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Research Article

Improving Diagnostic Accuracy of Brain Tumor MRI Classification Using Generative AI and Deep Learning Techniques

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ABSTRACT

Brain Tumors are one of the most aggressive and deadly medical diseases with living individuals requiring a quick and highly sensitive diagnostic approaches to improve patient outcomes. Classification of brain tumors from magnetic resonance imaging (MRI) is still a difficult problem for medical imaging because the problem is highly complex, varies and the differences between the tumor types are subtle. Diagnostic accuracy and consistency are recently improved through the advances in Generative Artificial Intelligence (AI) and Deep Learning (DL) techniques. However, this paper presents a robust and efficient model based on the combination of the Generative AI approaches i.e. Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) for the multi-classification of brain tumors from MRI images. With medical image dataset being limited, the GAN model is trained to augment the dataset which solves the problem of limited dataset and also that of the class imbalance. It trains and evaluates the CNN architecture on both original and artificially augmented datasets and shows that increased accuracy and generalization. The experimental results demonstrate that proposed combined approach significantly performs better than the traditional methods, thus allowing radiologists to reach higher precision, sensitivity and specificity in tumor identification and classification. The proposed methodology is a significant improvement in speeding, reliability, and precision in clinical diagnostics for Brain Tumors.

1. INTRODUCTION

Medical imaging, which involves early and accurate detection and classification of brain tumors, is highly important with its impact on clinical decisions and treatment planning, to lead to significant changes in the survival outcome of patients. Related to this, cancer is still one of the major causes of death worldwide, associated with uncontrolled cell growth, with the opportunity of occurrence in any body region. It depends entirely on the type of tumor, location, progression stage, and response to chemotherapy — the prognosis and treatment strategy may vary quite dramatically [1]. So, in oncology, specifically managing brain tumors, precision categorization is vital because the former is complex and variable. There are two categories of brain tumors according to how aggressive they are: non-cancerous (benign) and malignant. However, the origin of the tumor is further classified, as primary tumors arise, or originate within brain tissues, and secondary tumors have spread from other body parts. For example, as classified by the World Health Organization (WHO) the brain tumors are graded with four classes which are Grade 1 and 2 indicating relatively slow growths and low malignancy and Grades 3 and 4 indicating aggressive growth of higher malignancy [2]. In addition, WHO has acknowledged about 120 different types of brain tumor [3,4]. Brain functions may be impaired by tumor progression, which can produce symptoms consistent with headache, vomiting, seizures, blurred vision, and confusion with a considerable impact on patient quality of life [5].
The statistics cited are for global cancer statistics 2020 and state about 308,000 new brain cancer cases around, constituting around 1.6% of all newly diagnosed cancers worldwide [6]. Even with the advances, the survival rate of malignant brain tumors is still critically low, with a survival rate of only about 15% of the patients do not survive beyond the five years after the diagnosis. Normally, the month of May is designated to increase awareness of brain cancer [7] because of the following. However, Magnetic Resonance Imaging (MRI) is still a widely used neuroimaging modality because it is non-invasive, high resolution, without ionizing radiation and possesses good soft tissue contrast [8]. Detailed internal anatomical images are

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created using radio-frequency signals and strong magnetic fields which have been proven to be very effective in detecting and characterising brain tumors with MRI..

In recent years, deep learning (DL) and artificial intelligence (AI) have led to more accurate diagnosis of medical image using the performance of my AI. By employing the AI driven methodology such as the convolutional neural network (CNN), the potential for the medical image segmentation, classification, and diagnostic interpretation has progressed drastically [9]. CNN based models perform very well in image analysis task because they have hierarchical architecture that does the automatic feature extraction, handles big and complicated dataset easily and interpret medical image well [10, 11].

