# Diagnosis of Intracranial Tumour via Selective CNN Data Modelling Technique

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**Abstract.** A brain tumor occurs in human beings when a normal cell turns into an abnormal cell inside the brain. There are two types of brain tumors: benign tumors and malignant tumors. Nowadays machine learning and deep learning are playing a vital role in the field of medical and computer vision areas as this leads reduction in human judgment in the diagnosis and analysis of diseases in human beings. In brain tumor diagnosis we need high accuracy or else a minor error in diagnosis can cause a huge blunder. As deep learning is playing an important role in the medical field so in this paper we have implemented CNN and ANN of different configurations on binary classification which is based on machine learning with a given dataset of brain tumor MRI scans that depict a person is a brain tumor patient or not. This paper will focus on objective function value obtained by different CNN architectures with a minimum loss, maximum accuracy, and training time which can serve as a viable tool for physicians and the medical community to correctly identify the tumor patients. Experimental evaluations of the best architecture show that a maximum objective function value of 1.84, a validation accuracy score of 0.8275 is achieved & an AUC of 0.737 in the ROC curve to correctly identify whether a person is suffering from a brain tumor or not.

**Keywords:** Convolution neural network (CNN), Machine Learning, Artificial -neural network (ANN).

## 1    Introduction

A major increase in mortality among children and adults is due to the brain tumor. A brain tumor is a condition in which there is a development of abnormal cells in our brain. As the skull is present around the brain is hard so due to this reason abnormal development leads to a problem in human beings. As brain tumors can be classified on the origin of tumor, malignancy, and growth pattern. A cancerous brain tumor is a major tumor that is also known as a malignant tumor it originates either from the brain or it is the result of any other cancer caused to a person like breast cancer. A benign brain tumor is another form of tumor that looks like a low level of cancer this states that the starting growth is very slow and symptoms of having this tumor are less

compared to the malignant tumor [1]. In the U.S., 29000 peoples were diagnosed out of which nearly 13000 were suffering from primary malignant brain tumors each year according to the national brain tumor foundation (NBTF). One-quarter of all cancer death in children is caused by the brain tumor. The overall annual frequency of primary brain tumors in the U.S. is 11-12 per 100,000 peoples and for primary malignant brain tumors is 6-7 per 100,000. Over 4200 peoples with brain tumors were diagnosed in the U.K per year according to an estimation of 2007 and 1.6% i.e. 16 out of per 1000 cancer diagnosed were having brain cancer. Each year approximately 200 other types of tumors were diagnosed in the U.K. According to a report in 2007 total, 80271 cases were diagnosed in India with various types of tumors [2].

Benign and malignant are two classifications of brain tumors. As malignant is having non-uniformity in structure and it contains active cancer cells whereas in benign tumor there is uniformity and it doesn't contain any active cancer cells. Low-graded tumors i.e. benign tumors can be classified as gliomas and meningiomas and malignant tumors i.e. high-grade brain tumors can be classified as glioblastoma and astrocytomas [3]. There are many reasons due to which tumor causes and most of them are unknown this includes head injuries, hereditary syndromes, immune suppression electromagnetic fields prolonged exposure to ionizing radiations, or chemicals like vinyl chloride and formaldehyde. There are many symptoms of a brain tumor which include persistent headache, eyesight, hearing and speech problems, walking and balancing problems, memory lapse, nausea and vomiting, a problem in concentration, and seizures. For monitoring the anatomy, vascular supply, cellular structure of brain tumors we use Magnetic resonance imaging (MRI) which helps us to do diagnosis and have valuable treatment [4, 5].

MRI is a medical image processing that assists the medical diagnosers to diagnose and treat according to the condition of the patient. It is the process by which we can identify the disorders present inside the brain. It makes efficient use of the magnetic area, pulses, and computer visualizing for the area of bones, organs & structures of bodies of the patient for diagnoses. As viewing from a CT scan is much complicated so MRI offers the ability to understand the posterior brain brainstem efficiently. Segmentation plays an important role in finding the malicious region from the medical images which are complicated [6]. Magnetic resonance imaging (MRI) is having much application in imaging technique for the detection of brain tumors as it is a non-intrusive system, it can be utilized alongside other imaging modalities like magnetic resonance spectroscopy(MRS), computed tomography, and positron emission tomography(PET) so that we can get the more accurate structure of tumor [12,13]. For biopsy sampling MRI is used for tumor grading by pathologists it provides tumor location and we get information regarding the shape and size of the brain tumor by using MRI images [7].

