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# Automated classification of brain tumor-based magnetic resonance imaging using deep learning approach

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**ABSTRACT**

The treatment of brain tumors poses significant challenges and contributes to a significant number of deaths on a global scale. The process of identifying brain tumors in medical practice involves the visual analysis of photographs by healthcare experts, who manually delineate the tumor locations. However, this approach is characterized by its time-consuming nature and susceptibility to errors. In recent years, scholars have put forth automated approaches to early detection of brain tumors. However, these techniques face challenges attributed to their limited precision and significant false-positive rates. There is a need for an effective methodology to identify and classify tumors, which involves extracting reliable features and achieving precise disease classification. This work presents a novel model architecture that is derived from the EfficientNetB3. The suggested framework has been trained and assessed on a dataset consisting of 7,023 magnetic resonance images. The findings of this study indicate that the fused feature vector exhibits superior performance compared to the individual vectors. Furthermore, the technique that was provided showed superior performance compared to the currently available systems and attained a 100% accuracy rate. As a result, it is viable to employ this technique within a clinical environment for the purpose of categorizing brain tumors based on magnetic resonance images scans.



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## 1. INTRODUCTION

The brain holds paramount importance within the human body since it serves as the central regulator of all bodily systems and plays a pivotal role in the cognitive processes involved in decision making. The brain is responsible for regulating all of the body's automatic and involuntary physiological processes [1]. A brain tumor may arise due to the aberrant proliferation of cells within the brain. Brain tumors can manifest as either malignant or benign in nature. The growth of tumors, regardless of their benign or malignant nature, within the cranial cavity exerts pressure on the cerebral tissue and adjacent anatomical components. The potential consequences of this action include significant neurological impairment, potentially resulting in fatality [2], [3].

It is anticipated that brain cancer is expected to be ranked as the $10^{th}$ leading cause of cancer-related mortality in the year 2023, encompassing both males and females across all age groups. Globally, the prevalence of individuals afflicted with brain tumors stands at an estimated 700,000. Moreover, predictions indicate that an additional 95,000 cases will be diagnosed in the year 2023. In the year 2023, it is anticipated that 18,990 people would pass away as a result of a malignant brain tumor [4], [5].

The most observed brain tumors include gliomas, meningioma, and pituitary tumors. Brain tumors can be classified using many classification systems. One often utilized classification scheme involves categorizing brain tumors into two main types: benign tumors and malignant tumors. Benign brain tumors typically manifest as intracranial growths situated inside the confines of the cranial cavity, however external to the cerebral tissue [6], [7]. Meningiomas constitute a significant component within this cohort. Due to their limited propensity for infiltrating the adjacent brain tissue, these entities exhibit a considerable likelihood of surgical excision. Pituitary tumors, which originate in the pituitary glands responsible for hormone regulation and bodily activities, are referred to as pituitary tumors. Pituitary tumors are classified as benign neoplasms and lack the ability to metastasize to distant anatomical sites [6], [7]. Pituitary tumors can lead to enduring hormone insufficiency and visual impairment because of associated consequences. Gliomas represent the most common form of malignant brain tumor [7], [8].

The aforementioned entities are primarily responsible for the development of a majority of brain malignancies, as they consist of cells that exhibit unregulated growth. While it is uncommon, there is a possibility for the spread of these growths to the spinal cord or other organs within the body [7]. These growths exhibit rapid growth and have the potential to infiltrate the adjacent healthy tissues.

Therefore, it is crucial to rapid and accurately diagnoses brain tumors in order to safeguard patients from detrimental consequences. Healthcare providers encounter challenges in both the diagnosis and treatment of brain tumors owing to their complex nature. The prognosis for patients with brain tumors is significantly improved when prompt diagnosis and treatment are administered. The acquisition of a brain tumor biopsy necessitates surgical intervention, hence rendering the procedure more intricate compared to biopsies conducted on other organs. Therefore, it is imperative to identify a dependable substitute for invasive surgical techniques in the realm of diagnostic procedures [9], [10]. When it comes to the identification of brain tumors, magnetic resonance imaging (MRI) is considered the most reliable and widely accepted diagnostic technique. Typically, physicians utilize traditional assessment of MRI scans in tandem with the capacity of MRI technology to accentuate irregularities in the morphology, dimensions, or positioning of brain tissue, hence facilitating the detection of malignancies [11], [12].

