Multi-Class Classification Framework for Brain Tumor MR Image Classification by Using Deep CNN with Grid-Search Hyper Parameter Optimization Algorithm

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Summary
Histopathological analysis of biopsy specimens is still used for diagnosis and classifying the brain tumors today. The available procedures are intrusive, time consuming, and inclined to human error. To overcome these disadvantages, need of implementing a fully automated deep learning-based model to classify brain tumor into multiple classes. The proposed CNN model with an accuracy of 92.98 % for categorizing tumors into five classes such as normal tumor, glioma tumor, meningioma tumor, pituitary tumor, and metastatic tumor. Using the grid search optimization approach, all of the critical hyper parameters of suggested CNN framework were instantly assigned. Alex Net, Inception v3, Res Net -50, VGG -16, and Google - Net are all examples of cutting-edge CNN models that are compared to the suggested CNN model. Using huge, publicly available clinical datasets, satisfactory classification results were produced. Physicians and radiologists can use the suggested CNN model to confirm their first screening for brain tumor Multi-classification.

Key words:
Multi-classification, CNN model, Grid search technic, Hyper parameter optimization

1. Introduction

Brain tumors are lumps that arise as a result of aberrant brain cell proliferation and disrupt the brain's regulating mechanisms. The formation of tumor in the skull has the potential to grow, putting pressure on the brain and having a negative impact on overall healthiness. Initial detection and prevention of brain tumor is a crucial study topic in medical imaging since it assists in the selection of the best appropriate treatment option to save patients' lives. There are various classifications for brain tumors. The categorization of brain tumors into malignant and benign tumors is a standard procedure. Lumps that grow in the skull but not in the brain matter are known as brain benign tumors. Meningioma's constitute a sizable subset of this set. Unlike benign in the other body part, in the brain can occasionally induce severe complications. Some benign tumors, such as meningioma, can sometimes progress to malignant tumors. They are highly likely to be surgically removed because they rarely spread to neighboring brain tissue. Pituitary tumor is cancer it starts in the pituitary secretory organ, which govern physiological processes and control hormones. Pituitary tumors are benign, meaning they do not spread to other regions of the body. Pituitary tumors are usually benign; however, they do occasionally develop to malignant tumors. Problems of pituitary tumors might result in persistent hormone shortage as well as eyesight loss. Tumor cells which are malignant are irregular cells that replicate uncontrollably and irregularly. This type of tumors can compress, infest, and kill ordinary tissues. Metastatics are ones that have spread from another section of the body to the brain. They are most frequently found in the large intestine, lung, stomach, breast, prostate and skin. The general class of malignant tumor is a glioma. They are the origin of the vast majority of brain cancers and contain uncontrollable proliferating cells. They raise fast and may stretch into healthy nerves around them, despite the fact that they rarely stretched to spinal cord or further part of the body. Gliomas are classified further based on their grade. The World Health Organization (WHO) [3] categorizes gliomas into 4 grades (I to IV), is the most widely accepted glioma tumor classification today [15].

Brain tumor identification and true categorization are critical in case of diagnosing cancer, treatment scheduling, and treatment outcome assessment. Despite recent advances in medical technology, brain tumor classification still relies on biopsy samples' histopathology diagnosis. Clinical diagnosis and assessment of imaging techniques like MRI, CT, and pathological exams, are commonly used to get a definitive diagnosis. The primary disadvantages of this diagnostic procedure include the fact that it is intrusive, time-consuming, and prone to sample mistakes. It is potential to increase physicians' and radiologists' investigative capabilities and reduce the time necessary for a right diagnosis with the use of computer-aided completely automated identification and diagnosis devices that seek to produce fast and exact judgements by specialists.

The purpose of this research is developing a framework with CNN model for classifying brain tumors using freely accessible datasets. The grid search optimizer automatically tunes almost all CNN hyper parameters.

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The remaining sections of this work is structured as follows: Section 2 includes a thorough analysis of related studies. The Section 3 delves deeply into the proposed framework with CNN. Section 4 deals the experimental design of the suggested framework with CNN model. Section 5 discusses the outcomes of experiment and compares the suggested framework with the available methods. Section 6 concludes research work.

