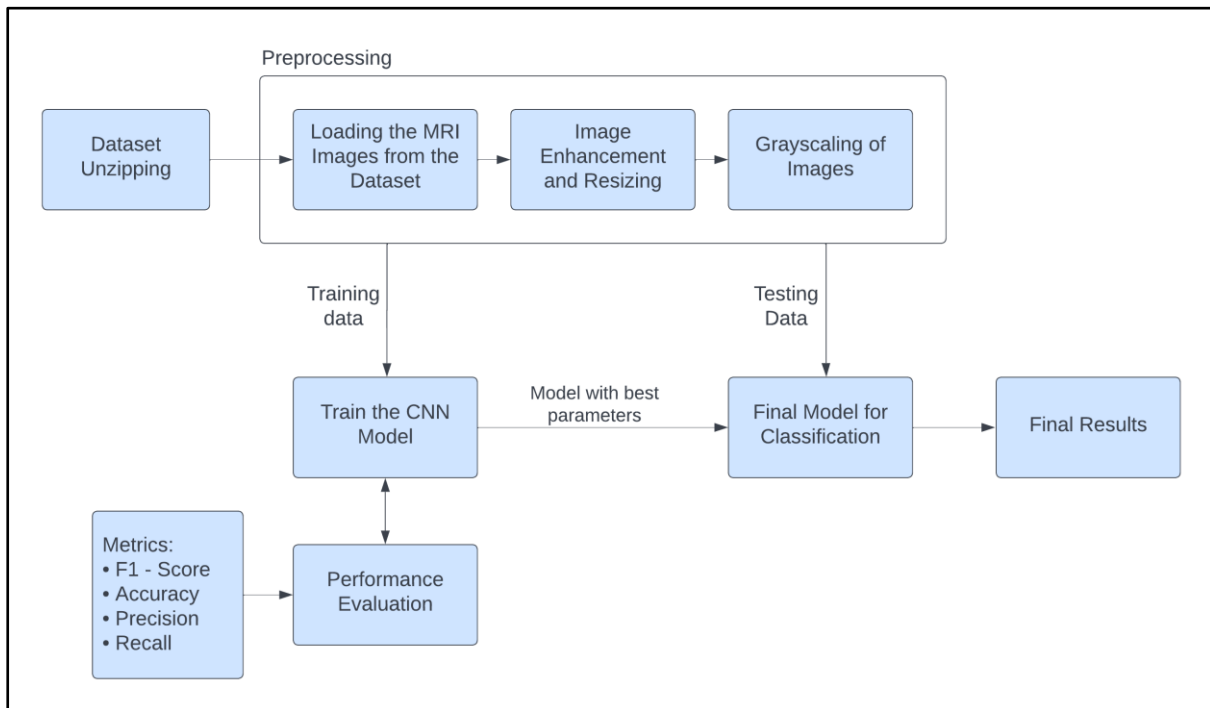

Fig. 5. Flow chart of model creation

3.3.3 Visual Explanation of Decisions made by the CNN Model using Grad-CAM and Guided Back Propagation

To explain why a deep learning network produces specific classification judgments, the gradient-weighted class activation mapping (Grad-CAM) is used. Grad-CAM determines which sections of the picture are most significant for classification by calculating the gradient of the classification score with respect to the features provided by the final convolutional layer of the network. Grad-CAM is termed as an extension of the CAM method (class activation mapping). It is class-discriminative and locates significant picture areas, but unlike pixel-space gradient visualization approaches, it lacks the capacity to show fine-grained features. Grad-CAM improves the transparency of CNN-based models by displaying input areas with high-resolution features that are critical for prediction.

Neurons are responsible for detecting features from an input image. However, for visualizing and understanding the features considered by neurons, direct display of features might be uninformative. As a result, the backpropagation training technique is employed to activate the filters for improved visualization. When backpropagating across ReLU layers, Guided Backpropagation visualizes gradients with respect to the picture, with negative gradients suppressed. This, on the surface, appears to be aimed at capturing pixels that are sensed by neurons, rather than those that inhibit neurons.