Visual diagnosis is highly dependent on the expertise of the examining physician; further challenges are posed by differences in medical training and image quality. It is challenging for a doctor to perform a rapid analysis of these images due to the presence of many abnormalities or noisy data. As data sets expand, it becomes harder to draw meaningful conclusions from them. It is more time-consuming and expensive to look for a brain tumor manually [9], [13]. Thus far, the application of computer-aided technologies for medical image processing has proven to be progressively advantageous for physicians in the detection of brain malignancies. Deep learning is a subfield of artificial intelligence that enables computational models to acquire and enhance their human-like capabilities. The system offers multiple levels of abstraction and facilitates data retrieval. Deep learning is a crucial component in the field of data science, as it significantly contributes to the development of analytical models using data. Data scientists find it advantageous to possess the ability to extract valuable insights from extensive databases [14], [15]. When deployed across numerous datasets, deep learning exhibits enhancements in both performance and accuracy, while concurrently optimizing and simplifying the process of data processing. The self-learning capabilities of deep learning-based techniques are attracting increasing attention for analysis of brain MRI images for tumor detection. When it comes to machine learning, deep learning is a more effective and robust approach in many areas, including medical image segmentation [16], [17].

Current developments in deep learning have allowed for the identification and classification of image patterns used in medical diagnostics. The ability to retrieve and derive knowledge from data rather than gaining that knowledge from experts or scientific literature is one example of the successes that have been achieved in this area. Many research on the diagnosis of brain tumors using a wide variety of diagnostic approaches and models have been carried out.

Meningioma, glioma, and pituitary tumors can all be detected with the help of techniques developed by [18]. Hidden features in photos were extracted and selected using a convolutional neural network (CNN) in their model. With four convolutional layers, four pooling layers, one fully connected layer, and four batch normalization layers, the proposed model was quite complex. In this model, the authors utilized a learning rate of 0.01 across ten epochs and 16 iterations each epoch. This analysis also made use of the dataset that Cheng had made available. Seventy percent of the data was used for training and thirty percent for system testing as part of a tenfold cross validation analysis of the suggested model's performance with 93.68% accuracy. Anaraki *et al.* [19] utilized a combined approach that integrated CNN with a genetic algorithm

(GA) for the purpose of identifying glioblastoma and various forms of brain tumors. The proposed methodology utilized a genetic algorithm to autonomously select CNN architecture. The researchers accurately predicted the presence of three different types of glioma with a 90.9% accuracy percentage. The classification accuracy of glioma, meningioma, and pituitary cancer in this study was determined to be 94.2% accuracy percentage.

Badzˇa and Barjaktarovic [20] proposed a 22-layered CNN model to classify brain tumor types. The study utilized a dataset consisting of 3064 T1-weighted contrast-enhanced MRI images. The model they created successfully achieved a classification accuracy of 96.56% in distinguishing between different types of brain tumors, namely meningioma, glioma, and pituitary tumors. In a separate investigation, Mzoughi *et al.* [21] introduced sophisticated multi-scale three-dimensional convolutional neural network architecture to assess the severity of brain tumors using volumetric three-dimensional MRI scans. The approach that was proposed demonstrated a classification accuracy of 96.49% in distinguishing between low-grade glioma and high-grade glioma in brain tumor images. Ayadi *et al.* [22] proposed a computer-assisted diagnostic (CAD) system for brain tumor categorization that utilizes a CNN. The 18-weighted layered CNN model was utilized to conduct experiments on three distinct datasets. The results of these experiments demonstrated a classification accuracy of 94.74% for brain tumor-type classification and 90.35% for tumor grading.