2. Literature Survey

In the past, especially in recent times, machine learning methods were utilized to classify brain tumors. Artificial neural networks and deep learning-based model have had a substantial impact on medical picture processing, especially in illness diagnosis [19] [20] [38]. Several studies on detecting the tumor and multi-class classification with CNN have also been undertaken in parallel. This section is a review of the related literature on CNN-based multi-class classification of tumors. The studies in the literature can be looked at in a number of different ways. For example, some researchers have classified brain tumors using their own CNN models, while others have employed the transfer learning approach. The following scientists developed CNN models to classify tumors in brain images. For e.g., Badza and Barjaktarovic [3] used 3064 T1 - weighted MRI data to create a 22 - layered CNN framework to classify the brain tumor into appropriate type. Their suggested approach correctly categorized the tumor as glioma, meningioma, or pituitary with the accuracy of 96.56%. Using volumetric 3D MRI data, a multi-scale and deep 3D CNN classifier of brain tumor classifying was given by Mzoughi et al. [24] in another work. With 96.49% accuracy, the suggested technique identified tumor as low- or high-grade glioma. For brain tumor classification, Ayadi et al. [2] introduced a computer-assisted diagnosis (CAD) approach based on CNN. Experiments utilizing the 18-weighted layered CNN model on 3 separate datasets yielded an accuracy of 95.64 % for brain tumor types and an accuracy of 91.25% for other tumor types. Pereira et al. [28] utilized CNN to assess tumor grade instantly from image data in 2018, eliminating the necessity of expert annotation of sequences. They compared two strategies for predicting tumors: using data of the entire brain and using data of a tumor location that was automatically defined. They were able to predict whole brain grade with 89.5% accuracy and tumor ROI grade with 92.98% accuracy. Abiwinanda [1] utilized the relatively simple CNN framework available to identify the 3 common kinds of tumors (glioma, meningioma, and pituitary) with an accuracy of 84.19%. Hossam et al. [34] introduced a CNN model in 2019 to categorize glioma, meningioma, and pituitary tumors, as well as distinguish between the 3 glioma grades (Grade II, III and IV).

Transfer learning was utilized by the following studies to classify brain tumors using pre-trained CNN models. C inar and Yildirim [6], for example, employed an improved version of the pre-trained ResNet-50 CNN architecture for brain tumor identification, substituting the last 5 levels with 8 new layers. They attained an accuracy of 97.2% using MRI scans and this adapted CNN architecture. To identify brain tumor MR Image scans as low, high - grade glioma or healthy Khawaldeh et al. [14] developed an improved version of the Alex Net CNN model. This model achieved 92.17% of accuracy by using 4069 input images. With the pre-trained ResNet-34 CNN architecture, Talo et al. [35] proposed exploiting MRI scans to detect brain cancers. While attaining a detection accuracy of 100%, the deep learning model only employed 613 photos, which is a small number for machine learning experiments. Using 3 pre-trained CNN architectures known as Alex Net, Google Net, and VGG-16, Rehman [29] recommended categorized brain malignancies into glioma, meningioma, and pituitary. The VGG-16 achieved the greatest classification accuracy of 98.69% using the transfer learning technique. They looked examined 3064 MR Image scans of the brain from 233 patients. On 696 T1-weighted MRI scans, Mehrotra et al. [21] employed classification algorithm based on machine learning approach to categorize tumor pictures as malignant or benign. The most prominent CNN architectures, including ResNet-101, ResNet-50, Google Net, Alex Net, and Squeeze Net, were employed and compared in the classification investigation. They attained the greatest accuracy of 99.04% using transfer learning and a pre-trained Alex Net CNN architecture. Deepak & Ameer [8] used a Google Net CNN architecture that has been pre-trained to differentiate between three forms of tumors: glioma, meningioma, and pituitary. The average accuracy rate of this 3-class classification task utilizing MRI scan was 98%. Yang et al. [39] looked at how a CNN trained using transfer learning and fine-tuning performed on MR images to classify low-grade glioma (LGG) and high-grade glioma (HGG) noninvasively (HGG). With pre-trained Google Net, they achieved 86.6% accuracy, while with pre-trained Alex Net, they achieved 87.4 % accuracy.