The following figures - Fig. 6.a, Fig. 6.b, and Fig. 6.c display the original image along with the Grad-CAM and Grad-CAM+ Guided Backpropagation mapping for input samples of 'meningioma', 'pituitary tumor' and sample with 'no tumor'. The following mappings indicate the vital features considered by the model while forming the prediction at the same time displaying the predicted and actual class of the image. These highlighted salient distinguishing features in the image help the model in predicting the correct class of the input samples.
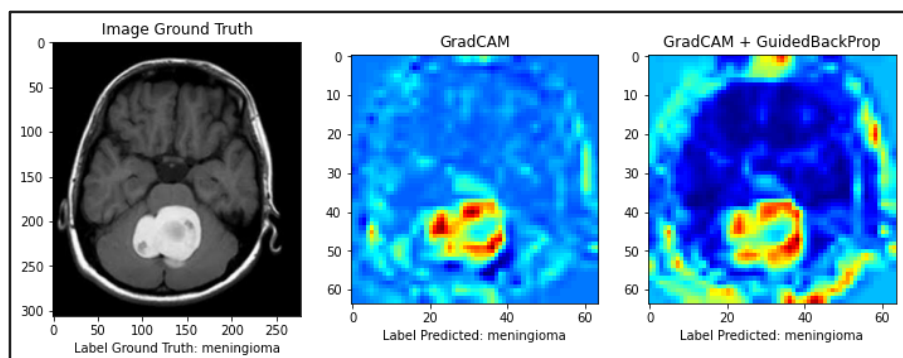

Fig. 6.a. Actual Image, Grad-CAM, Grad-CAM+ Guided Backpropagation visualization for Meningioma
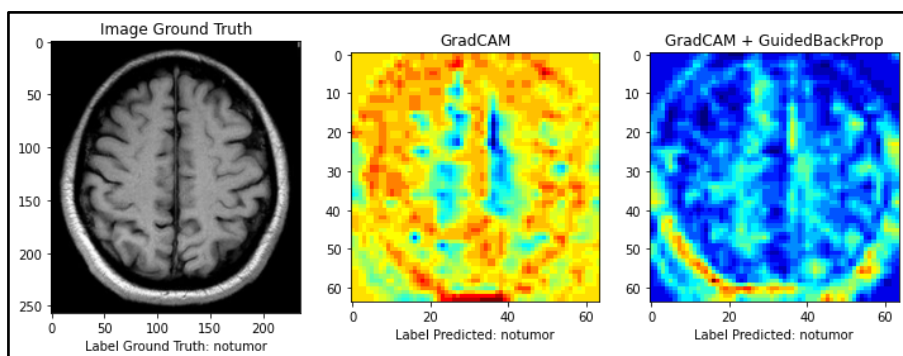

Fig. 6.b. Actual Image, Grad-CAM, Grad-CAM+ Guided Backpropagation visualization for 'no tumor' case
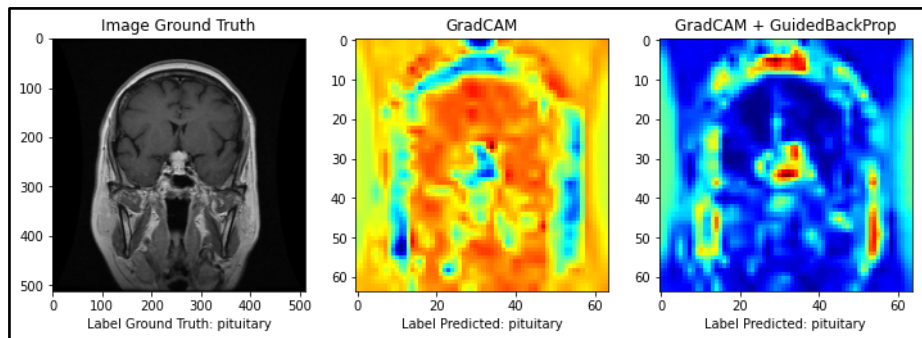
Fig. 6.c. Actual Image, Grad-CAM, Grad-CAM+ Guided Backpropagation visualization for Pituitary Tumor

