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Using Convolutional Neural Network and Transfer Learning Technique to Segment Brain MRI Images with Tumor Detection Approach

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Abstract

A brain tumor is a mass or abnormal growth of cells in the brain. Tumors are divided into two types, benign and malignant. The best diagnosis of brain tumor is obtained through MRI images. This research, using convolutional neural network, designed a model for classifying brain MRI images into four classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor with the approach of brain tumor diagnosis. To achieve the mentioned goal, transfer learning technique and EfficientNetB0 model were used. The design stages of this research were as follows: data preparation, dividing the data set into training and testing sets, using transfer learning, and training the proposed model, training, and validation, and finally evaluating the model using the confusion matrix. The accuracy of the proposed model in this study was about 98%. The precision of this model in the classification of glioma tumor, meningioma tumor, pituitary tumor and no tumor classes was obtained as 96%, 98%, 99% and 96% respectively. The use of transfer learning technique can have a significant effect in improving brain tumor diagnosis in MRI images; For this reason, the use of this model, which has high accuracy and precision, helps doctors in diagnosing this abnormality.

Keywords: Anxiety; Adolescents; Students; Academic stress

Abbrevations: CNN: Convolutional Neural Network; TL: Transfer Learning; MRI: Magnetic Resonance Imaging; ML: Machine Learning; AI: Artificial Intelligence; ANN: Artificial Neural Network; CT: Computed Tomography

Introduction

Brain tumor is one of the most aggressive diseases among children and adults [1]. Brain tumors account for 85-90% of primary central nervous system (CNS) tumors [2]. About 11,700 people are diagnosed with brain tumors every year [3]. The survival rate for people with a cancerous brain tumor is approximately 34% for men [4] and 36% for women [5]. Brain tumors are classified as follows: benign tumor [6], malignant tumor [7], pituitary tumor [8], etc. Proper treatment, planning and accurate diagnosis should be done to improve the life expectancy of patients [9]. The best way to diagnose brain tumors is (MRI) [10]. In this type of imaging, a huge amount of image data is generated through scans [8]. On the other hand, a manual examination can be prone to error due to the level of complexity involved in brain tumors and their characteristics [11]. Using automatic classification techniques using machine learning (ML) [12] and artificial intelligence (AI) [13] consistently provides higher accuracy than Manual classification is shown. Hence, proposing a system that performs diagnosis and classification using deep learning algorithms using Convolutional Neural Network (CNN), Artificial Neural Network (ANN) and Transfer Learning (TL) will be useful for clinicians worldwide [14]. Brain tumors are complex [15]. There are many abnormalities in the size and location of brain tumors [16]. This makes it difficult to fully understand the nature of the tumor and also a professional neurosurgeon will be required to analyze the MRI [17]. Often in developing countries, the lack of skilled physicians and lack of knowledge about tumors makes reporting from MRI really challenging and time-consuming. So, an automatic door system can solve this problem [18]. In the current research, an automatic segmentation system is introduced and implemented, which, after obtaining brain MRI images, categorizes them into four classes: Glioma Tumor, Meningioma Tumor, Pituitary Tumor, and No Tumor. This action is done by using Python programming language, convolutional neural network, transfer learning and EfficientNetB0 model. With this, the mentioned abnormalities can be recognized more easily.

Material and Method

Database

In this research, database [19] was used. This database includes CT scan images of the brain and has four tumor classes: glioma tumor, meningioma tumor, pituitary tumor, and no tumor images. There are a total of 394 images in this database. Table 1 shows the information about this database. The folder contains MRI data. The images are already split into Training and Testing folders. Each folder has four subfolders. These folders have MRIs of respective tumor classes. Figure 1 shows a simple example of the images in the database.