In the medical field of brain tumor detection machine learning and deep learning provides a major role by providing better diagnosis [8-11]. Besides, deep learning models like convolutional neural networks (CNNs) & artificial neural networks (ANNs) have improved the classification of objects and the detection of images [14, 15]. As a deep learning paradigm, CNNs [16] can be used to extract more and exact features from different types of raw input images from the dataset which consist

of different configurations of images [17]. In this paper, we discuss performance metrics achieved by different architectures configurations in which convolution neural networks (CNN) & artificial neural networks (ANN) are used in training the model. All CNN architectures gave different maximum accuracy, minimum loss & training time we calculated the objective function value of every architecture and then we have activated the neural network and evaluated the intermediate activation in CNN with Keras. By this brain tumor automatic diagnosis that is real-time deployment, we can achieve high accuracy with which we can save time and use computing power to detect tumors of patients efficiently. The rest of the paper is organized as follows:- 2. Related work, 3. Methods and Data 4. Experimentation and Results, 5.Conclusions, and Future Work. We evaluate different architectures of CNN and ANN to find out the best ideal architecture with maximum objective function value for the particular brain tumor dataset used in section 4.

## 2　　Related Work

Nowadays most of the medical field is getting contribution from machine learning and deep learning techniques so that the works get easier and simplified for the medical workers. As most of the research papers are oriented towards deep learning techniques like CNN and ANN for solving problems regarding brain tumors [18-20]. Thillaikkarasi *et al.* (2019) performed brain tumor segmentation by using an algorithm of deep learning which includes CNN with M-SVM that will segment the tumor automatically and the MRI images that were used were modified by using the Laplacian of Gaussian filtering method (LoG) and Contrast Limited Adaptive Histogram Equalization (CLAHE) and used segmentation for helping in CNN architectures and they gained accuracy of 84% in the evaluation of the overall model [23]. As there are many types of a tumor so Ghassemi *et al.* (2020) used a new deep learning technique i.e. generative adversarial network (GAN) on the dataset for extracting the robust and structured feature from the MRI images and imported them into convolution layers which consist of three types of tumors namely meningioma, glioma, and pituitary tumors that had 3064 total images and achieved accuracies of 93.01% and 95.6% for introduced split and random split [21]. For instances, see the simple CNN technique used by Seetha *et al.* (2018) and they achieved an accuracy of 97.5% in brain tumor detection by using CNN architectures where the weight of neuron was very small as compared to normal deep learning architectures and they calculated the loss function by using gradient descent algorithm it was implemented on a dataset which was from 2015 by BRAIN TUMOR IMAGE SEGMENTATION BENCHMARK (BRATS) [22].

Fuzzy C-Means (FCM) was used by Mohsen H *et al.* (2017) for separating the tumourous and nontumorous patients & also used multilevel Discrete wavelet transform (DWT) for the extraction of wavelet features from the model. They used Sequential Minimal Optimization(SMO) for the classification method and Linear Discriminant Analysis(LDA) & KNN for the model which obtain high accuracy of 96.97% for analyzing the DNN based brain tumor classification as complexity was very high but

the performance was very poor [24]. Classification accuracy of 81% was obtained by Pashaei *et al.* where he used 3*3 size of all filters and the model had five layers [25]. Performance of CNN features of the model by Pashaei was increased by using the extreme learning machines (ELM) techniques as results recall value of pituitary tumor was very high and meningioma was very low which unbiased the model. Capsule Network (CapsNet), was introduced into brain tumor detection that was used for utilizing the relating relationship between the tumor and its surrounding tissues. This was a modified form of CNN architectures which was introduced by Afshar *et al.* [26]. Transfer learning plays important role in the classification of tumors which was applied on content-based image retrieval (CBIR) and the evaluation was performed on a dataset that was available publicly and Swati *et al.* obtained well good results [27]. We can obtain great experimental values with pre-trained models. Jain *et al.* used the VGG-16 model which was pre-trained for the detection of Alzheimer's diseases from the images of MRI [28].

