# A Review on Comparison of VGG-16 and DenseNet algorithms for analysing brain tumor in MRI image

Aleena Joseph
CSE
SJCET
Pala, India
aleenajoseph2023@cs.sjcetpalai.ac.in

Diya Paramesh G
CSE
SJCET
Pala, India
diyaparameshg@cs.sjcetpalai.ac.in

Elza Mary Thomas
CSE
SJCET
Pala, India
elzamarythomas2023@cs.sjcetpalai.ac.in

Gayathri V
CSE
SJCET
Pala, India
gayathriv2023@cs.sjcetpalai.ac.in

Anu V Kottath
CSE
SJCET
Pala, India
anuvkottath@cs.sjcetpalai.ac.in

*Abstract*— **Brain tumor is a deadly disease for which proper treatment should be given. Brain tumor detection is usually done with the help of analyzing MR images. Accurate brain tumor detection is important for effective treatment. VGG-16 and DenseNet are two popular CNN algorithms used widely in medical fields in order to detect diseases from medical images. VGG-16 supports 16 layers. It has three fully-connected layers.It is capable of classifying thousand images of thousand different categories. DenseNets are divided into different dense blocks in which there are dense connections between layers through dense blocks. All the layers are connected using matching feature- map sizes and it works in a feed-forward nature. Each layers obtain additional inputs from all preceding layers and passesits own feature-maps to all subsequent layers. The proposed system has five major stages, namely, image pre-processing, image enhancement, image segmentation, brain tumor image classifica- tion using VGG-16 and brain tumor image classification using DenseNet. This work compares the performances of both vgg- 16 and DenseNet algorithms and find out which algorithm gives better accuracy in detection. Pre-trained vgg-16 and DenseNet models are used and around 4000 MRI scan images are used for testing and training.**

***Keywords— Brain Tumor,CNN,VGG16,DenseNet,MRI***

## I. INTRODUCTION (*HEADING 1*)

Brain tumors causes changes to the important structures of brain and thus it has a bad impact on the life of the patient. Treatments are suggested by the doctors according to the typeof brain tumor. Analyzing the brain tumor type is always challenging. Computer-aided analysis of MR images makes the task easier and will be extremely beneficial for medical use.

Systems with vgg-16 and DenseNet algorithms to predict brain tumor have been implemented. This work tries to com-

pare the two popular CNN algorithms vgg-16 and DenseNet. To the pre-trained vgg-16 and DenseNet models, the test

datasets are given to analyze whether the MR image contains tumor or not. The results of the work predicts the best among these two algorithms in the detection of brain tumorfromMR images. The proposed system automatically predicts the presence of tumor without an expert's supervision.

## II. OBJECTIVE AND SCOPE

The aim of the proposed system is to compare two popular CNN algorithms VGG-16 and DenseNet. For that we detect the presence of brain tumor disease in input MR images. We have 4600 MR images as input among which 80% is utilized for training separate VGG-16 and DenseNet models. The remaining 20% of the MR images are used for testing. The result is obtained by doing calculation using confusion metrics. Thus the accuracies achieved by both the models is compared and the best among them is find out.


DOI:10.5281/zenodo.8015938

**DOI:**

The proposed system is helpful in clinical applications, that the presence of brain tumor is detected from MRI scans without the supervision of an expert. The most accurate algorithm among the two is find out and can be used more prominently than the other.

## III. LITERATURE SURVEY

In the paper Brain tumor classification using deep CNN features via transfer learning S. Deepak et al[2019][1] focus on a 3-class classification issue to distinguish between the three common forms of brain cancers—gliomas, meningiomas, and pituitary tumors. The proposed classification system uses a pre-trained GoogLeNet to extract features from brain MRI images and implements the idea of deep transfer learning. The collected features are classified using integrated, tested classifier models. Using a MRI dataset from figshare, the experiment uses a five-fold cross-validation approach at the patient level. The proposed approach outperforms all cutting-edge techniques with a mean classification accuracy of 98%. The study also used the area under the curve (AUC), precision, recall, F-score, and specificity as performance indicators. By testing the system with fewer training examples, the article also solves a practical issue. The study's findings suggest that transfer learning is a practical method when there are few medical imagesavailable. It also offers a critical analysis of misclassifications.

