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# Detection and Classification of Brain Tumor on MR Imaging using Deep Neural Network based VGG-19 Architecture

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**Abstract***: The massive growth of abnormal cell development in the brain region is known as a tumor. It is treated as a high prior disease in the modern medical domain, and it is difficult to cure. This type of tumor can be controlled only if it is diagnosed at an earlier stage. For making the accurate analysis and diagnosis process, the MR imaging tool is used by the radiologist. The exact portion of the tumor can be addressed by an MR image from the brain region. A deep convolutional neural network-based (DCNN) on Visual Geometry Group (VGG-19) architecture is proposed to detect the malignant portion in the brain region from the brain magnetic resonance imaging (MRI) dataset. The publically available BraTS dataset is used in our experimental study. The proposed DCNN uses a layer-based automatic segmentation and classification technique, and the hierarchy of the system is followed by, preprocessing, segmentation, feature extraction, and classification. A softmax classifier is used alongside the classification process, in order to classify the brain MR images efficiently. All together, obtained training and testing accuracy outcome of the proposed system is 99.2%, and the training and testing loss outcomes are 0.158 and 0.138 respectively.*

Keywords: *Magnetic resonance imaging, BraTS dataset, DCCN, VGG-19, and Softmax classifier*.

## INTRODUCTION

The World Health Organization (WHO) has released the statement that states that cancer is treated as a second primary reason of death rate globally. The possibility of preventing or reducing the death rate can be done by diagnosing cancer at an earlier stage. The stages of cancer are classified as benign and Glioma respectively. Here, a benign tumor is considerably slow in spreading rate, it does not disturb other organs of the human body, and the life span of the patient is sufficiently higher than Glioma, and it is a curable tumor. Gliomas are the tumors that are found in brain tissues, and meningiomas are found in membranes of the brain, finally, the pituitary tumors are located inside the portion of the skull (MilicaM. Badža *et al*. (2020)). Magnetic resonance imaging tool is the common method to detect a tumor in a brain region, and it is based on human subjectivity and a small amount of human observation is required. However, the experienced clinicians may have a chance to detect the malignant portion in the earlier stage, and it depends on the expertise of the radiologists.

Lakshmi *et al*. (2014) proposed a system that has different stages such as preprocessing, ANFIS, feature extraction, and image analysis operation, and used to identify the tumor from the brain region. Figure 1. (a),(b) benign tumors; and (c),(d) malignant tumors. The image segmentation is the post process that is done after the preprocessing, and the brain tumor segmentation performance metric analysis obtained outcome are 0.78 of similarity

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index, 0.0098 of extra fraction, 0.723 of overlap function, and 99.4% of accuracy. The tumor diagnosis work has to be continued until to decide the tumor grade which is based on its characteristics. To distinguish the malignant and normal portions of the tumor by using the proper biopsy treatment is required. This particular treatment is used to provide the required information about the various tumors and their characteristics in the brain region, so it may have a possibility of avoiding surgical operations.

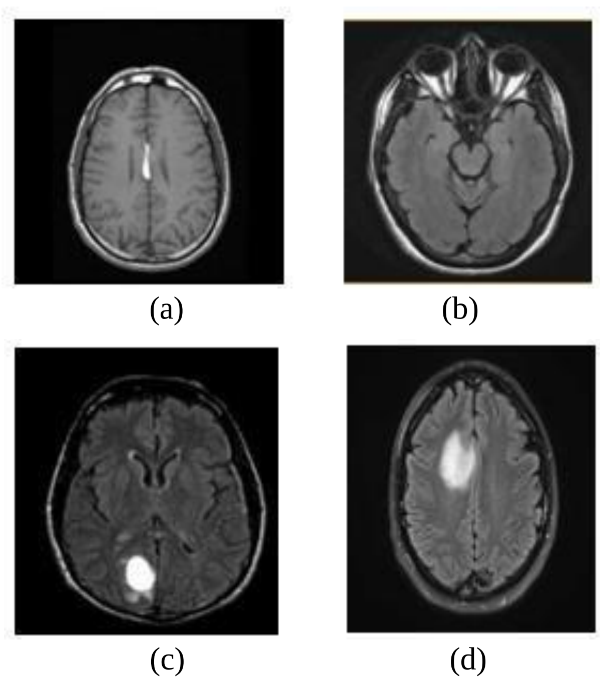


**Figure 1. (a),(b) benign MRI; (c),(d) malignant MRI**

The proposed system uses the DCNN method to detect the brain tumor portion in the MRI image dataset, and we have used VGG-19 architecture to train the deep neural network model (training and testing phase). The proposed DCNN based VGG-19 framework outcome accuracy is superior to the existing traditional techniques such as support vector machine and convolutional neural network.

