Enhanced Brain Tumor Classification with Convolutional Neural Networks

Athanasios Kanavos · Orestis Papadimitriou · Gerasimos Vonitsanos · Manolis Maragoudakis · Phivos Mylonas

Abstract Accurate brain tumor classification is crucial for advancing diagnostic precision and streamlining treatment strategies. This paper presents a brain tumor image classification methodology leveraging deep learning techniques, specifically convolutional neural networks (CNNs). Our method exploits CNNs to autonomously extract salient features from medical imaging data, enabling the differentiation of tumor types, including gliomas, meningiomas, and metastatic tumors. The architecture of our CNN comprises several convolutional layers, pooling layers, and fully connected layers designed to capture and interpret complex patterns in brain tumor imagery effectively. We enhance the model's performance through comprehensive data augmentation and rigorous hyperparameter tuning, achieving significant improvements in classification accuracy. Extensive experimental evaluations demonstrate the efficacy of our approach, underscoring its potential to significantly enhance diagnostic processes by providing accurate, automated tumor classification. The advancements detailed herein contribute to the broader application of machine learning in medical imaging, promising substantial impacts on patient care and treatment optimization.

Athanasios Kanavos and Orestis Papadimitriou
Department of Information and Communication Systems Engineering
University of the Aegean, Samos, Greece
E-mail: {icsdd20017, icsdd20016}@icsd.aegean.gr

Gerasimos Vonitsanos
Computer Engineering and Informatics Department
University of Patras, Patras, Greece
E-mail: mvonitsanos@ceid.upatras.gr

Manolis Maragoudakis
Department of Informatics
Ionian University, Corfu, Greece
E-mail: mmarag@ionio.gr

Phivos Mylonas
Department of Informatics and Computer Engineering
University of West Attica, Athens, Greece
E-mail: mylonasf@uniwa.gr

1 Introduction

Brain tumors represent a significant medical and societal challenge, affecting both adults and children with considerable mortality rates [4]. The urgency for early detection and precise classification of brain tumors is paramount to improving treatment outcomes and survival rates. The diagnostic process primarily relies on imaging techniques, notably magnetic resonance imaging (MRI), essential for accurate tumor assessment [33].

Despite advancements in imaging technology, the manual interpretation of these images remains a bottleneck, fraught with potential for error and variability in diagnostic accuracy [24]. The introduction of convolutional neural networks (CNNs) has begun to transform this landscape by automating medical image analysis, thereby enhancing the precision and efficiency of diagnostics [28, 34].

CNNs offer a significant advantage in classifying complex image data through their feature extraction capabilities. This paper focuses on applying CNNs to classify brain tumor images, aiming to surpass the accuracy of traditional methods by leveraging deep learning's ability to discern intricate patterns and subtle variations in medical images [8, 22, 30].

The specific challenges in brain tumor classification involve distinguishing between benign and malignant growths and accurately identifying tumor types such as gliomas, meningiomas, and metastatic tumors [36]. These distinctions are crucial for developing effective treatment plans. Conventional diagnostic practices often fail to address these challenges adequately, necessitating a shift towards more sophisticated, automated technologies [16].

Our study contributes to this field by developing a tailored CNN architecture optimized for the nuanced requirements of brain tumor imaging. This model incorporates advanced data processing and neural network techniques to improve classification accuracy and reliability [10, 18, 19]. Through detailed hyperparameter tuning and comprehensive dataset analysis, we ensure that our model achieves high-performance standards in real-world diagnostic applications [17, 26].

Furthermore, this research enhances diagnostic procedures and provides a foundation for future advancements in treating brain tumors. By improving diagnostic accuracy, our work aids in the quicker initiation of targeted therapies, which is crucial for patient outcomes [2, 23].

Accurate classification is underpinned by the World Health Organization's grading system, which categorizes tumors from Grades I to IV. This classification is essential for prognosis and treatment planning. CNNs can play a critical role by accurately determining the grade based on imaging characteristics, as outlined by Fletcher [9].

