Deep Learning for Brain Tumor Classification from MRI Images

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***Abstract*—Magnetic Resonance Imaging popularly known as MRI is one of the primary scans to visualize the brain tumor. The detailed pictures obtained from MRI when processed using deep learning methods help the neurologist in classifying brain tumor. The paper shows the exploratory analysis of brain MRI images based on extracted features and also a comparative analysis of different CNN based transfer learning models for the classification of MRI images for brain tumor. It shows the efficiency of deep learning techniques for the detection of brain cancer from the MRI images of the brain. The performance is measured in terms of training accuracy and test accuracy. Here binary classification is done with no tumor and with tumor classes. The goal of our study is to accurately detect tumors in the brain and classify it through the means of several techniques involving medical image processing, pattern analysis, and computer vision for enhancement, segmentation and classification of brain diagnosis.**

Keywords—Brain Tumor, Deep Learning, Machine Learning, Classification. Transfer Learning.

I. Introduction

Brain tumor is the leading cause of cancer across the globe. According to WHO, in 2020, 10 million deaths are due to cancer only. It is stated that most of the cancers can be prevented by avoiding the involved etiological factors and taking measures for cancer prevention [1]. Further, early detection of its presence, appropriate treatment and care of cancer patients can reduce the risk of death. With the help of diagnostic modalities such as magnetic resonance imaging (MRI) and computed tomography (CT), detailed scanned images of tissues and organs in the body can be obtained. MRI is one of the preferred scans done by radiologists and doctors for diagnosis of the brain tumor also. It provides detailed 2D images of organs and tissues which can be used for screening as well as staging of various cancers [2]. The growth patterns of tumor when observed from the MRI images of a patient depict the types and grades of the brain tumor. This may be benign or malignant [3]. Depending on this observation by detecting the early stage of the tumor, it becomes easy for the doctor to initiate treatment process.

II. Related Work

Increase in the number of patients and the amount of data to be analysed daily make the visual interpretation expensive and inaccurate. Some other factors like shape, size, contrast and high variations with respect to intensity in the tumor lead to a visual challenge for the observer. This demands for a computer aided diagnostic (CAD) system which can work as a helping hand to radiologists and doctors [4].

A CAD system can be an effective tool to classify brain tumors easily which can help in following a successful treatment plan. Such a system can acquire the MRI images as a first step from the MRI device. Recently, many researchers have proposed and developed different automated systems for classifying brain tumors using MRI scans. A CAD system was developed in 2013 by Sachdeva et.al which included image segmentation, feature extraction, and multiclass classification of six classes of brain tumors. By doing three different experiments using artificial neural networks, the overall classification accuracy came out to be 85% [5]. Emre et.al used machine learning technique namely support vector machine (SVM) for the classification of benign and malignant tumors. This system was able to classify the brain tumors with 91.49% accuracy, 90.79% sensitivity and 94.74% specificity [6]. Extracting the relevant features from the given data before performing classification task plays a significant role. For this, a hybrid feature extraction method with a regularized extreme learning machine (RELM) was proposed which was found to perform better as compared to other state-of-the-art approaches for classification [7].

Recent research shows that the deep learning methods perform well on image classification tasks and provide better accuracy than machine learning methods. Deep learning is that subset of machine learning which do not require manual feature extraction, which is an added advantage to such techniques. Paul et.al had developed a generalized method for brain tumor classification using fully connected neural networks and Convolution Neural Networks (CNN) and achieved an accuracy of 91.43% [8]. Brats 2013 is the benchmark dataset used by most of the researchers. Later, various CNN-based methods for classification of brain tumor were proposed. In one such method, three types of tumor: Meningioma, Glioma, and Pituitary tumors were classified, which yielded the classification accuracy of 97.3% [9]. In another work, the CNN based approach tried on three different datasets and after data augmentation using Deep CNN, it yielded 95.23% for Meningioma, 95.43% for Glioma, and 98.43% accuracy for Pituitary tumor [10].

