AIMS Bioengineering

AIMS Bioengineering, 12(2): 215–224.
DOI: 10.3934/bioeng.2025010
Received: 18 March 2025
Revised: 23 April 2025
Accepted: 28 April 2025
Published: 28 May 2025

https://www.aimspress.com/journal/Bioengineering

Research article

Enhanced brain tumor detection from brain MRI images using convolutional neural networks

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Abstract: The brain is one of the most important organs of a human body. It controls all activities of the body and hence is referred to as the CPU of human body. Fast, accurate and early diagnosis of brain tumors is essential for better treatment plans that potentially result in larger survival rates. Automatic and non-invasive brain tumor detection methods are highly relevant. Continuous efforts by researchers have resulted in a significant increase in brain tumor detection accuracy, but 100% accuracy on testing/validation data is still challenging to obtain. This paper presents a convolutional neural network model that significantly enhances brain tumor classification accuracy with low complexity. To do so, Kaggle's publicly available dataset titled "Brain_Tumor_Detection_MRI", consisting of 2891 brain MRI images annotated as "yes" (having tumors) or "no" (without tumors), was used. By leveraging advanced deep learning techniques, we achieved an accuracy of 99.31% on the test dataset. This value shows a significant improvement in classification accuracy, showcasing the potential of convolutional neural networks in medical imaging and diagnostic applications.

Keywords: Deep Learning; convolutional neural network; model; brain tumor detection; accuracy

1. Introduction

Brain tumors are a critical health challenge, contributing significantly to morbidity and mortality worldwide. Accurate and early detection of brain tumors is the best treatment plan, resulting in better patient outcomes. Magnetic resonance imaging (MRI) is one of the most effective techniques for brain tumor diagnosis due to its high-resolution imaging capabilities and non-invasive nature. However, interpreting MRI scans remains a complex and error-prone process, often requiring specialized expertise. The development of automated and accurate diagnostic tools has thus become a priority in modern medical research. Brain tumors can be broadly classified as primary or metastatic, with diverse histopathological characteristics that pose significant diagnostic challenges. MRI, with its superior contrast resolution and multi-planar imaging capability, plays an important role in identifying and characterizing these tumors. However, manual interpretation of MRI scans is subject to variability due to differences in expertise, fatigue, and the inherent complexity of tumor presentation.

The arrival of artificial intelligence in medical imaging has introduced transformative opportunities to overcome these challenges. Among various AI techniques, convolutional neural networks are a leading approach for brain tumor detection. A convolutional neural network model has ability to learn spatial hierarchies of features directly from imaging data. Their applications in brain tumor detection have produced outstanding results, demonstrating improved accuracy and efficiency compared to traditional machine learning methods. Despite these successes, the performance of CNN models is often constrained by limited and imbalanced datasets, variability in imaging protocols, etc.

The objective of our study is to design a light (low complexity) convolutional neural network model to enhance the accuracy of brain tumor classification by using brain MRI images and manipulating advanced preprocessing techniques and optimized CNN architecture and leveraging the hyperparameters. The findings from this research may contribute to the development of reliable, automated diagnostic systems, reducing the dependency on manual interpretation, and paving the way for more accessible and accurate brain tumor detection in clinical settings.

