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Enhancing Brain Tumor Detection on MRI Images Using an Innovative VGG-19 Model-Based Approach

Abdullah ŞENER *[1], Burhan ERGEN[1]

Abstract

Early detection and diagnosis of brain tumors have a critical impact on the treatment of brain tumor patients. This is because initiating interventions early directly impacts the patient's chances of continuing their life. In the field of medical research, various methods are employed for the detection of brain tumors. Among these methods, magnetic resonance imaging (MRI) is the most popular due to its superior image quality. By leveraging technological advancements, the utilization of deep learning techniques in the identification of brain tumors ensures both high accuracy and simplification of the process. In a conducted study, a new model was developed by utilizing the VGG-19 architecture, a popular convolutional neural network model, to achieve high accuracy in brain tumor detection. In the study, precision, F1 score, accuracy, specificity, Matthews correlation coefficient, and recall metrics were used to evaluate the performance of the developed model. The deep learning model developed for brain tumor detection was trained and evaluated on an open-source dataset consisting of MRI images of gliomas, meningiomas, pituitary tumors, and healthy brains. The results obtained from the study demonstrate the promising potential of using the developed model in clinical applications for brain tumor detection. The high accuracy achieved by the developed model emphasizes its potential as an auxiliary resource for healthcare professionals in brain tumor detection. This research aims to evaluate the model as a valuable tool that can assist physicians in making informed treatment decisions regarding brain tumor diagnosis.

Keywords: Brain tumor detection, image classification, VGG-19 architecture, deep learning, support vector machines.

1. INTRODUCTION

The brain, situated within the cranium, represents the most intricate and vital component of the central nervous system. It governs crucial functions such as the regulation of consciousness, emotions, movement, and other cognitive processes [1]. It processes sensory signals received from the body and serves as a central hub for generating appropriate responses to these signals [2]. Through intricate mechanisms of signal processing, the brain controls fundamental functions such as movement, emotion, and response [3]. Cancer, characterized by the uncontrolled and unrestrained proliferation of cells arising from genetic abnormalities, can manifest in

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any region of the human body. When such cellular abnormalities occur in the brain, it is referred to as a brain tumor. This medical condition involves the rapid, uncontrolled, and irregular proliferation of cells in the brain. Brain tumors can be classified broadly into benign and malignant forms. Benign brain tumors are generally less harmful and exhibit slower growth compared to malignant tumors. Conversely, malignant tumors grow rapidly, irregularly, and uncontrollably. Malignant brain tumors lack well-defined boundaries and have a tendency to infiltrate surrounding tissues and even distant areas of the body. As malignant brain tumors grow, they exert increased pressure on the skull, leading to structural abnormalities. Early diagnosis of this condition is crucial in preventing its progression to critical stages.

In recent years, there has been a significant increase in mortality rates associated with brain tumors, positioning them as one of the leading causes of death among both males and females. The timely detection of brain tumors holds utmost significance in enhancing the survival rates of patients. A wide array of diagnostic tests and medical imaging modalities are utilized in the identification and localization of brain tumors. The latest technology used in brain tumor diagnosis is augmented reality applications, which have been developed in recent years. Considering the researches on their use and the research results in education thanks to the successes achieved with augmented reality technology, it is normal that it is one of the popular study topics [4]. Another method used in the diagnosis of brain tumors is biopsy. Biopsy, which involves the surgical sampling of cells, fluids, or tissues from areas suspected of disease, is commonly used for cancer diagnosis. However, biopsies carry inherent risks and require prolonged decision-making processes [5]. Magnetic Resonance Imaging (MRI), X-ray imaging and Computed Tomography (CT) are among the commonly employed diagnostic modalities for the visualization and characterization of brain tumors. Another critical diagnostic approach for brain tumors involves the evaluation of magnetic resonance images (MRI) by specialists and radiologists. MRI imaging plays a pivotal role in detecting and classifying tumors as either benign or malignant. The accuracy of brain tumor detection from MRI images is greatly influenced by the proficiency and expertise of the reviewing physician, emphasizing the critical role of their knowledge in the diagnostic process. Brain tumors can be broadly classified into two main categories: benign tumors and malignant tumors. Glioma tumors, categorized as malignant, arise from the abnormal proliferation of glioma cells in the brain or spinal cord. Pituitary tumors, on the other hand, originate within the pituitary gland and are typically benign, arising from the excessive growth of pituitary cells. Meningioma tumors, predominantly benign, develop in the meninges, which are the membranes that cover the brain and spinal cord.

