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BRAIN TUMOR DETECTION IN MRI USING DEEP LEARNING TECHNIQUES

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ABSTRACT

A brain tumor is a disorder caused by the growth of abnormal brain cells. The survival rate of a patient affected with a tumor is difficult to determine because they are infrequent and appear in various forms. These tumors can be identified through Magnetic Resonance (MRI) Images, which plays an essential role in determining the tumor site; however, manual detection is a time-consuming and challenging procedure that can cause some errors in results.The adoption of computer-assisted approaches is essential to help in overcoming these constraints. With the advancement of artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images.In this study, a deep convolutional neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images. The image enhancement techniques are used by applying various filters to enhance the quality of the images. Data augmentation methods are applied to increase the data samples for better training of our proposed model. The results show that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by achieving the highest classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection.

Keyword: Healthcare, Convolutional Neural Network, Deep Learning, Artificial Intelligence.

I. INTRODUCTION

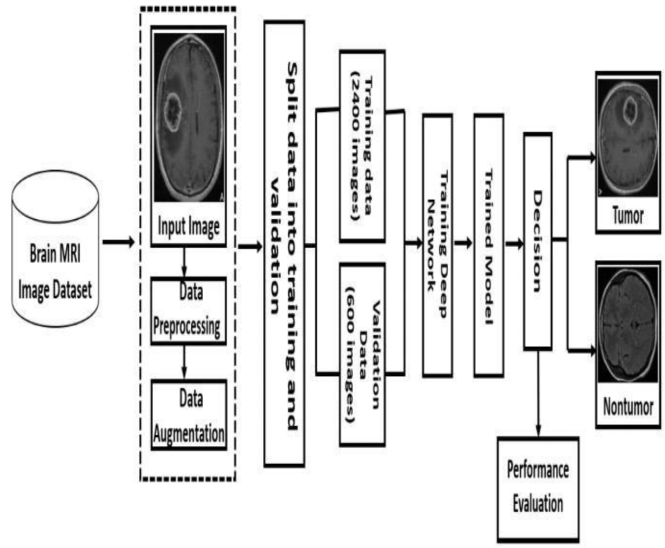
A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain. Cells generally reproduce and die in a regular sequence, with each new cell replacing the previous one. However, some cells become abnormal and continue to grow, causing severe damage to the brain functions, and often leading to death. A minimum of 120 multiple types of brain tumors and the central nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children under 15 will die due to brain and CNS tumors in 2021. The 5-year survival rate for the patients having brain tumors is only 36%, and the 10-year survival rate is 31% [2]. Furthermore, National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4]. One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR) images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of detection of these deadly tumors to save precious humanlives.

II. LITERATURE SURVEY

Abd-Ellahet al.[15] conducted a detailed research study of several diagnostic methodologies for brain MRI images. The authors also analyzed classical machine learning and deep learning techniques in terms of limitations and performance metrics. In this study [16] the authors presented several strategies for detecting brain cancers from MR images. For deeper segmentation, their study was based on three-dimensional based CNNs, SVMs, and multi-class SVMs. The DL methodology produced outstanding results and a reliable brain tumor classification and segmentation approach compared to other ML classifiers. In a different study [17] the authors proposed a deep learning neural model to extract the features of the MR images, which are provided as input to the ML classifiers (Naive Bayes, SVMs, and Multilayer perceptrons). The proposed method achieved 96% classification accuracy with SVMs as classifiers. Hossain et al. [18] proposed several machines and DL methods such as SVMs, K-NN, multi-layer perceptron, Naive Bayes, and random forest algorithms for brain tumor classification and segmentation. Among all these techniques, traditional SVMs achieved the highest accuracy of 92.4% in classification. They also proposed a five-layer custom CNN architecture that attained 97.2% accuracy in detecting brain tumors in MR images. Khan et al. [19] proposed VGG19 CNN architecture and K-means clustering for the classification and segmentation of brain tumors in MRI images. The proposed technique converts an input MR modality to slices, and then intensities are preprocessed using a statistical normalization approach. They achieved an overall accuracy of 94%. In the study [20] the authors presented a fusion approach by using 2D and 3D MRI images; they designed a DenseNet and custom 3D CNN architectures for classification and segmentation of multi-modal images, respectively.

III. PROPOSED RESEARCH METHODOLOGY

The proposed model with multiple layers and pre-trained algorithms will be thoroughly discussed in the subsequent sections. Figure 1 depicts the stages of the brain tumor image preprocessing, augmentations, training, and evaluation. The proposed transfer learning and fine-tuning method are based on DL algorithms that use numerous hyperparameters for training and optimization.