Normalization results in enhanced accuracy [1,2]. Pooling reduces computational complexity and, consequently, enhances learning rate [3]. Inclusion of a pooling layer accelerates learning [4]. Elimination of non-maximal elements accelerates the learning rate and prevents the vanishing gradient problem, consequently improving accuracy [5]. Average pooling provides smoother representation of feature maps, resulting in outlier prevention and restricting the risk of overfitting [6]. Akter A, N. Nosheen et al. employed a segmentation approach for brain tumor classification and obtained 97.7% accuracy [7]. Ramakrishnan A B, Sridevi M et al. applied a fusion hybrid approach and achieved an accuracy of 96.2% [8]. Deshpande A, Estrela V V et al. used a novel discrete Cosine transform image fusion combined with convolutional neural network and obtained a classification accuracy of 98.14% [9]. Gupta B B, Gaurav A et al. used a deep learning classification model for the classification of brain tumors and achieved an accuracy of 90% [10]. Rai H M and Chatterjee Kalyan used U-Net for detection of brain abnormalities classifying as normal and abnormal, and obtained an accuracy of 98% [11]. Islam M N, Azam M S, et al. designed a classification model and achieved an accuracy of 98.82% [12]. Al-Jammas M H, Al-Sabawi E A, et al. used a deep learning model and achieved an accuracy of 97.4% [13]. Khairandish M O, Sharma M, et al. used a hybrid CNN-SVM approach and achieved an overall accuracy of 98.4959% [14]. Patil S and Kirange D designed a deep ensemble model and achieved an accuracy of 97.77% [15]. Shanthi S, Saradha S, et al. employed an optimized hybrid deep neural network along with the adaptive rider optimization (ARO) algorithm for parameter extant selection for brain tumor classification and achieved an accuracy of 97.5% [16]. Rahman T and Islam M S proposed a novel parallel deep convolutional neural network architecture with dropout and batch normalization for brain tumor detection and classification. On three datasets, they achieved accuracy values of 97.33%, 97.60%, and 98.12% [17]. Swati Z N K, Zhao Q, et al. used a transfer learning approach using the pre-trained VGG-16 model as the base model and three customized fully connected layers and achieved an accuracy of 94.82% [18]. Agrawal T, Chaudhary P, Kumar V, et al. examined 10 well-known deep learning models for brain tumor detection using unbalanced datasets and found that dropout, early stopping, and trainable parameter reduction contribute to avoid overfitting [19]. Shivahare BD, Gupta SK, Katiyar AN, et al. suggested a framework using U-Net and CNN to denoise a medical image containing destructive Gaussian additive white noise [20]. Gursoy E and Kaya Y, proposed a fused deep learning model combining graph neural networks to recognize relational dependencies of image regions, and convolutional neural network to capture spatial features to improve brain tumor detection. The fused deep learning model achieved an accuracy value of 93.68% [21].

The aim of this study is to design a deep learning architecture with low complexity and improved accuracy, since most literature reports accuracy values lower than 99% on the test data. To properly serve the humanity, an automatic, robust diagnostic system with 100% accuracy on the test data is needed. This study is a humble effort in that direction.

2. Materials and methods

2.1. Model architecture

The architecture of the proposed model, represented in Figure 1, is as follows:

Layer 1: The first layer is a convolutional layer with 32 filters, each of size (5,5), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 2: The second layer is a convolutional layer with 64 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 3: The third layer is a convolutional layer with 128 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 4: The fourth layer is a convolutional layer with 128 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 5: The fifth layer is a convolutional layer with 128 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 6: The sixth layer is a convolutional layer with 128 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 7: The seventh layer is a convolutional layer with 128 filters, each of size (3,3), “relu” activation function, “same” padding, followed by a maxpooling layer.

Layer 8: The eighth layer is a flattened layer.

Layer 9: The ninth layer is the dropout layer.

Layer 10: The tenth layer is the dense layer.
Layer 11: The eleventh layer is a batch normalization layer.
Layer 12: The twelfth layer is another dense layer. It is the output layer.

