2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI) | 979-8-3503-1590-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ACCAI58221.2023.10200513

Classification and Detection of Brain Tumors from Magnetic Resonance Imaging Scans using Deep Transfer-Learning

[1] **BeebiNaseeba,** [2] **S Bhaskar Nikhil,** [3] **Niranjan S Nair,** [4] **AsutoshDoppalapudi,** [5*] **Nagendra Panini Challa,** [6] **Roopsai Katta**

[1, 2, 3, 4, 5, 6] *School of Computer Science and Engineering (SCOPE), VIT-AP University Amaravati, India*

* *Corresponding E-mail: nagendra.challa@vitap.ac.in*

Abstract-Detection and classification of tumors in brain using MRIs is a quite strenuous errand when done manually. Automation of these processes becomes an important task to fulfill. Magnetic Resonance Images (MRI) are widely used for medical imaging as the they provide an excellent image quality for tumors, tissues and other parts inside the body. Early interception or detection of tumors in the brain can play a significant role in treatment. Further, classifying the type of tumor based on their location in the brain can assist surgeons to treat the affected patient efficiently. Deep learning techniques are extensively applied for extraction of features and classification of images into different classes. Identification and classification of medical images like MRI scans is commonly done using CNN or Convolutional Neural Network architectures in deep learning. This paper proposes a transfer learning approach based on different pre-trained CNN architectures such as VGG-19 and ResNet101. A custom hybrid model based on a pre-trained Inception-Resnet-v2 with attributes of both Inception and ResNet architectures is proposed. Comparative analysis of all the models were done with accuracy and AUC as the evaluation metrics. The highest accuracy was procured by the Inception-Resnet-v2 based hybrid model, which came up to be 99.30%.

Keywords—CNN, MRI, Transfer-Learning, Brain-tumor, Classification, Detection, Hybrid model

I. INTRODUCTION

A tumor is essentially a clump or a gathering of abnormal cells. If present in the brain, they can be either cancerous, a.k.a malignant tumors or non-cancerous, a.k.abenigntumor. Brain tumors directly impact the central nervous system of the human body, and are hence the most dangerous type of tumor, if malignant. As the formation of malignant brain tumors is the starting stages of brain cancer, detecting the tumor at an early stage becomes extremely crucial so that it can be intercepted before it spreads more throughout the brain.

Oncologists typically perform initial evaluations of brain tumors using medical imaging techniques such as MRI, short for magnetic resonance imaging and CT or computer tomography scans. The manual detection and identification of type of brain tumors with respect to where in the brain they are located can be tedious and repetitive. Labeling is accurate as technologies have advanced throughout the years to produce detailed scans of the brain in the form of MRI scans. They are the most abundantly used, clearest imaging technology. They, unlike X-rays, seldom discharge any dangerous ionizing radiation during the imaging process.

Computer-aided (CAD) systems powered by AI and computer vision prove to be extremely useful in detecting even the tiniest of lesions/tumors in the brain. Deep learning models and image preprocessing techniques have helped in automating image classification tasks a lot in recent years. Applying them for detecting and classifying brain tumors.

Deep learning-based algorithms have proven to be extremely useful in a variety of applications, including medical image analysis. Convolutional neural network (CNN) is proven to be one of the most prominent algorithms in deep learning. They are widely used due to its performance being robust and considerably efficient and due to their ability to share weights through feature maps. They automatically draw out the underlying low-level and high-level features from the training data.

This paper focuses on performing a transfer learning-based approach using various baseline transfer learning architectures such as VGG19, ResNet101, InceptionV3 and a hybrid model for training and performing the classification. VGG19 is a convolutional network 19 layers deep made specifically for the purpose of image classification. Transfer learning is widely proven to be most useful for image classification tasks. Preprocessing and data augmentation were also done before passing it to the particular model for training. As traditional methods to classify the images require subject expertise, deep learning methods are used for feature extraction to detect the tumor locations in the MRI scans. The classification is done on 4 different classes, including no tumor class. These 4 classes are based on where the tumor is located and how it is shaped. The CNN architectures detect the various important features from the brain MRI scans to perform the classification tasks.

The goal is to obtain a high accuracy for classification on different types of images in any orientation or type of brain tumor that is cancerous.