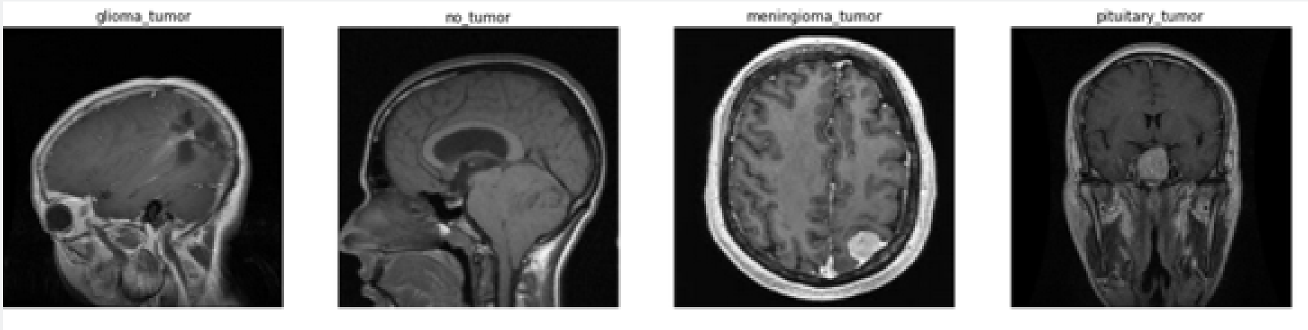

Figure 1: Sample image from each label.

Table 1: The number of images in the database by classes.

Class	Number of Images
Glioma Tumor	100
Meningioma Tumor	115
Pituitary Tumor	74
No Tumor	105

In this study, CNN is used to perform image classification in brain tumor dataset. Since this dataset is small, if we train a neural network on it, it won't really give us a good result. Therefore, we are going to use the concept of Transfer Learning to train the model to get really accurate results.

Study design

The design steps of this study are shown in figure 2.

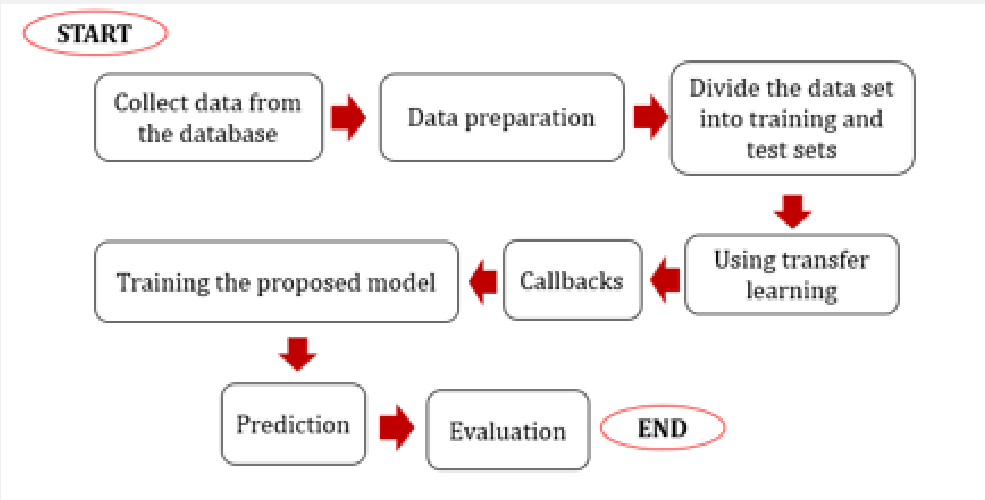

Figure 2: Study design flowchart.

Proposed

Deep convolutional neural network models can take days or even weeks to train on very large data sets. A way to shorten this process is to reuse model weights from pre-trained models developed for standard computer vision benchmark datasets, such as ImageNet image recognition tasks [20]. The best performing models can be downloaded and used directly or merged into a new model for our computer vision problems. In this study, we use the EfficientNetB0 model, which uses the weights of the ImageNet dataset. The EfficientNet-B0 architecture was not developed by engineers, but by the neural network itself. They developed this model using a multi-objective neural architecture search that op-

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timizes both accuracy and floating-point operations. The EfficientNetB0 model expects its inputs to be float tensors of pixels with values in the (0-255) range [21]. Efficient Net is a state-of-the-art convolutional neural network, released open source by Google Brain. The primary contribution in Efficient Net was to thoroughly test how to efficiently scale the size of convolutional neural networks. For example, one could make a Convent larger based on width of layers, depth of layers, the image input resolution, or a combination of all of those levers. Efficient Net forms the backbone for the state-of-the-art object detector Efficient [22]. Object detection goes one step further to localize as well as classify objects in an object. Figure 3 shows the architecture of an EfficientNetB0 model.