Demir *et al.* [23] introduced a novel deep learning model called the attention-convolutional-long short-term memory (LSTM) (3ACL) model, designed specifically for analyzing MRI data. The three ACL models incorporated convolutional and LSTM structures inside a unified learning architecture, employing an end-to-end learning technique. Consequently, the capacity to represent information of the features was enhanced. Furthermore, it should be noted that the 3D nature of the suggested model necessitated the utilization of 3D MR images directly within the 3ACL model, without any conversion of the 3D MR images into 2D data. Deep characteristics that are highly representative are taken from the fully connected layer of the 3ACL model. The support vector machine (SVM) receives the feature set as input. In addition, the utilization of the weighted majority vote technique, which incorporates the SVM prediction outcomes obtained from all slices, resulted in enhanced classification performance. The suggested technique achieved accuracies of 98.90% and 99.29% for the BRATS 2015 and 2018 datasets, respectively. Amin *et al.* [24] developed a novel hybrid deep learning model known as DeepTumorNet. That model was designed specifically for the classification of three forms of brain tumors: glioma, meningioma, and pituitary tumors. The authors employed fundamental CNN architecture as the basis for their model. The GoogLeNet architecture of the CNN model was employed as the foundational framework. During the development of the hybrid DeepTumorNet technique, the researchers opted to exclude the final five layers of the GoogLeNet architecture and instead introduced fifteen additional layers in their place. In addition, a leaky rectified linear unit (ReLU) activation function was employed in the feature map to enhance the model's expressive capabilities. The model under consideration was evaluated using a publicly accessible research dataset to assess its performance. The results indicated that the model achieved an accuracy of 99.67%, precision of 99.6%, recall of 100%, and an F1-score of 99.66%.

Rasool *et al.* [25] implemented a novel approach for classification utilizing a hybrid deep learning model that combines CNNs. The authors presented two distinct methods within this framework. The initial approach involves the integration of a pre-existing Google-Net model, which utilizes the CNN algorithm, to extract features; then combined with the SVM technique to do pattern categorization. The second approach is the integration of a meticulously calibrated Google-Net model with a soft-max classifier. The efficacy of the suggested methodology was assessed by employing MRI scans of the brain. The dataset consisted of a collective total of 1,426 glioma photos, 708 meningioma views, 930 pituitary tumor images, and 396 images of normal brain tissue. The findings of the study indicate that the precisely tuned Google-Net model attained an accuracy rate of 93.1%. Nevertheless, the combination of Google-Net as a feature extractor alongside an SVM classifier resulted in a notable enhancement in recognition accuracy, reaching an impressive 98.1%. Asif *et al.* [26] put forth five widely recognized deep learning architectures as the foundation for constructing a diagnostic system aimed at identifying brain cancers. The architectures employed in this study are Xception, DenseNet201, DenseNet121, ResNet152V2, and InceptionResNetV2. The classification accuracy of these designs has been enhanced by incorporating our deep dense block and softmax layer as the output layer in the final layer. This article outlines two primary experiments conducted to evaluate the efficacy of the suggested model. Firstly, the paper presents an analysis of three-class outcomes utilizing photos obtained from patients diagnosed with glioma, meningioma, and pituitary conditions. Next, the findings of four distinct categories are examined, employing visual representations of glioma, meningioma, pituitary, and healthy individuals. The findings indicate that the deep learning model utilizing the Xception architecture is the optimal choice for the detection of brain cancers. The model demonstrates a classification accuracy of 99.67% on the dataset with three classes, and a classification accuracy of 95.87% on the dataset with four classes. While earlier studies have diligently delved into the application of artificial intelligence (AI) in the detection and classification of brain tumors, a notable gap exists as they have not explicitly addressed the comprehensive classification criteria through the analysis of MRI images.

This study intends to develop a deep learning model for classifying three types of brain tumors (pituitary, meningiomas, and gliomas) using publicly available datasets. The primary objective is to expedite the treatment process and mitigate the dissemination of malignant tissues. The proposed deep learning classification approach demonstrates superior performance compared to existing state-of-the-art methods, as evidenced by achieving the highest accuracy on the MRI dataset.

## 2. AI-Based detection methods

### 2.1. Dataset

In the pursuit of this inquiry, a publicly available MRI dataset was employed as the primary resource. This dataset encompassed a comprehensive compilation of 7023 MRI scans depicting human brain structures. Subsequently, these scans were meticulously classified into four discernible categories, namely glioma, meningioma, absence of tumor, and pituitary, based on distinct pathological features and diagnostic criteria. It is noteworthy that the substantial portion of the imaging data utilized in this investigative endeavor originated from three principal repositories: Figshare, SARTAJ, and Br35H. These repositories serve as repositories for diverse medical imaging datasets, facilitating access to a broad spectrum of clinically relevant imaging data for research and analytical purposes. Through judicious selection and curation of MRI scans from these reputable sources, a robust foundation was established for the systematic analysis and exploration of brain pathology patterns in the context of tumor presence and classification [27], [28].