Artificial intelligence (AI) has gained significant popularity in various research domains, particularly in the field of medicine. In recent years, the use of AI techniques in brain tumor detection has been increasing [6]. Thank you to artificial intelligence and deep learning techniques, it is not only possible to detect brain tumors, but also to calculate the area covered by the brain tumor [7]. AI-based methods have demonstrated the ability to identify crucial details that may be overlooked during manual examinations by experts. As a result, numerous applications employing AI algorithms for the analysis of brain MRI images have emerged. The outcomes achieved through these applications have facilitated the development of novel methodologies, thereby improving the success rates in brain tumor detection. These AI-based applications leverage the inherent capabilities of deep learning and machine learning algorithms to effectively analyze and interpret brain MRI images. The algorithms are trained on large datasets containing diverse MRI images, enabling them to learn intricate patterns and features associated with different types of brain tumors. By utilizing the acquired knowledge, these AI systems can accurately detect the presence of tumors, classify them as benign or malignant, and provide valuable insights for clinical decision-making. The integration of AI techniques in brain tumor detection has demonstrated remarkable potential in complementing and enhancing the capabilities of healthcare professionals. By assisting in the detection of brain tumors, AI applications contribute to early diagnosis, thereby facilitating timely interventions and improving patient outcomes. The continuous advancements in AI algorithms and technologies hold promise for further refining and expanding the scope of brain tumor detection and classification, ultimately contributing to the advancement of medical practice.

The rapid advancement of technology has positively influenced the development of computer-based systems for brain tumor detection. These developed systems hold great importance in the diagnoses of medical professionals. Previously, brain tumor diagnosis by experts was a time-consuming method. However, computer-based systems utilizing artificial intelligence provide a more efficient, fast, and accurate approach to brain tumor detection. Deep learning techniques, a subset of machine learning, offer seamless and automated results in the diagnostic process of brain tumors for medical experts. In recent years, the application of machine learning and deep learning methodologies has demonstrated remarkable advancements in the field of brain tumor detection and classification. [5]. In the present study, a publicly accessible dataset comprising MRI images of three distinct tumor types along with healthy brain samples was employed for the purpose of deep learning-based brain tumor detection. A custom model utilizing the VGG-19 architecture, a prominent deep learning model, was devised to accurately detect and classify brain tumors. Remarkably, the developed model exhibited an impressive 95% accuracy in the identification of brain tumors. The outcomes derived from this investigation offer substantial support and represent a valuable asset for healthcare practitioners engaged in the realm of brain tumor detection.

Reviewing the rest of the paper; Section II includes recent work on brain tumor detection in MRI images using various deep learning models. Section III presents the research framework including brain MRI image enhancement and data augmentation, image preprocessing, CNN models and a detailed description of the classifier used for this research. The developed model is tested with the dataset and the corresponding results and complexity matrix are compared with other works in Section IV. Section V contains the conclusion.

2. METHODOLOGY

2.1. Data Set

To evaluate the performance of the classification model developed in this study, an open-source dataset consisting of MRI images of 4 classes was used [8]. The dataset consists of MRI images of pituitary, meningioma, glioma and healthy brain. Some of the images that make up the dataset are shown in Figure 1. Pituitary tumor is caused by abnormal growth of pituitary cells. Pituitary tumor is one of the benign tumors. Patients diagnosed with pituitary tumors remain asymptomatic and harmless throughout their lives. However, since the function of the pituitary gland is very important in the human body, it can cause serious health problems as the tumor grows and secretes hormones that the body does not need [9]. Meningioma tumors are among the most common primary brain tumors. It is a type of tumor that occurs in the meninges and is not dangerous. However, during the growth of these tumors, pressure on the brain or spinal cord can cause some problems [10]. Glioma tumors, classified as malignant neoplasms, are characterized by the aberrant proliferation of glioma cells within the central nervous system, specifically the brain or spinal cord. Glioma tumors can occur at any age. It tends to occur in older adults [11].

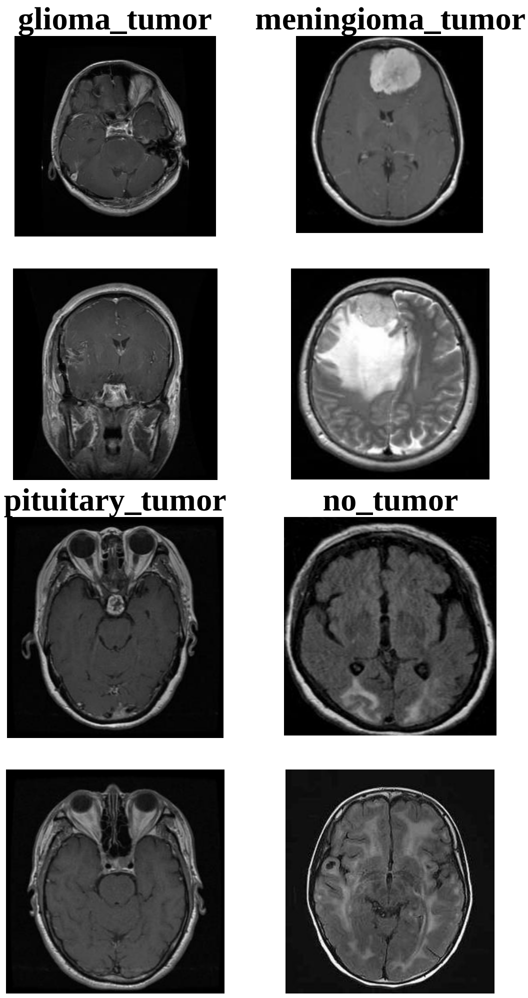

Figure 1 Sample images from the dataset used for the study [8]