II. LITERATURE SURVEY

A variety of papers and studies have been published and conducted in the field of brain tumor detection and classification. Both tasks have been widely studied and approached in multiple different ways on different kinds of data. A few of them are given below,

The paper referenced in [1] proposed a few D - CNN based architectures for classification of image data. Out of all the classifiers that were proposed, the CFIC classifier, also called the Combined Feature and Image - based Classifier is said to have performed the best with an accuracy of 0.9897. The dataset used in this study is taken from Kaggle

The study referenced in [2] proposes a state-of-the-art tumor classification model which combines the attention mechanism technology with a multiple-path network. The attention mechanism used in this paper is used to ignore irrelevant information while selecting only information that is critical. The multipath network used in the referenced paper assigns the data to multiple different channels and then combines the results of different channels into one. The dataset used in this paper consists of 3064 MR images and the model used gave an accuracy of 0.9861.

The paper referenced in [3] presents a comparative analysis of several pre-trained deep learning models on brain MR images. The pre-trained models based on transfer learning used in this paper include, VGG16, Inception-v3 and ResNet50. From evaluation, it was inferred that all the models used procured training accuracy greater than 0.90. The highest validation accuracy came up to be 0.8826. The dataset used in the referenced paper is an open-source dataset from Kaggle with 233 images.The following table consists of some of the research papers and journals along with their evaluation results.

TABLE I. COMPARISON OF ACCURACIES WITH PREVIOUS PAPERS

References	Models used	Accuracy (Max)
Ref [4]	CNN KSVM	97.4%
Ref [3]	VGG-16 ResNet50 Inception-V3	88.26%
Ref [5]	VGG-16	98.01%

III. METHODOLOGY

About Dataset

The dataset that is used for training and testing the brain tumor classification model consists of a total of 7023 MRI scan images. This dataset is a combination of FigShare, SARTAJ dataset and Br35H. It was conveniently combined in the open-source dataset in Kaggle and the consistency of data was maintained by the author.

These images are categorized into 4 classes which are:

Glioma: It is the growth of cells that starts either in the brain or spinal cord. These cells are very harmful and they look similar to the healthy cells in the brain called glial cells. As time passes these cells form as a group which is commonly known as tumor. Glioma occurs in adults and kids. It has symptoms such as headache, vomiting and memory loss. It can be cured by performing surgery, radiation and chemotherapy. The following image shows the MRI scan of a brain suffering from this type of tumor.

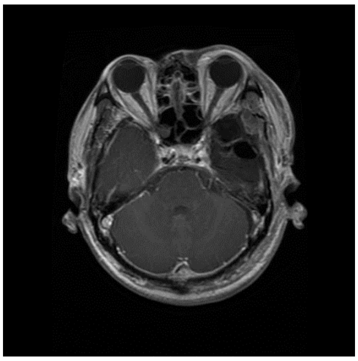


Fig. 1. Glioma tumor

Meningioma: This tumor arises in women mainly at old age from meninges which is a membrane around the brain and the spinal cord. Even though it is technically not a brain tumor but added into this category because it compresses the adjacent brain, vessels and nerves. It has symptoms like memory loss, loss of smell, decrease in the vision like blurriness and seeing double, hearing loss. Typically, surgery and radiation therapy are the given treatments for this tumor. The following image shows the MRI scan of a brain suffering from this type of tumor.

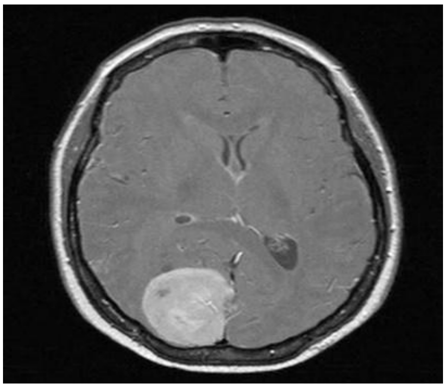


Fig. 2. Meningioma tumor

Pituitary: Pituitary is a brain tumor which grows in the pituitary gland or around the tissues of the pituitary gland. The pituitary gland is located in the base of the brain which is also an organ in the body. These tumors are not converted into cancer causing tumors or benign. This tumor is not spread to the other organs. It has symptoms such as headache, sinus, ear pain, drooping eyelid. It can be cured by endoscopic trans-nasal transsphenoidal surgery. The following image shows the MRI scan of a brain suffering from this type of tumor.