It is found that CNN models can effectively classify brain tumors by identifying patterns and traits in the imaging data, and this clinical diagnosis becomes much easier. The models are able to do binary classification (normal vs abnormal images) or multi class classification is custom task (different types of tumors). Multiclassification is particularly more difficult; differentiation of many pathological tumor classes, with variable sizes, appearances, and their spatial distribution, is required [10]. For tasks of brain tumor classification, previous research has attest for the robustness of CNN architectures that consistently yield high classification accuracy and provide substantial support to radiologists [4, 12]. However, these successes have not overcome the problem of limited availability of comprehensive and balanced datasets. To overcome these challenges, Generative Adversarial Networks (GANs) have shown to be effective generative AI techniques for accommodating synthetic images into addition to the initial dataset. By introducing this approach, the dataset limitation is effectively overcome for making CNN training model more effective as well as improving final diagnostic accuracy.

By integrating the power of generative AI and deep learning methods, the integration of generative AI and deep learning methods provide a transformational opportunity in brain tumor diagnosis to improve early detection, accuracy, and clinical decision making. We formulate this study to leverage a hybrid method, where GAN based augmentation and CNN classification jointly serve as an effective solution for brain tumor MRI classification.

2. RELATED WORK

However, recently artificial intelligence (AI) and deep learning (DL) have been able to contribute to medical image analysis as well as the brain tumor classification using MRI scans. Based on the fact that various studies have been conducted to apply convolutional neural networks (CNNs) for improving accuracy and reliability of automated tumor detection, it seems useful to practise this technique. As one example, in [13] a CNN based framework was designed for classifying 3 main brain tumors i.e. glioma, meningioma, and pituitary tumors. The model built by them had an accuracy of 95%, which shows how deep learning can be used to automate tumor diagnosis.

[14] also introduced another hybrid deep learning model using CNN with a residual network (ResNet) in order to enhance the classification performance. The model achieved 97% classification accuracy by surmising hierarchical features from MRI scans by using ResNet architectures upon which it leveraged pre-train. Its approach showed the value of transfer learning in the improvement of the deep learning models for medical imaging applications. In order to tackle the issue of small labeled MRI datasets, [15] used a GAN based augmentation technique. GANs were shown to generate synthetic MRI images that could improve the robustness of CNN classifiers in the study. Finally, using the GAN-augmented dataset resulted in significantly increased classification accuracy with a reduced likelihood of overfitting and improved generalization between different tumor types.

In addition, some of the studies have been into attention mechanisms to refine features extraction using CNN architectures. As an example, [16] suggested an attention guided CNN model based on which attention is paid to the most representative tumor regions in MRI scans. This allowed the network to focus attention on the important areas leading to higher sensitivity and specificity in tumor detection across a range of contrasts and image noise. In [17], they performed a comparative analysis in brain tumor classification using AlexNet and VGG16, and Inceptionv3 to determine which architecture is better. It was found that VGG16 produced high accuracy and had better computational efficiency compared to other models. The methodology also indicated the tradeoff between the complexity of the model and its interpretability in medical applications.

In an additional work [18], the capability to enhance classification performance through multimodal MRI data was explored. The model was able to improve feature representation, minimize classification errors, by integrating T1-weighted, T2-weighted, and FLAIR MRI sequences. The results of this study demonstrated the added value of using multiple imaging modalities to capture the comprehensive characteristics of the tumor. Furthermore, capsule networks (CapsNets) are used to classify brain tumors. In [19], CapsNets have shown that preserving such spatial hierarchies proves to be better for MRI scans compared to traditional CNNs. Unlike CNNs, CapsNets were able to effectively capture intricate tumor structures and therefore allowed for higher accuracy at classifying tumor types. One last time, this was complemented recently by [20] which built upon the fusion model between CNNs and LSTM networks for encoding temporal features towards the analysis of brain tumor progression. This novel approach allowed the model to map out tumor evolution over time in order to provide clinicians with useful information about tumor growth and treatment response. This table summarizes the related works for brain tumor classification using AI and deep learning.