## RELATED WORK

Sarath Chandra *et al*. (2020) the brain tumor detection has been done by utilizing the CNN and VGG16 model, and it is a deep neural network classification based convolutional neural model towards examining the visual descriptions. The use of CNN is used to sense the supervisions features that belong to the human direction. The use of VGG16 is just because of its superior feature and ease to use. It has 16 layers that are used to commonly address the crucial CNN model issues, and it is an off-the-shelf model for a given task. CNN provides a better accuracy result and enhances the performance of the system. This proposed system describes the experimental explanation and shows how the trained network obtains the outcome. Hassan Ali Khan *et al*. (2020) A CNN model has been used to analyze visual image representation learning and image detection. The data augmentation was used to process the image in order to segregate the malignant and non-malignant portions from the MRI brain scanned image. The author has used the transfer learning technique to compare the performance metric of different methods like VGG-16 and Inception-v3; these are considered as the pre-trained models.

Anushka Singh *et al*. (2020) proposed the customized DNN with a dataset that has small images in size, and the proposed framework operation is based on the VGG-16 model along with the classifier. The proposed system performance metric indexes were calculated and the obtained accuracy outcome is 97.6%. Otman Basir *et al*. (2022) stated that the proposed CNN model obtained the brain tumor classification accuracy of 90% and the fully connected softmax classifier has been used to obtain efficient outcomes in order to validate

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the image classification with respect to accuracy and F1 score values. The F1 score was used to examine the binary classification models and to examine and maintain the stability of recall and precision values. The obtained metric outcome of the softmax classifier is 0.95 of F1 score and 90% of accuracy. Isselmou Abd El Kader *et al*. (2021) Proposed a model that has two-different 2-layer wavelet auto-encoder architecture is used to slices the MR images. These 2-layers consist of 200 and 400 hidden units respectively. In order to detect the benign and malignant image, the training and testing phases have been done by the softmax layer. The MR image pixel pattern analysis has been used to identify the tumor classification accuracy, shirt time, and low thrashing examination. Therefore 2500 images have been unitized from BraTS 2012 to 2015 datasets. The proposed system's brain tumor classification accuracy outcome is 99.3%. Atınç YILMAZ (2021) the proposed multi channel R-CNN model along with 3 datasets have been used to classify the brain tumor portion in MR image datasets. The VGG-16 architecture was involved to obtain the classification accuracy, and it has been compared with other traditional classification techniques. The proposed model obtained brain tumor classification accuracy is 99.8%.

Taeho Jo *et al.* (2020) the best brain tumor classification performance was achieved by the combination of multimodal nero-imaging and fluid bio-markers. However the deep learning model is being used to enhance the performance and quality of the image classification, and to improve the transparency of the particular disease features. Xiaoqing Gu *et al.* (2021) proposed the classification of tumor MR image model by using the convolutional database learning with local constraint. This proposed framework integrates the multi level layer database learning to CNN structure in order to solve the irregular information. Sarath Chandra *et al*. (2020) stated that many of the CNN models that have been proposed such as VGG-16 and ResNet in order to perform training and testing the CNN model for the image classification. The VGG-16 model produces the expected outcome because of its simplicity, and it has 16 layers to produce better classification accuracy. Pallabi Sharma *et al.* (2020) the proposed model utilizes the various model of DCNN in order to train the neural network model and to examine the image dataset. This framework describes that the DCNN produces better image classification accuracy for the medical domain. To obtain the exact classification accuracy, it requires a large amount of dataset in order to perform the training and testing phase.

Ahmet Çinar *et al.* (2020) the objective of the proposed system is used to detect the grain tumor portion in MR images. Here, the CNN model is used for the learning process, and the ResNet50 model is a base of the CNN model. The rest of the ResNet50 architecture layers are removed and new 8 layers are added. The outcome of this model and its classification accuracy is 97.2%. Juan Miguel Valverde *et al.* (2021) a systematic overview of transfer learning towards the brain MR imaging task has been performed. There were 433 literature overviews are monitored, and it has been classified and extricated the most significant information such as type of task, function, label availability and machine learning techniques. Therefore, the brain MR image examined outcomes of particular transfer learning

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technique obtains better result in classification accuracy.