Deep learning was employed by a few researchers in concert with other methods to classify brain cancers. For example, Mohsen et al. [22] divided brain MR images into four types, they are metastatic, sarcoma, glioblastoma and normal tumors using a CNN model in conjunction with principal component analysis and DWT (discrete wavelet transform). The accuracy of this CNN classifier is 96.97%. A deep learning approach for categorizing tumor as cancer causing or non-cancer causing based on 253 brain MRIs was proposed by Khan et al. [13]. Before extracting features with a basic CNN classifier, they utilized edge detection for determining the area of interest within an MR image. They were able to classify with an accuracy of 89%. Kabir Anaraki et al. [12] proposed a CNN classification framework to classify MRI scans to different grades of glioma using genetic algorithm (GA)-based technique, in 2019. They classified three glioma grades with 91% accuracy and pituitary, meningioma and glioma tumor classes with 93.9% accuracy. For the challenge of glioma grading and classification of pathology images, Rubin and Ertosun [11] constructed an ensemble CNN with deep learning pipeline. In circumstances of information scarcity, which is a prevalent issue in the field of deep learning models, their strategy was found to be highly effective. On the HGG vs. LGG classification test, they were 96 % accurate, and on the LGG Grade I vs. Grade II class assignment, they were 71% accurate

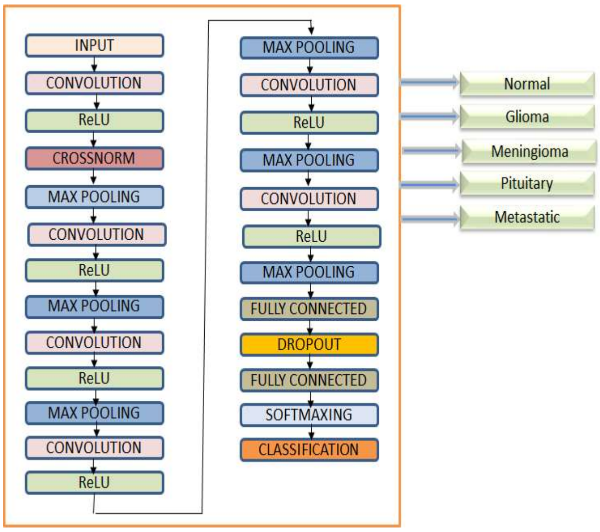
3. Proposed Model

3.1 CNN Model

CNN is one of the most widely used deep learning model in neural networks. Feature extraction and classification are the two components of a standard CNN model. The input, convolution, pooling, fully connected, and the classification layers are the five key layers that make up the CNN architecture. CNN extracts and categorizes features by placing sequentially trainable layers step by step. The fully connected and classification layers are often located in the classification section of the CNN, whereas the layer's convolution and pooling are typically found in the feature extraction section. Although CNNs have recently been focused on classification of images and accepts image as input, CNNs are also usually employed in a variety of additional disciplines where the audio and video signals are the input data [9].

The goal of this paper is to create a CNN model for multi-class classifying tumors in the brain MR images. Grid search optimization automatically tunes critical hyper-parameters in the CNN architecture. Normal tumor, glioma tumor, meningioma tumor, pituitary tumor, and metastatic tumors are the five forms of brain tumors classified by the proposed framework.

As illustrated in the Fig.1, the CNN model contains total 25 number of weighted layers: one input, six ReLU, six convolutions, six max pooling, one cross channel normalization, two fully connected, one SoftMax, one dropout, and one classification layer. Since the suggested



CNN framework is intended to classify the tumor MR image into five classes, the last layer (output) includes 5 numbers of neurons. The Soft Max classifier receives the output of the final fully connected layer, a 5-D feature vector, which produces the final tumor type prediction. See Table 1 for more details on the CNN architecture.

Fig. 1 Proposed CNN model Framework proposed

Table1: Structural particulars of proposed CNN framework

	Layer in CNN	***Type of Layer***	***Activations in Layer***
1	227x227x3 input layer	Input	227x227x3
2	128 convolutions of 6x6x3, stride [4 4], padding [0 0 0 0]	Convolution	56x56x128
3	ReLU-1 layer	ReLU	56x56x128
4	Cross channel normalization	Normalization	56x56x128
5	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	28x28x128
6	96 convolutions of 6x6x128, stride 11], padding [2222]	Convolution	27x27x96
7	ReLU-2 layer	ReLU	27x27x96