Although there are many techniques by which we can detect brain tumors in patients but we have several limitations but the main reason behind this detection is that the lack of dataset. As many radiologists face issues regarding this binary classification that enough information or data is not provided on sources for detection.

## 3 Methods and Data

In this section, we will discuss the methodology we have used in the classification process of Brain tumors using MRI images whether a person is suffering from a tumor or not. We also specify the dataset that we have used for detection and also the technology with which we have done the experimentation and computations re also mentioned in this section. This section maps out as follows 3.1 Dataset Used, 3.2 Image Augmentation, 3.3 Artificial Neural Network (ANN), 3.4 Convolutional Neural Network (CNN), 3.5 Software, and Hardware.

### 3.1 Dataset Used

The MRI images for Brain Tumor Detection of patients were collected from Kaggle by Navoneel Chakrabarty. He collected all the images from internet sources and gathered around 253 images [34]. A sample difference between a positive and a negative patient is shown in Fig.1. Table 1 describes the amount of MRI images taken for training and testing of the model.

**Table 1.** Dataset distribution and splitting of images taken into training and testing.

|           | Brain Tumor Patient | Normal |
|-----------|--------------------|--------|
| Training  | 1037               | 781    |
| Testing   | 234                | 137    |
| Total     | 1307               | 918    |

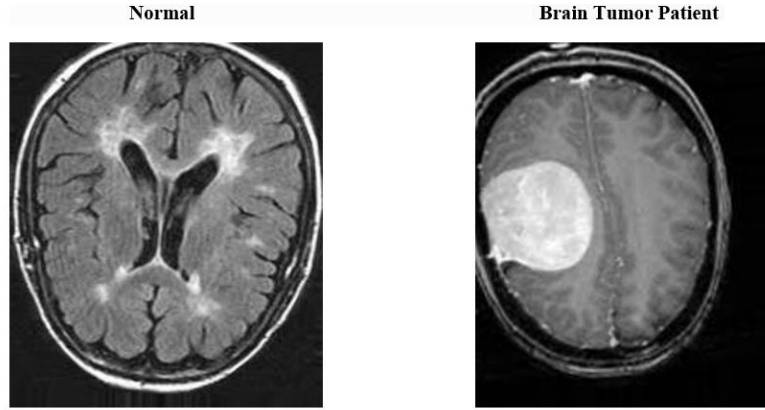**Normal**                                    **Brain Tumor Patient**



**Fig. 1.** (L) MRI of a normal person, and (R) of a brain tumor patient. The abnormal cell can be seen in the Tumor positive MRI image.

### 3.2 Image Augmentation

More accuracy can be gained only if we have a large number of datasets for training our model. In this case, data augmentation plays an essential role in increasing the data of the dataset. Data augmentation plays an important role in deep learning we can observe in various research papers regarding image augmentation it plays an important role in dataset [29-31]. If our model is having training on the large number of images the accuracy and stability of our model i.e. .hdf5 file will be more accurate and efficient. Image augmentation works on different parameters like shear, zoom, rescale, flipping, whitening transforms random rotations and shifts. In our approach, we rotate, shear, brightness increment, horizontal and vertical flipping, width, and height shifting in the training images for increasing and for having a wider variety of our training data.

### 3.3 Artificial Neural Network (ANN)

In Deep Learning, ANN plays an important role as a backbone in deep neural network. ANN is having a wide range of application in the field of deep learning it can be used in training models of Speech Recognition [35, 36], Face Recognition [37], Signature Verification Application [38]. ANN are powerful neural networks that are simple and they are highly interconnected with each other by which they transfer information by their dynamic state of response to any external user inputs. They are made up of multiple nodes that are just like biological neurons of the human brain. Links are connecting medium between the neurons and they can interact with each with the help of links. Nodes take up the input data and perform the various operations on the data and then the result of these operations is passed to other neurons and the output at every node is mentioned as activation value.