The dataset utilized in this study comprises a total of 7,678 grayscale images with varying resolutions. These images encompass 1,796 glioma, 1,784 meningioma, 2,162 healthy, and 1,936 pituitary tumor MRI images. The dataset was divided into three subsets, with 74% of the images allocated for training, 17% for testing, and 9% for validation purposes.

2.2. Data Augmentation

One of the primary obstacles encountered in machine learning and deep learning investigations pertains to the limited availability of training data to effectively train the network. Insufficient data can lead to overfitting issues, where the network memorizes the training samples and struggles to generalize to unseen data. To tackle this issue, researchers commonly adopt two prevalent strategies: augmenting the training data through various techniques and expanding the size of the available dataset. Increasing the training data involves acquiring additional samples to enrich the dataset. This can be done by collecting more data through various means, such as conducting additional experiments or collaborating with other institutions. By expanding the dataset, the network can learn from a more diverse range of examples and improve its ability to recognize and classify new instances. Data augmentation, on the other hand, is a technique used to artificially generate more training samples by applying various operations to the existing images. This approach helps to overcome the limitation of insufficient data by creating augmented versions of the original images. Common transformations employed in data augmentation include horizontal flipping, 90-degree rotation, adjusting brightness and contrast randomly, blurring, optical distortion, scaling the image with rotation, transposing, and grid distortion. Figure 2 illustrates some examples of data augmentation methods.

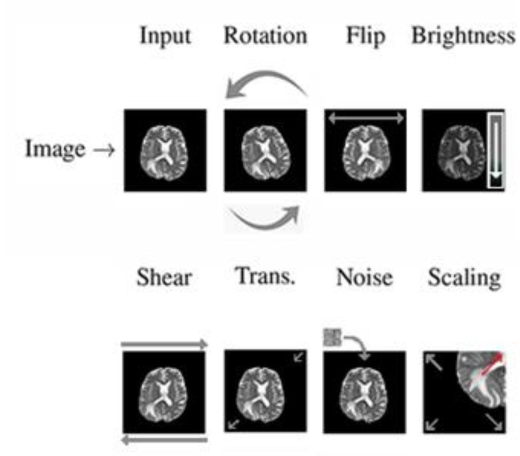

Figure 2 Some examples of data augmentation methods [12]

2.3. Deep Learning

Deep learning encompasses a class of artificial neural networks that consist of one or more concealed layers, along with machine learning methodologies that exhibit similar characteristics to these network architectures. [13]. The fundamental aim of deep learning is to extract novel insights and knowledge by leveraging artificial neural networks. Deep learning techniques can be classified into supervised, semi-supervised, and unsupervised learning paradigms, each tailored to specific learning objectives and data availability [14]. Artificial neural networks were initially developed to model information processing and infer new knowledge from data, drawing inspiration from the functioning of the human brain. Although artificial neural networks and the human brain share the common objective of performing tasks, they exhibit distinct disparities in their characteristics and functionalities. Neural networks tend to be static and symbolic, whereas the brain operates dynamically and in an analog fashion [13-16].

Convolutional Neural Networks (CNNs) have emerged as a prominent deep learning methodology, garnering substantial attention and widespread recognition within the research community [17-19]. The architecture of CNNs is specifically engineered to emulate the intricate operations of the visual cortex, effectively integrating comparable features to facilitate object recognition within image data [20, 21]. The CNN architecture comprises several layers, each performing distinct operations. The building blocks of CNNs consist of several essential layers, encompassing the convolution layer, nonlinearity layer, pooling layer, smoothing layer, and fully connected layers [19]. In the CNN architecture, the convolution layer plays a crucial role as it involves extensive mathematical operations. The convolution layer, serving as the cornerstone of the CNN architecture, assumes the crucial role of detecting features at various levels, employing filters to process input images.

