Grenze International Journal of Engineering and Technology, June Issue

Brain Tumor Detection and Classification using Deep Learning

Annam Vandana[1], V. Krishna Sree[2], S.Sai Charan[3] and J. Karan Raju[4]
[1, 3, 4]UG Student, ECE Dept, Telangana, India
Email: vandanaannam27@gmail.com, saicharan15v23@gmail.com, karanjummala.kj@gmail.com
[2]Associate Professor,Ece Dept,Telangana,India
Email: krishnasree_v@vnrvjiet.in

***Abstract*—A brain tumor is a growth of abnormal brain cells, some of which develop into tumors. Brain tumors are among the most well-known causes of brain dysfunction. Magnetic resonance imaging is the most accurate and consistent technique for finding brain tumors (MRI). The scans generate a lot of images. The radiologists evaluate these images. Manual assessment takes time and increases the risk of making a false cancer diagnosis. In recent years, decision-making has been practiced in practically every sector of the economy, including financial services, healthcare, marketing, and agreements. Deep learning has become a recognized quality in these areas. For more accurate brain tumor prediction and better patient care, machine learning and deep learning algorithms are used to MRI data. The radiologist can make speedy decisions thanks to these results. In this study, brain cancers are detected and categorized into different groups using a convolution neural network (CNN). We put forth a model that categorizes brain cancers using pre-trained convolutional neural networks. Four classes make up the dataset, three of which are tumor types and one of which is non-tumor. The networks used are ResNet50 and EfficientNet. The size of the Dataset is also increased through Data Augmentation. The accuracy of various networks is used to evaluate models performance.**

***Index Terms*— Brain tumor, MRI Scan, Convolution neural network (CNN), EfficientNet, ResNet50, Deep Learning.**

I. INTRODUCTION

A. Brain Tumor and Detection

The brain is the body's most crucial and critical organ. One of the most frequent causes of brain dysfunction is brain tumors. Simply said, unchecked cell proliferation causes tumors. One of the deadliest conditions that can afflict both children and adults is a brain tumor. About 11,700 people are affected by brain tumors each year. For detecting brain cancer, magnetic resonance imaging is the most reliable technique (MRI). Large amounts of picture data are produced by the scanning. The radiologist examines these images. The manual inspection takes time and could lead to erroneous cancer detection.

In almost every area where decisions are made, including financial matters, medical services, promotion, and negotiations, deep learning has recently acquired noticeable quality. Automated classification systems based on machine learning (ML) and artificial intelligence (AI) have consistently surpassed manual classification. In this study, we are creating a classifier to recognize brain tumors in MRI scan images.

Grenze ID: 01.GIJET.9.2.22_2
© Grenze Scientific Society, 2023

B. Convolutional Neural Network

Multiple-layer Artificial Neural Networks are referred to as Deep Learning, also known as Deep Neural Networks. Deeper hidden layers are currently outperforming earlier techniques in a number of disciplines, including pattern recognition. One well-known deep neural network is the convolutional neural network (CNN). Deep learning neural networks used for image processing are called convolutional neural networks (CNNs). These networks are effective at performing tasks like image segmentation and classification as well as detection. A convolutional layer in CNN completes the element extraction process, and a fully associated layer near the end uses the convolutional layer output to predict the image class. Convolutional neural networks integrate classifiers and feature extractors. Features are extracted using convolutional layers, and the data is subsequently classified using fully linked layers depending on the features. The basic organizational structure of CNN is depicted in the graphic below.

C. Transfer Learning

The use of weights from a model that has already been trained on a dataset is referred to as "transfer learning" [7]. In this work, 1000 classes were defined using weights from the model that was trained using the ImageNet Dataset. Applying what a model has learnt from one task with a lot of labelled training data to another task with little to no training data is the core principle. We use patterns that were established by finishing a similar task rather than starting the learning process from scratch. Transfer learning has several benefits, but the three that matter most are that it takes less time to train, performs better on neural networks, and doesn't need a lot of data. Transfer learning is useful in situations where access to vast amounts of data is not always attainable but is nevertheless necessary to train a neural network from the beginning. Transfer learning enables pre-training of the model, which enables the development of a workable machine learning model with less training data. A deep neural network may require days to train from scratch on a difficult problem. As a result, training time is also reduced. It has been applied to employ ResNet50 and EfficientNet pre-trained models.