Mathematically, we can represent as $input \rightarrow x$ then transforming a set $S \subset AE^x$ of input signals where (a $x$ – neuron on $S$) is a function.

6

$$U : AE^x \times S \ni \left(\vec{b},\vec{c}\right) \rightarrow U\left(\vec{b},\vec{c}\right) = f\left(< \vec{b},\vec{c} >\right) \ni AE \tag{1}$$

where $\vec{b}$ is a weight vector ;

$< . , . >$ is a real scalar product,
And we have

$$f : AE \rightarrow Æ$$

is called as activation function of the neuron in ANN layers. If $f$ is a linear operator then the neuron will be linear.

A function;

$$U^* := U\left(\vec{b},.\right) : S \ni \vec{c} \rightarrow U^*\left(\vec{c}\right) \in AE \tag{2}$$

is called a model that is trained on $x - $ neuron on $S$.

   Bounded functions are mostly used for representing the activation functions in output layers. The above equations show that a two vector variable are having neuron as a function whereas comparing to trained neuron, there is a weight vector fit in trained neurons therefore we can state that a mapping of only one vector variable is known as a trained neuron. Activation functions are the most important part of ANN. There are numerous types of activation functions such as Sigmoid, ReLu, TanH, Softmax, and Swish are commonly used. In ANN most interesting thing is that the output of any neuron works as an input for other neurons in process of deploying the model.
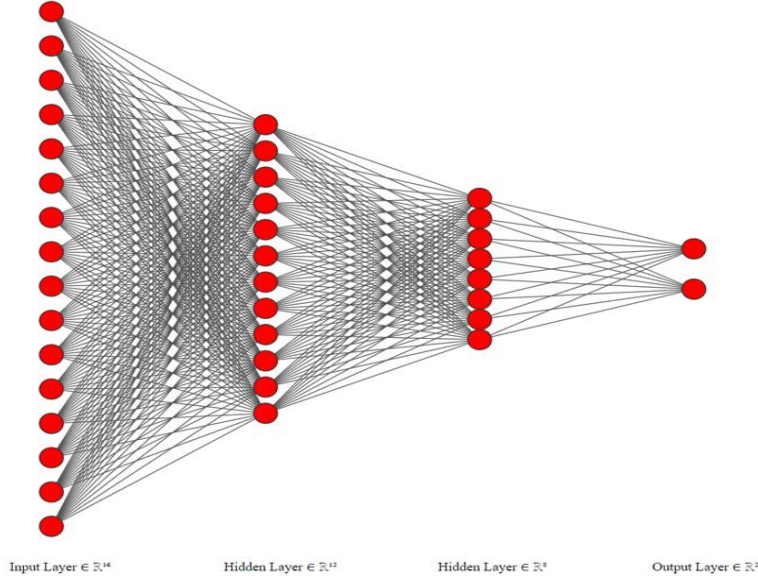
Input Layer $\in \mathbb{R}^{14}$      Hidden Layer $\in \mathbb{R}^{12}$      Hidden Layer $\in \mathbb{R}^{8}$      Output Layer $\in \mathbb{R}^{2}$

**Fig. 2.** Artificial Neural Network (ANN).

Above Fig. 2 shows the connection of ANN layers with each other in order of Left to Right in a layer-wise manner i.e. {16, 12, 8, 2 }. The input layer consists of 16 nodes where the inputs are provided and they are attached with two hidden layers having nodes 12 and 8 respectively. The output layer consists of 2 nodes as a person will either suffer from a tumor or not it is a binary case so softmax function comes into play in the output layer which will help for summing up the values to unity.