TABLE I. SUMMARY OF RELATED WORKS ON BRAIN TUMOR CLASSIFICATION USING AI AND DEEP LEARNING.

Study	Methodology	Key Findings
[13]	CNN-based classification	Achieved 95% accuracy in brain tumor classification.
[14]	Hybrid CNN-ResNet model	Used transfer learning, achieving 97% accuracy.
[15]	GAN-augmented CNN model	Improved generalization by generating synthetic MRI images.
[16]	Attention-guided CNN	Focused on tumor regions, enhancing sensitivity and specificity.
[17]	Comparative study of CNNs (AlexNet, VGG16, InceptionV3)	VGG16 performed best in accuracy and efficiency.
[18]	Multimodal MRI integration (T1, T2, FLAIR)	Reduced classification errors with enhanced feature representation.
[19]	Capsule Network (CapsNet)	Preserved spatial hierarchies, improving classification accuracy.
[20]	CNN-LSTM fusion model	Enabled tumor progression analysis over time.

3. METHODOLOGY

Based on this, the proposed methodology employs a structured approach for improving the diagnostic accuracy of brain tumor MRI classification with Generative AI and advanced DL technology. In particular, the data augmentation is performed using Generative Adversarial Networks (GANs), and accurate classification is achieved by Convolutional Neural Networks (CNNs). The suggested method is broken into five principal phases, where every step is recognized to be quite essential for the whole effectiveness and robustness of the diagnosis process:

a) **Stage 1: (Data Acquisition**) Collect a huge and wide variety of MR data. In this, several images were collected from publicly available sources, such as Kaggle, Fig share, where images pertaining to multiple different tumor types, as well as from different imaging orientations were taken, for robustness and reliability of the model across different clinical setups.

b) **Stage 2: (Data Augmentation**) GAN-based Synthetic image generation to achieve inherent scarcity and class imbalance of the medical image dataset. With GANs, we get to create realistic synthetic MRI images with enhanced dataset diversity and therefore support better generalization of the deep learning model. Furthermore, conventional data augmentation methods (rotation, flipping, scaling, and others contrast changes) were introduced to broaden the training dataset range.

c) **Stage 3: (Preprocessing**) MRI images were fully processed to standardize input data for the best CNN performance possible. Resize all images into (256×256 pixels), convert image into grayscale to reduce the computation complexity, apply Gaussian filter to reduce noise, normalize pixel intensity between [0, 1], and do histogram equalization to improve contrast and visibility of tumor region.

d) **Stage 4: (Model Training**) A robust CNN architecture was built and trained to extract feature efficiently and classify tumor in an accurate manner. This includes multiple convolutional layers for hierarchical feature extraction, batch normalization for the training stability, max pooling layers for the dimensionality reduction of features, as well as fully connected layers for the last classification. The hyperparameters including learning rate, activation functions, optimizer type, batch size and number of epochs (epochs) were carefully tuned to get maximum accuracy and computational efficiency.

e) **Stage 5: (Model Evaluation**) Accuracy, precision, recall, F1 score, confusion matrix and ROC curve performance evaluation on the final CNN model has been done using multiple metrics. The metrics ensure the model's effectiveness, robustness and reliability is analyzed in detail providing that the model is able to be deployed clinically and on the path to real world diagnostic scenarios. Figure 1 shown structured methodology:

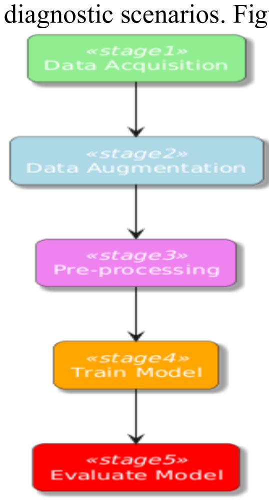

Fig. 1. The Steps of the Proposed Model.