Ambeshwar Kumar et al[2019][2] in the paper A deep neural network-based classifier for brain tumor diagnosis aims to identify brain cancers using various categorization techniques are earlier research activities. Nevertheless, current classification methods have substantial False Alarm Rates (FARs). The Weighted Correlation Feature Selection Based Iterative Bayesian Multivariate Deep Neural Learning (WCFS- IBMDNL) technique is suggested in this work to enhance the early-stage brain tumor diagnosis via classification.

When classifying the diagnosis of a brain tumor at an early stage, the WCFS-IBMDNL algorithm takes into account medical datasets. In order to classify brain tumors, the WCFS-IBMDNL technique first performs Weighted Correlation-Based Feature Selection (WC-FS). This is done by choosing subsets of medical data. The Iterative Bayesian Multivariate Deep Neural Network (IBMDNN) classifier is used by the WCFS-IBMDNL technique to reduce the misclassification error rate of brain tumor identification when the feature selection phase is complete. The epileptic seizure recognition dataset was used to test the WCFS-IBMDNL technique in JAVA using the disease diagnosis rate (DDR), disease diagnosis time (DDT), and FAR parameter.

Md. Saikat Islam Khan et al[2022][3] in the paper Accurate brain tumor detection using deep convolutional neural network says that the development of CAD, machine learning, and deep learning in particular now enable the radiologist to more accurately diagnose brain cancers. For classification purposes, the conventional machine learning techniques used to this problem call for a manually created feature. When getting accurate classification results, deep learning methods can be created so that no manual feature extraction is necessary. In order to distinguish between binary (normal and pathological) and multiclass (meningioma,glioma, and pituitary) brain tumours, this research suggests two deep learning models. We make use of two freely accessible datasets are used where each contain 152 and 3064 MRI pictures. As there are many MRI pictures available for training, we first use a 23-layer convolution neural network (CNN) on the first dataset to create our models. The proposed "23-layers CNN" architecture, however, encounters overfitting issues when working with small data sets, as is the case in the second dataset. Here Transfer is employed to solve this problem and combine the VGG16 architecture with the reflection ofour suggested "23 layers CNN" architecture. In the end, we compare oursuggested models to those that have been documented in the literature. According to the experimental findings, the models outperform all other cutting-edge models in terms of classification accuracy, achieving up to 97.8% and 100% for the datasets utilized, respectively.

Abdul Hannan Khan et al[2022][4] in the paper Intelligent Model for Brain Tumor Identification Using Deep Learning deals with a sophisticated method for identifying and categorising brain tumours. The study's innovative aspect is the use of a hierarchical deep learning approach to categorise brain cancers into glioma, meningioma, and pituitary. For a speedy and effective cure, the diagnosis and tumour classification are crucial, and medical image processing utilising a convolutional neural network (CNN) is producing remarkable results in this area. CNN trains the data and classifies the tumour kinds using the image fragments. For the purpose of identifying and categorising brain tumours, CNN is used to propose the hierarchical deep learning-based HDL2BT classification system. Glioma, meningioma, pituitary, and no-tumor are the four categories of tumours that the suggested system divides into. The proposed model outperforms existing techniques for identifying and segmenting brain tumours, with 92.13% precision and a miss rate of 7.87%.

Neelum Noreen et al[2020][5] in the paper A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor suggests a technique for multi-level feature extraction and concatenation for brain tumor earlydiagnosis. This model is valid due to the two pre-trained deep learning models, Inception-v3 and DensNet201. Two distinct scenarios of brain tumor detection and classification were assessed using these two models. In order to classify brain tumors, the characteristics from various Inception modules were first retrieved from the pre-trained Inception-v3 model then concatenated. Following that, the softmax classifier received these features in order to categorize the

DOI:

brain tumor. Second, features from various DensNet blocks were extracted using pre-trained DensNet201. The brain tumor was then classified using the softmax classifier after these features were concatenated. With the aid of a publicly accessible three-class brain tumor dataset, both possibilities were assessed. Using Inception-v3 and DensNet201 on testing samples, the suggested technique provided 99.34% and 99.51% testing accuracy results, respectively, and reached the maximum performance in the detection of brain tumours. The suggested strategy, which concatenates features from pre-trained models, outperformed existing state-of-the-art deep learning and machine learning-based methods for classifying brain tumours, according to the results.