## MATERIALS AND METHODS

### Deep Convolutional Neural Network

The proposed DCNN framework is used to classify the brain MR image, and it has

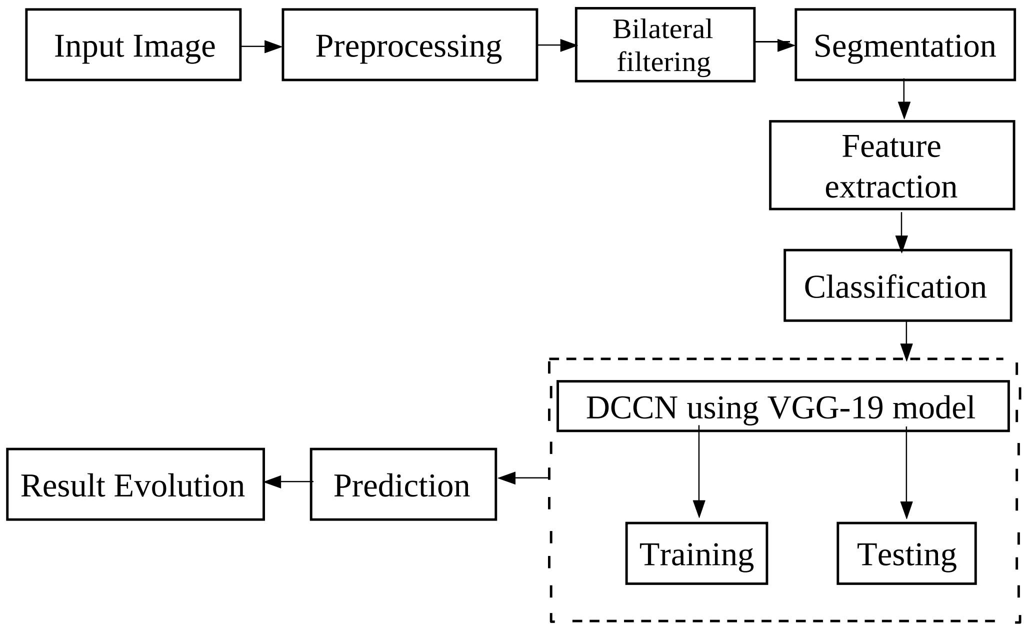


**Figure 2. Block diagram of proposed system**

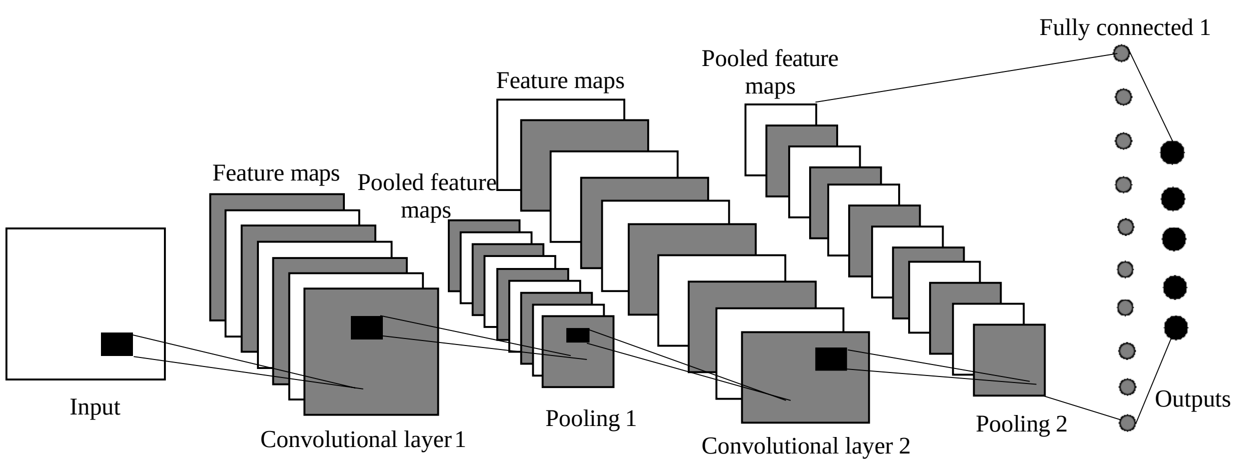


**Figure 3. Proposed deep convolutional neural network architecture**

multiple functional layers in order to obtain the classification image accuracy. The layers presented in the DCNN model are input, convolution, rectified linear activation unit, and pooling. The outcome of the DCNN model is involved with the fully connected layer in order to produce the label score value between 0 and 1. Figure 2, illustrates the basic block diagram of proposed DCNN framework. The local features are extracted by the trainable kernels of the convolutional layer, and the feature map is calculated. All the units may

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share the weight in every individual feature map and it is used to diminish the parameter count in order to address the feature of portion towards the input image. There are numerous non-linear activation functions like; *tanh*, *ReLU* and *Sigmoid*. Here, the ReLU [*f(x) =max (0, x)*] is used to make the training operation faster than others. The feature map output size is calculated based on the stride and size of the filter values used to convolve