The nonlinear layer plays a pivotal role in identifying nonlinearities inherent in the system. Additionally, the pooling layer is responsible for downsampling feature maps, effectively reducing the network's parameter and weight count. This reduction is typically achieved through operations such as maximum pooling (dividing the image into nxn matrices and selecting the highest value within each matrix) or average pooling (dividing the image into nxn matrices and calculating the average of the values within each matrix). The smoothing layer plays a crucial role in the CNN architecture by preparing the data for the ultimate component, referred to as the fully connected layer. This layer integrates and processes the features extracted from previous layers to generate the final output. This is often accomplished by transforming the incoming data into a one-dimensional matrix. The fully connected layer establishes correlations between the input and output layers [22, 23].

2.4. VGG-19

VGG-19 is a convolutional neural network renowned for its depth, comprising a total of 24 layers. These layers encompass 16 convolutional layers, 5 pooling layers, and 3 fully connected layers, collectively contributing to the network's intricate architecture [24]. It is pre-trained on more than one million images from the ImageNet database. The VGG-19 network has an image input of 224 x 224 pixels. The VGG-19 architecture consists of approximately 138 million parameters [25]. To effectively minimize the parameter count within the VGG-19 architecture, the convolutional layer is designed to employ 3x3 pixel-sized filters. This strategic choice optimizes the network's efficiency while preserving its ability to capture and extract meaningful features from input data.

2.5. Support Vector Machines

In the realm of classification tasks, the Support Vector Machine (SVM) stands out as a prominent supervised learning technique widely employed for its efficacy and versatility. SVM aims to separate data points belonging to different classes by drawing a line on a plane. The key objective is to position the line in such a way that it maximizes the distance from the points of the two separated classes. This method is particularly effective for small to medium-sized datasets with complex structures [26]. An example of SVM classification is illustrated in Figure 4, where two distinct classes, black and white, are depicted. The primary goal in classification tasks is to determine the class to which a new shape will be assigned. To achieve class separation, a line is drawn, and the green region shown in Figure 3, called the Margin, represents the area between ±1 of this line. The wider the margin, the better the classification performance.

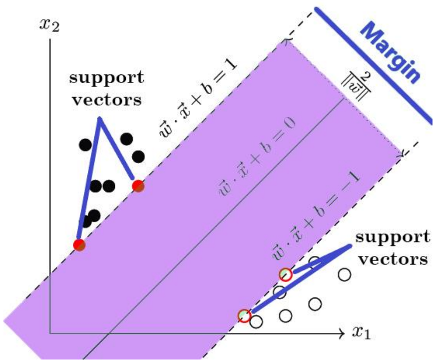

Figure 3 Support Vector Machines classification example

In Support Vector Machines (SVM), as depicted in Figure 3, the weight vector is denoted by w, the input vector by x, and the deviation by b. In the example of SVM classification, if the computed value is less than 0, the new instance will be classified as being closer to the white dots shown in Figure 4. Conversely, if the computed value is equal to or greater than 0, the new instance will be considered closer to the black dots depicted in Figure 3. The calculation formula employed in Support Vector Machines is presented in Equation 1

$$y = \begin{cases} 0 \text{ eğer } w^T.x + b < 0, \\ 1 \text{ eğer } w^T.x + b \geq 0 \end{cases} \tag{1}$$

2.6. Recommended Approach

This study introduces a pioneering approach in brain tumor detection, presenting a novel model built upon the VGG-19 architecture. The performance assessment of the proposed model is carried out utilizing a publicly available dataset consisting of brain MRI images, enhancing the credibility and applicability of the findings. To ensure balanced representation of image classes within the dataset, efforts were made to address any class imbalance issues. To expand the dataset and enhance training efficacy, diverse data augmentation techniques were implemented, resulting in a larger pool of images for model training. The augmented dataset was partitioned into distinct subsets, with 74% allocated for training purposes, 17% for testing, and 9% reserved for validation, ensuring robust evaluation and effective model generalization. In the subsequent stage of the investigation, a preprocessing step was implemented to standardize the sizes and resolutions of images, ensuring consistency and compatibility for further analysis. The images were resized to a uniform dimension of 224x224 pixels, serving as the standardized input size for the proposed model. This standardization process facilitates seamless integration and enables accurate and efficient processing within the model framework. Resizing the input images to a fixed size is performed to accelerate the classification process and manage computational memory usage effectively. It is crucial to strike a balance when resizing the images, avoiding excessive reduction that could hinder the extraction of essential information required for accurate classification. Once the images are resized, the classification is performed on images with a consistent size and resolution. The overall framework of the proposed approach is presented in Figure 4.

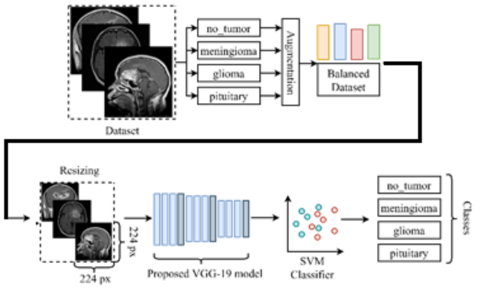

Figure 4 Overall design of the proposed approach

The model shown in Figure 4 consists of 25 layers in total. The model consists of 16 Convolution, 5 Maximum Pooling, 1 Smoothing, 2 Fully Connected Kaman and 1 dense layer. The developed model consists of 139,586,628 parameters.