III. Proposed Approach

The proposed approach includes mapping of data features with given MRI images. Features are selected using popular texture-based selection technique of gray-level co-occurrence matrix. The images are pre-processed with various feature selection, cleaning, standardization and normalization techniques. After that, the images are resized to 224 X 224 for input to various transfer learning models and finally after training, the classification is done for tumor class. The methodology is explained in the Fig.1.

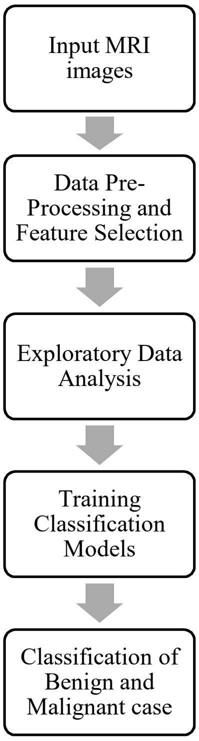

Fig. 1. Flowchart of the Proposed Model

IV. Experiments And Discussions

A. Dataset

The experiments are performed on brain tumor MRI images dataset by BRATS2015 [11]. First-order and second-order features are extracted from the MRI images using gray level co-occurrence matrix [12-13]. It is a very popular technique used for image texture analysis. There are 3764 images out of which 80% is used for training with 10% or 0.1 validation split in training model and 20% is used for testing to evaluate the model accuracy. The model is trained for 120 epochs with a batch size of 32.

B. Parameters

Total 14 features are used for studying the properties of the MRI images. Five first-order statistical features and eight second-order texture features are extracted. One feature is class label.

First-order features include basic statistical aspects like mean, variance, standard deviation, skewness and kurtosis.

Second-order features include energy, contrast, angular second moment (ASM), entropy, homogeneity, dissimilarity, correlation and coarseness. The features are mapped with the training dataset MRI images based on the labels of 0 for no tumor and 1 for no tumor. A CSV file is created for all the extracted features and is mapped with original image files also. Fig. 2 gives the glimpse of some test MRI brain images which are used for training and further classification of images using transfer learning models based on convolution neural networks.

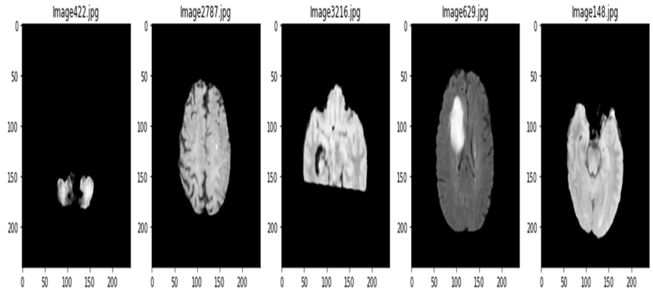

Fig. 2. Brain MRI Images

C. Experimental Results

Exploratory data analysis is done on the features of images which include mean, variance, standard deviation, entropy, skewness, kurtosis, contrast, energy, ASM, homogeneity, dissimilarity, correlation and coarseness. Fig. 3 describes the relation between various statistical features of MRI images using heat map.