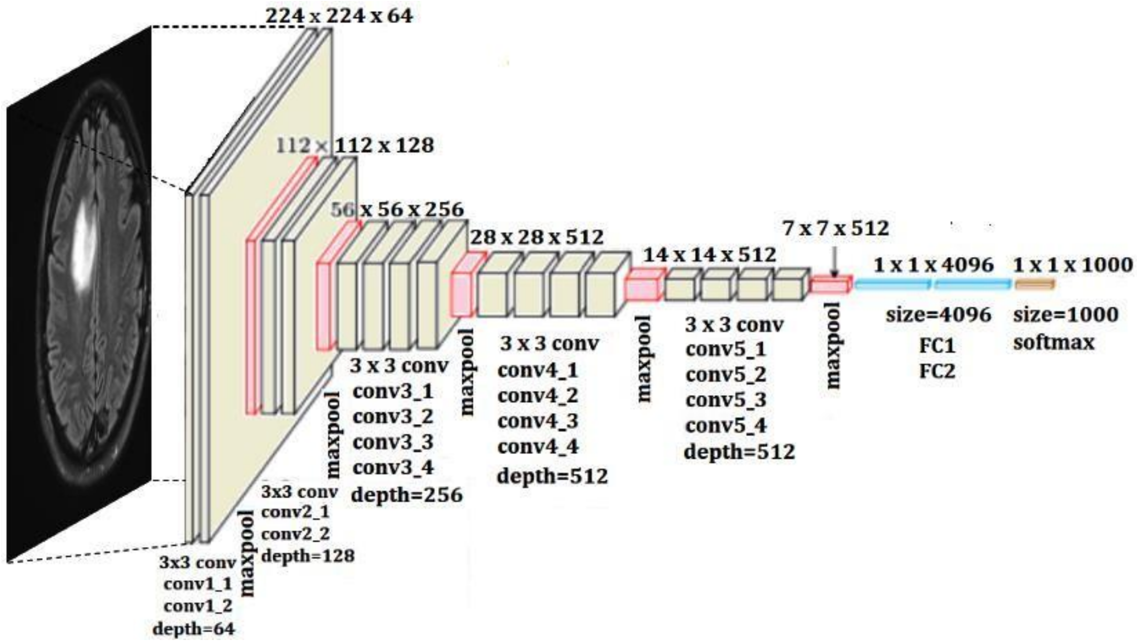


**Figure 4. proposed VGG-19 architecture**

the input image with a size of (X*X) over the size of the filter is (Y*Y), and the stride (S), than the size of the output is expressed as,

$$Z = [\frac{X-Y}{S}] + 1 \quad (1)$$

The down sampling is used to diminish the preceding feature maps resolution. It achieves the invariance towards the small distortion, and the inputs are divided as displace portions with the size of (M*M) in order to obtain the each portion output, and it is expressed as,

$$P = [\frac{Z}{M}] \quad (2)$$

The topmost portion or layer of CNN is consider as fully-connected layer and it is very related to feed-forward network in order to extract the inputs of global features. These layer units are associated with the previous layer hidden units. The softmax classifiers is a last layer of the model, the posterior probability is evaluated for each class label over the classes 'C', and expressed as,

$$x_i = \frac{\exp(-y_i)}{\sum_{j=i}^{C} \exp(y_i)} \quad (3)$$

The preprocessing is used to provide an accurate MR image without noise; in order to remove the noise; it consists of a few features such as information wiping, conversion, combination, and data customization. At last, the process of normalization is performed in order to enhance the quality of the image.

Bilateral filtering is used to reduce the average channel accumulation issue and to provide a sufficient and reliable image. The average channel value is used to replace the pixel values and its average value is 3x3 or 5x5 of central pixel, and it leads to protect the edge. The process of image division is called as

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segmentation, and used to make the image analysis as simpler. The feature extraction is a process to diminish the larger image dataset in to smaller image collection, and to maintain the image accuracy and consistency. Figure 3, represents the structure of proposed deep convolutional neural network.

**Visual Geometry Group-19**

The VGG-19 is a well and pre-trained architecture for classification of image and the