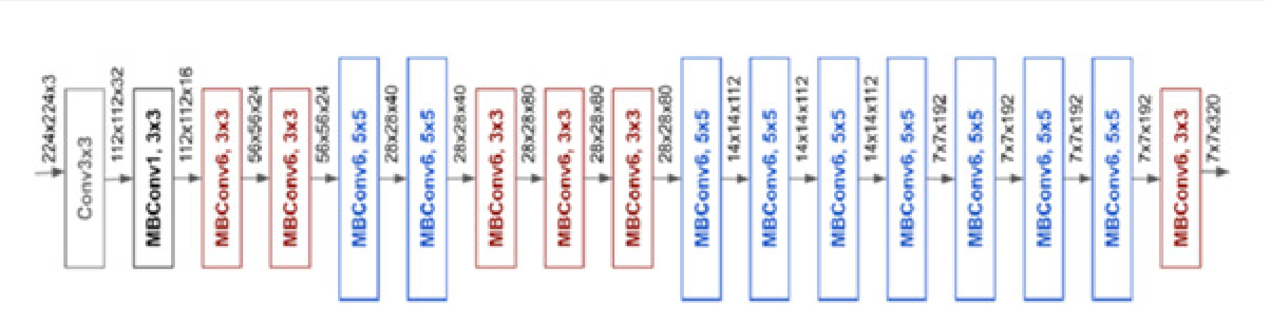

Figure 3: EfficientNetB0 model architecture.

The required data is received from the database. Then data preparation should be done; We start off by appending all the images from the directories into a Python list and then converting them into numpy arrays after resizing it. Then we divide the data set into training and test sets. In the next step A hot encoding is performed on the labels after converting it to numerical values. Then transfer learning technique is used; Deep convolutional neural network models may take days or even weeks to train on very large datasets. A way to short-cut this process is to re-use the model weights from pre-trained models that were developed for standard computer vision benchmark datasets, such as the ImageNet image recognition tasks. Top performing models can be downloaded and used directly or integrated into a new model for your own computer vision problems. In this study, we'll be using the EfficientNetB0 model which will use the weights from the ImageNet dataset. The include top parameter is set to False so that the network doesn't include the top layer/ output layer from the pre-built model which allows us to add our own output layer depending upon our use case. Then we use callback. Callbacks can help us fix bugs more quickly and can help us build better models. They can help us visualize how our model's training is going and can even help prevent overfitting by implementing early stopping or customizing the learning rate on each iteration. By definition, "A callback is a set of functions to be applied at given stages of the training procedure. we can use callbacks to get a view on internal states and statistics of the model during training." In this study, we'll be using Tensor Board, Model Check point and Reduce LROn Plateau callback functions. Then we train our proposed model. After training the model, Prediction of model should be done. we've used the "argmax" function as each row from the prediction array contains four values for the respective labels. The maximum value which is in each row depicts the predicted output out of the 4 possible outcomes. So, with "argmax", we are able to find out the index associated with the predicted outcome. Finally, with the confusion matrix, the proposed model is evaluated [23].

Result

Model evaluation

The evaluation of this model is done using the confusion matrix and parameters of accuracy, precision, recall and F1 score. The confusion matrix has four parameters: true positive (TP), true negative (TN), false positive (FP) and false negative (FN). These parameters can be defined as follows:

*True Positives (TP): The number of correct features that are correct and detected.

*True negative (TN): number of false features that are correctly detected.

*False positives (FP): the number of correct features that are falsely and incorrectly recognized.

*False negatives (FN): the number of incorrect features that are mistakenly correctly and correctly detected.

The accuracy of a model is obtained from the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

The precision of a model is also based on the following formula:

$$\Pr ecision = \frac{TP}{TP + FP}$$

The recall rate of a model is obtained using the following formula:

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$$Recall = \frac{TP}{TP+FN}$$

F1-score is also based on the following formula:

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

After implementing the proposed model, its accuracy was about 98%. Table 2 shows the amount of precision, recall, f1-score and support of our model. Table 3 also shows the amount of macro average and weighted average in our proposed model. Figure 4 shows the heat map of confusion matrix of the proposed model. Support is the number of occurrences of each class in the true responses. It can be calculated by summing the rows of the confusion matrix (Figure 5 & 6).

Table 2: The amount of precision, recall, f1-score, and support in the proposed model.

Class	Precision	Recall	F1-Score	Support
glioma tumor	0.96	0.96	0.96	93
meningioma tumor	0.98	0.95	0.96	96
pituitary tumor	0.99	1	0.99	87
no tumor	0.96	1	0.98	51

Table 3: The amount of macro average and weighted average.