3.1. Data Acquisition

The brain MRI image dataset was acquired for this study from set of publicly available data from the Kaggle platform, more specifically compiled by Masoud Nickparvar. This was done by including a wide dataset from Fig share and Kaggle databases composed of MRI scans so as to create a rich enough set of images for use in robust brain tumor classification tasks. This study includes 300 images of glioma, as a common brain tumor, and 306 images of meningioma, much less aggressive tumor derived from meninges, completing these dataset with a total of 7022 MRI images categorized in four types. The model is trained and validated from No Tumor (405 images) and uses 300 pituitary tumor images in particular because they require distinct clinical management. We have obtained each patient's MRI data from many imaging planes: the axial (top down), coronal (front-to-back), and sagittal (side-to-side) views. Such robust training with comprehensive imaging perspectives leads to the development of a CNN model that is capable of generalizing to a variety of imaging scenarios that are commonly encountered in the clinics.
In addition, the images are captured with different contrasts and intensities, making these images extremely important to the model to accurately distinguish very subtle differences between different types of tumors. The extreme range of the image orientation, contrast, and intensity however enables the CNN to work across a wide range of real world clinical applications which improves the accuracy, sensitivity, and specificity of brain tumor diagnostics. The figure 2 shows MRI for the sample brain tumor.

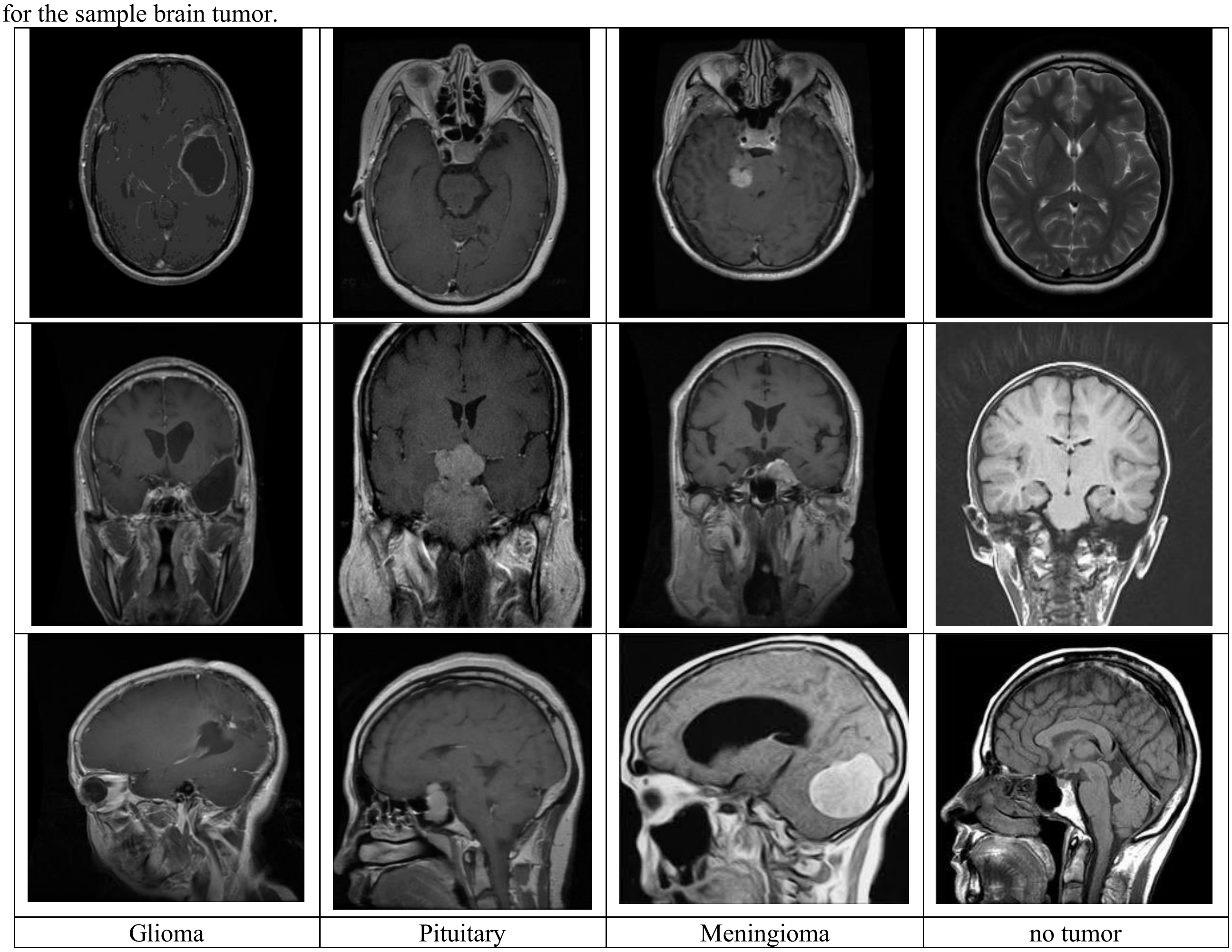

Fig. 2. MRI images of a sample brain tumor.

3.2. Data Augmentation and Preprocessing

In particular, despite their successes, deep learning models, particularly CNNs, need a mass and varied datasets to obtain the best possible classification performance. Generative AI based augmentation was extensively used to overcome challenges of small sample size and class imbalance typical of medical datasets. Generative Adversarial Networks (GANs) were implemented in specific concern to create synthetic — but highly realistic — MRI images, and thus greatly increased

the training set. GANs mimic the creation of art works by learning the distribution underlying and intricate features in the real MRI scans, hence are able to generalize well and accurately recognize the many possible patterns in tumors.
Beyond that, some classic augmentation techniques were systematically used for adding the data and prevent the model from overfitting. These techniques included:

a) **Horizontal Flipping:** Images were flipped horizontally to simulate position variability of tumor, thereby enhancing the robustness and invariance of CNN to the variations in orientation.