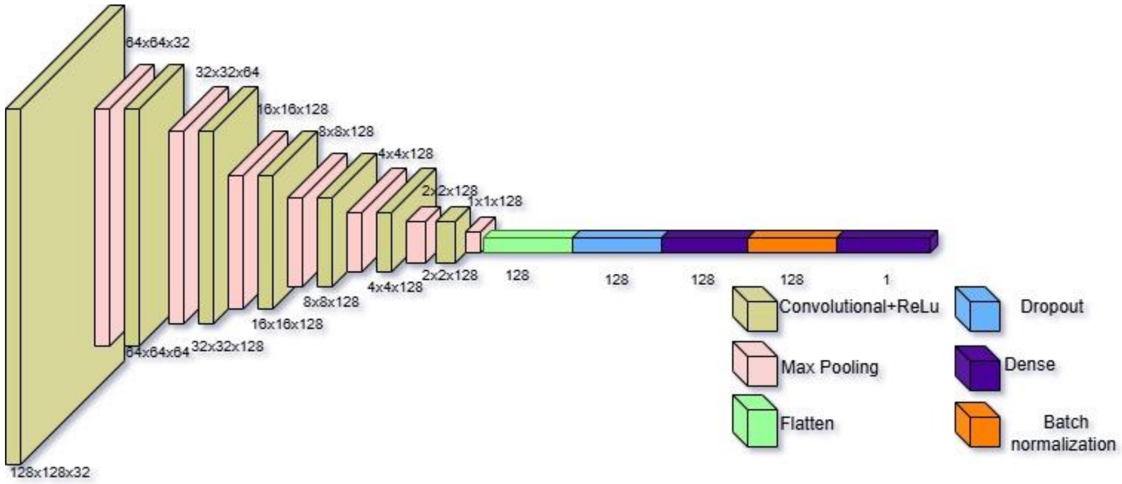

Figure 1. Architecture of our proposed model.

2.2. Dataset

In this research study, Kaggle's publicly available dataset titled "Brain_Tumor_Detection_MRI" was used, which consists of 2891 brain MRI images annotated as "yes" (having tumors) and "no" (without tumors). In total, 2023 MRI images were used for training purposes and 868 MRI images were used for validation. The MRI images were resized to size (128,128,3). No augmentation technique was applied to augment the dataset. The proposed convolutional neural network architecture consists of 7 convolutional layers, each followed by maxpooling layers, then followed by a flatten layer, a dropout layer, a dense layer, a batch normalization layer, and another dense layer. Early stopping and dropout were used to prevent overfitting [19]. Performance was evaluated using accuracy metrics. The model was trained using Adam optimizer with a learning rate of 0.0001. The loss function used was binary cross entropy. Batch size was 128 and epochs used were 30.

2.3. Complexity analysis

The proposed model was trained on a dataset consisting of 2023 brain MRI images resized to 128 × 128 pixels. The testing dataset consisted of 868 brain images.

The total parameters used were 702273 (2.68 MB). Trainable parameters were 702017 (2.68 MB). Non-trainable parameters were 256 (1.00 KB).

The computation work was conducted on Google Colab. The model was trained using TensorFlow Keras API using Tesla T4 GPU with a batch size of 128 and 30 training epochs. The average time per epoch was approximately 1 s with a mean of 75 ms per step.

3. Results

The following Table 1 presents the accuracies achieved by various researchers and our model. Our model shows an outstanding accuracy of 99.31% on the test dataset. Figure 2 presents the histogram representation of the accuracies of our model and the other models. Figure 3 presents the loss occurred V/s epochs during the training process and the testing process. Figure 4 presents the accuracy V/s epochs graph during the training process and the testing process.

Table 1. Accuracies achieved by other models and our model.

S. No.	Ref.	Year	Method	Accuracy
1	A. Akter, N. Nosheen, et al.	2024	CNN + U-Net	97.70%
2	A. B. Ramakrishnan, M. Sridevi, et al.	2024	Hybrid CNN	96.20%
3	A. Deshpande, V. V. Estrela et al.	2021	DCT-CNN-ResNet50	98.14%
4	B. B. Gupta, A. Gaurav, et al.	2024	Deep CNN	90.00%
5	H. M. Rai and K. Chatterjee	2020	Novel Lu-Net	98.00 %
6	Md. N. Islam, Md. S. Azam, et al.	2024	CNN + Ensemble	97.40%
7	M. H. Al-Jammas, E A Al-Sabawi, et al.	2024	Deep Learning	98.82%
8	M. O. Khairandish, M. Sharma, et al.	2022	CNN-SVM	98.50%
9	S. Patil, and D. Kirange	2023	Ensemble DL	97.77%
10	S. Shanthi, S. Saradha, et al.	2022	Hybrid DNN	97.50%
11	T. Rahman, and Md. S. Islam	2023	Parallel Deep CNN	98.12%
12	Z. N. K. Swati and, Q. Zhao, et al.	2019	Transfer Learning	94.82%
13	Our proposed model		Deep CNN	99.31%