Parameter	Precision	Recall	F1-Score	Support
accuracy			0.97	327
macro average	0.97	0.98	0.97	327
weighted average	0.97	0.97	0.97	327

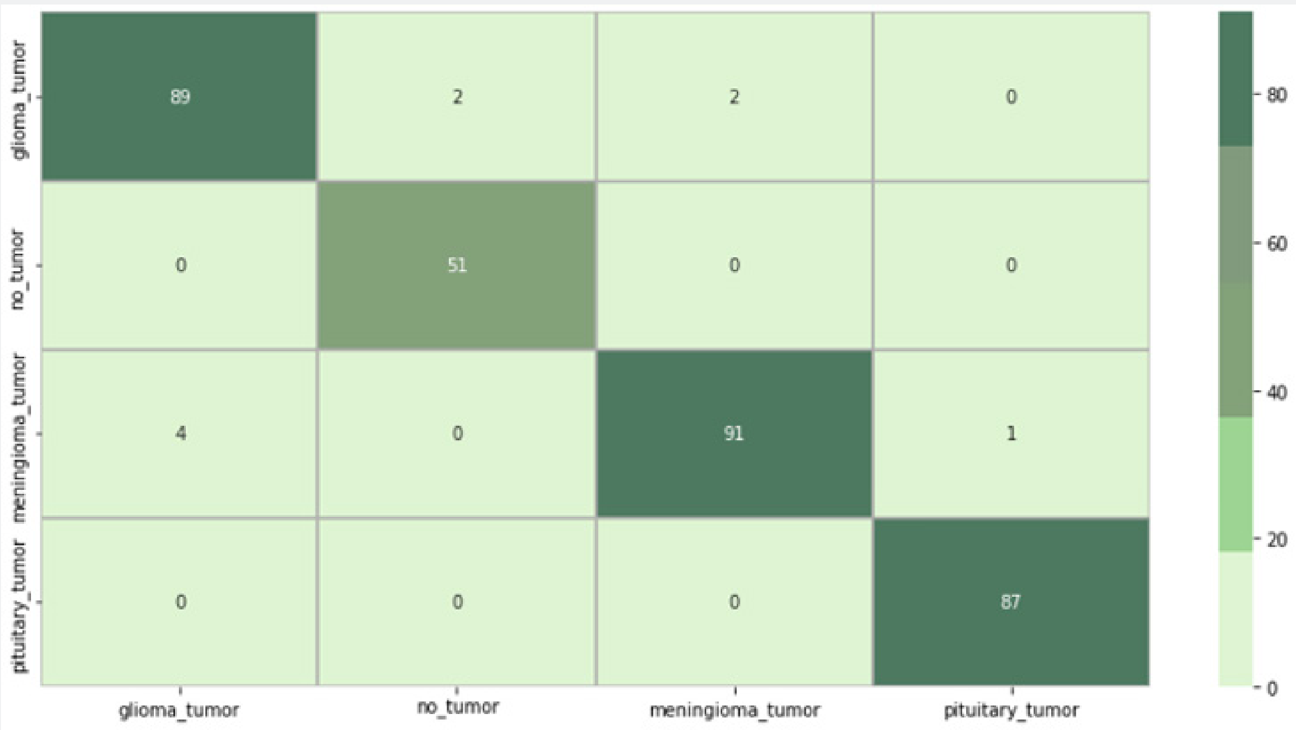

Figure 4: Heat map of confusion matrix.