### 3.4 Convolutional Neural Network (CNN)

Image recognition and classification is a major field in machine learning and when the image comes into role then Convolutional Neural Networks are the backbone in algorithms of deep learning. From the learning of the model to calculating the results, CNN plays an important role. More number of layers with parameters will give more accurate and stable results. CNN consists of two parameters namely weights and biases. More layers will give more accuracy but a minimum of three layers are compulsory on the implementation of CNN layers i.e. Convolution Layer, Pooling Layer, and Fully Connected Layer. Deep learning model with CNN plays an important role in detection of diseases like malaria detection [46], heart disease detection [47, 48]. CNN can be used in microbial detections where nuclei segmentation comes as a major example in this field [49, 50] and CNN can be used widely across in field of chronic diseases and health care sector [51, 57]. Each layer will perform a different tasks on the input dataset and they have several different parameters that can be optimized. CNN have many applications in day-today like decoding facial recognition [39], Analyzing Documents [40], Understanding Climate [41], Predicting earthquakes [42] and many more [43-45].
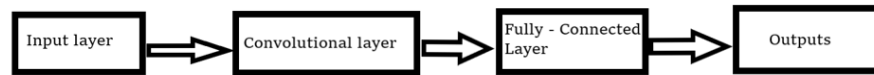


**Fig. 3.** Convolutional Neural Networks (CNN).

Fig. 3 shows a basic block diagram of CNN architecture that can be used in any model for the dataset. Convolutional networks are mainly inspired or attracted to the pattern of images. They understand the parameters by itself and extract the right features for training the model and we need not provide it. As pixels are present in every picture we analyze the results by filters that consist of weights, kernels, and features detecting the edges of the images are a major part, and filters are used to detect it. It will help in filtering out unwanted information to enhance image filters and quality. Filters are also known as 2-D matrices or kernels.

CNN architectures are equivariant which can be represented as

$$a\big(b(x)\big) = b\big(a(x)\big) \tag{3}$$

If there is any image 'I', $a$ is a convolutional operation and is $b$ image translation operation.

Convolutional is equivariant to translation operation. The equation states that first convolving the image and then translating the image or vice versa both will lead to the same result at the end. Equivariant helps its sharing parameters. A pooling layer is present thereafter convolutional layer which operates independently on each of the feature maps. Pooling layer reduces the spatial sizes simultaneously so that the computation and parameters present in the network are reduced. Most commonly max pooling is used in the pooling layer section.
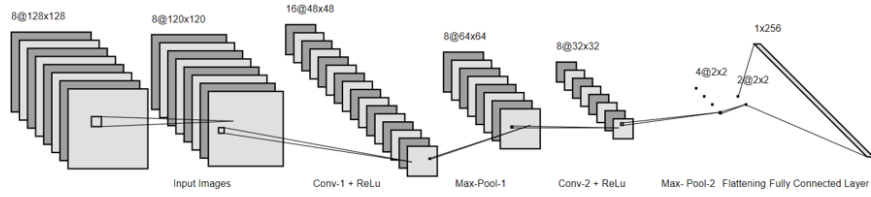


**Fig. 4.** Convolutional Architecture of 2- layered CNN model.

After max-pooling flattening is the most essential part as it converts all the parameters and data that are multi-dimensional into a 1-D array format which makes work easier for connecting all the layers. At last full connection of neurons is there at the end of CNN where the ReLu function plays an important in the full connection of CNN architecture. Fig. 4 shows all connections and different layers in 2 –layered full CNN neural network.

### 3.5 Software and Hardware

Various CNN architectures trained for this machine learning analysis Python 3 with the Keras and TensorFlow were used with a jupyter notebook. Hardware workstation is with Intel i5 $8^{th}$ generation and 16 GB RAM.

## 4 Experimentation and Results

In this section, we elaborate everything regarding experimentation performed on the dataset through different architectures which consist of different parameters and we select the best model for classification which is more stable in performance. We divide this section as 4.1 Experiments and Analysis, 4.2 Results of Selected Architecture.

### 4.1 Experiments and Analysis

We implemented different parameters in different CNN architectures for finding the best model. For the different implementations, we had various parameters such as the number of artificial layers and convolutional layers, regularization parameters like L1, L2, Batch normalization and Dropout, image input sizes, kernel sizes, pooling matrix sizes, and analogize all the architectures on a basis of maximum accuracy achieved during training and least cross-entropy loss encountered during training. The best model was selected based on objective function value which can be expressed as