A. EFFICIENTNET BASELINE MODEL

EfficientNet is a CNN model developed by the Google Brain Team [32]. These researchers examined network scaling and found that optimizing network depth, width, and resolution can boost performance. To create a new model, they scaled a neural network to construct more DL models that yield much higher efficacy and accuracy compared to the previously used CNNs. For the ImageNet, EfficientNet performed large-scale visual recognition with accuracy and consistency exemplary established. This series of CNN architectures is around eight times smaller and six times faster to infer. EfficientNet-B0 uses a composite scaling method that creates different models in the convolution neural network family. The number of layers in a network corresponds to the network depth. The convolutional layer width is proportional to the number of filters it contains. The height and width of the input image determine the resolution. Figure 2 presents the latest EfficientNet-B0 baseline model that accepts a $224 \times 224 \times 3$ input image. This algorithm captures characteristics across layers using numerous convolutional (Conv) layers with a 3 × 3 receptive field and the mobile inverted bottleneck Conv. Equation (1-5) illustrates how the authors propose scaling the depth, width, and resolution regarding ø.

$$d = \alpha^{\phi}, \quad (1)$$
$$w = \beta^{\phi}, \quad (2)$$
$$r = \gamma^{\phi}, \quad (3)$$
$$\text{s.}t \quad \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \quad (4)$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1. \quad (5)$$

B. PROPOSED LAYERS

This work is primarily related to implementing the EfficientNet-B0 model with the updated last layers inserted through layer freezing by fine-tuning and training to solve the problematic classification and detection of brain cancers in MR images. After performing data enhancement and augmentation to images measuring 224 × 224 × 3, the images were sent into the pre-trained EfficientNet-B0 model, which automatically extracted the features. These characteristics could be color and shape descriptors like edges, circularity, roundness, and compactness. Figure 3 represents the proposed final layers for the EfficientNet-B0 composed of flattening, dropout, two fully connected (FC) layers, and a sigmoid classifier. We directed the feature sets from the sixth MBConv layer and converted them into a 1D array using a flattened layer. After flattening, it is passed to a dense layer with 128 hidden units. We used rectified linear unit ReLu as an activation function coupled to another dense layer with one neuron representing our provided labels before predicting the results. This method generated a probability by linearly applying a fresh set of weights and biases to each feature map. In addition, we used a dropout layer with a 20% rate after the hidden layer of 128 neurons to eliminate the overfitting problem. We used sigmoid [35] as our final selected classifier. Equation 6 shows the mathematical function of a sigmoid classifier with a recognizable S-shaped curve. Sigmoid is a logistic function that performs a binary classification. It assigns values to 0 or 1 by setting up the threshold value of 0.5, where 0 represents non-tumor and 1 represents tumor images. The neuron at the last dense layer represents these classes.

$$f(x) = \text{Sigmoid}(x) = \frac{1}{1 + e^{-x}}. \quad (6)$$

C. TRANSFER LEARNING AND FINE TUNING

This section demonstrates how we trained and refined our model. Figure 4 demonstrates our proposed finalized model. First, the Keras library has imported a pre-trained EfficientNet-B0 base model trained on the ImageNet dataset. The pre-initialized weights from ImageNet allowed the base model to use its features and enhance image recognition capability immediately. The weights obtained by training with the ImageNet dataset include features that can assist in detecting shapes, edges and other essential components required for image classification [36]. This strategy accelerated the process while requiring less work than arbitrarily initialized

D. HYPERPARAMETERS AND LOSS FUNCTION

This section describes the hyperparameter settings and loss function settings chosen for the task to produce efficient outcomes. The performance of a DL model depends not only on accuracy but also on loss [38]. The fundamental goal of a DL model is to achieve the absolute lowest rate of errors, considering that a model with a lower computed loss is more efficient. We used cross-entropy (CE) to obtain the average measure of the difference between the expected and predicted values. The loss measurement for the binary classification is shown in Equation 7, where y represents binary values of 0 or 1, and p represents the probability [39].

IV. CONCLUSIONS

MR imaging for the detection of brain tumor research has gained significant popularity because of the rising requirement for a practical and accurate evaluation of vast amounts of medical data. Brain tumors are a deadly disease, and manual detection is time-consuming and dependent on the expertise of doctors. An automatic diagnostic system will be required to detect abnormalities in MRI images. Therefore, this study developed an efficient, fine-tuned EfficientNet- B0 based transfer learning architecture to identify brain cancers from MRI scans. The proposed technique achieved the maximum performance in brain tumor detection, with 98.87% validation accuracy. Although this study focused on five other convolutional models and transfer learning designs for brain tumors in the medical imaging field, further research is needed. We will investigate more significant and influential deep CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will increase the number of MRI scans in the dataset used for this study. Furthermore, we will also be applying the proposed approach to other medical images such as x-ray, computed tomography (CT), and ultrasound which may serve as a foundation for future research.

V. REFERENCES

1. D. Y. Lee, ‘‘Roles of mTOR signaling in brain development,’’ Experim. Neurobiol., vol. 24, no. 3, pp. 177-185, Sep. 2015.