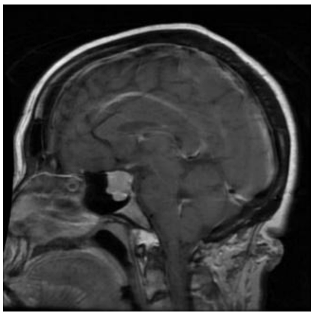


Fig. 3. Pituitary tumor

No Tumor: It means that the person does not have any tumors in the brain. The image below shows the MRI scan of a healthy person's brain who has no tumor.

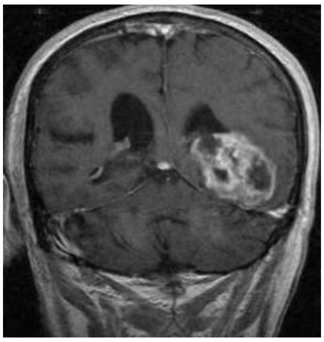


Fig. 4. No tumor

For training, there are 1321 Glioma MRI images,1339 of meningioma,1595 with no tumor and 1457 of pituitary tumors, a total of 6320 images. The dataset may not be exactly balanced but the count is acceptably close. The rest of the 703 images are used for testing the neural model. All the three types of classes were MRIs taken from different angles; sagittal, axial and coronal.

The dataset images are of different sizes hence, making preprocessing essential for the classification task efficiency.

Pre - processing and Augmentation

For the tumor classification task, the images are first reshaped into the dimensions of (224,224). These dimensions are the image input size for most pretrained models that are to be using for accomplishing this task using the transfer learning models.

The data was preprocessed using the open-cv python library by resizing the images. When resizing or distorting an image from a particular grid of a pixel to a different one, image interpolation is used. Image resizing is required when the count of pixels in a specific image needs to be varied according to the task to be performed. On the other hand, re-mapping may occur when rectifying for distortion in lens or for image rotation. In this case the technique used is inter-cubic interpolation.

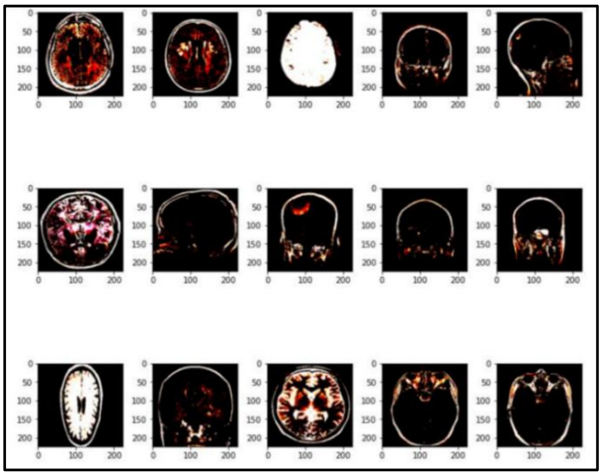
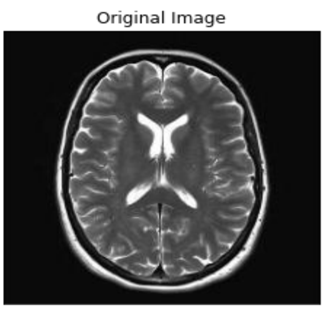


Fig. 5. MRI images after pre – processing

To get more data for training, image data augmentation techniques were used in order to get more variations of the same training data. Data augmentation is useful for improving the effectiveness and outputs of most models that use deep learning, by adding a variety of different samples to the dataset used to train the model. When the dataset used to make the model learn is plentiful and adequate, the model performs better and produces more accurate results.For each image different variants were produced by performing image manipulation. They include,

- Rotation
- Width and height shift
- horizontal and vertical flipping
- Shearing
- Zooming



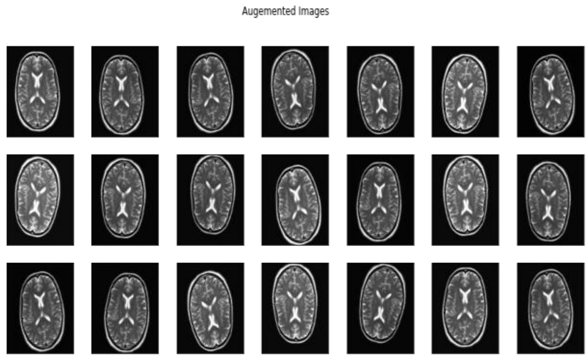


Fig. 6. Original MRI brain image and Augmented images

C. Models and Architecture

Accomplishing the process of image classification using deep learning requires the reduction of processing and computation cost. Therefore, transfer learning methods are used.