D. Languages and Tools Used

Jupyter Notebook

Jupyter Notebook allows users to create and share documents with narrative text, live code, equations, and visualizations. Users may assemble all the parts of a data project in one place, which makes it simpler to explain the entire procedure.

Python

Python is an interpreted programming language that is object-oriented. The source code doesn't contain any declarations of the types of variables, parameters, functions, or methods. The outcome is a short, flexible piece of code. One of Python's key advantages is the abundance of libraries and frameworks it provides.

II. Related Work

P Gokila Brindha proposed Brain tumor detection from MRI images using deep learning techniques[1]. Its main goal is to create ANN and CNN model architecture. The ANN model used in this instance has seven layers. The model is run through 200 epochs using training and validation datasets. This ANN model achieves testing accuracy of 65.21%. Accuracy can be enhanced by adding more image data. It has been found that one of the best algorithms for analysing image datasets is CNN. The CNN predicts by lowering the image size without sacrificing the information required for prediction. [1]. In the journal of scientific and technology research volume they proposed brain tumor detection using machine learning [2]. Pre-processing of images is done using two tools MATLAB and Image J. Four different classification algorithms are applied to these features using WEKA 3.6, which also calculates the precision/recall, the F-measure, the proportion of correctly categorized photos, and the time required to create each model. The results of the studies indicate that the neural network classification algorithm performed the best after MRI pre-processing. Lazy-IBk performed admirably and finished second. The J48 decision tree and Naive Bayes came in last [2]. [3] This paper presents a deep learning-based Depth-wise Separable Convolutional Neural Network application. All the necessary steps of pre-processing are done inside this Image Data Generator method of keras library. the Mobile Net architecture makes advantage of depth-wise separable convolutions. Model is trained for 150 epochs so that the model can learn different complex patterns with maximum accuracy of 92%. The experimental results reveal that Depth-wise Separable Convolution Neural Network outperforms K Nearest Neighbor, Support Vector Machine and Convolution Neural Network, in terms of accuracy. [3]. It was revealed in the research [4] that brain tumor detection automation is very significant since high accuracy is required when human lives are at stake. Utilizing feature extraction and classification with a machine learning system, malignancies may be automatically found in MR images. This study presents a method for automatically identifying tumors in MRI images. The primary aim of this study is to show how segmenting MRI images using thermal information from brain tumors can frequently result in fewer false positive and false negative outcomes. Sonali B. Gaikwad, Madhuri S. Joshi proposed Principal Component Analysis and Probabilistic Neural Network for the classification[5]. The proposed approach to detect tumours automatically and classify them into benign, normal, and benign categories using the PNN classifier. The meningioma and glioma types of tumors are further identified from the malignant picture. 97.14% accuracy is the maximum. The PNN classifier demonstrated good accuracy, a negligible amount of retraining time, a short training period, and robustness to weight changes. PNN is frequently used to solve classification issues. The fact that PNN training is quick and simple is its main benefit. PNN therefore operates at a high speed [5]. Deep learning-based brain tumor detection from MRI images using the hybrid CNN and NADE model [6]. For hybrid architecture, a three-stage learning process is presented in this paper. It consists of categorization, feature exploitation, and density estimation. Four partitions make up the model's structure: A fully linked network, two CNNs, and a distribution estimator are used. The NADE model is trained to pick the suitable joint distribution during the density estimation phase. This study developed a classification model for brain tumor MRI images using a hybrid structure and convolutional neural network architecture that not only eliminates undesirable traits but also smoothens the borders of brain tumors[6].