When the proposed model is examined, 16 convolution and 5 pooling (maximum) layers are applied to the brain MRI input image in gray format. After the convolution and pooling layers are completed, smoothing and full connectivity layers are applied. Full connectivity-1 (FC1) layer and bulk normalization-1 layers are applied after the smoothing process. After these layers, the forgetting process is performed with a dropout rate between 0.3 and 0.5. In the developed model, the forgetting layer is used to prevent the network from memorizing. Then the full connectivity-2 layer and aggregate normalization-2 layers are used. In the next stage, forgetting is performed again with a dropout rate between 0.3 and 0.5. In the last part of the model, the Softmax optimization algorithm is used to obtain an output with 4 classes. In addition, ReLU activation function is used in the convolution layers of the model.

All training and testing of the network models was performed on a workstation with hardware features such as Intel(R) Xeon(R) CPU @ 2.30GHz, 24 GB RAM, and Tesla T4-16GB graphics card. Frameworks such as Python, Tensorflow and Keras were also used for software coding for the proposed model.

3. RESULTS AND DISCUSSION

The conducted research involved partitioning a brain MRI dataset comprising a total of 7678 images into distinct subsets to facilitate the training, testing, and validation stages. Specifically, approximately 74% of the images, corresponding to 5682 images, were allocated for training purposes. This strategic data allocation ensures a sufficient volume of samples for the model to learn from, thereby promoting robust learning and generalization capabilities. Around 17% of the images (1311 images) were allocated for testing, and the remaining 9% (685 images) were used for validation. Figure 5 provides a graphical representation of the accuracy rate and loss values achieved during the training phase of the developed model. The graphs demonstrate the rapid learning of the network, as observed from the fluctuations in the curves from the 10th iteration to the 150th iteration. Upon completion of the training process, the developed model achieved an accuracy rate of 95%.

The results of this study demonstrate that brain MRI images can be effectively analyzed and accurately classified using machine learning methods. The developed model attained a high accuracy rate due to being trained on an adequate number of samples. This can contribute to the development of deep learning models to be used in the diagnosis of brain diseases or treatment planning in future similar studies.

The evaluation of the developed classification model's performance often involves the utilization of a confusion matrix, which is widely used in classification tasks. The confusion matrix incorporates the terms True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) to provide a comprehensive assessment. Using these terms, the model's Precision, Sensitivity, Accuracy, F1-Score and Matthews correlation coefficient (MM) [27] values can also be calculated. Accuracy is the ratio of correct predictions to all predictions in classification problems. Sensitivity is the effectiveness of the model in predicting the positive class label of the target variable, i.e., the ratio of correctly classified positive samples to the total number of positive samples.

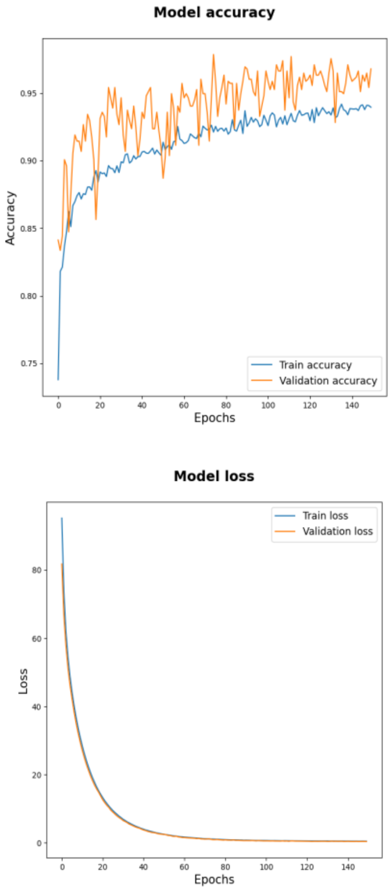

Figure 5 Accuracy and loss graph of the developed model

Precision is the ratio of correctly classified positive samples to the total number of positive predicted samples. The F1 score is the harmonic mean of the precision and sensitivity performance evaluation criteria and provides the ability to consider both criteria together. Matthews (MCC) measures the correlation of classification results with precision in the basic categories TP, TN, FP, FN. These four categories are used to evaluate the performance of the model by comparing the classification results with the actual values. The mathematical operations given in equations 2, 3, 4, 5 and 6 are used to calculate these values.