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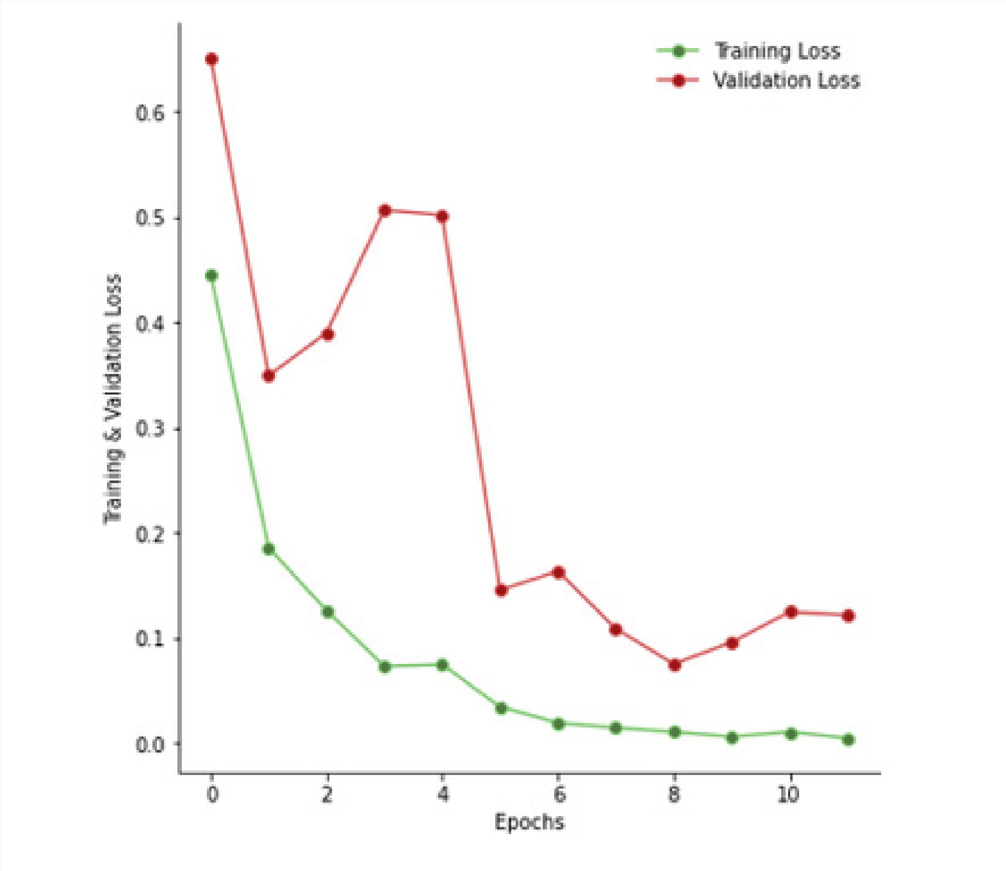

Figure 5: Shows the loss rate of model training and validation and Figure 6 also shows the accuracy of model training and validation.

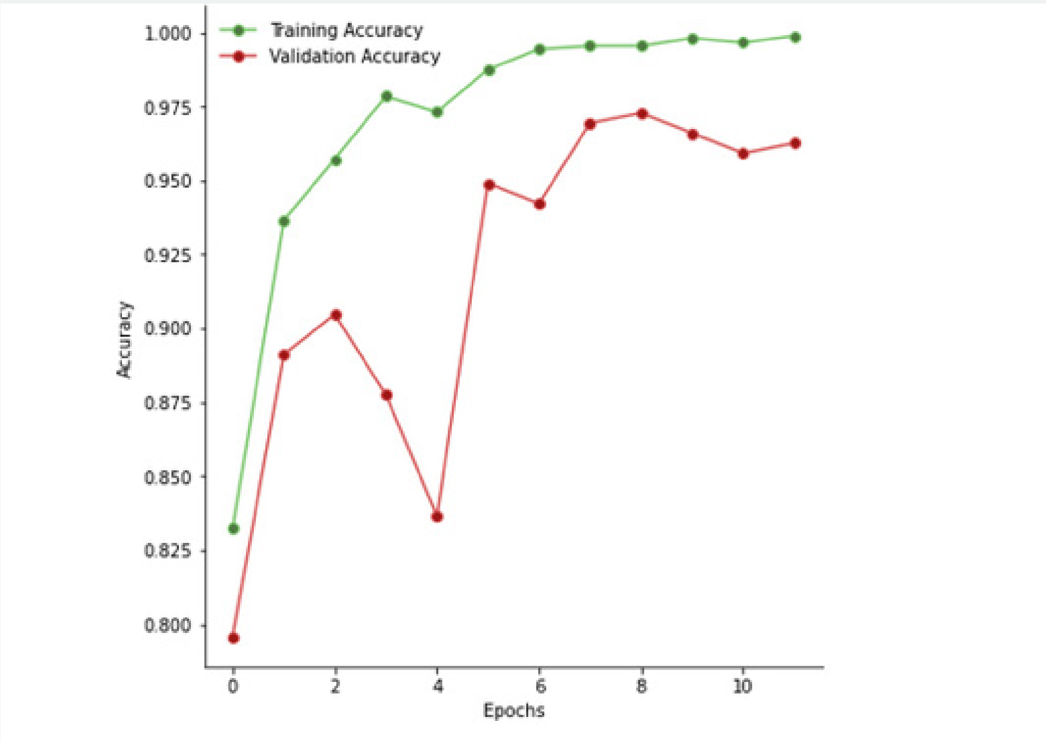

Figure 6: Epochs vs. training and validation accuracy.