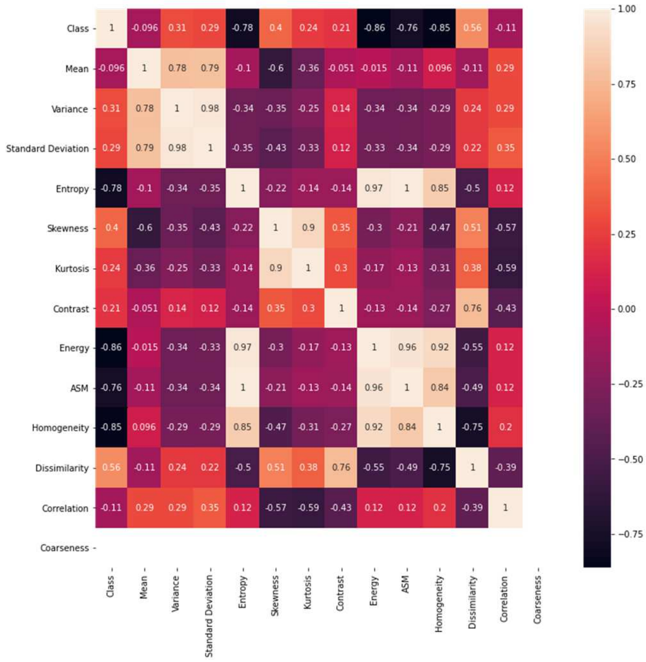

Fig. 3. Heat Map of MRI Image Features

Box plot analysis of some second-order featues show that dissimilarity in textures of images has much variation and outlier values as compared to other features like entropy, coarseness, correlation and homogeneity. Fig. 4 gives the visual description for the same.

There is a strong correlation between homogeneity and dissimilarity and homogeneity and entropy while a very weak correlation between correlation and homogeneity as well as correlation and entropy. Fig. 5 gives a detailed correlation matrix.

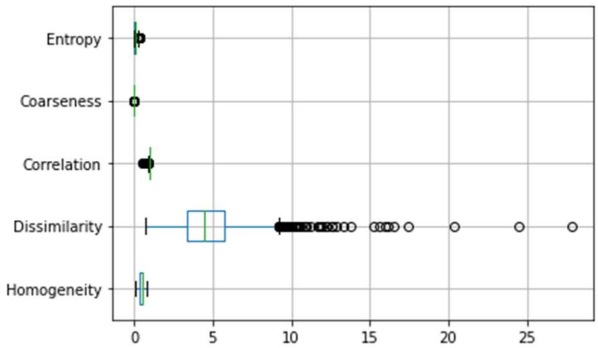

Fig. 4. Box plot of Image Features

	Homogeneity	Dissimilarity	Correlation	Entropy
Homogeneity	1.00	-0.75	0.20	0.85
Dissimilarity	-0.75	1.00	-0.39	-0.50
Correlation	0.20	-0.39	1.00	0.12
Entropy	0.85	-0.50	0.12	1.00

Fig. 5. Correlation matrix of images features

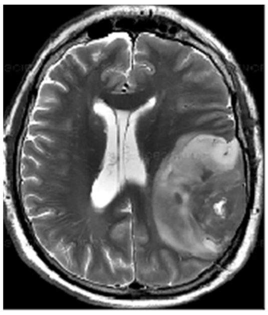

Fig. 6. Cropped MRI image of Brain

Original MRI images are processed by first finding the biggest contour and then cropping them after finding the extreme points. Fig. 6 shows the cropped image.

Cropping of original image from different axes is done and is studied for the brain tumor and for further analysis of gravity. The images are resized to 224 X 224 for input to training models. Different classification models are used to classify brain tumor. Different transfer learning models like VGG16, Inception_V3, and ResNet are compared with SVM and Random Forest classifiers. Similar parameters are explained for ResNet and VGG16. Batch size is taken as 132 with activation function in middle layers as ReLU. Number of epochs is 120. Figures 7 to 12 show the description of accuracy and loss plots with respect to training and validation data for VCG16, Inception_V3 and ResNet models.

