

Detecting and Classifying Brain Tumors Using Deep Learning

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Abstract

Millions of people globally suffer from brain tumors, which are among the most serious and potentially fatal medical disorders. In 2022, there were about 321,731 new instances of brain and central nervous system tumors worldwide, according to the International Agency for Research on Cancer. Effective treatment planning depends on an accurate and prompt diagnosis, especially in places with limited access to medical knowledge. Promising technologies, such as computer vision and machine learning, help medical professionals diagnose these problems more quickly and accurately. This research explores the development of an automated system that uses deep learning and image-processing methods to detect and classify brain tumors. The system processes MRI images using a Convolutional Neural Network (CNN) to identify the kind and presence of tumors. The research also uses data augmentation techniques to diversify the training data to improve the system's resilience to changes in image circumstances. The findings will assist medical practitioners by enhancing treatment planning and reducing diagnostic delays.

Methodology

Two MRI datasets were used: a dataset for training and validation from Msoud Nickparvar [4] and an external dataset from Md Shahriar Mannan et al. [5] for generalization testing. Images underwent preprocessing by normalizing pixel values using rescaling and were initially augmented with a random horizontal flip. A Convolutional Neural Network (CNN) was then trained using this baseline augmentation strategy. Subsequently, extended augmentation techniques, including rotations, zoom transformations, and brightness adjustments, were included to enhance data variability and robustness and mimic real-world variations in image quality, focusing on improving recall for critical brain tumor detection. The model's performance was evaluated on both datasets using accuracy, precision, recall, and F1-score to ensure reliable and clinically relevant results.