### 2.2. Preprocessing phase

In the realm of image classification, the preprocessing stage plays a pivotal role in ensuring precise and dependable outcomes [29] Prior to inputting the dataset into deep learning algorithms, various preprocessing techniques are employed. These techniques enable models to better comprehend the inherent characteristics of the data. Preprocessing is widely used in machine vision applications and exerts a direct influence on ML-based models' performance [30]. To preprocess datasets for image classification, multiple steps were executed. Initially, the dataset was divided into training, validation, and testing sets with an 80% split ratio for training data and 10% each for validation and testing respectively.

Afterward, the image files underwent resizing to dimensions of 224×244 pixels [30]. The purpose of resizing is to ensure consistent dimensions and simplify further processing and analysis. Subsequent to the resizing process, each pixel in the images was normalized by subtracting the mean RGB value calculated from the training set to alter the statistical properties of the images, aligning them with the data used for pretraining.

Finally, the ImageDataGenerator class from Keras was utilized to augment the preprocessed images which generate augmented images by applying various transformations such as flipping, zooming, shearing, and rotation. The augmentation process aids in diversifying the dataset, which could potentially improve the model's ability to handle variations in input images and generalize better. Furthermore, segmentation and decoding were employed as additional techniques to enhance the preprocessing pipeline. Segmentation entails dividing the image into different regions or items of interest, which can be beneficial in isolating specific features. Decoding is employed to transform the image file format into a more suitable representation for further analysis [23].

In order to enhance brain tumor detection, we propose a new model architecture based on deep learning approaches. Our model architecture is based on the EfficientNetB3 [23]. Convolutional neural network that has been pre-trained on "ImageNet" [31]. To tailor this base model for brain tumor detection, we fine-tuned it by integrating extra layers like batch normalization, a dense layer with regularization ($weights$ =0.01), dropout regularization with a dropout rate of 0.5, and a final dense layer for classifying tumor images into various categories. The model was trained using 4 epochs on 64-pixel images. The proposed model architecture takes advantage of EfficientNetB3's powerful feature extraction abilities while incorporating these extra layers to prevent overfitting and improve generalization performance.

The suggested design of the model offers various benefits. Initially, through the utilization of EfficientNetB3's pre-trained weights, the model effectively captures essential characteristics from the brain tumor images inputted, eliminating the necessity for extensive training on a vast dataset. Consequently, this substantially minimizes the resources and time required for training. Additionally, the incorporation of batch normalization guarantees that the input data is standardized, enhancing the training process's stability and speed. Third, the dense layer with regularization helps prevent overfitting by introducing penalties on the weights and activities of the model. Fourth, the dropout regularization technique randomly drops out a certain percentage of neurons during training, which helps reduce the model's reliance on specific features and improves its generalization ability.

## 3. RESULT AND DISCUSSION

Recent developments in the field of medical image analysis technologies have afforded healthcare professionals increased convenience in the timely detection of diseases at their nascent stages. These breakthroughs are facilitating its utilization in diverse domains of medicine, encompassing disease detection, treatment, and expedited clinical decision-making. On a daily basis, hospitals produce a substantial volume of medical data. Medical informatics research plays a crucial role in aiding healthcare professionals and researchers in their quest to identify optimal strategies for effectively utilizing the continuously expanding quantities of data available to them. The timely identification and implementation of suitable therapeutic interventions are crucial for the optimal management of brain tumor conditions. The selection of treatment options is contingent upon the stage, kind, and grade of the tumor at the time of diagnosis. Conventional identification systems utilize rudimentary algorithms with artificial intelligence capabilities that extract a restricted set of features.

The objective of this study was to develop a deep learning-based classification model for brain tumors. The model was trained and validated on a dataset of MRI brain tumor images. The training and validation loss achieved was approximately 0.11 and 0.12 respectively as shown in Figure 1, indicating that the model was able to minimize the error during the training and validation process.

The training and validation accuracy achieved was 100% and 99.6% respectively as shown in Figure 2, indicating that the model was able to correctly classify all the training samples. Based on the outcomes obtained from training and validation, it can be inferred that the model learned the key features and patterns present in the training data, leading to the accurate classification of brain tumors during training. Additionally, the model's high validation accuracy indicates that it performed well when tested on new test data, demonstrating its generality. Table 1 presents the evaluation metrics of the proposed model on the test dataset. The results provide insights into the performance of the model in accurately detecting brain tumors.

