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Comparative Analysis on Deep Convolutional Neural Network for Brain Tumor Data Set

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***Abstract*---**Deep Learning is a subdivision of machine learning and Artificial intelligence (AI). Autonomous Deep learning enables human brain to think and learn computers. In recent days Deep learning is used in many domains, especially in medical field. It is used mainly in classification. The Convolutional Neural Network (CNN) is one among the best technique in DL. It is best suitable in image classifications. CNN is directed to process the data into multiple layers of arrays. It is used for computationally efficient. Brain Tumor is one of the dangerous diseases in India as well as the whole world. A brain tumor is an unwanted cell in the brain. Brain tumor symptoms are based on size, location and type .There are two types of brain tumor. Brain tumor tissue affects on the brain that is called primary tumor. Brain tumor tissue affects in outside the brain that is called as secondary tumor (metastatic).In this paper, we are analyzing various Deep Convolution Neural Network on brain tumor perspectives. Here, LeNet, AlexNet, ResNet-18, VGG Net-16 are discussed and Evaluation metrics like Accuracy, F1 score, Precision, Recall are used to identify the performance of the above techniques.

***Keywords*---**deep learning, CNN, LeNet, AlexNet, VGG Net-16, ResNet-18.

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Introduction

Deep Learning (DL) algorithm has been used in the health care mainly for the Classification of brain tumor data. MRI brain tumor image helps to extract brain tumor. DL is an emerging field of artificial intelligencethat has become an art and science topic in a wide range of scientific disciplines. The success of DL reflects in day to day life mainly in education, medical, transportation, manufacturing and automotive etc.

A brain tumor is an uncontrolled cell in brain. One type of brain tumor that start in the brain, known as the primary tumor, another type brain tumor that the body and migrate towards the brain, known as the secondary tumor (metastasis tumor). Headaches, vomiting, personality changes and confusion these are the symptoms of brain tumor. The tumors are split into different grades such as grade1 & grade 2tumor. Grade 1 tumor grow quite slowly, known as non-cancerous (benign) tumor, and the grade 2 tumor grow more quickly, known as cancerous (malignant) tumor [14].

A meningioma is a tumor that develops inside the skull cover that the brainor spinal cord. Meningioma tissue affect in brain that is called as primary tumor. Meningioma tumor grows quite slowly, known as benign tumor. Meningioma can start in the central nervous system. Some meningioma tumor grows more quickly, known as malignanttumor.A pituitary tumor is an unwanted growth in pituitary gland. Pituitary tumor can start in the brain that is called as primary tumor. Pituitary tumor grows quite slowly, known as benign tumor and don’t spread to other organs. Pituitary tumor makes hormones that affect more other glands and more functions in your body.Some pituitary tumor grow more quickly, known as malignant tumor. A glioma is a tumor that develops in the brain and spinal card. Gliomas are divided into four grades (I to gradeIV) [5].

A Convolutional Neural Network is nothing but an efficient recognition algorithm. CNNs are used for pattern recognition and image processing. There are two types of CNN features. The low level features such as edges, blobs, color and gradient orientation etc. The high level features such as objects and events. Image processing techniques are used to low level feature extraction. Machine learning techniques are used to high level feature extraction [14].Convolution Neural Network algorithm is used for image processing to say the brain images are benign tumor and malignant tumor [12].

Literature review

In [8], they described about the development of Convolutional Neural Network architectures together with their main features. In this paper, Deep Learning CNN was performed based on ends with the evolution matrix, benchmark datasets. These also help to several performance features are universal learning approach, robustness, generalization and scalability. CNN architecture contains Convolutional Layer, Pooling Layer, Activation Function, Fully Connected Layer, and Loss Functions. Convolutional Layers contains Kernel, Convolutional Operation, Sparse Connectivity and Weight Sharing. Pooling Layer consists of tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max pooling. Activation Layer consists of Sigmoid, TanH, ReLU, Leaky ReLU, Noisy ReLU, and Parametric Linear Units. Fully Connected Layercontains multiple-layer perceptron, neural network, feed-forward ANN and fattening also. Loss Functions Consists of Cross-Entropy or Softmax Loss Function, Euclidean Loss Function and Hinge Loss Function. Regularization to CNN was performed to avoid over-fitting and under-fitting. Regularization to CNN contains Dropout, Drop-Weights, Data Augmentation and Batch Normalization. CNN learning process was founded on numerous learnable parameters or minimizing the error. There are two major issues. : The first issue is the learning algorithm selection and another one is the use of many enhancements.