8	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	13x13x96
9	96 convolutions of 2x2x96, stride [1 1], padding [2 2 2 2]	Convolution	16x16x96
10	ReLU-3 layer	ReLU	16x16x96
11	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	8x8x96
12	24 convolutions of 6x6x96, stride [1 1], padding [2 2 2 2]	Convolution	7x7x24
13	ReLU-4 layer	ReLU	7x7x24
14	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	3x3x24
15	24 convolutions of 6x6x24, stride [1 1], padding [2 2 2 2]	Convolution	2x2x24
16	ReLU-5 layer	ReLU	2x2x24
17	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	1x1x24
18	34 convolutions of 4x4x4, stride [1 1], padding [2 2 2 2]	Convolution	2x2x32
19	ReLU-6 layer	ReLU	2x2x32
20	2x2 max pooling layer with [2 2] stride and [0 0 0 0] padding	Max Pooling	1x1x32
21	512 fully connected layer	Fully Connected	1x1x512
22	30% dropout layer	Dropout	1x1x512
23	5 fully connected layer	Fully Connected	1x1x5
24	Soft Max layer	Soft Max	1x1x5
25	**Output layer**	**Classification**	**---**

3.2. Performance Evaluation

In order to scientifically justify the study's findings, it is necessary to analyze classification performance in image classification investigations. The classification research would be inadequate and academically poor if this were not the case. Several performance evaluation criteria have long been utilized in the study of picture classification and have since become standard in comparable studies. They are: accuracy, specificity, precision, and sensitivity, these measures are also employed in this work to analyze the reliability and accuracy of the classification process, as they are widely acknowledged as standard measures for evaluating the performance in the study of image classification. Furthermore, the AUC is used to estimate the models' performance. Formulas for each of these metrics are shown in below the equations.

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

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

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

Where TP - True Positive, TN - True Negative, FP - False Positive, and FN - False Negative.

4. Experimental Design

4.1. Dataset

Four separate datasets were used in this investigation, all of which were collected from publicly accessible databases. The reference image database for assessing therapeutic response (RIDER) [4] is the first dataset. The RIDER dataset has the collection of 19 glioblastoma patients' MRI multi-sequence pictures (Grade IV). There are 70,220 photos in this dataset. REMBRANDT [16] is the second dataset, it contains MR image multi sequence pictures of 130 individuals with glioma grades I, II, III, and IV. Total 110,020 number of photographs in this second dataset. The TCGA-LGG is the third dataset [27]. There are 241,183low-grade glioma MRI scans (grade I and grade II) in the TCGA-LGG dataset of 199 patients. These three datasets were contributed by the cancer imaging archive (TCIA) project [7]. In each example, T1-contrastenhanced and FLAIR pictures were employed. The fourth dataset [5] has 3064 T1-weighted contrast enhanced pictures of 233 patients through 3 different forms of tumors: meningioma (709 images), glioma (1424 images), and pituitary (931 images). Some of the data store samples are shown in Fig. 2. For the Classification work, 3950 photos were collected, including 950 gliomas, 850 normal, 700 pituitaries, 700 meningioma, and 750 metastatic tumor MR images. Information about this dataset is described in Table.2.

Table 2 Description of the Dataset

Tumor Type	***Images***	***Total Images***
Normal	850	3950
Glioma	950	
Meningioma	700	
Pituitary	700	
Metastatic	750	