In summary, this paper's contributions are twofold: first, it demonstrates the efficacy of CNNs in the complex task of brain tumor classification, and second, it highlights the potential for these technologies to revolutionize the field of medical diagnostics, offering substantial benefits in terms of treatment efficiency and patient care.

2 Related Work

Advancements in computational methods for classifying brain tumors have significantly influenced the field of neuro-oncology, mainly through the use of neural networks, CNNs, and deep learning (DL). These technologies are pivotal for enhancing diagnostic accuracy and expediting treatment initiation.

Recent studies utilizing pre-trained CNNs have underscored the value of DL in medical diagnostics. Deep features extracted from these networks, when fine-tuned to specific medical tasks, have achieved survival time predictions with high accuracy. Notably, one approach using leave-one-out cross-validation on a standard dataset reached an accuracy of approximately 81%, highlighting the effectiveness of CNNs in clinical applications [1].

Hybrid approaches that integrate genetic algorithms (GA) with support vector machines (SVM) have also been explored. These methods enhance feature extraction and classification accuracy, enabling more detailed and accurate image analysis, which is critical for distinguishing between different tumor types [3].

Further refining classification techniques, research has also introduced novel DL methods such as local constraint-based convolutional dictionary learning. These have been particularly successful in differentiating between benign and malignant MRI brain tumor images, improving over conventional classifiers [11, 20]. The introduction of modified deep convolutional neural networks (DCNN) and DL-based opposition crow search (DL-OCS) methods have significantly evolved brain tumor classification. These approaches have enhanced the specificity and sensitivity of tumor detection, using a variety of MRI modalities to achieve notable accuracy rates [12, 32].

Addressing challenges associated with small dataset sizes, the field has increasingly turned to transfer learning to prevent model overfitting. This technique has been extensively applied across different types of cancer diagnosis, demonstrating its broad utility. For instance, pre-trained models like Inception V3, VGG-16, and AlexNet have been adapted for tasks ranging from kidney and breast cancer detection to diagnosing neurological disorders such as Alzheimer's disease, showing the adaptability and potential of transfer learning in enhancing medical diagnostic processes [5, 6, 14, 15, 21].

In summary, integrating advanced computational models, particularly CNNs, into medical diagnostics for brain tumors has substantially improved the precision and speed of disease classification. This ongoing research advances the technical capabilities of medical imaging and significantly impacts patient management and treatment outcomes, setting a new standard in neuro-oncology diagnostics.

3 Methodology Foundations

This section presents the foundational techniques and computational tools employed in our approach to brain tumor classification through DL. By integrating CNNs with sophisticated development frameworks such as TensorFlow and Keras, we enhance the precision and efficiency of medical image analysis. The following subsections describe each technology and method in detail, highlighting their specific roles and contributions to improving the accuracy of tumor diagnosis and classification.

3.1 Convolutional Neural Networks

CNNs leverage pixel arrangement in images to detect patterns, making them highly effective for tasks such as medical diagnosis [29, 31]. During training, CNNs identify complex patterns in different parts of an image, enhancing their capability for accurate medical analysis. These networks automatically learn to detect features through convolution and pooling layers, supplemented by fully connected layers for detailed classification [7].

CNNs comprise an input layer, multiple hidden layers, and an output layer. The convolutional layers focus on extracting essential features from images, while downsampling operations improve computational efficiency. This structured approach allows CNNs to interpret complex visual information effectively with minimal preprocessing, which is crucial for advanced medical diagnostic applications.

3.2 Tensorflow

TensorFlow is an open-source framework that supports DL models by facilitating complex mathematical computations. It utilizes a system of dataflow graphs where operations are represented as nodes and data connections as edges, making it highly efficient for managing large-scale, complex computing tasks [27]. The framework is adaptable to various computing environments, from mobile devices to large data centers equipped with CPUs and GPUs. It is ideal for deploying DL models that require intensive computational power.

3.3 Keras

Keras is a high-level Python library designed to operate with TensorFlow. It simplifies the process of building and training DL models by abstracting many of the complicated lower-level details involved in directly manipulating tensors [25]. It provides a Sequential API that allows for straightforward model construction by stacking layers, simplifying the setup and experimentation of DL architectures.

