Classification of the Type of Brain Tumor in MRI Using Xception Model

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***Abstract*—A brain tumor is recognized as one of the most invasive things to operate on. Cancer develops inside the brain due to unregulated and aberrant cell partitioning. The recent breakthroughs in deep learning greatly aided the medical imaging sector in diagnosing numerous diseases. In MR images, visual learning and image recognition have been used to classify the type of brain tumor. The researchers utilized a Convolutional Neural Network (CNN) approach, Data Augmentation, and Image Processing to organize brain MRI scans as cancerous or noncancerous. Using the transfer learning method, the researchers compared the performance of the primary CNN model to that of pre-trained CNN and Xception models. However, the experiment was conducted on a limited dataset. Later results reveal that the model's accuracy result is very effective and has a meager complexity rate, attaining 96% accuracy on the Xception Model.**

***Index Terms*—Brain Tumor, Convolutional Neural Networks, Magnetic Resonance Imaging, Deep Learning, Xception Model**

I. Introduction

Medical imaging classification and analysis are crucial in detecting abnormalities in various body organs, such as brain tumors [1]. Furthermore, organ abnormalities often lead to the rapid growth of tumors, the world's leading cause of death [2]. A brain tumor can be defined as abnormal and uncontrolled cell growth in the brain [3]. Any unexpected growth may damage human function based on the affected area of the brain, and it may even extend to other body organs [4]. In the worst-case scenario, it could cause brain damage, which could be life-threatening [4]. According to the world cancer report published by the World Health Organization (WHO), brain cancer accounts for less than 2 percent of human cancer; however, severe complications are produced [5]. Individuals of any age can develop a brain tumor, but the impact on everyone may differ. Similarly, brain tumors in adults are most common between the fifth and seventh decades of life. Due to the brain's complex structure, diagnosing a brain tumor is a complicated task.

The analysis of brain tumors is of particular interest because of the emerging innovation in medical image processing. According to the National Brain Tumor Foundation's (NBTF) overview, the improvement of brain tumor diagnosis among patients and the death rate due to brain tumors are succeeding over the world based on previous years' insights [6] as cited in [7]. Images convey information when an input image is processed to produce an output image. Images in today's world are stored digitally. Clinical professionals have been supported in providing better patient care by the development of information technology and e-healthcare systems in the medical industry in recent years. Thus, a range of imaging techniques can be used to detect and classify brain tumors; however, MRI is proven to be one of the most widely used non-invasive techniques [3].

The early detection and classification of brain tumors is a crucial research domain in medical imaging since it aids in selecting the most appropriate treatment option for patients [8]. According to Shoaib et al., brain tumors can be classified as noncancerous (benign) or cancerous (malignant) [9]. The World Health Organization (WHO) [10] grading system classifies gliomas into four grades, starting from grade I (benign) to grade IV (malignant) [11]. Deep learning and other machine learning advancements help identify and classify medical image patterns. Deep Learning (DL) is a machine learning subfield used in multiple applications, notably in the medical field, to handle complicated issues that demand exceptionally high accuracy and sensitivity. DL is most employed in brain image analysis for various applications such as normal and abnormal brain tumor classification, segmentation (edema, enhancing and non-enhancing tumor region), and so on [12]. Convolution neural network (CNN), on the other hand, is a type of deep learning model commonly utilized for classifying and segmenting medical images [13]. It is along with this premise that this study will be conducted. By employing deep learning, it hopes to contribute to developing reliable, accurate, and rapid analysis while also assisting radiologists in their final selection process.

II. Related Works

Various works and research have already been conducted on brain tumor classification utilizing different methods or algorithms to perform brain tumor classification. Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN) are examples of algorithms that can be used. A paper worked