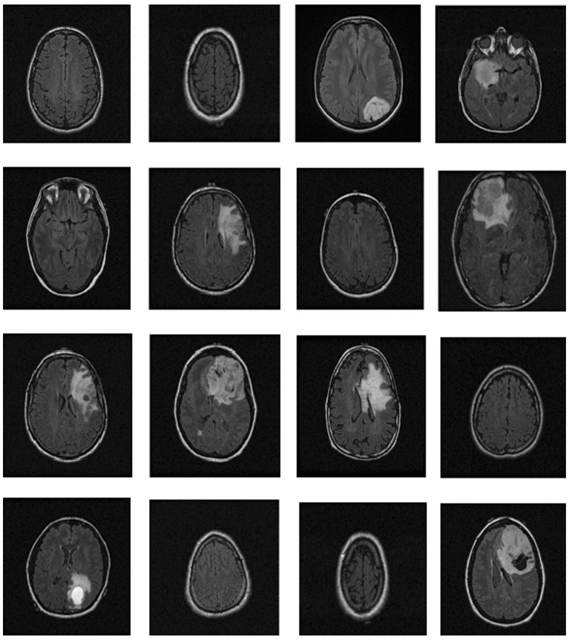


Fig. 2 Sample MR Images of brain tumor in the dataset

4.2. Optimization of Hyper Parameters

With the increased utilization CNNs in medical image analysis, a number of challenges have arisen in their application. As the architectures designed to obtain more effective results become deeper and the input images become higher quality, greater computing costs occur. Both the utilization of powerful hardware and the tuning of the existing network's hyper-parameters are critical to lowering these computing costs and achieving more successful results. As a result, the grid search optimization method is used to automatically adjust virtually all of the essential hyper parameters in the proposed CNN architecture. If the possible choices for parameters are minimal then grid-search optimization technique is one of the effective options for hyper parameter tuning of CNNs. The grid search seeks out the optimal range combinations for which the network has been trained.

CNN models have a lot of hyper-parameters and are fairly sophisticated. Hyper-parameters can be divided into two types: structural and fine adjustment. The number of convolution & max pooling, fully connected, filters, size of filters, and activation functions are the structural hyper-parameters. l2 regularization, momentum, size of mini-batch, and learning rate are the fine adjustment hyper-parameters. In this work, Algorithm 1 is utilized to optimize architectural hyper-parameters first. Algorithm 2 is utilized to fine tune the fine adjustment hyper-parameters after the structural hyper-parameters have been obtained.

Algorithm 1: Grid Search technique for optimizing structural hyper parameters

Step-1: Set 5-D grid for five hyper parameters, which are to be optimized
No. of convolution & max-pool layers
No. of fully connected layers
No. of filters
Size of Filters
Activation Function

Step-2: Create potential value intervals for each and every dimension.
No. of convolution& max-pool layers = [1,2,3,4]
No. of fully connected layers = [1,2,3,6]
No. of filters = [16,24,32,48,64,96,128]
Size of Filters = [2,4,5,6,7]
Activation Function = [ELU, SELU, GELU, ReLU, Parametric ReLU, Leaky ReLU]

Step-3: Look over all possible combinations and choose the one that gives the maximum overall accuracy.
Ex: combination1: (2,4,16,3, ELU)→***accuracy=95%***
combination2: (4,4,96,7, SELU)→***accuracy=97%***
combination3: (2,3,64,6, ReLU)→***accuracy=99%***

Algorithm 2: Grid Search technique for optimizing fine adjustment hyper parameters

Step-1: Set 4-D grid for four fine adjustment hyper parameters, which are to be optimized
l2 Regularization
Momentum
Size of Mini Batch
Learning Rate

Step-2: Create potential value intervals for every dimension.
l2 Regularization= [0.0001,0.0005,0.001,0.005]
Momentum = [0.80,0.85,0.90,0.95]
Size of Mini Batch= [4,8,16,32,64]
Learning Rate= [0.0001,0.0005,0.001,0.005]

Step-3: Look over all possible combinations and choose the one that gives the maximum overall accuracy.
*Ex:*combination1:(0.0001,0.80,8,0.0001)→***accuracy=94%***
combination2: (0.0005,0.90,32,0.001)→***accuracy=98%***
combination3: (0.001,0.90,64,0.001)→***accuracy=99%***

In this proposed study, the grid search algorithms are applied on the training set using a five-fold cross-validation approach. The given dataset is separated into six sets, with four being used for training and the fifth being used for testing. For the Classification job, there are 3950 photos that are randomly divided into training, validation, and test sets with a 60:20:20 ratio. In essence, the grid search algorithm evaluates all potential parameter value combinations and delivers the one with the maximum accuracy. In Algorithm 1, 5 parameters must be improved to attain the best accuracy. There are a multitude of methods to combine these factors, including 4, 4, 7, 5, and

6. As a result, there are 3360 possible combinations to test: 4 x 4 x 7 x 5 x 6.

The grid-search technique meant to tune the structural parameters of the CNN architecture is conducted 16,800 times since there are 3360 possible combinations to check through the fivefold cross validation method. Similarly, 4 parameters must be tuned in Algorithm 2 in order to attain the best accuracy. These characteristics can also be combined in a number of different ways, including 4, 5, and 4. As a result, there are 320 possible combinations to test: 4 x 4 x 5 x 4. Since there are 320 options to check with the fivefold cross validation approach, the grid search technique run 1600 times. Table 3 shows the best hyper parameter values for the CNN framework as obtained by the grid search optimization techniques.