III. DATASET

The Kaggle dataset for brain tumor imaging was used. This dataset is a combination of datasets from “figshare”, “SARTAJ”, and “Br35H”. It has 7022 MRI scans of the human brain divided into four categories: glioma, meningioma, no tumor, and pituitary. Two folders training and testing make up the dataset.

TABLE.3.1 DETAILS ABOUT DATASET

	Glioma	Meningioma	No Tumor	Pituitary
Testing	300	306	405	300
Training	1321	1339	1595	1457

IV. METHODOLOGY

The images were cropped and background was eliminated first. Following that, image augmentation is applied to the input images to boost the amount of data. The features in those MRI images were then extracted using pre-trained convolutional layers. After that, we used a fully connected artificial neural network that we had created to categorize the input MRI brain images.

A. Data augmentation

Several factors need to be taken into account when training our machine learning model. The data is one of the most crucial aspects. It is exceedingly challenging to get datasets for datasets like the classification of brain tumours. We employ data augmentation to boost the amount of data we wish to train with. Data augmentation [9] is the process of altering the data to increase the supplied Dataset. There will always be data that is missing and notable discrepancies in the diversity of data because it is acquired from different sources and from a real-world application. In order to improve the functionality of machine learning models, data is produced using the data augmentation method.

Images make up the dataset under consideration. The Dataset can be expanded by flipping, rotating, shearing, cropping, and shifting these photos. Our model receives more data with this larger dataset, but those data are definitely different from the initial data. When the original data is coupled with the enhanced data, model accuracy can be increased. Data augmentation techniques have been shown to be beneficial in areas like NLP and computer vision. In computer vision, transformations including cropping, flipping, and rotation are a few examples. Data manipulation techniques include random insertion, deletion, and swapping, the NLP enhancement techniques. The augmentation employed in this study consists of a 45-degree rotation, a 0.05-degree width shift, a 0.05-degree height shift, a horizontal flip, and a fill mode.

B. Grabcut Algorithm

The Grabcut algorithm is used to separate the foreground image from the background image. The foreground image is the subject that we are interested in and we train our model on this foreground image. This reduces