Mathematically, Grad-CAM can be created by following three primary steps. The first step entails computing the gradients which is done by calculating the partial derivative of the score obtained for a particular class with respect to the convolutional features generated by the last convolutional layer. It can be represented as, $\frac{\partial y^t}{\partial A^k}$ where, y^t denotes the classification score obtained for the target class t, i.e., it represents the output generated from the last convolutional layer before converting it into probability using the softmax function. A^k indicates the k features maps produced by the convolutional layer. For an image of height h and width w the shape of the gradient is represented as $[k, h, w]$.

The second step involves determining the alpha values for respective gradients. This is achieved by the global average pooling technique. These alpha values are used in correspondence to a neuron's weight. The mathematical equation to determine the alpha value for an image belonging to class t, having k feature maps, is given as follows:

$$\alpha_k^t = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^t}{\partial A^k} \tag{1}$$

where, the partial differential term denotes the gradients computed in the previous step while the summation over the specified lower limits i (indexing the dimension corresponding to the width) and j (indexing the dimension corresponding to the height of the image) represents global average pooling. Thus, the α value corresponding to first feature map for the target class glioma is computed as follows.

$$\alpha_1^{t=glioma} = averaging \left(\frac{\partial y^{t=glioma}}{\partial A^1} \right) \tag{2}$$

Similarly, k number of α values can be computed for k corresponding feature maps.

$$\alpha_k^{t=glioma} = averaging \left(\frac{\partial y^{t=glioma}}{\partial A^k} \right) \tag{3}$$

The next step involves application of the ReLU function to the linear combination of the gradients and their respective alpha values (weights). This operation results in the formation of the Grad-CAM which can be visualized as a heatmap. The linear combination can be represented as follows,

$$LC_{t=glioma} = \alpha_1^{glioma} A^1 + \alpha_2^{glioma} A^2 + \ldots + \alpha_k^{glioma} A^k = \sum_{i=1}^{k} \alpha_i^t A^i \tag{4}$$

Thus, the Grad-CAM can be obtained by applying ReLU on this linear combination, as indicated in the formula no. 5.

$$Grad\ CAM_t = ReLU\ (LC_t) = ReLU\ \left(\sum_{i=1}^{k} \alpha_i^t A^i \right) \tag{5}$$

The obtained Grad-CAM is of size (h x w) and thus, $Grad\ CAM_t \in \mathbb{R}^{h \times w}$. The resultant Grad-CAM and guided backpropagation mappings for some input samples as displayed in the figures - Fig. 6.a, Fig. 6.b, and Fig. 6.c are obtained through the above mathematical modelling.

4. Results

The proposed CNN model utilizes an Adam optimizer during the training process. It is a highly effective optimization approach used for deep neural network training that incorporates the advantages of both AdaGrad (Adaptive Gradient Algorithm) and RMSProp (Root Mean Square Propagation) [14]. A loss of 5.56% and an accuracy of 98.93% is obtained after testing the model on test data. The loss function utilized in the model is categorical cross entropy. To ensure an efficient and optimal training process methods like EarlyStopping and ReduceLRonPlateau are used. The EarlyStopping method monitors the value of loss function and has a patience of 12 epochs before stopping early if the value of the model performance metrics to be monitored doesn't improve.