3.4 Convolutional Layers

Convolutional layers are crucial in CNNs for detecting spatial features such as edges, textures, and shapes within images. These layers operate by sliding a filter or kernel across the input image and computing the dot product of the filter with the pixel values at each position, thus generating a feature map:

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(i + m, j + n) \cdot K(m, n) \tag{1}$$

where $S(i, j)$ represents the output feature map, indicating how the filter interacts with the input image I at each position (i, j). The kernel or filter K detects specific features by focusing on small regions of the input image. The indices (m, n) traverse the dimensions of the kernel, applying the dot product operation across the extent of the image to produce the feature map. The output feature map S

serves as the transformed representation of the original image, carrying forward the most significant features for subsequent layers to process.

3.5 Pooling Layers

Pooling layers play a vital role in CNNs by reducing the dimensions of the feature maps, which decreases the computational load and enhances the network's performance and generalizability. These layers typically use operations like max pooling to extract the most significant features from regions of the feature map:

$$P_{max}(i,j) = \max_{a=0}^{n-1} \max_{b=0}^{n-1} F(i \cdot s + a, j \cdot s + b) \tag{2}$$

where $P_{max}(i,j)$ represents the maximum value within the pooling window, which becomes the output for the position (i,j) on the new, reduced feature map; the original feature map is denoted by F, with $n \times n$ specifying the dimensions of the pooling window, and s representing the stride or the step size for moving the window across the feature map. Variables a and b iterate over the window's dimensions to apply the maximum operation, effectively reducing the size of the feature map while retaining the most prominent features.

3.6 Batch Normalization

Batch Normalization (BN) is critical for enhancing the stability and efficiency of neural network training by standardizing each layer's inputs to zero mean and unit variance. The process is defined as:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \tag{3}$$

where x_i is the input to a layer, μ_B and σ_B^2 are the batch mean and variance, and ϵ is a small constant for numerical stability. By maintaining consistent input distributions, BN enables higher learning rates and prevents saturation in activation functions, accelerating the training process and improving the model's performance [13].

3.7 Dropout

Dropout is a regularization technique that prevents overfitting in neural networks by randomly deactivating neurons during training. This method helps reduce the network's reliance on any specific neurons, increasing its generalization capabilities:

$$x' = d \cdot x \tag{4}$$

where x represents a neuron's output, and d is a random variable from a Bernoulli distribution, where d is 1 with probability p (the retention rate) and 0 with probability $1 - p$. This selective deactivation of neurons creates a variety of network architectures during training, enhancing the network's ability to perform well on new, unseen data [35].

4 Architecture of Proposed CNN Models

This section describes the architecture of the CNNs developed for automated brain tumor detection through DL. Our investigation focuses on integrating Artificial Intelligence (AI) with image classification techniques to explore various CNN designs, each tailored to efficiently and accurately analyze complex image data.

The diversity in CNN model designs is examined through different architectural configurations, each intended to evaluate the structural impacts on model performance. These models undergo initial assessments using various techniques to determine optimal configurations, followed by a performance comparison within a standardized evaluation framework. Table 1 summarises the distinctive features of these architectures, detailing the sequence and function of layers in each model.

Table 1 Summary of CNN Architectures

Number	Architecture
1st	(Conv2D $\times 2 \rightarrow$ BatchNorm $\rightarrow$ MaxPooling2D) $\times 4 \rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax
2nd	(Conv2D $\times 3 \rightarrow$ BatchNorm $\rightarrow$ MaxPooling2D) $\times 4 \rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax

Key layers integral to all proposed architectures include:

- **Input()** initializes a symbolic tensor named "images" to hold the image data.
- **Conv2D()** constructs a convolution kernel that extracts features such as edges and shapes for mask detection.
- **Batch Normalization ()** normalizes outputs per batch, ensuring stable mean and variance.
- **MaxPooling2D()** reduces spatial dimensions by computing the maximum value in each input window.
- **Flatten()** reshapes the data into a 1D array for input to subsequent layers.
- **Dropout()** randomly omits units during training to prevent overfitting.
- **Dense()** a fully connected layer that processes features learned by convolutional layers.
- **Softmax()** normalizes the final layer's output distribution over predicted classes.