$$Objective\ Function\ Value = \frac{MVA}{TT + LVCEL} \qquad (4)$$

Table 3 contains all the information regarding all the 15 different CNN architectures with maximum accuracy, least cross-entropy loss with training time in seconds for the training of the model, and Table 2 consists of all meaning of abbreviations used in Table 3. Fig. 4 tells us about structure regarding each architecture based on LVCEL, MVA, and TT. Fig. 6 plots the training accuracy and Fig. 7 plots the cross-entropy loss of each architecture concerning each epoch. From table 3 we observed that architecture 4 performed poorly concerning MVA and LVCEL as it had the least objective function value of 0.6073. This might be happened due to batch normalization as when BatchNorm is implemented it reduces training time with the drop in accuracy which leads to a fall in objective function value of this architecture and it restricted the model from building relationships with the dataset. We also noticed a directly proportional connection between the training time and our different CNN architectures. As in architectures 5, 6, and 13 we have fed image size of (64, 64) which reduced training time drastically so we can conclude that TT is highly dependent upon IS. More number of layers the computational task increases on training the models and load on computational power in training the neural network increases when the intensive task is performed. Earlier, as we have mentioned regarding TT (Fig.5 (c)) changes drastically when there is an increase or decrease in architecture size i.e. when we increase or decrease the layers of CNN and ANN or apply different parameters but in Table 3 LVCEL and MVA there is no drastic change. However, the maximum objective function value was achieved by the 13th model which was 1.84 and the minimum objective function value was scored by the 4th model as 0.6073. By this, we can finally conclude that simple architecture performs better and are more stable and accurate. Either model will overfit or underfit if we implement more features and layers. For further consideration, we have taken architecture 13 as an ideal model to evaluate model performance on the brain MRI dataset in the next section.
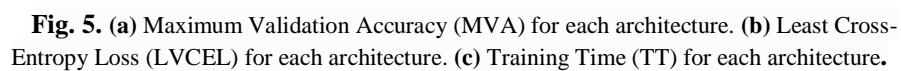
**Table 2.** Abbreviations used in Table 3.

| Abbreviation | Meaning |
|---|---|
| CL | The number of CNN Layers in an architecture. |
| AL | The number of CNN Layers in an architecture. |

| L1 | Level 1 regularizations |
|---|---|
| L2 | Level 2 regularizations |
| BN | Batch Normalization |
| DO | Dropout |
| IS | Input Size of image (64x64 or 128x128) |
| FD | Feature detected in a convolutional layer, layer-wise. |
| KS | Kernel Sizes for each convolutional layer, layer-wise. |
| PS | Pooling Sizes followed by every convolutional layer always assumed to be a square matrix. |
| TT | Time taken in seconds to train the model. |
| LVCEL | Least Validation Cross-Entropy Loss achieved during training. |
| MVA | Maximum Validation Accuracy was achieved during training. |

**Table 3.** Performance of 15 different CNN architectures on various parameters.

| S. no. | CL | AL | Regularization | | | | IS | FD | KS | PS | LVCEL | MVA | TT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | L1 | L2 | BN | DO | | | | | | | |
| 1 | 2 | 3 | ✗ | ✗ | ✗ | ✗ | (128, 128) | {64,32} | {9,3} | {4,2} | 0.3339 | 0.8518 | 195 |
| 2 | 2 | 4 | ✗ | ✗ | ✗ | ✗ | (128, 128) | {64,32} | {9,3} | {4,2} | 0.3710 | 0.8491 | 209 |
| 3 | 2 | 4 | ✗ | ✗ | ✓ | ✓ | (128, 128) | {64,32} | {9,3} | {4,2} | 0.3800 | 0.8491 | 216 |
| 4 | 2 | 4 | ✗ | ✗ | ✓ | ✗ | (128, 128) | {64,32} | {9,3} | {4,2} | 0.3801 | 0.8329 | 219 |
| 5 | 2 | 4 | ✗ | ✗ | ✗ | ✓ | (64,64) | {64,32} | {9,3} | {4,2} | 0.5461 | 0.7358 | 131 |
| 6 | 2 | 2 | ✗ | ✗ | ✗ | ✗ | (64,64) | {64,32} | {9,3} | {4,2} | 0.5651 | 0.7224 | 134 |
| 7 | 2 | 3 | ✗ | ✗ | ✓ | ✓ | (128, 128) | {64,32} | {9,3} | {4,2} | 0.3281 | 0.8464 | 220 |
| 8 | 3 | 4 | ✗ | ✗ | ✓ | ✗ | (128, 128) | {128,64,32} | {9,6,3} | {4,2,2} | 0.3900 | 0.8518 | 211 |
| 9 | 3 | 5 | ✗ | ✓ | ✗ | ✗ | (128, 128) | {128,64,32} | {9,6,3} | {4,2,2} | 0.3811 | 0.8383 | 196 |
| 10 | 4 | 4 | ✓ | ✗ | ✗ | ✓ | (128, 128) | {128,64,32,16} | {9,6,3,3} | {4,2,2,2} | 0.4100 | 0.8167 | 192 |
| 11 | 4 | 5 | ✓ | ✓ | ✗ | ✗ | (128, 128) | {128,64,32,16} | {9,6,3,3} | {4,2,2,2} | 0.3486 | 0.8652 | 181 |