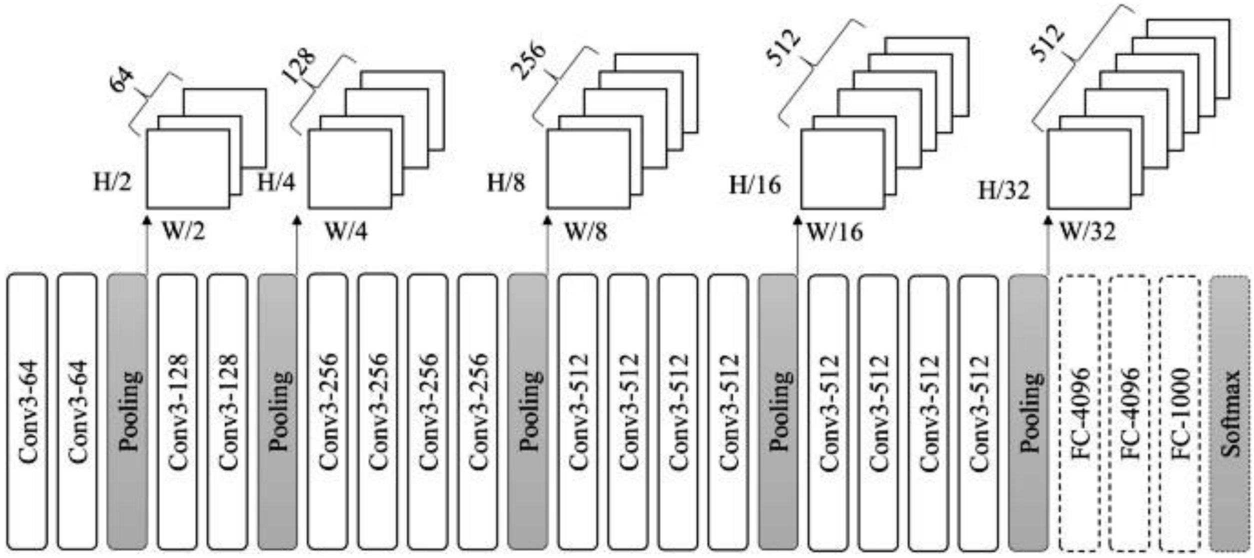


**Figure 5. Intuitive layer operation of proposed VGG-19 model**

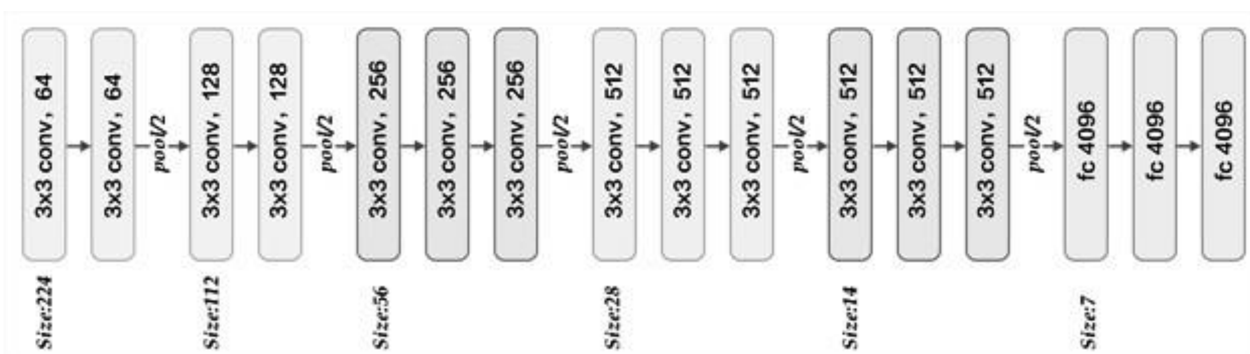


**Figure 6. Different filter size of VGG-19 model**

outcome of this model is bit higher than the existing models such as, ResNet and Alexnet. Figure 4, represents the architecture of VGG-19 model and it has 16 convolution layers, 5 pooling layers and 3 dense layers. The overview of the convolution and pooling layers for VGG-19 described as,

**VGG-19 Intuitive Layer Flow**

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***Start;***

***Step1***: *Convolution using 64 filters*

***Step2***: *Convolution using 64 filters + Max pooling*

***Step3***: *Convolution using 128 filters*

***Step4***: *Convolution using 128 filters + Max pooling*


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***Step5**: Convolution using 256 filters*
***Step6**: Convolution using 256 filters*
***Step7**: Convolution using 256 filters + Max pooling*
***Step8**: Convolution using 512 filters*
***Step9**: Convolution using 512 filters*
***Step10**: Convolution using 512 filters + Max pooling*
***Step11**: Convolution using 512 filters*
***Step12**: Convolution using 512 filters*
***Step13**: Convolution using 512 filters + Max pooling*
***Step14**: Fully connected with 4096 nodes*
***Step15**: Fully connected with 4096 nodes*
***Step16**: Output layer with Softmax activation with 1000 nodes*
***End;***

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The information retrieved from Figure 5&6, and it is described as, the two preamble layers are referred as convolutional layers and their filter size is 3*3, and it uses 64 filters with stride of '1' which produces the volume size 224*224*64. Next, the pooling layer is involved with 2*2 size of max-pool with the stride of '2'in order to reduce the height and width volume up to 112*112*64. This new volume outcome is further convolved by 2 more layers along with 128 filters, and then the dimension outcome is 112*112*128. Next, the concern of pooling layer is used to reduce the dimension up to 56*56*256. Further, the addition of 2 more convolutional layers along with filter size of 512, and the dimension is reduced as 28*28*512 by using the down sampling. The volume of last pooling layer is 7*7*512 and it is firmed in to a fully connected layer along with the channel size of 4096, and the outcome of the softmax is 1000 in classes (1*1*1000). The output layer (VGG-19 model) training modes are, (i) image augmentation, (ii) training and evaluation, (iii) executing the model, and (iv) compilation.

## RESULTS AND DISCUSSION

### Dataset Availability

The BraTS 2021 dataset has been used in our proposed system, and it is the publically available dataset. From the dataset, we have taken 650 images and it has been separated into 2 different phases; phase-1(training) and phase-2(testing). However, phase-1 consists of 290 tumor images and 290 normal images respectively. Also, phase-2 consists of 70 images (a combination of both tumor and normal images). Finally, the phase-1 and phase-2 are used to train and test the proposed DCNN framework.