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Discussion

A brain tumor is an abnormal mass in the brain that can be benign or malignant depending on the nature of the constituent cells. The origin of the tumor may be from the brain tissue, or it may spread to the brain from another place, or it may metastasize. A brain tumor, in other words, is a hard and lumpy intracranial neoplasm, or a tumor n (abnormal cell growth), inside the brain or central spinal canal. Brain tumors include all intracranial tumors or tumors in the central spinal canal. These tumors arise through uncontrolled and abnormal cell division, and typically originate either in the brain itself (including neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, Schwann myelin-producing cells), lymphoid tissue, blood vessels), or They are formed in cranial nerves, meninges, skull, pituitary gland and pineal gland. Also, these tumors can be the result of the spread of malignancies that have primarily involved other organs, in which case it is called a metastatic tumor. Although any brain tumor is inherently serious and life-threatening due to its aggressive and spreading nature in the limited space of the skull, brain tumors (even their malignant types) are not always fatal. Brain tumors or intracranial tumors can be cancerous (malignant) or non-cancerous (benign); However, the definition of a malignant or benign neoplasm in the brain is different from the definitions that are commonly used in other types of cancerous or non-cancerous tumors involving other parts of the body. The degree of threat of a tumor depends on a combination of various factors, such as: type of tumor, location and size of the tumor, and how it spreads and develops. Since the brain is completely covered by the skull, rapid and early diagnosis of brain tumor is only possible if Para clinical tools and appropriate diagnostic tools that define the condition of the cavity inside the skull are available and used quickly [24].

But usually, the diagnosis of brain tumor occurs in the advanced stages of the disease and when the presence of the tumor has caused unexplained signs and symptoms in the patient. There are different divisions for brain tumors: One of the divisions is based on the cellular characteristics of the tumor, which includes benign and malignant tumors. Of course, today the World Health Organization has divided brain tumors into 4 groups based on their aggressiveness, of which grade I is the most benign and grade IV is the most malignant [25]. Another division is based on the origin of the tumor, whether it is from brain tissue (primary) or metastatic (spread from another place in the body). Primary (true) brain tumors originate from neuroepithelial tissue (astrocyte-oligodendrocyte-microglia-ependymal cell, etc.) and usually appear in the posterior cranial cavity in children and in the anterior two-thirds of the cerebral hemisphere in adults. Although these types of brain tumors can affect any part of the brain. Glioma (50.4%), meningioma (20.8%), pituitary adenoma (15%) and nerve sheath tumors are the most common primary brain tumors [25]. New studies show that proton radiation therapy is the most effective treatment method for the most common brain tumor in children (medulloblastoma). Secondary brain tumors are the same metastatic and lymphoma tumors, whose primary origin is primary cancer in other parts of the body and invade the intracranial space. This means that the cancer cells have spread from the primary tumor that originates from a tumor in another organ and then enter the lymphatic system and blood vessels. These cells will then circulate through the blood circulation system and settle in the brain. In the future, these cells will continue to grow and divide indiscriminately, and turn into another invasive neoplasm, which is a type of primary cancer tissue. Secondary brain tumors are very common and common tumors and are often seen in patients who have metastasized from an incurable cancer [26]. In this research, primary brain tumors were discussed.

Conclusion

In this study, a system was designed that after proper training is able to classify brain MRI images into four classes glioma tumor, meningioma tumor, pituitary tumor and no tumor with an accuracy of about 98%. This system was designed using CNN, transfer learning technique and EfficientNetB0 model. Due to the high accuracy of this system, it can be used to help doctors diagnose brain tumors better and more accurately.