The ReduceLRonPlateau method monitors the validation loss and reduces the learning rate to ensure improved model performance. Fig. 7 displays the confusion matrix for the CNN model.
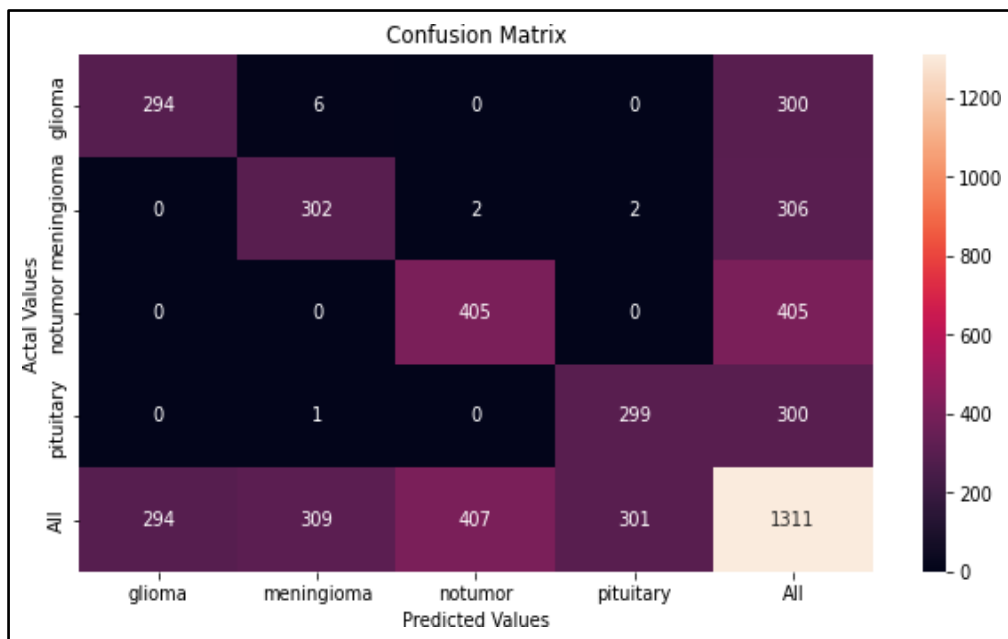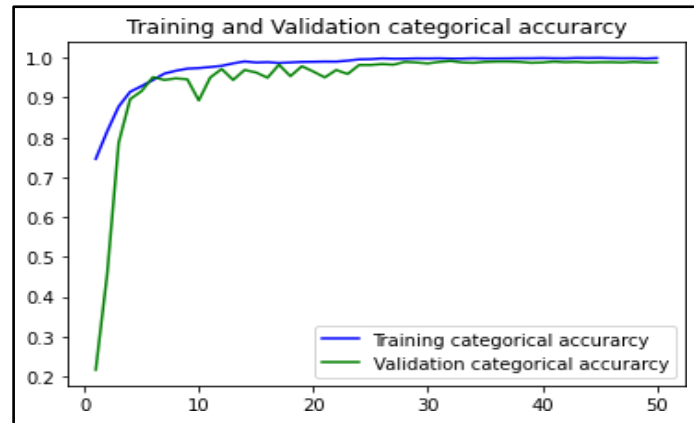

Fig. 7. Confusion matrix

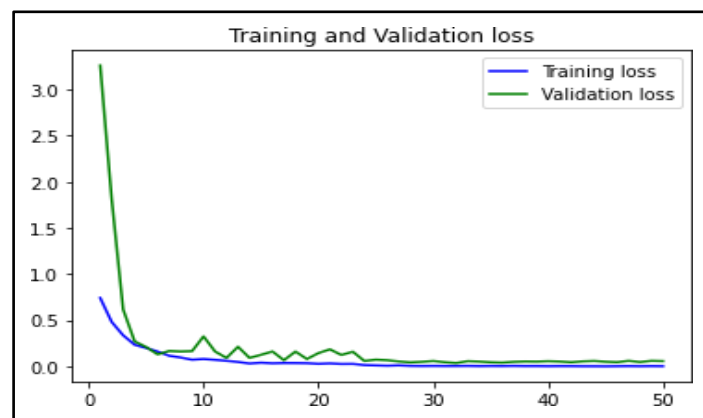**Fig. 8. Training and validation categorical accuracy of the model**

Fig. 9. Training and validation loss of the model

While training the model, the MRI data from the training set is taken in a batch size of 32. The accuracy and loss of the model over the training set and validation set for 100 epochs, with an early stopping at the 50th iteration, are shown in Fig. 8 and Fig. 9, respectively.