Transfer learning: It uses base models which are pre-trained using other huge image datasets. This helps in eliminating the time and resource needs required to build and train the model from scratch. This pre-trained model can be used for performing the same task on a different dataset in this case, image classification.

Different models built by different organizations or research groups are available in the python Keras module and some of those are used for the purpose of this paper. The base CNN models that are trained and tested are;

- VGG-19
- Resnet101
- Inception-Resnet-v2

VGG-19: VGG is short for Visual Geometry Group, a group of researchers at Oxford. This particular variant of VGG consists of 19 layers in its architecture, hence the name. The model was pre-trained on the popular ImageNet dataset which consists of 1000 different classes of images and a training set of 1.2 million images.

Some layers were modified and frozen in the network such that in a total of 21 million parameters, approximately 6 million of them were kept to be trainable parameters. A global average pooling layer was added at the end of the convolution steps in order to produce a feature map for each corresponding class for classification. In the end a few dense layers were added with 1024 and 512 neurons consecutively along with a dropout probability of 10% for reducing the complexity and preventing overfitting of data.

ResNet101: The ResNet models, also called residual networks, were developed by Microsoft. Resnet101 consists of 101 layers. ResNet CNN models are easier to optimize and improve accuracy which is attributed to the depth of the network. Its speciality is that it can overcome the problem of vanishing gradient despite being many layers deep. The input image size of ResNet101 is (224,224,3) and it was trained on the Imagenet dataset.

At the end of the network, a few dense layers were added after flattening the feature maps to make some linear computations and improve the predictions. The dropout probability of each of the layers were set to 20%. Batch normalization was also applied on each layer. The activation function was set as ReLU for each of the layers.

From a total of approximately 146 million parameters, 103 million of them were set as trainable.

Inception-Resnet-v2: This model combines the attributes of the Inception model developed by Google and the Residual network model. This model too was trained initially on the imagenet dataset. It uses the Inception models as base and in addition implements residual connections in ResNet. The network consists of 164 layers.

The architecture diagram of the custom Inception-Resnet-v2 model is as given,

The baseline CNN models were trained on the dataset with some common hyperparameters. The loss function used is categorical cross entropy as it is a multi-class classification task. The *Adam* optimizer was used which is a renowned and efficient optimizer for loss functions. The learning rate is adjusted to a value of 0.001.

The data was passed batchwise to the models with a batch size of 32. Batch sizes 64 and 16 were also tried but were not as efficient or effective. The number of epochs for which the models VGG-19 and Resnet-101 were run for is 20 and the Inception-Resnet-v2 was run for 40 epochs. An early stopping callback was applied for which the model stopped training when the training accuracy exceeded 99.5%