Milica M. Badža et al[2020][6] in the paper Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network describes a brand-new CNN architecture for classifying three different forms of brain tumors. The created network was evaluated on T1-weighted contrast- enhanced magnetic resonance imaging and is less complex than pre-existing, pre-trained networks. Four different approaches—combinations of two 10-fold cross-validation techniques and two databases—were used to assess the network's performance. Subject-wise cross-validation, one of the 10-fold approaches, was used to assess the network's generalization capacity, and an enhanced picture database was used to test for improvement. The record-wise cross- validation for the enhanced data set produced the best results for the 10-fold cross-validation approach, and in that case, the accuracy was 96.56%. The newly constructed CNN architecture has strong generalization capabilities and execution speed, making it a useful decision-support tool for radiologists in medical diagnosis.

Ayesha Younis et al[2022][7] in the paper Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches uses the Visual Geometry Group (VGG 16) to find brain tumors, implementing a convolutional neural network (CNN) model architecture, and setting parameters to train the model for this problem were the objectives ofthis study. Because of its effectiveness, VGG is one of thebest CNN models employed. In addition, the study created a useful method for MRI-based brain tumour detection tohelp with making prompt, effective, and accurate decisions. Convolutional feature maps were created by Faster CNN usingthe VGG 16 architecture as its primary network.

These maps were subsequently categorized to produce recommendations for tumour regions. Accurate advanced A.I. and neural network classification algorithms can successfully achieve early disease diagnosis when it comes to brain tumours. The goals of this study were to develop a convolutional neural network (CNN) model architecture, train the model for this issue, and use the Visual Geometry Group (VGG 16) to identify brain tumours. VGG is one of the greatest CNN models used because of its efficacy. The study also developed a practical technique for quick, precise, and accurate decision- making for MRI-based brain tumour identification. Faster CNN was used to generate convolutional feature maps with the VGG 16 architecture as its main network. After being categorised, these maps were used to generate suggestionsfor tumour regions.

Raheleh Hashemzehi et al[2020][8] in the paper Detection of brain tumors from MRI images based on deep learning using hybrid model CNN and NADE analyses detection of cerebellar malignancies from MRI images, based on deep learning, utilizes hybrid model CNN and NADE analyses. This study employs these images to train a new hybrid paradigm that combines a convolutional neural network and a neural autoregressive distribution estimation (NADE) (CNN). Then, using 3064 T1-weighted contrast-enhanced pictures of three different types of brain tumors, we put this model to the test. The results show that despite the limited supply of medical images, the hybrid CNN-NADE has a high classification performance.

Navid Ghassemi et al[2019][9] in the paper Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images an innovative deep learning technique for classifying tumours in MR images is provided in this research. To extract reliable features and learn the structure of MR pictures in its convolutional layers, a deep neural network is first pre-trained as a discriminatorin a generative adversarial network (GAN). This is done on several datasets of MR images. The entire deep network is then trained as a classifier to differentiate between three tumour classifications after the fully connected layers are replaced. There are six layers and around 1.7 million weight parameters in the deep neural network classifier. A GAN is prevented from overtraining on a small dataset by pre- training as a discriminator and using other methods like data augmentations (image rotation and mirroring) and dropout.

Hossam H.Sultan et al[2020][10]in the paper Multi-Classification of Brain Tumor Images Using Deep Neural Network, propose a DL model based on convolutional neural networks to classify different types of brain tumors using two publicly available datasets. The first classifies tumorsas (meningioma, glioma, and pituitary tumor). Another distinguishes three grades of glioma (grade II, grade III, and grade IV). The data sets included 233 and 73 patients with a total of 3064 and 516 contrast-enhanced T1-weighted images for the first and second data sets, respectively. The proposed network structure provides significant performance with the highest overall accuracy of 96.13% and 98.7% in both studies, respectively. The results indicate the ability of the model to use multiple

**DOI:**

classifications of brain tumors.