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

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

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$F1 - Score = \frac{2*Precision*Sensivity}{Precision+Sensivity} \tag{5}$$

$$MM = \frac{(FP*FN-TP*TN)}{\sqrt{((TN+FP)*(TN+FN)*(TP+FN)*(TP+FP))}} \tag{6}$$

The results of the analysis of the classification processes obtained using the test data of the proposed model are shown in Table 1.

Table 1 Analysis results of classification processes

Classes	***Support***	***Sensitivity***	***Precision***
Glioma	300	97%	83%
Meningioma	306	83%	97%
Healthy	405	100%	99%
Pituitary	300	100%	97%
	F1-Score	***Matthews***	***Accuracy***
Glioma	89%	87%	95.5%
Meningioma	90%	86%	94.74%
Healthy	99%	99%	99.62%
Pituitary	98%	98%	99.31%

Figure 6 displays the confusion matrix formed based on the results obtained from the classification process of the developed model.

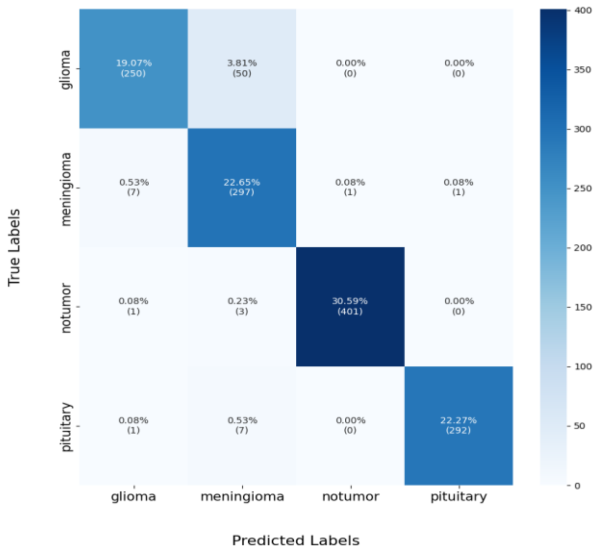

Figure 6 Confusion matrix of the model

Table 2 showcases a comparative analysis between the outcomes achieved by the proposed model and the results obtained from other models focusing on brain tumor detection. This evaluation encompasses not only the dataset utilized in this study but also analogous datasets documented in the existing literature.

Table 2 Comparison of studies with similar datasets

Ref.	***Architecture/Method***	***Results (%)***
[28]	EWS ResNet50 and ResNet50	90 - 92
[29]	CNN	91.43
[30]	CNN	94.58
[31]	LSTM Network	78.33
[32]	AlexNet CNN	91
[33]	CNN	84.19
[34]	SVM and kNN	91.28
[35]	Capsnet	90.89
[36]	Random Forest Classifier	86
[37]	BrainMRNe	96.05
[38]	Transfer Learning	92.34
[39]	Markov Random Field Alg.	87
Prop. App.	VGG-19	95

The studies conducted for brain tumor detection are presented in Table 2 in the literature. The results obtained from these studies demonstrate the popularity and significance of the topic. Sharma et al. [28] developed a modified ResNet50 model based on the watershed segmentation (EWS) algorithm. They achieved an accuracy rate of 90% with their modified ResNet50 model and 92% with the ResNet50 model. Paul et al. [29] obtained results with an accuracy rate of 91.43% using their modified CNN model. Sajad et al. [30] achieved a 94.58% accuracy rate in classifying brain tumor images using their CNN-based approach. Kumar et al. [31] demonstrated a classification accuracy of 78.33% by utilizing an LSTM network for brain tumor image classification.

Khwaldeh et al. [32] achieved a classification accuracy of 91% using the widely adopted CNN model, AlexNet. Abiwinanda et al. [33] reported a classification accuracy of 84.19% by employing a pre-trained sequential CNN model. Cheng et al. [34] achieved a classification accuracy of 91.28% through the utilization of kNN and SVM classifiers for brain tumor image classification. Afshar et al. [35] developed a Capsnet CNN model that yielded an accuracy rate of 90.89%. Soltaninejad et al. [36] achieved a classification accuracy of 86% by employing a random forest classifier on brain MRI datasets. Togacar et al. [37] proposed a novel convolutional neural network model, achieving an impressive classification accuracy of 96.05%. Anaya-Isaza and Mera-Jiménez [38] utilized transfer learning techniques and achieved an accuracy of 92.34% for brain tumor image classification. Faruk et al. [39] compared and analyzed the performance of image segmentation methods in brain tumor detection. In the study, Markov Random Field Algorithm gave better results than other methods in the study with an accuracy rate of 87%.