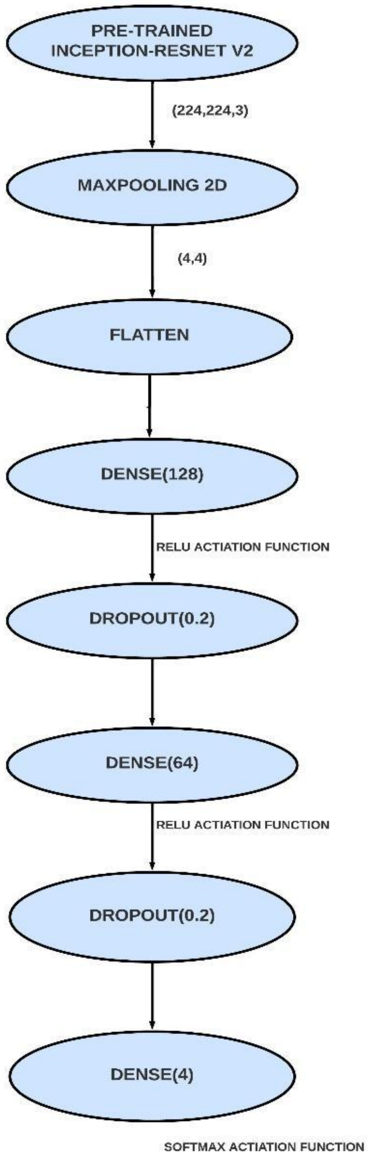


Fig. 7. Architecture of custom inception-ResNet-v2 model

D. Workflow

To summarize the whole process, a workflow is presented below;

Firstly, the dataset taken from Kaggle is imported to the environment. Then, the labels from the images in the dataset are separated. The data is then further split into a training set and testing set. Next, data augmentation is done on the training set which is then followed by a few pre-processing steps done using cubic interpolation. After pre - processing the data, the images are reshaped according to the input size of the base models. Through transfer learning, the pre-trained base models are then concatenated with a few custom pooling and dense layers with compatible activation functions at the end. Hyperparameters are set and callbacks are defined. Then the CNN model is compiled with callbacks and epochs with a suitable optimizer and loss function. The training dataset is passed to train the model and the validation dataset is passed to cross validate the model. After compiling the model, predictions are made by evaluating the model on the validation set.

The following image shows the workflow diagram.

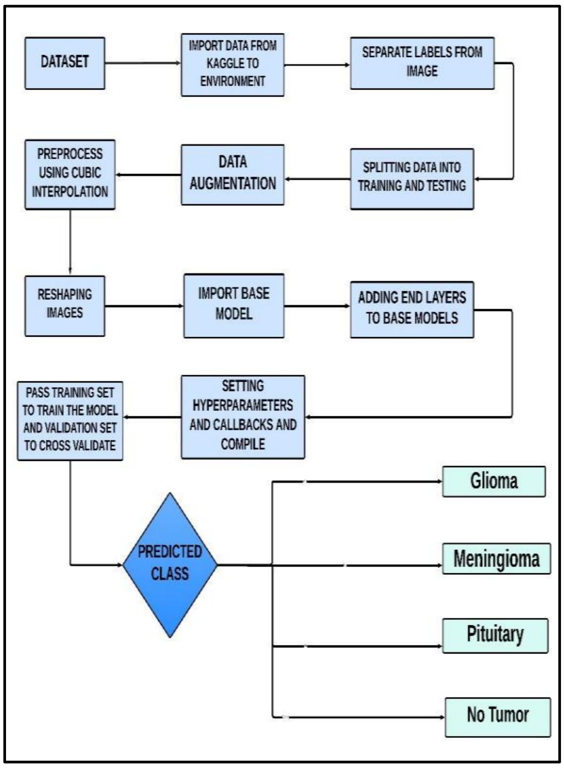


Fig. 8. Workflow block diagram

IV. Results

A. VGG19:

The CNN model gave an accuracy of 97.8%

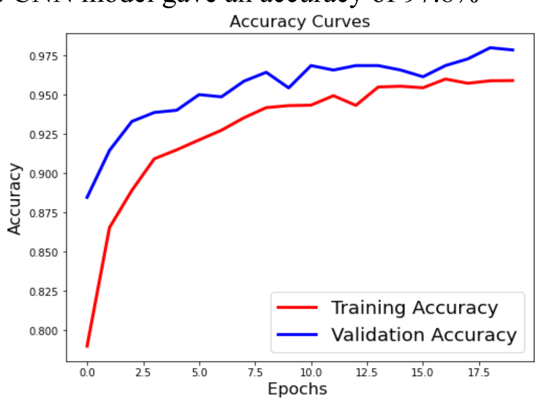


Fig. 9. Accuracy Curve for VGG19

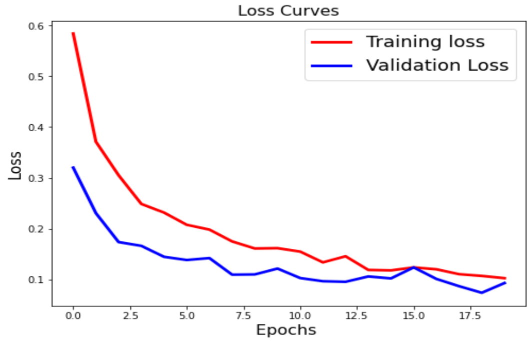


Fig. 10. Loss Curve for VGG19

ResNet101:

This model gave an accuracy of 98.14%.