In [17], LeNet was used to classifying images according to the tumor type. In this paper, the LeNet architecture is used to improve the accuracy by some modification in the arrangement and number of layers. LeNet classification method takesgrayscale images as the input.It combines two convolutions and the pooling layer used to process the output. In [15], LeNet was used to a similar comparison and similar analysis. In this paper, LeNet classification was performed based on DBAP layer and optimizer was selected accordingly. DBAP layer is used to capture local features of images. In [10] for both dataset sizes, F-scores and accuracy of LeNet were consistently high. In order to calculate overhead, the LeNet model with entropy-based images was used because it was the most secure. In [6] the architecture, LeNet, is made up of two convolution layers and two fully connected layers. The first convolution layer is made up of 6 filters in size 3x3 with maximum pooling in size 2x2, and the second convolution layer is made up of 16 filters in size 5x5 with maximum pooling in size 2x2. The first fully connected layer is made up of 120 nodes.There are 84 nodes in the second fully connected layer. Each node in the output makes use of LeakyRelu activation. The most appropriate architecture for representing the multispectral image-pigment content relationship is LeNet.

As described in [9], Image classification has been used in the medical field for the classification of brain tumors. The dropout function helps to avoid overfitting. In this method, relatively large amounts of data are used. In [13], AlexNet architecture was used to classify glioma, meningioma, and pituitary brain tumors. AlexNet architecture contains five layers are convolution layers and the last three layers are fully connected layers. It is used to train on millions of images. It is able to classify an image into 1000 different object categories. AlexNet architecture was used to make it compatible with brain tumor classification.

SnehaGrampurohit et al. [16] proposed the classifier network and region proposal network. It combines two of the most common approaches to classification. The first approach uses detection and the second approach uses classification. The results showed that this improved method is able to achieve an average precision of 89.45% for meningioma, 75.18% for glioma, and 68.18% for a pituitary tumor. Additionally, this paper presents a performance measure. The results showed that this improved algorithm achieved a mean average precision of 77.60% for all the classes.

Deepa P L et al. [3] proposed automating the detection process. Technique for automating detection processes using pre-trained networks such as ResNet. The ResNet 101 architecture is one of the most commonly used architecture for detecting brain tumors and automating the process. In [11], For the ResNet model, various setups of ResNets with 18, 34, 50,101, and 152 layers. In this paper, ResNet layers are used to compose of several blocks. Reset is the most widely used architecture to achieve minimum computation running time compared to other techniques.

Methodology

A Deep learning algorithm has been used in the medical field for the Classification of brain tumor. MRI brain tumor image helps to extract brain tumor. CNN architecture contains Convolutional Layer, Pooling Layer, Activation Function, Fully Connected Layer, and Loss Functions. Convolutional Layers are analyzed by Kernel, Convolutional Operation, Sparse Connectivity and Weight Sharing. Pooling Layers consists of tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max pooling. Activation Layers contains Sigmoid, Tanh, ReLU, Leaky ReLU, Noisy ReLU, and Parametric Linear Units. Fully Connected Layerconsists of multiple-layer perceptron, neural network, feed-forward ANN and fattening also.

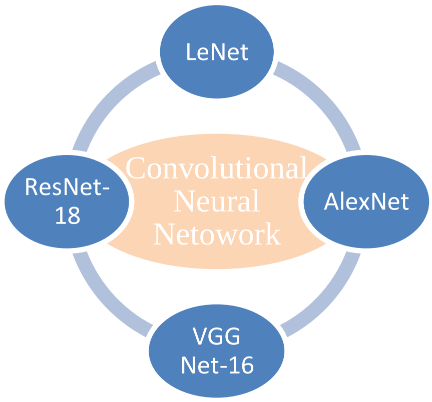

Figure 1. Types of CNN

LeNet

LeNet is a CNNs structure developed by YannLeCun et al. in 1989 [1].LeNet architectures contains 3 Convolution Layers and 2 fully connected layers. Pooling layers are used to speed up the learning process and to reduce the size of dimensions. Here, Average pooling is used to find the average value patches of a feature map. Padding and stride are used shift in one layer to another layer.The following fig 2 represents the architecture of LeNet.