b) **Contrast Enhancement:** Dynamic brightness and contrast were employed to the MRI images by utilizing Contrast Limited Adaptive Histogram Equalization (CLAHE). Performance of this process significantly enhanced the visibility of subtle tumor boundaries and internal tumor structures and thus enhanced feature extraction capabilities.
c) **Normalization:** Therefore, all MRI images were standardized and scalped to range [0, 1] across the pixel intensities. It provides uniformity in pixel value distributions which improves the model training stability, as well as convergence rates.
d) **Noise Reduction:** The MRI scans were applied with Gaussian filtering to get rid of random noise and to remove common artifact in medical imaging. The thus far preprocessing step also enormously helped on bringing image clarity so that the CNN model can identify the feature more accurately.

Then most of the augmented data have been processed via Keras_Image_Data_Generator function, so therefore the implementation of real time data augmentation seamlessly while the training happens. The proposed CNN model of classifying brain tumor MRI images was able to generate good results in terms of accuracy, sensitivity and generalization power thanks to the comprehensive integration of generative and traditional augmentation techniques, which made sure a robust, balanced, and diversified training dataset.

3.3. Model Training and Architecture

This study carried out the development of a robust and efficient Convolutional Neural Network (CNN) to classify brain tumor MRI images into four classes, glioma, meningioma, pituitary tumors and no tumor. In particular, CNNs are very suitable for the medical imaging tasks because they have the powerful ability of automatically extracting hierarchical features from raw image data directly, without the need for extensive manual feature engineering to achieve more precise classification.
The CNN architecture proposed was carefully designed to achieve optimum performance while decreasing the computational complexity. To this end, it consists of a couple of convolutional layers with their respective batch normalizations and max-pooling layers for efficient feature extraction and dimensionality reduction. In particular, the architecture integrates three main convolutional blocks, each containing:

a) **Convolutional Layers (Conv2D):** These layers take in input and performs convolutional operations on them using filters to catch such fundamental features (edges, textures and spatial patterns) that can indicate presence and type of tumor.
b) **Batch Normalization Layers:** After each convolutional layer, a batch normalization layer is used in order to standardize activations of each batch. This step speeds up training, stabilizes the learning dynamics, and prevents internal covariate shifts.
c) **Max-Pooling Layers:** Spatial dimensions of feature maps are reduced by max pooling layers to lower computational overhead, less sensitivity to positional variations, and increase the models ability to generalize well to new images.