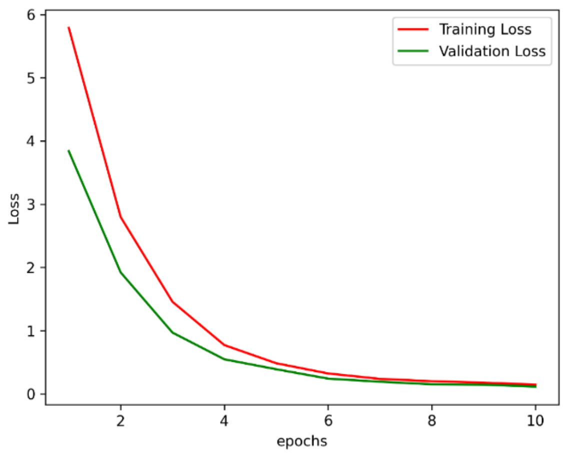


Figure 1. Training and validation loss

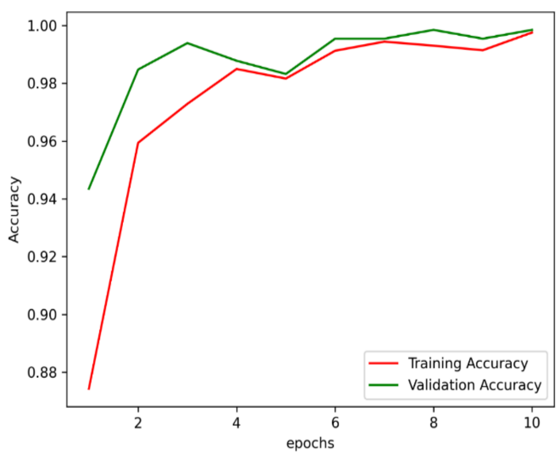


Figure 2. Training and validation accuracy

Table 1. Performance metrics on the test dataset

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Glioma | 1 | 0.99 | 0.99 | 151 |
| Meningioma | 0.98 | 1 | 0.99 | 164 |
| No tumor | 1 | 1 | 1 | 192 |
| Pituitary | 1 | 0.99 | 1 | 149 |
| Proposed model | | 1 | | |

The model's capability to classify brain tumors was very high. This can be seen in Figure 3, which presents the confusion matrix which shows a high number of true positives and a low number of false negatives. Additionally, the model shows a high level of precision with a low number of false positives.

The model exhibited an exceptionally elevated capacity for the classification of brain tumors, yielding a substantial abundance of true positives coupled with a minimal occurrence of false negatives. Moreover, the model demonstrated a commendable level of accuracy and precision, characterized by a minimal occurrence of false positives. These findings offer valuable insights into the robust performance of the model, particularly in its ability to accurately detect brain tumors. Table 2 presents a comparison between our proposed tumor detection and classification models and the existing approaches, utilizing accuracy as the parameter of evaluation.