Table 3 Results gained by Algorithm 1 and Algorithm 2 for proposed CNN

Hyper Parameter	***Possible values***	***Best value***
No. of convolution & max pool layers	[1,2,3,6]	**6**
No. of Fully Connected layers	[1,2,3,4]	**2**
Number of filters	[16,24,32,48,64,96,128]	**128, 96, 96, 24, 24, 32**
Size of Filters	[2,4,5,6,7]	**6, 6, 2, 6, 6, 4**
Activation function	[ELU,SELU,GELU,ReLU, Parametric ReLU, Leaky ReLU]	**ReLU**
Size of Mini Batch	[4,8,16,32,64]	**64**
Momentum	[0.80,0.85,0.9,0.95]	**0.9**
Learning rate	[0.0001,0.0005,0.001,0.005]	**0.0001**
l_2 Regularization	[0.0001,0.0005,0.001,0.005]	**0.001**

5. Experimental Results

The suggested model's performance is tested using a fivefold cross-validation approach for the multi-class classification task. The data set is separated into five sets, four of which are utilized for training and the fifth for testing. The experimentations are repeated five times. The model's average classification performance is calculated after the task's classification performance is evaluated for each fold.

The activations of the CNN convolution layers may be used to see the characteristics that CNN has learnt after training. We can observe what the network has learnt using this visualization. The activations of the convolution layers one and two are shown in Fig.3 a & b, respectively. Color and edges are learned by the convolution layer one of the CNN frameworks, whereas more complicated characteristics like brain tumor boundaries are learned by the convolution layer two of the CNN framework. The succeeding (deeper) convolution layers' features are built up by merging the features learned by the previous convolution layers. For the Classification job, the first convolution layer of CNN includes 128 channels, 96 of which are illustrated in Fig. 3a. Fig. 3b depicts the second convolution layer, which has 96 channels. Each layer of CNN is made up of channels, which are 2-D arrays. Fig. 3a. Each channel output in the convolution layer one. In these photos, white pixels have a lot of positive activation, whereas black pixels have a lot of negative activation. Grey pixels in the input picture indicate weakly active channels in the same way. In the first convolution layer, activations of particular channel and robust activation channel are displayed in Fig. 4 b and c. The appearance of white pixels in the Fig. 4 c channel suggests that it is strongly active at the tumor site. Despite never being prompted to learn about tumors, it is reasonable to conclude that the CNN has learnt that tumors are differentiating traits that may be utilized to discriminate across picture classes. These convolution neural networks can acquire relevant characteristics on their own, unlike prior artificial neural network techniques, which were typically deliberately developed to be problem-specific. Learning to recognize tumors assists in the distinction of a timorous picture from a non-timorous image in this article.

For the Classification task, the suggested model's performance is assessed using the fivefold cross-validation process. The data set is separated into five sets, with four being utilized for training purpose and the fifth being utilized for testing purpose. Five times the experiments are carried out. The model's average classification performance is obtained after the task's classification performance is evaluated for each fold. Because there are 3950 samples in the research, there are enough images to divide them into training, validation, and test sets in a 60:20:20 ratio, as shown in Table 4. To test the model, one hundred fifty-eight photos are picked at random from each class's dataset. The suggested CNN model for Classification challenge obtains 92.98 % of accuracy after 294 iterations. The AUC of the ROC curve is 0.9981, as illustrated in Fig. 5. These findings support the suggested CNN model's capacity to classify different forms of brain tumors. For more information on accuracy measures such as true positive, true negative, false positive, false negative, precision, specificity, accuracy and sensitivity, see in Table 5 and Fig. 6. As indicated in Table 5, for the Classification job, 97.85 % for glioma, 97.59 % for meningioma, 97.34 % for metastatic, 96.08 % for healthy brain, and pituitary tumor type attained accuracy of 96.96 % (Fig. 5).