This structured methodology optimizes CNN architectures for precise image categorization, ensuring each component's effective integration and functionality.

5 Experimental Evaluation

5.1 Dataset Description

The Brain Tumor Classification dataset[1] used in this study comprises three distinct folders: "yes," "no," and "pred," containing a total of 3,060 Brain MRI Images. The "yes" folder includes 1,500 images with tumors, while the "no" folder contains 1,500 images without tumors, as detailed in Table 2.

---

[1] https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection

Table 2 Distribution of MRI Images in the Dataset

Folder	Number of Images
Yes (Tumorous)	1,500
No (Non-tumorous)	1,500
Pred (To be predicted)	60
Total	**3,060**

Brain tumors are a significant health concern that affects all age groups and are one of the most common types of primary Central Nervous System (CNS) tumors. Approximately 11,700 new brain tumor cases are diagnosed annually in the United States, with the 5-year survival rates for malignant brain tumors at about 34% for men and 36% for women.

5.2 Performance Analysis

This subsection details the evaluation of two CNN architectures developed in this study, assessed across varying batch sizes. We focus on key performance metrics—loss, accuracy, and computational time—to determine the most effective configurations for practical application. The comparative results are summarized in Table 3, showing how different batch sizes influence each model's training dynamics and effectiveness.

Table 3 Comparative Performance Evaluation of Proposed CNN Architectures

Epochs	Loss	Accuracy	Time	Loss	Accuracy	Time	Loss	Accuracy	Time
1st: (Conv2D ×2 → BatchNorm → MaxPooling2D) ×4 → (Flatten → Dropout → Dense) → Softmax									
	Batch Size = 64			Batch Size = 128			Batch Size = 256		
1	2.917	0.6008	97	3.161	0.4783	97	1.059	0.3913	107
5	0.3394	0.8577	88	0.3994	0.8182	91	0.6126	0.6640	93
10	0.1607	0.9605	88	0.1917	0.9328	92	0.4175	0.8142	92
15	0.0582	0.9802	90	0.1033	0.9644	92	0.2754	0.8775	92
20	0.0291	0.9960	91	0.0503	0.9921	90	0.2006	0.9289	92
2nd: (Conv2D ×3 → BatchNorm → MaxPooling2D) ×4 → (Flatten → Dropout → Dense) → Softmax									
	Batch Size = 64			Batch Size = 128			Batch Size = 256		
1	2.119	0.5099	84	3.131	0.5217	82	0.9945	0.4269	83
5	0.3435	0.8617	77	0.3965	0.8300	75	0.6548	0.6324	70
10	0.1897	0.9368	76	0.1704	0.9368	77	0.3270	0.8538	76
15	0.0950	0.9684	77	0.0799	0.9723	69	0.2230	0.9130	71
20	0.0667	0.9802	70	0.0552	0.9842	75	0.1679	0.9447	71

Both models show a promising decrease in loss and a significant increase in accuracy as epochs progress. Initially, the first architecture demonstrates a higher accuracy and a steeper decline in loss compared to the second, suggesting its efficiency in feature extraction right from the early stages of training. As training continues, the second architecture gradually improves performance, underscoring the benefit of additional convolution layers in capturing more complex features, albeit at a slightly slower pace.

Regarding computational time, the first architecture requires more seconds per epoch on average, which could be attributed to its simpler yet computationally intensive configurations. On the other hand, despite having more convolution layers, the second architecture benefits from improved time efficiency, indicating a better optimization of computational resources.

The analysis indicates that smaller batch sizes lead to faster learning but are susceptible to overfitting. In contrast, larger batch sizes ensure more stable learning at the cost of increased computational time.

6 Conclusions and Future Work

This study has demonstrated the practical application of CNNs in the automated detection and classification of brain tumors from MRI images. Through developing and evaluating two distinct CNN architectures, we have identified key factors that influence their performance, including layer configuration, batch size, and epoch number. The first architecture achieved high accuracy, showcasing its potential for immediate clinical application. In contrast, the second architecture, with more convolutional layers, showed promise in handling more complex image features over extended training sessions.