BraTS 2021 dataset link:
https://www.kaggle.com/dschettler8845/brats-2021-task1

### Experimental Results

The proposed DCNN model performance metric analysis is obtained based on the training and testing procedures in order to achieve image classification accuracy. The proposed model classification accuracy outcome is compared with other existing models such as SVM, RF, and CNN. Here, Table 1, shows the validation accuracy and loss values of proposed and other existing techniques based on training and testing operations. Table 1, describes the proposed model classification accuracy is better than the other existing techniques, and the obtained validation loss is lower than the other existing model values. In addition to that, a few more parameter indexes are added to evaluate the classification accuracy of the proposed model, and it has been evaluated and compared with other techniques. The newly added parameter indexes names and their mathematical evaluation is shown below,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} \quad (7)$$

These parameters are used in our proposed DCNN VGG-19 model to evaluate and classify the tumor image detection accuracy.

**Table 1. Comparison of training and testing accuracy of proposed and other techniques**

| Procedures | SVM | | RF | | CNN | | DCNN | |
|---|---|---|---|---|---|---|---|---|
| | Accuracy (%) | Loss(%) | Accuracy (%) | Loss(%) | Accuracy (%) | Loss(%) | Accuracy (%) | Loss(%) |
| Training | 96.1 | 0.32 | 96.9 | 0.27 | 97.9 | 0.21 | 99.4 | 0.17 |
| Testing | 95.5 | 0.3 | 96.3 | 0.25 | 97.3 | 0.19 | 98.8 | 0.15 |
| Training | 96 | 0.31 | 96.8 | 0.26 | 97.8 | 0.2 | 99.3 | 0.16 |
| Testing | 95.4 | 0.29 | 96.2 | 0.24 | 97.2 | 0.18 | 98.7 | 0.14 |
| Training | 95.9 | 0.31 | 96.7 | 0.26 | 97.7 | 0.2 | 99.2 | 0.16 |
| Testing | 95.5 | 0.28 | 96.3 | 0.23 | 97.3 | 0.17 | 98.8 | 0.13 |
| Training | 95.6 | 0.3 | 96.4 | 0.25 | 97.4 | 0.19 | 98.9 | 0.15 |
| Testing | 95.2 | 0.29 | 96 | 0.24 | 97 | 0.18 | 98.5 | 0.14 |
| Training | 95.4 | 0.3 | 96.2 | 0.25 | 97.2 | 0.19 | 98.7 | 0.15 |
| Testing | 95.2 | 0.28 | 96 | 0.23 | 97 | 0.17 | 98.5 | 0.13 |
| **Average** | **95.58** | **0.298** | **96.38** | **0.248** | **97.38** | **0.188** | **98.88** | **0.148** |

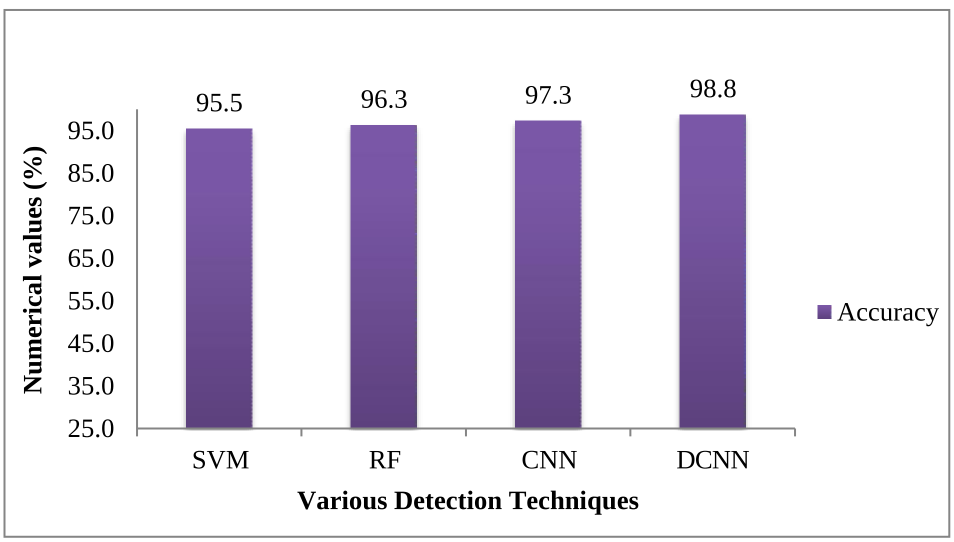


**Figure 7. Graphical illustration of proposed and various detection techniques testing accuracy outcomes**

From Table 1, the average value of training and testing accuracy of the proposed system is considered, and their graphical illustration is shown in Figure 7. Here, Table 2, describes the various parameter index comparison of proposed and existing techniques, and the proposed DCNN model achieves better results in all the parameters. However, the training and

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testing phase accuracy value of all detection techniques are shown in Table 1, and the proposed deep convolutional neural network model obtains a good result in all aspects when compared with other detection techniques. The detection and classification of brain tumor images is much essential in the medical domain, and their accuracy value is provided the essential information in order to predict the malignant portion in earlier stage whereas to increase the survival rate of the patient.