References

1. DeAngelis LM (2001) Brain tumors. New England journal of medicine 344(2): 114-123.
2. McFaline FJR, Lee EQ (2018) Brain tumors. The American journal of medicine 131(8): 874-882.
3. Fisher LJ, Schwartzbaum JA, Wrensch M, Wiemels JL (2007) Epidemiology of brain tumors. Neurologic clinics 25(4): 867-890.
4. Zülch KJ (2013) Brain tumors: their biology and pathology. Springer-Verlag.
5. Kaye AH, Laws Jr, Edward ER (2011) Brain Tumors E-Book: An Encyclopedic Approach. Elsevier Health Sciences.
6. Ghajar Rahimi G, Kang KD, Totsch SK, Gary S, Rocco A, et al. (2022) Clinical advances in oncolytic virotherapy for pediatric brain tumors. Pharmacology & therapeutics 108193.
7. Ullah N, Khan JA, Khan MS, Khan W, Hassan I, et al. (2022) An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning. Applied Sciences 12(11): 5645.
8. Raza A, Ayub H, Khan JA, Ahmad I, Salama SA, et al. (2022) A hybrid deep learning-based approach for brain tumor classification. Electronics 11(7): 1146.
9. Xie Y, Zaccagna F, Rundo L, Testa C, Agati R, et al. (2022) Convolutional neural network techniques for brain tumor classification (from 2015 to 2022): Review, challenges, and future perspectives. Diagnostics 12(8): 1850.
10. Shaik NS, Cherukuri TK (2022) Multi-level attention network: application to brain tumor classification. Signal, Image and Video Processing 16(3): 817-824.
11. Mehnatkesh H, Jalali SMJ, Khosravi A, Nahavandi S (2023) An intelligent driven deep residual learning framework for brain tumor classification using MRI images. Expert Systems with Applications 213: 119087.
12. Yadav AS, Kumar S, Karetla GR, Cotrina Aliaga JC, Arias Gonzáles JL, et al. (2023) A Feature Extraction Using Probabilistic Neural Network and BTFSC-Net Model with Deep Learning for Brain Tumor Classification. Journal of Imaging 9(1): 10.

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13. Demir F, Akbulut Y, Taşcı B, Demir K (2023) Improving brain tumor classification performance with an effective approach based on new deep learning model named 3ACL from 3D MRI data. Biomedical Signal Processing and Control 81: 104424.

14. Shahin AI, Aly W, Aly S (2023) MBTFCN: A novel modular fully convolutional network for MRI brain tumor multi-classification. Expert Systems with Applications 212: 118776.

15. Ahmad B, Sun J, You Q, Palade V, Mao Z (2022) Brain tumor classification using a combination of variational autoencoders and generative adversarial networks. Biomedicines 10(2): 223.

16. Ait Amou M, Xia K, Kamhi S, Mouhafid M (2022) A Novel MRI Diagnosis Method for Brain Tumor Classification Based on CNN and Bayesian Optimization. In Healthcare 10(3): 494.

17. Neelima G, Chigurukota DR, Maram B, Girirajan B (2022) Optimal DeepMRSeg based tumor segmentation with GAN for brain tumor classification. Biomedical Signal Processing and Control 74: 103537.

18. Öksüz C, Urhan O, Güllü MK (2022) Brain tumor classification using the fused features extracted from expanded tumor region. Biomedical Signal Processing and Control 72: 103356.

19. https://www.kaggle.com/code/arfaouisana/brain-tumor-classification.

20. Anand V, Gupta S, Koundal D, Nayak SR, Shafi J, et al. (2022) Segmentation and Classification of Skin Cancer Using K-means Clustering and Efficient Net Bo Model. In Advances in Communication, Devices and Networking 902: 471-481.

21. Fayyadl A, Bima M (2022) Klasifikasi Tumor Otak pada Citra MRI Menggunakan Convolutional Neural Network Model EfficientNetB0 (Doctoral dissertation, Universitas Muhammadiyah Malang).

22. Koonce B, Koonce B (2021) Convolutional Neural Networks with Swift for Tensor flow: Image Recognition and Dataset. Categorization, pp. 109-123.

23. Rao CS, Karunakara K (2022) Efficient detection and classification of brain tumor using kernel based SVM for MRI. Multimedia Tools and Applications 81(5): 7393-7417.

24. Koelsche C, von Deimling A (2022) Methylation classifiers: Brain tumors, sarcomas, and what's next. Genes, Chromosomes and Cancer 61(6): 346-355.

25. Nalepa J, Marcinkiewicz M, Kawulok M (2019) Data augmentation for brain-tumor segmentation: a review. Frontiers in computational neuroscience 13: 83.

26. Hashemzehi R, Mahdavi SJS, Kheirabadi M, Kamel SR (2020) Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE. biocybernetics and biomedical engineering 40(3): 1225-1232.

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