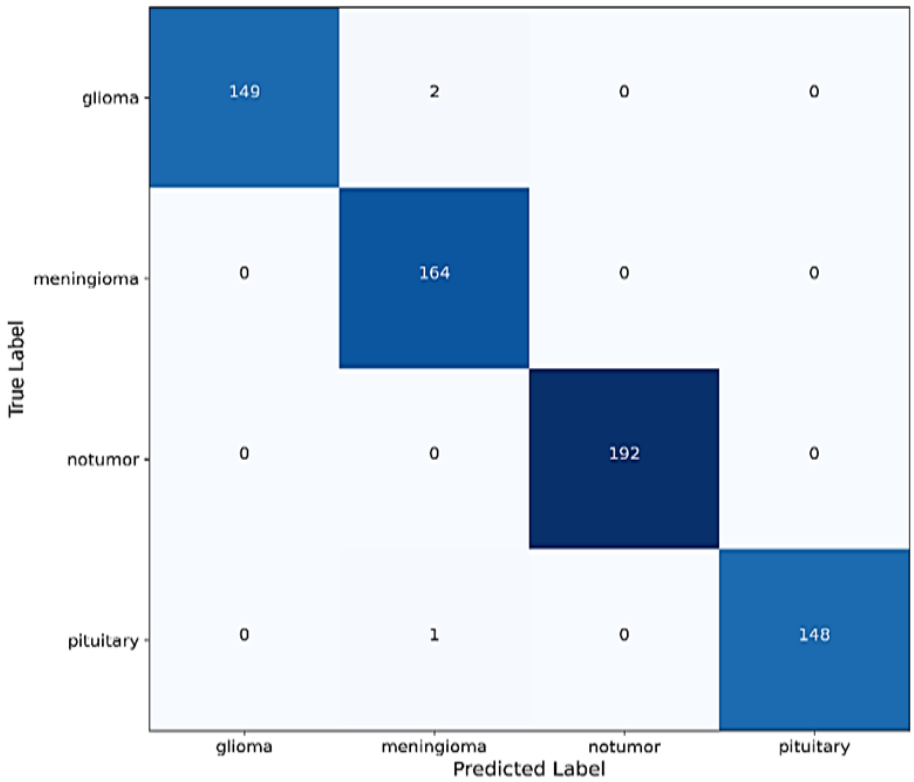


Figure 3. The confusion matrix

Table 2. A comparison between our proposed tumor detection and classification models and the existing approaches

| Reference | Technique | Accuracy % |
|---|---|---|
| [18] | CNN | 93.68 |
| [19] | CNN with a genetic algorithm | 94.2 |
| [20] | CNN | 96.56 |
| [21] | 3D CNN | 96.49 |
| [22] | Hybrid ensemble model | 97.3 |
| [23] | Attention-Convolutional-LSTM | 98.9 |
| [24] | GoogLeNet | 99.67 |
| [25] | Google-Net model | 98.1 |
| [26] | Xception, DenseNet201, DenseNet121, ResNet152V2, and InceptionResNetV2 | 99.67 |
| Proposed study | EfficientNetB3 | 100 |

The findings of our study underscore a profound association between the remarkable accuracy and precision achieved in the classification of brain tumors and the consequential enhancement of treatment efficacy. The method proposed in our research holds immense promise, primarily due to its alignment with the stringent criteria governing brain tumor treatment protocols. By leveraging advanced computational algorithms and sophisticated analytical techniques, our approach demonstrates unparalleled efficacy in accurately delineating distinct tumor subtypes, thereby facilitating targeted therapeutic interventions tailored to individual patient profiles. Notably, the adoption of our method promises to confer significant advantages from the standpoint of medical practitioners, as it furnishes them with a robust framework that harmonizes seamlessly with established clinical paradigms. Moreover, the seamless integration of our methodology into existing clinical workflows ensures minimal disruption to patients' therapy plans, thereby optimizing the continuum of care and fostering favorable treatment outcomes. This amalgamation of cutting-edge technological innovation with patient-centric care paradigms underscores the transformative potential of our approach in advancing the landscape of brain tumor diagnosis and management.

## 4. CONCLUSION

Advancements in medical image analysis technologies have provided healthcare workers with more convenience in promptly identifying diseases during their early stages. These advancements are enabling its application in various fields of medicine, including disease identification, therapy, and accelerated clinical decision-making. Hospitals generate a significant quantity of medical data on a daily basis. The field of medical informatics research is of paramount importance in supporting healthcare practitioners and researchers in their efforts to determine the most effective approaches for using the ever-growing volumes of data at their disposal. The prompt recognition and application of appropriate therapeutic strategies are essential for the effective management of brain tumor situations. The determination of appropriate treatment modalities is dependent on the stage, kind, and grade of the tumor at the point of initial diagnosis. Traditional identification systems employ basic algorithms that have limited artificial intelligence capabilities to extract a constrained collection of features.

The primary aim of this research endeavor was to construct a classification model for brain tumors utilizing deep learning techniques. The model underwent training and validation using a dataset consisting of MRI brain tumor images. The obtained training and validation loss values were roughly 0.11 and 0.12, respectively, suggesting that the model successfully minimized the error during the training and validation phases. The model demonstrated a training accuracy of 100% and a validation accuracy of 99.6%, confirming its ability to accurately categorize all training samples. Based on the results derived from the training and validation processes, it can be deduced that the model successfully acquired the essential characteristics and patterns inherent in the training dataset, hence enabling precise categorization of brain tumors during the training phase. Moreover, the model's elevated validation accuracy suggests its strong performance in the evaluation of novel test data, so showcasing its generalizability. The model exhibited a high level of proficiency in classifying brain tumors, as evidenced by the confusion matrix displaying a substantial count of true positives and a minimal count of false negatives. Furthermore, the model demonstrates a notable degree of precision while exhibiting a minimal occurrence of false positives.