**Table 2. Parameter comparison of proposed and other techniques**

| Techniques | Accuracy | Recall | Precision | Specificity |
|---|---|---|---|---|
| SVM | 88.2 | 87.4 | 88.4 | 87.7 |
| RF | 92.4 | 91.8 | 92.3 | 91.9 |
| CNN | 98.1 | 97.1 | 97.7 | 97.8 |
| DCNN | 99.2 | 98.5 | 98.8 | 98.7 |

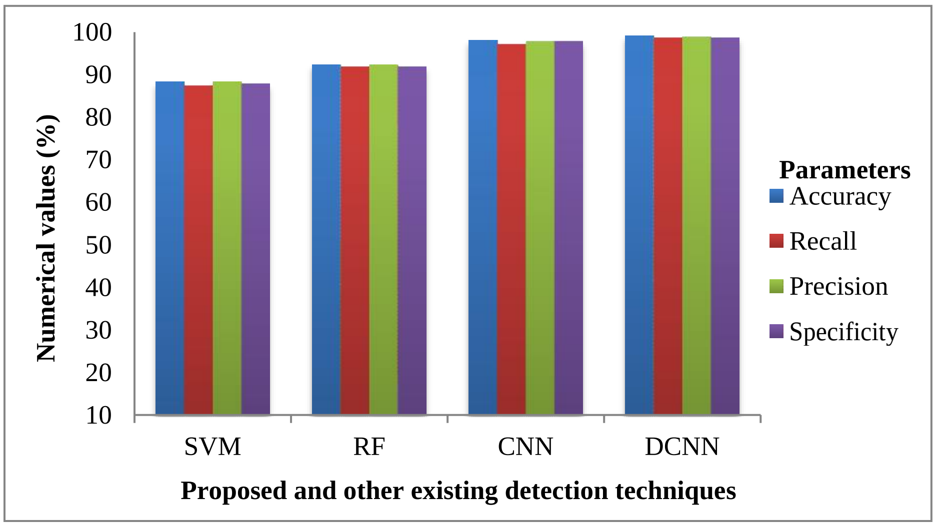


**Figure 8. Graphical illustration of parameter comparison of proposed and other existing techniques**


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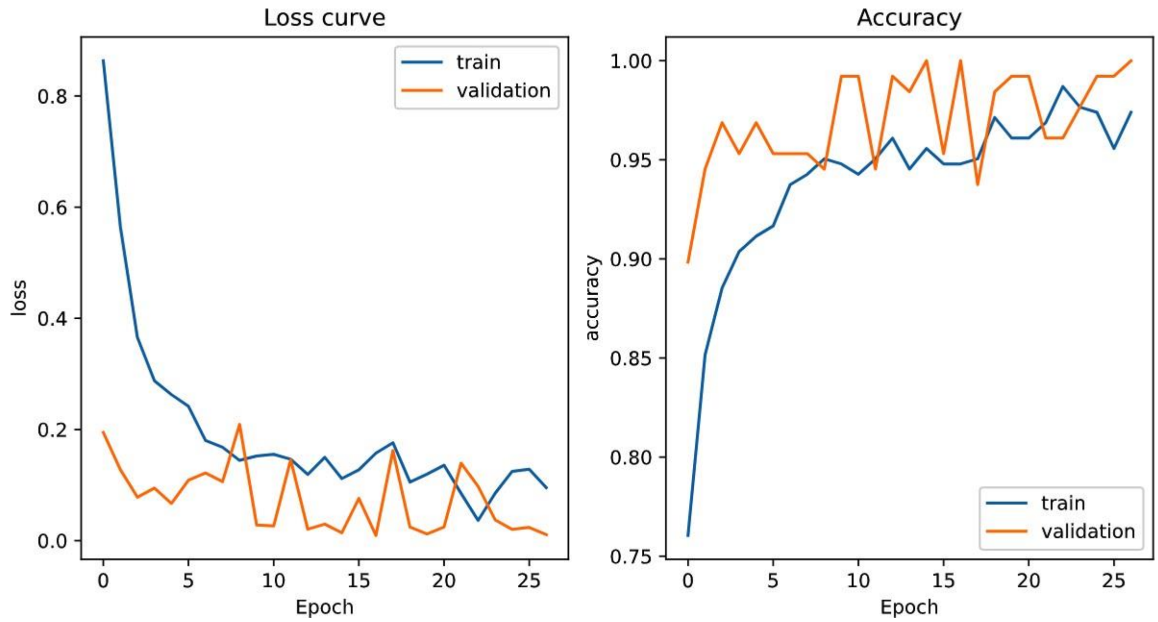


**Figure 9. Performance analysis of VGG-19 DCNN architecture**

Figure 8, illustrates the graphical illustration of obtained parameter index outcome of proposed and existing techniques. Figure 9, represents the loss curve and accuracy value of proposed VGG-19 DCNN architecture.