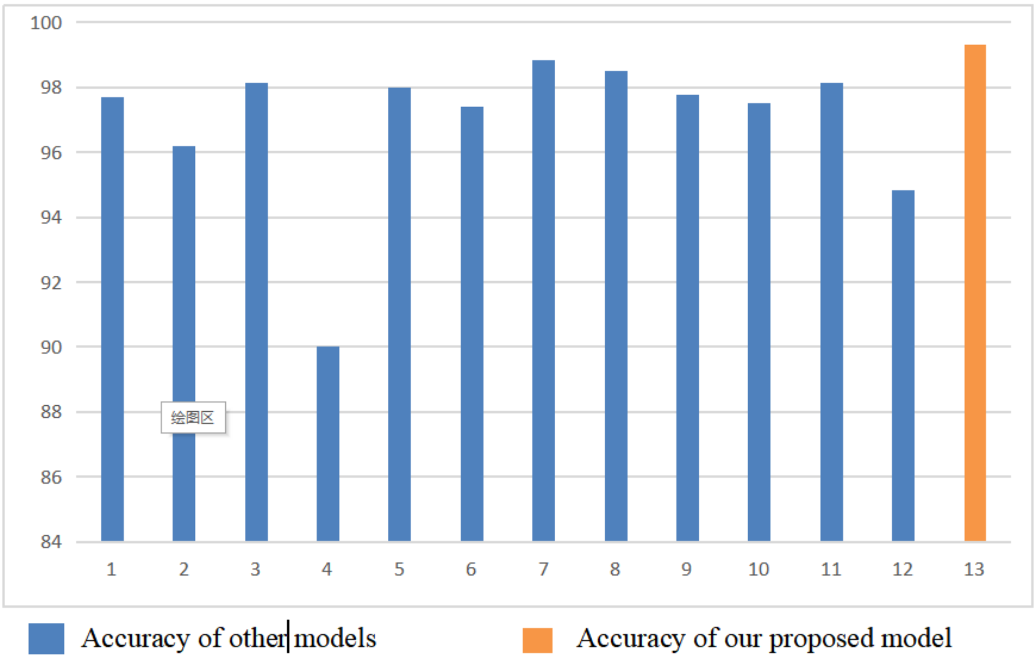

Figure 2. Accuracies of other models and our model.