We recognize the necessity for further investigation and validation of the effectiveness of our proposed method. The realm of brain tumor identification within medical imaging remains a focal point of research, and our study utilizes five distinct convolutional models and transfer learning architectures to contribute to this area. However, opportunities for further exploration and enhancement persist in this field. The ongoing evolution of brain tumor detection systems through continuous research endeavors holds promise for refining diagnostic accuracy for both patients and medical practitioners in the arduous battle against brain cancers. By refining detection methodologies and advancing knowledge boundaries in this domain, we can cultivate improved diagnostic capabilities and enhance patient outcomes. Moreover, subjecting this expanded dataset to rigorous performance assessments will offer insights into the model's capacity to distinguish among different types of brain lesions. While the current dataset marks an initial stride in brain tumor detection, future investigations should aim to incorporate a more varied and clinically pertinent assortment of brain lesions to address the intricacies of real-world diagnostic complexities.

## REFERENCES


[1] L. S. Costanzo, *Physiology, E-Book*. Elsevier Health Sciences, 2009.

[2] L. M. DeAngelis, “Brain tumors,” *New England journal of medicine*, vol. 344, no. 2, pp. 114–123, 2001.

[3] J. R. McFaline-Figueroa and E. Q. Lee, “Brain tumors,” *The American Journal of Medicine*, vol. 131, no. 8, pp. 874–882, Aug. 2018, doi: 10.1016/j.amjmed.2017.12.039.

[4] M. S. Majib, M. M. Rahman, T. M. S. Sazzad, N. I. Khan, and S. K. Dey, “VGG-SCNet: a VGG Net-based deep learning framework for brain tumor detection on MRI images,” *IEEE Access*, vol. 9, pp. 116942–116952, 2021, doi: 10.1109/ACCESS.2021.3105874.

[5] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, “Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture,” *Microscopy Research and Technique*, vol. 84, no. 1, pp. 133–149, Jan. 2021, doi: 10.1002/jemt.23597.

[6] S. Z. Kurdi, M. H. Ali, M. M. Jaber, T. Saba, A. Rehman, and R. Damaševičius, “Brain tumor classification using meta-heuristic optimized convolutional neural networks,” *Journal of Personalized Medicine*, vol. 13, no. 2, Jan. 2023, doi: 10.3390/jpm13020181.

[7] K. J. Zülch, *Brain tumors: their biology and pathology*. Springer-Verlag, 2013.

[8] H. Mehnatkesh, S. M. J. Jalali, A. Khosravi, and S. Nahavandi, “An intelligent driven deep residual learning framework for brain tumor classification using MRI images,” *Expert Systems with Applications*, vol. 213, Mar. 2023, doi: 10.1016/j.eswa.2022.119087.

[9] S. Y. Kandimalla, D. M. Vamsi, S. Bhavani, and M. V.M., “Recent methods and challenges in brain tumor detection using medical image processing,” *Recent Patents on Engineering*, vol. 17, no. 5, Sep. 2022, doi: 10.2174/1872212117666220823100209.

[10] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain, “Brain tumor detection and classification using intelligence techniques: an overview,” *IEEE Access*, vol. 11, pp. 12870–12886, 2023, doi: 10.1109/ACCESS.2023.3242666.

[11] A. E. Babu, A. Subhash, D. Rajan, F. Jacob, and P. A. Kumar, “A survey on methods for brain tumor detection,” in *2018 Conference on Emerging Devices and Smart Systems (ICEDSS)*, Mar. 2018, pp. 213–216, doi: 10.1109/ICEDSS.2018.8544353.

[12] B. D. Weinberg, “Book review: brain tumor imaging,” *Neurosurgery*, vol. 81, no. 5, pp. 880–881, Nov. 2017, doi: 10.1093/neuros/nyx419.