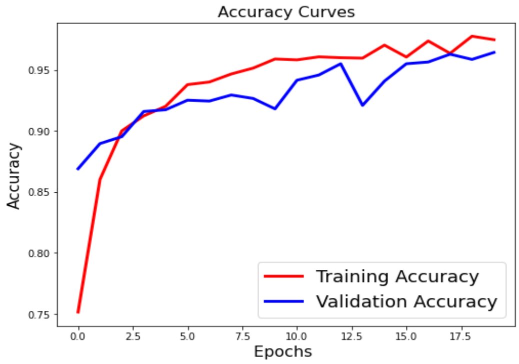


Fig. 11. Accuracy Curve for ResNet101

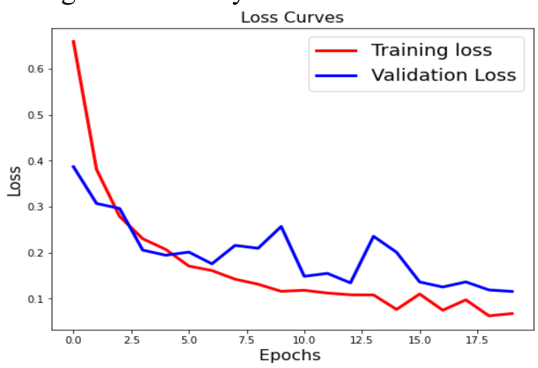


Fig. 12. Loss Curve for ResNet101

Inception-ResNet-V2:

Inception-ResNet Hybrid gave us the highest accuracy of about 99.30%.

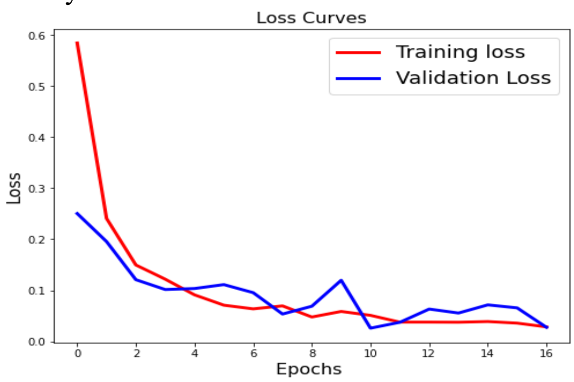


Fig. 13. Loss Curve for Inception-ResNet-V2

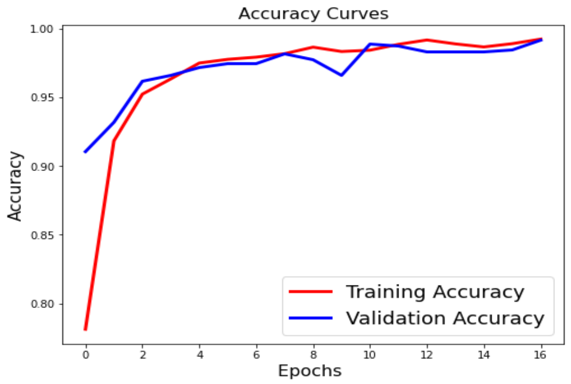


Fig. 14. Accuracy Curve for Inception-ResNet-v2

V. CONCLUSION

Deep Learning techniques are becoming quite popular for image classification type of problems in recent times. CNN models are being widely used to classify images into different categories. The dataset used for this paper provides us with a rich variety of brain MRI images. There are about 7000 images in the dataset that was chosen for this study. After preprocessing the data, several CNN models like VGG19 and ResNet101 were used to identify the type of brain tumor a person has in their brain. Among the basic transfer learning models that were used in this paper, ResNet101 gave the highest accuracy, which came up to be around 98.14%.

A hybrid model was also used for the classification task. Hybrid models are designed by the fusion of two or more CNN classifiers. Hybrid models used for the classification task in general have shown promising results. Inception-ResNetV2 hybrid model was used, which is a fusion of Inception and ResNet model. The model has 164 layers.