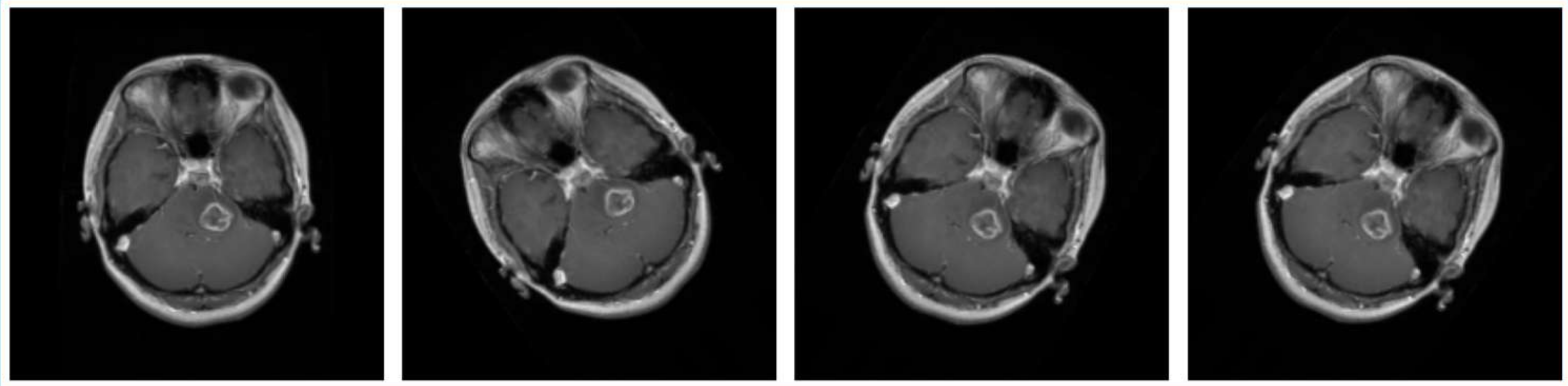


Figure 1: Examples of synthetic images from random rotation augmentation

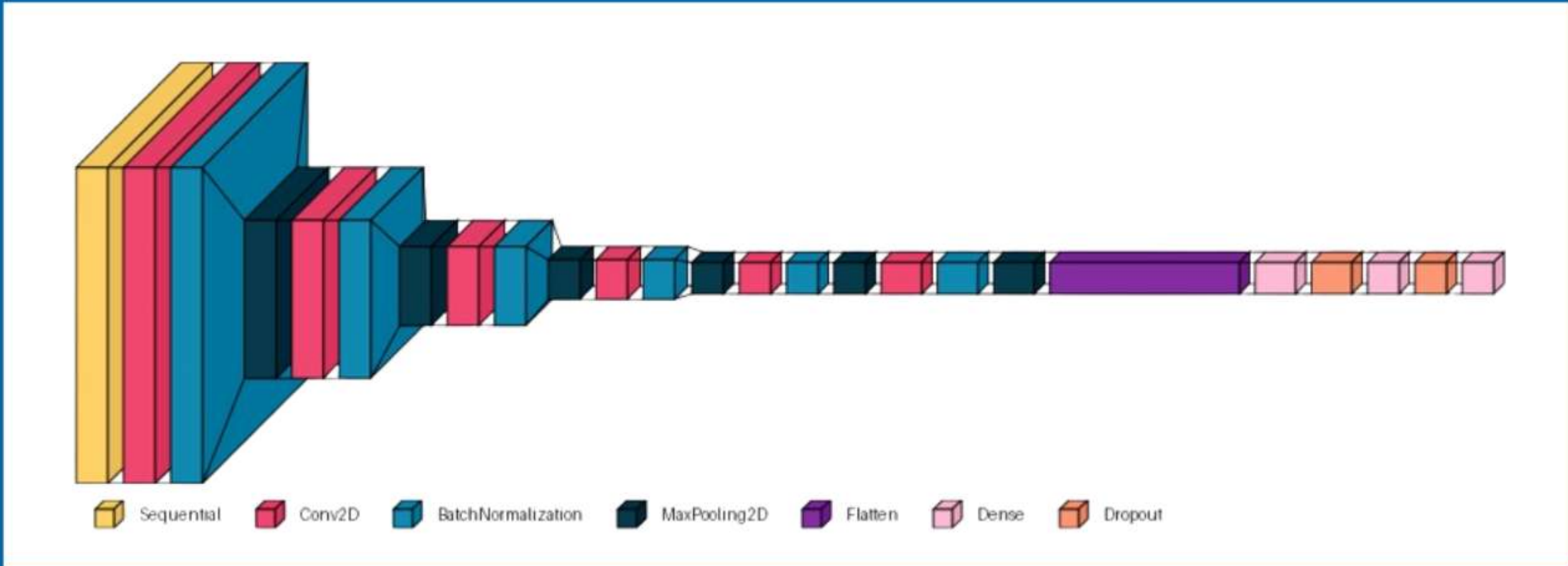


Figure 2: CNN Model Architecture

Results

Figure 4: Baseline Model (Minimal Augmentation) - Internal & External Evaluation

	precision	recall	f1-score	support
glioma	0.99	0.97	0.98	300
meningioma	0.97	0.96	0.96	306
notumor	0.98	1.00	0.99	405
pituitary	0.98	1.00	0.99	300
accuracy			0.98	1311
macro avg	0.98	0.98	0.98	1311
weighted avg	0.98	0.98	0.98	1311

	precision	recall	f1-score	support
glioma	0.99	0.66	0.79	373
meningioma	0.92	0.77	0.84	363
notumor	0.79	0.99	0.88	396
pituitary	0.81	1.00	0.89	373
accuracy			0.86	1505
macro avg	0.88	0.85	0.85	1505
weighted avg	0.88	0.86	0.85	1505

Figure 5: Enhanced Model (Extensive Augmentation) - Internal & External Evaluation

	precision	recall	f1-score	support
glioma	1.00	0.93	0.96	300
meningioma	0.96	0.93	0.94	306
notumor	0.96	1.00	0.98	405
pituitary	0.95	1.00	0.97	300
accuracy			0.97	1311
macro avg	0.97	0.96	0.96	1311
weighted avg	0.97	0.97	0.97	1311

	precision	recall	f1-score	support
glioma	0.99	0.86	0.92	373
meningioma	0.98	0.75	0.85	363
notumor	0.87	1.00	0.93	396
pituitary	0.82	1.00	0.90	373
accuracy			0.90	1505
macro avg	0.92	0.90	0.90	1505
weighted avg	0.91	0.90	0.90	1505

Discussion

Extended image augmentation techniques can enhance model robustness and improve recall on external datasets while maintaining high overall accuracy. Dataset size is considered a critical factor in determining the classification performance of a CNN architecture. While baseline augmentation achieved high accuracy, further tuning of augmentation parameters—such as rotations, zoom, and brightness—is needed to boost generalizability. Limitations in compute power prevented using hyperparameter optimization tools like keras-tuner [3], which could have provided a more comprehensive search for optimal settings. Additionally, the effectiveness of transfer learning is a promising strategy to improve accuracy and generalization, suggesting that future work could potentially integrate pre-trained models to enhance brain tumor detection performance.

Conclusion

Overall, this study shows that extended augmentation enhances the robustness and recall of a CNN for brain tumor detection, particularly on external datasets. Limitations in compute power prevented optimal hyperparameter tuning. Future research should focus on refined augmentation and transfer learning approaches to significantly boost accuracy and overall generalization.

Bibliography

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