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by Choudhury et al. (2021) entitled Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network [14] similarly focuses on Brain tumor classification using a Convolutional Neural Network (CNN). In contrast, the author proposed a new system based on a model of CNN consisting of 3 – layered CNN Architecture. The authors were able to differentiate and label the brain MRI images that were cancerous and not. The model used achieved a high percentage for the metric used. The accuracy is 96.08%, with an F1-Score of 97.3%. The model utilizes a three-layer of CNN, which requires a few pre-processing steps to produce the result in 35 epochs. Furthermore, the authors highlighted that diagnostic machine-learning applications and predictive treatment are essential in the medical field. A study by Sotiras et al. (2021) [15] used a deep-learning model to classify brain tumors. The model achieved an accuracy of 93.55% from internal test data of MRI images of seven image classes, consisting of one healthy class and six tumor classes. Then the authors conducted another execution of the model, specifically for the external test dataset, wherein it includes two tumor types which are high-grade and low-grade glioma. The model for the external test dataset has an accuracy of 91.95% in determining the classification of the brain tumor. Chakrabarty added that the positive predictive value or the probability that patients with a positive screening test carry the disease ranges from 85 to 100 percent [15]. The probability that patients with a negative screening test that does not carry any disease ranges from 98 to 100 percent out of all the classes. In the study of Noreen et al. (2021) entitled "Brain Tumor Classification Based on Fine-Tuned Models and the Ensemble Method" [16], the authors proposed six different models to classify brain tumors. The models are evaluated using performance metric measurement. The metric measurements that were utilized are Precision, Recall, and F-1 score. The Inception-v3 model paired with SoftMax was merged with other models. It is merged with the model's Inception- v3-RF, Inception-v3-KNN, Inception-v3-SVM, and ensemble. The Xception model and its integration with other models were also evaluated. The models are Xception-RF, Xception-KNN, Xception-SVM, and the ensemble technique. The highest accuracy of 94.34% results from the model of Ensemble1, which is the highest compared to other models of brain tumor classification.

Another related study is the work done by Sharif et al. (2020) entitled "Active Deep Neural Network Features Se- lection for Segmentation and Recognition of Brain Tumors Using MRI Images." [17] This study focuses on the classification and segmentation of brain tumors using active deep learning. The authors employed a procedure built using the CNN architecture for brain tumor detection like the current study. There are two main steps performed to develop this method. First, the SDL model was utilized to segment brain tumors. Another technique called DRLBP fusion was applied to improve the functionality using the particle swarm optimization (PSO) algorithm. The Softmax classifier was utilized for classification purposes in this study. The contrast improvement step aids in the coordination of image division, and DRLBP was built with classification functionality. The outcome displayed the dice score, and the result was a core tumor (CT) at 88.34%, whole tumor (WT) at 91.2%, enhancing tumor (ET) at 81.84% with the BRAST2018 dataset, and with an average accuracy which showed excellence than the 92% with the BRATS2013-BRATS2018 dataset. Furthermore, this work concentrated only on classifying low-grade glioma (LGG) and high-grade glioma (HGG). For this reason, the researchers chose to integrate pre-trained Xception and CNN models. The models used a transfer learning approach for detecting and classifying the type and grade of the brain tumor.

III. Materials and Method

A. Dataset

The deep learning model was trained and tested using an MRI dataset of 3,264 brain MRI slices. Meningioma, glioma, pituitary, and no tumors are all represented in the dataset. There are 937 images of meningioma tumors, 926 images of glioma tumors, 901 images of pituitary tumors, and 500 images with no tumor. The JPG picture format was used to process the brain tumor dataset.

B. Data Preparation

The process of picking suitable data to generate a training/validation set from the original data and prepping it for deep learning is known as data preparation. Before retrieving training and validation sets, the Brain MRI Dataset needed pre-processing procedures to modify the raw data.

1) Image Resizing: The images from the dataset are resized to ensure they are fixed-sized before inputting them into the Convolutional Neural Network. Resizing it to a smaller image also allows the model to train faster.

2) One-Hot Encoding: To preprocess categorical features, one-hot encoding is used to create dummy variables, which are duplicate variables that represent the data category, so that the machine can interpret each word.

C. Image Augmentation

The process of utilizing photos out of the original training set to increase the amount of the training data is known as image augmentation. It entails transforming photos in the training dataset into modified ones of the same class as the original.

During training, the ImageDataGenerator class from Keras is utilized to dynamically generate different images after a series of random changes to the training images. Random rotation, zoom, and image shift are used to help the model to generalize better. Other approaches, such as color space transformations and kernel filters, are not implemented to prevent transformed images that are substantially different from the original images.

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D. Convolutional Neural Networks

Convolutional Neural Networks, also known as ConvNet or CNN, is a type of deep learning (DL) used in image analysis and computer vision applications. It is an essential machine-learning technique for medical image segmentation and classification [18].

1) GlobalAveragePooling2D: The GAP layer performs average pooling on each feature map, which reduces the dimensions of an image. It aids in reducing the machine's computational load during training.

2) Dropout: Dropout is a method for removing or ignoring neurons from a neural network during training. This layer removes some of the neurons from the layer at each phase, making the neurons more independent of their neighbors. It aids in the avoidance of overfitting.

3) Dense Layer: It is a deeply connected layer that classifies the image into one of the four possible classes. It uses a softmax function because the model is for classifying brain tumors which is a multi-classification.