Table 3. Classification report

	Precision	Recall	F1-Score	Support
Glioma	1.00	0.98	0.99	300
Meningioma	0.98	0.99	0.98	306
No Tumor	1.00	1.00	1.00	405
Pituitary	0.99	1.00	1.00	300
Accuracy	NA	NA	0.99	1311
Macro Avg	0.98	0.99	0.99	1311
Weighted Avg	0.98	0.99	0.99	1311

The model's performance measure indices are presented in Table 3 along with their respective values. It demonstrates that the model is assessed using evaluation parameters like precision, recall, the F1-score, and support. The F1-score obtained for 'glioma', 'meningioma', 'no tumor', and 'pituitary tumor' are 99%, 98%, 100%, and 100%, respectively.

Each performance metric's mathematical representation is provided below:

$$\text{Accuracy} = \frac{TP+TN}{TP + FN + FP + TN} \tag{6}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{8}$$

$$\text{F1 score} = 2 \text{ x } \frac{Precision \text{ } X \text{ } Recall}{Precision + Recall} \tag{9}$$

Here, 'TP' stands for True Positive, 'TN' denotes True Negative, 'FP' represents False Positive, and 'FN' indicates False Negative.
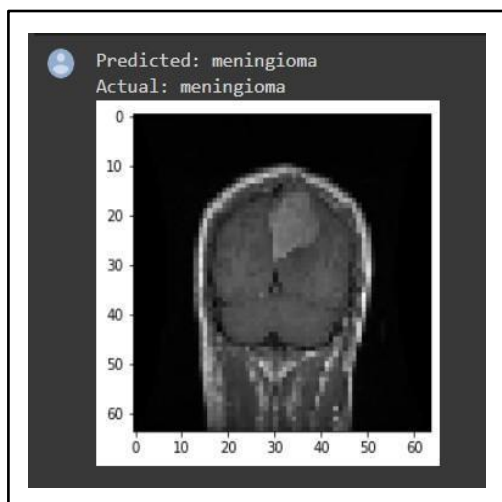

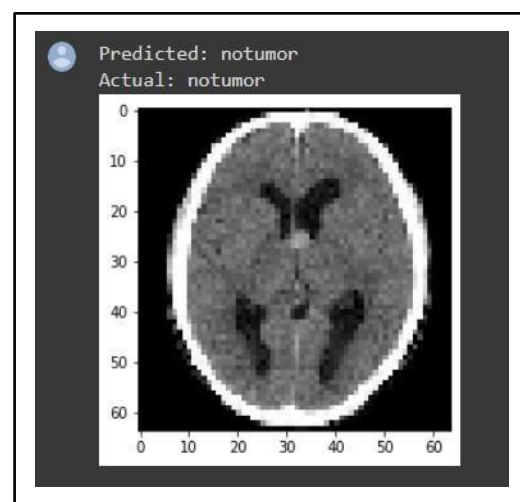**Fig. 10.a. Model predicting meningioma**   **Fig. 10.b. Model predicting 'no tumor'**

The above figures Fig. 10.a. and Fig. 10.b. displays the results of classification for two samples from the test data.

5. Conclusion

Convolutional Neural Networks have been used intensively for image classification tasks. It helps in reducing the rate of error and increasing the accuracy. The application of CNNs for brain tumor categorization has paved a way for improved accuracy and precision in detection and diagnosis of tumors. A CNN model is proposed in this paper to aid in the classification and prediction of brain tumors into four different classes of brain MRI images. The proposed approach is used to address a number of issues, including accuracy, tumor quality and tumor detection time. The model is trained and tested using MRI scans in the axial, coronal and sagittal planes, and gives an accuracy of 98.93% for 1311 testing images. This technique can serve as an accessible and convenient tool for general physicians with limited training and resources and physicians, who are not well acquainted to deal with brain

tumors and their types. In future various classifiers can be added to the model to create a more advanced classification system and make the treatment for patients more efficient.

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