Despite these advances, several avenues remain for future work. First, expanding the dataset and including more varied cases from diverse imaging conditions could further refine the models' accuracy and generalizability. Additionally, implementing advanced techniques such as transfer learning and deeper network architectures could enhance the sensitivity and specificity of tumor detection. Lastly, future research could also focus on integrating these CNN architectures into real-time diagnostic systems used in medical facilities. Developing user-friendly interfaces that allow radiologists to interact with the model predictions could significantly enhance diagnostic workflows and patient outcomes. By bridging the gap between DL advancements and clinical practice, we can ensure that such technologies provide tangible benefits in healthcare settings.

References

1. Ahmed KB, Hall LO, Goldgof DB, Liu R, Gatenby RA (2017) Fine-tuning convolutional deep features for MRI based brain tumor classification. In: Medical Imaging: Computer-Aided Diagnosis, SPIE, vol 10134, p 101342E
2. Amin J, Sharif M, Haldorai A, Yasmin M, Nayak RS (2021) Brain tumor detection and classification using machine learning: A comprehensive survey. Complex & Intelligent Systems pp 1–23
3. Bangare SL, Pradeepini G, Patil ST (2017) Brain tumor classification using mixed method approach. In: International Conference on Information Communication and Embedded Systems (ICICES), IEEE, pp 1–4
4. Bondy ML, Scheurer ME, Malmer B, Barnholtz-Sloan JS, Davis FG, Il'yasova D, Carol Kruchko BJM, Rajaraman P, Schwartzbaum JA, Sadetzki S, Schlehofer B, Tihan T, Wiemels JL, Wrensch M, Buffler PA (2008) Brain tumor epidemiology: Consensus from the brain tumor epidemiology consortium. Cancer 113(S7):1953–1968

5. Deepak S, Ameer PM (2019) Brain tumor classification using deep CNN features via transfer learning. Computers in Biology and Medicine 111
6. Deniz E, Sengür A, Kadiroglu Z, Guo Y, Bajaj V, Budak Ü (2018) Transfer learning based histopathologic image classification for breast cancer detection. Health Information Science and Systems 6(1):18
7. Desai M, Shah M (2021) An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (mlp) and convolutional neural network (cnn). Clinical eHealth 4:1–11
8. Febrianto DC, Soesanti I, Nugroho HA (2020) Convolutional neural network for brain tumor detection. In: IOP Conference Series: Materials Science and Engineering, vol 771, p 012031
9. Fletcher-Heath LM, Hall LO, Goldgof DB, Murtagh FR (2001) Automatic segmentation of non-enhancing brain tumors in magnetic resonance images. Artificial Intelligence in Medicine 21(1-3):43–63
10. Gordillo N, Montseny E, Sobrevilla P (2013) State of the art survey on mri brain tumor segmentation. Magnetic Resonance Imaging 31(8):1426–1438
11. Gu X, Shen Z, Xue J, Fan Y, Ni T (2021) Brain tumor mr image classification using convolutional dictionary learning with local constraint. Frontiers in Neuroscience 15:679,847
12. Hemanth DJ, Anitha J (2019) Modified genetic algorithm approaches for classification of abnormal magnetic resonance brain tumour images. Applied Soft Computing 75:21–28
13. Ioffe S, Szegedy C (2015) Batch normalization: Accelerating deep network training by reducing internal covariate shift. CoRR abs/1502.03167
14. Jain R, Jain N, Aggarwal A, Hemanth DJ (2019) Convolutional neural network based alzheimer's disease classification from magnetic resonance brain images. Cognitive Systems Research 57:147–159
15. Kanavos A, Mylonas P (2023) Deep learning analysis of histopathology images for breast cancer detection: A comparative study of resnet and VGG architectures. In: 18th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP), IEEE, pp 1–6
16. Kanavos A, Kolovos E, Papadimitriou O, Maragoudakis M (2022) Breast cancer classification of histopathological images using deep convolutional neural networks. In: 7th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM), IEEE, pp 1–6
17. Kanavos A, Papadimitriou O, Kaponis A, Maragoudakis M (2023) Enhancing disease diagnosis: A cnn-based approach for automated white blood cell classification. In: IEEE International Conference on Big Data, pp 4606–4613
18. Kanavos A, Papadimitriou O, Maragoudakis M (2023) Enhancing COVID-19 diagnosis from chest x-ray images using deep convolutional neural networks. In: 18th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP), IEEE, pp 1–6
19. Kanavos A, Papadimitriou O, Mylonas P, Maragoudakis M (2023) Enhancing sign language recognition using deep convolutional neural networks. In: 14th International Conference on Information, Intelligence, Systems & Applications (IISA), IEEE, pp 1–4
20. Kang J, Ullah Z, Gwak J (2021) Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers. Sensors 21(6):2222