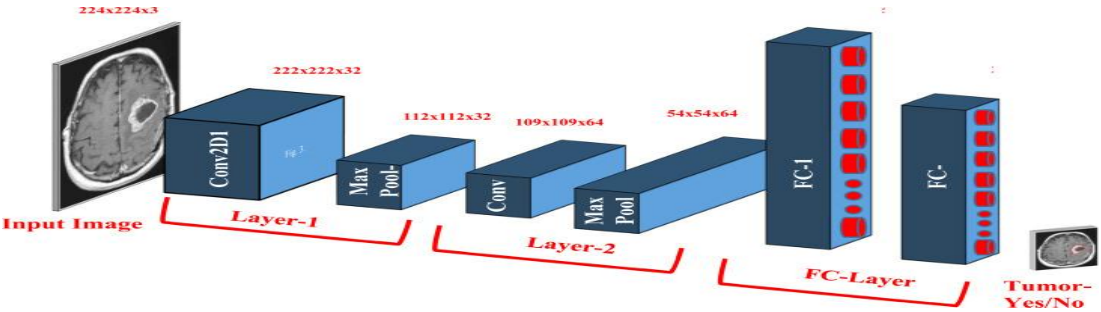

Figure 2. LetNet architecture

The following Table 1represents the LeNet layers details.

Table 1
LeNet Layers Detail

No of Layers (5)	Input Image Size	Filter	Filter Size	Feature Map	Activation
Conv Layer 1	32x32x1	6	5x5	28x28x6	Tanh
Avg Pool -1	28x28x6	6	2x2	14x14x6	Tanh
Conv Layer 2	14x14x6	16	5x5	10x10x16	Tanh
Avg Pool-2	10x10x16	16	2x2	5x5x16	Tanh
Conv Layer 3	5x5x16	120	5x5	1x1x120	Tanh
Full Connected Layer 4	-	-	-	84	Tanh
Full Connected Layer 5	-	-	-	10	Softmax

LeNet Algorithm	
Step 1:	Input the image (32x32x1)
Step 2:	Convolutional layer 1(5x5 size 6 filters are used). It produces output of the feature map size 28x28x6.
Step 3:	Average pooling is used (2x2 size 6 filters are used) It produces output of the feature map size 14x14x6.
Step 4:	Convolutional layer 2(5x5 size 16 filters are used). It produces output of the feature map size 10x10x16.
Step 5:	Average pooling is used (2x2 size 6 filters are used) It produces output of the feature map size 5x5x16.
Step 6:	Convolutional layer 3(5x5 size 120 filters are used). It produces output of the feature map is 1x1x120.
Step7:	Layer 4 is the Fully Connected Layer.
Step8:	Layer 5 is an output layer. (Softmax activation function is used).

AlexNet

AlexNet is a CNN structure developed by Krizhevsky et al [2]. in 2012.AlexNet architecture consists of 8 layers, in which by 5 Convolution Layers and 3 fully connected layers. Pooling layers are used to speed up the learning process and to reduce the size of dimensions. Padding is used for the area of an image shift from one layer to another layer. Stride is usedshifts pixel in one layer to another layer. The following fig 3 shows the architecture of AlexNet.