Asaf Raza et al[2022][11] in the paper A Hybrid Deep Learning-Based Approach for Brain Tumor Classification presents a hybrid deep learning model dubbed DeepTumorNetfor the categorization of three different forms of brain tumours (BTs): glioma, meningioma, and pituitary tumours. The CNN model's GoogLeNet architecture served as the foundation. The final five levels of GoogleNet were eliminated while creating the hybrid DeepTumorNet technique, and fifteen newlayers were added in their place. In order to make the model more expressive, a leaky ReLU activation function is used in the feature map. A publicly accessible research dataset was used to test the suggested model, and the results were 99.67% accuracy, 99.6% precision, 100% recall, and a 99.66% F1-score. When compared, the suggested methodology had the highest accuracy. A publicly accessible research dataset was used to test the suggested model, and the results were 99.67% accuracy, 99.6% precision, 100% recall, and a 99.66% F1-score. When compared against the most recent categorization results from Alex Net, ResNet50, Darknet53, Shufflenet, GoogLeNet, SqueezeNet, ResNet101, Exception Net, and MobileNetv2, the proposed methodology had the greatest accuracy. The suggested model demonstrated its advantage over the currently used approaches for classifying BT from MRI images.

Driss Lamrani et al[2022][12] in the paper Brain Tumor Detection using MRI Images and Convolutional Neural Network uses convolution neural network (CNN) with the goal of identifying the presence of a brain tumor, and its performance is examined. The major goal of this paper is to use convo- lutional neural networks as a machine learning tool to detect and classify brain tumours. The pre-trained architecture modelachieves 96% precision and classification accuracy rates based on training and testing results. CNN shows to be the more accurate method for predicting the existence of brain tumours in the dataset.

## IV.CONCLUSION

From this review, we identified different methods for brain tumor detection. All these are hybrid models which integrate various algorithms for brain tumor detection. The most commonly used algorithm is the CNN algorithm which uses image compression to reduce the size of the images while maintaining the information. We can analyze that CNN models give good precision, fast execution, and higher classification result. MRI and CT Scan techniques are used for getting brain images. MRI images can be taken as most appropriate because it detects abnormalities in the early stage and avoids allergic features. The review shows lack of maintainability of the stages and less exploration of finetune techniques are the basic disadvantages. In addition to having more redirected features and maintaining low complexity features, DenseNet is thought to offer high gradient flow, parameter efficiency, and computational effectiveness. CNN uses image compression to reduce the size of the images while maintaining the information. The VGG-16 and DenseNet models are the popular algorithms that are good for brain tumor identification. In future we can use these two algorithms for brain tumor identification in MR Images in hybrid model and compare which one is better. The researchers can use this paper to identify the existing systems in brain tumor.

## References

[1] Deepak, S. and Ameer, P.M. (2019) *“Brain Tumor Classification using Deep CNN features via transfer learning,”* Computers in Biology and Medicine, 111, p. 103345.

[2] Kumar, A. et al. (2019) “A deep neural network based classifier for brain tumor diagnosis,” , Applied Soft Computing, 82, p. 105528.

[3] Khan, M.S. et al. (2022) *“Accurate brain tumor detection using deep convolutional neural network,”* ,Computational and Structural Biotechnology Journal, 20, pp. 4733–4745.

[4] Khan, A.H. et al. (2022) *“Intelligent model for Brain tumor identificationusing deep learning,”* Applied Computational Intelligence and Soft Computing, 2022, pp. 1–10.

[5] Noreen, N. et al. (2020) “A deep learning model based on concatenation approach for the diagnosis of brain tumor,” ,IEEE Access, 8, pp. 55135–55144.

[6] Badža, M.M. and Barjaktarović, M.Č. (2020) “Classification of brain tumors from MRI images using a convolutional neural network,” ,AppliedSciences, 10(6), p. 1999.

[7] Younis, A. et al. (2022) “Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches,” ,Applied Sciences, 12(14), p. 7282.

[8] Hashemzehi, R. et al. (2020) “Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and Nade,”,Biocybernetics and Biomedical Engineering, 40(3), pp. 1225–1232.

[9] Ghassemi, N. et al. (2019) *“Deep neural network with generative adversarial networks pre-training for Brain Tumor Classification based on Mr Images,”* , Biomedical Signal Processing and Control, 57, p. 101678.

[10] Sultan, H.H. et al. (2019) “Multi-classification of brain tumor images using Deep Neural Network,” ,IEEE Access, 7, pp. 69215–69225.

[11] Raza, A. et al. (2022) “A hybrid deep learning-based approach for Brain Tumor Classification,” ,Electronics, 11(7), p. 1146.

[12] Lamrani, D. et al. (2022) *“Brain tumor detection using MRI images and convolutional neural network,”* International Journal of Advanced Computer Science and Applications, 13(7).