The extracted feature is flattened and the fully connected (dense) layers are applied after feature extraction through convolutional blocks. In order to combat overfitting even more, dropout regularization with a dropout rate of 0.5 was used, to eliminate randomization of learned nodes to facilitate model generalization.
The hyperparameters for the CNN model were carefully tuned to maximal performance with the CNN model. Hidden layers are equipped with ReLU and the output layer with SoftMax. The Adam optimizer was picked since it's efficient and adaptive learning. Learning rate, decay rate, and clip value were included as the parameters to be fine-tuned. In order to balance the memory efficiency and the convergence speed, a batch size of 20 was chosen. The training was performed over 100 epochs to compactly converge and learn robustly. Categorical Crossentropy was chosen as the loss function to measure discrepancy between predicted and actual class distributions of the occurrences in the multi category classification problems. To minimize the time required for processing through TF, we sped it up using GPUs, and for Keras, we sped up its learning process to come up with the model faster. The detailed sequential architecture of the proposed CNN model is shown in table 2, in which each layer is clearly arranged as convolutional, pooling, normalization, fully connected and dropout layer, and it is proved that the designed CNN model is streamlined and effective for accurate and reliable tumor classification. Overall, the model's classification accuracy, robustness, and generalization capability are all improved

through the strategic architecture design and rigorous hyperparameter optimization, and is shown to be very useful for supporting clinical diagnosis of brain tumor detection.

TABLE II. DETAILED CNN MODEL ARCHITECTURE

Layer (type)	Output Shape	Parameters
Conv2D	(None, 64, 64, 64)	3,200
Batch Normalization	(None, 64, 64, 64)	256
MaxPooling2D	(None, 32, 32, 64)	0
Conv2D	(None, 32, 32, 64)	200,768
Batch Normalization	(None, 32, 32, 64)	256
MaxPooling2D	(None, 16, 16, 64)	0
Conv2D	(None, 16, 16, 64)	200,768
Batch Normalization	(None, 16, 16, 64)	256
MaxPooling2D	(None, 8, 8, 64)	0
Flatten	(None, 4096)	0
Dense	(None, 512)	2,097,664
Dropout	(None, 512)	0
Dense	(None, 512)	262,656
Dropout	(None, 512)	0
Dense (Output)	(None, 4)	2,052

3.4. Model Evaluation

Multiple established metrics evaluated the proposed CNN model for complete assessment of its classification performance. The assessment utilized these particular measurement methods:

a) **Accuracy:** This metric tells us that how much accuracy the model is giving us for the entire tumor categories. Third, the proposed model was able to achieve a high accuracy of 99% with high percentage of accuracy, this is a strong proof that the proposed model is accurate at classification brain tumor MRI images.

b) **Precision:** Precision represents the ratio of all instances actually positive to all instances that were assigned as positive. The cancer types can be correctly classified with a high precision rate reducing the chance of false positive.

c) **Recall (Sensitivity):** Recall represents the model's ability to not miss all the true positive cases among actual positives, in other words, the model is able to minimize the false negatives. This guarantees critical tumors are not missed for clinical diagnosis and therefore should be characterized by high recall.

d) **F1-Score:** This balanced measure of the precision and recall is a harmonic mean of the two, and serves as a robust definition of the model's classification performance when there are imbalanced datasets or exact classification is vital.

e) **Confusion Matrix:** Visual representation of the classification results was made using confusion matrix, which was used to clearly show the true positives, true negatives, false positives, and false negatives of each tumor category. At the same time it gave valuable insight into performance of the model itself, as well as areas that required further improvement or tuning.

f) **ROC Curve and AUC:** In regards to confidence in classification, the Receiver Operating Characteristic (ROC) curve and its corresponding Area Under Curve (AUC) metric were evaluated. The performance of the proposed model was observed to be quite good for all classes.