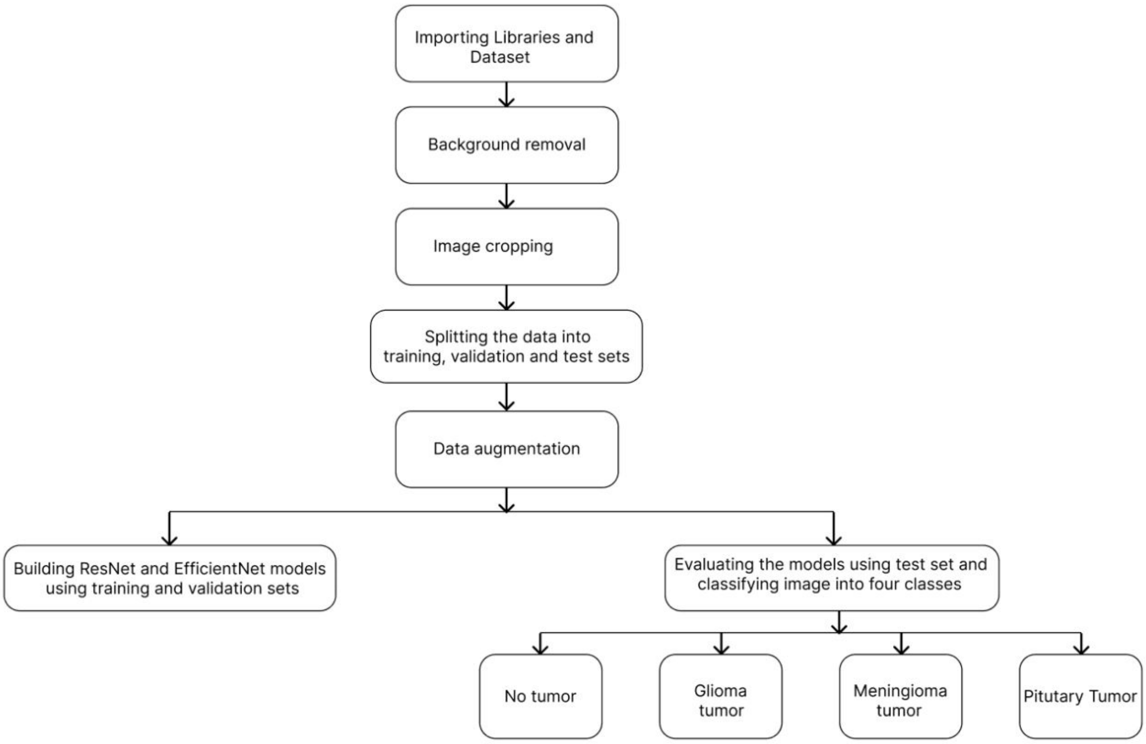

Fig.4.1 Block diagram of Brain Tumor Classification

unnecessary background noise which helps our model train well. In this algorithm, the model draws rectangles which are referred to as Region of Interest (ROI). ROI given by the user encloses the subject we are looking for. Mainly, the segmentation amount between the foreground and the background will be decided by the user, thereby deciding our ROI. Then a Gaussian Mixture Model (GMM) is performed on this ROI which segregates the ROI pixels into two categories, the Source node, and the Sink node. Pixels related to the foreground image belong to the Source node and the rest of the pixels will be assigned to the Sink node. The pixels along the edge of the foreground and background are assigned weights according to the probability that the pixel belongs to the foreground or background. These assigned weights are summated to give us the cost function and an algorithm is performed to segment the graph of the Source and Sink node. After segmentation, Source node pixels are labeled as foreground and Sink node pixels are labeled as background.

C. Model Building

Afterwards, categorization models were put into practice. Our study made use of the ResNet50 and EfficientNet models.

ResNet50

The Residual Network was first proposed in 2015 by Microsoft Research specialists. The Residual Blocks concept was developed by this design to solve the gradient vanishing/exploding issue. In this network, it employs a technique called as skip connections. The skip connection connects layer activations to the succeeding layers by skipping a few levels in between. A residual block is created as a result of this. These leftover pieces are stacked to create ResNets.

The Vanishing Gradient Problem in Machine Learning appears during the back propagation training of neural networks. The weights of a neural network are updated using the backpropagation process. To lessen the model's loss, each weight is altered utilizing the backpropagation method. This issue makes it challenging to learn and adjust the parameters of the network's earlier layers. The vanishing gradients problem is one form of unstable behavior we will encounter while training a deep neural network. It depicts the situation in which a deep multilayer feed-forward network fails to convey useful gradient data from the model's output layers to its input end. Regularization will skip any layers that have a negative impact on the architecture's performance by creating this type of skip connection. This avoids the issues that can arise when training a highly deep neural network with vanishing/exploding gradients.

ResNet-34, which featured 34 weighted layers, was the initial ResNet design. A convolution layer with 64 kernels, a max pooling layer with two sized stride, nine layers with 33, 64 kernels, another with 11, 64 kernels, and a third with 11, 256 kernels comprise the 50-layer ResNet. This sequence is repeated three times. 12 layers with 11,128 kernels, another layer with 33,128 kernels, and a third layer with 11 512 kernels. This process is performed four times. There are 18 layers with 11,256 kernels and another with 33, 256 and 11, 1024 kernels. This is repeated six times. 9 layers containing 11 512 kernels, 33 512 kernels, and 11 2048 kernels are repeated three times.