|    |   |   |   |   |   |   | (128,128) | {128,64,32,16} | {9,6,3,3} | {4,2,2,2} | 0.4146 | 0.8571 | 180 |
|----|---|---|---|---|---|---|-----------|----------------|-----------|-----------|--------|--------|-----|
| 12 | 4 | 5 | ✕ | ✕ | ✕ | ✕ | (128, 128) | {128,64, 32,16} | {9,6 ,3,3 } | {4,2,2, 2} | 0.4146 | 0.8571 | 180 |
| **13** | **4** | **5** | **✕** | **✕** | **✕** | **✕** | **(64,6 4)** | **{64,32,3 2,16}** | **{9,6 ,3,3 }** | **{2,2,2, 2}** | **0.4480** | **0.8275** | **106** |
| 14 | 5 | 5 | ✕ | ✕ | ✕ | ✕ | (128, 128) | {128,64, 64,32,16 } | {9,6 ,6,3, 3} | {2,2,2, 2,2} | 0.4012 | 0.8464 | 184 |
| 15 | 5 | 6 | ✕ | ✕ | ✕ | ✕ | (128, 128) | {128,64, 64,32,16 } | {9,6 ,6,3, 3} | {2,2,2, 2,2} | 0.4040 | 0.8356 | 182 |



**Fig. 5.** (a) Maximum Validation Accuracy (MVA) for each architecture. (b) Least Cross-Entropy Loss (LVCEL) for each architecture. (c) Training Time (TT) for each architecture.
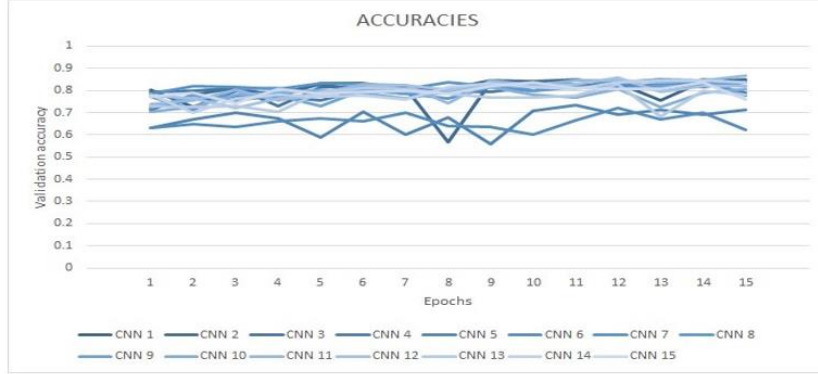
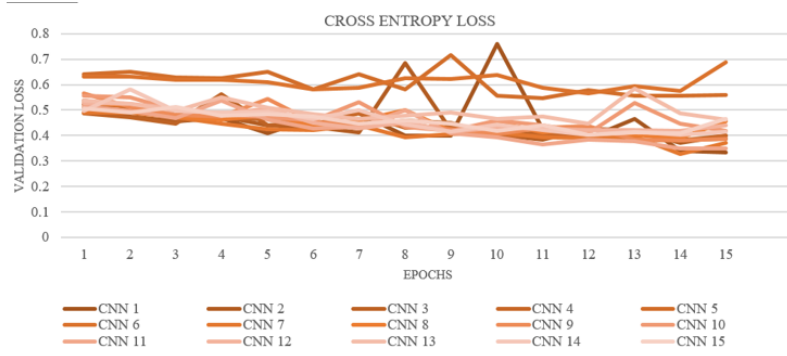**Fig. 6.** Validation accuracy training curve for each architecture per epoch.