Table 4 Proposed CNN framework of learning scheme

Class	*Images*	*Total*	*Training (60%)*	*Validation (20%)*	*Testing (20%)*
Normal	850	3950	2370	790	790
Glioma	950				
Meningioma	700				
Pituitary	700				
Metastatic	750				

6. Comparison of Existing Models with the Proposed CNN framework

Image categorization using a convolutional neural network has recently become popular in medical condition diagnosis. A CNN model is utilized in this study to determine the type of tumor. The main challenge with CNN is determining the best effective network model the given problem. The selection of proper hyper-parameters is critical for achieving effective outcomes, especially in convolutional neural networks. This study uses the grid search optimizer to create the most effective CNN framework and to improve the CNN framework's hyper-parameters. Acceptable classification outcomes are produced using big and widely accessible clinical data sets. The categorization of brain tumor kinds is done with a 92.98 % accuracy. Performance evaluation criteria such as ROC curve AUC, precision, specificity, accuracy and sensitivity are used to evaluate the suggested framework's results.

It's interesting to compare the suggested CNN models' results to the outcomes of existing popular advanced CNN models. The same experiment is carried out with the same dataset utilizing standard famous pretrained CNNs as Alex Net, Inception v3, Res Net - 50, VGG - 16, and Google - Net. These models' results are presented in Table 6. The accuracy and AUC acquired throughout the experiments are compared between the suggested CNN model and several popular frameworks. In the classification challenge, the proposed CNN model outperforms other networks, as shown in Table 6. The VGG-16 model, which is closed to the suggested CNN model, obtains an accuracy of 88.87 % in the challenge of classification of tumor class. Pre-trained deep learning frameworks are created and learned on generic data sets for common image classification problems, which might explain why the suggested CNN models outperform them. On the divergent, the suggested CNN model is intended for a more explicit problem, namely the classification of brain tumors. Furthermore, the suggested model is trained and tested on MRI images of brain tumors. Another reason why the proposed CNN model outperforms the pre-trained models are that the suggested CNN architecture was improved for the explicit purpose and utilized the hyper-parameters that produce the finest outcomes for the classification task.

Looking through the literature, some researchers looked into how to categorize pictures into grades, while others looked into how to classify different classes of tumors. MRI pictures have also been classed as brain tumor or non-tumor images by other researchers. These investigators attained an accuracy of 96.13 % in the Classification job. Another team of researchers, Kabir Anaraki et al. [12], used CNN with genetic algorithms to obtain 94.2 % classification accuracy for the Classification challenge. Sajjad et al. [30] utilized CNN with considerable data augmentation to achieve an overall accuracy of 90.81 % in a classification challenge. The suggested CNN model in this research attained an overall accuracy of 92.98% for the classification job. The suggested model for the Classification job obtains a high degree of accuracy despite categorizing tumor photos into 5 kinds (glioma tumor, meningioma tumor, pituitary tumor, normal brain tumor, and metastatic tumor). For multi-class classification of brain tumor MR images, the CNN model suggested in this research clearly outperforms previous approaches.

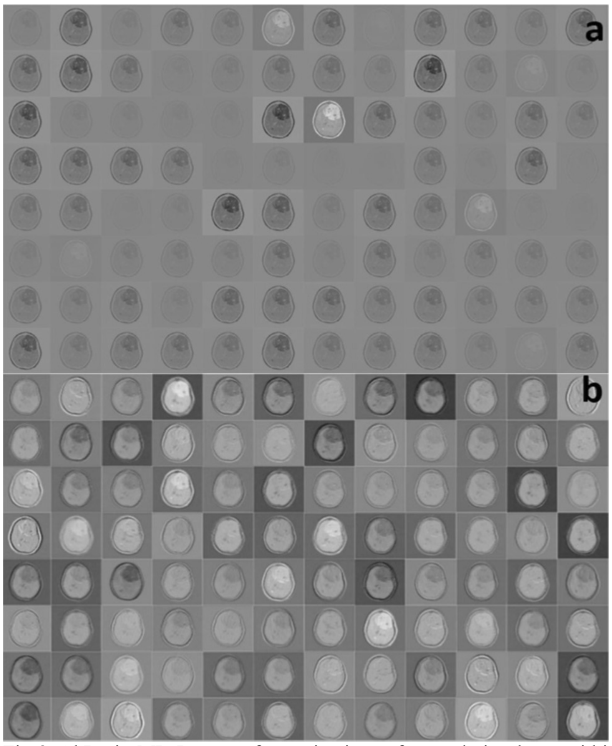


Fig 3a&bBrain MR Images after activations of convolution layer within the proposed CNN model.