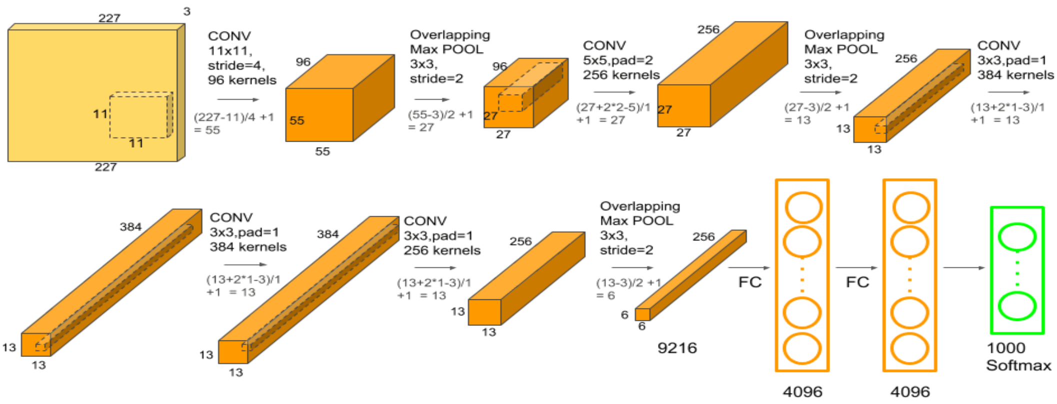

Figure 3. AlexNet architecture

The following Table 2shows the AlexNet layers details

Table 2
AlexNet layers detail

No of Layers (8)	Input Image Size	Filters	Filter Size	Feature Map	Activation
Conv Layer 1	227x 227x3	96	11x11	55x55x96	ReLu
Max Pool1	55x55x96	96	3x3	27x27x96	Relu
Conv Layer 2	27x27x96	256	5x5	27x27x256	Relu
Max Pool2	27x27x256	256	3x3	13x13x256	Relu
Conv Layer 3	13x13x256	384	3x3	13x13x384	Relu
Conv Layer 4	13x13x384	384	3x3	13x13x384	Relu
Conv Layer 5	13x13x384	256	3x3	13x13x256	Relu
Max Pool3	13x13x256	256	3x3	6x6x256	Relu
Fully Connected Layer 6	-	-	-	4096	Relu
Fully Connected Layer 7	-	-	-	4096	Relu
Fully Connected Layer 8	-	-	-	1000	Softmax

AlexNetAlgorithm	
Step 1:	Input the image (227x227x3)
Step 2:	Convolutional layer 1(11x11 size 96 filters are used). It produces output of the feature map size 55x55x96.
Step 3:	Max pooling is used (3x3 size 96 filters are used) It produces output of the feature map size 27x27x96.
Step 4:	Convolutional layer 2(5x5 size 256 filters are used). It produces output of the feature map size 27x27x256.

Step 5:	Max pooling is used (3x3 size 256 filters are used)It produces output of the feature map size 13x13x256.
Step 6:	Convolutional layer 3(3x3size 384 filters are used). It produces output of the feature map size 13x13x384.
Step7:	Convolutional layer 4(3x3size 384 filters are used). It produces output of the feature map size 13x13x384.
Step 8:	Convolutional layer 5(3x3size 256 filters are used). It produces output of the feature map size 13x13x256.
Step 9:	Max pooling is used (3x3 size 256 filters are used)It produces output of the feature map size 6x6x256.
Step 10:	Layer 6 and 7 is the Fully Connected Layer.
Step 11:	Layer 8 is an output layer. (Softmax activation function is used).

VGG 16

VGG-16 is a CNN structure developed by Karen Simony et al. in 2014[4].VGG-16 the architecture contains 13 Convolution Layers and 3 fully connected layers. Pooling layers are used to speed up the learning process and to reduce the size of dimensions. Padding and stride are used shifts from one layer to another layer. The following fig 4 represents the architecture of VGG-16.

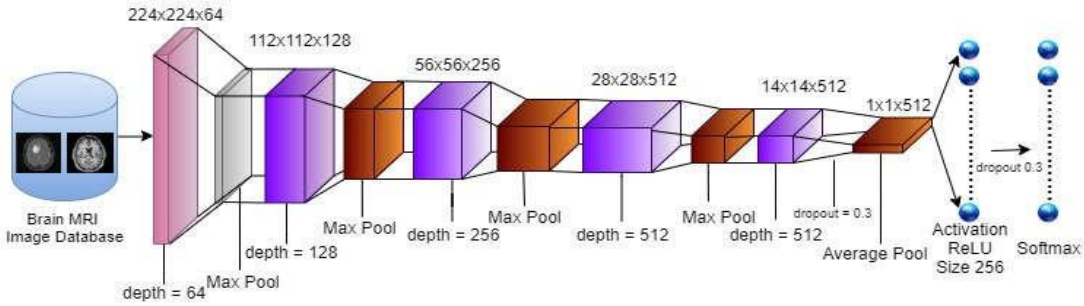

Figure 4. VGG-16 architecture

The following Table 3 represents the AlexNet layers details.