4) Callback: A callback is a group of functions used at specific points to help visualize the internal states of the model while it is in the training process. ModelCheckpoint, EarlyStopping, and ReduceLROnPlateau are used as callback functions in the model.

E. Transfer Learning

Transfer learning is an approach for applying knowledge from a previously trained model to a new task. Training a Deep ConvNet can take a long time when dealing with a large dataset. The model weights from a previously trained model can be used to speed up the training process and avoid having to train a model for days. Instead of creating a custom CNN model, an Xception model is used as our base model. Image classification has been utilized using Francois Chollet's Xception Model. Based on Keras' documentation of their various models, the Xception model is the most accurate. The ImageNet database, which contains over fourteen million images, was used to train Xception, which has the advantage of understanding all of the features of distinct images. The fine-tuned Xception model utilized the weights from the ImageNet dataset.

IV. Results and Discussion

The dataset was split into two sections: training and testing. Because it is ideal for separating the training and testing sets into custom sizes, the training and testing files are added to NumPy arrays to aggregate all photos. 90% of the data is utilized in training, while the remaining 10% is used in testing. The model was trained for 14 epochs due to early stopping, with a batch size of 32.

1) Xception Model Evaluation: The trained model was tested using 10% of the entire dataset. During the training phase, the Xception model employs several hyperparameters. The loss function and Adam optimizers were used to finetune these parameters. The proposed model was trained in 14 epochs, 32 batch sizes, a 0.001 learning rate, a categorical cross-entropy loss function, SoftMax as a classifier activation function, and an Adam optimizer.

Fig. 1 shows a good fit learning curve since both plots are close to one another and decrease to the point of stability. Since the ninth epoch has the best model weights because it has the lowest validation loss, the model restored and saved the weights from the ninth epoch.

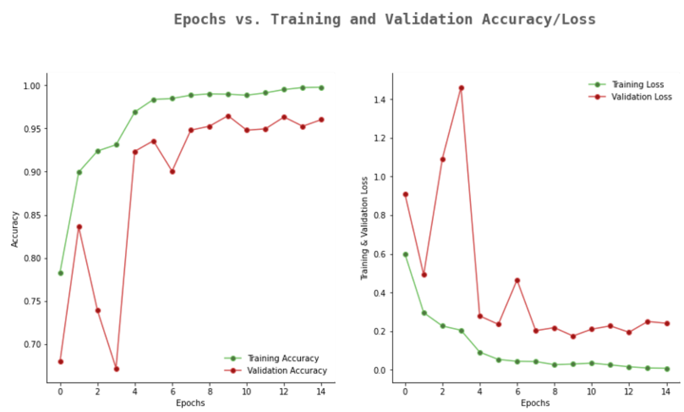

Fig. 1. Epochs vs. Training and Validation Accuracy/Loss.

2) Performance Evaluation: The model was evaluated on the testing data using a classification report. The Xception model showed 96% accuracy on our testing data.

The performance metrics used are from sklearn's classification report that computes the accuracy, precision, recall, and f-1 score. True and false positives (TP & FP) and true and false negatives (TP & FN) were used to calculate these metrics. These metrics help define how well the model performs in terms of prediction [19]. The performance metrics are calculated using the following formula:

$$accuracy = \frac{TN + TP}{TP + FP + TN + FN} \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2 * \frac{precision * recall}{precission + recall} \tag{4}$$

TABLE I
CLASSIFICATION REPORT

Classification	Precision	Recall	F1-Score	Support
glioma tumor	0.94	0.96	0.95	168
no tumor	0.98	0.96	0.97	108
meningioma tumor	0.98	0.94	0.96	201
pituitary tumor	0.97	0.99	0.98	176
accuracy	0.97	0.95	0.96	653
macro average	0.97	0.97	0.97	653
weighted average	0.97	0.96	0.96	653

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V. Conclusion and Future Works

The use of the Xception model for the classification of brain tumors is presented in this study. The Xception model performed well in feature extraction, delivered accurate findings, and showed higher accuracy than other deep-learning models for brain tumor classification. The research findings might have clinical significance for the study of brain tumors. The proposed method may be beneficial in detecting tumors in patients with brain tumors and may have prognostic value. To boost model performance further, an optimization method to find the best hyper-parameter value and a better data preparation & preprocessing strategy may be considered. A larger dataset and further Image augmentation might also help the model predict an unseen dataset more accurately. The Xception model for the classification of brain tumors established in this study can assist doctors and radiologists in speeding up diagnosing patients and accurately classifying them.