**Fig. 7.** Validation cross-entropy loss training curve for each architecture per epoch.

## 4.2 Result of Selected Architecture

We have selected architecture 13 as the model performance was good and achieved a higher objective function value. As the evaluation metrics, we use the confusion matrix and calculate the precision, recall, and F1 score.

$$Precision = TP/(TP + FP)$$

(5)

$$Recall = TP/(TP + FN)$$

(6)

$$F1\ Score\ = \frac{(2 \times Precision \times Recall)}{(Precision +\ Recall)} \qquad (7)$$

Where TP, TN, FP, and FN are True Positive, True Negative, False Positive, and False Negative respectively. See Fig.8 illustrates the confusion matrix of the selected model where augmented testing was done on 371 images but for evaluation of confusion matrix and calculation, we have used 51 images for calculating the accuracy and stability of our model. A dataset was small we implemented data augmentation to enlarge our dataset and for testing, we cannot use augmented images so we considered 51 images that are not augmented then testing was performed on architecture.



**Fig. 8.** The confusion matrix for architecture 12 (see **Table 3**). From the figure, we see that TP=28, TN=19, FP=3 and FN=1.

From equation 3, 4 and 5 we calculated $Precision = 0.90322$ , $Recall = 0.9655$, and $F1 - Score = 0.93331$. All three metrics are above 90% this indicates that our model was accurate and performed excellently in diagnosing the positive brain tumor and also negative cases. Moreover, the ROC curve is illustrated in See Fig. 9 where the area under the curve (AUC) was found to be 0.737 which is good. These metrics are good and are comparable with various architectures based on Brain tumor detection.
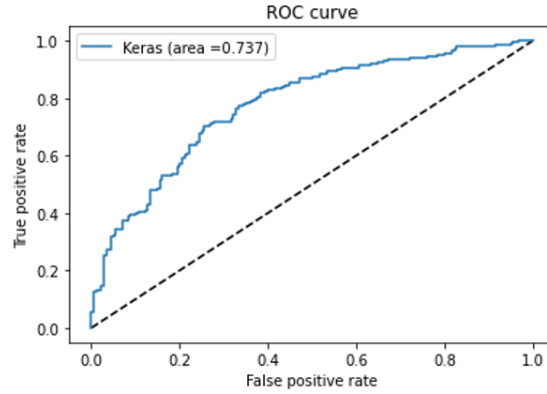
**Fig. 9**. The receiver-operating characteristics (ROC) curve for 13th CNN architecture. The area under the curve is calculated to be 0. 737 units.

## 5. Conclusions and Future Work

In this paper, we make an effort to find out the best approach for brain tumor detection using MRI images by comparing all the performance by 15 different CNN architecture. Based on objective function value we selected the ideal model which is easy to train, detecting tumor faster as compared to other architectures, and training time was less with more accuracy and stability. The metrics of selected architecture compared to other ones are simpler as if architectures get complex the training time increases and there is no such increase in accuracy and quality of the model. As learned from the findings in research work, we recommend that the simpler architectures perform best and are more stable and reliable than the complex ones. We admit that architecture 13 can perform better and can gain higher level accuracy and stability if we do small adjustments and experimented upon more. Future work on brain tumor detection can also be done through ResNet and different architectures and models can be trained for getting better results in less time so that they can be taken along with Brain MRI images for better diagnosis of the tumor. ECG classification can also be used in detection of brain tumor as models will be highly stable with high accuracy with less complexity [52]. Generative modelling can also be used as machine learning technique for brain tumor detection for finding the best parameters without large fluctuations in accuracy of dataset [53]. Transfer learning with CNN can play an important role as models are highly trained on heavy parameters and stability of model can be increased by transfer learning technique as we can see paddy crop detection gave good accuracy [54-56]. So brain tumor detection which is sensible case can give best outcome via transfer learning and can be a better diagnosis of tumor.

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