## CONCLUSION

With the automatic detection and classification of brain tumors, the proposed DCNN technique is achieved better results in all aspects. This system has obtained the enhanced detection accuracy outcome, and it is superior to other techniques such as support vector machine, random forest, and convolutional neural network. Here, the average training and testing loss of DCNN is reduced up to 0.158 and 0.138 respectively. Finally, the proposed DCNN VGG-19 model achieves the 99.2% of classification accuracy, and the training and testing loss outcomes are 0.158 and 0.138 respectively. At last, the imperative involvement of this proposed research work is mainly focused on image segmentation, feature extraction, and image classification based on deep convolutional neural network.

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## REFERENCES

1. Otman Basir, Kalifa Shantta, 2021, 'Deep Learning Feature Extraction for Brain Tumor Characterization and Detection', IRA-International Journal of Applied Sciences, vol.16, issue.01, pp.1-15.
2. MilicaM. Badža, Marko C, Barjaktarovic, 2020, 'Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network', Applied sciences, vol.10, issue.01, pp.1-13.
3. Lei Cai, Jingyang Gao, Di Zhao, 2020, ' A review of the application of deep learning in medical image classification and

segmentation', Annals of Translational Medicine, vol.08, issue.11, pp. 1-15.

4. Hassan Ali Khan, Wu Jue, Muhammad Umer Mushtaq, 2020, 'Brain tumor classification in MRI image using convolutional neural network', Mathematical Biosciences and Engineering, vol.17, issue.05, pp.6203-6216.
5. Anushka Singh, Rajeshwari Deshmukh, Riya Jha, Nishi Shahare, Sonam Verma, 2020, 'Brain tumor classification using CNN and vgg16 model', International Journal of Advance Research and Innovative Ideas in Education, vol.06, issue.02, pp.1331-1336.
6. Saleh Albelwi, Ausif Mahmood, 2017, 'A Framework for Designing the Architectures of Deep Convolutional Neural Networks', Entropy, vol.19, no.242, pp.1-20.
7. Isselmou Abd El Kader, Guizhi Xu, Zhang Shuai, Sani Saminu, Imran Javaid, Isah Salim Ahmad, Souha Kamhi, 2021, 'Brain Tumor Detection and Classification on MR Images by a Deep Wavelet Auto-Encoder Model', Diagnostics, vol.11, no.1589, pp.1-19.
8. Atınç YILMAZ, 2021, 'Brain tumor detection from MRI images with using proposed deep learning model: the partial correlation-based channel selection', Turkish Journal of Electrical Engineering & Computer Sciences, vol.29, pp.2615-2633.
9. Taeho Jo, Kwangsik Nho, Andrew J. Saykin, 2019, 'Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data', Frontiers in Aging Neuroscience, vol.11, pp.1-14.
10. Xiaoqing Gu, Zongxuan Shen, Jing Xue, Yiqing Fan, Tongguang Ni, 2021, 'Brain Tumor MR Image Classification Using Convolutional Dictionary Learning With Local Constraint', Frontiers in Neuroscience, vol.15, pp.1-12.
11. Sarath Chandra, Sai Priya, Durga Maheshwari, Ramesh Naidu, 2020, 'Detection of Brain Tumour by integration of VGG-16 and CNN Model', International Journal of Creative Research Thoughts, vol.08, issue.07, pp.298-304.
12. Pallabi Sharma, Imayanmosha Wahlang, Sugata Sanyal, Arnab Kumar Maji, 2020, 'Soft Computing: Theories and Applications', pp.559-569. Doi: https://doi.org/10.1007/978-981-15-0751-9_52.
13. Ahmet Çinar, Muhammed Yildirim, 2020, 'Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture', Medical Hypotheses, vol.139, no.109684, pp.1-8.
14. A.LAKSHMI, Dr.T.ARIVOLI, 2014, 'Computer Aided Diagnosis System for Brain Tumor Detection and Segmentation, Journal of Theoretical and Applied Information Technology, vol.64, no.02, pp.1-8.
15. Juan Miguel Valverde, Vandad Imani, Ali Abdollahzadeh, Riccardo De Feo, Mithilesh Prakash, Robert Ciszek, Jussi Tohka, 2021, 'Transfer Learning in Magnetic Resonance Brain Imaging: A Systematic Review', Journal of imaging, vol.7, issue.66, pp.1-21.


https://doi.org/10.37896/pd91.4/9144

ISSN: 0369-8963

16. Mengxin Liu, Jun Yang, 2021, 'Image Classification of Brain tumor based on Channel Attention Mechanism', Journal of Physics, no. 012029, Doi: 10.1088/1742-6596/2035/1/012029.
17. Abdelhakim El Boustani, Mohamed Aatila, Essaid El Bachari, Ahmed El Oirrak, 2021, 'MRI Brain Images Classification Using Convolutional Neural Networks', Springer Nature Switzerland AG 2020, AISC 1105, pp.308–320.
18. Fangrong Zhou, Yi Ma, BoWang, Gang Lin, 2021, 'Dual-channel convolutional neural network for power edge image recognition', Journal of Cloud Computing: Advances, Systems, vol.10, issue.18, pp.1-9.