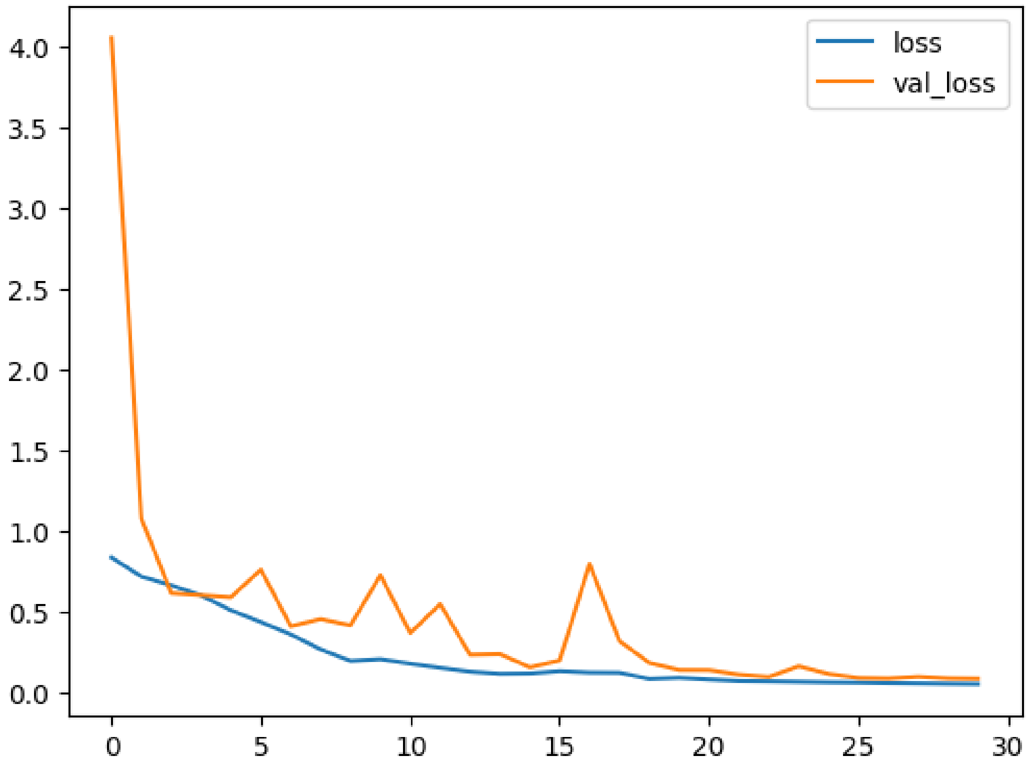

Figure 3. Loss occurred in training and testing.

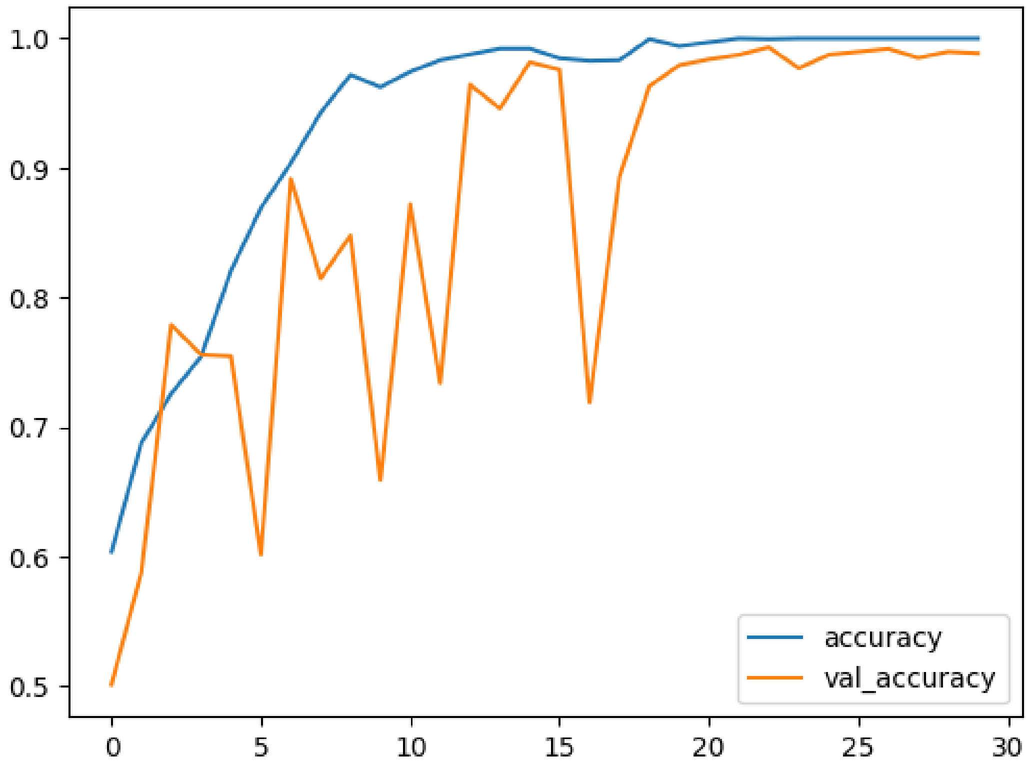

Figure 4. Accuracy obtained in training and testing.