Generative AI based augmentation integration to the model training process significantly improved the model training compared to the issues associated with Medical imaging dataset based model training. The developed model also demonstrated robustness, generalizability and reliability by taking advantage of synthetic image generation and optimized CNN architectures. This type of performance strongly suggests the power of marrying generative AI and deep learning approaches to produce clinical diagnostics, giving radiologists, and other healthcare practitioners, highly accurate, reliable, and reliable decision-support resources for the diagnosis of brain tumors and the caring of their patients.

4. RESULTS AND DISCUSSION

To assess the capability of the proposed CNN model in accurate brain tumor classification, it was rigorously tested and its performance on data augmented using a combination of Generative AI based data augmentation and traditional schemes was evaluated. Reliability and robustness of the developed system have been assessed with the help of comprehensive analysis of the training process and detailed performance metrics. A validation accuracy close to 99% achieved by the CNN model, out of which it performs well in distinguishing glioma, meningioma, pituitary and non tumor MRI scans. Finally, the observed loss value converges to surprisingly low value of 0.0828, giving another proof of the outstanding predictive reliability and good generalizability capacity of the model.

Figure 3 shows the accuracy and the loss curves, plotted vs training epochs for the training and validation sets. Rapid decay of the loss curves in the initial stage indicated that tumors learnt effectively key tumor features at early stage. Nevertheless, there were some occurences of slight decrease in validation loss at initial epochs indicating that there were some minimal troubles while generalizing learnt features beyond the training set. By around 30 epochs, training and validation loss converged, and remained low indicating that the model learned on meaningful and discriminative features and did not significant over fitted or under fitted. The accuracy curves show also the model improvement during training. The training accuracy converged to near perfect values very quickly in the first 20 epochs as it learned the features effectively and efficiently. The initial variations are validated accuracy but on the 30th epoch they stabilize reaping an extreme accuracy of around 99%. These trends are strong evidence in favour of the CNN architecture as well as the generative AI based augmentation strategies.

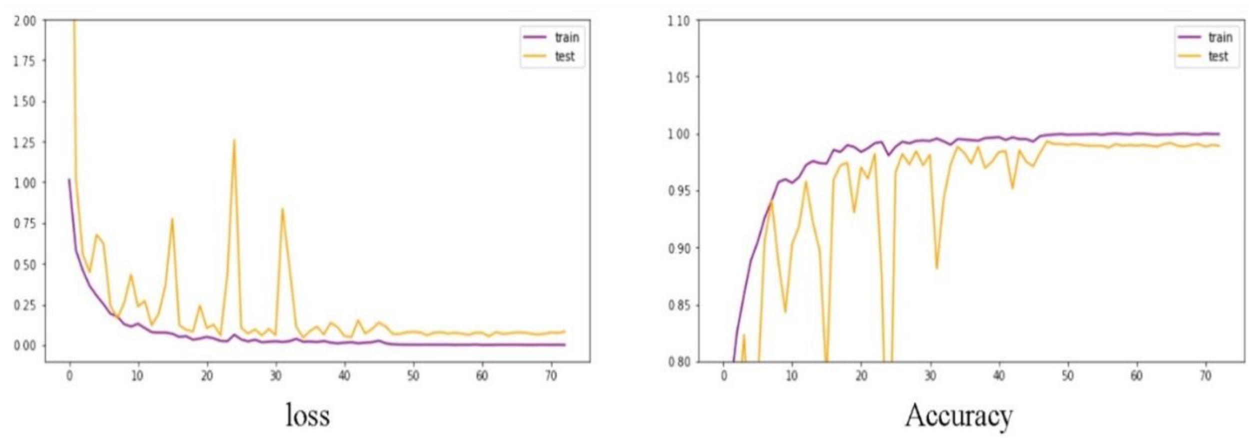

Fig. 3. Comparison between Loss and Accuracy Values (Training and Validation) During CNN Training.