21. Kaur T, Gandhi TK (2020) Deep convolutional neural networks with transfer learning for automated brain image classification. Machine Vision and Applications 31(3):20

22. Khan MA, Lali IU, Rehman A, Ishaq M, Sharif M, Saba T, Zahoor S, Akram T (2019) Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection. Microscopy Research and Technique 82(6):909–922

23. Louis DN, Ohgaki H, Wiestler OD, Cavenee WK, Burger PC, Jouvet A, Scheithauer BW, Kleihues P (2007) The 2007 who classification of tumours of the central nervous system. Acta Neuropathologica 114:97–109

24. Mabray MC, Barajas RF, Cha S (2015) Modern brain tumor imaging. Brain Tumor Research and Treatment 3(1):8–23

25. Manaswi NK (2018) Understanding and working with keras. Deep Learning with Applications Using Python pp 31–43

26. Mathesul S, Swain D, Satapathy SK, Rambhad A, Acharya B, Gerogiannis VC, Kanavos A (2023) COVID-19 detection from chest x-ray images based on deep learning techniques. Algorithms 16(10):494

27. Pang B, Nijkamp E, Wu YN (2020) Deep learning with tensorflow: A review. Journal of Educational and Behavioral Statistics 45(2):227–248

28. Papadimitriou O, Kanavos A, Maragoudakis M (2023) Automated pneumonia detection from chest x-ray images using deep convolutional neural networks. In: 14th International Conference on Information, Intelligence, Systems & Applications (IISA), IEEE, pp 1–4

29. Papadimitriou O, Kanavos A, Mylonas P, Maragoudakis M (2023) Advancing weather image classification using deep convolutional neural networks. In: 18th International Workshop on Semantic and Social Media Adaptation and Personalization (SMAP), IEEE, pp 1–6

30. Papadimitriou O, Kanavos A, Mylonas P, Maragoudakis M (2023) Classification of alzheimer's disease subjects from MRI using deep convolutional neural networks. In: 3rd International Conference on Novel & Intelligent Digital Systems (NiDS), Lecture Notes in Networks and Systems, vol 784, pp 277–286

31. Papadimitriou O, Kanavos A, Maragoudakis M, Gerogiannis VC (2024) Chess piece recognition using deep convolutional neural networks. In: 4th Symposium on Pattern Recognition and Applications (SPRA), vol 13162, p 1316202

32. Raj RJS, Shobana SJ, Pustokhina IV, Pustokhin DA, Gupta D, Shankar K (2020) Optimal feature selection-based medical image classification using deep learning model in internet of medical things. IEEE Access 8:58,006–58,017

33. Sajjad M, Khan S, Muhammad K, Wu W, Ullah A, Baik SW (2019) Multigrade brain tumor classification using deep CNN with extensive data augmentation. Journal of Computational Science 30:174–182

34. Savvopoulos A, Kanavos A, Mylonas P, Sioutas S (2018) LSTM accelerator for convolutional object identification. Algorithms 11(10):157

35. Srivastava N, Hinton GE, Krizhevsky A, Sutskever I, Salakhutdinov R (2014) Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research 15(1):1929–1958

36. Weizman L, Sira LB, Joskowicz L, Rubin DL, Yeom KW, Constantini S, Shofty B, Bashat DB (2014) Semiautomatic segmentation and follow-up of multicomponent low-grade tumors in longitudinal brain mri studies. Medical Physics 41(5):052,303