EfficientNet

With the growing need for convolution neural networks in the field of image classification, one of the main concerns is the efficiency of the given network. To improve the model efficiency, the depth of the network is deepened. This is known as depth scaling. This works up to a certain extent, but as we go on increasing the depth of the network, there is saturation that is achieved, i.e., the accuracy of the model remains constant even though we increase the depth. This is due to the vanishing gradient problem.

To overcome this problem up to a certain extent, EfficientNet is developed. In EfficientNet, our focus is not only on depth scaling but also on other factors like Resolution scaling and Width scaling. In Resolution scaling, we take images of higher resolution to work on complex features present in the image. This complex feature extraction helps our model to perform better as we can draw more information compared to low-resolution images. In Width scaling, to extract more features from the images, we need to have more feature maps or a greater number of channels. As we are processing higher-resolution images, we need to work with denser networks. Hence depth scaling also plays a major role here. It has been observed that increasing resolution, depth, and width increases our model accuracy, but for bigger models, the gain diminishes. To work with our model more efficiently, it is important to balance the network width, depth, and resolution. The factor up to which we can increase the resolution, width, and depth of the network is decided by compound scaling. In compound scaling, we take a baseline model to generate other efficient models. In EfficientNet, the baseline model that we choose is the Efficient-B0 network. This was developed by Neural Architecture Search (NAS). The depth, width, and resolution factors are considered as α, β, and γ, respectively. By performing a grid search, we get constant values of α, β, and γ, 1.20, 1.10, and 1.15 respectively. It explains that if we increase the resolution of our model by 15%, we need to perform width scaling by 10% and depth scaling by 20%. In this way, our model works well.

Fully Connected Layers

We use fully connected layers for classification. In our model, we need to classify only four classes. Hence the pre-trained model architectures utilized cannot be used because they have 1000 output classes. The new architecture was defined, and it consists of a global average pooling layer, two dropout layers, and two dense layers with relu and softmax activation functions.

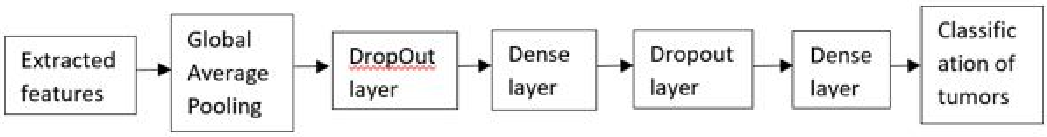

Fig.4.2 Architecture of Classification of tumors

D. Model Evaluation

Kaggle was used to train the model. Categorical cross-entropy was the loss function used, and the Adam optimizer was used to minimize the loss function. In Adaptive moment estimation learning rate is not constant, and it has adaptive learning rates. It updates the model in response to the output of the loss function. Categorical cross-entropy is used to find the error, It represents the discrepancy between actual and expected output.

The dataset was divided in the ratio of 8:2. In which 80% of the Dataset is for training, 10% is for validation and 10% is for testing. During training, accuracy and loss of training set and validation set were monitored.

Making a decision about how many training epochs to utilize while training neural networks can be challenging. When there are too many epochs in the training dataset, overfitting occurs, and when there are too few, underfitting occurs. Overfitting results in a minor training error but a significant testing error. Underfitting, on the other hand, results in high training and test mistakes. Early stopping is an approach that allows you to create an arbitrary large number of training epochs and then stop training when the model's performance on a hold-out validation dataset no longer improves. To protect the model and perform early halting, validation loss was tracked during training. Model training was terminated if the validation loss did not decrease for six consecutive epochs, with a maximum epoch size of 30 and a batch size of 20.

V. RESULTS

A. Results of the ResNet50 model

Confusion Matrix

The confusion matrix is used to assess the model's performance when the output can be divided into two or more classes. It gives information about predicted values and actual values of the test set. The accuracy of the test set can be calculated using a confusion matrix by finding the ratio of correctly predicted values to the total number of values. The obtained test accuracy is 0.9644.