The hybrid model gave us an accuracy of 99.30% which is better than the other base models used in this paper.

Future work can include using a bigger dataset with more images and even more types of tumors. Tumors may also be classified as malignant and benign based on its size. Replacing the final dense layers of the neural network models with a more sophisticated classifier or ensemble models such as SVM, Random Forest Classifier, XGboost and many others. Using clipped or cropped MRIs may also help more than just segmenting using computer vision techniques.

REFERENCES

[1] Veeramuthu A., Meenakshi S., Mathivanan G., Kotecha K., Saini JR., Vijayakumar V. and Subramiyaswamy V., "MRI Brain Tumor Image Classification Using a Combined Feature and Image-Based Classifier", Front. Psychol. 13:848784 doi:10.3389/fpsyg.2022.848784

[2] Jun, W., Liyuan, Z., "Brain Tumor Classification Based on Attention Guided Deep Learning Model". Int J ComputIntellSyst 15, 35 (2022). doi: 10.1007/s44196-022-00090-9

[3] Srinivas C., K S NP., Zakariah M., Alothaibi YA., Shaukat K., Partibane B., Awal H., "Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor", J Healthc Eng. 2022 Mar 8; 2022:3264367. doi: 10.1155/2022/3264367. PMID: 35299683; PMCID: PMC8923754

[4] Islam R., Imran S., Ashikuzzaman M., Khan M., "Detection and Classification of Brain Tumor Based on Multilevel Segmentation with Convolutional Neural Network", Journal of Biomedical Science and Engineering, 13, 45-53, doi: 10.4236/jbise.2020.134004

[5] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches," Applied Sciences, vol. 12, no. 14, p. 7282, Jul. 2022, doi: 10.3390/app12147282.

[6] M. B. Khan, P. S. Saha and A. D. Roy, "Automatic Segmentation and Shape, Texture-based Analysis of Glioma Using Fully Convolutional Network," 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ACMI53878.2021.9528282.

[7] Sejuti Z.A and Islam M.S., "An efficient method to classify brain tumor using CNN and SVM", (2021) Proceeding of the IEEE 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), pp 644-648, IEEE, Dhaka, Bangladesh.

[8] Cheng J., Huang W., S Cao S, Yang R, Yang W, Yun Z, et al. (2015) "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition", PloS One, 10(12): e0144479. doi:10.1371/journal.pone.0144479

[9] Thejaswini P., Bhat M.B., Prakash M. K, "Detection and Classification of Tumor in Brain MRI", Int. J. Eng. Manufact (IJEM), vol. 9, no. 1, pp. 11-20, 2019

[10] Kaplan, Kaplan & Kaya, Yilmaz &Kuncan , Melih&Ertunc, H. M.. (2020). "Brain Tumor Classification using Modified Local Binary Patterns (LBP) Feature Extraction Methods," Medical Hypotheses, 139. 109696., doi: 10.1016/j.mehy.2020.109696.

[11] B.C.Santamaria, E.C. Carreño and A.G. Barrera, "Classification of Primary Brain Tumors Using Convolution Neural Network (CNN)," 2022 IEE Colombian Conferenceon Applications of Computational Intelligence (CoICACI), Cali, Colombia, 2022, pp. 1-6, doi:10.1109/ColCACI56938.2022.9905365.

[12] Dipu N.M., Shohan S.A., Salam K.M.A, "Deep Learning Based Brain Tumor Detection and Classification," 2021 International Conference on Intelligent Technologies (CONIT), Hubli, India, 2021, pp. 1-6, doi: 10.1109/CONIT51480.2021.9498384.

[13] N. Yadav,P. Kumar Jain, "Brain Tumor Detection and Optimization using Hybrid Classification Algorithm," 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2021, pp. 1148 – 1153, doi: 10.1109/I-SMAC52330.2021.9641033

[14] M. Constantin Daniel and L. Mihaela Ruxandra, "Brain Tumor Classification Using Pre Trained Convolutional Neural Networks," 2021 16th International Conference on Engineering of Modern Electric Systems (EMES), Oradea, Romania, 2021, pp. 1-4, doi: 10.1109/EMES52337.2021.94841.