4. CONCLUSION

A brain tumor is a pathological condition characterized by the uncontrolled proliferation of cells within the cranial cavity. It can be broadly categorized into two distinct classes: benign and malignant brain tumors. Benign tumors are non-cancerous in nature and generally exhibit a slow growth pattern. Conversely, malignant tumors are characterized by their cancerous properties, manifesting as rapid and uncontrolled cell growth. The timely detection of brain tumors holds immense significance in improving patient prognosis, as it enables prompt intervention and management before the disease advances to an irreversible stage.

The primary objective of this research is to design and evaluate a deep learning model capable of accurately and efficiently detecting and classifying brain tumors from brain MRI images. The model architecture employed in this study is based on the widely recognized VGG-19 convolutional neural network (CNN) model. To train and evaluate the model, a publicly available dataset containing a diverse range of brain MRI images, including three distinct tumor classes and healthy brain images, is utilized. The model is trained and assessed using grayscale images with standardized dimensions of 224x224 pixels. Furthermore, the performance of the developed model is compared with other state-of-the-art models used in previous studies employing the same dataset. The comparative analysis reveals that the proposed model surpasses its counterparts in terms of classification accuracy, achieving an impressive success rate of 95%.

In future investigations, the aim is to make adjustments to the developed deep learning model to increase its accuracy percentage and evaluate its applicability in various domains beyond brain tumor detection.

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Authors' Contribution
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The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

REFERENCES

[1] M. Tanveer, M.A. Ganaie, I. Beheshti, T. Goel, N. Ahmad, K. T. Lai, C. T. Lin. “Deep learning for brain age estimation: A systematic review”. Information Fusion, 2023.

[2] S. Solanki, U. P. Singh, S. S. Chouhan, S. Jain. “Brain Tumor Detection and Classification using Intelligence Techniques: An Overview”. IEEE Access, 2023.

[3] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, J. Si. “Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images”. IEEE Access, vol. 10, pp. 34716-34730, 2022.

[4] H. N. Kilinç, Y. Uzun. “Beyin Cerrahisi İçin Artırılmış Gerçeklik Uygulaması Gerçekleştirmek”. Avrupa Bilim ve Teknoloji Dergisi, vol. 33, pp. 290-296, 2022.

[5] R. K. Gupta, S. Bharti, N. Kunhare, Y. Sahu, N. Pathik. “Brain Tumor Detection and Classification Using Cycle Generative Adversarial Networks”. Interdisciplinary Sciences: Computational Life Sciences, pp. 1-18, 2022.

[6] Z. Zhou, Z. He, Y. Jia. “AFPNet: A 3D fully convolutional neural network with atrous-convolution feature pyramid for brain tumor segmentation via MRI images”. Neurocomputing, vol. 402, pp. 235-244, 2020.

[7] B. Kapusiz, Y. Uzun, S. Koçer, Ö. Dündar. "Brain Tumor Detection and Brain Tumor Area Calculation with Matlab". Journal of Scientific Reports-A, vol. 052, pp. 352-364, 2023.

[8] Dataset: : https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri Access Date: 05.07.2022.

[9] A Tiwari., S. Srivastava, M. Pant. "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019. Pattern Recognition Letters, vol. 131, pp. 244-260, 2020.

[10] K. Dağlı, O. Eroğul. "Classification of Brain Tumors via Deep Learning Models". In 2020 Medical Technologies Congress (TIPTEKNO) (pp. 1-4). IEEE, 2020.

[11] G. Mohan, M. M. Subashini. "MRI based medical image analysis: Survey on brain tumor grade classification". Biomedical Signal Processing and Control, vol. 39, 139-161, 2018.

[12] M. Cossio. "Augmenting Medical Imaging: A Comprehensive Catalogue of 65 Techniques for Enhanced Data Analysis". arXiv preprint arXiv:2303.01178, 2023.

[13] X. Liu, Z. Deng, Y. Yang. "Recent progress in semantic image segmentation". Artificial Intelligence Reiew, vol. 52, pp. 1089-1106, 2019

[14] K. Sharifani, M. Amini. "Machine Learning and Deep Learning: A Review of Methods and Applications". World Information Technology and Engineering Journal, vol. 10, no. 07, pp. 3897-3904, 2023.

[15] N. Kanwisher, M. Khosla, K. Dobs. "Using artificial neural networks to ask 'why'questions of minds and brains". Trends in Neurosciences, vol. 46, no. 3, pp. 240-254, 2023.

[16] A. H. Marblestone, G. Wayne, K. P. Kording. "Toward an integration of deep learning and neuroscience". Frontiers in computational neuroscience, 94, 2016.

[17] S. Cong, Y. Zhou. "A review of convolutional neural network architectures and their optimizations". Artificial Intelligence Review, vol. 56, no. 3, pp. 1905-1969, 2023.

[18] J. Gu, Z. Wang, J. Kuen, L. Ma, A. Shahroudy, B. Shuai, T. Chen. "Recent advances in convolutional neural networks". Pattern recognition, vol. 77, pp. 354-377, 2018.