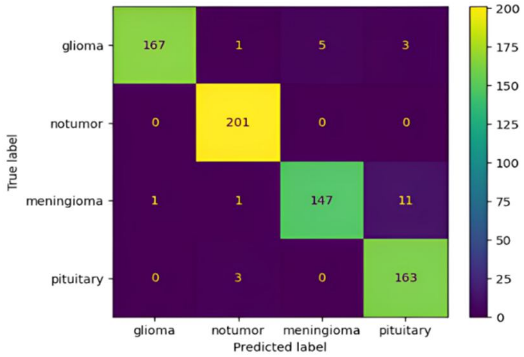

Fig.5.1 Confusion Matrix for Resnet50

Training accuracy vs Validation accuracy plot

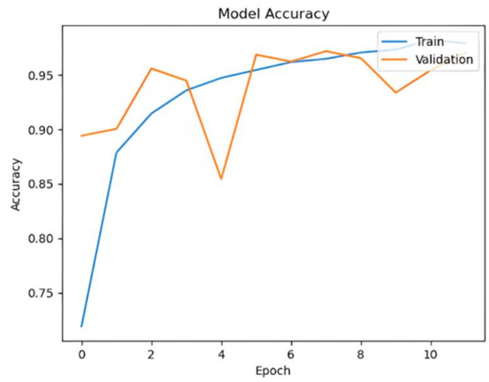

Fig.5.2 Training accuracy vs Validation accuracy plot for ResNet50

Training loss vs Validation loss plot

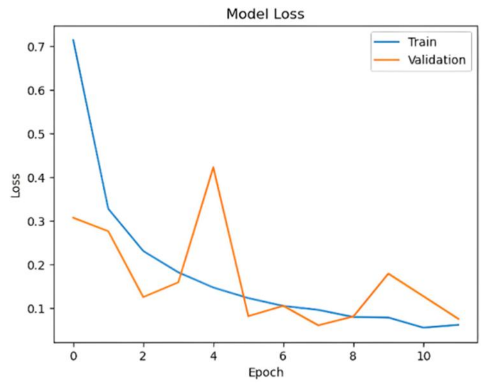

Fig.5.3 Training loss vs Validation loss plot for ResNet50

B. Results of EfficientNet Model

Confusion Matrix

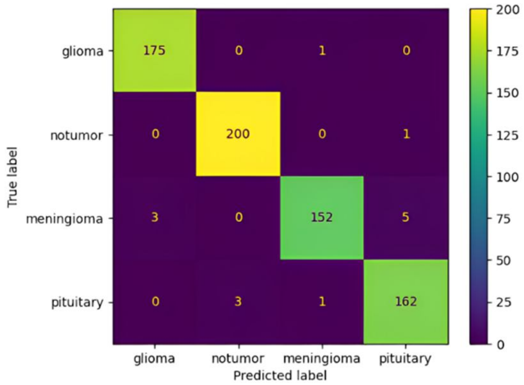

Fig.5.4 Confusion Matrix for EfficientNet

Accuracy plot for EfficientNet

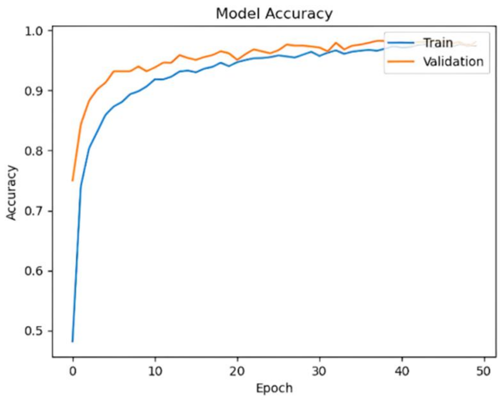

Fig.5.5 Accuracy plot for EfficientNet

Loss Plot for EfficientNet

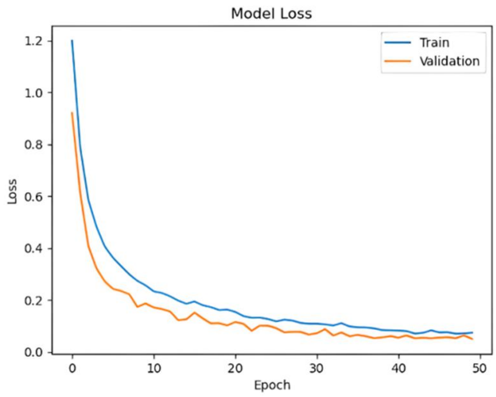

Fig.5.6 Loss plot for EfiicientNet

C. Comparison of proposed models with Base paper

TABLE.5.1 COMPARISON OF PROPOSED MODELS

Model	Accuracy	Loss
ResNet50	0.9644	0.0940
EfficientNet	0.9801	0.0509

VI. Conclusion

The detection and classification of brain tumors using machine learning are presented in this research. In order to overcome the negative effects of a small dataset and limited computing power, transfer learning and image augmentation were applied. ResNet50 model has achieved testing accuracy of 0.9644 and testing loss of 0.094. EfficientNet modal has achieved testing accuracy of 0.9801 and testing loss of 0.0509.

More data should be collected for more accurate classification in future study. Other models can be developed, and their accuracy can be compared to choose the best model. Here we only used one fully connected architecture for both the models. Instead, various architectures can be utilized to improve accuracy.

References

[1] P Gokila Brindha ," Brain tumor detection from MRI images using deep learning techniques", IOP Conference Series: Materials Science and Engineering,2020.

[2] M. Aarthilakshmi, S. Meenakshi, A. Poorna Pushkala, V. Rama@Ramalakshmi, N.B. Prakash.," Brain Tumor Detection Using Machine Learning", international journal of scientific & technology research volume 9, issue 04, 2020.