2. F. Islami, C. E. Guerra, A. Minihan, K. R. Yabroff, S. A. Fedewa, K. Sloan, T. L. Wiedt, B. Thomson, R. L. Siegel, N. Nargis, R. A. Winn, L. Lacasse, L. Makaroff, E. C. Daniels, A. V. Patel, W. G. Cance, and A. Jemal, ‘‘American Cancer Society’s report on the status of cancer disparities in the United States, 2021,’’ CA, Cancer J. Clinicians, vol. 72, no. 2, pp. 112-143, Mar. 2022.

3. Q. T. Ostrom, G. Cioffi, H. Gittleman, N. Patil, K. Waite, C. Kruchko, and J. S. Barnholtz-Sloan, ‘‘CBTRUS statistical report: Primary brain and other central nervous system tumors diagnosed in the United States in 2012-2016,’’ Neuro-Oncol., vol. 21, no. 5, pp. v1-v100, Nov. 2019.

4. World Health Organisation. (2021). Cancer. Accessed: Jan. 23, 2022. [Online]. Available: https://www.who.int

5. G. Raut, A. Raut, J. Bhagade, J. Bhagade, and S. Gavhane, ‘‘Deep learning approach for brain tumor detection and segmentation,’’ in Proc. Int. Conf. Converg. Digit. World Quo Vadis (ICCDW), Feb. 2020, pp. 1-5.

6. T. C. Hollon, B. Pandian, A. R. Adapa, E. Urias, A. V. Save, S. S. S. Khalsa, D. G. Eichberg, R. S. D’Amico, Z. U. Farooq, S. Lewis, and P. D. Petridis, ‘‘Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks,’’ Nature Med., vol. 26, no. 1, pp. 52-58, Jan. 2020.

7. F. Saeed, A. Paul, P. Karthigaikumar, and A. Nayyar, ‘‘Convolutional neural network based early fire detection,’’ Multimedia Tools Appl., vol. 79, nos.13-14, pp. 9083-9099, Apr. 2020.

8. F. Saeed, A. Paul, W. H. Hong, and H. Seo, ‘‘Machine learning based approach for multimedia surveillance during fire emergencies,’’ Multime¬dia Tools Appl., vol. 79, nos. 23-24, pp. 16201-16217, Jun. 2020.

9. K. Simonyan and A. Zisserman, ‘‘Very deep convolutional networks for large-scale image recognition,’’ 2014, arXiv:1409.1556.

10. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, ‘‘Going deeper with convolutions,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 1-9.

11. K. He, X. Zhang, S. Ren, and J. Sun, ‘‘Deep residual learning for image recognition,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 770-778.

12. K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque, ‘‘Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey,’’ IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 2, pp. 507-522, Feb. 2021.

13. M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, ‘‘Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks,’’ Eurasip J. Image Video Process., vol. 2018, p. 97, Dec. 2018.

14. Z. Hu, J. Tang, Z. Wang, K. Zhang, L. Zhang, and Q. Sun, ‘‘Deep learning for image-based cancer detection and diagnosis a survey,’’ Pattern Recog¬nit., vol. 83, pp. 134-149, 2018.

15. M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, ‘‘A review on brain tumor diagnosis from MRI images: Practical impli¬cations, key achievements, and lessons learned,’’ Magn. Reson. Imag., vol. 61, pp. 300-318, Sep. 2019.

16. S. Somasundaram and R. Gobinath, ‘‘Current trends on deep learning models for brain tumor segmentation and detection—A review,’’ in Proc. Int. Conf. Mach. Learn., Big Data, Cloud Parallel Comput. (COMITCon), Feb. 2019, pp. 217-221.

17. G. Latif, G. B. Brahim, D. N. F. A. Iskandar, A. Bashar, and J. Alghazo, ‘‘Glioma Tumors’ classification using deep-neural-network-based features with SVM classifier,’’ Diagnostics, vol. 12, no. 4, p. 1018, Apr. 2022.

18. G. Kumar, P. Kumar, and D. Kumar, ‘‘Brain tumor detection using convo¬lutional neural network,’’ in Proc. IEEE Int. Conf. Mobile Netw. Wireless Commun. (ICMNWC), Dec. 2021, pp. 1-6.

19. A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, and Z. Mehmood, ‘‘Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification,’’ Microsc. Res. Tech¬nique, vol. 84, pp. 1389-1399, Feb. 2021.

20. H. Yahyaoui, F. Ghazouani, and I. R. Farah, ‘‘Deep learning guided by an ontology for medical images classification using a multimodal fusion,’’ in Proc. Int. Congr. Adv. Technol. Eng. (ICOTEN), Jul. 2021, pp. 1-6.

21. J. Kang, Z. Ullah, and J. Gwak, ‘‘MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers,’’ Sen¬sors, vol. 21, no. 6, p. 2222, Mar. 2021.