3.1. Statistical analysis

The performance of the proposed model was quantitatively evaluated using classification accuracy as the performance metric. The model was trained on 2023 MRI images and tested on a separate dataset containing 868 MRI images, to ensure unbiased performance estimation. The achieved accuracy score reflects the proportion of correctly classified images out of the total test images.

The evaluation did not include cross-validation; instead, a conventional train-test split strategy was employed. As this study focuses on a fundamental convolutional neural network architecture, no additional baseline models were considered for comparison. Furthermore, no statistical hypothesis testing or confidence interval estimation was performed. Future work may incorporate more advanced evaluation techniques.

4. Discussion

As shown by Figure 4, the accuracy of our model becomes approximately saturated after 23 epochs. The model achieves an accuracy value of 99.31%, outperforming all other models in the literature, as shown in the Table 1. Figure 2 also shows that the accuracy obtained by our model is much higher than achieved by other models. After 23 epochs, the training and validation, as shown in Figure 3, become nearly constant, which shows the saturation of the model. The complexity of other models is much higher than our model. The total memory consumption of our model was 2.68 MB. Trainable parameters occupy approximately 2.68 MB, and non-trainable parameters occupy approximately 100 KB. This model is able to learn features from MRI images, - both from low-level (edges) and high-level (tumor patterns) images. From image input to classification, this model allows end-to-end work-flow which reduces complexity and minimizes human intervention. Once the model is trained, it can be scaled to thousands of medical images without any additional cost. The model provides improved diagnostic support, which helps radiologists. The model also presents a few drawbacks. It may overfit on limited data and lacks explainability, since convolutional neural networks are black-box models. If the data is imbalanced, the model will perform poorly to other populations. This model may support diagnosis but cannot be a replacement of an expert radiologist.

5. Conclusion

The objective of this study was to enhance the accuracy of brain tumor detection using brain MRI images by leveraging the hyperparameters and architecture of the convolutional neural network. The experimental results obtained show that the model outperforms other techniques used for brain tumor detection and classification. The proposed model showed a notably high accuracy of 99.31%. Despite the outstanding results, several challenges still remain. The requirement for big labelled datasets is a major limitation. Another is the variation in MRI acquisition protocols and image quality across different medical institutions, which limits model generalization. To address these challenges, further research is needed.

This research highlights the effectiveness of convolutional neural networks in enhancing the accuracy of brain tumor detection from MRI images. By leveraging the hyperparameters of the deep learning model, significant improvements are observed in classification performance compared to traditional methods. However, challenges related to data availability, model generalization, and interpretability remain critical areas for future exploration. To further improve CNN-based tumor detection, future research should focus on integrating multimodal imaging data, developing lightweight yet efficient architectures, and employing explainability techniques to bridge the gap between artificial intelligence and clinical decision-making. Once these aspects are addressed, it will facilitate the deployment of AI-driven diagnostic tools in real-world medical settings, ultimately contributing to more accurate and timely brain tumor diagnoses, resulting in more and improved patient outcomes.

This study underscores the potential of convolutional neural networks in advancing the field of medical image analysis and paves the way for more intelligent, accurate, fast, and efficient diagnostic tools in healthcare.

Use of AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

The authors are thankful to the management and administration of their parent institutions for providing the facility required to conduct this research. Also, the authors are thankful to Shivam Singh, student of B. Tech, (IT) at Bhagwan Parshuram Institute of Technology, Rohini, Delhi, India, for his cooperation in execution of the code. Special thank goes to Google Colab for providing the computing facility, without which it could have not been possible.

Conflict of interest

Authors declare that they have no conflict of interest

Author contributions:

Abhimanu Singh: Concept, drafting, design, data acquisition, editing, experimenting. Analysis.
Smita Jain: concept, design, manuscript reviewing, analysis.

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