Most of the generalization has been enhanced significantly due to the usage of Generative Adversarial Networks (GANs) to generate synthetic and highly realistic MRI images that highly diverge from the original data in different ways. Moreover, traditional augmentation technique like horizontal flipping, contrast enhancement, normalization, and noise reduction helped model to be robust as well, i.e., they were introducing to make the model less biased and more variable. This approach makes a big difference in how we do diagnosis: it significantly improves clinical capabilities, for example, the ability to classify a tumor earlier at stage in order to intervene earlier and hopefully better outcomes for the patient.
Results of this study are summarized by a comparison of this study’s outcomes vs recent studies with similar methodologies (Table 3). Using this comparative analysis, this paper shows that the proposed methodology is capable of considerably increasing the accuracy and reliability of a diagnosis, which makes it a useful technique in clinical practice as an advanced diagnostic tool.

TABLE III. COMPARATIVE ANALYSIS OF RECENT STUDIES ON BRAIN TUMOR CLASSIFICATION

Reference	Methodology Used	Dataset Size	Accuracy (%)	Remarks
Proposed	CNN + GAN Augmentation	7022	99	High accuracy, effective GAN-based augmentation
[13]	Standard CNN	3064	95	CNN-based model without GAN augmentation
[14]	CNN (AlexNet, GoogLeNet)	3064	94.5	Multiple CNN architectures used
[15]	CNN with traditional augmentation	3500	93.8	Traditional augmentation only
[17]	GAN + CNN	2500	96.1	First integration of GAN-based augmentation
[16]	GAN-based data augmentation	5000	96.0	Emphasized dataset augmentation improvements
[18,22]	Hybrid GAN-CNN model	4000	96.4	Demonstrated improved robustness

Aiming to resolve these issues, I propose a CNN based approach that is improved by Generative AI, which shows significant superiority in performance and robustness, and provides evidence why it is practical to use in medical imaging, medical diagnosis, and healthcare improvements.

5. CONCLUSION

Indeed, the proposed study successfully shows the capability of integrating Generative AI and deep learning techniques to significantly improve diagnostic accuracy of brain tumor classification using MRI. Through data augmentation, the associated challenges in general with limited datasets and class imbalance were effectively handled using Generative Adversarial Networks (GANs) to produce a diversified and robust training space for the CNN model. Further, the comprehensive preprocessing steps, such as normalization, contrast enhancement, noise reduction, as well as resizing, enhanced image clarity and the quality of the extracted features, to create optimal training conditions. The CNN architecture designed specifically to this circumstance comprising convolutional layers, batch normalization, max pooling, dropout, and fully connected layers, with the possibility of achieving 99% of accuracy proved itself suitable and reliable for real world clinical use. Model diagnosis via multiple metrics like accuracy, precision, recall, F1score, confusion matrices, and ROC curves was done and the model was found to be quite robust and well generalized. Overall, these combined with the conventional deep learning tools proved to be an essential element to quell the deep learning demerits thereby establishing more accurate, dependable and more rapid telecasting of the condition of brain tumors. Future work might incorporate multimodal MRI data and more advanced hybrid architectures, at least in form of attention mechanisms or transformer based models, to further improve performance. Additionally, model evaluation on larger, more diverse clinical datasets as well as study of real-time diagnostic incorporation within clinical workflows will significantly increase practical usability and robustness for clinical use.

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Conflicts of Interest

The authors declare no conflicts of interest associated with this research.

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