[3] Dheiver Santos, Ewerton Santos," Brain Tumor Detection Using Deep Learning",medriv for health services January 25, 2022.

[4] Javaria Amin, Muhammad Sharif, Anandakumar Haldorai, Mussarat Yasmin & Ramesh Sundar Nayak "Brain tumor detection and classification using machine learning: a comprehensive survey", Complex & Intelligent Systems volume 8, pages3161–3183 (2022) 23

[5] Sonali B. Gaikwad, Madhuri S. Joshi, "Brain Tumor Classification using Principal Component Analysis and Probabilistic Neural Network", International Journal of Computer Applications (0975 – 8887) Volume 120 – No.3, 2015

[6] Raheleh Hashemzehi , Seyyed Javad Seyyed Mahdavi , *, Maryam Kheirabadi , Seyed Reza Kame," Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE", Biocybern Biomed Eng,2020.

[7] Nayak, D.R.; Padhy, N.;Mallick, P.K.; Zymbler, M.; Kumar, S.Brain Tumor Classification Using Dense Efficient-Net. Axioms 2022, 11,34.

[8] Das, S.; Aranya, O.R.; Labiba, N.N. Brain tumor classification using a convolutional neural network. In Proceedings of the 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 3 May 2019; IEEE: New York, NY, USA, 2019; pp. 1–5.

[9] Sajja, V.R. Classification of Brain tumors using Fuzzy C-means and VGG16. Turk. J. Comput. Math. Educ. (TURCOMAT) 2021, 12, 2103–2113.

[10] K. G. Khambhata, and S. K. Panchal, "Multiclass classification of brain tumor in MR images," in Int. J. Innov. Res. Comput. Commun. Eng.,vol. 4 (5), pp. 8982–8992, 2016.

[11] J. Seetha, and S. Selvakumar Raja "Brain tumor classification using convolutional neural networks," in Biomed. Pharmacol. J. 2018, vol.11(3), 2018

[12] Pankaj sapra, Rupinder pal Singh, Shivani Khurana, "brain tumor detection using neural network", international journal of science and modern engineering, ijisme, issn: 2319-6386, volume-1, issue-9, august 2013.