[13] S. Gull and S. Akbar, "Artificial intelligence in brain tumor detection through MRI scans: advancements and challenges," *Artificial Intelligence and Internet of Things*, pp. 241–276, 2021.
[14] X. Li *et al.*, "Deep learning attention mechanism in medical image analysis: Basics and beyonds," *International Journal of Network Dynamics and Intelligence*, pp. 93–116, Mar. 2023, doi: 10.53941/ijndi0201006.
[15] M. I. Razzak, S. Naz, and A. Zaib, "Deep learning for medical image processing: overview, challenges and the future," in *Lecture Notes in Computational Vision and Biomechanics*, 2018, pp. 323–350.
[16] P. Jyothi and A. R. Singh, "Deep learning models and traditional automated techniques for brain tumor segmentation in MRI: a review," *Artificial Intelligence Review*, vol. 56, no. 4, pp. 2923–2969, Apr. 2023, doi: 10.1007/s10462-022-10245-x.
[17] Z. Liu *et al.*, "Deep learning based brain tumor segmentation: a survey," *Complex & Intelligent Systems*, vol. 9, no. 1, pp. 1001–1026, Feb. 2023, doi: 10.1007/s40747-022-00815-5.
[18] A. Pashaei, H. Sajedi, and N. Jazayeri, "Brain tumor classification via convolutional neural network and extreme learning machines," in *2018 8th International Conference on Computer and Knowledge Engineering (ICCKE)*, Oct. 2018, pp. 314–319, doi: 10.1109/ICCKE.2018.8566571.
[19] A. Kabir Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 1, pp. 63–74, Jan. 2019, doi: 10.1016/j.bbe.2018.10.004.
[20] M. M. Badža and M. Č. Barjaktarović, "Classification of brain tumors from MRI images using a convolutional neural network," *Applied Sciences*, vol. 10, no. 6, Mar. 2020, doi: 10.3390/app10061999.
[21] H. Mzoughi *et al.*, "Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification," *Journal of Digital Imaging*, vol. 33, no. 4, pp. 903–915, Aug. 2020, doi: 10.1007/s10278-020-00347-9.
[22] W. Ayadi, I. Charfi, W. Elhamzi, and M. Atri, "Brain tumor classification based on hybrid approach," *The Visual Computer*, vol. 38, no. 1, pp. 107–117, Jan. 2022, doi: 10.1007/s00371-020-02005-1.
[23] F. Demir, Y. Akbulut, B. Taşcı, and K. Demir, "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*, vol. 81, Mar. 2023, doi: 10.1016/j.bspc.2022.104424.
[24] J. Amin, M. Sharif, M. Raza, T. Saba, and A. Rehman, "Brain tumor classification: feature fusion," in *2019 International Conference on Computer and Information Sciences (ICCIS)*, Apr. 2019, pp. 1–6, doi: 10.1109/ICCISci.2019.8716449.
[25] M. Rasool *et al.*, "A hybrid deep learning model for brain tumour classification," *Entropy*, vol. 24, no. 6, Jun. 2022, doi: 10.3390/e24060799.
[26] S. Asif, M. Zhao, F. Tang, and Y. Zhu, "An enhanced deep learning method for multi-class brain tumor classification using deep transfer learning," *Multimedia Tools and Applications*, vol. 82, no. 20, pp. 31709–31736, Aug. 2023, doi: 10.1007/s11042-023-14828-w.
[27] S. Ghosh and S. Gupta, "BrainMNet: a unified neural network architecture for brain image classification," *Network Modeling Analysis in Health Informatics and Bioinformatics*, vol. 13, no. 1, pp. 1-17, 2024, doi: 10.1007/s13721-024-00443-8.
[28] M. Nickparvar, "Brain tumor MRI dataset," Kaggle, 2021. https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset (accessed Feb. 10, 2024).
[29] S. Pudaruth, M. F. Mahomoodally, N. Kissoon, and F. Chady, "MedicPlant: a mobile application for the recognition of medicinal plants from the Republic of Mauritius using deep learning in real-time," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 10, no. 4, pp. 938–947, Dec. 2021, doi: 10.11591/ijai.v10.i4.pp938-947.
[30] Z. Ye, X. Hou, X. Zhang, and J. Yang, "Application of bat algorithm for texture image classification," *International Journal of Intelligent Systems and Applications*, vol. 10, no. 5, pp. 42–50, May 2018, doi: 10.5815/ijisa.2018.05.05.
[31] W. Liu, Z. Su, and L. Liu, "Beyond vanilla convolution: random pixel difference convolution for face perception," *IEEE Access*, vol. 9, pp. 139248–139259, 2021, doi: 10.1109/ACCESS.2021.3117955.


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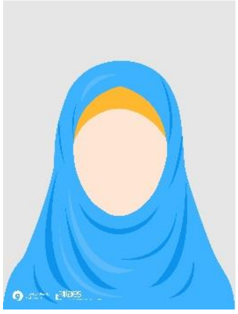

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