References

[1] T. Saba, A. S. Mohamed, M. El-Affendi, J. Amin, and M. Sharif, "Brain tumor detection using fusion of hand crafted and deep learning features," *Cognitive Systems Research*, vol. 59, pp. 221–230, 2020.

[2] H. Fahad, M. U. Ghani Khan, T. Saba, A. Rehman, and S. Iqbal, "Microscopic abnormality classification of cardiac murmurs using anfis and hmm," *Microscopy Research and Technique*, vol. 81, no. 5, pp. 449–457, 2018.

[3] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," *IEEE access*, vol. 7, pp. 69 215–69 225, 2019.

[4] J. S. Barnholtz-Sloan, Q. T. Ostrom, and D. Cote, "Epidemiology of brain tumors," *Neurologic clinics*, vol. 36, no. 3, pp. 395–419, 2018.

[5] M. J. Wiseman, "Nutrition and cancer: prevention and survival," *British Journal of Nutrition*, vol. 122, no. 5, pp. 481–487, 2019.

[6] K. Baalamurugan, P. Singh, and V. Ramalingam, "A novel approach for brain tumor detection by self-organizing map (som) using adaptive network based fuzzy inference system (anfis) for robotic systems," *International Journal of Intelligent Unmanned Systems*, 2021.

[7] M. Hameurlaine and A. Moussaoui, "Survey of brain tumor segmentation techniques on magnetic resonance imaging," *Nano Biomed. Eng*, vol. 11, no. 2, pp. 178–191, 2019.

[8] E. Irmak, "Multi-classification of brain tumor mri images using deep convolutional neural network with fully optimized framework," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 45, no. 3, pp. 1015–1036, 2021.

[9] J. Seetha and S. S. Raja, "Brain tumor classification using convolutional neural networks," *Biomedical & Pharmacology Journal*, vol. 11, no. 3, p. 1457, 2018.

[10] S. H. Torp, O. Solheim, and A. J. Skjulsvik, "The who 2021 classification of central nervous system tumours: a practical update on what neurosurgeons need to know—a minireview," *Acta Neurochirurgica*, pp. 1–12, 2022.

[11] C. Horbinski, T. Berger, R. J. Packer, and P. Y. Wen, "Clinical implications of the 2021 edition of the who classification of central nervous system tumours," *Nature Reviews Neurology*, vol. 18, no. 9, pp. 515–529, 2022.

[12] G. S. Tandel, M. Biswas, O. G. Kakde, A. Tiwari, H. S. Suri, M. Turk, J. R. Laird, C. K. Asare, A. A. Ankrah, N. Khanna *et al.*, "A review on a deep learning perspective in brain cancer classification," *Cancers*, vol. 11, no. 1, p. 111, 2019.

[13] T. Wang, C. Lu, G. Shen, and F. Hong, "Sleep apnea detection from a single-lead ecg signal with automatic feature-extraction through a modified lenet-5 convolutional neural network," *PeerJ*, vol. 7, p. e7731, 2019.

[14] C. L. Choudhury, C. Mahanty, R. Kumar, and B. K. Mishra, "Brain tumor detection and classification using convolutional neural network and deep neural network," in *2020 international conference on computer science, engineering and applications (ICCSEA)*. IEEE, 2020, pp. 1–4.

[15] S. Chakrabarty, A. Sotiras, M. Milchenko, P. LaMontagne, M. Hileman, and D. Marcus, "Mri-based identification and classification of major intracranial tumor types by using a 3d convolutional neural network: A retrospective multi-institutional analysis," *Radiology: Artificial Intelligence*, vol. 3, no. 5, 2021.

[16] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, and M. O. Alassafi, "Brain tumor classification based on fine-tuned models and the ensemble method," *Computers, Materials & Continua*, vol. 67, no. 3, pp. 3967–3982, 2021.

[17] M. I. Sharif, J. P. Li, M. A. Khan, and M. A. Saleem, "Active deep neural network features selection for segmentation and recognition of brain tumors using mri images," *Pattern Recognition Letters*, vol. 129, pp. 181–189, 2020.

[18] G. A. Sampedro, M. A. P. Putra, D.-S. Kim, and J.-M. Lee, "3d printer state prediction: A deep learning model approach," in *2021 1st International Conference in Information and Computing Research (iCORE)*. IEEE, 2021, pp. 135–138.

[19] G. A. Sampedro, D. J. Agron, S. L. Huyo-a, M. Abisado, D.-S. Kim, and J.-M. Lee, "3d printer state monitoring mobile application through a deep learning approach," in *2022 IEEE International Symposium on Advanced Control of Industrial Processes (AdCONIP)*. IEEE, 2022, pp. 283–284.

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