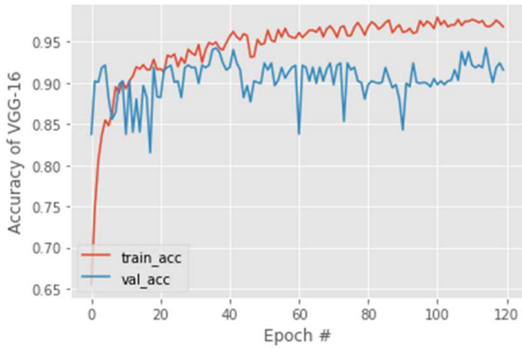

Fig. 7. Accuracy plot for VCG-16 model

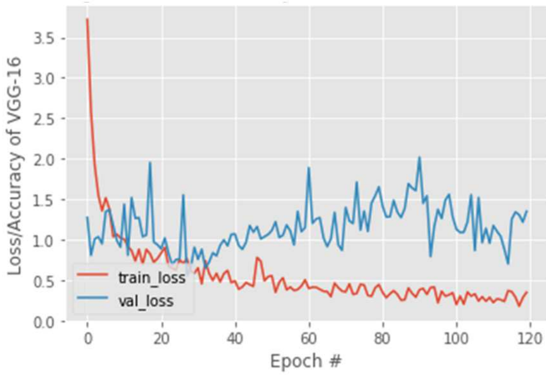

Fig. 8. Accuracy plot for VCG-16 model

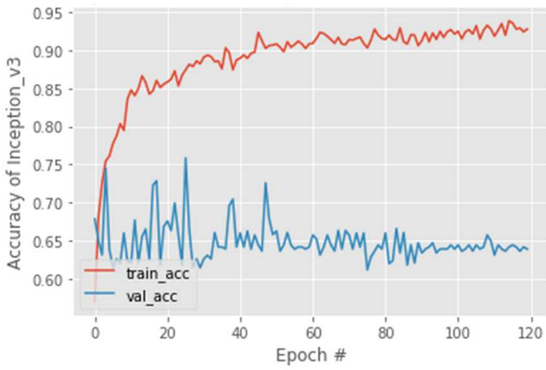

Fig. 9. Accuracy plot for Inception_V3 model

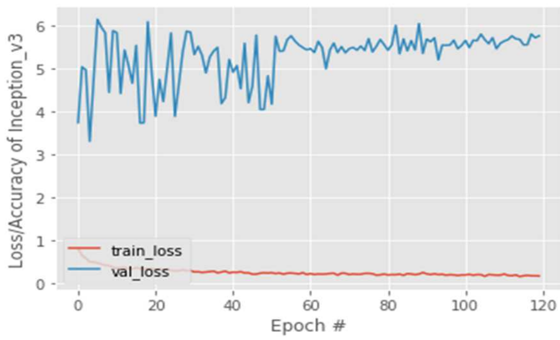

Fig. 10. Loss plot for Inception_V3 model

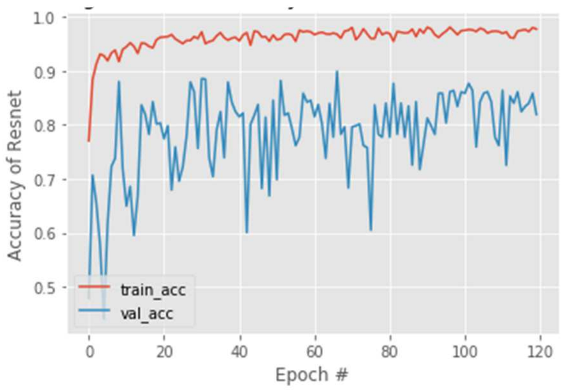

Fig. 11. Accuracy plot for ResNet model

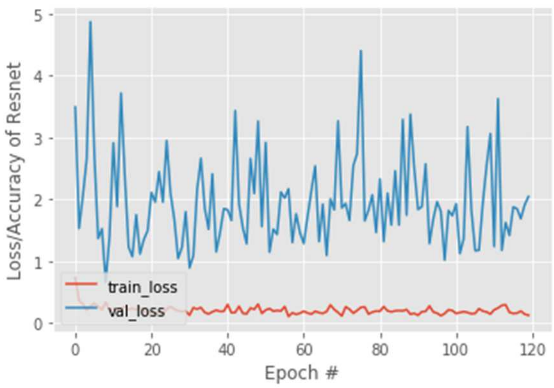

Fig. 12. Loss plot for ResNet model

Table 1 gives the training and Validation accuracy results with a comparative analysis of machine learning classification models like Support Vector Machine (SVM), Random Forest Classifier with deep learning models like VGG16, Inception_V3 and ResNet. It can be easily seen that VGG19 has outperformed rest all of the classification models. Overall deep learning approaches are better than traditional machine learning classification approaches.