Table 3
VGG-16 layers detail

No of Layers (16)	Input Image Size	Filters	Filter Size	Feature Map	Activation
Conv Layer 1	224x224x3	64	3x3	224x224x3	ReLu
Conv Layer 2	224x224x3	64	3x3	224x224x3	ReLu
Max - pool	224x224x3	64	2x2	112x112x64	ReLu
Conv Layer 3	112x112x64	128	3x3	112x112x128	ReLu
Conv Layer 4		128	3x3	112x112x128	ReLu
Max-pool	112x112x128	128	2x2	56x56x128	ReLu
Conv Layer 5	56x56x128	256	3x3	56x56x256	ReLu
Conv Layer 6	56x56x256	256	3x3	56x56x256	ReLu
Conv Layer 7	56x56x256	256	3x3	56x56x256	ReLu
Max - pool	56x56x256	256	2x2	28x28x256	ReLu

Conv Layer 8	28x28x256	512	3x3	28x28x512	ReLu
Conv Layer 9	28x28x512	512	3x3	28x28x512	ReLu
Conv Layer 10	28x28x512	512	3x3	28x28x512	ReLu
Max-pool	28x28x512	512	2x2	14x14x512	ReLu
Conv Layer 11	14x14x512	512	3x3	14x14x512	ReLu
Conv Layer 12	14x14x512	512	3x3	14x14x512	ReLu
Conv Layer 13	14x14x512	512	3x3	14x14x512	ReLu
Max-pool	14x14x512	512	2x2	7x7x512	ReLu
Fully Connected Layer 14	-	-	-	4096	ReLu
Fully Connected Layer 15	-	-	-	4096	ReLu
Fully Connected Layer 16	-	-	-	1000	Softmax

VGG -16 Algorithm	
Step 1:	Input the image (224x224x3).
Step 2:	Convolutional layer 1(3x3size 64 filters are used). It produces output of the feature map size 224x224x64.
Step 3:	Convolutional layer 2(3x3size 64 filters are used). It produces output of the feature map size 224x224x64.
Step 4:	Max pooling is used (2x2 size 64filters are used) It produces output of the feature map size 112x112x64.
Step 5:	Convolutional layer 3(5x5 size 128 filters are used). It produces output of the feature map size 112x112x128.
Step 6:	Convolutional layer 4(5x5 size 128 filters are used). It produces output of the feature map size 112x112x128.
Step 7:	Max pooling is used (2x2 size 128filters are used)It produces output of the feature map size 56x56x128.
Step 8:	Convolutional layer 5(3x3size 256 filters are used). It produces output of the feature map size 56x56x256.
Step9:	Convolutional layer6(3x3size 256 filters are used). It produces output of the feature map size 56x56x256.
Step 10:	Convolutional layer7(3x3size 256 filters are used). It produces output of the feature map size 56x56x256.
Step 11:	Max pooling is used (2x2 size 256 filters are used)It produces output of the feature map size 28x28x256.
Step 12:	Convolutional layer 8(3x3size 512filters are used). It produces output of the feature map size 28x28x512.
Step 13:	Convolutional layer 9(3x3size 512 filters are used). It produces output of the feature map size28x28x512
Step 14:	Convolutional layer 10(3x3size 512 filters are used). It produces output of the feature map size 28x28x512.
Step 15:	Max pooling is used (2x2 size 512filters are used) Pooling layer output of the feature map is 14x14x512.
Step 16:	Convolutional layer 11(3x3size 512filters are used). It produces output of the feature map size 14x14x512.
Step 17:	Convolutional layer12 (3x3size 512 filters are used). It produces output of the feature map size 14x14x512.

Step 18:	Convolutional layer 13(3x3size 512 filters are used). It produces output of the feature map size 14x14x512.
Step 19:	Layer 14 and 15is the Fully Connected Layer.
Step 20:	Layer 16 is an output layer. (Softmax activation function is used).

ResNet-18

ResNet-18 is a CNN structure developed by Kaiming Heet al.in 2015 [7]. ResNet-18 architecture is consists of 18 layers, in which 13 Convolution Layers and 3 fully connected layers. Pooling layers are used to speed up the learning process and to reduce the size of dimensions. Padding is used for the area of an image shift from one layer to another layer. Stride is used to shiftspixel from one layer to another layer. The following fig 5 shows the architecture of ResNet -18.