[19] S. Min, B. Lee, S. Yoon."Deep learning in bioinformatics". Briefings in bioinformatics, vol. 18, no. 5, pp. 851-869, 2017.

[20] M. Mirbabaie, S. Stieglitz, N. R. J. Frick. "Artificial intelligence in disease diagnostics: A critical review and classification on the current state of research guiding future direction". Health Technology (Berl) vol. 11, no. 4, pp. 693-731, 2021.

[21] K. Hanbay. "Hyperspectral image classification using convolutional neural network and two-dimensional complex Gabor transform". Journal of the Faculty of Engıneerıng and Architecture of Gazi Unıversity, vol. 35,no. 1, 443-456, 2020.

[22] M. Niepert. M. Ahmed, K. Kutzkov. "Learning convolutional neural networks for graphs". In International conference on machine learning, . Germany, vol. 2016. pp. 2014-2023, 2014.

[23] F. Kurt. “Investigation of the Effect of Hyper Parameters in Neural Networks”. Ankara:Hacettepe University, 2018.

[24] M. Toğaçar, B. Ergen, F. Özyurt. “Classification of Flower Images Using Feature Selection Methods in Convolutional Neural Network Models”. Fırat University Journal of Engineering Sciences, vol. 32, no. 1, pp. 47-56, 2020.

[25] M. Mateen, J. Wen, S. Song, Z. Huang. “Fundus image classification using VGG-19 architecture with PCA and SVD”. Symmetry, vol. 11, no. 1, 1, 2018.

[26] S. Huang, N. Cai, P. P. Pacheco, S. Narrandes, Y. Wang, W. Xu. “Applications of support vector machine (SVM) learning in cancer genomics”. Cancer genomics & proteomics, vol. 15, no. 1, pp. 41-51, 2018.

[27] F. Bulut. “Sınıflandırıcı topluluklarının dengesiz veri kümeleri üzerindeki performans analizleri”. Bilişim Teknolojileri Dergisi, 9(2), 153, 2016.

[28] A. K. Sharma, A. Nandal, A. Dhaka, D. Koundal, D. C. Bogatinoska, H. Alyami .“Enhanced watershed segmentation algorithm-based modified ResNet50 model for brain tumor detection”. BioMed Research International, 2022.

[29] J. S. Paul, A. J. Plassard, B. A. Landman, D. Fabbri. “Deep learning for brain tumor classification'” Proc. SPIE, vol. 10137, Art. no. 1013710, 2017.

[30] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, S. W. Baik. “Multi-grade brain tumor classification using deep CNN with extensive data augmentation” Journal of Computational Science, vol. 30, pp. pp. 174-182, 2019.

[31] S. Kumar, A. Sharma, T. Tsunoda. “Brain wave classification using long short-term memory network based Optical predictor” Scientific Reports, vol. 9, no. 1, pp. 1-13, 2019.

[32] S. Khawaldeh, U. Pervaiz, A. Rafiq, R. Alkhawaldeh. “Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks” Applied Science, vol. 8, no. 1, p. 27, 2017.

[33] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, T. R. Mengko. “Brain tumor classification using convolutional neural network” in Proc. World Congress on Medical Physics and Biomedical Engineering Singapore: Springer, pp. 183-189, 2018.

[34] J. Cheng, W. Huang, S. Cao, R. Yang, W. Yang, Z. Yun, Z. Wang, Q. Feng. “Enhanced performance of brain tumor classification via tumor region augmentation and partition” PLoS ONE, vol. 10, no. 10, Art. no. e0140381, 2015.

[35] P. Afshar, K. N. Plataniotis, A. Mohammadi. “Capsule networks for brain tumor classification based on MRI images and coarse tumor boundaries” in Proceedings IEEE International Conference of Acoustic, Speech and Signal Processing (ICASSP), pp. 1368-1372, 2019.

[36] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T. L. Jones, T. R. Barrick, F. A. Howe, X. Ye. “Supervised learning based multimodal MRI brain tumor segmentation using texture features from supervoxels” Computer Methods Programs in Biomedicine, vol. 157, pp. 69-84, 2018.

[37] M. Toğaçar, B. Ergen, Z. Cömert. "BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model". Medical hypotheses, 134, 109531, 2020.

[38] A. Anaya-Isaza, L. Mera-Jiménez. "Data Augmentation and Transfer Learning for Brain Tumor Detection in Magnetic Resonance Imaging". IEEE Access, vol. 10, pp. 23217-23233, 2022.

[39] F. Bulut, İ. Kılıç, İ.F. İnce. "Comparison And Performance Analysis Of Image Segmentation Algorithms On Brain Tumor Detection". Dokuz Eylül University Faculty of Engineering Science and Engineering Journal, 20(58), pp.173-186, 2018.