TABLE I. COMPARATIVE ANALYSIS OF CLASSIFICATION ACCURACIES

Model	Training Accuracy	Validation Accuracy	Testing Accuracy
SVM Classifier	71.34	52.56	50.51
Random Forest Classifier	72.78	64.3	64.23
VGG16	96.3	92.23	90.54
Inception_V3	93.4	64.8	63.94
ResNet	99.7	82.12	81.92

V. CONCLUSIONS

Deep learning models give better accuracy in classification than basic machine learning techniques. Inception_V3 seems tends to over fit but can be managed with adding drop out. VCG16 is performing best among all the models for classification of the given dataset. The work can be extended to classification of brain tumor into different levels of malignancy. The accuracy can be improved with applications of optimization algorithms along with classification techniques and hyper parameter tuning. Transfer learning models are quite helpful in training medical images with very good accuracy. The video sequencing dataset can be considered for classification and prediction of brain tumor as compared to static images as future scope.

REFERENCES

[1] B. F. Ferlay J, Ervik M, Lam F, Colombet M, Mery L, Piñeros M, Znaor A, Soerjomataram I, "Global Cancer Observatory: Cancer Today," Lyon, France: International Agency for Research on Cancer, 2020. https://gco.iarc.fr/today (accessed Aug. 25, 2021).

[2] A. Işın, C. Direkoğlu, and M. Şah, "Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods," Procedia Comput. Sci., vol. 102, pp. 317–324, 2016, doi: 10.1016/j.procs.2016.09.407.

[3] C. Peri, "Types of Brain Cancer," Medically Reviewed by Michael W. Smith, MD, 2020. https://www.webmd.com/cancer/brain-cancer/brain-tumor-types (accessed Aug. 25, 2021).

[4] J. Kang, Z. Ullah, and J. Gwak, "MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers," Sensors, vol. 21, no. 6, p. 2222, Mar. 2021, doi: 10.3390/s21062222.

[5] J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, "Segmentation, feature extraction, and multiclass brain tumor classification," J. Digit. Imaging, vol. 26, no. 6, pp. 1141–1150, 2013, doi: 10.1007/s10278-013-9600-0.

[6] E. Dandıl, M. Çakıroğlu, and Z. Ekşi, "Computer-Aided Diagnosis of Malign and Benign Brain Tumors on MR Images," in In: Bogdanova A., Gjorgjevikj D. (eds) ICT Innovations 2014. ICT Innovations 2014. Advances in Intelligent Systems and Computing, vol 311., Springer, Cham, 2015, pp. 157–166.

[7] A. Gumaei, M. M. Hassan, M. R. Hassan, A. Alelaiwi, and G. Fortino, "A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification," IEEE Access, vol. 7, pp. 36266–36273, 2019, doi: 10.1109/ACCESS.2019.2904145.

[8] J. S. Paul, A. J. Plassard, B. A. Landman, and D. Fabbri, "Deep learning for brain tumor classification," in Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging, Mar. 2017, vol. 10137, no. 2, p. 1013710, doi: 10.1117/12.2254195.

[9] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, and D. González-Ortega, "A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network," Healthcare, vol. 9, no. 2, p. 153, Feb. 2021, doi: 10.3390/healthcare9020153.

[10] W. Ayadi, W. Elhamzi, I. Charfi, and M. Atri, "Deep CNN for Brain Tumor Classification," Neural Process. Lett., vol. 53, no. 1, pp. 671–700, Feb. 2021, doi: 10.1007/s11063-020-10398-2.

[11] B. H. Menze et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Trans. Med. Imaging, vol. 34, no. 10, pp. 1993–2024, Oct. 2015, doi: 10.1109/TMI.2014.2377694.

[12] Jakesh Bohaju, "Brain Tumor." Kaggle, 2020, doi: 10.34740/KAGGLE/DSV/1370629

[13] Sebastian V, B., Unnikrishnan, A., & Balakrishnan, K. (2012). Gray level co-occurrence matrices: generalisation and some new features. *arXiv preprint arXiv:1205.483*