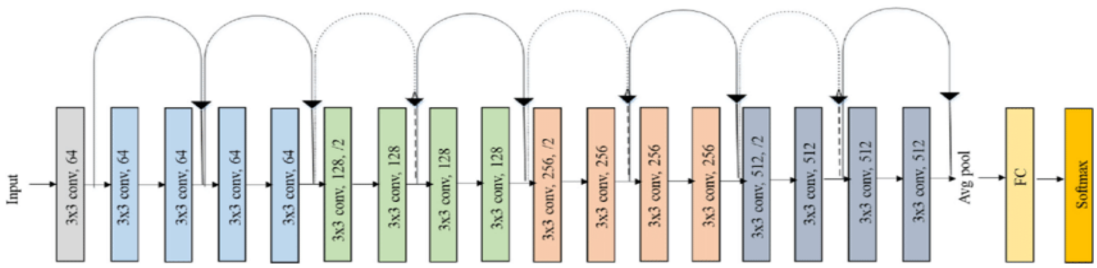

Figure 5. ResNet-18 architecture

The following Table 4 represents the ResNet-18 layers details.

Table 4
ResNet-18 layers detail

No of Layers (18)	Input Image Size	Filters	Filter Size	Feature Map	Activation
Conv Layer 1	227x277x3	64	7x7	112x112x64	ReLu
Max-pool	112x112x64	64	3x3	56x56x64	ReLu
Conv Layer 2	56x56x64	64	3x3	56x56x64	ReLu
Conv Layer 3	56x56x64	64	3x3	56x56x64	ReLu
Conv Layer 4	56x56x64	64	3x3	56x56x64	ReLu
Conv Layer 5	56x56x64	64	3x3	56x56x64	ReLu
Conv Layer 6	56x56x64	128	3x3	28x28x128	ReLu
Conv Layer 7	28x28x128	128	3x3	28x28x128	ReLu
Conv Layer 8	28x28x128	128	3x3	28x28x128	ReLu
Conv Layer 9	28x28x128	128	3x3	28x28x128	ReLu
Conv Layer 10	28x28x128	256	3x3	14x14x256	ReLu
Conv Layer 11	14x14x128	256	3x3	14x14x256	ReLu
Conv Layer 12	14x14x128	256	3x3	14x14x256	ReLu
Conv Layer 13	14x14x128	256	3x3	14x14x256	ReLu
Conv Layer 14	14x14x128	512	3x3	7x7x512	ReLu
Conv Layer 15	7x7x512	512	3x3	7x7x512	ReLu
Conv Layer 16	7x7x512	512	3x3	7x7x512	ReLu
Conv Layer 17	7x7x152	512	3x3	7x7x512	ReLu
Average pool	7x7x152	512	7x7	1x1x512	ReLu
Layer 18	1x1x152			1000	Softmax

ResNet-18 Algorithm
Step 1: Input the image (277x277x3). Step 2: Convolutional layer 1(7x7size 64 filters are used). It produces output of the feature map size 112x112x64. Step 3: Max pooling is used (3x3 size 64filters are used) It produces output of the feature map size 56x56x64. Step 4: Convolutional layer 2(3x3size 64 filters are used). It produces output of the feature map is 56x56x64. Step 5: Convolutional layer 3(3x3size 64 filters are used). It produces output of the feature map size 56x56x64. Step 6: Convolutional layer 4(3x3size 64 filters are used). It produces output of the feature map size 56x56x64. Step 7: Convolutional layer 5(3x3size 64 filters are used). It produces output of the feature map size 56x56x64. Step 8: Convolutional layer 6(3x3size 128 filters are used). It produces output of the feature map size 28x28x128. Step 9: Convolutional layer 7(3x3size 128 filters are used). It produces output of the feature map size 28x28x128. Step 10: Convolutional layer 8(3x3size 128 filters are used). It produces output of the feature map size 28x28x128. Step 11: Convolutional layer 9(3x3size 128 filters are used). It produces output of the feature map size 28x28x128. Step 12: Convolutional layer 10(3x3size 256 filters are used). It produces output of the feature map size 14x14x256. Step 13: Convolutional layer 11(3x3size 256 filters are used). It produces output of the feature map size 14x14x256. Step 14: Convolutional layer 12(3x3size 256 filters are used). It produces output of the feature map size 14x14x256. Step 15: Convolutional layer 13(3x3size 256 filters are used). It produces output of the feature map size 14x14x256. Step 16: Convolutional layer 14(3x3size 512 filters are used). It produces output of the feature map size7x75x12. Step 17: Convolutional layer 15(3x3size 512 filters are used). It produces output of the feature map size 7x75x12. Step 18: Convolutional layer 16(3x3size 512 filters are used). It produces output of the feature map size 7x75x12. Step 19: Convolutional layer 17(3x3size 512 filters are used). It produces output of the feature map size 7x75x12. Step 20: Average pooling is used (7x7 size 512 filters are used)It produces output of the feature map size 1x1x512. Step 21: Layer 18 is an output layer. (Softmax activation function is used).