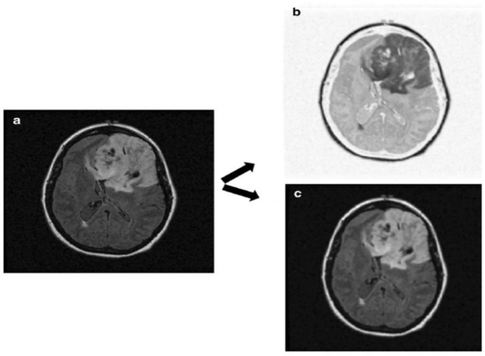


Fig 4 a – Input image, b – Image after activation within a specific channel, c–Image after strong activation channel of the first convolution layer in the proposed CNN model

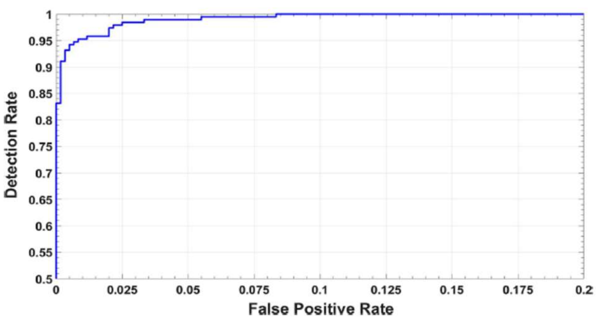


Fig 5 ROC curve of the proposed CNN framework

Table 5 Performance measures for each brain tumor class: Accuracy, Specificity, Sensitivity and Precision in terms of TP, TN, FP, FN.

Class	*TP*	*TN*	*FP*	*FN*	*Accuracy (%)*	*Specificity*	*Sensitivity*	*Precision*
Glioma	182	591	9	8	**97.85**	0.985	**0.958**	**0.953**
Meningioma	131	640	10	9	**97.59**	0.985	0.936	0.929
Metastatic	137	632	8	13	**97.34**	**0.988**	0.913	0.945
Normal	160	599	18	13	**96.08**	0.971	0.925	0.899
Pituitary	132	634	12	12	**96.96**	0.981	0.917	0.917

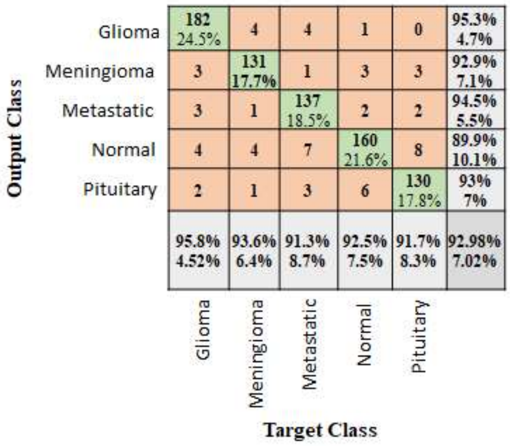


Fig. 6 Confusion matrix for multi-class classification problem

Table 6 Comparison of the suggested model's performance to that of other models

Classification Model	*Accuracy (%)*	*AUC*
Alex Net	83.12	0.8421
Inceptionv3	82.38	0.8319
ResNet-50	75.93	0.8022
VGG-16	88.87	0.8998
Google Net	78.87	0.8117
Proposed CNN Model	**92.98**	**0.9981**

7. Conclusion

Machine learning studies and research have shifted from feature engineering to architectural engineering as a result of recent improvements in deep learning. The multi-class classification of brain tumors for initial diagnosis is described in this study utilizing CNN models, nearly all of which are automatically tweaked using grid search. Using publicly accessible medical picture datasets, a strong CNN model for classifying the brain tumor is defined. The accuracy of proposed framework for brain MR images classification into five classes is 92.98%. On a big enough number of medical pictures, the suggested CNN model is trained and evaluated. The results acquired by the suggested CNN model and comparisons with famous approaches illustrate the usefulness of the CNN model built with the given optimization framework. Physicians and radiologists can use the CNN model established in this research to validate their first screening for multi-classification of brain tumor.

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