Experimental Setup

Dataset Description

Dataset is from the Kagglewebsite. The dataset comprises 3264 brain MRI imagesclassified into four classes: glioma, meningioma, pituitary, and no tumor, with image numbers 926,937, 901, and 500, respectively.

Evaluation Metrics

Accuracy

Accuracy is anevaluationmetric. Accuracy is used to ensure the model performs across all classes and that all classes are of equal importance. A prediction's accuracy is represented by the ratio of correct predictions to total predications.

$$\text{Accuracy} = \frac{\text{True}_{\text{positive}} + \text{True}_{\text{negative}}}{\text{True}_{\text{positive}} + \text{True}_{\text{negative}} + \text{False}_{\text{positive}} + \text{False}_{\text{negative}}} \qquad \text{Equation (1)}$$

Precision

Precision is the fraction of relevant instances among the retrieved instances. It is deliberate as the ratio between the numbers of positives to the total numbers of positives (either positive or negative).

$$\text{Precision} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}} + \text{False}_{\text{positive}}} \qquad \text{Equation (2)}$$

Recall

The recall is the selection of proper instances that were rescue. It is calculated as the ratio between the numbers of positives to the total numbers of positives.

$$\text{Recall} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}} + \text{False}_{\text{negative}}} \qquad \text{Equation (3)}$$

F1 Score

There are two buildings of the F1 Score. One is precision and the other one is recall. F1 Score is used to combine the precision and recall metrics into a single metric.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad \text{Equation (4)}$$

Results

Performance evaluation is based on accuracy, precision, Recall, F1 Score. To compare the performance with different architectures, LeNet, AlexNet, VGG Net and ResNet are selected for performance comparison.

Table 5
Performance analysis of various deep CNN techniques

	Accuracy	Precision	Recall	F1 Score
LeNet	0.8775	0.8912	0.8647	0.8753
AlexNet	0.8975	0.8841	0.9119	0.899
VGG Net-16	0.9000	0.9124	0.8883	0.8985
ResNet-18	0.9450	0.9406	0.9495	0.9453

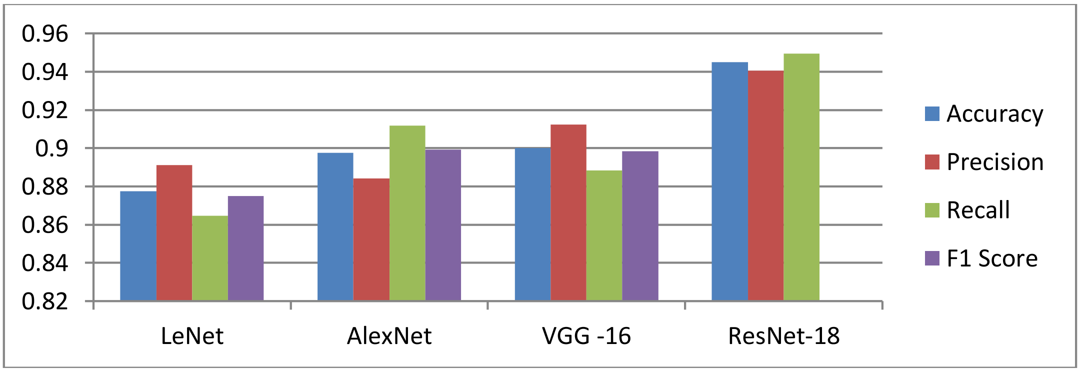

Figure 6. Graphical representation

Conclusion

The conclusion of this extensive research must be preceded by a brief discussion including all relevant data. For the brain tumor analysis, its performance was compared with that of pretrained LeNet, AlexNet, VGGNet, and ResNet. The kaggle brain tumor data set contains 3264 records. In the process of model building and evaluation, we used a tenfold cross validation approach, where we divided the data set into 10 mutually exclusive partitions using a stratified sampling technique. Out of the ten partitions, seven were used for training, and the remaining was used for testing. Accuracy, Precision, Recall, F1Score, are calculated for all four models. We found that ResNet performs well with an Accuracy measure of 96%.

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